Network cognition

Roberta Dessí[*], Edoardo Gallo[†] and Sanjeev Goyal [‡§]

July 2015

Abstract

We study individual ability to memorize and recall information about friendship networks using a combination of experiments and survey-based data. In the experiment subjects are shown a network, in which their location is exogenously assigned, and they are then asked questions about the network after it disappears. We find that subjects exhibit three main cognitive biases: *(i)* they underestimate the mean degree compared to the actual network; *(ii)* they overestimate the number of rare degrees; *(iii)* they underestimate the number of frequent degrees. We then analyze survey data from two 'real' friendship networks from a Silicon Valley firm and from a University Research Center. We find, somewhat remarkably, that individuals in these real networks also exhibit these biases.

The experiments yield three further findings: *(iv)* network cognition is affected by the subject's location, *(v)* the accuracy of network cognition varies with the nature of the network, and *(vi)* network cognition has a significant effect on economic decisions.

[*]Toulouse School of Economics (IDEI and GREMAQ), and CEPR; email: *roberta.dessi@tse-fr.eu*

[†]Faculty of Economics and Queens' College, University of Cambridge; email: *edo@econ.cam.ac.uk*.

[‡]Faculty of Economics and Christ's College, University of Cambridge; email: *sg472@cam.ac.uk*

[§]We thank Tiziana Casciaro for making her data available to us. We thank Olivier Darmouni, Peter Schwardmann and James Tremewan for excellent research assistance. We thank Antonio Cabrales, Gary Charness, Andrea Galeotti, Margaret Meyer, Werner Raub, Patrick Rey, Robert Sugden, Christophe Vanberg and seminar/conference participants at Cambridge, the ESF Workshop on Information and Behavior in Networks (Oxford), BEE Workshop (Lyon), the Workshop on Social Networks and Economics (Microsoft Research, Cambridge), the WIN Conference (NYU) and UEA. Financial support from the TSE Fondation Jean-Jacques Laffont Seed Funding Programme is gratefully acknowledged.

1 Introduction

A growing body of theoretical and empirical research argues that the structure of social networks is a crucial determinant of individual behavior and welfare.[1] In light of the recent development of social networking sites and tools, individuals have arguably become even more aware of the structure of the social relationships in which they are embedded.[2] However, learning and using information about network structure is far from being a simple task. A salient feature of networks is their complexity: there are thousands of potential network configurations even in a group with just a dozen members. Moreover, the nature of social interactions often makes it difficult to record or access information other than through memory, making this a cognitively demanding task.

The objective of this paper is to investigate individual cognition of social networks. Is there significant heterogeneity in the way individuals process, recall and use network information? Are there common systematic biases? Do they affect individuals' economic decisions? These are some of the questions we address. A distinctive feature of our work is that we use data drawn from a combination of laboratory experiments and surveys from the field. We examine the cognition of the distribution of connections (the so called 'degree' distribution) and how cognition varies with location in the network.[3] Our focus on the distribution of connections is motivated by recent theoretical research highlighting its key role in understanding individual behavior and in investigating aggregate social and economic dynamics in networks.[4]

In the laboratory experiment, we use the following novel methodology: subjects are shown a graphical representation of an imaginary friendship network and they are (randomly) assigned to be a node in the network. After a fixed amount of time (typically 1 minute[5]), the network disappears and subjects are asked questions about the structure of friendship relations in the group. For instance, the question *"How many people in the group (including yourself) have exactly x friends?"* allows us to generate the subjects' perception of the degree distribution by aggregating the answers for the different values of x.

We find substantial individual heterogeneity in network cognition. However, three main biases emerge clearly. First, subjects *underestimate the average degree in the network*. The cognitive mean degree is (roughly) 4 while the actual mean degree is over 4.6.

[1] See Goyal [2007], Jackson [2008] and Vega-Redondo [2007] for overviews of this work.

[2] In a special report, the *Economist* magazine asserts that "social-networking sites [...] have made people's personal relationships more visible and quantifiable than ever before"("A world of connections," *The Economist*, January 28, 2010).

[3] The *degree* of a node is the number of its direct connections. The degree distribution in a network tells us the number of nodes with different degrees. For formal definitions refer to section 2.

[4] See Galeotti et al. [2010] for a study of the relationship between network degree distributions and strategic behavior, and Vega-Redondo [2007] for an exposition of the literature which relates a variety of dynamic processes in networks to the underlying degree distribution.

[5] We decided to allocate one minute in most cases after obtaining feedback from a pilot.

Second, subjects *overestimate the number of rare types* in the network, where the "type" of a node is its degree. Specifically, they perceive that there exist individuals of types 1, 2, 5, 6, and 8, which are actually absent from the real network. Third, they *underestimate the number of frequent types in the network*: there are five nodes for each of types 3, 4 and 7 and subjects perceive a significantly lower number.

The laboratory setting allows a researcher to control the parameters of the experiment, but this tight control raises questions about the scope of the findings. The first issue is internal validation: we choose specific networks to show to the subjects and the network information is shown using a visual representation. A natural question is therefore whether our findings are sensitive to the specific networks used and to our choice of conveying the information with a visual representation. The second issue is external validation: do these biases also arise in actual social networks or are they an artifact of the experimental methodology? We address these concerns by analyzing two well-known survey data sets on social networks. The first data set is the friendship network of a Silicon Valley firm, which was first studied in Krackhardt [1987]. The second data set is the friendship network in a University Research Center, which was first studied in Casciaro [1998].

We show that individual cognition of the real friendship networks in these two data sets exhibits the three main biases identified in our experimental work. In particular, individuals in the Silicon Valley firm network perceive a lower mean connectivity than the true mean, they overestimate rare types and underestimate (almost all) frequent types. Individuals in the University Research Center network perceive a lower mean connectivity than the true mean, they overestimate (most) rare types and underestimate (most) frequent types. This congruence of findings from our experiment and from the field data is, in our view, quite striking. It provides corroborating evidence of the existence of the specific cognitive biases that we identified in the laboratory experiments. Moreover, it allows us to make a more general methodological point: the network cognition processes in the laboratory appear to be similar to the cognition processes of individuals located in actual social networks.

The laboratory methodology enables us to make three important additional contributions relative to the analysis of survey data. First, we are able to investigate in a clean way location effects: by randomly assigning subjects to different nodes in the network, we can avoid the endogeneity problems typically present in survey data. We find that indeed *location affects cognition*: low and high "type" (degree) subjects differ in their perception of the network along two dimensions: the perception of other low types, and the identity of key individuals in the network. Second, we are able to study whether the *accuracy of network cognition varies with the architecture of the network*: we find that a mean preserving spread of the degree distribution leads to greater cognitive accuracy.[6] Third, we are able to investigate whether *network cognition affects subjects' economic decisions*. Having answered a range of questions designed to probe how they process and

[6]For formal definitions see section 2.

recall network information, our subjects then face two decision problems. Both involve a decision to contribute in a network public good game, where other players' contribution decisions are assigned by the experimenter and communicated to the subject, thereby removing any strategic uncertainty. The subject therefore faces what would be a very simple decision problem if she had complete knowledge of the network: in one problem, the payoff-maximizing strategy is to contribute, while in the other it is more profitable not to contribute. However, the subject does not have access to network information while making her decision: she has to rely on her memory. The memory task is more demanding in one of the decision problems. We find, as expected, that in this case subjects are less likely to choose the action that maximizes their monetary payoff. Moreover, two measures of an individual's cognitive accuracy obtained in the earlier part of the experiment significantly predict behavior. The first is a measure of how accurately the individual perceives very low (degree) types in the network. This is particularly relevant for one of the decision problems, and indeed its effect is only significant for that problem. The second measures one of the cognitive biases we identified earlier, namely the tendency to overestimate the number of rare types in the network. This bias appears to increase the probability of contribution to the public good in *both* problems, suggesting that subjects with a very inaccurate perception of the network are unable to pick the payoff-maximizing strategy.

The validation of the results using both the laboratory and survey-based methodologies allows us to remain agnostic about the specific mental processes at work when individuals memorize and recall information about their social network. It is not necessary for the validity of our results that individuals actually use mental visualizations of the network structure to memorize social network information in their real life, because cognitive biases *(i)*-*(iii)* also emerge in the survey-based method where the elicitation of the networks is not based on any visual aid or tool. Our claim is that the two elicitation methods we use capture some aspect of the way individuals elicit social network information in real-life, and this allows us to identify actual cognitive biases despite the fact that our elicitation methods may differ from the ones used by individuals in everyday life. The investigation of the actual mental processes involved in the memorization and recollection of social network information is a fascinating question which we leave to further study.

The remaining part of this section surveys the related literature. Section 2 briefly introduces basic concepts and notation on networks, and explains the design of the experiment. Section 3 presents the main results of the laboratory experiment. Section 4 presents the results of the analysis of the survey-based data sets. Section 5 presents further results from the laboratory experiments. Section 6 concludes. Appendix A contains the instructions which were shown to the subjects participating in the experiment, and Appendix B contains all the network images which were displayed to subjects in the various treatments.

1.1 Literature review

The study of network cognition is still a largely unexplored area and, to the best of our knowledge, the present paper is the first in economics to study network cognition. So we see it as a stepping stone to further experimental/empirical work which can be used to assess existing theory and also as an input to formulate more realistic assumptions on network cognition in theoretical models.[7]

In the psychology and behavioral economics literature there has been a sustained interest in the calibration of probabilities. Early contributions include Alpert and Raiffa [1969/1982]; for a survey see Tversky and Kahneman [1982]. This research elicits individuals' confidence intervals for quantities they do not know. The findings suggest that confidence intervals are too narrow, implying that subjective probability distributions are too 'tight': individuals assign relatively too much weight to 'middle' values and too little weight to values at the 'periphery' of the distribution. Our work has two novel features in relation to this body of work. First, we study distributions in the context of networks. Second, we find that individuals exhibit three specific biases: underestimation of the mean number of connections, overestimation of rare types and underestimation of frequent types.[8]

In a series of influential contributions, Robin Dunbar and his collaborators (see Dunbar [1998]) have proposed and empirically studied the "social brain hypothesis": a specific part of the brain (the neocortex) deals with processing and synthesizing information on social relationships, and therefore the volume of the neocortex is a constraint on the maximum group size. Several empirical studies on both humans and different primate species support the social brain hypothesis (see Dunbar [2003] for a comprehensive review). This work has received wide attention, and the approximate threshold of 150 for group size for humans is popularly known as "Dunbar's number." Our work shares Dunbar's research premise that there are cognitive constraints in individuals' ability to process and recall information about human relationships. However, we focus on the consequences of these constraints for individuals' perception of the structure of their social environment, instead of Dunbar's focus on the consequences for the size of social groups.

In social psychology there is an active research programme on the study of network cognition using a survey-based methodology (see Moreno [1960], Newcomb [1961], Roeth-

[7] Existing experimental work on networks in economics typically provides subjects with specific network information; for an interesting recent paper in this tradition, see Charness et al. [2014]. See Choi et al. [2015] for a comprehensive review of experimental work on networks.

[8] There is a distinguished tradition of work on perception of distributions in the context of choice under uncertainty. Early work by Preston and Baratta [1948] suggested that individuals overestimate returns from gambles with low probability of success and underestimate returns from gambles with high probability of success. In prospect theory, these, and related observations, have been reconciled through the assignment of non-linear weights to probabilities of uncertain events. In particular, the evidence is consistent with low probabilities being assigned large weights and high probabilities being assigned small weights, see Kahneman and Tversky [1979] and Wakker [2010].

lisberger and Dickson [1939] and Krackhardt [1987].) In recent years, Kumbasar et al. [1994], Krackhardt and Kilduff [1999], Casciaro [1998], Smith et al. [2011], and others have used this methodology to identify a variety of cognitive biases in network perception. There are three main differences between this literature and our work. The first difference is about the object of study: their work focuses on the cognition of specific ties, while we study the degree distribution which is a statistic about the whole network. The second difference concerns methodology: existing work has, with a few exceptions, used only surveys of real networks, while our primary source of data comes from a laboratory experiment. The laboratory setting allows an unambiguous identification of the effects of network structure on cognition and behavior, which is not possible using survey data due to severe endogeneity issues. We then exploit the methodological complementarity between survey based work and the experimental approach by re-analyzing the data from two surveys, from Krackhardt [1987] and Casciaro [1998], to validate our experimental work. The third difference is that we investigate the link between network cognition and economic decisions.

The psychology literature has also explored how different visual layouts of networks influence individuals' perceptions of a network. McGrath et al. [1996] show that subjects are able to see two subsets or communities in the network in the standard layout with the two communities spatially separated in the visualization or even when one node is misplaced in the other community in the visual representation, but they fail to do so when the nodes are visually arranged in three communities. McGrath et al. [1997] show that the perceived prominence of a node tends to increase when the node is more central in the visualization, but perception of the most prominent nodes is not significantly affected by the visual arrangement. Huang [2007] uses eye tracking methodology to investigate how the crossing of edges in the visualization affects subjects' speed in searching paths and locating nodes in a network. In our experimental design we draw insights from this research to choose network visualization layouts that facilitate the subjects' task to memorize the network information. The purpose of our paper is quite different from this literature as we do not focus on the effects of network visualization on perception, but we strive to pick a visualization that seeks to minimize any bias from the visual representation in order to study individuals' ability to memorize and recall information about their social network independent of the methodology chosen to convey this information in the lab.

2 Set-up

Section 2.1 introduces some basic notation and definitions on networks. Section 2.2 describes the set-up of the experiments, and Section 2.3 describes the procedures used in the experiment.

2.1 Basic notation

It is useful to briefly introduce some basic concepts and notation on networks. Let $N = \{1, 2, , 3, ...n\}$ be a set of nodes; in our experiments, $n = 15$. Denote by $g_{ij} \in \{0, 1\}$ a friendship between two nodes i and j, so the variable g_{ij} takes on a value of 1 if there exists a friendship between i and j, and a value of 0 otherwise. The set of nodes taken along with the friendships between them defines a network denoted by g. Let $N_i(g) = \{j|g_{ij} = 1\}$ denote the nodes with whom node i shares a friendship relation; this set will be referred to as the *friends* of i. Let $\eta_i(g) = |N_i(g)|$ denote the *degree* of node i, which is the number of friends of node i in g. We will refer to the degree of a node as its *type*. The *mean* degree in network g is defined as $\hat{\eta}(g) = \sum_{i \in N} \eta_i(g)/n$.

Let $\mathbf{N}_k(g)$ be the number of nodes in network g with degree equal to k. The degree distribution in a network is a vector P, where $P(k) = |\mathbf{N}_k(g)|/n$ is the fraction of nodes with degree k. This degree distribution has support on $\mathcal{D} = \{0, 1, 2, ..., n - 1\}$. The degree distribution allows for an elegant way to study changes in network structure. In particular, the idea of redistributing links is captured by a Mean Preserving Spread (MPS) of the degree distribution. Given a degree distribution P, let the cumulative distribution function be denoted by $\mathcal{P} : \{1, 2, ..., n - 1\} \to [0, 1]$, where:

$$\mathcal{P}(\eta) = \sum_{x=0}^{\eta} P(x). \tag{1}$$

Let P and P' be two degree distributions defined on $\{0, 1, 2..., n - 1\}$ and $\mathcal{P}$ and $\mathcal{P}'$ the corresponding cumulative distribution functions.

Definition 1. P' is a mean preserving spread (MPS) of P if and only if P and P' have the same mean and

$$\sum_{k=1}^{x} \mathcal{P}(k) \leq \sum_{k=1}^{x} \mathcal{P}'(k) \tag{2}$$

for every $x \in \{1, 2, ...n - 1\}$.

A simple example of a MPS shift for a network with $n = 4$ nodes arises when we move from a line network in which $g_{12} = g_{23} = g_{34} = 1$ to a star network in which $g_{12} = g_{13} = g_{14} = 1$.

2.2 Experimental design

Structure and information. All subjects in our experiment participated in sessions with the same structure, consisting of five stages, summarized below and described in detail in the instructions provided in Appendix A.

In the first stage the focus is on the perception of the overall structure of the network, the second stage explores how perception varies with changes in network structure, the third stage investigates perception of specific links in a network, and finally in the last two stages we study individual decision making in a context where knowledge of the network is important. The core part of this paper focuses on the cognition of the overall network, and therefore on the results of the first stage. In the last part of the paper we also present the results of how perception varies with changes in the network (Stage 2) and how limitations in network cognition affect economic behavior (Stages 4 and 5). We leave for future work the analysis of Stage 3 because of the different focus on the perception of specific links in the network rather than the overall network structure.

Each stage of our experimental sessions was self-contained and explained to participants after the end of the previous stage. No feedback on performance was given until after all the stages were completed. Participants were not allowed to use any writing tool (e.g. pencils, pens) and they were not allowed to use paper throughout the experiment. In addition, we asked a set of questions about the network degree distribution in Stage 1, and then again at the end of Stage 5 using the same network structure, to check whether increasing familiarity with the task affected accuracy of responses (see below for further discussion).

In each of the first three stages, subjects are shown a graphical representation of a network for a given length of time, and then they are asked questions about it after the network has disappeared. Subjects cannot go back to previous screens or alter their answers once they have moved to the following screen. They can take as much time as they wish to answer any of the questions. The subjects are instructed to imagine that the nodes of the network represent other students in the university, and that connecting lines between nodes represent friendships. Just before viewing the network, they are told that they will see the network for t seconds, and then the diagram will disappear from the screen, and they will be asked a set of questions about the relationships they have just seen. No information is given about the nature of the questions to follow, to ensure that participants are not led to focus on specific features of the network.

In each stage there are two treatments. All subjects see the same network, but subjects in a treatment condition will see a different node colored in 'red' and labeled "YOU", relative to subjects in the other treatment. Here is a more detailed summary of these first three stages; all the Figures referred to in the text are in Appendix B:

- **Stage 1 - Degree distribution.** Subjects are shown the network at the top of Figure 11 (first treatment) or the network at the bottom of Figure 11 (second treatment) for 60 seconds. We chose one minute after trying this out in a small pilot experiment and obtaining feedback from pilot participants. After the network disappears they are asked a number of questions, including questions such as *"How many people in the group (including yourself) have exactly x friends?"* which allow us to generate subjects' perception of the degree distribution. Each question appears on a separate screen; after answering the current question, participants click to move on to the next screen.

- **Stage 2 - Changes in the network.** This stage investigates how perception varies when we modify the structure of the network while holding constant the mean degree (see section 2). In the first treatment subjects are shown the network at the top of Figure 12 for 30 seconds, and then the network at the bottom of Figure 12 for 30 seconds. Note that the second network is a mean preserving spread of the first network. In the second treatment subjects are first shown the network at the top of Figure 13 followed by the network at the bottom of Figure 13: the only difference between treatments, apart from the assigned location, is that the mean preserving spread network is shown before the original network in the second treatment. The subjects are then asked a number of questions about the two networks, which are different from the questions asked in Stage 1.

- **Stage 3 - Specific links.** Subjects are shown the network at the top of Figure 14 (first treatment) or the network at the bottom of Figure 14 (second treatment) for 60 seconds. They are then asked a different set of questions from the first two experiments, which focus on the perception of specific links in the network.

In the last two stages, subjects are shown a graphical representation of a network for 60 seconds, and then they have to make an economic choice which depends on their ability to remember who their friends (and friends of friends) are. The decision problem is akin to a binary-action best-shot game with a threshold. Subjects are given an endowment of 2 pounds, they are shown the network, and after the network disappears they are told which other individuals in the network have decided to contribute (the other individuals' contribution decisions are set by the experimenter in order to remove strategic uncertainty and ensure participants face the same decision problem). The choice faced by all subjects is whether to contribute or not. If they contribute and a minimum number of friends (and friends of friends) also contribute then they earn an additional 4 pounds, otherwise they lose their endowment. There is a unique treatment so all subjects are assigned to the same node in the network and they are told the same information about the names of the other individuals who contribute. This is a more detailed summary of the last two stages, all the Figures referred to in the text are in Appendix B:

- **Stage 4 - Unknown decision problem.** First, subjects are simply told that they are going to face a decision problem with real monetary payoffs, and that the effects of decisions on payoffs will depend on the way players are connected. They are then shown the network at the top of Figure 15 for 60 seconds. Second, the network disappears and they are told about the decision problem: they earn 4 pounds if the sum of their contribution, the contributions made by each of their friends, and the contributions made by each friend's friends, is equal to or more than 6 pounds. Finally, they are told the names of the individuals in the network who contributed, and they are asked whether they want to contribute or not.

- **Stage 5 - Known decision problem.** First, subjects are told about the decision problem: they earn 4 pounds if the sum of their contribution and the contributions made by each of their friends is equal to or more than 4 pounds. Second, subjects are shown the network at the bottom of Figure 15 for 60 seconds. Finally, they are told the names of the individuals in the network who contributed, and they are asked whether they want to contribute or not. After they have announced their decision (to contribute or not), subjects are asked the same set of questions about the degree distribution as in Stage 1. Note that the network shown in Stage 5 is the same as the one in Stage 1 except for the names attached to each node. A further difference with the task in Stage 1 is that all the subjects were assigned to the same node. The reason to have these questions is to check for the effect of experience and learning in the course of the experiment (see below).

Incentives. Participants received a fixed participation fee (£3) and earnings related to their performance. At the beginning of the experiment they were told that their final remuneration would depend on their decisions/answers and on those of the other participants. After completing Stage 5, participants were asked to guess how well they had performed in the experiment, in absolute terms and relative to the other participants, and correct guesses were remunerated (see Appendix A for details). We expected this, together with the intrinsic interest of the task, to provide sufficient motivation for the stages focusing on network perception.[9] On the other hand, we provided explicit monetary incentives in the last two stages, where we studied economic decision-making.

Learning. While no feedback on performance was provided until the end of the experiment, it is still possible that responses in later stages were affected by experience of the previous stages. First of all, this is not a concern for the core results of the paper in Section 3: they are exclusively based on responses in Stage 1 and therefore subjects have no prior experience from the experiment that may influence them. A further important reason to make the results in Section 3 the core of the paper is that they are the results that can be corroborated using the survey-based data in Section 4, which we believe it is crucial for the external validity of our findings (see Section 4 for further discussion). For subsequent stages, the design of each stage was quite different, making different cognitive demands on participants. We cannot therefore exclude that *(i)* the experience of previous stages and *(ii)* the fact that subjects were exposed to different treatments may have had an influence on their behavior. However, we provide corroborating evidence that these effects are negligible. At the end of the decision problem in Stage 5, we asked subjects the same questions as in Stage 1 about the network figure they had seen in Stage 5 before

[9]For an interesting cognitive task, similar to an IQ test, Gneezy and Rustichini [2000] found that performance was actually better when subjects were offered no monetary rewards for performance than when they were offered small rewards. Dessi and Rustichini [2011], using an IQ test, found no significant differences in performance with a piece rate of zero, one cent, and one euro.

the decision problem. If *(i)* had any significant effect, then we would expect that their answers would differ, but, as we discuss in Section 3, the results are unchanged. Moreover, a difference between the Stage 5 and Stage 1 is that in the former all the subjects were assigned to the same node, unlike in Stage 1 where the treatment is the assignment to a specific node. As we discuss in Section 3, there is no difference between the responses of subjects in Stage 5 depending on the treatment they were assigned to in Stage 1, which shows that the impact of *(ii)* is negligible.

2.3 Experimental procedures

Before conducting the experiment, we ran a small pilot with student participants at the Toulouse School of Economics. We obtained verbal feedback from participants on the quality of the instructions and adequacy of the time allowed for viewing networks. The time was judged adequate. We were told some examples of how decisions would affect payoffs in the Stage 4 decision problem might be helpful, and therefore we modified the instructions to include some examples.

The main experiments were conducted at the University of Cambridge and programmed using the software z-Tree (Fischbacher [2007]). Subjects were recruited using the online recruitment system ORSEE; they received a fixed participation fee of £3 plus additional earnings depending on their performance in the experiment, according to the rules detailed in the Experimental Instructions (see Appendix A). On average they earned approximately £10, which is in line with typical experimental earnings in the laboratory. Sessions were scheduled with 90 minute slots, inclusive of the time needed for participants to receive their remuneration individually and confidentially, in cash, at the end of their session. In total 80 subjects participated in the experiments. The subjects were all students of the University of Cambridge. Two subjects did not provide information about their gender or educational status when completing the personal questionnaire after the end of the experiment. Of the 78 who did, 37 were male and 41 female students; 45 were undergraduates and the remainder were graduates; 19 were studying for a degree in economics, business or finance, while the remainder were drawn from a wide variety of other disciplines.

At the beginning of each session, after signing informed consent forms, subjects chose randomly their ID codes and then sat in front of a computer. Each subject typed in his/her ID code and all data was collected anonymously, identified only by the ID code. The instructions in Appendix A appeared on their screens. At the end of the session, payments were made again using the ID codes.

3 Experimental results on cognition

In Stage 1 we asked subjects to recall the degree distribution of the network in Figure 1.[10] Figure 2 shows the mean and variance of the degree distribution of the cognitive network of each subject: the black circles denote subjects assigned to be high type and the hollow triangles denote subjects assigned to be low type. Throughout the paper the mean and variance of the cognitive network are computed using subjects' perceived number of nodes rather than the actual number, but the results would be unchanged using the latter as subjects are quite accurate in their perception of the overall number of nodes (see Table 1).[11] The data reveal that this cognitive task is rather demanding and there is a fair amount of heterogeneity in subjects' reports.

Figure 3 shows the aggregated data for all subjects within the same treatment: it compares the degree distribution of the actual network (in black) with the degree distribution of the cognitive networks of subjects assigned to high (in gray) and low (in white) type. To test whether differences between the real and the cognitive networks are statistically significant, we use the Wilcoxon signed ranks test (WSR), where for each subject the "control" outcome was the actual network (i.e. the outcome that would obtain with perfect recall) and the "treatment" outcome was the outcome of the experiment (i.e. the outcome subject to cognitive constraints). Unless explicitly stated otherwise, the significance levels we discuss in this section are after the application of a Bonferroni correction to account for multiple testing, where the number of tests is per treatment so we divide the actual significance level by 13.[12]

We observe three main biases in subjects' perception of the degree distribution of the network. The *first* bias is that subjects *underestimate the mean degree in the network.* The cognitive degree distribution of high type subjects has mean degree 4.194 and the cognitive degree distribution of low type subjects has mean degree 4.047. These perceived means are significantly lower than the actual mean degree, which is 4.667 (WSR, $p = 0.000$).[13] A difference between the means of two distributions is a sufficient statistic to reject the null hypothesis that the two distributions are the same, so this first bias is sufficient to show that the cognitive degree distributions are different from the degree distribution of the actual network.

The *second* bias is that subjects *overestimate the number of rare types in the network.* On average they perceive that there exist individuals of types 1, 2, 5, 6 and 8 even though

[10] 5 subjects out of 80 did not complete at least one question, and they are therefore excluded from the analysis of Stage 1. In total, there are 36 subjects assigned to be high type and 39 subjects assigned to be low type.

[11] For instance, the mean of subject's i's cognitive network is equal to $(\sum_d d\mathbf{N}_d(g^i))/(\sum_d \mathbf{N}_d(g^i))$ where $\mathbf{N}_d(g^i)$ is the number of nodes with degree equal to d in i's cognitive network. The alternative would be to use the formula $(\sum_d d\mathbf{N}_d(g^i))/15$ where the denominator is the number of nodes in the actual network. All our results would be qualitatively unchanged using this alternative formulation.

[12] For instance, a significance level of 1% means $p < 0.00077$.

[13] A p-value of 0.000 denotes significance at the 0.001 level.

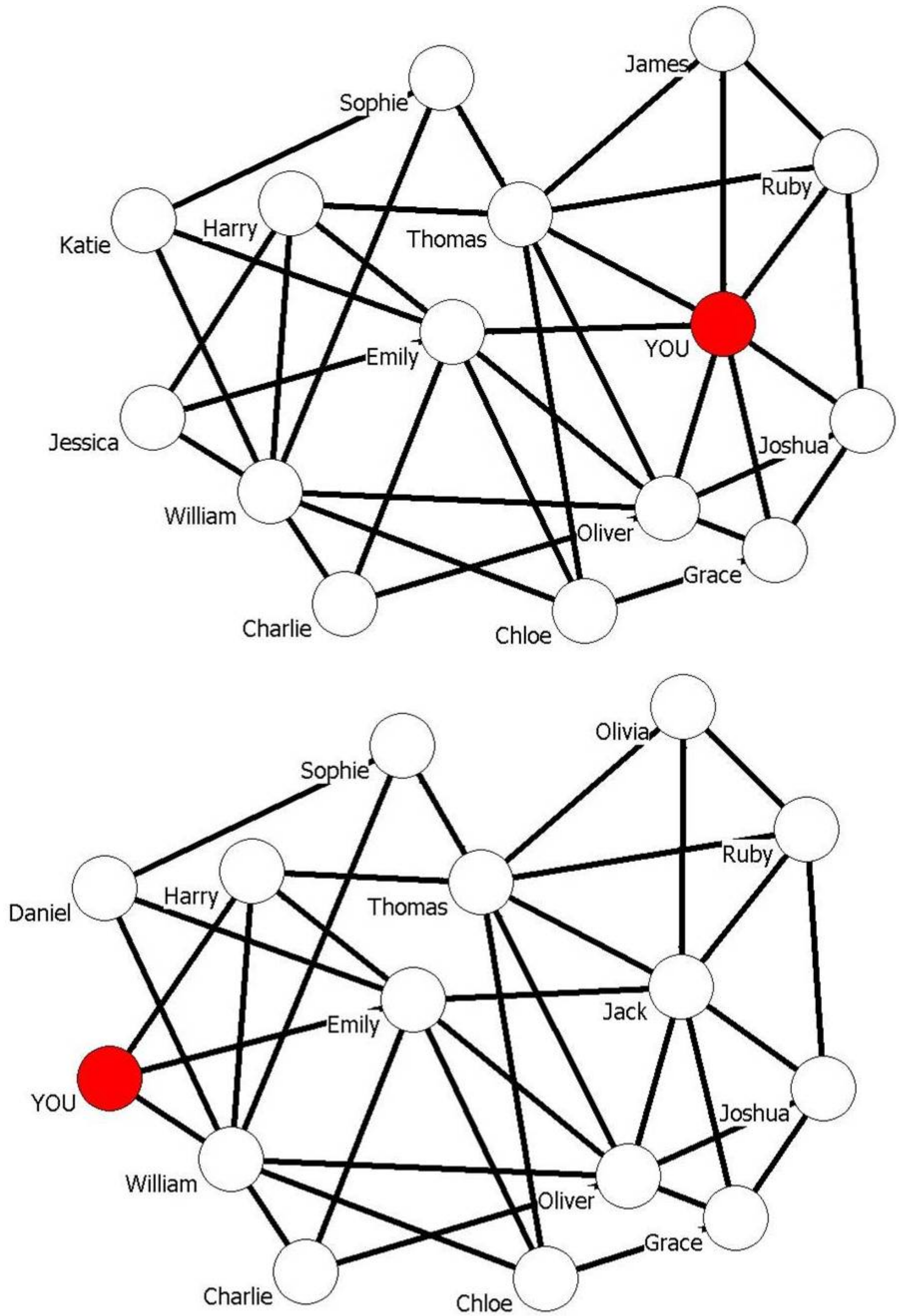

Figure 1: Network pictures shown to subjects in Stage 1. Top: Treatment 1 - High type with degree=7. Bottom: Treatment 2 - Low type with degree=3.

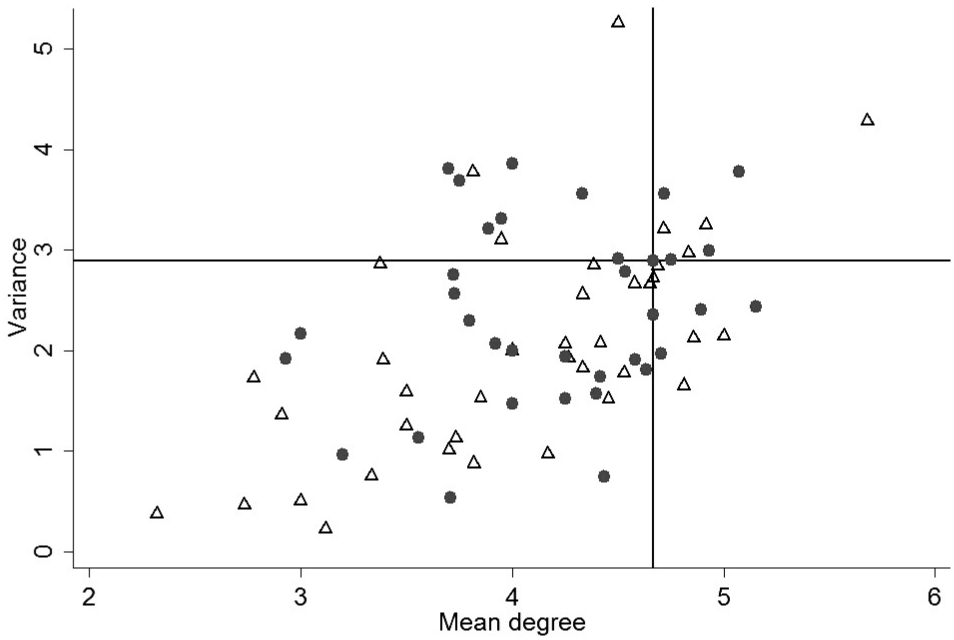

Figure 2: Mean and variance for the cognitive network of each subject computed using the data from Stage 1. Solid lines indicate the mean and variance of the actual network. Black circles indicate subjects assigned to be high type and hollow triangles indicate subjects assigned to be low type. Both mean and variance are computed using subjects' perceived number of nodes in the network rather than the actual number. The Figure would look qualitatively unchanged if we were to use the actual number (i.e. 15) of nodes.

they are absent in the actual network.[14] The *third* bias is that subjects *underestimate the number of frequent types in the network.* There are five nodes for each of types 3, 4 and 7 in the actual network, but subjects on average perceive a significantly lower number. Table 1 shows that these biases are statistically significant independently of the subject's exogenously assigned location in the network.[15]

There is a further difference between the real and perceived distributions, which we believe is a consequence of the last two biases for the specific network: subjects tend to perceive the presence of a larger number of types than there are in the actual network. In

[14]As a robustness check, it would be interesting to explore whether this bias is still present when the number of rare types in the actual network is non-zero. In the design of this experiment we have chosen a network with only three types of nodes to simplify the subjects' cognitive task of memorizing and recalling the network. A direction for future work is to explore whether this bias is present in other networks, including networks where the rare types are non-zero. We thank two referees for this suggestion.

[15]There is one notable exception which is discussed in detail in section 5.1: low type ($d = 3$) subjects on average perceive the correct number of degree 3 nodes in the network. We argue there that this is due to the presence of an offsetting "projection" bias.

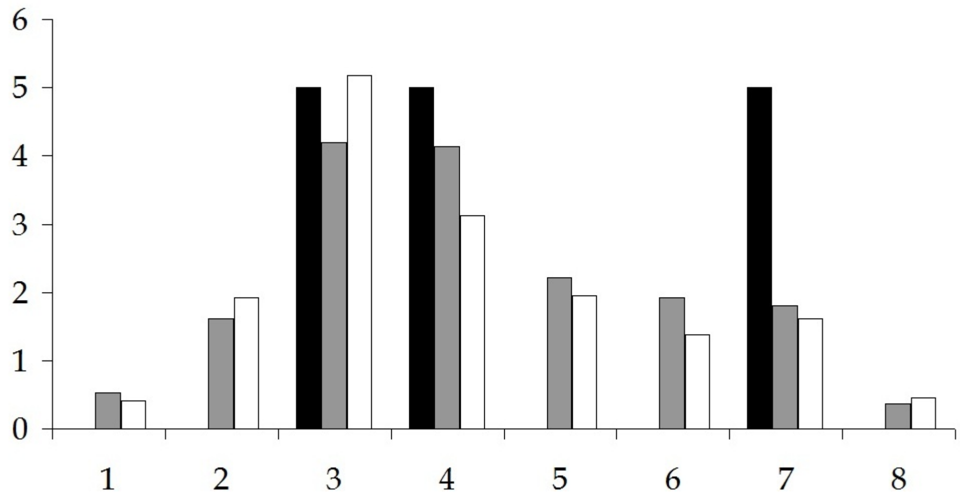

Figure 3: Degree distribution for the actual network (in black) and for the cognitive networks averaged out over all subjects assigned to be high (in gray) and low (in white) type.

the actual network there are only 3 types of individuals, with degree 3, 4 and 7, respectively. However, subjects, on average, perceive that there are 5.293 types of individuals in the network, and the difference is highly significant (WSR, $p = 0.000$). The overestimation of the number of types is a consequence of the overestimation of the rare types, because in the network used in the experiment the rare types are actually absent types.

The last row of data in Table 1 shows the difference between the perceived and the actual number of nodes in the network; the perceived number is obtained by aggregating answers for each type of node. While the perceived number of nodes exceeds on average the actual number, the difference is not statistically significant (WSR, $p = 0.419$ for high types, $p = 0.955$ for low types), suggesting that the tendency to underestimate the mean degree in the network is not driven by a tendency to overestimate the number of nodes.[16]

We now present additional evidence from Stage 5 which suggests that these cognitive biases are robust. We study robustness by asking if perception biases disappear as subjects become more familiar with our experimental methodology. After the subjects play the decision problem in Stage 5, we asked them the same questions about the degree distribution as in Stage 1, but for the network in Figure 4 which was used in the decision

[16]Interestingly, subjects were also asked a direct question, "How many people are there altogether in the group?", *before* the questions about the degree distribution. Answers to this question show a significant tendency to *underestimate* the number of nodes in the network. We treat this evidence with caution though, since the question did not specify *including yourself* (whereas the degree distribution questions did), which could have led some subjects to estimate the number of people in the network without including themselves.

	Cognitive-Actual		High-Low
	High type	**Low type**	**Type**
Type 1	0.528**	0.410 (**)	0.118
Type 2	1.611***	1.923***	-0.312
Type 3	-0.806**	0.179	-0.985 (**)
Type 4	-0.861**	-1.872***	1.011
Type 5	2.222***	1.949***	0.273
Type 6	1.917***	1.385***	0.532
Type 7	-3.194***	-3.385***	0.191
Type 8	0.361**	0.462*	-0.101
Number of types	2.528***	2.077***	0.450
Mean degree	-0.472***	-0.619***	0.147
Variance	-0.526 (**)	-0.844***	0.318 (**)
Number of nodes	1.41	0.78	0.73

Table 1: Second and third columns: Difference between cognitive and actual networks. Last column: difference between cognitive networks of high and low type subjects. The statistical significance levels (*** 0.01, ** 0.05 and * 0.1) are after applying a Bonferroni correction to account for the multiple comparison per treatment ($n = 13$). Because the Bonferroni correction is quite conservative and increases the probability of type II error (see, e.g., Rothman [1990]), we also report in brackets the significance level without the correction for the cases in which Bonferroni changes the outcome from significant to insignificant. In columns 2 and 3, significance levels are based on the Wilcoxon signed rank test, and in column 4 the are based on the Mann-Whitney-Wilcoxon test for independent samples.

problem. Note that the network is exactly the same as the network in Stage 1 apart from the labels of the nodes. However, all subjects were assigned to the same location in the network, which is a node of degree 7 (i.e. high type) located next to the node assigned to low type subjects in Stage 1.

Figure 5 is the equivalent of Figure 3: it shows the aggregated data for all subjects dividing them according to their treatment assignment in Stage 1. Specifically, it compares the degree distribution of the actual network (in black) with the degree distribution of the cognitive networks of subjects assigned to a high (in gray) and a low (in white) type in Stage 1. The Figure shows that the three biases originally identified are present in Stage 5 as well: subjects underestimate the mean degree in the network and they overestimate (underestimate) the number of rare (frequent) types in the network.

These results also allow us to exclude the alternative explanation that the emergence of the location effects is due to the location of the low type node in the bottom-left part

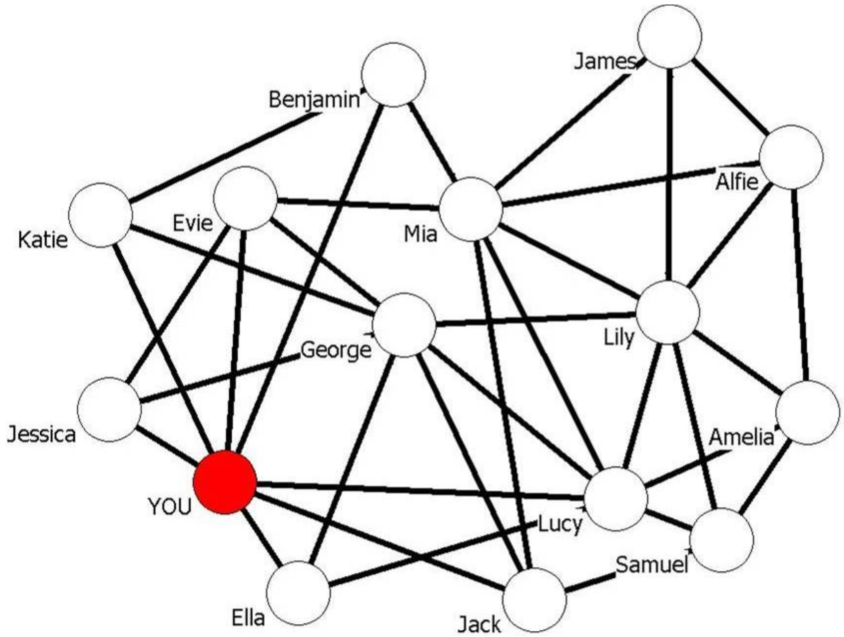

Figure 4: Network picture shown to subjects in Stage 5.

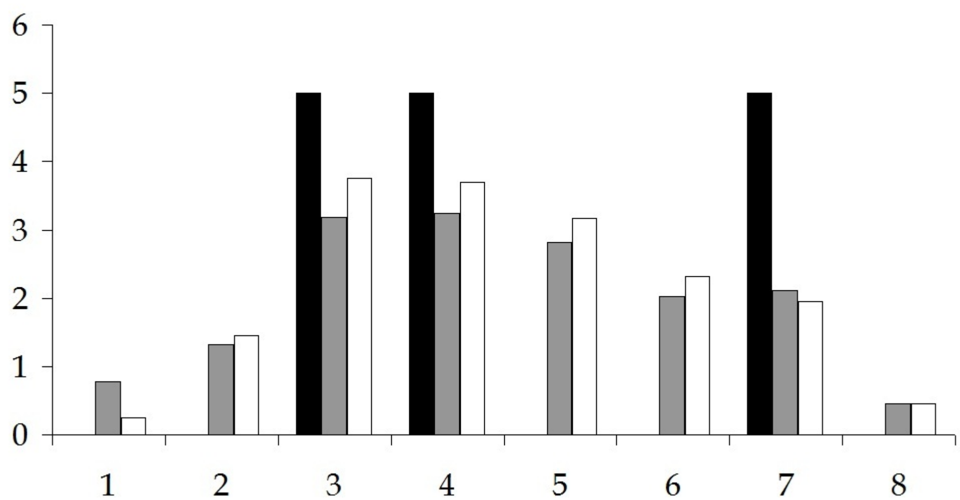

Figure 5: Degree distribution for the actual network (in black) and for the cognitive networks in Stage 5. For ease of comparison with Stage 1, we averaged out the cognitive networks over all subjects assigned to be high (in gray) and low (in white) type *in Stage 1*. Note that all subjects were assigned to the same location in Stage 5.

of the network *image*. This is because in Experiment 5 all the subjects are assigned to the high type node which is *the closest one in the network image* to the node that low type subjects were assigned to in Stage 1 of the experiment. If the projection bias were due to the low type subjects' location on the image in Experiment 1 then we should observe that all subjects have a projection bias in Experiment 5, but Figure 5 shows that this is clearly not the case.

4 Cognition in the field

The laboratory setting allows the researcher to control the parameters of the experiment, but this tight control in turn raises questions about the scope of the findings. A first question is the internal validity of our results. The first issue related to internal validation is whether our findings on biases are sensitive to the specific networks we use and the particular visualization of the chosen networks.[17] The second issue is whether our findings are sensitive to the choice of displaying network information visually rather than by another channel (e.g. a textual description). A second question is the external validity of our findings beyond the laboratory: do these biases also arise in actual social networks or are they an artifact of the experimental design? The aim of this section is to provide a systematic response to these concerns.

Our strategy is to ask how individuals perceive their real friendship network. We study data from two networks – a friendship network in a Silicon Valley firm (SVF) and a friendship network in an Italian University Research Center (URC). These networks were first studied in Krackhardt (1987) and Casciaro (1998), respectively, and have been the subject of influential research in social psychology and sociology. Our main finding is that individuals' cognition of these real world networks, which they themselves inhabit, exhibits biases which are similar to those we identified in our laboratory experiment. In particular, individuals in the SVF network perceive a lower mean connectivity than the true mean, they overestimate rare types and underestimate (almost all) frequent types. Individuals in the URC network perceive a lower mean connectivity than the true mean, they overestimate most rare types and underestimate most frequent types.

[17] Our objective to show that the findings are not sensitive to a specific network motivated our experimental design choice to investigate network structures which were different from the ones in the survey-based data. This has the disadvantage that the findings may be due to different network-dependent drivers rather than a bias that is general and therefore emerges in different networks. We believe that the latter explanation is more likely, but a future direction of inquiry would be to test for the existence of these biases in the same network using different methodologies. An experiment that uses the same network as in the survey-based data would also help in shedding light on the mechanisms leading to the biases. We thank a referee for pointing out this important direction for future research.

4.1 Constructing cognitive social networks

The tradition of using surveys to understand network cognition has a long and distinguished history in the social sciences (see Moreno [1960] for an early reference). In recent years, the literature has used the following methodology which was introduced in Newcomb [1961], Roethlisberger and Dickson [1939] and Krackhardt [1987]. Researchers give an $n \times n$ matrix to each of the n participants of a group. Each row/column of the matrix is labeled with the name of one of the members of the group, and participants have to input a 0 or a 1 for each cell in the matrix. Imagine that the social relation of interest is friendship. If participant K inputs 1 in the (i, j) entry then it means that K thinks that there is a friendship from i to j. The real social network is constructed by looking at the entries by i and j on their link with each other: if both i and j input 1 in the (i, j) and (j, i) entries of their matrix then we say that there is a friendship between i and j in the real network. We provide an example to illustrate more concretely how the methodology works. Consider a group of three individuals $1, 2, 3$ and imagine that the cognitive network matrices are as follows.

$$M_1 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ & & \end{pmatrix} \qquad M_2 = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ & & \end{pmatrix} \qquad M_3 = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ & & \end{pmatrix}$$

The real network is a line with individual 2 in the middle because $(1, 2) = (2, 1) = 1$ in M_1, $(1, 2) = (2, 1) = (2, 3) = (3, 2) = 1$ in M_2 and $(2, 3) = (3, 2) = 1$ in M_3. The cognitive network of 1 is the same as the real network. However, 2's cognitive network is a triangle because $(1, 3) = (3, 1) = 1$ in M_3. On the other hand, 3's cognitive network is disconnected with 1 as an isolated individual because $(1, 2) = 0$ in M_3.[18]

We use two survey-based data sets from well-known studies in the social psychology literature. The first data set is publicly available in the UCINET package for analysis of network data: it was collected by David Krackhardt and it is described in Krackhardt's (1987) contribution. It includes the cognitive network data for 21 managers at a 10-year old Silicon Valley firm producing high-tech machinery.[19] The second data set is from

[18] This is not the only way to construct a real/cognitive network given the data. The choice of the criteria to construct the networks is driven by the nature of the social relationship that the data represents. In our case we will be looking at friendship, a relationship which is more naturally viewed as reciprocal. Thus, a friendship between i and j in the real network exists if and only if *both* i and j state that both the (i, j) and (j, i) entries are equal to 1 in M_i and M_j. Similarly, the friendship between i and j is correctly perceived by k if and only if both the (i, j) and (j, i) entries are equal to 1 in M_k. However, if we were to examine advice, which is arguably non-reciprocal, then we may want to define that an advice link from i to j exists in the real network if and only if *both* i and j state that the (i, j) (but not necessarily the (j, i) entry) is equal to 1 in M_i and M_j.

[19] Note that Krackhardt collected two different sets of data with the same group of 21 managers: the

Casciaro [1998] and it includes the cognitive network data for 24 (out of 25) members of a research center in an Italian University. The data sets will be hereafter referred to as SVF (Silicon Valley Firm) and URC (University Research Centre) respectively.[20]

4.2 Analysis of survey data

In this part we replicate the analysis in section 3 on the SVF and URC network data to investigate whether the biases that we found in the experimental data are present in the field data as well.

The first bias that we have identified in the experimental data is that individuals *underestimate the mean degree in the network*, and this bias is present in both the SVF and the URC data. In the SVF network individuals perceive the average number of friends to be 1.06, while the true average is 1.81; this difference is significant (WSR, $p = 0.001$, so significant at the 10% level after Bonferroni). In the URC network, individuals perceive the average number of friends to be 2.56, while the true number is 3.33; this difference is marginally significant (WSR, $p = 0.036$. so not significant after Bonferroni). Given that the significance is weaker after Bonferroni, we also test the null hypothesis that the cognitive and real degree distributions are the same using a χ^2 test, and we find that the null is rejected in both the SVF ($p = 0.01$) and URC ($p = 0.005$) data.

The other two biases that we have identified in the experimental data are that *participants overestimate (underestimate) the number of rare (frequent) types in the network*. Figure 6 is the equivalent of Figure 3 for the survey-based data: it compares the degree distributions for the real (in black) and cognitive (in white) friendship networks for the SVF (above) and URC (below) data. The top part of Figure 6 shows that these biases are present in the SVF network. Apart from type 0 individuals, the pattern is as in the experimental data: there is overestimation of rare types and underestimation of frequent types. Participants tend to perceive a lower number of types 1, 3 and 4, which are frequent types in the real network. Conversely, they tend to perceive a higher number of type 2 individuals who are rare types in the real network. Table 2 shows that all these

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first set is the cognitive network data for the advice network (UCINET's file name: $KRACKAD$) and the second set is the cognitive network data for the friendship network (UCINET's file name: $KRACKFR$). In this paper we only use the friendship network. Krackhardt's (1987) paper is based on the advice network data.

[20] The two data sets have been collected using slightly different methods. In the SVF data, each participants had to answer a question like "Who is X friend with?" by checking the names of X's friends on a list of the other managers of the organizations (including the participant). The cognitive network matrix of a participant is constructed from the participant's answer to 21 such questions, including the question in which X is the participant himself. In the URC data, each participant had to fill in the matrix representing the cognitive network directly. Specifically, the instructions stated the following: "By putting an 'X' in the cells of the following matrix, please indicate whether you think the people listed in each row (from 1 to 25) considers the people listed in each column (from A to Z) as personal friends."

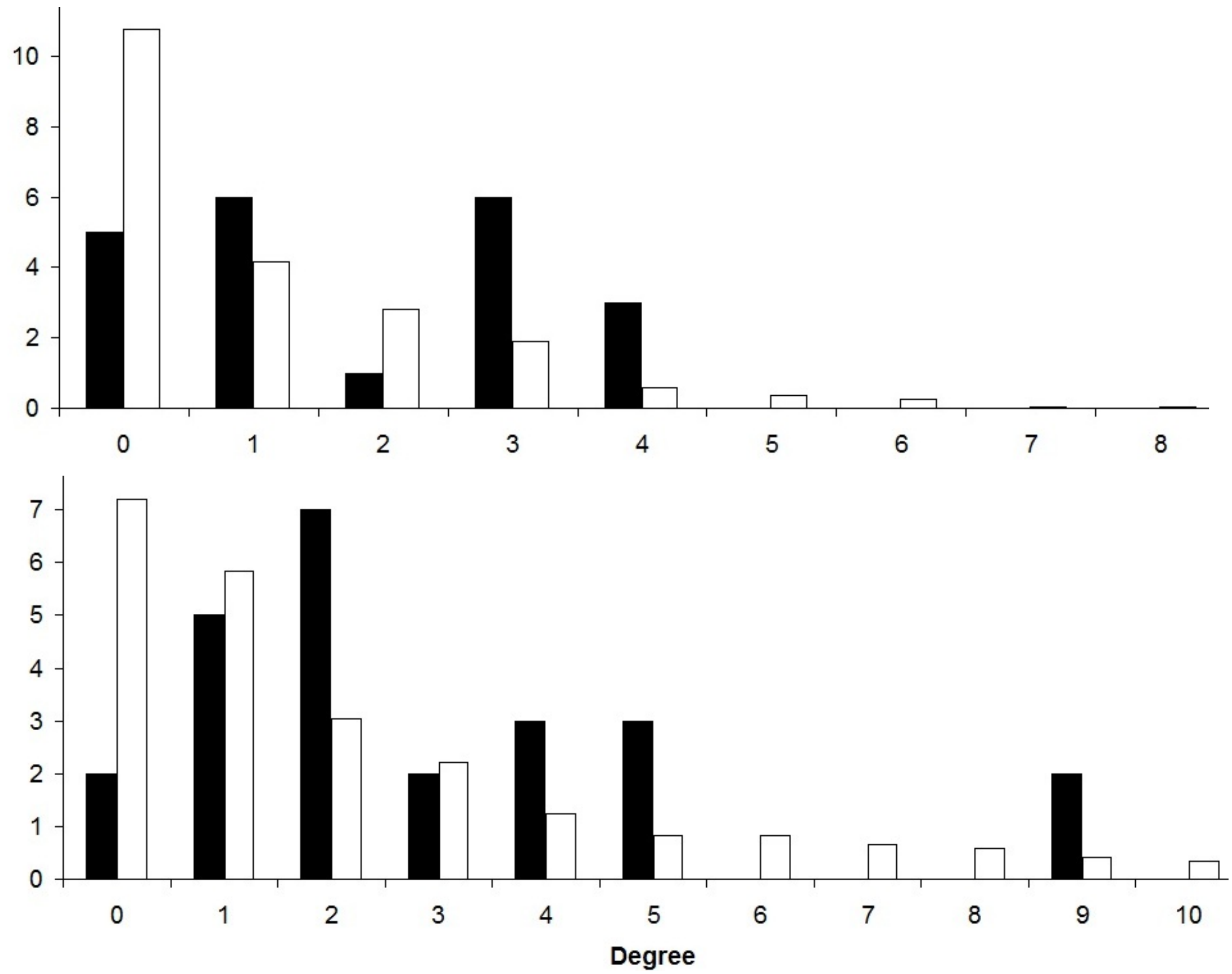

Figure 6: Degree distribution for the real (in black) and cognitive (in white) friendship networks from the SVF (above) and URC (below) data.

	Survey-based data	
Degree	Krackhardt [1987]	Casciaro [1998]
0	5.76***	5.21***
1	-1.86***	0.83
2	1.81***	-3.96***
3	-4.10***	0.21
4	-2.43***	-1.75***
5	0.38 (**)	-2.17***
6	0.24	0.83***
7	0.05	0.67**
8	0.05	0.58 (**)
9		-1.58***
10		0.33 (**)
Mean	-0.75***	-0.77 (**)

Table 2: Difference between cognitive and actual networks in the SVF and URC data. The statistical significance levels (*** 0.01, ** 0.05 and * 0.1) are after applying a Bonferroni correction to account for the multiple comparison per dataset ($n = 11$ for the SVF and $n = 13$ for the URC). Because the Bonferroni correction is quite conservative and increases the probability of type II error (see, e.g., Rothman [1990]), we also report in brackets the significance level without the correction for the cases in which Bonferroni changes the outcome from significant to insignificant. All significance levels are based on the Wilcoxon signed rank test.

biases are highly significant even after the application of a Bonferroni correction. Moreover, individuals perceive that there are type 5 individuals, who are absent in the real network. The case of type 0 individuals is difficult to compare with the experiment as in the laboratory there were no individuals of type 0.

The bottom part of Figure 6 shows that, with a few exceptions[21], there is a bias toward overestimation of rare types and underestimation of frequent types in the URC network. In particular, individuals perceive a lower number of types 2, 4, 5 and 9, than there actually exist in the real network. Conversely, they tend to perceive the presence of types 6, 7 and 8 even though they are absent in the real network. Table 2 shows that all these biases are highly significant even after the application of a Bonferroni correction. Finally, individuals significantly overestimate the number of type 0 individuals. This case is not directly comparable with the experimental data, as in the social network in the laboratory we did not have individuals of type 0.

[21]Individuals accurately perceive the number of type 1 and type 3 individuals.

5 Other experimental findings

This section discusses three other findings from our experiment. There are two main reasons to relegate these findings in this section rather than in the main part of the paper. The first reason is that the nature of these findings does not allow us to check whether they are present in the survey-based data, and therefore we are unable to use the survey-based data to address the concerns about internal and external validity of the experimental data. The second reason is that the findings in sections 5.2 and 5.3 occur after subjects have been exposed to the experience of previous stages and different treatments in each stage. As we discuss in sections 2.2 and 3, the data from Stage 5 shows that these effects are negligible, but we report these results here to separate them from the main results in Section 3 which are unaffected by previous experiences in the experiment.

The *first* finding is that network cognition exhibits significant location effects. The main effect is that subjects assigned to be a low type exhibit a *projection bias*: they misperceive the type of other low type individuals and assign them the same type as themselves. The *second* finding is that the accuracy of individual cognition varies with the nature of the network: when we redistribute links in the original network (in the sense of creating a mean preserving spread of the degree distribution), individuals have a more accurate perception of the new network. The *third* finding is that network cognition affects economic decisions: on average, subjects are less likely to pick their payoff-maximizing strategy when the decision problem is made cognitively more demanding. Moreover, individuals with less accurate network cognition are also less likely to pick the payoff-maximizing strategy.

5.1 Location and cognition

A major research programme in social psychology and social anthropology studies how individual location in a network shapes his/her perception of the network (see the discussion in section 1.1). The existing literature relies, for the most part, on survey data. As location is shaped by individual choices on socialization, existing evidence on location effects is potentially subject to problems of endogeneity and omitted variable biases. One goal of our experiment was to address these concerns: we exogenously assign subjects to a different position in the network in each treatment, so that any difference in perception between treatments can clearly be attributed to the effect of location in the network. We test for the statistical significance of such differences by applying the Mann-Whitney Wilcoxon (rank-sum, MWW hereafter) test for independent samples.

We see from Table 1 that subjects assigned to be high type ($d = 7$) tend to underestimate the number of type 3 individuals in the network, but subjects assigned to be low type ($d = 3$) do not. Since type 3 is one of the frequent types in the network, the underestimation by subjects assigned to be high type is consistent with the third bias in section

3. In contrast, subjects who are themselves assigned to be type 3 do not underestimate the frequency of this type in the network. This difference in perception of the number of type 3 individuals is marginally significant (MWW, $p = 0.051$, so not significant after Bonferroni).

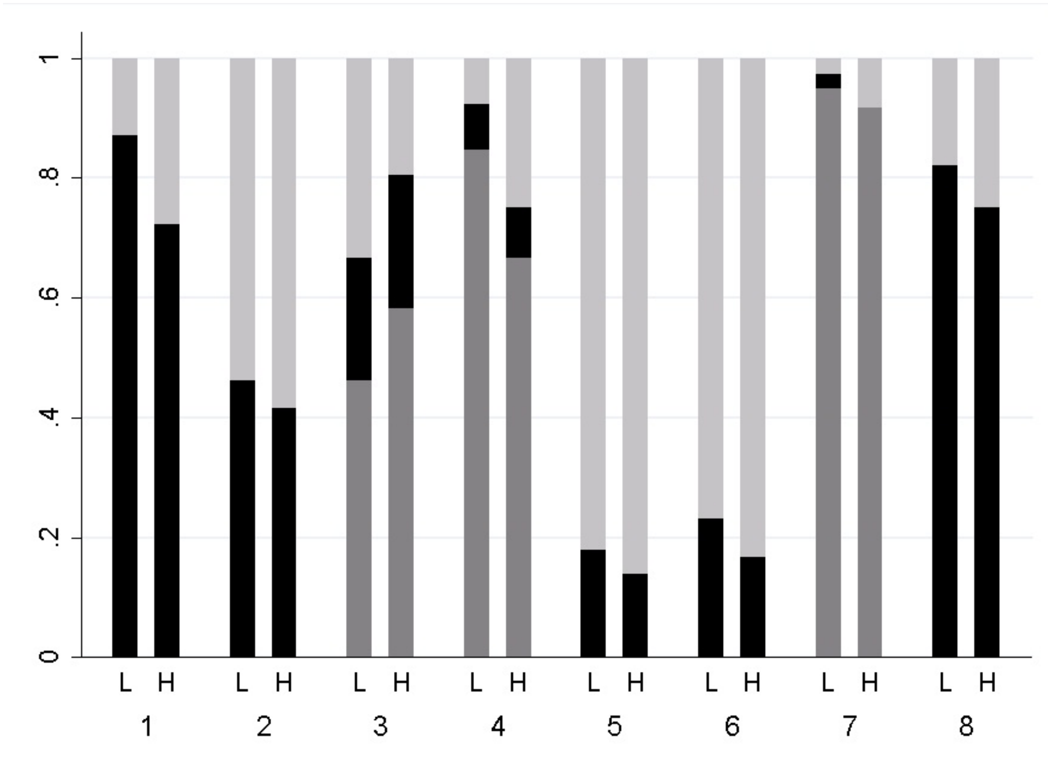

Figure 7: Proportion of subjects that overestimate (in light gray), underestimate (in dark gray) and accurately (in black) indicate the number of individuals of each type in the network. Left bar: subjects assigned to be low type. Right bar: subjects assigned to be high type.

Figure 7 allows us to gain further insight into the nature of this bias. We have two bars for low and high type subjects, showing the proportion of subjects that overestimate (in light gray), underestimate (in dark gray) and accurately (in black) indicate the number of individuals of each type in the network. Focusing on the estimate of the number of type 3 individuals, we see that the proportion of subjects that accurately indicates the number of type 3 individuals in the network is the same for both high and low type subjects. However, there is a larger proportion of low type subjects that *overestimates* the number of type 3 individuals in the network. If we now focus instead on the estimate of number of type 4 individuals, the opposite holds: there is a larger proportion of low type subjects that *underestimates* the number of type 4 individuals in the network. These two findings are related: subjects that overestimate the number of type 3 individuals in the network also tend to underestimate the number of type 4 individuals *more* than other subjects. In other words, subjects assigned to be low type display a *projection bias*: they misperceive the degree of other low type individuals because they mistakenly perceive them as "like themselves", i.e. they "project" their own type onto them. Interestingly, this projection bias is not present for subjects assigned to be high type.

Furthermore, we also have some experimental evidence on the robustness of the projection bias. As we explain in detail in section 3, in Stage 5 we showed subjects the network in Figure 4 and after they completed the decision problem we asked them the same questions about the degree distribution. Note that the network is exactly the same as the network in Stage 1 apart from the labels of the nodes. However, all subjects were assigned to the same location in the network, which is a high type ($d = 7$) located next to the node assigned to low type subjects in Stage 1. Thus, we expect that the projection bias should disappear in Stage 5 given that all subjects were assigned to be of high type.

Figure 5 shows that the projection bias disappears in Stage 5. This result also allows us to exclude the alternative explanation that the emergence of the projection bias is due to the location of the low type node in the bottom-left part of the network *image*. This is because in Stage 5 all the subjects are assigned to the high type node which is *the closest one in the network image* to the node that low type subjects were assigned to in the first part of the experiment. If the projection bias were due to the low type subjects' location on the image in Stage 1 then we should observe that all subjects have a projection bias in Stage 5, but Figure 5 shows that this is clearly not the case.

A second location effect is on subjects' perception of the key individuals in the network. We asked subjects *"In your opinion, who are the key individuals in the group?"*. We then compared, for each individual in the network, the probability of being identified as a key individual by high type and low type subjects. For most individuals in the network these probabilities did not differ significantly. However, there are two exceptions: the individuals named Harry and William who are of type 4 and 7 respectively. Crucially, both are directly linked to the low type subjects and neither is linked directly to the high type subjects. We find that low type subjects are *more* likely to identify Harry (MWW, $p = 0.033$) and William (MWW, $p = 0.026$) as key individuals as compared to high type subjects.[22] This is evidence that low type individuals have a tendency to attribute more importance to their own connections in the context of the overall network compared to the importance given to those individuals by a subject who is not connected to them. The converse effect is not present for high type individuals, possibly because high type subjects have many connections and therefore they do not deem an individual important just because that individual is one of their connections.[23]

[22]Although neither finding is significant after the application of the Bonferroni correction.

[23]An alternative explanation is that low type subjects noticed that they were directly connected to

5.2 Changing the structure of the network

This section examines the relation between the structure of the network and the accuracy of network cognition. In other words, we would like to understand whether some network architectures are easier to understand and recall as compared to others. This question is of interest in the context of network design: for instance, if cognition costs are higher for some networks then optimal design should reflect these costs. It is also of interest if we wish to study the relation between network structure and individual behavior.

A widely used concept to compare the structure of different networks is a mean preserving spread (MPS) of the degree distribution - see the formal definition in Section 2. Intuitively, if we change a network so that the degree distribution of the new network is a mean preserving spread of the degree distribution of the original network then the new network will have a higher number of poorly connected nodes and a higher number of highly connected nodes compared to the original network. For instance, the network on the right side of figure 8 has three nodes with only one connection and one node with eleven connections, and it is a mean preserving spread of the network on the left side of figure 8 whose most poorly and highly connected nodes have degrees three and five respectively.

An example of the application of this concept is Galeotti et al. [2010] who develop a number of results which relate the (subjectively perceived) degree distribution of a network to the equilibrium behavior of individuals, and then show how behavior varies if ones take a MPS of the network. Other contributions that show how economic outcomes vary with a MPS of the network include Jackson and Rogers [2007] in the context of diffusion and Gallo [2014] in the context of social learning. In an experimental set-up, when we vary the network, individual behavior may be affected both by the change in the network itself *and* also by the changes in the accuracy of the perception of the network. So it is important to understand if the accuracy of individual cognition of a network varies with the structure of the network.

We carried out two treatments, which varied the subject's location and the order in which they saw the two networks. In the first treatment, subjects were assigned to be high type, and they saw the original network *before* seeing the MPS network. This is the order represented in Figure 8. In the second treatment, subjects were assigned to be low type, and they saw the original network *after* seeing the MPS network. This is the order shown in Figure 9. All subjects were then asked questions that elicited their perceptions of the lower and upper tail of the degree distribution for each of the two networks. Specifically, they were required to specify the number of individuals in the network who had fewer than two friends, and the number of individuals who had at least three friends.

Figure 10 illustrates the results for the original network (on the left) and the MPS (on the right) by showing the number of individuals with fewer than two friends and at least

individuals with the same name as the second and third in the line of succession to the throne of the United Kingdom.

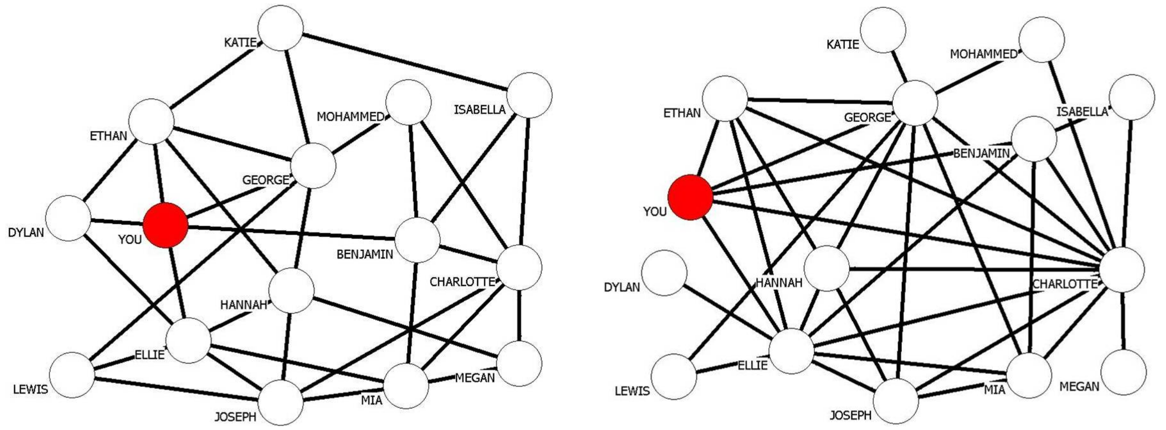

Figure 8: Network pictures shown to subjects in Treatment 1 of Stage 2 (high type). Left: Original network shown in the first 30 seconds. Right: Mean-preserving spread of original network shown in the last 30 seconds.

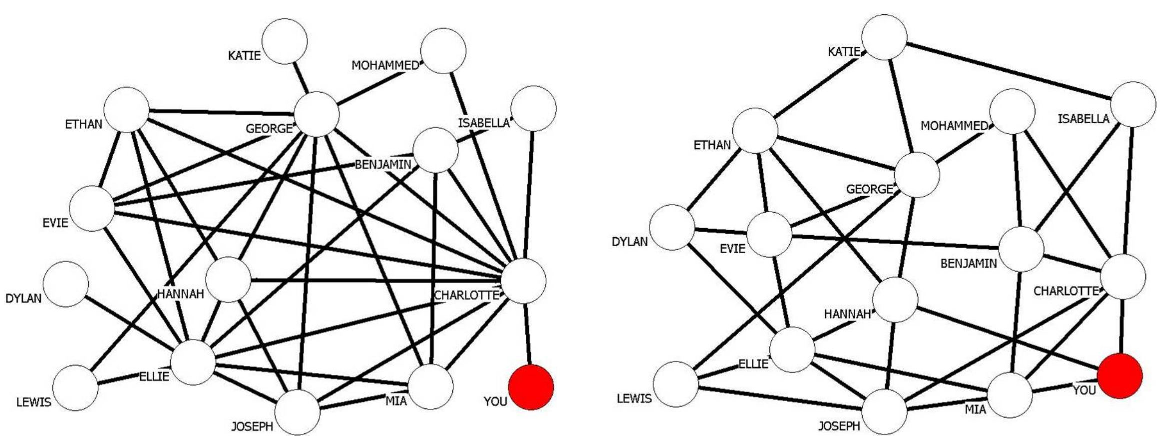

Figure 9: Network pictures shown to subjects in Treatment 2 of Stage 2 (low type). Left: Mean-preserving spread of original network shown in the first 30 seconds. Right: Original network shown in the last 30 seconds.

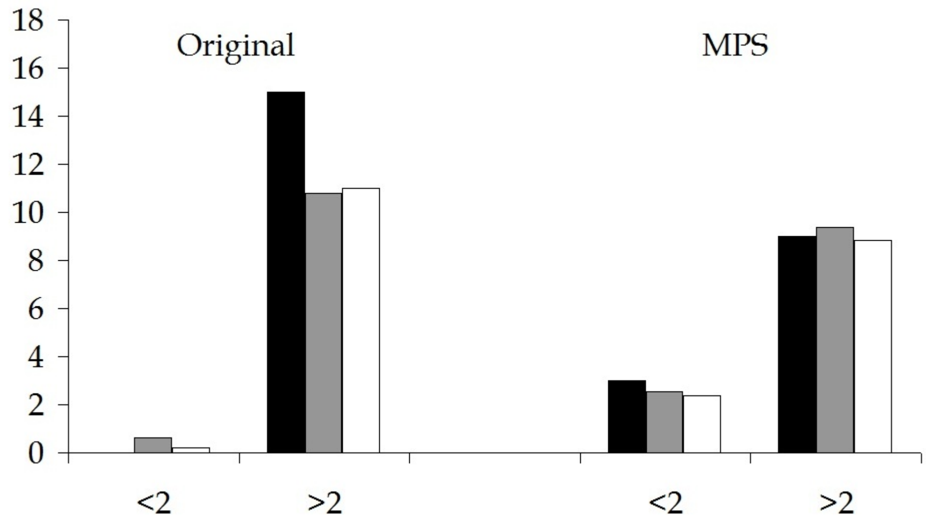

Figure 10: Number of individuals with fewer than two connections and at least three connections in the real network (in black) and in the cognitive networks of high type (in gray) and low type (in white) subjects. The results for the original network are in the left panel, and the results for the MPS network are in the right panel.

three friends for the real network (in black), the cognitive network of high type (in gray) and low type (in white) subjects. The most striking feature of the results is clearly the substantial underestimate, by all subjects, of the number of individuals with at least three friends in the original network. The actual number is 15, but the mean perceived number is only 10.615 (WSR, $p = 0.0000$) for high type subjects and 10.976 (WSR, $p = 0.0000$) for low type subjects. These differences are highly significant even after a Bonferroni correction.[24] In contrast, perception of the number of individuals with at least three friends is surprisingly accurate for the MPS network, and subjects of both types show no significant bias in this case: the mean perceived number is 9.231 (WSR, $p = 0.6883$) for high type subjects and 8.805 (WSR, $p = 0.7349$) for low type subjects. Turning to the lower tail of the degree distribution, we find that subjects overestimate the number of individuals with fewer than two friends in the original network, and underestimate it in the MPS network. The differences in both cases are statistically significant, but they are small in magnitude and some are not significant after Bonferroni.[25] In summary, subjects

[24]In the analysis of Stage 2 we conduct 8 WSR tests so the Bonferroni correction means dividing the significance level by 8. For instance, a significance level of 1% means $p < 0.00125$.

[25]Specifically, the true number for the original network is zero, while the mean perceived number is 0.692 (WSR, $p = 0.0002$, significant at 1% level after Bonferroni) for high type subjects and 0.220 (WSR, $p = 0.0456$, insignificant after Bonferroni) for low type subjects. For the MPS network, the actual number is three, while the mean perceived number is 2.564 (WSR, $p = 0.0666$, insignificant after Bonferroni) for

appear to perceive more accurately the MPS network.

How can we account for this improvement in accuracy of network cognition? A MPS of a network would usually lead to the types in the network being further apart, and this is indeed the case for the MPS network in Stage 2. Thus, it may be that as the types are pushed apart it becomes easier for individuals to differentiate them and this improves accuracy of perception of the network. Another difference between the MPS network and the original network is that the MPS network has a larger number of types. In general, a MPS of a network may increase, decrease or leave unchanged the number of types, but it may be that changing the number of types leads to a variation in the accuracy of perception of the network. The results for the specific MPS in Stage 2 suggest that there is an improvement in the accuracy of perception of the degree distribution when the number of types increases. While both these conjectures are plausible, we view them as preliminary and would like to explore them in future work.

5.3 Cognition and behavior

The focus in this paper is on network perception, but we also take a first step to examine the relationship between accuracy of perception and behavior. We included two stages in which subjects face a decision problem where the payoff-maximizing decision depends on their knowledge of the network. The problems are described in section 3 (and in greater detail in Appendix A): the choice is straightforward if the subject can see the network when making the choice, but it requires the ability to recall details about the network when the network picture is no longer available.[26]

We vary the cognitive difficulty of the task in the two stages. In Stage 4, subjects are shown the network *before* they learn the nature of the decision problem they will be confronted with: all they know when they see the picture is that they will be playing an economic game with real monetary payoffs, where the effects of their decisions and other players' decisions will depend on the way players are connected. This makes the cognitive task demanding, since subjects cannot focus attention on a particular feature or subset of the network while looking at the picture. In Stage 5, on the other hand, subjects see the network *after* learning the nature of the decision problem: in particular, they learn that the only individuals who can have an impact on their payoffs are their friends. Other individuals' decisions are payoff-irrelevant, so that a subject seeking to maximize his payoff can simply focus attention on his friends.

We would therefore expect subjects to make the "wrong" decision more often in Stage 4 than in Stage 5. This is indeed the case: 55% of subjects fail to pick the payoff-maximizing

high type subjects and 2.390 (WSR, $p = 0.0001$, significant at 1% level after Bonferroni) for low type subjects.

[26] 2 subjects out of 80 did not complete the post-experimental questionnaire and 1 further subject failed to give an answer to at least one question in Stage 4 and 5 so these 3 subjects are excluded from the analysis of Stage 4 and 5.

	Stage 4			
Probability of picking the the payoff-maximizing action	**Coeff.**	**Stand. Error**	z	$P > \|z\|$
Stage 1: (Mean Bias)^2	0.214	0.182	1.18	0.239
Stage 1: (Underestimate Frequent Types Bias)^2	0.043	0.064	0.68	0.499
Stage 1: (Overestimate Rare Types Bias)^2	0.137	0.072	1.90	0.057*
Stage 2: Accuracy Perception Low Degree (ON)	0.023	0.543	0.04	0.966
Stage 2: Accuracy Perception High Degree (ON)	0.070	0.377	0.19	0.852
Stage 2: Accuracy Perception Low Degree (MPS)	0.652	0.340	1.92	0.055*
Age	-0.064	0.048	-1.34	0.181
Gender	0.312	0.328	0.95	0.341
Education	0.351	0.252	1.39	0.164
Econ	-0.362	0.391	-0.92	0.356
Constant	0.021	1.224	0.02	0.986
n	77			
R^2	0.0740			

Table 3: Probit regression to assess performance in Stage 4. The binary dependent variable takes value of 1 if the subject picks the correct decision, and 0 otherwise. ON=Original Network. MPS=Mean-Preserving Network.

action in the more demanding Stage 4, compared with 26% in Stage 5.[27]

We then check whether individual behavior in these stages is related to cognition in the previous stages. We construct several measures of cognitive accuracy based on answers to the questions about network perception in the first two stages. For the first stage, which elicited subjects' cognitive degree distribution, we use three measures, corresponding to the three main biases identified in Section 3: the first captures inaccuracy in perception of the number of rare types in the network, the second inaccuracy in perception of the number of frequent types in the network, and the third inaccuracy in perception of the mean degree. For the second stage, which investigated differences in perception as we varied network structure, we construct three measures: the first one captures the accuracy in answering questions about the number of low types in the original network, the second one captures the accuracy in answering questions about the number of high types in the original network and the third one captures the accuracy in answering questions about

[27]Note that owing to a programming glitch, subjects in Stage 5 were told that Olivia, Grace and Sophie had chosen to contribute, when in fact these names did not appear in the network for Stage 5. This may have made the problem harder and contributed to the rather high proportion of wrong decisions. We therefore take the 26% as an upper bound on the proportion of wrong answers for the cognitively easier task. Obviously, a lower proportion would make the difference with the cognitively more demanding task even greater.

	Stage 5			
Probability of picking the the payoff-maximizing action	**Coeff.**	**Stand. Error**	z	$P > \|z\|$
Stage 1: (Mean Bias)^2	0.025	0.171	0.15	0.884
Stage 1: (Underestimate Frequent Types Bias)^2	0.083	0.086	0.96	0.335
Stage 1: (Overestimate Rare Types Bias)^2	-0.416	0.223	-1.87	0.062*
Stage 2: Accuracy Perception Low Degree (ON)	-0.484	0.579	-0.84	0.403
Stage 2: Accuracy Perception High Degree (ON)	-0.126	0.445	-0.28	0.777
Stage 2: Accuracy Perception Low Degree (MPS)	-0.568	0.379	-1.50	0.134
Age	-0.035	0.042	-0.84	0.402
Gender	-0.278	0.369	-0.75	0.451
Education	0.249	0.273	0.91	0.362
Econ	0.606	0.485	1.25	0.212
Constant	3.165	1.348	2.35	0.019
n	77			
R^2	0.0740			

Table 4: Probit regression to assess performance in Stage 5. The binary dependent variable takes value of 1 if the subject picks the correct decision, and 0 otherwise. ON=Original Network. MPS=Mean-Preserving Network.

the number of low types in the mean-preserving spread network.

Tables 3 and 4 report our main results on the link between network cognition in the first two stages and behavior in the last two. We find two highly significant effects. First, individuals who are more prone to *overestimate the number of rare types* in the network are also *more likely to contribute* to the local public good. This is true in *both* stages. Remembering that the payoff-maximizing decision is to contribute in Stage 4, and *not* to contribute in Stage 5, this suggests that individuals with a very inaccurate perception of the network have difficulty picking the payoff-maximizing action, and resort partly to other criteria in making their choice. We conjecture that their tendency to privilege contribution may be related to the fact that the decision problem is framed in terms of contributions to a local public account, with potential positive externalities on friends (and their friends).[28]

The second significant effect concerns perception of very low degree types. Out of the first three stages, only Stage 2 had such types. Specifically, the network obtained by taking a mean preserving spread of the base network degree distribution did contain several

[28]Interestingly, we find that among our subjects, the proportion of contributors is lower for economics students than for students from other disciplines. This is true in both stages, but the difference is much greater for Stage 5, where contributing is *not* the individual's payoff-maximizing action.

individuals with degree one. The ability to perceive correctly degree one individuals plays an important role in Stage 4, because identifying the payoff-maximizing action hinges on accurate perception of one such individual (Olivia). This is not the case in Stage 5. Indeed, we find that subjects who perceive very low types more accurately in Stage 2 are also significantly more likely to choose the payoff-maximizing action in Stage 4 (and not in Stage 5).

6 Conclusion

We studied individual ability to memorize and recall information about friendship networks using a combination of experiments and survey-based data. In our experimental work subjects are shown a network and also assigned a location in this network. They are then asked questions about the network. The experimental data suggests that subjects exhibit three main cognitive biases. The first one is that they underestimate the mean degree compared to the actual network. The second one is that they overestimate the number of rare types. The third one is that they underestimate the number of frequent types. We then analyze survey data from two 'real' friendship networks – the friendship network of a Silicon Valley firm (first studied in Krackhardt [1987]) and the friendship network in a University Research Centre (first studied in Casciaro [1998]). We find, somewhat remarkably, that individuals in these 'real' networks exhibit the same cognitive biases.

Our laboratory experiment yields three further findings. First, location affects cognition: low and high type subjects differ in their perception of the network along two dimensions: the perception of low degree types, and the identity of key individuals in the network. Second, the accuracy of network cognition varies with the architecture of the network: a mean preserving spread of the degree distribution leads to greater cognitive accuracy. Third, network cognition affects economic behavior: when we make the decision problem more cognitively demanding, subjects on average perform less well. Moreover, subjects who perceive the network more inaccurately, as captured by the tendency to overestimate the number of rare types, find it harder to pick their payoff-maximizing action.

Our findings suggest that exploring further the biases in the way people process, recall and use information about social networks, and the relationship between network cognition and economic behavior, represents a promising avenue for future research.

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A Experimental Instructions

Welcome; you are going to participate in an economics experiment. Your answers and decisions will have no consequences whatever for your course grades or your degree.

This experiment studies decision-making. There are no right or wrong decisions – you should simply decide according to your preferences.

The experiment will be remunerated. You will receive the remuneration at the end. I will call in each participant individually to give him or her the amount earned. The amount you receive will depend on your decisions/answers and on those of the other participants. I will explain the rules of the experiment in a moment.

Please now switch off your mobile phones, and do not talk to each other during the experiment. If you have a question, raise your hand and I will come and answer.

Are there any questions?

If there are no questions, we can start. You will see some instructions on your screens. Take the time you need to read them carefully before clicking on "Next" to move to the next screen. Whenever you are asked a question, take the time you need to answer. If you see the phrase "waiting for the other participants" on your screen, please wait patiently: it means some of the other participants have not yet clicked on "Next". If you want to ask a question during the experiment, please raise your hand.

General rules

During this experiment you will be asked at times to take decisions that will affect your outcome and the outcome for other participants. It is important for you to know that your decisions will remain completely confidential.

Each person will be assigned a fictitious name, depending on the ID code he or she picked at the beginning.

When we need to refer to specific participants in the instructions, we will always use their fictitious name and never their real name or any other information that might allow others to identify them.

Please type in your ID code, exactly as it is written on the ticket you picked at the beginning.

If you have a question, please raise your hand.

If there are no questions, we can move on to the specific instructions.

Specific instructions (Stage 1)

There are several parts to this experiment. We will provide specific instructions for each part before the start.

In the first part, we will show you a visual representation (a diagram) showing a set of relationships within a group of people, including yourself. Imagine that the other people are, like you, students of this university. In the diagram, each dot represents a person, and has a (fictitious) name. A line joining two dots means that those two people are connected: they are friends. We are going to show you the diagram for 60 seconds, then the diagram will disappear from your screen, and we will ask you some questions about the set of relationships you have just seen.

If you have any question, raise your hand.

When you are ready to see the diagram, click on "Next".

[Subjects are shown the networks in Figure 11 for 60 *seconds]*

On the next screen you will be asked to describe the set of relationships you have just seen, in your own words. You will have 60 seconds to do this.

Pressing "Enter" will cause what you have written to be saved, and then disappear from the text box. Saved text will be displayed in the top half of the screen. When the 60 seconds is up, please press Enter.

When you are ready to answer the question, click on "OK".

Q1 Describe the set of relationships you have just seen, in your own words. You have 60 seconds to do this.

Q2 How many people are there altogether in the group?

Q3 In your opinion, who are the key individuals in the group?

Q4 How many people in the group (including yourself) have exactly one friend?

Q5 How many people in the group (including yourself) have exactly two friends?

Q6 How many people in the group (including yourself) have exactly three friends?

Q7 How many people in the group (including yourself) have exactly four friends?

Q8 How many people in the group (including yourself) have exactly five friends?

Q9 How many people in the group (including yourself) have exactly six friends?

Q10 How many people in the group (including yourself) have exactly seven friends?

Q11 How many people in the group (including yourself) have exactly eight friends?

Specific instructions (Stage 2)

In the next part of the experiment, we will show you visual representations (diagrams) of two sets of relationships within a group of people, still including yourself. Once again, imagine that the other people are students of this university.

In the diagrams, dots and connecting lines have the same interpretation as in the previous diagram. We are going to show you the first diagram for 30 seconds, then the diagram will disappear from your screen, and we will show you the second diagram, also for 30 seconds. After this diagram also disappears from your screen, we will ask you some questions about the two new sets of relationships you have just seen.

If you have any question, raise your hand.

When you are ready to see the diagrams, click on "Next".

[Subjects in Treatment 1 are shown the networks in Figure 12 for 30 *seconds each and subjects in Treatment 2 are shown the networks in Figure 13 for* 30 *seconds each]*

Q1 Are there more people in the first group than in the second group?

Q2 How many people have at least three friends in the first group?

Q3 How many people have at least three friends in the second group?

Q4 How many people have fewer than two friends in the first group?

Q5 How many people have fewer than two friends in the second group?

Q6 Is the number of friends more variable in the first group than in the second group?

Q7 Is the number of friends more variable in the second group than in the first group?

Specific instructions (Stage 3)

We are now going to show you one more visual representation (diagram) of a set of relationships within another group of people. Once again, imagine that you are part of the group, and the other people are students of this university.

In the diagram, dots and connecting lines have the same interpretation as in the previous diagrams. We are going to show you the diagram for 60 seconds, then the diagram will disappear from your screen, and we will ask you questions about the new set of relationships you have just seen.

If you have any question, raise your hand.

When you are ready to see the diagram, click on "Next".

[Subjects are shown the networks in Figure 14 for 60 *seconds]*

Q1 How many people are there altogether in the group?

Q2 Are the following people friends: Evie, Charlotte

Q3 Are the following people friends: Mia, James

Q4 How many friends does George have?

Q5 How many friends does Lucy have?

Q6 Which of the following are Ella's friends: Charlotte, Jack, Lucy, Evie, Samuel?

Q7 Which of the following are Mia's friends: George, Benjamin, Evie, Lucy?

Specific instructions (Stage 4)

In the next part of the experiment, you will play an economic game, with real monetary payoffs. We will describe the game before you start to play. It is a group game, in which each player's payoff depends on his or her decisions, and on the decisions of other group members. Moreover, *the effects of decisions on payoffs depend on the way players are connected.* We will use a diagram like the ones used earlier in this experiment to show how you and the other players are connected. You will see this diagram on your screen for 60 seconds; it will then disappear and we will explain the game to be played.

Note that you will not be shown the diagram again before playing the game.

If you have any question, raise your hand.

When you are ready to see the diagram, click on "Next".

[Subjects are shown the network at the top of Figure 15 for 60 *seconds.]*

We now describe the economic game. Each player in the game is given an endowment of **2 pounds**. He or she has to decide whether to **keep** this endowment or to **contribute** it to a local public account.

Once all contribution decisions have been made, each player earns **4 pounds** if the sum of his/her contribution, the contributions made by each of his/her friends, and the contributions made by each friend's friends, is equal to or more than 6 pounds.

Each player's payoff from the game consists of his/her earnings plus the endowment if it has not been contributed.

Examples: if you contribute and at least two other players who are your friends or friends of your friends contribute, your payoff will be 4 pounds.

If you do not contribute and at least three other players who are your friends or friends of your friends contribute, your payoff will be 6 pounds.

If you do not contribute and fewer than three other players who are your friends or friends of your friends contribute, your payoff will be 2 pounds.

If you contribute and fewer than two other players who are your friends or friends of your friends contribute, your payoff will be 0 pounds.

In a moment, we will ask you to play this game as if you knew how the other players would play it. Specifically, we will assign contribution decisions to the other players in the group, and *tell you who chose to contribute.* We will then ask you for your contribution decision.

Here are the names of the other players who have chosen to contribute: *Olivia, Ruby.*

The other players have chosen not to contribute. Please specify your decision:

- I contribute my endowment to the local public account, or
- I do not contribute to the local public account

Specific instructions (Stage 5)

We will now ask you to play a different economic game. We first describe the game, then we will show you the ways different players are connected, and finally you will play the game. Here we describe the economic game. As in the previous game, each player is given an endowment of **2 pounds**. He or she has to decide whether to **keep** this endowment or to **contribute** it to a local public account.

The difference from the previous game is as follows. Once all contribution decisions have been made, each player earns **4 pounds** if the sum of his/her contribution and the contributions made by each of his/her friends is equal to or more than 4 pounds. As before, each player's payoff from the game consists of his/her earnings plus the endowment if it has not been contributed.

In a moment, we will ask you, once again, to play this game as if you knew how the other players would play it. Specifically, we will assign contribution decisions to the other players in the group, and tell you who chose to contribute. We will then ask you for your contribution decision.

First, we are going to show you how all the players, including yourself, are connected, on a diagram like the ones used previously. You will see the diagram for 60 seconds, then it will disappear from your screen, and the names of the players who have chosen to contribute will appear.

If you have any question, raise your hand.

When you are ready to see the diagram, click on "Next".

[Subjects are shown the network at the bottom of Figure 15 for 60 *seconds.]*

Here are the names of the other players who have chosen to contribute:

Olivia, Grace, Sophie.

The other players have chosen not to contribute. Please specify your decision:

- I contribute my endowment to the local public account, or
- I do not contribute to the local public account

We now ask you some questions about the set of relationships between players in the game you have just played.

Q1 How many people in the group (including yourself) have exactly one friend?

Q2 How many people in the group (including yourself) have exactly two friends?

Q3 How many people in the group (including yourself) have exactly three friends?

Q4 How many people in the group (including yourself) have exactly four friends?

Q5 How many people in the group (including yourself) have exactly five friends?

Q6 How many people in the group (including yourself) have exactly six friends?

Q7 How many people in the group (including yourself) have exactly seven friends?

Q8 How many people in the group (including yourself) have exactly eight friends?

Specific instructions (Stage 6)

In this final part of the experiment, we ask you to guess the proportion of correct answers you have given to the questions you have been asked so far. We also ask you to guess how well you have done relative to other participants. You will be remunerated for each correct guess; the amount will be shown on your screen before you make each guess.

Please click on "Next" to see the first question.

What proportion (%) of questions so far do you believe you have answered correctly? You will receive two pounds in addition to your other earnings if you guess correctly.

0 - 10%
11 - 20%
21 - 30%
31 - 40%
41 - 50%
51 - 60%
61 - 70%
71 - 80%
81 - 90%
91 - 100%

If we rank all participants in the session according to the proportion of correct answers they have given, from the top (those with the highest proportion) to the bottom (those with the lowest proportion), in which quintile do you think you will be? You will receive 2 pounds in addition to your other earnings if you guess correctly.

First quintile (top 20%)
Second quintile
Third quintile
Fourth quintile
Fifth quintile (bottom 20%)

Do you think your combined earnings from the two economic games are above or below average? You will receive 1 pound in addition to your other earnings if you guess correctly.

Above average
Below average

Final instructions (Stage 6)

Number of pounds earnt in Stage 4:

Number of pounds earnt in Stage 5:

Number of pounds earnt in Stage 6:

Show-up Fee:

Total:

The experiment has now ended. Thank you for your participation. We now ask you to complete the following questionnaire. As soon as you finish the questionnaire you can leave the laboratory.

B Network pictures used in the experiment

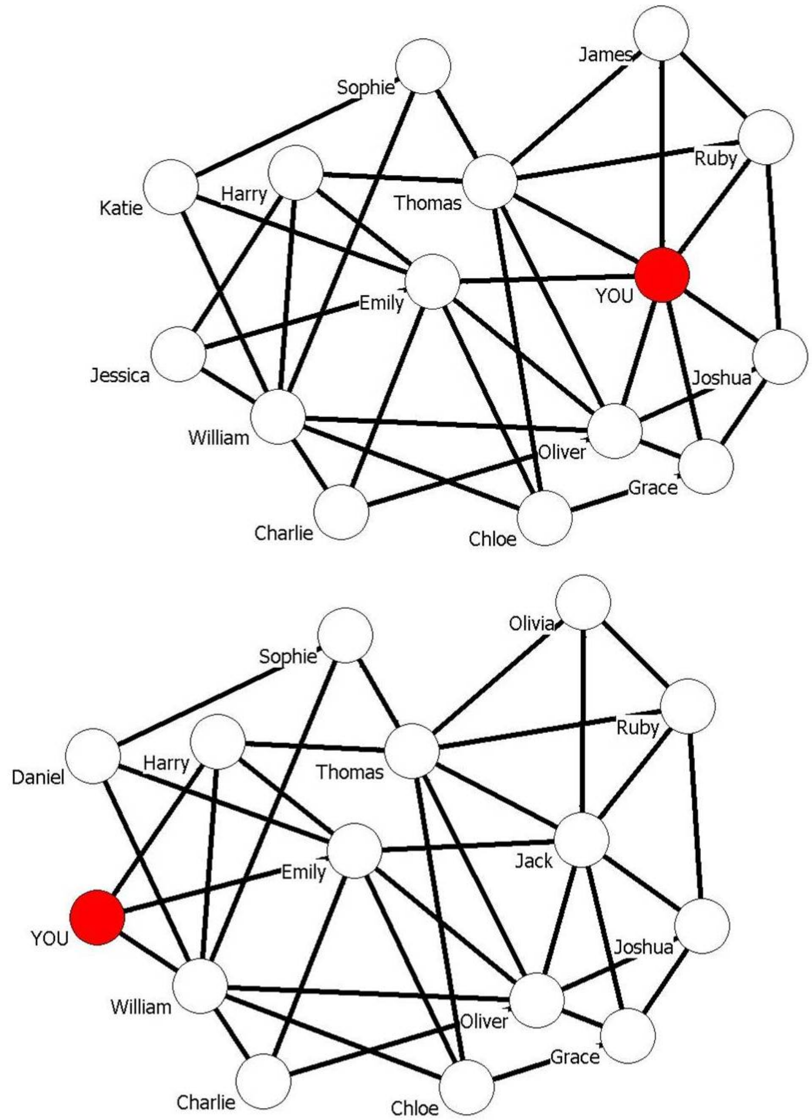

Figure 11: Network pictures shown to subjects in Stage 1. Top: Treatment 1 - High type with degree=7. Bottom: Treatment 2 - Low type with degree=3.

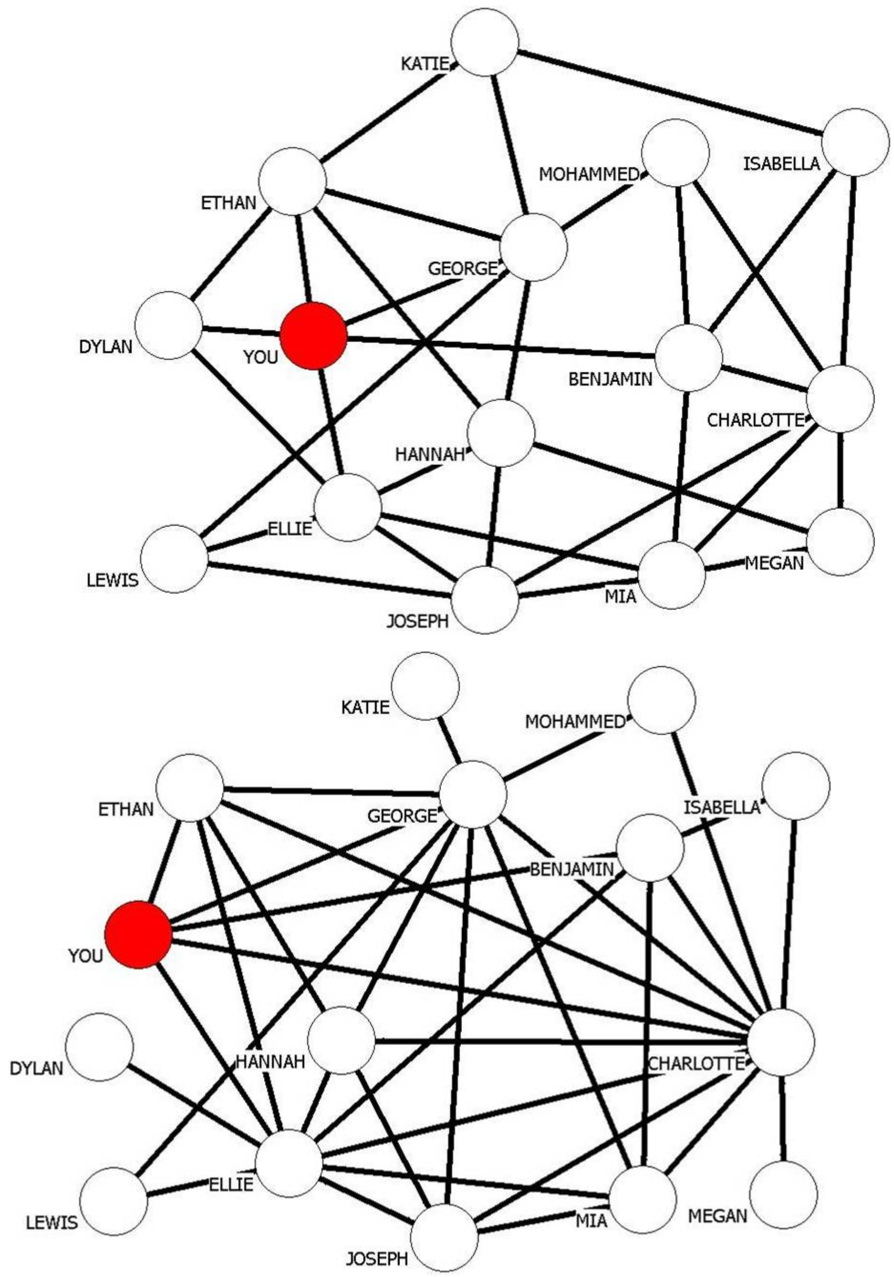

Figure 12: Network pictures shown to subjects in Treatment 1 of Stage 2 (high type). Top: Original network shown in the first 30 seconds. Bottom: Mean-preserving spread of original network shown in the last 30 seconds.

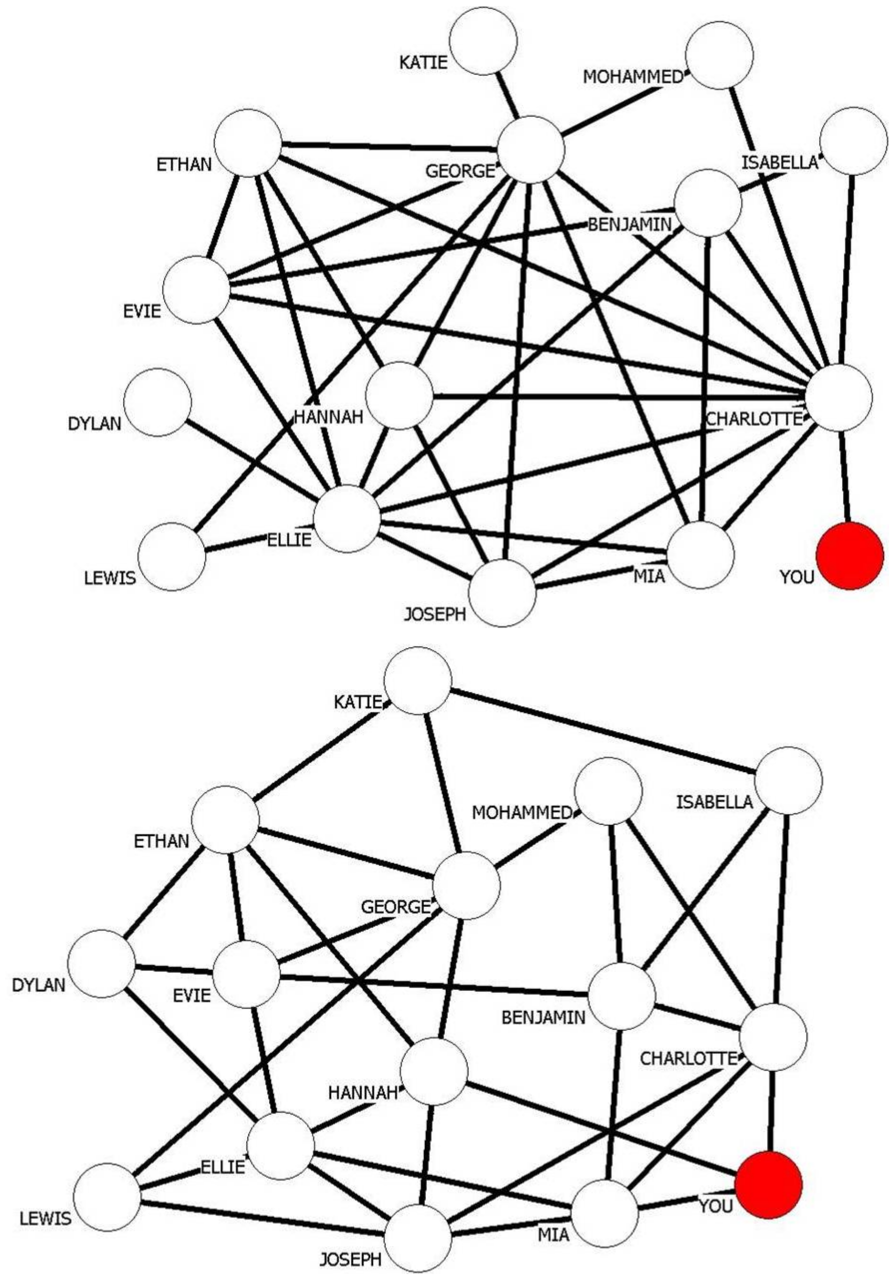

Figure 13: Network pictures shown to subjects in Treatment 2 of Stage 2 (low type). Top: Mean-preserving spread of original network shown in the first 30 seconds. Bottom: Original network shown in the last 30 seconds.

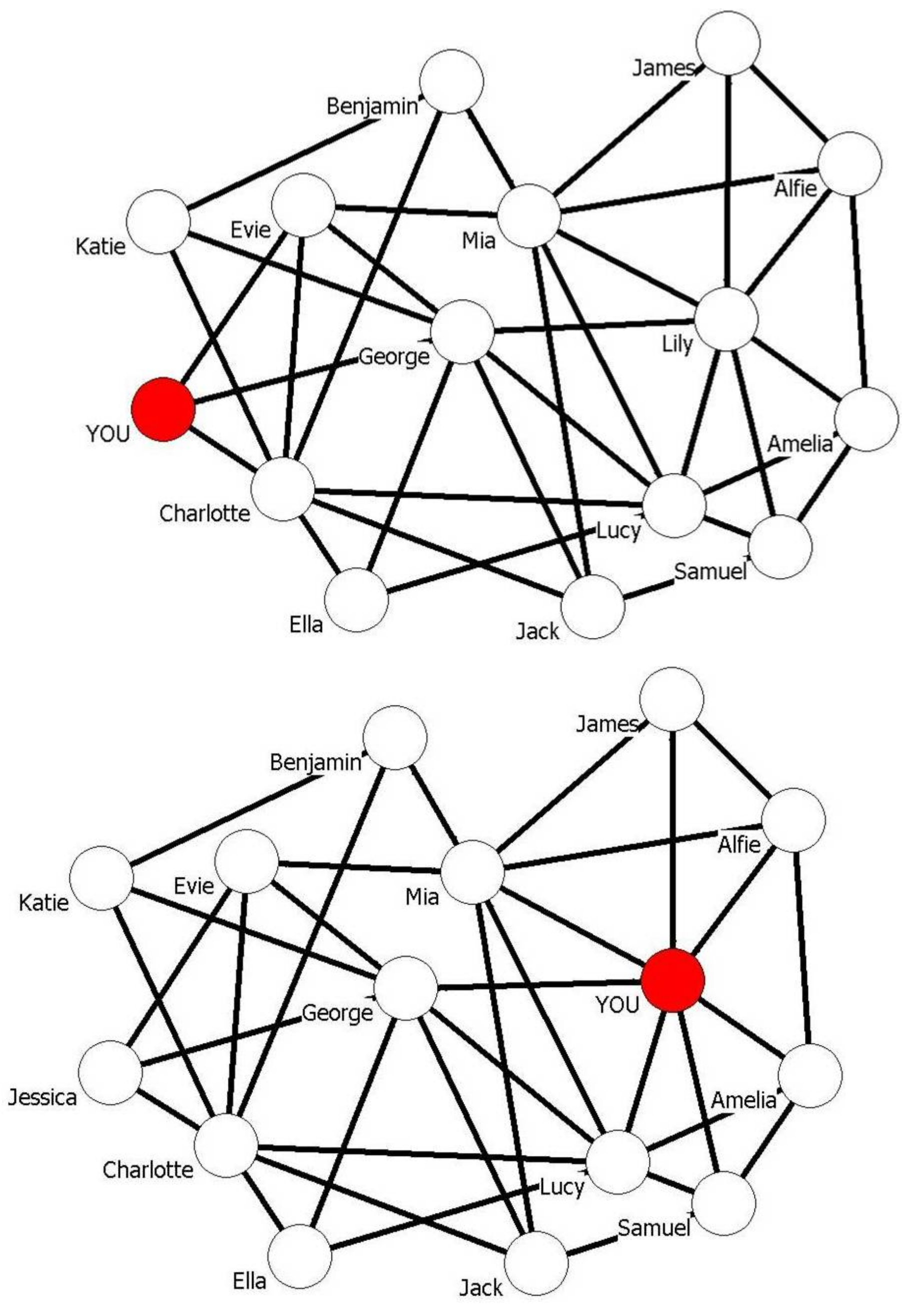

Figure 14: Network pictures shown to subjects in Stage 3. Top: Treatment 1 - Low type with degree=3. Bottom: Treatment 2 - High type with degree=7.

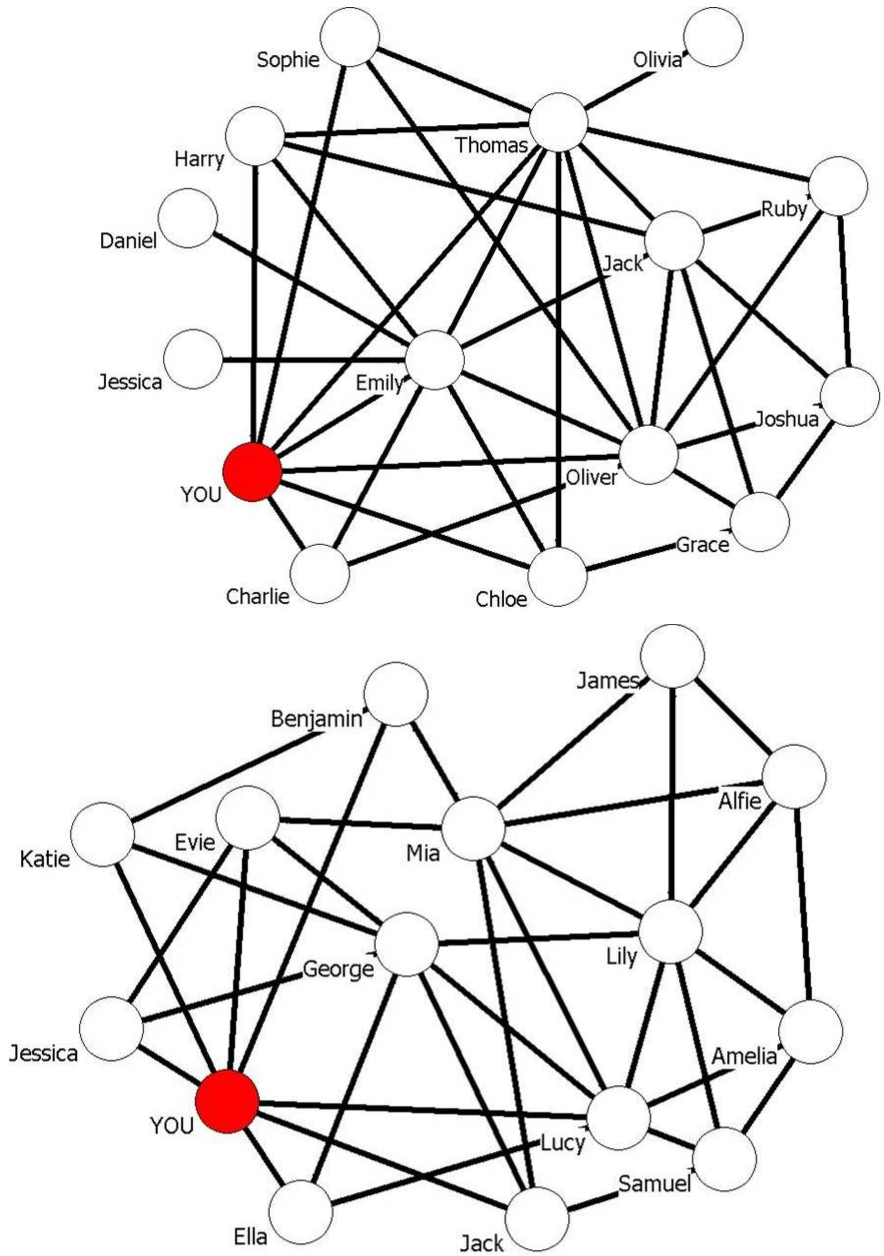

Figure 15: Top: network picture shown to subjects in Stage 4. Bottom: network picture shown to subjects in Stage 5.