Gender differences in networking*

Friederike Mengel †

University of Essex & Lund University

February 4, 2020

Abstract

Gender differences in networking have been cited as an important reason behind gender earnings and promotion gaps. Despite this fact there is comparatively little evidence on whether such differences exist or what they look like. We conduct a series of experiments to gain insight into these questions. The experiments are designed to understand differences in the strategic use of networks, when both men and women have the same opportunities to network. While we do find evidence of gender earnings and promotion gaps in the lab, we do *not* find evidence of gender differences in network formation, except for the fact that men display more homophily than women. Women and men do, however, *not* systematically differ in terms of their in- or out-degree nor in terms of their centrality in the network. Earnings and promotion gaps appear partly because male decision-makers are more likely to reward their (predominantly male) network neighbours with increased earnings as well as promotion.

JEL Codes: J16, J71, C92.

Keywords: gender, earnings and promotion gaps, networking, lab experiments.

*I thank Andrea Galeotti, Rachel Kranton, Joshua Miller, Steve Pudney, Carmit Segal, Martin Strobel, Nick Vriend, Ro'i Zultan, two anonymous Reviewers and seminar participants in Essex, Frankfurt, Geneva (EEA 2016), Hamburg, London (experimental workshop 2015), Muenchen (workshop on Decisions, Groups and Networks), Norwich (BiNoMa Networks workshop 2016), Sussex (RES conference 2016) and the BEE-Lab meeting in Maastricht for helpful comments, Sara Godoy for assistance in running the experiments and Edward Ruchevits for programming. Financial support from Dutch Science Foundation (NWO, VENI grant 016.125.040) is gratefully acknowledged.

†Department of Economics, University of Essex, Wivenhoe Park, Colchester CO4 3SQ *and* Department of Economics, Lund University, SE-220 07 Lund, Sweden. *e-mail*: fr.mengel@gmail.com

1 Introduction

Persistent gender earnings and promotion gaps have attracted much attention in research and policy debates in recent years (see Goldin and Rouse (2000), Niederle and Vesterlund (2007), Black et al. (2008), Bagues and Esteve-Volart (2010) or Sandberg (2013) among many others).[1] Potential explanations for gender earnings and promotion gaps include differences in competitiveness and career ambition, differences in child rearing responsibilities, cultural pressures but also outright gender discrimination.

One of the most commonly cited explanations for gender earnings and promotion gaps are gender differences in networking (Saloner (1985); Gersick et al. (2000); Sandberg (2013)). Since Granovetter (1973) a number of authors have pointed out the importance of social connections for obtaining jobs and job-related advantages (Montgomery (1991); Hwang and Kim (2009); Renneboog and Zhao (2011); Beaman and Magruder (2012)). Gender differences in obtaining and using such connections via networking have been named a key factor to limits womens' success in labor markets. Consequently, the amount of resources spent on womens' networking events, designed to address presumed differences in networking, is enormous.[2] Despite these facts there is little evidence on whether gender differences in networking exist or what they look like.[3]

The principal aim of this paper is to test for the existence of gender differences in networking and to better understand their nature. Identifying gender differences in networking in the field presents a number of difficulties. First, real-life networks can often not be observed. Even if networks can be elicited, it is often hard to distinguish types of relationships. It is also difficult to measure failed attempts at linking and to observe how the network (and networking efforts) change with incentives. Finally, the position a person occupies in a network will be endogenous to her as well as others' characteristics and past decisions, a fact that makes identification of gender differences difficult (McDowell et al., 2005).[4] All these difficulties can be overcome in a lab experiment. Some important features of real-life interactions are, however, absent in the lab. Obstacles to networking for women often include factors, such as e.g. child-care duties, which prevent women from spending time networking after work (Campbell, 1988). In the field it is difficult to disentangle such lack of opportunities from preferences or strategic choices (Moore, 1990). In the lab opportunities are the

[1]Academia is no exception. While in some fields of academia gender promotion and earnings gaps have converged, this is not true in others. Economics is one of the fields where promotion and earnings gaps are particularly persistent and cannot be easily explained (Ceci et al., 2014). Earnings gaps among US full professors in Economics are even higher in 2010 than they were in 1995 with female full professors earning less than 75% of their male counterparts (Ceci et al., 2014).

[2]A google search on womens' networking events returns more than 21 million results (google.co.uk, May 2015). The UK's Daily Telegraph (http://www.telegraph.co.uk/ women/ womens-business/ 10129034/ Women-only-events-Does-anyone-else-have-networking-fatigue.html) asks "does anyone else have networking fatigue" in the light of so many "women only" networking events? BBC Radio 4 has a programme called "Networking Nation" (http://www.bbc.co.uk/programmes/b04l0gdl) and organizations like the "Women in Business Network" (wibn.co.uk), "Enterprising Women" (www.enterprising.women.org) or "Forward Ladies" (forwardladies.com) hold regular networking events.

[3]Literature is reviewed in detail below.

[4]The example studied in McDowell et al. (2005) are co-authorship networks in academia. Findings that women tend to co-author less than men (have fewer links in co-authorship networks) could be due, among others, to lower productivity or propensity to publish, but also to selection into different research areas etc.

same for men and women. Hence we can identify whether there are gender differences in how men and women form and use networks strategically if both have the same opportunity in doing so.

In our experiment participants first performed a real effort task. The second stage was the networking stage. In the third stage one group member was selected to be "decision-maker" and to allocate the overall surplus among all group members. All three stages (task, networking and allocation of surplus) were repeated ten times. Treatments differed in two dimensions.

Our first treatment variation concerns the networking stage. Networking can have many functions including joint production, coordination, forming agreements, acquiring or passing on information. A minimal networking variation focuses on the information aspect of networking. If i forms a link to j, then j is informed about i's score but not vice versa. Hence under this variation, forming a link allows participants to pass on information, but not to acquire information.[5] Under the second variation, if i forms a link to j, a chat window opens and i and j can chat for 3 minutes. This open communication variation hence allows participants to network in a less restrictive format and it allows participants both to pass on but also to acquire information, to explicitly discuss and reach agreements etc.

Our second treatment variation changes how the "decision-maker" is selected. We focus on three different environments, which differ in how promotion — defined as being selected as a decision-maker — is determined. In the first environment, it is determined by performance. In the second, by the number of incoming connections. In the third, by designation by others. Understanding in which of these settings networking differences appear (if at all) can help us understand the origin of networking differences. It also has consequences for organizational design if one of the aims is to reduce gender gaps.[6]

We find substantial gender earnings and promotion gaps in our experimental treatments. Men earn between $12-30\%$ more than women in three treatments. They are between $9-10\%$ more likely to be promoted in two treatments. Only in two of our six treatments we find neither earnings nor promotion gaps.

In terms of networking, we find few differences in how networks are formed. Mens' networks display more homophily than womens' in almost all treatments.[7] In two treatments men also have a somewhat higher out-degree (more outgoing links) compared to women. Otherwise there are no gender differences in network formation. Neither homophily, nor out-degree are, however systematically related to earnings or promotion on average across both genders. In line with a conjecture by Ibarra (1993) we find, though, that men benefit from homophilous ties while women don't. We also find

[5]This minimal networking condition could reflect networking activities such as passing one's CV or newest research paper, e-mailing colleagues highlighting ones contribution to a project or communicating another achievement to a target person.

[6]Typical work environments have features of all three. If we think, e.g., about promotions in an academia, performance (in terms of publications, teaching evaluations etc.) clearly matters. However, there is also an element of designation as typically those who are already at a higher level of the hierarchy, e.g. full professors, decide on promotions of those at a lower level, e.g. associate or assistant professors. And finally networking is seen by many to play an important role as colleagues share information about their work. How important each of these components is will differ across different work environments.

[7]Throughout the paper we will use the term "homophily" to refer to the mere statistical fact that men are over-proportionately connected to men and women with women (McPherson et al., 2001).

gender differences in how networks are used. While neither women nor men discriminate between genders *per se*, men have a tendency to favor their network neighbours. In particular, men are $\approx 40\%$ of a standard deviation more likely to designate network neighbours to succeed them as decision-makers. They tend to reward network neighbours by $\approx 16\%$ higher earnings in the treatments where earnings gaps have been identified. Neither men nor women do receive preferential treatment in either of these dimensions *per se*. However, as most neighbours of male decision-makers are male, the fact that men, but not women, reward their network neighbours can explain a substantial part of the earnings and promotion gaps we observe. This fact also explains why men benefit from homophily while women don't.

Our paper contributes to the literature on gender differences in networking by providing what is to our knowledge the first experimental study of gender differences in strategic networking. Gender differences in networking has been an active research area in organizational behaviour and sociology (Eder and Hallinan, 1978; Campbell, 1988; Burt, 1992, 1998; Ibarra, 1992, 1993). In the context of his seminal work on structural holes Burt (1998) has shown that early promotion correlates to network properties in opposite direction for men and women. For men it is better to have diverse contacts. Women get promoted earlier, the more their relations are directly or indirectly concentrated in a single contact. Particularly interesting in our context is work by Ibarra (1993) who studies personal networks of women and minorities in management. She develops two hypotheses related to homophily within this context: (i) women will have a smaller percentage of same-sex ties and (ii) homophily and positional power of network contacts will be negatively associated for women, but not for (white) men.[8] Despite the fact that there are no pre-existing structural asymmetries between men and women in our experiment, our results are in line with both these hypotheses. Our results also shed light on a number of other conjectures on the origin of networking differences that have been circulated in existing popular as well as academic literature. Roughly speaking, these conjectures can be divided into three categories. The first category claims that networking is not as useful for women as it is for men, either because women can expect less positive reciprocity than men (Heilman and Chen, 2005; Aguiar et al., 2009), because there are fewer women in powerful positions or because networking women are perceived as less likeable (Mc Ginn and Tempest, 2000; Sandberg, 2013). Our evidence partly supports these conjectures. Women do less often benefit from positive reciprocity in our experiment. The reason is, however, not that men or women would discriminate against women per se. Instead men (and only men) do substantially reward their network neighbours and those neighbours happen to be predominantly men. Conditional on who they are linked to, men and women benefit equally from positive reciprocity. The second category of explanations claims that women network less effectively, because they use networks less strategically (Rudman, 1998). We find little evidence supporting this conjecture when it comes to network formation. Women in our experiment form equally many links as men in almost all treatments and their networking activities depend on achievements (performance) in the same way as men's. A third category of explanations focuses on differences in opportunities such as the fact that women have less time to engage in networking activities because they are more involved with e.g. childcare (Campbell, 1988).

[8] Those are Hypotheses 1 and 3 in Ibarra (1993).

As discussed above, such differences are outside the scope of our experiment. While this means that some aspects of networking cannot be studied in this paper, it also means that we are able to isolate differences in the strategic use of networks under ex ante equal opportunities.

Our study is also related to research on gender differences in the workplace more generally (see e.g. Delfgaauw et al. (2013)). There is an empirical literature studying how referrals from current employees (the "old boy network") can reduce employer uncertainty about worker productivity (e.g. Simon and Warner (1992)). These papers do not usually focus on gender differences in networking. Exceptions include Marmaros and Sacerdote (2002) who study how college seniors use social networks to obtain their first jobs or Lalanne and Seabright (2014) who find that salaries of male, but not female executive board members are an increasing function of influential people they have met in the past. Because of the difficulties with field data described above, neither of these studies can identify networking differences. The findings by Lalanne and Seabright (2014), in particular, are however consistent with our finding that men tend to favor network neighbours. This can lead to earnings gaps if there is homophily in networks. The effect of homophily could be compounded if, unlike in our experimental setting, there are more men in powerful positions to start with. Zeltzer (2016) shows that part of the Medicare Physician Pay Gap can be explained by gender homophily in referral networks, illustrating how gender homophily can contribute to occupational inequalities. Also Ibarra (1992) has demonstrated the existence of homophily in a study conducted in an advertising firm. She concluded that men appeared to reap greater network returns from homophilous relationships. As discussed above, this is in line with our evidence.[9] Several other researchers have documented gender differences in existing networks (Benenson, 1993; Moore, 1990; Lindenlaub and Prummer, 2014; Buechel et al., 2014). This research has produced rich accounts of women and men's positions in networks, though the evidence on what the differences are is a bit mixed. Such differences in existing networks of men and women could come about via differences in networking, but also via differences in preferences, abilities or organizational and social constraints. Our study contributes to this literature by providing experimental variation on incentives to network. Because we are able to observe strategic formation of networks starting from a fully symmetric situation, we are able to show what type of differences in existing networks are likely due (or not due) to gender differences in strategic networking.

The finding that predominantly men tend to favour network neighbours contributes a new aspect to the gift exchange and reciprocity literature (Fehr et al., 1993, 1998). This literature has focused on documenting how people exchange favors in work settings (typically trading effort for fixed wages). Our paper identifies another dimension of work interactions in which gift exchange plays an important role. Predominantly men reward their network neighbours through earnings and promotions, which can contribute to gender earnings and promotion gaps.

Finally we also contribute to the literature that documents and discusses reasons behind gender earnings and promotion gaps, which are not directly related to networking differences. Some re-

[9] Gender differences in the formation of friendship networks have been studied by Mayer and Puller (2008). While there will likely be some common elements in friendship and professional network formation, the latter serves different aims and many of the elements discussed above (share of women in powerful positions, likeability of networking women etc.) will not be present or substantially weakened in friendship networks.

searchers have, for example, documented gender biases in performance evaluations (see e.g. Goldin and Rouse (2000), Krawczyk and Smyk (2016), Boring (2017) or Mengel et al. (2019)), in education (Mondschein et al. (2000), Halim and Ruble (2010)) or gender differences in preferences (see e.g. Gneezy et al. (2003); Niederle and Vesterlund (2007)). All of these can be additional channels leading to earnings and promotion gaps. In this sense our paper complements this evidence.

The paper is organized as follows. In Section 2 we describe the experimental design as well as the results from our control treatment. Section 3 shows our evidence on earnings and promotion gaps, Section 4 discusses gender differences in networking and Section 5 discusses some mechanisms and additional results. Section 6 concludes. More information about the sample, experimental instructions as well as additional tables and figures can be found in an Appendix.

2 Design and Procedures

In this section we describe the experimental sample (Section 2.1), design and procedures (Section 2.2) and discuss evidence from our control treatment (Section 2.3). At the end of the Section we summarize the research questions and give a road-map for the rest of the paper (Section 2.4).

2.1 Sample

We describe some characteristics of our sample. More details are provided in Appendix A. Our participants have signed up at Essex Lab at the University of Essex to participate in social sciences experiments. Most participants are University students, but there is a non-negligible share (12%) of non-students participating in the experiment. The sample is overall gender balanced: 50.88% of participants are male in the minimal treatments and exactly 50% in the treatments with chats. Appendix Figure A.4 shows the distribution of group compositions in terms of gender. The typical group in the experiment was gender balanced with three male and three female participants. There were no exclusively male or female groups, but several groups with either 33 percent or 66 percent women and some groups with only one woman (or one man). The age distribution among male and female participants is plotted in Appendix Figure A.1. Women were on average 22.39 (22.38 in the treatments with chats) years old ranging from 18 to 62 (18 to 69). Men were on average 22.71 (23.28) years old with a range from 18 to 54 (18 to 77). Appendix Figures A.2 and A.3 show the distribution of participants' nationalities. Most participants are from Europe (non UK), followed by the UK and South- and East-Asian countries. Finally, Appendix Table A.1 reports balancing tests, which shows no statistically significant differences across treatments according to the sample characteristics we elicited.

2.2 Design

All of our treatments consist of 10 repetitions of the following game of three stages: (i) first participants solve a task and receive a *score* reflecting their performance (**task stage**), (ii) they can form links to others (**networking stage**) and (iii) one group member allocates the groups' surplus (**allocation stage**). These three stages are meant to represent highly stylized work environments, where first work is produced and then networking is used to achieve work-related benefits, such as pay increases or promotion. We will describe the three stages in turn. First, however, we will describe how gender identity was communicated in the experiment.

Gender Identity At the start of the experiment participants were asked to enter some basic demographic information, such as age, gender, nationality, student status etc. Afterwards participants were informed on the screen that they were assigned an avatar which was shown to them on the screen. They were also informed that "*All women have been assigned a female "avatar" and all men a male "avatar". Other than that the pictures have no connection to the information provided by you.*" Hence they were informed that behind a female (male) avatar is always a female (male) participant, but this information was framed in the context of an assurance of their anonymity. When filling in the demographics participants did not know yet that there would be avatars in the experiment.[10] We used 24 different female and male avatars to reduce the risk that particular facial features might trigger responses by others.[11] With this design we hoped to credibly communicate gender identity while at the same time minimize the risk that participants consider this an experiment about gender or wonder why gender information is given.[12]

Participants were then randomly assigned into groups of six participants and remained in these groups throughout the experiment. We chose repeated interaction as it is often described as an essential part of an environment for networking to be effective (Jones et al., 1997). We now describe the three stages of the experiment: the task, networking and allocation stage. The stages were repeated ten times in the same groups.

Task stage We asked participants to count the number of "1" entries in a Boolean 20×20 matrix with only 0 and 1 entries (Abeler et al., 2011). Participants had 75 seconds to enter their count. A screenshot of the task can be found in Appendix Figure C.3. Denote by Δ_i the absolute value of the difference between the true number of "1" entries in the matrix and participant i's count.[13] Participant i then receives a score SC_i which equals

$$SC_i = \begin{cases} 20 - \Delta_i & \text{if } \Delta_i \leq 20 \\ 0 & \text{else} \end{cases}$$

The group score is the sum of the scores of all group members and hence ranges between

[10]The instructions do not make any mention of avatars, so participants learn that avatars exist only after they have filled in the demographic information (see the instructions in Appendix B). Demographic information was cross-validated by an experimenter (see Appendix C for details).

[11]Figures C.6 and C.7 in Appendix C show all avatars with their average score and earnings.

[12]Text analysis suggests that this was successful. Participants refer to others in the chat as he/she depending on the gender of the avatar used. When referring to another participant in the chat such gendered words are used 96% of the time.

[13]The number of "1" entries in these matrices across rounds was (135;129;167;145;182;117;235;151;142;190) in this order.

$\{0, ..., 120\}$. After the task, participants were informed about their own score and their rank in the group of six. Ties were broken randomly by the flip of a fair coin. Participants were also informed about the group score, but not about the individual scores of other group members.[14]

Networking stage In the networking stage participants could form links to other group members. Links last only for the current rounds, i.e. have to be renewed in each period. Participants received an endowment of 10 tokens in each period and each link costs 2 tokens. Only the participant initiating the link had to pay for it. Remaining endowments from the network stage were converted into GBP at a rate of 1:1 and added to participant's earnings at the end of the experiment. There are two treatment variations on the networking stage both focused on information transmission.[15] Under the first participants learned the individual scores of the group members who established a link to them. Appendix Figures C.4 and C.5 show screenshots of the linking stage and the associated information stage. This minimal networking condition, where a link initiated by i only reveals i's score to j could reflect networking activities such as passing one's CV or newest research paper or communicating another achievement to a target person. While this condition allows us to have full control about which information participants hold at any given time, it may be too restrictive to capture what "networking" is about for our participants.

We hence also study an open communication variation which allows participants to network in a less restrictive format. Under this second treatment variation, if either participant i established a link to j or vice versa, then a bilateral chat window opened in which participants i and j could chat for three minutes. If participants held multiple links at the same time, all chats happen simultaneously on a split screen.[16] This treatment variation hence also breaks the tight link between transmitting information about performance and networking which is present under the first variation. Instead it allows participants to communicate, make agreements or transmit information in whichever way they would like. We label the treatments with this open form of communication with a suffix **-COMM**.

Allocation stage After the networking stage the group score was converted into pounds (GBP) at a rate of 1:1 and a "decision-maker" allocated the earnings among the six group members (in any way s/he likes). The allocation of earnings hence took place in a multi-person dictator game with the "decision-maker" being the dictator.[17] At the end of each round, participants were informed about the group score, their own score, who was decision-maker, how much the decision-maker allocated

[14]Giving participants information about individual scores could be interesting when there are benefits to linking with participants with higher performance (e.g. if network neighbours engaged in joint production where performance matters). This is not the case here. Note, though, that participants can still hold information about past scores as well as past roles (decision-maker or not) of others. See paragraphs "*Networking Stage*" and "*Allocation Stage*" below.

[15]As discussed in the Introduction networking can have other functions as well, such as acquiring human capital or producing a joint output. In order not to make the design too complex, we decided to focus on one function of networking only, which is sharing of information.

[16]This places a cognitive constraint on how many conversations participants can entertain. Comparison with the minimal treatments, however, suggests that this constraint was rarely binding. More importantly, even if the constraint was binding, this presumably would be the same for both genders.

[17]Dictator games following real effort tasks have been studied by Ruffle (1998) or Oxoby and Spraggon (2008) among others. Heinz et al. (2012) find that female dictators tend to reward performance more than male dictators. Ruffle (1998) and Oxoby and Spraggon (2008) do not explicitly study and report gender differences.

to them and their payoff in this round (allocation by the decision-maker plus remaining endowment from the networking stage).

Treatments also differed in how the "decision-maker" is determined. In treatments **PERF** and **PERF-COMM** the best performing group member (with the highest score SC_i) becomes decision-maker. In treatments **DESIG** and **DESIG-COMM** one participant is randomly chosen to be the decision-maker in period 1. In all subsequent periods the current decision-maker designates the next period decision-maker. Participants cannot designate themselves. In treatments **NET** and **NET-COMM** the group member with the highest in-degree in the network (i.e. who most others linked to) becomes decision-maker.

These three conditions highlight three aspects of typical "promotions": performance, designation and networking. Comparing these treatments will help us understand to which extent networking differences depend on the role networking is given in the institutional environment. See Section 2.4 for more details and research questions. We also ran a control condition (**CONTROL**) which we will describe in Section 2.3. Table 1 summarizes the number of observations and the gender distribution for each treatment. While the aim of the paper is *not* to test predictions of standard game theory, theoretical predictions for the different treatments can be found in Appendix E.[18]

	Observations		Gender Distribution	
	Observations	Groups(Clusters)	women	men
PERF	600	10	29	31
NET	600	10	30	30
DESIG	660	11	31	35
PERF-COMM	720	12	36	36
NET-COMM	720	12	38	34
DESIG-COMM	600	10	28	32
CONTROL	220	-	10	12

Table 1: The table summarizes the number of observations, clusters (i.e. groups of six participants) and the gender distribution in the different treatments.

Other Details At the end of the experiment one period was selected randomly for payment. Participant's earnings are the show up fee of 3 pounds, the remaining amount from their endowment in the networking stage as well as the share of the group score the decision-maker allocated to them. Earnings ranged between 4 GBP and 124 GBP with an average of 22.90 GBP. The experiments were conducted at Essex Lab at the University of Essex in March 2014 using the software z-tree (Fischbacher, 2007). Participants were recruited using the recruitment system hRoot. More detailed description of the sample as well as balancing tests can be found in Appendix A. Ethical approval was obtained by the FEC (Faculty Ethics Committee) at the University of Essex under Annex B.

[18] Broadly speaking, since in treatments **PERF** and **DESIG** , networking does not have any benefits under standard game theoretic assumptions, but does come with a cost, we should not observe any networking in these treatments and equilibrium networks should be empty. This is different in treatment **NET**, where the networking game is a game of coalition formation. In equilibrium we should see a coalition of $n \geq 3$ players who are linked in a complete graph. Each of these players becomes decision-maker with probability $\frac{1}{n}$. See Appendix E for details and underlying assumptions.

2.3 Control condition

The control condition was conducted to see whether there are substantial performance differences between men and women in this task in the absence of a networking or allocation stage. In the control condition participants performed the task ten times repeatedly and were paid simply their score SC_i from a randomly drawn period (in addition to the show-up fee).

	Accuracy		Speed	
	female	male	female	male
mean	15.19	13.43	70.38	68.04
median	15.9	15.5	70.7	68.65
std.dev.	2.97	5.36	5.00	5.85
0-25	13.8	11.8	69.25	63.8
75-100	17.6	17.7	74.8	74.5
ranksum test	$p = 0.6680$		$p = 0.3199$	
Participants	12	10	12	10
Observations	120	100	120	100

Table 2: Performance differences in **CONTROL**. In columns (1) and (2) the table shows summary statistics for individual scores averaged across participants and all ten matrices, separately for men and women. Columns (3) and (4) show summary statistics on the average time taken to complete a task.

Table 2 shows that the performance of men and women in the control treatment is very similar. This is true both for accuracy (their score) and speed (how long it took them to enter the score). The median score for women is 15.9 and for men 15.5 points meaning that they were off by about 4.1 to 4.5 numbers in their count on average across the 10 matrices they faced. The number of different women in the **CONTROL** condition with the maximal score of 20 is ten, and the number of men 7. Hence more than 70 percent of participants reach the maximal score at least once. The distribution of individual average scores (across the ten rounds) is not different between men and women according to a ranksum test ($p = 0.6680$).[19] Appendix Figure H.1 (Panel (a)) shows the cumulative distribution of all scores for both men and women. The Figure shows that, while there are somewhat more zero scores among men, the distribution of scores is otherwise very similar.[20]

In terms of the time taken to enter their decision (speed), both men and women are relatively close to the time out of 75 seconds. On average (across the 10 matrices faced) they enter their count about 5 seconds before that. Appendix Figure H.1 (Panel (b)) shows the cumulative distribution of time taken in all rounds separately for men and women. It can be seen that the screen times out for men and women in about 50% of the cases. 70% of both men and women finish the task with less than 10 seconds to spare. Among those that make relatively quick decisions (between 55-65 seconds) men are a bit faster than women.

Taken together the evidence suggest that the task was easy, but not trivial for participants. There are no substantial gender differences neither in terms of accuracy nor in terms of speed, i.e. time taken to enter the count.

[19] If we do not average across individuals, giving the ranksum test greater power to detect differences, the difference is still not significant ($p = 0.3231$).

[20] In Appendix H we also illustrate performance differences in the main treatments (Figure H.2) and show that there are no substantial gender differences in these treatments either.

2.4 Research Questions

Before we start presenting our main results in the next section, we summarize our research questions and hypotheses. The presentation of our results will then follow the structure outlined in this Section.

First we briefly discuss the motives to network in the different treatments. In treatment **PERF** the only clear reason to network is to communicate one's own performance to a potential future decision-maker. This could serve as a signal of one's ability or effort. As the group score is known in addition it also serves as a (noisy) signal of others' effort or ability. The **COMM**-variation adds an element of persuasion to this motive where participants can explicitly ask for a certain share of the earnings as a result of their performance. According to standard game theory there are, however, no incentives to network in these treatments (Appendix E). A direct and explicit impact of networking on promotion is added in treatment **NET** where the network explicitly determines who becomes decision-maker via a form of popularity contest. Hence, in this treatment, there is a potential motive for favor exchange as each link formed to a person helps them to reach power (become decision-maker). The **COMM**-variation allows for explicit discussion of linking strategies and explicit coordination on who to link to. The favor exchange element is reinforced in treatments **DESIG** where there is an equilibrium in which two participants form a coalition and share power among themselves (see Appendix E). While such agreements have to be reached tacitly in **DESIG** , in **DESIG-COMM** open communication allows reaching such agreements explicitly. There can be non-tangible reasons for forming a link as well, such as establishing likeability or "connection" in a vague sense. These non-tangible elements are present in all treatments. However, we would expect them to be stronger in the **COMM**-treatments with open communication. For all our research questions we will ask how the extent to which the institutional environment creates a space for informal arrangements and favor exchange affects gender differences.

We now state our research questions and the road-map for the following Sections. As much of our motivation comes from the role networking plays for earnings and promotion gaps, we first ask whether there are earnings and/or promotion gaps in our experiment. We also ask how the answer to this question depends on the role networking is given in the institutional environment.

Q1 *Are there gender earnings and promotion gaps and do they depend on the role networking is given in the institutional environment?*

Research question Q1 will be addressed in Section 3. The second question relates to gender differences in networking, specifically to identifying differences in network formation.

Q2 *Are there gender differences in networking and do they depend on the role networking is given in the institutional environment?*

Answering this question comprehensively also tests a set of conjectures discussed in the Introduction. If women network less effectively as they are more reluctant to communicate achievements (Rudman, 1998), then we should see women forming fewer links (have a lower out-degree) in **PERF** compared to men, particularly among the group of high performers. If women network less effectively as they use networks less strategically, then this can lead to multiple differences in network formation we should detect. In **PERF** women's networking activities should react less to performance than men's, in **DESIG** we should see fewer reciprocal links etc. We should also detect larger gender differences in the treatments where networks have more of a strategic role. Research question Q2 will be addressed in Section 4.2. Our third question relates to how network are used.

Q3 *Are there gender differences in how networks are used and do they depend on the role networking is given in the institutional environment?*

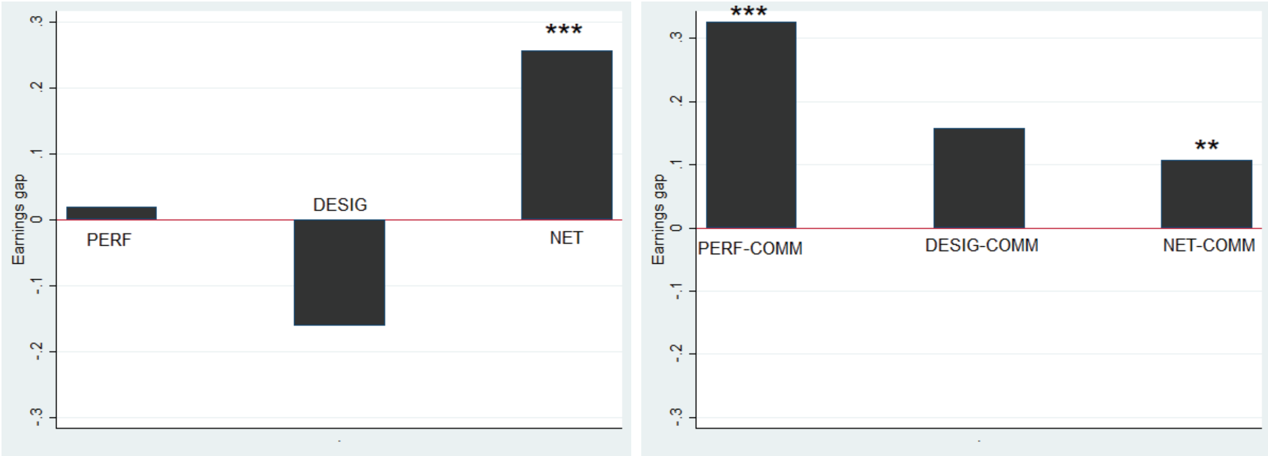
In addressing this question we will give special attention to the question of favor exchange. Hence we will ask whether there are gender differences in the extent to which women and men use networks to exchange favors. Differences in how networks are used can impact on how beneficial it is for men and women to network and hence can shed light on Heilman and Chen (2005)'s conjecture that women may network less because they are less likely to benefit from reciprocity (see also Aguiar et al. (2009)). Research question Q3 will be addressed in Section 4.3. We now turn to our main results.

3 Gender earnings and promotion gaps

We ask whether there are earnings and promotion gaps in our experiment starting with earnings gaps. To answer this question we focus on average earnings from periods 6-10 of the experiment disregarding show up fees and remaining endowments from the networking stage. We focus on periods 6-10 to capture mature behaviour after some learning has taken place and we disregard show up fees and remaining endowments for this analysis to capture as closely as possible the type of monetary earnings differences typically referred to as "earnings gaps". Differences in networking and associated costs will be studied further below.

Earnings, thus defined, can differ across genders for three reasons. First, the frequency with which women and men are decision-makers can differ (promotion gap). Second, the amount of money male and female decision-makers allocate to themselves could differ and third the amount decision makers allocate to males and females who are not decision-makers could differ. The second difference is maybe best interpreted as differences in altruism or generosity between men and women in this setting.[21] For the purpose of defining earnings gaps in this paper, we are interested in the third difference. We hence define the earnings gap as the percentage gap between earnings of male and female participants who are *not* decision maker.

[21] While gender differences in altruism are not the focus of this paper, they could - combined with a promotion gap - create additional imbalances in earnings. Hence it is worthwhile pointing out that we do not detect statistically significant gender differences. Female decision-makers allocate on average (64, 52, 46, 47, 32 and 33 %, respectively, of the pie to themselves in treatments (**PERF**,**DESIG**, **NET**, **PERF-COMM**, **DESIG-COMM** and **NET-COMM**)), while for male decision-makers the same numbers are (61,51,48,44,28 and 32 percent). While there are no gender differences, there are two noticeable patterns in these shares. First, participants allocate more to themselves in treatments **PERF** and **PERF-COMM**, where the decision-maker has the highest performance and hence the highest contribution to the group earnings. Second, participants allocate less to themselves in the **COMM**-treatments, where they can be directly challenged by others for their allocation decisions in the chats.



(a) Base treatments (b) COMM treatments

Figure 1: Percentage gap between earnings of male and female participants who are *not* decision maker across the three treatments **PERF** , **DESIG** , and **NET** (left panel) and **PERF-COMM**, **DESIG-COMM** and **NET-COMM** (right panel). Positive differences mean men earn more and negative differences mean women earn more. Stars indicate significance levels according to two-sided ranksum tests (***1%, **5%, **10%).

Panel (a) in Figure 1 shows the earnings gap for the Base treatments, where networking involves only minimal communication (i.e. passing on information about one's score). Conditional on not being decision-maker in treatment **NET** men earn 11.00 pounds on average which is 25 percent more than women who earn 8.83 pounds in that case. In treatment **PERF** and **DESIG** there are no statistically significant gender differences in earnings. Panel (b) in Figure 1 shows the earnings gap for the **COMM** treatments. Men earn substantially more than women in all treatments with open communication. The earnings gap is almost 30% in **PERF-COMM** and $\approx$ 10% in **NET-COMM**. In **DESIG-COMM**, the difference between female and male earnings is not statistically significant at conventional levels.

Table 3 report the results of regressions where we regress the earnings of participants who are *not* decision makers on a gender dummy (= 1 if the participant is male) and their performance (score) in the task as well as some controls. It can be seen that a higher performance increases earnings in all treatments, albeit not significantly so in **DESIG**. In treatments **NET**, **PERF-COMM** and **NET-COMM** there is an additional effect of gender. Men earn $\approx 1.50 - 3.40$ GBP more than women even after performance is controlled for (columns (3), (4) and (6)). After accounting for mean performance of men and women the earnings gap ranges between 12% to 30%.[22]

Promotion Gap Table 4 focuses on promotions, in particular on the probability to become decision-maker. Performance increases participants' chances to become decision-maker only in treatments **PERF** and **PERF-COMM**, where, by design, the highest scoring group members become decision-maker. There is no significant effect of performance on the chances to become decision-maker in any of the other treatments. There are possibly gender gaps in treatments **NET** and **DESIG-COMM**. Men are between $9 - 10\%$ more likely to become decision-makers in these treat-

[22] The mean score of men is 14.94, 12.68 and 13.00 in **NET**, **PERF-COMM** and **NET-COMM**, respectively (15.02, 13.06 and 13.68 for women).

	Earnings Gap					
	(1) PERF	(2) DESIG	(3) NET	(4) PERF-COMM	(5) DESIG-COMM	(6) NET-COMM
`male`	-0.233	-1.254	1.556*	3.408***	2.422	2.151**
	(1.357)	(1.363)	(0.810)	(0.865)	(2.587)	(0.878)
`score`	0.127**	0.030	0.290***	0.245***	0.202***	0.340***
	(0.049)	(0.034)	(0.069)	(0.074)	(0.051)	(0.055)
Observations	250	275	250	300	250	300
Number of Participants	60	66	59	72	60	71

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Earnings as a function of gender dummy and performance (score) in the task. Random effects OLS regressions based on data from periods 6-10 of the experiment. Standard errors are clustered at the (matching) group level and do account for auto-correlation at the individual level. Controls for age, nationality as well as session fixed effects are included. Earnings regressions include only participants not in the role of decision maker.

	Promotion Gap					
	(1) PERF	(2) DESIG	(3) NET	(4) PERF-COMM	(5) DESIG-COMM	(6) NET-COMM
`male`	-0.086	0.033	0.092*	0.025	0.102	-0.078
	(0.059)	(0.042)	(0.050)	(0.055)	(0.074)	(0.081)
`score`	0.014***	0.001	-0.002	0.015***	-0.002	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	300	330	300	360	300	360
Number of Participants	60	66	60	72	60	72

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Promotion as a function of gender dummy and performance (score) in the task. Random effects OLS regressions based on data from periods 6-10 of the experiment. Standard errors are clustered at the (matching) group level and do account for auto-correlation at the individual level. Controls for age, nationality as well as session fixed effects are included.

ments (columns (3) and (5)). However, those are either only marginally significant at the 10% level (**NET**) or just outside of 10% statistical significance (**DESIG-COMM**).

How does the institutional environment affect gender earnings and promotions gaps? We conjectured in Section 2.4 that environments that create more space for informal arrangements and favor exchange could lead to bigger gender differences in earnings and promotion. We do find some support for this conjecture, as in our basic treatment variations we find earnings or promotion gaps only in treatment **NET**. In the **-COMM** variations, by contrast, we do identify earnings gaps also in **PERF-COMM**, possibly because with chats favour exchange is also possible in this environment. We analyze chat content in Section 5.3.

Robustness Appendix G reports a few robustness checks and additional results. Appendix Table G.1 reports some descriptive statistics. Appendix Tables G.2 and G.3 explicitly show all controls used in Tables 3 and 4. We also conducted our regressions with avatar fixed effects. The problem with this exercise is that each avatar exists only in one gender. Male avatars can hence jointly absorb the effect of the `male` dummy. Still results are robust under such exercises and, importantly, no single avatar receives systematically higher or lower earnings than others (see also Figures C.6 and C.7 in Appendix B).

4 Networking

To study whether earnings and promotion gaps can be (at least partially) explained by differences in networking, we first ask whether certain network positions are positively related to earnings and promotion (Section 4.1). We then ask whether women and men differ in how they form networks and in terms of the network positions they occupy (Section 4.2). Finally, we ask whether women and men differ in how they use existing networks (Section 4.3). As before we focus on mature behaviour in the second half of the experiment, i.e. across periods 6-10.

4.1 Importance of network position for earnings and promotion

A network is defined as a collection of nodes $\mathcal{N} = \{1, ..., 6\}$ and a set of edges (links between the nodes) defined as $\Xi \subseteq \{(i,j)|i \neq j \in \mathcal{N}\}$, where an element (i,j) indicates that i has established a link to j. Note that $(i,j) \in \Xi$ does not imply $(j,i) \in \Xi$ reflecting the fact that the network is directed, as (i) only the agent who establishes the link bears the cost and (ii) in the treatments with minimal communication information along (i,j) flows only from i to j.

We consider the following network characteristics. Agent i's out-degree summarizes how many links s/he has formed in the network, i.e. counts the number of edges $(i,j) \in \Xi$. Among network characteristics out-degree is probably the closest measure of "networking" as it measures how active an agent is in terms of forming links. Out-degree is also the only network characteristic that agents have full control over, i.e. it does not depend on decisions of others.

In-degree, by contrast, is defined as the number of others linked to an agent, i.e. it counts edges $(j,i) \in \Xi$. In-degree, just as out-degree, ranges between 0 to 5. We would not think of in-degree as a good measure of networking, as it cannot be controlled (directly) by the agent. However it can be seen as a measure of popularity and is in treatments **NET** and **NET-COMM** mechanically related to promotion, as those with the highest in-degree become decision-maker in these treatments.

A variable that has been linked to networking success in the sociological literature is homophily. Homophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people, where similarity can be race, gender or any other dimension (McPherson et al., 2001). In our context (gender-based) homophily measures the share of actual within-gender links relative to the share implied by random linking. More precisely we define homophily as follows. Denote by s_g the share of same-gender links of a person of gender g and by ω_{gk} the share of people of gender g in group k. The homophily index we then use is Currarini et al. (2009)'s inbreeding homophily index defined as

$$\frac{s_g - \omega_{gk}}{1 - \omega_{gk}}$$

Homophily takes the value 0 if the share of within-gender links equals the share implied by random linking. If it exceeds 0 participants establish disproportionately more links within gender. If it is negative they establish disproportionately more links across gender (heterophily).[23] Homophily

[23]Consider, for example, a group of 4 women and 2 men. Random linking would imply that 60 percent of a woman's links in this group are to other women (since she can't link to herself) and 40 percent to men. If now a woman in

(in-degree) reports this measure for an agent's in-degree and homophily (out-degree) for an agent's out-degree, by measuring s_g among participants' incoming and outgoing links, respectively. Note that it is in principle both possible (i) for one gender to display more homophily than the other gender in terms of out- *and* in-degree as well as (ii) for one gender to display more homophily in in-degree while the other gender displays more homophily in out-degree. Appendix Figure H.3 illustrates this point. It has been argued in the literature that having homophilous networks is beneficial for men, but not for women (Ibarra, 1993). This is a conjecture we will test below.

Eigenvector centrality is a measure of how central a person is in the network. It reports an agent's eigenvector centrality in the undirected adjacency matrix.[24] Unlike the degree measures eigenvector centrality not only accounts for how many people one is linked to, but also who these people are, i.e. how important they are in terms of their network position. Eigenvector centrality is considered important in the literature on diffusion of information in social networks (Jackson, 2015).

Appendix Figures H.4 and H.5 show the distributions for these different network characteristics across treatments. The figures show that there is substantial variation in all five network characteristics. They also show that there are very few treatment differences in homophily and eigenvector centrality. It can be seen, however, that more links are formed and received in the **NET** treatments compared to the **PERF** and **DESIG** environments.[25]

We now ask how network position affects earnings and promotion in the experiment. To this end we estimate the following equation for each condition and network characteristic separately

$$y_i^t = \alpha + \beta_1 \texttt{male}_i + \beta_2 \texttt{score}_i^t + \beta_3 \texttt{NW-characteristic}_i^t + \epsilon_i^t, \tag{1}$$

where y_i is our outcome of interest, i.e. either earnings (Table 5) or promotion (Table 6), and `NW-characteristic` is one of the following network characteristics: in-degree, out-degree, eigenvector centrality, homophily (in-degree) and homophily (out-degree). We chose not to control for these network characteristics at the same time as they tend to be strongly correlated. Tables 5 and 6 report β_3 for each network characteristic.

In terms of the impact of network position on earnings (Table 5), there are only two network characteristic for which β_3 has the same sign across all treatments. Those are in-degree and eigenvector centrality. Both of them are consistently associated with higher earnings. However this effect is statistically significant in only one treatment for in-degree and in three treatments for eigenvector centrality. Out-degree and homophily do not seem to have a consistent effect on earnings or promotion.

this group has two links, one to a woman and one to a man, the homophily index would be (0.5-0.6)/(1-0.6)=-0.25 indicating heterophily. See e.g. Currarini et al. (2009).

[24] Loosely speaking, eigenvector centrality measures how many others an agent connects, where connections to other 'important' agents contribute more to the influence of the agent in question than equal connections to 'unimportant' others. Hence it is a recursively defined measure (see Appendix D for the precise definition). Google's PageRank is a variant of the eigenvector centrality measure.

[25] We also considered two further well-known network characteristics: betweenness centrality and clustering. We find that neither of them has any significant impact neither on earnings nor promotion. Because there is very little variation for these measures in our networks, these null-results are not too meaningful. As a consequence we chose to omit these measures from our analysis.

	Effect of network position on earnings (Coefficients β_3)					
	(1)	(2)	(3)	(4)	(5)	(6)
	PERF	DESIG	NET	PERF-COMM	DESIG-COMM	NET-COMM
`in-degree`	1.195	0.630	0.577	1.273	3.476**	0.742
	(0.759)	(0.682)	(0.460)	(1.015)	(1.074)	(0.514)
`out-degree`	0.549*	0.976**	-0.008	0.752	0.020	-0.037
	(0.283)	(0.404)	(0.232)	(0.590)	(0.374)	(0.202)
`EV-centrality`	4.574	7.603*	0.976	5.697	31.638**	15.297***
	(3.555)	(3.866)	(2.844)	(3.711)	(11.254)	(4.073)
`homophily (in)`	-0.034	0.706	-0.404	-1.448	0.200	0.609
	(0.401)	(0.540)	(0.386)	(1.005)	(0.820)	(0.505)
`homophily (out)`	-0.016	0.846	0.058	-0.355	0.631	1.070
	(0.490)	(1.270)	(0.651)	(0.940)	(1.024)	(0.624)
Observations	250	275	250	300	250	300

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of network position on earnings. Coefficients β_3 from different OLS regression of earnings on gender dummy, score and one network characteristics based on data from periods 6-10 of the experiment. Standard errors clustered at the matching group (network) level are in parentheses. All regressions include controls for age and nationality as well as session fixed effects.

	Effect of network position on promotion (Coefficients β_3)					
	(1)	(2)	(3)	(4)	(5)	(6)
	PERF	DESIG	NET	PERF-COMM	DESIG-COMM	NET-COMM
`in-degree`	-0.006	0.067*	0.157***	0.053**	0.068**	0.185***
	(0.017)	(0.030)	(0.017)	(0.019)	(0.023)	(0.017)
`out-degree`	-0.062***	0.012	-0.016	-0.000	0.005	-0.002
	(0.012)	(0.009)	(0.015)	(0.024)	(0.010)	(0.009)
`EV-centrality`	-0.507*	0.448*	1.229***	0.187	0.786***	1.059***
	(0.241)	(0.229)	(0.214)	(0.163)	(0.204)	(0.202)
`homophily (in)`	-0.019	0.037	0.044	-0.097**	0.015	0.008
	(0.023)	(0.025)	(0.039)	(0.033)	(0.032)	(0.021)
`homophily (out)`	0.013	-0.054	0.028	-0.032	-0.022	-0.076**
	(0.024)	(0.033)	(0.018)	(0.032)	(0.035)	(0.029)
Observations	300	330	300	360	300	360

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of network position on promotion. Coefficients β_3 from different OLS regression of promotion on gender dummy, score and one network characteristics based on data from periods 6-10 of the experiment. Standard errors clustered at the matching group (network) level are in parentheses. All regressions include controls for age and nationality as well as fixed effects for the number of male group members as well as session fixed effects.

It should also be noted that earnings gaps remain even after network characteristics are controlled for. In the three treatments, where statistically significant earnings gaps have been identified (**NET**,**NET-COMM** and **PERF-COMM**), the coefficient β_1 is in the same range as in the original regression and always statistically significant.[26] This suggests that network position cannot explain the differences in earnings we observe.

The results are similar with respect to promotion gaps. Promotion gaps remain even after network characteristics are controlled for. Now in-degree is positively associated to promotion in all treatments, but treatment **PERF**. In **NET** and **NET-COMM** we would expect this association by construction. There it is hence a purely mechanical effect. As in-degree measures the number of links received, this positive association could also reflect an attempt by participants to link to others who they believe are likely going to be decision-maker. No other network characteristic shows a consistent sign of β_3 across all treatments, but eigenvector centrality has a statistically significant and positive relation to promotion in four out of six treatments.

In particular also homophily has no consistent sign and is never statistically significant on average, i.e. across both genders. This is the case for both earnings and promotion. According to a conjecture by Ibarra (1993), however, homophily should have a positive effect for men and a negative effect for women. Indeed we do find some evidence for such an effect. On average across the treatments without chats, we find that homophily in out-degree is positively associated with earnings and promotion for men ($\beta_3 = 1.370$ for earnings and $\beta_3 = 0.935^{***}$ for promotion), but not for women ($\beta_3 = 0.379$ for earnings and $\beta_3 = -0.103$ for promotion). For the **COMM** variations we find that homophily has a positive effect on earnings for men (on average across the three decision environments) with raw coefficients $\beta_3 = 1.197$ for mens' earnings and $\beta_3 = 0.030$ for promotion. For women, by contrast, both these coefficients are negative with $\beta_3 = -0.123$ for earnings and $\beta_3 = -0.059^{**}$ for promotion. While not all these coefficients are statistically significant, it seems that forming links within gender (homophily) might indeed be beneficial for men, but not for women, as conjectured by Ibarra (1993).

Robustness Checks We also conducted a number of robustness checks and additional analyses. Tables G.4 and G.5 show results separately for majority-female, gender-balanced and majority-male groups with no differential patterns across these groups. Tables G.6 and G.7 in Appendix G show the results of running regression (1) on past average network characteristics, i.e. earnings or promotion at time t are explained via the mean of `NW-characteristic` across periods 1,...,t instead of simply by $\texttt{NW-characteristic}_i^t$. This exercise hence allows for the fact that earnings or promotion may be affected by the network position of agents over a longer horizon rather than just their position in the current round. Table G.6 shows results that are very similar under this exercise. The only network characteristic that reliably affects earnings is eigenvector centrality. Earnings gaps appear in the same treatments as in the regressions focused on current network characteristics. They are also of the same magnitude. Table G.7 shows that the effect of past eigenvector centrality is weaker and in most treatments not statistically significant, suggesting that current rather than past eigenvector

[26] For **NET** it ranges between 1.699^{*} and 3.107^{**}, for **PERF-COMM** between 3.799^{***} and 5.110^{***} and for **NET-COMM** between 1.959^{*} and 2.010^{**}.

centrality matters more for promotion. Past in-degree is mostly statistically insignificant in line with the idea that some of the effect of current in-degree might not be causal.

4.2 Gender differences in network formation

In this section we ask whether there are gender differences in network formation, in particular whether men and women end up with different network positions. Of course we will be particularly interested in those network characteristics that seem to systematically affect earnings and promotion.

	PERF		DESIG		NET		PERF COMM		DESIG COMM		NET COMM	
	W	M	W	M	W	M	W	M	W	M	W	M
in-degree	1.468	1.534	1.141	0.982	1.853	1.866	0.383	0.566	1.142	1.006	1.594	1.594
β	0.066		-0.159		0.013		0.183*		-0.136		-0.000	
out-degree	1.448	1.252	1.109	0.948	1.580	2.140	0.388	0.655	0.971	1.418	1.431	2.252
β	-0.196		-0.161		0.560*		0.266		0.447		0.821**	
EV centrality	0.176	0.159	0.155	0.176	0.162	0.170	0.149	0.182	0.167	0.165	0.155	0.179
β	-0.018		0.020		0.007		0.033		-0.001		0.023	
homophily (in)	-0.181	0.081	-0.331*	0.073	-0.635***	0.066	-0.163	0.084	-0.447	0.122	-0.609*	0.111
β	0.262		0.405*		0.702***		0.248		0.569*		0.720*	
homophily (out)	-0.114	0.022	-0.245*	0.089*	-0.327**	0.087	-0.179	0.082	-0.254	0.094	-0.243	0.035*
β	0.136		0.334**		0.415***		0.261**		0.349**		0.278*	

Table 7: Network Characteristics: mean across periods 6-10 by gender as well as β from panel OLS regression $y_i = \alpha + \beta \texttt{male}_i$, where y_i is the outcome (network characteristic) we are interested in. Standard errors are clustered at the matching group level. Stars on means of homophily measures indicate significance levels from F-test of $\alpha = 0$ for women and $\alpha + \beta = 0$ for men, respectively.

Table 7 shows the mean value of all network characteristics discussed in Section 4.1 for both men and women and across our 6 main treatments. The table also shows gender difference in these characteristics measured by the β coefficient in an OLS regression

$$y_i = \alpha + \beta \texttt{male}_i + \epsilon_i,$$

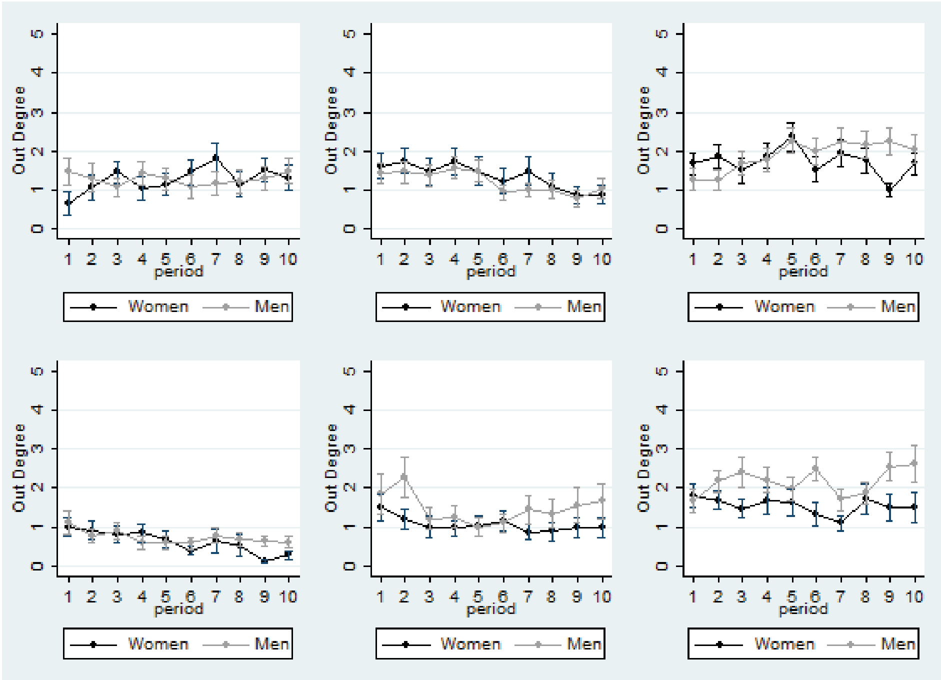
where y_i is the network characteristic of interest.[27]

As discussed above out-degree is the only network characteristic that is fully under the participant's control and arguably the best measure of networking. We hence focus on this measure first. Overall, the fewest number of links are formed in treatment **PERF-COMM** (about one link every other period) and most links are formed in **NET** and **NET-COMM** with about 1.5 links formed and received by women and about 2 links formed and received by men. These are also the only treatments where men are somewhat more active than women in networking, forming 0.56 or 0.821 links more on average per period.[28] In all other treatments men and women form and receive about the same number of links across all treatments.

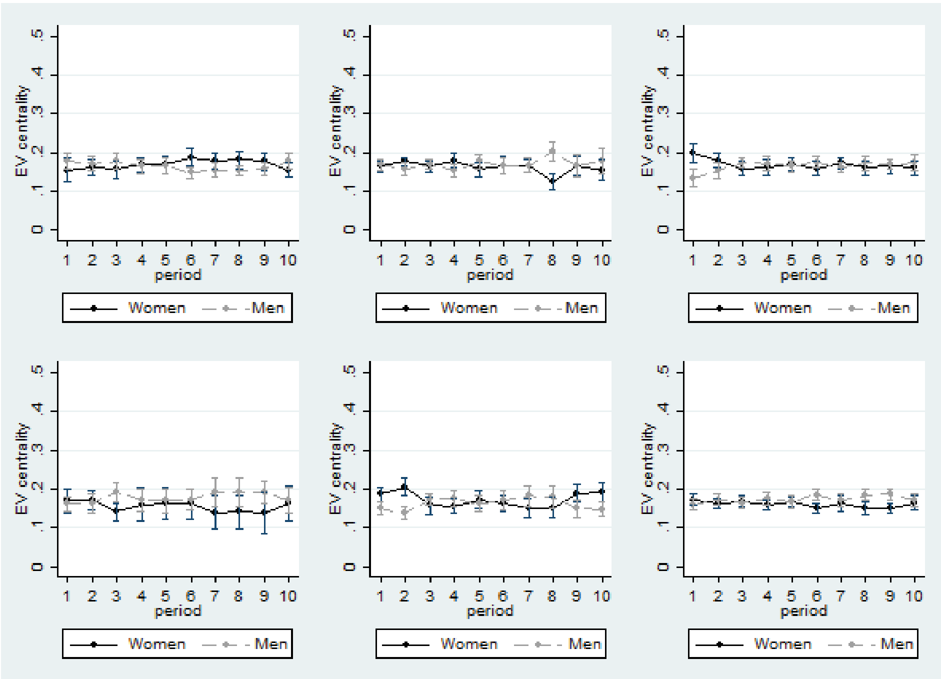
As one of the reasons to form links could be to signal performance, we checked for gender differences in how participants' propensity to form links reacts to performance in more detail. To do

[27]Other network characteristics, such as clustering or betweenness centrality do not deliver significant gender differences. These measures, however, lack variation and include many zeros. Hence it is hard to interpret these distributions.

[28]Remember that in these treatments those with the highest in-degree are more likely to become decision-maker. Hence forming many links here (high out-degree) c.p. reduces one's chances to become decision-maker, as it increases those of other group members.



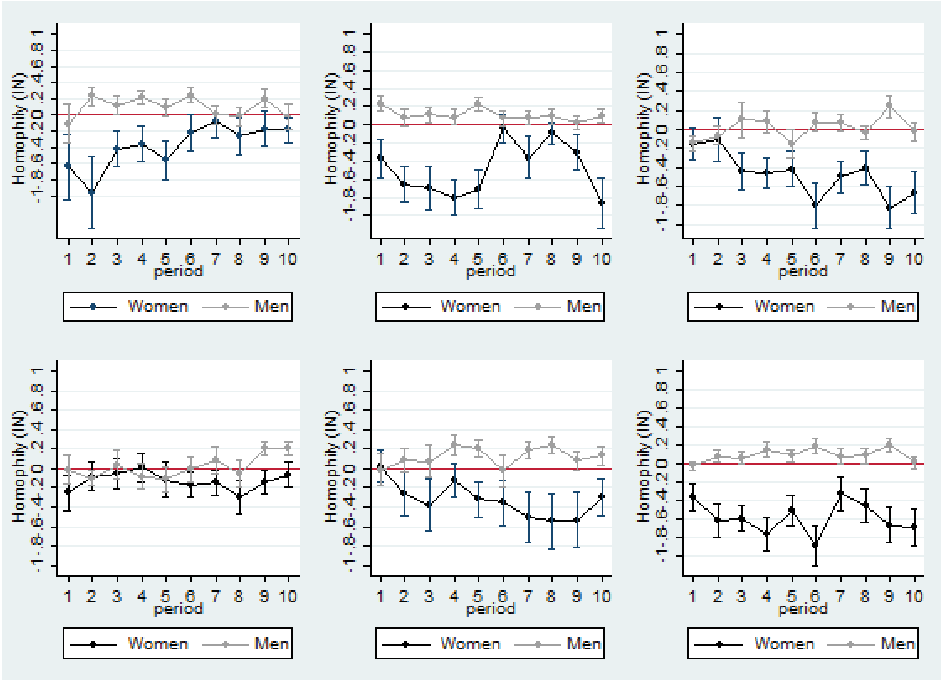
(a) Out-degree



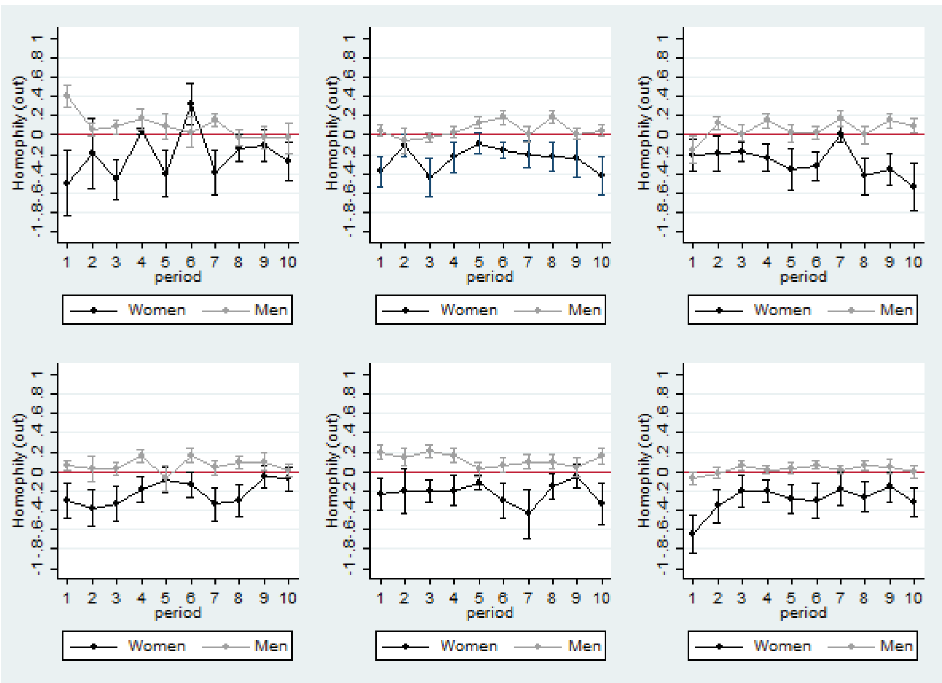
(b) EV centrality

Figure 2: Average network characteristics of men and women over time. Top panel shows treatments **PERF**,**DESIG** and **NET**. Bottom panel shows treatments **PERF-COMM**,**DESIG-COMM** and **NET-COMM**. Black solid line are women, gray dashed line men.

this we regressed out-degree (number of links formed) on score and ask whether men or women's out-degree reacts more strongly to score. In the minimal communication treatments we see some (small) positive association of out-degree with score, which is only in statistically significant for men in **DESIG** and **NET** (see Appendix Table G.8. In the **COMM**-variation out-degree does not



(a) Homophily (IN)



(b) Homophily (Out)

Figure 3: Average degree of homophily (in- and out-degree) of men and women over time. Top panel shows treatments **PERF**,**DESIG** and **NET**(from left to right). Bottom panel shows treatments **PERF-COMM**,**DESIG-COMM** and **NET-COMM**(from left to right). Black solid line are women, gray line men. The reference line shows the case of zero homophily implied by random linking. Above the reference line networks display homophily, i.e. over-proportional linking within gender. Below the reference line networks display heterophily, i.e. under-proportional linking within gender.

react to score neither for men nor for women. Here all coefficients are close to zero. Crucially, however, there is no statistically significant gender difference in how out-degree reacts to score in any of the treatments. If we split the sample by score we also find no gender differences in out-degree neither for "low achieving" (ranked 4-6) nor "high achieving" (ranked 1-3) participants. Hence there is no evidence that women network less or are more reluctant to communicate achievements in our context. Panel (a) in Figure 2 illustrates the mean out-degree of men and women over time in the six treatments.

Most gender differences arise in terms of homophily. Men display homophily in all treatments ($\alpha + \beta > 0$) both in terms of in- and out-going links, i.e. they link more to men and receive more links from men compared to what gender-blind linking would suggest. Women, by contrast display heterophily in all treatments ($\alpha < 0$). Except for treatment **PERF** the gender difference in homophily is always statistically significant for out-degree and it is statistically different in four out of six treatments for in-degree.[29] These differences are illustrated in Figure 3. As homophily is positively related to earnings for men and negatively for women (Section 4.1), this difference is in line with both genders following earnings-maximizing strategies.

Apart from homophily, we find few differences between how women and men form networks. Importantly, differences between women's and men's eigenvector centrality are small and statistically insignificant. Panel (b) in Figure 2 illustrates mean eigenvector-centrality of men and women over time in the six treatments illustrating that they are virtually identical and statistically no different in any of the treatments.

4.3 Strategic Use of Networks

In the previous section we saw that differences in network formation (and resulting network positions) are not able to explain earnings and promotion gaps by themselves. In this section we will try to understand whether there are differences in how men and women use networks in their decisions and whether and how such differences can be part of the explanation for gender earnings and promotion gaps. In particular, we will focus on decision makers in this section and ask whether there are any differences between how male and female decision-makers use networks in their decisions regarding earnings and promotion. To these ends we run the following regression

$$\begin{aligned} y_{ij}^t &= \alpha + \beta_1 \texttt{score share}_j^t + \beta_2 \texttt{network share}_j^t + \beta_3 \texttt{female}_j^t \\ &+ \gamma_1 \texttt{score share}_j^t \times \texttt{male}_i^t + \gamma_2 \texttt{network share}_j^t \times \texttt{male}_i^t + \gamma_3 \texttt{female}_j^t \times \texttt{male}_i^t + \epsilon_{ij}^t \end{aligned} \quad (2)$$

where x_{ij}^t denotes the amount decision-maker i allocates to j in round t and $y_{ij}^t = \frac{x_{ij}^t}{\sum_{k \neq i} x_{ik}^t}$ hence denotes the share of the group score remaining (after i has allocated some to herself) that decision maker i allocates to j in period t. We exclude agent i from all measures in the regression because we are interested in how i treats j *compared to other group members* and not in e.g. how much i keeps

[29]Note that it is in principle both possible (i) for one gender to display more homophily than the other gender in terms of out- *and* in-degree as well as (ii) for one gender to display more homophily in in-degree while the other gender displays more homophily in out-degree. Appendix Figure H.3 illustrates this point.

	Minimal communication treatments					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	PERF	DESIG	NET	DESIG	DESIG
`score share` (β_1)	0.286***	0.267*	0.353*	0.233**	0.190	0.327
	(0.082)	(0.139)	(0.165)	(0.094)	(0.237)	(0.247)
`network share` (β_2)	-0.023	-0.000	-0.045	-0.022	-0.142*	-0.144
	(0.024)	(0.039)	(0.034)	(0.025)	(0.077)	(0.084)
`female` (β_3)	0.017	0.035	0.001	0.012	0.117	0.132
	(0.014)	(0.020)	(0.036)	(0.007)	(0.071)	(0.078)
`score share` $\times$ `male DM` (γ_1)	-0.084	-0.142	-0.160	0.044	0.053	-0.212
	(0.071)	(0.112)	(0.146)	(0.073)	(0.214)	(0.202)
`network share` $\times$ `male DM` (γ_2)	0.088*	0.054	0.129	0.054	0.526***	0.506***
	(0.046)	(0.084)	(0.073)	(0.034)	(0.144)	(0.153)
`female` $\times$ `male DM` (γ_3)	-0.001	0.051	-0.011	-0.028	-0.208*	-0.201*
	(0.029)	(0.068)	(0.054)	(0.024)	(0.098)	(0.103)
`past DM`						-0.056
						(0.086)
`past DM` $\times$ `male DM`						0.284**
						(0.106)
Constant	0.136***	0.126**	0.136***	0.149***	0.062	0.038
	(0.019)	(0.037)	(0.029)	(0.023)	(0.043)	(0.041)
$\beta_1 + \gamma_1$	0.202**	0.117	0.194*	0.276**	0.241	0.114
$\beta_2 + \gamma_2$	0.069**	0.061	0.084*	0.032	0.385***	0.362***
$\beta_3 + \gamma_3$	0.016	0.091	-0.010	-0.016	-0.091*	-0.069
Observations	775	250	275	250	275	275
R-squared	0.034	0.056	0.038	0.061	0.073	0.111

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS regression shown in equation (2) with "decision maker gender interactions". Standard Errors are clustered at the (matching) group level and account for autocorrelation at the individual level. For each period 6,...,10 and each group each regression contains five datapoints indicating how much each decision-maker allocated to each group member (columns (1)-(4)) and whether or not a group member was designated to be the next decision-maker (columns (5)-(6)).

to herself.[30] Since each agent has five group members, $y_{ij} = 0.2, \forall j$ if i treats all group members equally. y^t_{ij} is regressed on (i) `network share` $\sum_{\tau=1}^{t-1} \frac{\texttt{link}^{\tau}_{ij}}{\sum_{k \neq i} \texttt{link}^{\tau}_{ik}}$: the share j occupies in i's network (i.e. which share of of $i's$ incoming links in past periods stem from agent j) and (ii) `score share` $\frac{\texttt{score}^t_j}{\sum_{k \neq i} \texttt{score}^t_k}$: the share that j's performance ($\texttt{score}_j$) contributed to the group score *exclusive* of i's performance. If the denominator in any of these variables (y^t_{ij}, `score share` or `network share`) is zero, then we set the value of the variable to 0.2 reflecting the fact that all five group members are equal. The dummy $\texttt{female}_j$ indicates whether the recipient j is female or not. All three variables are then also interacted with decision-maker gender indicated by the dummy `male`.

Table 8 shows the results of this regression for the minimal communication treatments. In columns (1)-(4) the outcome is earnings and in columns (5)-(6) it is promotion. Columns (5)-(6) exist only for treatment **DESIG**, as it is only in this treatment that decision-makers make decisions regarding promotion.

Across all treatments both women and men tend to allocate more to group members with better performance, i.e. to those whose score contributes more to the group score. Increasing the contri-

[30]Gender difference in altruism is an interesting and much studied topic (see e.g. the survey by Croson and Gneezy (2009) and the discussion in footnote 21). Here we are interested, however, in whether and how networking contributes to gender differences in earnings and promotion gaps.

bution to the group score from 0.2 (median) to 0.3 leads to an $\approx 3\%$ increase in the share of the group score allocated to that person. Given the median group score and allocations this implies that improving the score by one will increase earnings by between 7-20 cents.[31] Male decision-makers reward performance in similar ways as female decision-makers. γ_1 is small, changing in sign and statistically insignificant across all the treatments. Higher performance has an additional reward in treatment **DESIG**. In this treatment decision-makers reward high performers by nominating them to be the next decision-makers (column (5)), even though the effect is not statistically significant.

Apart from rewarding performance, female decision-makers seem to treat all group members equally when it comes to allocating the group score. In particular they do not discriminate against nor favor women and they do not react to network share, i.e. they neither discriminate against nor favor those who establish more links to them. Also male decision-makers do not discriminate against nor favor women, certainly not in terms of earnings, though there may be a an effect with respect to promotions (columns (5)). Unlike women, however, men reward those who establish more links to them. The effect is sizeable. In terms of earnings, a 1% higher frequency to be among the decision makers' neighbours leads to an $\approx 0.07\%$ increase in the share allocated to that person (column (1)). This coefficient size is about a third compared to that associated with a 1% increase in performance. The effect is even bigger when it comes to promotions ($\gamma_2 = 0.526$ in column (5)). This coefficient is $\approx 275\%$ bigger compared to the coefficient associated with an increase in performance (score share).

Column (6) explores an additional factor which is that decision-makers in **DESIG** can use arrangements to designate each other in turn as decision-makers.[32] In column (6) we include a dummy variable "`past DM`" which indicates whether j was decision-maker in $t-1$ and hence designated i to be the decision-maker in t. A positive coefficient on this dummy indicates reciprocal favor exchange in terms of designations. Column (6) shows that female decision-makers do not seem to reciprocate in this manner and tend to designate others (e.g. those with high scores) as decision-makers. Male decision-makers do, however, engage in such reciprocal designations as indicated by the interaction "`past DM` $\times$ `male DM`". We will study the role of such reciprocal arrangements in more detail in Section 5.1.

Results for the **COMM**-treatments are reported in Table 9. Again both men and women reward better performance, though in most treatments the effect is not statistically significant and in treatment **DESIG-COMM** it is even negative. Hence with open communication (and hence possibilities for explicit discussion and agreements) performance seems less important a factor in allocating earnings. Also here neither men nor women discriminate against or favor one gender per se. Men again reward their network neighbours with higher earnings in treatments **PERF-COMM** and **NET-COMM** ($\beta_2 + \gamma_2$). Interestingly, now also women reward their network neighbours with increased promotion in **DESIG-COMM** (column (5)). Column (6) shows that reciprocal designations play a very important role under this communication structure for both female and male decision-makers, though the effect is more than twice as big for male decision-makers. In Section 5.1 we study desig-

[31]We averaged the coefficients for men and women do do this computation. Score has a mean of 14.4 in treatment **PERF** (15.27 in **NET**) with a standard deviation of 6.8 (6.5 in **NET**). The amount allocated to others has a standard deviation of 6.24 in **PERF** and 7.92 in **NET**. See Appendix Table G.1.

[32]Such strategies can be part of Nash equilibrium in this treatment. See Appendix E.

			Comm treatments			
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	PERF	DESIG	NET	DESIG	DESIG
`score share` (β_1)	0.181	0.104	-0.208	0.368*	-0.287	-0.059
	(0.118)	(0.163)	(0.194)	(0.178)	(0.314)	(0.266)
`network share` (β_2)	-0.008	-0.010	0.063	-0.055**	0.186**	0.192***
	(0.017)	(0.023)	(0.040)	(0.018)	(0.081)	(0.068)
`female` (β_3)	-0.017	0.040	-0.053	-0.043**	-0.107	-0.066
	(0.023)	(0.032)	(0.063)	(0.019)	(0.073)	(0.061)
`score share` $\times$ `male DM` (γ_1)	-0.025	0.215	0.104	-0.186*	0.336	0.146
	(0.098)	(0.164)	(0.162)	(0.086)	(0.306)	(0.262)
`network share` $\times$ `male DM` (γ_2)	0.008	0.042	-0.095	0.081***	-0.253**	-0.265***
	(0.026)	(0.036)	(0.053)	(0.020)	(0.099)	(0.083)
`female` $\times$ `male DM` (γ_3)	-0.010	-0.143*	0.066	0.036	0.083	0.049
	(0.037)	(0.066)	(0.071)	(0.025)	(0.089)	(0.074)
`past DM`						0.243***
						(0.078)
`past DM` $\times$ `male DM`						0.364***
						(0.098)
Constant	0.177***	0.171***	0.233***	0.157***	0.187***	0.060
	(0.019)	(0.029)	(0.016)	(0.033)	(0.064)	(0.055)
$\beta_1 + \gamma_1$	0.155**	0.318*	-0.010	0.182	0.048	0.086
$\beta_2 + \gamma_2$	0.000	0.032*	-0.030	0.035*	0.439***	-0.072
$\beta_3 + \gamma_3$	-0.027	-0.010*	0.010	-0.016	-0.024	-0.017
Observations	850	300	250	300	250	250
R-squared	0.025	0.099	0.026	0.167	0.030	0.330

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: OLS regression shown in equation (2) with "decision maker gender interactions". `COMM` treatments. Standard Errors are clustered at the (matching) group level and account for autocorrelation at the individual level. For each period 6,...,10 and each group each regression contains five datapoints indicating how much each decision-maker allocated to each group member (columns (1)-(4)) and whether or not a group member was designated to be the next decision-maker (columns (5)-(6)).

nation patterns and show that indeed the open communication structure is much more conducive to reciprocal designations.

To sum up, while both female and male decision-makers reward performance in most treatments and neither favors one or the other gender per se, there is a difference when it comes to how network neighbours are treated. In particular male decision-makers do reward network neighbours with higher earnings and they engage to a much larger extent in reciprocal designations compared to female decision-makers.

Network neighbours are rewarded by men irrespective of their performance and their gender. How many of these network neighbours are women? In treatment **DESIG** 39% of the neighbours of male decision-makers are female, while in treatments **DESIG-COMM** and **NET-COMM** 37% or 48 %, respectively are female. Hence in all treatments, where network neighbours seem to be rewarded women are a minority of such neighbours. As a result of this men will over-proportionately reward men when they reward their network neighbours simply because more of their neighbours are men.

As it is predominantly men who reward their network neighbours, one of the implications of these findings is that homophily should be associated with higher earnings and increased promotion chances for men, while the opposite should be true for women (Ibarra, 1992). We have seen above (Section 4.2) that this is indeed the case. A second implication of this finding is that earnings gaps should arise mostly if decision-makers are male. We also find some evidence for this. In treatment

NET men earn 41%*** more than women if the decision-maker is male and 10% more if she is female. In **PERF-COMM** men earn 67%*** more if the decision-maker is male and 21%** if s/he is female. In treatment **DESIG-COMM** men are 33% more likely to be promoted compared to a woman if the decision-maker is male and 11% more likely if the decision-maker is female. In all other treatments there are no statistically significant differences in earnings or promotion gaps depending on decision-maker gender.

5 Discussion

In this section we present additional results and uncover in somewhat more detail some of the patterns identified above. Section 5.1 focuses on designation patterns in treatments **DESIG** and **DESIG-COMM**. Section 5.2 asks to which extent network formation is in line with incentives provided by the behaviour of decision-makers. And Section 5.3 contains an analysis of chats.

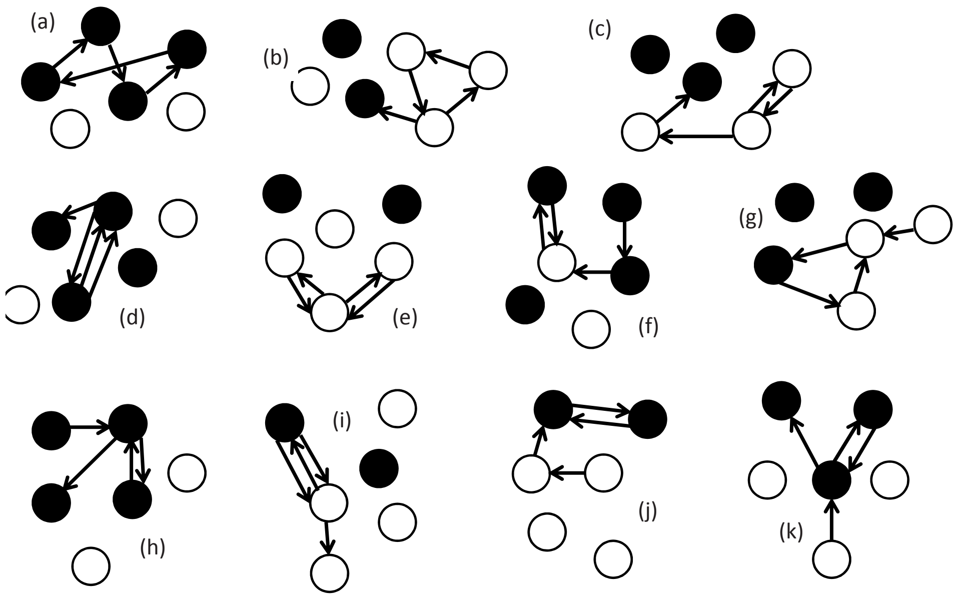
5.1 Designation Networks

This section takes a closer look at "designation networks", i.e. the directed networks illustrating who nominates who to be decision-maker in treatments **DESIG** and **DESIG-COMM**. Figure 4 shows such designation networks. Men are represented by black nodes and women by white nodes. A directed link from node i to j means that i has designated j to be decision-maker in the following period. The figure, as the rest of the analysis focuses on periods 6-10. A first glance at the figure illustrates a striking effect of open communication. While in **DESIG** designation networks involve between 3-4 different nodes (Panel (a)), in **DESIG-COMM** six out of ten networks involve only two nodes who designate each other in turn to be decision-maker (Panel (b)).

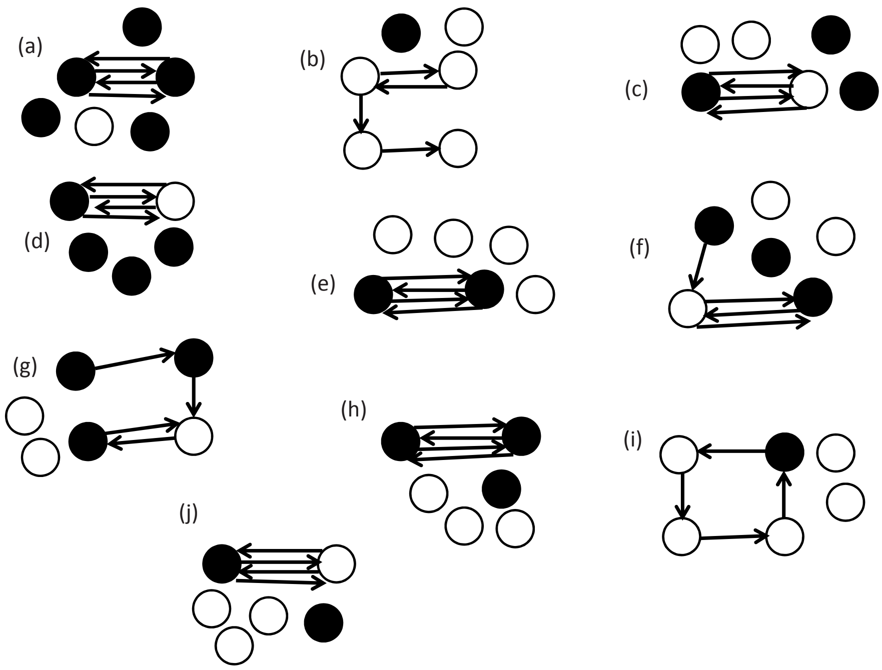
In **DESIG** networks (d) and (i) come closest to a pattern where two participants keep nominating each other in turns. Most networks are more inclusive, involving more participants. There are three exclusively male networks ((a), (d) and (h)) and one exclusively female network ((e)). A striking feature of designation networks is the extent of homophily they display. Men are 50% more likely to designate a men, while women are 25% more likely to designate a woman compared to what chance would suggest. This is consistent with the evidence seen in the previous section. Men tend to reward their network neighbours with designations and these tend to over-proportionately be men. As a consequence designation networks display substantial homophily. In terms of other gender differences, we find that men have a higher degree than women. This simply reflects the fact that men are decision-makers more often, i.e. that there is a gender promotion gap.[33] In **DESIG-COMM** there is more reciprocation. 75 percent of nodes in fully reciprocal designation networks are men and 61 percent of nodes in designation networks involving some reciprocation are men (across **DESIG** and **DESIG-COMM**). This contrasts with only 53 percent of participants being male.[34]

[33]Path dependence does not seem to be a big issue. Out of the randomly selected decision-makers in period 1 47% were female and the remainder male.

[34]Note that reciprocity here is instrumental. As such it is different from the type of positive reciprocity (trustworthiness) identified in trust games, where sometimes women have been found to be more trustworthy (Croson and



(a) **DESIG**



(b) **DESIG-COMM**

Figure 4: Designation networks across periods 6-10. Black nodes represent men and white nodes women.

Such reciprocation could possibly explain an additional part of the observed promotion gaps. There seems to be more such reciprocity in the **COMM**-variations, possibly because it allows participants to explicitly agree on such arrangements. Text analysis suggests that participants do indeed discuss such arrangements (Section 5.3). Given the importance of reciprocity in the designation treatments,

Buchan, 1999; Alesina and LaFerrara, 2002). See also the survey by Croson and Gneezy (2009).

one may wonder whether those who are not decision-maker in the first half of the experiment stop forming links in later rounds. There is some evidence that this might be the case, but conditional on the level of activity in first rounds differences between those who were and were not decision-maker in the first half of the experiment are small and not statistically significant. There are also no gender differences in these reactions.

5.2 Incentives to Network

In this section we briefly discuss incentives to network and to which extent they are in line with what we observe. We first describe the subgame perfect Nash equilibria of the induced 10-period games under standard game theoretic assumptions. Under such assumptions, networking does not have any benefits in treatments **PERF** and **DESIG**. As it does come with a cost, equilibrium networks should be empty in these treatments. This is different in treatment **NET**, where the networking game is a game of coalition formation. In equilibrium we should see a coalition of $n \geq 3$ players who are linked in a complete graph. Each of these players becomes decision-maker with probability $\frac{1}{n}$.

In all treatments there is an equilibrium where all players provide high effort. In treatment **PERF** decision-makers will keep all the surplus to themselves according to the game theoretic prediction. High effort is provided simply to maintain one's chances to become decision-maker. In both **DESIG** and **NET** , incentives to provide high effort are maintained by the allocation choices of decision-makers. Participants outside the coalition of decision-makers are paid the minimal amount needed to incentivize high effort. Decision-makers claim the rest to themselves. For details and underlying assumptions see Appendix E. Standard (gender-blind) assumptions of course do not imply any gender differences in networking, nor can they explain the presence of homophily or earnings or promotion gaps. In line with these equilibrium predictions, we do however see that more links are formed per person and round in treatments **NET** and **NET-COMM** (≈ 1.8) compared to the remaining treatments (≈ 0.9) where equilibrium networks are empty (Table 7). The standard game theoretic predictions summarized above rely on particular assumptions, that we had no particular prior to be satisfied and find empirically refuted. Still, these predictions can provide a useful benchmark to understand incentives.

Can alternative assumptions explain our findings? One modeling alternative would allow for alternative sharing rules among dictators, e.g. motivated by altruism or other factors. This might explain some of the allocations we find, but could not explain gender differences in earnings or promotions in our experiment, unless we assume that women or men differ in some way in their sharing rules (combined with homophily). Empirically we can refute two such assumptions, namely that (i) women or men differ in how much they reward performance (see coefficient γ_1 in Tables 8 and 9) and (ii) that women or men differ in how altruistic they are (see footnote 21). Another possibility would be to consider gender differences in reciprocity. We do find that men both tend to reward network neighbours more than women (subsection 4.3) and that they are more often involved in reciprocal designation networks (subsection 5.1). However these differences seem specific to the networking context rather than reflecting a general tendency of men to be more reciprocal. In trust games, commonly used to elicit positive reciprocity, it is typically found that, if at all, women are more reciprocal than men (Croson and Buchan, 1999).

What are incentives to network conditional on the empirically observed behaviour by decision-makers? To answer this question we first use our evidence from Section 4.3 and ask how much can be gained from being linked to a male/female decision-maker? In treatment **NET**, for example, male decision-makers reward their network neighbours by an increased share of earnings allocated to other group members of 0.032 (coefficient $\beta_2 + \gamma_2$ in Table 8). Multiplied with the mean amount allocated to other group members of ≈ 45 this yields a gain of ≈ 1.44 GBP from being linked to a male decision-maker. This means that on average the gain from such a link is just slightly below its cost of 2GBP. Similar calculations yield a gain of 1.12 GBP in **PERF-COMM** and a gain of 1.92 in **NET-COMM** on top of any gains from increased chances of becoming decision-maker oneself.[35] Since female decision-makers do not reward neighbours with increased earnings in most treatments, a rational reaction would be to link predominantly to men, i.e. display homophily in out-degrees for men and heterophily for women. We do indeed see this (Table 7), suggesting that participants do at least partially react to these incentives.

5.3 Chat Analysis

In the last subsection we analyze the chats from the **COMM**-treatments to understand what participants discussed with their connections. The five topics we focus on are (i) performance, (ii) networks, (iii) agreements or deals among participants (as e.g. those described in 5.1), (iv) the behaviour of other participants or (v) gender.[36]

We categorize chat content in two ways. First, we study the proportion of chats which mechanically contain certain key words for each topic (see Table 10 for the keywords for each category). Second, we sent a random sample of 75 chats (25 per treatment) to external raters using an international online survey company and ask them what they thought the chat was about. We allowed them to pick multiple from eight possible answers (see Appendix Figure F.1). For each topic, we are then interested in the percentage of chats that were classified as being about this topic by at least (90,50,10) percent of external raters. There were 56, 56 and 54 raters respectively across the three treatments **PERF-COMM**, **DESIG-COMM** and **NET-COMM**. Raters were UK nationals, but otherwise the sample was not restricted.[37] Participants were paid 1GBP for answering all 25 questions, but were not paid if they failed an attention check or answered the 25 questions in under

[35] These calculations are over-simplified as coefficients reported are based on the network share not just one one given link. They hence correspond to the thought experiment where one link is formed in a situation where no other group member has links to the decision-maker. If there are more links, then any given link will be worth less.

[36] We also conducted some analysis on basic chat characteristics, in particular the length of chats and the percent of chats where the person who initiates the chat does not receive a reply. Those are reported in Appendix Table F.1. We do not find statistically significant gender differences neither in terms of the length of the chats, nor in terms of the share of initiated chats that do not receive a reply. There is one exception, which is that chats with two male chat participants are longer in **DESIG-COMM** compared to mixed chats or chats with two female participants.

[37] We restricted to UK residents as some of the chats contain informal language that might not be easily understood by non-UK residents.

two minutes.[38] If both the mechanical method and the method using external raters yield similar results we are confident that we have identified key patterns in the chats.

		PERF-COMM	DESIG-COMM	NET-COMM
Performance	$\geq$ 90% of raters	0.16	0.20	0.12
	$\geq$ 50% of raters	0.68	0.52	0.76
	$\geq$ 10% of raters	0.96	0.96	0.96
	Words: score, rank(ed), count(ed)	0.68	0.68	0.72
Networks	$\geq$ 90% of raters	0.00	0.00	0.00
	$\geq$ 50% of raters	0.04	0.08	0.00
	$\geq$ 10% of raters	0.16	0.36	0.28
	Words: link(s), connection(s), linking	0.08	0.20	0.32
Agreements	$\geq$ 90% of raters	0.00	0.00	0.00
	$\geq$ 50% of raters	0.04	0.08	0.00
	$\geq$ 10% of raters	0.16	0.36	0.28
	Words: agree, deal, arrangement, split	0.00	0.16	0.04
Others	$\geq$ 90% of raters	0.00	0.00	0.00
	$\geq$ 50% of raters	0.00	0.04	0.04
	$\geq$ 10% of raters	0.16	0.28	0.20
	Words: labels of other participants	0.28	0.16	0.12
Gender	$\geq$ 90% of raters	0.00	0.00	0.00
	$\geq$ 50% of raters	0.08	0.04	0.04
	$\geq$ 10% of raters	0.16	0.20	0.28
	Words: male, men, man, women, woman, female	0.00	0.00	0.00

Table 10: Analysis of Chat Content. For each topic category (performance, links, agreement, others, gender) we list the percentage of chats that were classified as being about this topic by at least (90,50,10) percent of external raters or by a mechanical analysis of whether they contain the listed key words.

Table 10 shows the results. Performance is discussed in most chats. Between 68-72 percent of chats contain one of our key words and most chats are classified by a majority of raters as being about performance. There are no statistically significant treatment differences in these proportions. Networks is the second most discussed topic according to both the mechanical analysis and the external raters. Here we do detect treatment differences with higher proportions of chats being about networks in **NET-COMM** (32 percent) and **DESIG-COMM** (20 percent) compared to **PERF-COMM** (8 percent). Some level of discussion about agreements is picked up by external raters with the highest percentage in treatment **DESIG-COMM** followed by **NET-COMM** and **PERF-COMM**. These are not picked up as much by our mechanical analysis, possibly because our choice of words was not rich enough to capture these discussions. In line with the evidence from Section 5.1 the discussion of agreements in **DESIG-COMM** is also the only topic where we detect some gender differences. Men discuss agreements more often compared to women, but the difference is only marginally statistically significant (two-sided ranksum test, $p < 0.1$). Finally, we also detect some level of discussion about other participants. External raters also pick up some discussion about gender, but this is not at all backed up by our mechanical analysis. Note also that apart from performance none of the topics is picked up by a large percentage of external raters. This could partly be due to the fact that many chats that are about networks or agreements are *also* about performance and not all raters tick multiple options even though this was possible.

In summary our content analysis shows that in **PERF-COMM** most chats are about performance and some are about other participant's behaviour. No other topic is consistently identified by both methods to matter in more than 10 percent of chats. Also in **DESIG-COMM** performance

[38] This happened only in one case.

is the most common topic, but here networking, agreements and other participants' behaviour are also consistently identified as important topics (discussed in more than 10 percent of chats according to both classification methods). In **NET-COMM** performance is the most important topic, but also networking and other participants' behaviour is frequently discussed. These results are intuitive. The more importance the environment gives for agreements or networking, the more often these are discussed in chats.

6 Conclusions

We conducted an experiment to understand gender differences in networking and how they contribute to gender earnings and promotion gaps. In our experiment participants interacted in environments, where promotion and earnings depend on performance, networking or designation in different treatments. We do find evidence of gender earnings and promotion gaps. However, with the exception of homophily we do *not* find much evidence of gender differences in networking. In particular women and men do *not* systematically differ in terms of their in- or out-degree nor in terms of their centrality in the network. Earnings and promotion gaps appear, because male decision-makers reward their network neighbours with increased earnings as well as promotion and these network neighbours happen to be predominantly male. It is useful to remember at this stage that our experiment was gender balanced. In many real-life situations, where gender earnings and promotion gaps can be observed the share of women is well below 50 percent overall and even lower among decision-makers. In such situations the combined effect of homophily and men rewarding network neighbours could have even bigger consequences. Similarly in bigger groups with more levels of hierarchy, effects could compile if they are found at every level of the hierarchy.

To the extent that our results prove to have external validity, there are potential actionable consequences in terms of measures to address gender networking differences. Such measures should not focus as much on presumed strategic networking differences, for which we found little evidence, but rather on opportunities and factors that limit the benefit of networking for women. One possibly important factor outside of the scope of this study are limited opportunities for women which, rather than strategic differences in networking, could cause gender differences in networks outside the lab.

Our findings also have implications for the design of work environments in view of reducing gender earnings and promotion gaps. While networking increases information flows and seems to lead to less rent extraction by decision-makers, work environments where designation and networking play important roles can lead to larger gender differences in earnings and promotion. This could be particularly the case in areas that are ex ante characterized by large gender imbalances. In areas that are more gender balanced interventions could include the encouraging of mixing between male and female workers to reduce homophily. Future research could be aimed at testing the effectiveness of such interventions in the field.

Another direction for future research is to study the strength and type of links more explicitly in a lab design. Ibarra (1993) finds, for example, that women have more supportive relationships while men form a a greater number of instrumental relationships. Related to that it would also be interesting to study settings where networking has different functions, such as e.g. producing joint output or acquiring human capital. It would be interesting to see if the effects we identified in this paper are also observed in these contexts.

In this paper we made the choice that ties can be formed unilaterally. Participants can unilaterally choose to start a conversation with someone or provide them with some information. As in many real-life interactions the recipient cannot prevent others from sending the information (e.g. via e-mail outside the lab) or starting a conversation, however they can choose how much attention to pay to the information and whether to engage or not in the conversation.[39] There could be other situations where link formation is bilateral, i.e. where the consent of both parties is needed even to initiate a link. This is another direction for future research.

Finally, it should be kept in mind that this paper speaks to networking differences given ex ante equal opportunities. Gender differences in networking that arise e.g. because women are more involved with child-care and hence have less time for after-work activities are outside the scope of this paper, but potentially very important in contributing to gender earnings and promotion gaps.

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[39]Indeed, as we saw in Section 5.3 not all initiated chats receive a reply in our experiment.

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