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Heuristic Decision Making in Network Linking

Marjolein J.W. Harmsen - van Hout* Benedict G.C. Dellaert† P. Jean-Jacques Herings‡

Abstract

Network formation among individuals constitutes an important part of many OR processes, but relatively little is known about how individuals make their linking decisions in networks. This article provides an investigation of heuristic effects in individual linking decisions for network formation in an incentivized lab-experimental setting. Our mixed logit analysis demonstrates that the inherent complexity of the network linking setting causes individuals' choices to be systematically less guided by payof but more guided by simpler heuristic decision cues, and even stronger less motivated by the payoff for others. Furthermore, we show that the specific complexity factors value transferability and social tradeoff aggravate the former effect. These heuristic effects have important research and policy implications in areas that involve network formation.

JEL Classification: A14, C25, C91, D85

Keywords: network formation, individual decision making, heuristic effects, laboratory experiment, mixed logit

1 INTRODUCTION

Network formation among individuals has important effects in many social, operational, and economic contexts, ranging from word-of-mouth communications among consumers (e.g., Iacobucci & Hopkins, 1992) and virtual communities (e.g., Wellman et al., 1996) to job opportunities (e.g., Granovetter, 1995) and mortality (e.g., Berkman & Syme, 1979). Therefore,

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the OR community has lately modeled such decentral network creation processes (e.g., Fabrikant et al., 2003; Baron et al., 2006; Monsuur, 2007; Demaine et al., 2012; Janssen & Monsuur, 2012; Harmsen - van Hout et al., 2013; Hellmann & Staudigl, 2014; Olaizola & Valenciano, 2014). The applications of these models vary from military and other communication networks to large-scale networking settings as the Internet and their approaches differ from non- or pairwise-cooperative game theory to structural optimization mechanisms.

The network formation process is typically a complex decision setting, for individuals' utilities are not only dependent on multiple characteristics of the choice alternatives, like in most consumer choices (e.g., Swait & Adamowicz, 2001), and even not only additionally on the number of other individuals choosing the same alternative, like with global network externalities (e.g., Katz & Shapiro, 1985). They depend on all individuals in the entire pattern of network links, differently by their exact positions (e.g., Sundararajan, 2007). Furthermore, this network complexity varies depending on whether the type of value that is exchanged through the network only affects direct neighbors or is rather transferable via indirect links (Harmsen - van Hout et al., 2013) and depending on whether decision makers care about the effects of their choices on other individuals (Fehr & Schmidt, 2003). Therefore, when studying linking decisions, laboratory experiments are advantageous as to control the numerous influencing factors.

There exists a recent and increasing experimental literature on network formation. One stream in this literature is involved with testing integral game-theoretic models of network formation. They include variants of Bala and Goyal's (2000) noncooperative network formation model (e.g., Callander & Plott, 2005; Berninghaus et al., 2006), Jackson and Wolinsky's (1996) pairwise cooperative network formation model (e.g., Deck & Johnson, 2004), and fully cooperative network formation models like Jackson and Van den Nouweland's (2005) (e.g., Charness & Jackson, 2007). This research identifies several conditions under which theoretically stable network structures are reproduced in the laboratory and addresses these networks' efficiency. Another stream of experimental studies examines the role of network formation as endogenously emerging in other relevant settings of cooperative decision making (e.g., Hauk & Nagel, 2001; Brown et al., 2004; Kirchsteiger et al., 2005; Corbae & Duffy, 2008; Di Cagno & Sciubba, 2010). This research shows that cooperation decisions are considerably influenced when individuals are allowed to choose their partners versus when a fixed interaction structure is imposed.

An issue that has been largely ignored in this game-theoretic experimental work is that the complexity that individuals face in the network formation decisions due to compound externality patterns may cause errors in their evaluation of different link formation options and hence in their choice process. Although previous research acknowledges the mere existence of errors (e.g., Charness & Jackson, 2007), these are typically simply modeled as random and the underlying process remains undisclosed. The objective of the current paper is to systematically investigate whether heuristic shifts occur in individual decision making in network formation as a function of complexity in the network linking setting. Such complexity effects have been studied in several other choice contexts (e.g., Timmermans, 1993; Bonner, 1994; Sung et al., 2009; Dellaert et al., 2012).

Thus, we comply with the recent call by Hämäläinen et al. (2013) to explicitly consider behavioral phenomena within OR processes, as these are highly sensitive to behavioral effects. Accordingly, the abovementioned OR models on decentral network creation may result in opposite recommendations for optimal interventions. Although their modeling approaches vary in several respects, they all take optimizing individuals as a starting point, at most with a random deviation therefrom in each step of the dynamic process (e.g., Baron et al., 2006; Hellmann & Staudigl, 2014), whereas we investigate in how far real people systematically deviate from this assumption.

For this purpose, we focus on a static, non-interactive network setting in which the decision maker can choose to create or delete one link or to do nothing. Such a situation constitutes the simplest network linking decision context, which allows us to study the effects of complexity under highly controlled conditions. We thus perform an individual decision making experiment in which we vary three complexity factors that are relevant in the context of network linking. The first factor is baseline opacity of choice consequences, induced by absence versus presence of a numerical payoff overview. The second factor is transferability of value in the network, induced by influence of indirect versus only direct neighbors on own payoff. The third factor is social tradeoff between own payoff and others' payoff, induced by presence versus absence of impact of own choices on others' payoff. These factors complicate the choices that individuals make about creating and maintaining links in the network. We examine whether these choices therefore become systematically less payoff-motivated but more guided by simpler heuristic decision cues, and furthermore whether they become even stronger systematically less socially motivated, that is, less guided by the payoff generated for other individuals.

In order to test our hypotheses, we confront participants in the lab with multiple linking choice situations. Their choices have a direct impact on their monetary rewards in the experiment, which differ with respect to the three abovementioned complexity factors (baseline payoff opacity, value transferability, social tradeoff), leading to different treatments. We perform a comprehensive parametric test of the hypotheses by estimating a mixed (i.e., random parameters) logit model (McFadden, 2001; Hensher et al., 2005) incorporating several payoff and control variables as well as their interactions with the complexity factors. This allows us to investigate the impact of complex network properties on individuals' decisions, while allowing for heterogeneity of the decision makers.

Using this approach, we identify two cues that are merely qualitatively related to payoff but appear to have a significant additive impact on linking decisions: whether the choice alternative implies a deviation from the status quo or not, and the number of direct neighbors of the (potential) linking partner involved in the choice alternative. The effects of these heuristic cues are different under the various complexity factors. Furthermore, we demonstrate that social preferences throughout strongly rely on a numerical overview of choice consequences (which is usually provided in the laboratory but missing in real life), since apparent pro-social decision behavior in treatments with such an overview disappears in identical treatments without.

In Section 2, we present our theoretical framework and hypotheses. Section 3 describes the experimental design and the approach used for the mixed logit estimation. The results of our experiment and hypotheses tests are reported in Section 4. In Section 4.2.2 we perform several robustness checks, among which whether the observed shifts in behavior may as well be captured by differences in randomness among complexity conditions. Section 5 concludes the paper with a discussion.

2 THEORETICAL FRAMEWORK

The objective of this section is to present our hypotheses about heuristic effects in individual decisions of network formation and compare them to predictions on individual choice behavior underlying the previous experimental network formation literature. After a description of our setting, the predictions based on prior theories are reviewed in Section 2.1 and our hypotheses are presented in Section 2.2.

The focus of our research is to investigate individuals' heuristic decision response to variations in complexity in the network formation context. We address the relatively simple case of single link formation decisions by individuals. Doing so allows us to investigate complexity effects in a tightly controlled yet relevant setting of network formation decisions. To prevent possible confounding effects that do not originate from complexity of the network setting but from strategic interaction among individuals, we focus on individual one-period decisions, so decisions of others in the network are deliberately excluded.

Thus a typical decision task as we study would be described as follows. An individual ("you" in the example of Figure 1) is connected with several other individuals in a network and is facing the one-shot choice problem to change at most one link: her choice alternatives are to delete one of her existing links (with "a" or "d" in the example), to create a link with one individual that she is currently not directly connected to ("b" or "c" in the example), or not to change anything. This results in a new network structure that generates value for "you" as well as for "a" through "d" according to a function that is varied in complexity, whereas "a" through "d" themselves are not allowed to make any changes to the network.

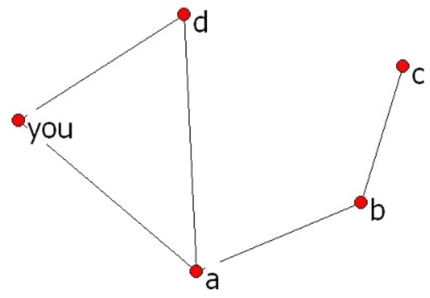


Figure 1: Example network formation setting.

2.1 Prior Decision Models

Economic theory (e.g., Varian, 1992, Ch. 7) models experienced utility, that is, utility on which actual decisions are based, as follows. The experienced utility that individual i derives from choosing alternative j is given by:

$$U_j^i = f^i\left(\mathit{Payoff}_j\right),$$

where Payoff_j is the payoff, that is, benefits minus costs, obtained by i when she chooses j and f^i is a strictly increasing function. For empirical applications, a random factor can be added (e.g., Hensher et al., 2005, Ch. 3):

$$U_j^i = f^i\left(\mathit{Payoff}_j\right) + \varepsilon_j^i.$$

We refer to this as the *classical payoff-based model*. For the example of Figure 1, this model predicts that from the five choice alternatives allowed, "you" chooses one alternative that provides her with the highest payoff.

Social preferences theory (Fehr & Schmidt, 2003) augments this model by explicitly allowing for the fact that in addition to their own payoff, individuals may take the payoff for other individuals into account when making their decisions. In this case, the experienced utility that individual i derives from choosing alternative j is given by:

$$U_j^i = f^i\left(\mathit{OwnPayoff}_j, \left(\mathit{OthersPayoff}_j^h\right)_{h \neq i}\right) + \varepsilon_j^i,$$

where $\mathit{OwnPayoff}_j$ is the payoff personally obtained by i when she chooses j, $\mathit{OthersPayoff}_j^h$ is the payoff obtained by another individual h when i chooses j, and f^i is a function reflecting how i holds others-guided utility components in mind (e.g., inequity aversion, efficiency preferences, etc.). We refer to this as the *classical payoff-based model extended with social preferences*. For the example of Figure 1, this model predicts that from the five choice alternatives allowed, "you" chooses one alternative that causes her subjectively optimal combination of payoff for herself and payoff for "a" through "d".

2.2 Hypotheses

Our anticipation is that these prior utility models are not sufficient to explain link choice behavior due to the presence of a specific type of complexity. This complexity arises due to local network effects: an individual's payoff from her own choice now is affected by all individuals in the entire pattern of network links, differently by their exact positions (e.g., Sundararajan, 2007). Therefore, she finds it an inherently complex task to determine the precise payoff of linking choice alternatives.

As humans are boundedly rational (Camerer, 1998), they cope with complexity in decision making by simplification, which commonly involves assessing a judgment object (e.g., linking choice alternative) using only the subset of properties of the object that are most accessible, that is, that come most readily to mind, rather than using all relevant properties (Gigerenzer et al., 1999), as long as this leads them to a satisfying situation (Simon, 1956). This is clearly illustrated in the literature about the effects of task complexity in several other contexts, like job candidate selection (Timmermans, 1993), audit judgment (Bonner, 1994), consumer choice (Swait & Adamowicz, 2001; Dellaert et al., 2012), and betting markets (Sung et al., 2009), but no empirical research to date has addressed such effects in making complex network formation decisions.

We propose two main types of heuristic shifts: (i) the complexity in the network linking setting makes individuals' choices systematically less payoff-guided than predicted by the classical payoff-based model while they are additionally motivated by other heuristic cues (Section 2.2.1) and (ii) it makes them deviate even stronger from the predictions of the classical payoff-based model extended with social preferences in being less socially motivated (Section 2.2.2). Furthermore, we examine whether these effects are stronger under more complex linking decision making conditions, where we vary the presence of value transferability and social tradeoff (Section 2.2.3).

2.2.1 *Payoff orientation*

In the network formation setting, the decision maker's payoff depends on the network structure after completion of her choice, where having more connections is on the one hand beneficial, since they provide access to additional resources, and on the other hand costly, for it takes time and effort to maintain them. Because of network effects, it is typically a complex task for individuals to judge the exact payoff consequences of link choice alternatives and we examine whether therefore individuals systematically deviate from payoff orientation.

A psychological process of judgment simplification is encountered in the literature about conjunctive probability assessment, which shows that individuals make predictions based on a correlation they assume to exist between the assessment variable and some other variable (e.g., Broniarczyk & Alba, 1994). Accordingly, individuals could partly substitute the payoff value of a link choice alternative by descriptive attributes that can be determined more easily and that are qualitatively related to it. Consequently, they could shift their orientation from exact payoff to the most basic cues (i) whether a link choice alternative involves actively deleting or creating a link or rather doing nothing (cf. Kahneman et al., 1991), and (ii) how many direct links the individual involved in the choice alternative has in the network (cf. Freeman, 1979). This is in line with qualitative process theory, which suggests that human reasoning is more likely to depend on qualitative rather than quantitative relations (Forbus, 1993). Therefore, in our model we allow for individuals' use of the type of action or individual as simpler heuristic cues in addition to the precise expected payoff.

We hypothesize:

> *H1 (reduction of payoff orientation): Individuals' network linking choices are affected less strongly by their payoff consequences than predicted by the classical payoff-based model (Section 2.1) while they are also systematically based on heuristic cues.*

Pursuing the above line of reasoning, we formulate the experienced utility that individual i may derive from choosing alternative j with the following heuristic cues:

$$U_j^i = f^i\left(Payoff_j, Complexity \times \left(Payoff_j, Formation_j, Degree_j\right)\right) + \varepsilon_j^i, \tag{1}$$

where *Complexity* is the network choice complexity that i is facing, $Formation_j$ is a dummy variable indicating by zero that j involves remaining with the status quo and by one that it involves link deletion or creation, $Degree_j$ is the number of direct links of an individual with whom i deletes or creates a link in j, and f^i is a function increasing in $Payoff_j$ and decreasing in the interaction of *Complexity* with $Payoff_j$. For the example of Figure 1, this model predicts that from the five choice alternatives allowed, "you" chooses one that seems to provide her with the highest payoff, which she partly bases on the simple cues (i) whether the choice alternative implies a deviation from the status quo (which is the case for four alternatives) and (ii) the degree of the node involved in the choice alternative (which varies between zero and three among alternatives) rather than on the quantitative amount.

2.2.2 *Social preferences*

The presence of social tradeoff is a further complicating factor in the network setting, implying that an individual's choices not only affect her own value, but also the value for her neighbors, her neighbors' neighbors, etcetera (e.g., Jackson & Wolinsky, 1996; Bala & Goyal, 2000). This aspect of network formation choices makes it more complex for individuals with social preferences to judge the exact value of link choice alternatives, because besides their own payoff they also have to consider the payoff of other individuals, of which typically in a network there are more than one.

We investigate whether individuals deal with the complexity of social tradeoff by focusing on the payoff aspect that can be determined most easily (Gigerenzer et al., 1999), that is, own payoff. Therefore, we examine whether individuals tend to pay systematically less attention to others' payoff due to the greater complexity of evaluating this social payoff. In the past, behavioral economists have found empirical evidence for social preferences. Recently, Falk and Kosfeld (2003), Goeree et al. (2008), and Van Dolder and Buskens (2008) found social motives in network formation, but this was in lab environments where choice complexity was largely mitigated by explicit payoff information, which directly presented participants with the numerical payoff consequences for themselves as well as for others of their choice options. We expect a smaller influence of payoff consequences for other individuals on choice when this is not the case. Obviously, since payoff for one other individual is at least as opaque as own payoff, we then anticipate a baseline shift from payoff to heuristic cues as predicted by *H1* also for others' payoff. However, with multiple others, we additionally expect a heuristic shift from others' to own payoff when complexíty is not artificially removed. This shift may be both due to a concious shift of consideration away from social payoff or due to a stronger shift to the use of heuristic cues for social payoff. Thus, we propose the following hypothesis:

> *H2 (reduction of social preferences): Individuals' network linking choices are affected far less strongly by their payoff consequences for other individuals than predicted by the classical payoff-based model extended with social preferences (Section 2.1) while complexity more strongly reduces the impact of social payoff than the impact of own payoff on these choices.*

We include this heuristic effect in the experienced utility that individual i derives from choosing alternative j as follows:

$$\begin{aligned} U_j^i \;=\; & f^i\Big(\mathit{OwnPayoff}_j, \left(\mathit{OthersPayoff}_j^h\right)_{h\neq i}, \\ & \mathit{Complexity} \times \Big(\mathit{OwnPayoff}_j, \left(\mathit{OthersPayoff}_j^h\right)_{h\neq i}, \mathit{Formation}_j, \mathit{Degree}_j\Big)\Big), \end{aligned} \tag{2}$$

where f^i is a function decreasing in the interaction of *Complexity* with $\left(\mathit{OthersPayoff}_j^h\right)_{h\neq i}$. For the example of Figure 1, this model predicts that from the five choice alternatives allowed, "you" chooses one that seems to cause her subjectively optimal combination of payoff for herself and payoff for the other individuals, where we expect the latter payoff to get systematically less attention.

2.2.3 *Reinforcing complexity conditions*

Finally, we hypothesize that in addition to the baseline opacity of choice consequences in this context due to the fact that network externalities have to be taken into account, two specific complexity aspects of networks may strengthen individuals' tendencies to switch from payoff to heuristic cues orientation and to reduce their social preferences.

Value transferability The first network factor regarded here is value transferability, which refers to the fact that an individual derives value not only from her direct neighbors, but also indirectly from her neighbors' neighbors, etcetera. This network property makes it even more complex for individuals to judge the exact payoff of link choice alternatives, because it requires additional cognitive work to be forward-looking over indirect links. This leads to the following hypotheses:

> *H3 (moderating effects of value transferability):*
>
> *H3a: The presence of value transferability in a network decreases the impact of payoff on an individual's link formation choices while it increases the impact of heuristic cues.*
>
> *H3b: The presence of value transferability in a network decreases the impact of others' payoff on an individual's link formation choices while it increases the impact of heuristic cues.*

Social tradeoff Another complexity property we consider is social tradeoff, implying that an individual's choices not only affect her own value, but also the value for her neighbors, her neighbors' neighbors, etcetera (cf. Section 2.2.2). This network property makes it more complex for individuals with social preferences to judge the exact value of link choice alternatives, because besides their own payoff they have to consider the payoff of (possibly many) other individuals, which requires extra cognitive effort. Therefore, the presence of social tradeoff will not only cause a shift of preferences from others' to own payoff (*H2*), but we also expect it to have a strengthening effect on their shift from payoff to heuristic cues orientation. This can be formulated in the following hypothesis:

> *H4 (moderating effect of social tradeoff): The presence of social tradeoff in a network decreases the impact of payoff on an individual's link formation choices while it increases the impact of heuristic cues.*

We include these moderating effects of complexity factors in the experienced utility that individual i derives from choosing alternative j as follows:

$$\begin{aligned} U^i_j \;=\; & f^i\Big(\mathit{OwnPayoff}_j, \big(\mathit{OthersPayoff}^h_j\big)_{h\neq i}, \\ & \mathit{ComplexityCondition} \times \Big(\mathit{OwnPayoff}_j, \big(\mathit{OthersPayoff}^h_j\big)_{h\neq i}, \mathit{Formation}_j, \mathit{Degree}_j\Big)\Big), \end{aligned} \tag{3}$$

where *ComplexityCondition* is the network choice complexity condition that i is facing - concerning both the baseline opacity of choice consequences due to externalities and the reinforcing complexity of value transferability and social tradeoff - and f^i is a function in which the hypothesized interaction effects with *ComplexityCondition* are included.

3 METHODS

In this section we describe the experimental design as well as the parametric approach used for testing our hypotheses.

3.1 Experimental Design

Our experiment presented participants with six network formation link choice problems similar to that in Figure 1. In these problems a participant was allowed to change at most one direct link, that is, to delete a link that already exists between her and another individual, to create a link between her and another individual if there is not yet one, or to change nothing. The choice problems are illustrated in Table A.2 (1 - 3) and Table A.3 (4 - 6), Appendix A. They were created such that they represent a variety of network linking decisions while enabling mutual comparison. The number of individuals as well as the total number of links was kept constant in all six choice problems. Pilot studies conducted by the authors before the experiment indicated that most other structural complexity factors like the number of visual crossings between links did not affect participants' choices. An exception was whether the decision maker was connected to the rest of the network at the moment of choice or not. Therefore, three of the six choice problems involved a connected position and the other three an isolated position for the participant. Furthermore, to avoid unanticipated biases due to other structural factors, the order of choice problems was rotated among participants.

To test for the hypothesized shifts in behavior due to value transferability and social tradeoff, we employed four experimental treatments where these two characteristics were between-subjects factors. Thus, each participant faced one of four particular complexity conditions (see Section 2.2.3). The experimental design is summarized by Table 1. A within-subject manipulation for the treatments *social* and *both* will be discussed later in this section.

		social tradeoff	
		NO	YES
value	NO	*none*	*social* (part 1, part 2)
transferability	YES	*transfer*	*both* (part 1, part 2)

Table 1: Experimental design.

Each participant was confronted with a payoff function matching her treatment. This function reflected the benefits and costs of link formation according to a typical situation in communication networks with high cost of link specificity as modelled by Harmsen - van Hout et al. (2013). The more direct connections an individual has to maintain with other individuals, the less she is able to specify her attention per link. Therefore, her value per link for others declines and she also derives less value from each link with others. Two connected agents contribute to their bilateral process of communication value creation according to a standard Cobb–Douglas production function with as inputs the amount of time invested by each agent in the link. High link specificity implies unit output elasticities in each bilateral value production process and therefore low advantage of being connected with several others. The respective payoff function was explained in words to the participants in the instructions (see the Supplementary material, Appendix C).

For a participant i in treatment *none* or *social* there was no value transferability, so value was derived from direct neighbors only. This reflects a situation where social value is derived from communication (Harmsen - van Hout et al., 2013). The payoff function was then given by:

$$\Pi_i = \begin{cases} \sum_{j \in N_i} \frac{1}{\mu_i \mu_j} & \text{if} \quad \mu_i > 0 \\ 0 & \text{if} \quad \mu_i = 0, \end{cases}$$

where N_i is the set of individuals with whom i has a direct link, individual j is a neighbor of i if $j \in N_i$, and $\mu_i = |N_i|$ is the number of neighbors of i, that is, the degree of i.

For treatments *transfer* and *both* there was value transferability, so value was derived from direct as well as indirectly connected individuals. This reflects a situation where informational value is derived from communication (Harmsen - van Hout et al., 2013). The payoff function was then given by:

$$\Pi_i = \begin{cases} \sum_{j \in \bar{N}_i} \sum_{p \in \mathcal{P}_{i,j}} \frac{1}{\mu_i \mu_j \prod_{k \in \breve{p}} (\mu_k)^2} & \text{if} \quad \mu_i > 0 \\ 0 & \text{if} \quad \mu_i = 0, \end{cases}$$

where $\bar{N}_i$ is the set of individuals with whom i has either a direct or an indirect link, $\mathcal{P}_{i,j}$ is the set of paths between i and j, where a path is defined as a sequence of consecutive links without repeated individuals, $\breve{p}$ is the set of individuals on path p between i and j excluding i and j themselves, and μ_i is the degree of i. In the instructions, these payoff functions were not presented in formulas but in elementary verbal descriptions, illustrated by an example (see the Supplementary material, Appendix C).

For treatments *none* and *transfer* there was no social tradeoff. The participants were informed that nobody else was affected by their choices. For treatments *social* and *both* there was social tradeoff. The participants were informed that the other individuals in the choice problems were not reflecting real people with the ability to influence their payoff, that the payoff their choices generated for these fictive individuals were determined analogously to their own payoff, and that the total payoff their choices generated for these fictive individuals would be divided equally among the other participants in the room. Thus, a simple form of social preferences, not involving distributional issues, was evoked. It can be checked that the six choice problems introduced above are selected such that they each provide the opportunity to explicitly reveal social preferences in both the treatments with and without value transferability. For example, in choice problem 5 (as visualized with options' respective payoff at the top of Table 2), participants can exhibit (only) weak social preferences in the sense that while keeping their own payoff at its maximum they can choose better or worse for the others in the treatments without value transferability (e.g., by selecting option d versus option c), and participants can exhibit (only) strong social preferences in the sense that by giving up some of their own payoff they can improve the payoff for others in the treatments with value transferability (e.g., again by selecting option d versus option c). No information or feedback about the tasks and choices of the other participants was provided during the experiment in order to underline that strategic motivations are ineffective, since the choices of other participants do not influence the payoffs in the own decision problems.

To control for (individual differences in) social preferences, for participants in treatments *social* and *both* where payoff for other participants had to be considered, an additional part was added to the experiment. This was exactly the same as the first part, but for each choice option the payoff for the participant as well as for the others was mentioned explicitly. This is illustrated in Figure A.1, Appendix A. Charness et al. (2004) and Gürerk and Selten (2012) showed that providing participants with such a comprehensive payoff table is an effective way to systematically reduce complexity. The objective of this extra manipulation was to test in how far participants take others' payoff into account when the complexity of doing so is practically removed. The payoffs for all choice problems are given in Table A.4 in the same appendix. Thus, for the treatments *social* and *both*, whether or not numerical payoff information was provided was incorporated as a within-subjects factor. Note that for the treatments without social tradeoff, it is obvious that participants would always choose optimally when provided with a payoff overview, so we do not bother them with such a second part.

The experiment took place in a computer lab with students and employees of various faculties of Maastricht University, the Netherlands. The 48 male and 66 female participants from diverse nationalities were randomly assigned to the four between-subject treatments. Thus, the number of independent observations is larger than common in the existing experimental network formation literature, e.g., Di Cagno and Sciubba (2010) run only six sessions (with six interdependent participants each) per treatment. Participants were informed how the payoffs they would earn in the experiment would be converted into cash euros afterwards, see the Supplementary material (Appendix C) for details. After each choice, feedback was given to the participant about the payoff she earned for herself and if relevant for the other participants in the room, and the respective maximum and minimum payoffs that could have been earned in the specific choice problem. Participants could only start the experiment after answering a number of control questions correctly to make sure the instructions were understood correctly and after two really paid-out practice rounds with only three choice alternatives, see Table A.1, Appendix A. Our pilot experiments already increasingly confirmed that the instructions were generally understood after working through the example (see the Supplementary material, Appendix C). At the end of the experiment participants were asked to comment on their motives and the way they made their choices in a debriefing part. Average earnings were €6.03 and the post-hoc correlations between payoffs and heuristic cues as well as between own and others' payoffs were below 0.31.

3.2 Mixed Logit Estimation

We perform a comprehensive parametric test of our hypotheses by estimating a mixed (i.e., random parameters) logit model (Hensher et al., 2005). This estimation approach enables us to establish the roles of several attributes of link alternatives in the network formation process, while allowing for heterogeneity across individuals. The total potential experienced utility that individual i under treatment t derives from choosing alternative j in choice problem c is affected by both payoff and other factors as well as the complexity treatment she is facing, and is formalized as follows:

$$\begin{aligned}
U_{cj}^{ti} = & \sum_{k\in K}\beta_k^i P_{kcj}^t + \sum_{m\in M}\gamma_m^i C_{mcj} + \sum_{k\in K}\varphi_k T^t P_{kcj}^t + \sum_{m\in M}\chi_m T^t C_{mcj} \\
& +\theta S^t P_{1cj}^t + \sum_{m\in M}\xi_m S^t C_{mcj} + \zeta T^t S^t P_{1cj}^t + \sum_{m\in M}\eta_m T^t S^t C_{mcj} \\
& + \sum_{k\in K}\psi_{1k} I_c^t P_{kcj}^t + \sum_{m\in M}\psi_{2m} I_c^t C_{mcj} + \sum_{k\in K}\psi_{3k} I_c^t T^t P_{kcj}^t + \sum_{m\in M}\psi_{4m} I_c^t T^t C_{mcj} \\
& +\varepsilon_{cj}^{ti},
\end{aligned}$$

where:

K	is the set of payoff indices $\{1, 2\}$,
P_{1cj}^t	is the own payoff generated under t when in c she chooses j,
P_{2cj}^t	is the payoff generated for the other participants,
M	is the set of control variable indices $\{1, 2\}$,
C_{1cj}	is a control dummy variable indicating deviation from the status quo,
C_{2cj}	is a control variable indicating the number of direct links of an individual with whom a link is deleted or created,
T^t	is a dummy variable indicating the presence of value transferability, that is, treatment *transfer* or *both*,
S^t	is a dummy variable indicating the presence of social tradeoff, that is, treatment *social* or *both*,
I_c^t	is a dummy variable indicating the presence of numerical payoff information (within-subject manipulation), and
ε_{cj}^{ti}	is a stochastic variable drawn from a standard Gumbel distribution.

Notice that interactions between S and P_2 or between S, T and P_2 do not provide additional information to P_2 or the interaction between T and P_2 respectively and therefore are not included, and that interactions including both I and S do not provide additional information to interactions only including S and therefore are not incorporated either. Interactions among payoff and control factors (e.g., between P_1 and C_2) are not included due to lack of interpretability.

In random parameter β_k^i, superscript i allows for heterogeneity due to individuals' personal preferences as follows:

$$\beta_k^i = \beta_k + \nu_k^i,$$

where ν_k^i is a stochastic variable drawn from a normal distribution. Analogously, random parameters are included for the main effects of the control variables on choice (γ_m^i).

Then, under the usual assumptions, the unconditional probability that individual i will choose alternative j equals the expected value of the logit probability over all possible values of the random parameters. The model is estimated by Maximum Likelihood with NLOGIT 5.0, Econometric Software, Inc., implementing 1000 Halton draws in the Monte Carlo simulation.

4 RESULTS

4.1 Illustrative Descriptive Results

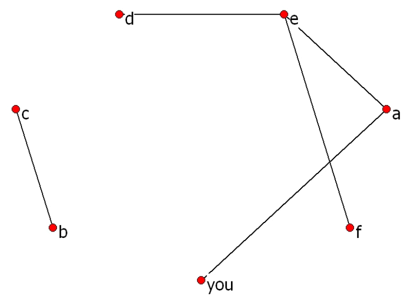
Before turning to a more formal analysis, we first present some illustrative results for the choices made in the different treatments. Hereby the focus is first on choice problem 5 (Table 2; above this table with choice percentages in the different treatments, the respective choice problem and its payoffs are replicated for the reader's comfort).

In treatment *none* (first row Table 2), without value transferability and social tradeoff, all participants choose one of the optimal alternatives, that is, nothing, b, c, d, or f. However, in treatment *transfer*, where value transferability is included, only 67.8% of the respective participants chooses one of the optimal alternatives, that is, b or c. This is in line with *H3a*. Comparing *none* to *transfer*, the percentage of participants choosing to maintain the status quo decreases from 43.3 to 17.9 and linking to b, which has a degree of one only, becomes even more popular. This complies with the heuristic cues introduced in Section 2.2.1 for *H1*.

In treatment *social* (second row Table 2), where social tradeoff is included, only 10.7% of the respective participants turns out to opt for changing nothing, which would reveal social preferences in the sense that it maximizes the payoff for the other participants, given maximum own payoff. All these participants still maximize their own payoff though. However, in the second part of the experiment, when payoff information is given, thus eliminating complexity, 53.6% of the same participants prefers this option. This pattern corresponds to *H2*. Note that changing nothing maintains the status quo, which again relates to one of the heuristic cues.

In treatment *both* (third row Table 2), with both value transferability and social tradeoff, only 42.9% of the respective participants chooses one of the options with optimal own payoff, that is, b or c, whereas the rest seems to reveal social preferences in the sense that they reduce their own payoff in order to increase others' payoff. Note that 21.3% even chooses a

Pareto inferior option, that is, a, d, e, or f. However, in the second part of the experiment, when payoff information is given, thus eliminating complexity, the proportion with optimal own payoff increases to 71.4%. Also, only 3.6% chooses a Pareto inferior option. This result is in line with *H4*. Notice that the option to link to e, which has the relatively high degree of three, remains impopular in all treatments, which is in accordance with one of the heuristic cues once more.



value transferability NO			value transferability YES		
	you	others		you	others
nothing	5	41.67	nothing	6.39	47.5
a	0	40	a	0	46.67
b	5	31.67	b	6.94	40.45
c	5	31.67	c	6.94	40.45
d	5	38.33	d	6.25	44.17
e	3.75	36.25	e	5	40.94
f	5	38.33	f	6.25	44.17

none		*transfer*	
choice	%	choice	%
nothing	43.3	nothing	17.9
a	0.0	a	0.0
b	40.0	b	60.7
c	10.0	c	7.1
d	3.3	d	0.0
e	0.0	e	3.6
f	3.3	f	10.7
social / payoff info NO		*social* / payoff info YES	
choice	%	choice	%
nothing	10.7	nothing	53.6
a	0.0	a	0.0
b	39.3	b	21.4
c	7.1	c	7.1
d	17.9	d	7.1
e	0.0	e	3.6
f	25.0	f	7.1
both / payoff info NO		*both* / payoff info YES	
choice	%	choice	%
nothing	35.7	nothing	25.0
a	0.0	a	0.0
b	28.6	b	46.4
c	14.3	c	25.0
d	7.1	d	3.6
e	7.1	e	0.0
f	7.1	f	0.0

Table 2: Descriptive results choice problem 5.

In Table 3 an overview across all choice problems is provided of how often participants choose optimally in the different treatments and in Table 4 of how often participants maximized other participants' payoff given own maximal payoff and how often they choose a Pareto inferior option in the sense that both own and others' payoff could be strictly improved by choosing a different option. The tables confirm that participants were more effective in optimization the less complex the treatment.

		social tradeoff		
		NO	YES, without payoff info	YES, with payoff info
value transferability	NO	97%	89%	96%
	YES	47%	45%	78%

Table 3: Optimal choice in the complexity treatments.

		social tradeoff			
		YES, without payoff info		YES, with payoff info	
value transferability	NO	max others | max own	27%	max others | max own	58%
		Pareto inferior	11%	Pareto inferior	4%
	YES	max others | max own	39%	max others | max own	73%
		Pareto inferior	30%	Pareto inferior	7%

Table 4: Social preferences in the complexity treatments.

In Table 5 we count frequencies of how often participants remained with the status quo in the three choice problems where the decision maker is not isolated, as in the three choice problems with an isolated start position, remaining with the status quo is consistently very bad for payoff and was chosen accordingly rarely in all treatments. Prominent differences appear in the treatments with social tradeoff: in *social* without payoff information, the percentage of status quo choices is considerably lower than in *social* with payoff information (and even lower than when each of the seven choice options would have been chosen with equal probability), whereas in *both* without payoff information, the percentage of status quo choices is considerably higher than in *both* with payoff information. In Table 6 the average degree of the nodes involved in the chosen options across all problems is listed. With random choice, the average degree would be 1.31, and with a random selection of one of the options that provide optimal own payoff, the average degree would be 0.98 and 1.06 without and with value transferability respectively. Thus, in treatment *none* participants over-selected low-degree options and in the treatments with value transferability (and no payoff overview) participants over-selected high-degree options.

		social tradeoff		
		NO	YES, without payoff info	YES, with payoff info
value	NO	24%	11%	36%
transferability	YES	21%	24%	14%

Table 5: Remaining with the connected status quo in the complexity treatments.

		social tradeoff		
		NO	YES, without payoff info	YES, with payoff info
value	NO	0.83	0.96	0.90
transferability	YES	1.36	1.26	1.00

Table 6: Average degree of the nodes involved in the chosen options in the complexity treatments.

The above crosstab results are in line with our hypotheses, but cannot be interpreted as direct evidence, since alternative explanations for differences between choice frequencies in the treatments are possible. For example, it could be that all differences in complexity just lead to differences in choice precision, implying that allowing for conditional random error terms in network formation modelling would be sufficient, whereas we hypothesize more systematic changes in decision making. Also, even though we restricted our focus to the very simple setting of a static, non-interactive network in which the decision maker can choose to create or delete one link or to do nothing, it could be that confounding effects play a role, for instance, the exact payoffs in the treatments with value transferability are by definition different from those in the treatments without (although the order of magnitude of these differences is relatively small). In the mixed logit approach in the next section these alternative explanations can be accounted for. Namely, confounding effects are dealt with by the comprehensiveness of the model itself, where for example both exact payoffs and simple heuristic cues are included as explanatory variables. Explicit comparison to shifts in randomness is made in the last robustness check of Section 4.2.2.

Notice that we did not hypothesize that the *payoff* derived from heuristic network linking decisions would be far from optimal. In fact, across all choice problems, participants earned a fraction of 0.9 from the own payoffs they could have earned in the treatments *social* part 1, *transfer*, and *both* part 1, and even 0.99 in the treatment *none*, whereas pure random selection would only have lead to a proportion of 0.8 from the own payoffs that could have been earned. So in that sense, if heuristics were used, they may be considered rather "smart" (cf. Gigerenzer et al., 1999).

Further descriptive results, primarily from the debriefing part, are given in Appendix B.

4.2 Mixed Logit Results

A comprehensive parametric test of the hypotheses is conducted by estimating a mixed logit model across all treatments (Section 4.2.1). A p-value of 0.05 is taken as cut-off value for significance. In Section 4.2.2 several robustness checks are performed.

4.2.1 *Hypothesized model*

The estimation results for all experimental treatments including the interaction effects of an explicit payoff overview are given in Table 7.

In these results we find support for the reduction of payoff orientation in this complex setting (*H1*), since besides the own payoff, the degree of the individual involved in the choice alternative appears to be significantly influential on a linking decision, where individuals with many links are avoided in comparison with relatively isolated individuals (negative γ_2^i). This might be based on the qualitative notion that maintaining links is costly. For the treatments with social payoff, where the within-subjects factor of numerical payoff information was included, this is reconfirmed by the positively significant ψ_{11}-coefficient, indicating that when participants were provided with such a comprehensive payoff overview, the impact of payoff on their linking choices increased.

With respect to the expected reduction of social preferences in the network formation context (*H2*), we find strong confirmation as the β_2^i-coefficient is not significant at all, whereas in the situation where participants were provided with numerical payoff information, the corresponding coefficient (ψ_{12}) is positively significant, showing that the same individuals were more willing to consider the consequences of their choices for others than they actually did in the first round of the experiment. Also, this effect is stronger than for own payoff, while in the treatments with social tradeoff, exact own payoff is still considered, as $|\theta_1| < \beta_1^i$.

The hypothesized moderating effects of value transferability are supported with respect to the reduction of payoff orientation (*H3a*): the φ_1-coefficient of the payoff interaction term turns out to be negatively significant. We see that instead, participants stuck significantly more to the status quo (negative χ_1) and reversed their preference for isolated versus central individuals (χ_2). The former might be subscribed to the fact that it is now more complex to calculate what it brings to deviate from already satisfying situations, whereas the latter might be due to the qualitative notion that since value is now transferable over indirect links, having more links is more beneficial. Since others' payoff were already completely ignored in the choices of the participants, it is no longer possible for the additional complexity factor value transferability to significantly decrease their effect (*H3b*).

variable	parameter	estimated mean (p-value)	estimated st. dev. (p-value)	cf. hyp.
own payoff	β_1^i	1.814 (0.000)	0.476 (0.000)	
others' payoff	β_2^i	-0.014 (0.732)	0.135 (0.000)	2
formation	γ_1^i	0.501 (0.232)	1.023 (0.000)	1
degree	γ_2^i	-0.848 (0.000)	0.165 (0.252)	1
transferability * own payoff	φ_1	-1.075 (0.002)		3
transferability * others' payoff	φ_3	-0.022 (0.689)		3
transferability * formation	χ_1	-1.456 (0.012)		3
transferability * degree	χ_2	1.500 (0.000)		3
social tradeoff * own payoff	θ_1	-1.133 (0.001)		4
social tradeoff * formation	ξ_1	1.444 (0.039)		4
social tradeoff * degree	ξ_2	-0.117 (0.723)		4
transferability * social tradeoff * own payoff	ζ	1.261 (0.002)		
transferability * social tradeoff * formation	η_1	-1.450 (0.117)		
transferability * social tradeoff * degree	η_2	0.034 (0.930)		
payoff info * own payoff	ψ_{11}	0.872 (0.002)		1
payoff info * others' payoff	ψ_{12}	0.136 (0.004)		2
payoff info * formation	ψ_{21}	-1.992 (0.009)		
payoff info * degree	ψ_{22}	0.477 (0.196)		
payoff info * transferability * own payoff	ψ_{31}	0.518 (0.201)		
payoff info * transferability * others' payoff	ψ_{32}	-0.098 (0.159)		
payoff info * transferability * formation	ψ_{41}	3.136 (0.002)		
payoff info * transferability * degree	ψ_{42}	-0.983 (0.044)		

Table 7: Mixed logit estimations.

The hypothesized moderating effect of social tradeoff on payoff orientation ($H4$) is corroborated as well, for the θ_1-coefficient is also significantly negative. Here, respondents had the tendency to deviate from the status quo (positive ξ_1). This overactivity might be related to the fact that it is complex to calculate whether situations satisfying with respect to own payoff will be also beneficial for the others now involved, which suggests that some latent social motives are still present, but the situation is too complex to deal with them like in the less complex part with direct payoff information.

Finally, respondents' behavior significantly varies among participants in several respects as can be concluded from the significant random parameter standard deviations in the next to last column of Table 7.

4.2.2 *Robustness*

In this section, we check whether our estimation results are robust for several control variables.

Order effects The model is re-estimated where additionally interaction terms are included of each of the four main variables with a control variable tracking the position of the respective alternative in the list of choice options, to check for robustness against order effects. We find one small but significant order effect: the interaction effect of others' payoff with the order variable is 0.004 (0.005), indicating that others' payoff becomes systematically slightly more relevant for lower-listed choice options. Importantly, almost all previously found heuristic effects remain. The single exception is the positive interaction effect of social tradeoff with formation (ξ_1), which becomes insignificant now (p-value 0.202). However, the interaction effect of social tradeoff and own payoff (θ_1) remains significantly negative, indicating that *H4* still holds, but suggesting that there is a shift to some heuristic cue left unidentified in the current exploratory model.

Learning effects The model is re-estimated for the first part of the experiment only (without numerical payoff information) - for the second part of the experiment, when payoff tables are provided to the same participants, it is not straightforward how to extend the definition of the experience variable - where additionally interaction terms are included of each of the four main variables with a control variable measuring experience by tracking how many problems the participant already solved at the respective moment of choice, to check for robustness against learning effects. We find that almost all previously found heuristic effects remain, with the same exception as at the robustness check against order effects described above. It turns out that more experienced individuals have a significantly stronger tendency to avoid individuals with many links, so the heuristic effects in network formation decisions as explored in the current paper are definitely not transitory.

Random shift effects Finally, we compare our model to a more restricted model where instead of including the specific interaction effects for the treatments, we only allow the variance of the error term to linearly depend on them, to check whether differences among treatments as predicted by *H2* through *H4* are possibly merely due to shifts in choice precision (Salisbury & Feinberg, 2010), so whether more complexity only leads to more randomness. This rival model turns out to perform significantly worse in terms of model fit (the loglikelihood decreases from -1540.872 to -1647.825), strengthening our claim of more systematic effects of complexity on link choice behavior.

5 DISCUSSION

5.1 Conclusions

A concise summary of our results is given in Table 8.

The hypothesis that individuals' network linking choices are affected less strongly by their payoff consequences than predicted by the classical payoff-based model (*H1*) is supported by the mixed logit estimation of Section 4.2.1, as it indicates that these choices are also based on heuristic cues. Already in the baseline treatment where payoffs are obscured due to network externalities, a lower degree of the node involved in the alternative significantly explains choice whereas the exact payoff was also included as an explanatory variable. In the treatments with value transferability, higher degrees become significantly more attractive and remaining with the status quo becomes an additional heuristic cue. In the treatments with social tradeoff, we even find a reverse status quo bias, which is quite unique in the literature (cf. Mengel, 2011), but this requires further research as it is not robust against order and learning effects. These results are also reflected in the descriptive Tables 5 and 6 in Section 4.1.

The hypothesis that individuals' network linking choices are affected far less strongly by their payoff consequences for other individuals than predicted by the classical payoff-based model extended with social preferences (*H2*) is strongly supported by the mixed logit estimation, as it indicates that these choices do not merely become more socially motivated when the complexity is largely removed by a comprehensive payoff overview (as reflected in descriptive Table 4 in Section 4.1), but they are even not socially motivated at all without such a numerical table. Indeed, the impact of own payoff on choices does not suffer to this extent from the same level of complexity. Note that some respondent answers in the debriefing part of the experiment suggest that this shift of the impact from social to own payoff as a consequence of social tradeoff is partly due to a a concious shift of consideration away from social payoff (Appendix B, item 5). Our explanation of the reverse status quo bias in Section 4.2.1 suggests that it is also partly due to a stronger shift to the use of heuristic cues for social payoff.

hypothesis	result
heuristic effects of complexity on linking choice	
H1: reduction of payoff orientation	supported (low degree as heuristic cue in baseline)
H2: reduction of social preferences	supported (numerical payoff necessary to consider other individuals' payoff at all)
moderating effects of specific complexity factors	
H3: value transferability	supported for reduction of payoff orientation (high degree and remaining with status quo as heuristic cues); social preferences could not be further reduced
H4: social tradeoff	supported (deviating from status quo as heuristic cue)

Table 8: Summary experimental results.

The hypothesized moderating effects of the complexity factors value transferability and social tradeoff (*H3*, *H4*) are also supported by the mixed logit estimation, as their presence further decreases the impact of payoff on an individual's link formation choices, which is also reflected in descriptive Table 3 in Section 4.1.

Thus, this study shows that complexity in the network formation setting influences individual link choice behavior in a systematic way, since individuals' choices are guided less by payoff, where the attention appears to be shifted to factors only qualitatively related to payoff, and moreover, they are even stronger less motivated by social payoff. Furthermore, we demonstrate that the specific complexity factors value transferability and social tradeoff aggravate the former effect. In Section 4.2.2 (Random shift effects) it was confirmed that these changes in behavior cannot accurately be captured by a model only allowing for differences in choice precision (or randomness) among complexity treatments.

5.2 Implications

The current study initiates empirical research into the issue of heuristic effects in individual decisions of network formation. Our results should raise interest in future research into this realm, for they have important implications for theoretical and experimental research as well as application areas of network formation.

Our results show that behavioral effects play a crucial role in the process of decentral network formation. Therefore, theoretical OR models of network creation (e.g., Fabrikant et al., 2003; Baron et al., 2006; Monsuur, 2007; Demaine et al., 2012; Janssen & Monsuur, 2012; Harmsen - van Hout et al., 2013; Hellmann & Staudigl, 2014; Olaizola & Valenciano,

2014) should take such effects into consideration. In particular, the current experiment was based on payoff functions used in Harmsen - van Hout et al. to model communication network formation with high link specificity. This kind of models should not only allow for random error to become more realistic, but should explicitly include human tendencies as found by our analysis to base complex linking decisions on heuristic cues like status quo and node degree rather than exact payoff. As seen in Section 4.1, the consequences for payoffs in the simplest setting may not be very high, but it may very well be expected that the structural and efficiency predictions and therefore recommendations for interventions resulting from these more complex models differ largely if their agents are no longer optimizing but consider much simpler decision cues instead (cf. Hämäläinen et al., 2013). For example, the model with high link specificity by Harmsen - van Hout et al. predicted a wide range of networks in situations without value transferability, including non-standard networks like highly connected and "small world" networks, and highly fragmented, efficient networks in situations with value transferability. Similarly, predictions were made for other levels of link specificity and several recommendations for network moderation were based hereupon. It should be investigated in how far these still hold with agents behaving heuristically rather than purely optimizing.

On the other hand, our results suggest that the existent network formation models are already correct in not taking social preferences into account, for even though previous laboratory research indicated that people do have them, we show that the complex decision environment keeps them from being revealed.

Furthermore, experimental research practice is often disposed to make the payoff consequences of choices as transparent as possible for participants to prevent biased findings due to their wrong understanding of the instructions. However, we claim that this explicit information modifies participants' behavior in a systematic way, since it eliminates complexity that they otherwise would handle by heuristic shifts.

Finally, in many contexts of network formation among individuals such as job opportunities (e.g., Granovetter, 1995) and mortality (e.g., Berkman & Syme 1979), it matters to be aware of heuristic effects as found in this study. For example, with word-of-mouth communications among consumers (e.g., Iacobucci & Hopkins, 1992), for the supplier of the respective product or service it is interesting to know when consumers have a tendency to talk with isolated or central peers and that they neglect benefits that peers derive from their communication decisions. Also, suppliers can exploit the finding that this behavior is dependent on the complexity of the network environment, for example, by facilitating information about social payoffs.

5.3 Future Research

Diverse linear transformations to convert points earned to euro payments - which we used over complexity conditions to equalize the average monetary rewards with which our participants leave the laboratory - might influence decisions (Maddox et al., 2003). Although we think it unlikely that participants in our experiment were able to comprehend more than the fact that earning more points would increase their ultimate monetary payoff as well (see the Supplementary material, Appendix C), future work could account for this in another way.

In order to prevent interference of complexity types that are not the focus of the current research, we studied a relatively simple network linking decision that is only one-shot and involves only one active participant changing at most one link. Also, the payoff information is complete and certain. Future research could study whether and in how far additional complexity types such as strategic interaction, dynamics, multi-link deviation, incomplete information, and uncertainty strengthen the heuristic effects shown by the current paper.

Furthermore, in this exploratory study we could find significant shifts from exact payoff to the descriptive attributes qualitatively related to it that to the best of our knowledge can be determined most easily by a decision maker, namely remaining with vs. deviating from the status quo and the degree centrality of a node. Issues like cognitive distinctions between deleting or creating a link and more advanced centrality or other social network measures could be considered in future work.

Another direction that follow-up studies could take concerns the question in how far the complexity types and heuristic effects we considered are specific for the network context. For example, in how far does complexity systematically reduce social preferences in other choice settings? Moreover, future experiments could generate further insights in the linking choice process of individuals by concentrating on specific effects from the rich range of heuristic tendencies explored here.

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APPENDIX A: CHOICE PROBLEMS

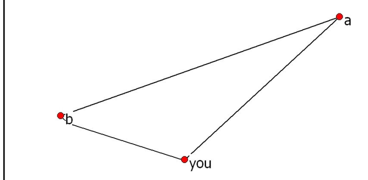
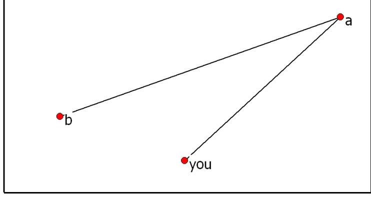
p1		What do you choose? ☐ I do nothing. ☐ I delete the link with a. ☐ I delete the link with b.
p2		What do you choose? ☐ I do nothing. ☐ I delete the link with a. ☐ I create a link with b.

Table A.1: Practice rounds.

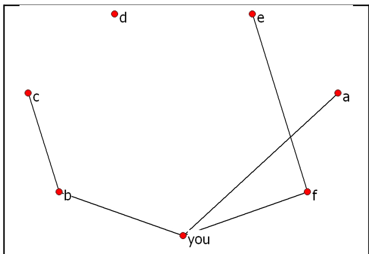
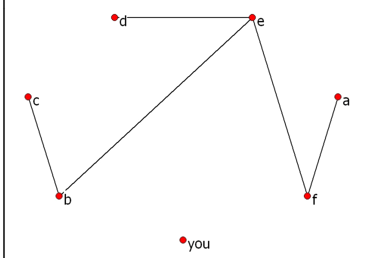
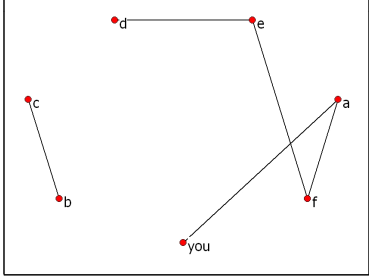
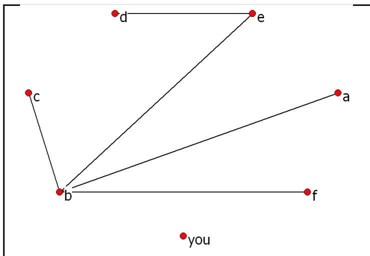
1		What do you choose? ☐ I do nothing. ☐ I delete the link with a. ☐ I delete the link with b. ☐ I create a link with c. ☐ I create a link with d. ☐ I create a link with e. ☐ I delete the link with f.
2		What do you choose? ☐ I do nothing. ☐ I create a link with a. ☐ I create a link with b. ☐ I create a link with c. ☐ I create a link with d. ☐ I create a link with e. ☐ I create a link with f.
3		What do you choose? ☐ I do nothing. ☐ I delete the link with a. ☐ I create a link with b. ☐ I create a link with c. ☐ I create a link with d. ☐ I create a link with e. ☐ I create a link with f.

Table A.2: Choice problems 1 - 3.

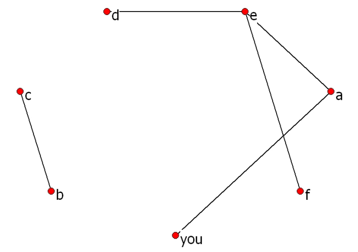
4



What do you choose?

- ☐ I do nothing.
- ☐ I create a link with a.
- ☐ I create a link with b.
- ☐ I create a link with c.
- ☐ I create a link with d.
- ☐ I create a link with e.
- ☐ I create a link with f.

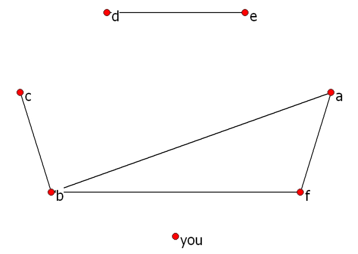
5



What do you choose?

- ☐ I do nothing.
- ☐ I delete the link with a.
- ☐ I create a link with b.
- ☐ I create a link with c.
- ☐ I create a link with d.
- ☐ I create a link with e.
- ☐ I create a link with f.

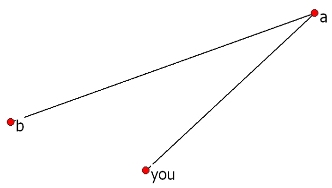
6



What do you choose?

- ☐ I do nothing.
- ☐ I create a link with a.
- ☐ I create a link with b.
- ☐ I create a link with c.
- ☐ I create a link with d.
- ☐ I create a link with e.
- ☐ I create a link with f.

Table A.3: Choice problems 4 - 6.



What do you choose?

- ☐ I do nothing. This means that I earn 5 points and 15 points will be divided equally among the other participants in this room.
- ☐ I delete the link with a. This means that I earn 0 points and 20 points will be divided equally among the other participants in this room.
- ☐ I create a link with b. This means that I earn 5 points and 10 points will be divided equally among the other participants in this room.

Figure A.1: Illustration payoff information.

	indirect payoffs: NO			indirect payoffs: YES		
1		you	others		you	others
	nothing	6.67	26.67	nothing	8.33	32.92
	a	5	25	a	7.5	30.31
	b	7.5	37.5	b	8.75	42.5
	c	6.25	21.25	c	7.5	26.48
	d	7.5	27.5	d	8.75	34.45
	e	6.25	21.25	e	7.5	26.48
	f	7.5	37.5	f	8.75	42.5
2		you	others		you	others
	nothing	0	33.33	nothing	0	41.25
	a	5	33.33	a	6.58	41.51
	b	3.33	32.22	b	5.03	39.72
	c	5	33.33	c	6.58	41.51
	d	5	35	d	6.25	42.5
	e	2.5	32.5	e	4.06	39.14
	f	3.33	32.22	f	5.03	39.72
3		you	others		you	others
	nothing	5	45	nothing	6.72	51.09
	a	0	45	a	0	51.25
	b	5	35	b	7.11	44
	c	5	35	c	7.11	44
	d	5	40	d	6.64	46.56
	e	4.17	39.17	e	5.83	44.58
	f	4.17	40.83	f	5.38	45.59
4		you	others		you	others
	nothing	0	27.5	nothing	0	35.31
	a	5	30	a	6.05	37.15
	b	2	26	b	3.5	32.7
	c	5	30	c	6.05	37.15
	d	5	27.5	d	6.52	35.74
	e	3.33	26.67	e	4.93	34.24
	f	5	30	f	6.05	37.15
5		you	others		you	others
	nothing	5	41.67	nothing	6.39	47.5
	a	0	40	a	0	46.67
	b	5	31.67	b	6.94	40.45
	c	5	31.67	c	6.94	40.45
	d	5	38.33	d	6.25	44.17
	e	3.75	36.25	e	5	40.94
	f	5	38.33	f	6.25	44.17
6		you	others		you	others
	nothing	0	38.33	nothing	0	43.33
	a	3.33	38.89	a	4.57	43.58
	b	2.5	37.5	b	3.91	42.03
	c	5	40	c	6.18	44.79
	d	5	33.33	d	7.5	40.83
	e	5	33.33	e	7.5	40.83
	f	3.33	38.89	f	4.57	43.58

Table A.4: Payoffs choice problems.

APPENDIX B: DESCRIPTIVE RESULTS

1. Duration: average 40,2 min., stand. dev. 14,8 min.
2. Almost all participants tried to earn as much as possible, whereas 17 subjects indicated other goals: best choices (6), fun / interest (2), optimal own payoffs and not too bad payoffs for the others (4), optimal own payoffs and minimal payoffs for the others (1), structural goals (4).
3. In the first choice problem (practice round), participants chose as follows: at random: 1, by calculation: 60, by intuition: 34, using a rule: 13, namely connect to the one with the least neighbors / shortest paths (13), otherwise: 6, namely mix of intuition and calculation (5), mistake in understanding instructions at first (1).
4. Thereafter, did participants change their strategies? No: 67, for the strategy was good or convenient and the problems were similar, yes: 47, switch (more) to calculation (12), intuition / experience (22), or rule mentioned in descriptive 3. (11), or consider other participants more (2).
5. In conditions *social* and *both*, did participants take into account the points created for other participants? 36 did not, since they didn't think about it (4), didn't care about it (16), didn't know how (5) or didn't like the effort (11), 20 did, where they (conditionally) maximized (≥ 8) or minimized (≥ 3) the points for the others, two participants seem not to understand that dividing among other participants does not include yourself.
6. Strategies in the second part (with numerical payoff information) of conditions *social* and *both*: (conditionally) maximizing payoffs for the others (25), choosing not too badly for the others (7), (conditionally) minimizing payoffs for the others (6), trying to repeat first part (8), unclear (10).
7. Strategic considerations in conditions *social* and *both*? No: 18, since they didn't think about it (7), thought that the other participants wouldn't care (5), the other participants are outside control (4), or it would be too difficult (2), yes, but did not influence choices: 9, yes, hoping for a favorable group: 5, or expecting an unfavorable group: 2, yes, unclear how: 22 (at least five of these seem not to understand that this question is about the others creating points for you and not about you creating points for the others).
8. Difficulties were mentioned in the following fields: calculation: 33, choice complexity: 35, instructions: 26, equivalent options: 5, none: 16.
9. Further remarks: interesting / nice: 12, want to know more about the experiment: 10, confirming what was said before: 5, suggestions: 10.
10. Age: average 22,5 yrs., stand. dev.: 3,4 yrs.
11. Male: 48, female: 66.
12. Dutch: 40, German: 43, Chinese: 9, other: 22.
13. Faculty of Economics & Business Administration: 90, other: 24.
14. 90 participants did not participate in a similar experiment before; 24 did.
15. 112 participants would like to participate in future experiments, two would not.
16. In conditions *social* and *both*: 40 participants did not know any of their fellow session participants, 12 knew one and four knew more.

APPENDIX C: SUPPLEMENTARY MATERIAL

The experimental instructions associated with this article can be found in the online version, at http://dx.doi .org/...

APPENDIX C: INSTRUCTIONS

Dear participant, Welcome in this Choice Experiment! If you encounter anything that is unclear to you during the experiment, feel free to ask questions. Just raise your hand to inform me. Please do not communicate with the other participants in the room during the experiment. Take your time to think about your choices. If you are finished with the experiment, please stay seated quietly until all participants are finished. Thereafter I will calculate and hand over each participant's earnings. Success!

(Below, bold text was used in treatments without value transferability and italics in treatments with value transferability.)

1 Social Tradeoff NO, Value Transferability NO *YES*

Please read the following instructions carefully. You have also received a print-out of them for future reference.

In this experiment you are asked to respond to eight choice problems. You can earn points depending on the choices you make in these problems. The total number of points that you have at the end of the experiment determines your monetary payoff.

In each problem, you see a picture of a network in which you and several other nodes are interconnected by links. In order to generate points, you are allowed to change at most one link. You have the following options to do this: (1) you can delete one link that already exists between you and any other node, (2) you can create one link between you and any other node if there is not yet any link between you and this node, or (3) you can choose not to change anything.

You can determine the number of points you receive due to your choice for a specific problem, as follows. **For each node you are directly linked with (we call such a node a neighbour) you obtain points.** *For each path that links you to some other node you obtain points.* However, there is also some cost associated with being connected: **the number of points you receive for each of your direct neighbours equals 10 divided by two components: (i) the number of direct neighbours you have, and (ii) the number of direct neighbours this neighbour has.** *the number of points you receive for each path that links you to some other node equals 10 divided by three components: (i) the number of direct neighbours you have in the network, (ii) the number of direct neighbours this other node has in the network, and (iii) the square of the number of direct neighbours that any of the further nodes on the path between you and the other node has in the network.*

[EXAMPLE, see Section 3]

After each of the eight problems, the number of points that you earned will be reported.

Note that there are no real people behind the other nodes in a network: you are the only one able to change a link and earn points by this.

At the end of the experiment, points are exchanged for euros in the following way: amount in euros you receive = 4 + **0.4** *0.3* (total number of points that you earned - **33.68** *45.17*).

2 Social Tradeoff YES, Value Transferability NO *YES*

This experiment consists of two parts. In the first part as well as in the second part you can earn money by making choices. The choices you make in one part do not affect the payoffs from the other part in any way. Please continue to the instructions for the first part.

Please read the following instructions carefully. You have also received a print-out of them for future reference.

In this first part you are asked to respond to eight choice problems. You can earn points depending on the choices you make in these problems. Moreover, your choices can also generate points for the other participants in the room. The total number of points that you have at the end of the experiment determines your monetary payoff.

In each problem, you see a picture of a network in which you and several other nodes are interconnected by links. In order to generate points, you are allowed to change at most one link. You have the following options to do this: (1) you can delete one link that already exists between you and any other node, (2) you can create one link between you and any other node if there is not yet any link between you and this node, or (3) you can choose not to change anything.

You can determine the number of points you receive due to your choice for a specific problem, as follows. **For each node you are directly linked with (we call such a node a neighbour) you obtain points.** *For each path that links you to some other node you obtain points.* However, there is also some cost associated with being connected: **the number of points you receive for each of your direct neighbours equals 10 divided by two components: (i) the number of direct neighbours you have, and (ii) the number of direct neighbours this neighbour has.** *the number of points you receive for each path that links you to some other node equals 10 divided by three components: (i) the number of direct neighbours you have in the network, (ii) the number of direct neighbours this other node has in the network, and (iii) the square of the number of direct neighbours that any of the further nodes on the path between you and the other node has in the network.*

[EXAMPLE, see Section 3]

After each of the eight problems, the number of points that you earned will be reported.

The other nodes in the choice problems receive points in the same way as you do. There are no real people behind these nodes and you are the only one able to change a link in a network. However, the points that the other nodes receive due to your choices do have a consequence for the other participants in this room. In fact, these points will be divided equally among them.

[EXAMPLE continued, see Section 3]

The number of points that you generated for the other participants will also be reported after each problem.

At the end of the experiment, points are exchanged for euros in the following way: amount in euros you receive for this first part = 4 + **0.06** *0.07* (total number of points that you earned in this first part - **265.51** *320.63*).

You finished the first part of the experiment. Now, the second part will folow. The choices you made in the first part do not influence the payoffs in this part and the choices you will make in this part do not influence the payoffs in the previous part.

In this second part you are asked to respond to eight choice problems. You can earn points depending on the choices you make in these problems. Moreover, your choices can also generate points for the other participants in the room. The total number of points that you have at the end of the experiment determines your monetary payoff.

At the end of the experiment, points are exchanged for euros in the following way: amount in euros you receive for this second part = 0.5 + **0.03** *0.035* (total number of points that you earned in this second part - **265.51** *320.63*).

3 Example

3.1 *Social tradeoff NO, Value transferability NO*

For example, in the above network [Figure 1 in the article] you have two direct neighbours: a and d. For neighbour a you get 10 points divided by 2 (since you have two direct neighbours) divided by 3 (since a has three direct neighbours). For neighbour d you get 10 points divided by 2 (since you have two direct neighbours) divided by 2 (since d has two direct neighbours). In total you therefore receive 10/6 + 10/4 = 25/6 points in this example.

3.2 *Social tradeoff NO, Value transferability YES*

For example, in the above network [Figure 1 in the article] there are two paths between you and c. For the path via a and b you get 10 points divided by 2 (since you have two direct neighbours in the network) divided by 3 * 3 (since a has three direct neighbours in the network) divided by 2 * 2 (since b has two direct neighbours in the network) divided by 1 (since c has one direct neighbour in the network). For the path via d, a, and b you get 10 points divided by 2 (since you have two direct neighbours in the network) divided by 2 * 2 (since d has two direct neighbours in the network) divided by 3 * 3 (since a has three direct neighbours in the network) divided by 2 * 2 (since b has two direct neighbours in the network) divided by 1 (since c has one direct neighbour in the network). In total you therefore receive 10/72 + 10/288 = 25/144 points for the paths between you and c. In the same way you get 10/36 + 10/144 points for the paths between you and b, 10/6 + 10/24 points for the paths between you and a and 10/4 + 10/36 points for the paths between you and d. In total you therefore receive 775/144 points in this example.

3.3 *Social tradeoff YES, Value transferability NO*

For example, in the above network [Figure 1 in the article] you have two direct neighbours: a and d. For neighbour a you get 10 points divided by 2 (since you have two direct neighbours) divided by

3 (since a has three direct neighbours). For neighbour d you get 10 points divided by 2 (since you have two direct neighbours) divided by 2 (since d has two direct neighbours). In total you therefore receive 10/6 + 10/4 = 25/6 points in this example.

[continued] In the example above, node c has one direct neighbour: b. Therefore, she receives 10 points divided by 1 (since c has one direct neighbour) divided by 2 (since b has two direct neighbours), which implies 5 points. In the same way, node b gets 10/2 + 10/6 = 20/3 points, node a gets 10/6 + 10/6 + 10/6 = 5 points, and node d gets 10/4 + 10/6 = 25/6 points. In total therefore 5 + 20/3 + 5 + 25/6 = 125/6 points will be divided equally among the other participants in the room in this example.

3.4 *Social tradeoff YES, Value transferability YES*

For example, in the above network [Figure 1 in the article] there are two paths between you and c. For the path via a and b you get 10 points divided by 2 (since you have two direct neighbours in the network) divided by 3 * 3 (since a has three direct neighbours in the network) divided by 2 * 2 (since b has two direct neighbours in the network) divided by 1 (since c has one direct neighbour in the network). For the path via d, a, and b you get 10 points divided by 2 (since you have two direct neighbours in the network) divided by 2 * 2 (since d has two direct neighbours in the network) divided by 3 * 3 (since a has three direct neighbours in the network) divided by 2 * 2 (since b has two direct neighbours in the network) divided by 1 (since c has one direct neighbour in the network). In total you therefore receive 10/72 + 10/288 = 25/144 points for the paths between you and c. In the same way you get 10/36 + 10/144 points for the paths between you and b, 10/6 + 10/24 points for the paths between you and a and 10/4 + 10/36 points for the paths between you and d. In total you therefore receive 775/144 points in this example.

[continued] In the example above, there is one path between nodes a and c. Therefore, c receives 10 points divided by 1 (since c has one direct neighbour) divided by 2 * 2 (since b has two direct neighbours) divided by 3 (since a has three direct neighbours) = 5/6 points for the paths between her and a. In the same way c gets 10/2 points for the path between her and b, 10/72 + 10/288 points for the paths between her and d, and 10/72 + 10/288 points for the paths between her and you. In total c therefore receives 445/72 points. In the same way node b gets 10/2 + 10/6 + 10/36 + 10/144 + 10/36 + 10/144 points, node a gets 10/12 + 10/6 + 10/6 + 10/24 + 10/6 + 10/24 points, and node d gets 10/72 + 10/288 + 10/36 + 10/144 + 10/6 + 10/24 + 10/4 + 10/36 points. In total therefore 445/72 + 265/6 + 20/3 + 775/144 = 2995/48 points will be divided equally among the other participants in the room in this example.