**Choosing for others: The influence of incentives, similarity, and previous experience**

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**Summary**

Relatively little is known about how we make decisions for others, but we do know that people are generally not very good at knowing what their recipient would choose for themselves. However, researchers have yet to investigate whether people are able to learn the preferences of others (through observation) and subsequently choose for them. Here, much like what we experience in the real world, we provide subjects with the opportunity to observe another’s previous choices before making choices for them. Using process tracing methodology, a variety of incentive schemes, and a quantifiable measure of similarity (between the subject and the recipient), we aim to address several important open questions about how we choose for others and how we might improve our surrogate abilities.

**Motivation**

In recent years, research on surrogate decision making has found varied — and sometimes conflicting — results regarding our ability to choose on another’s behalf. However, a fairly robust and consistent finding is that people are not very good at choosing what another person would choose for themselves (Fagerlin et al., 2001; Faro & Rottenstreich, 2006; Fernandez-Duque & Wifall, 2007; Garcia-Retamaro & Galesic, 2012). In important domains such as health, physical safety, interpersonal relationships, and monetary risk, surrogates tend to choose options that are too safe (or too risky, depending on the domain) for their recipient. However, if people are given the chance to learn another’s decision tendencies via observation of this other’s choices, can they improve?

Our past research (Smith & Krajbich, in preparation) has demonstrated the ability of people to learn another person’s film preferences via immediate feedback. However, this finding has yet to be extended to an environment where people are actually making choices for another person (rather than simply estimating their preferences). Moreover, this project fills a gap that is present in most surrogate decision-making literature. Specifically, while most of this research shows that people aren’t very good at making decisions for others, the literature has yet to offer any processes/methods/mechanisms by which people might improve their surrogate abilities. If we can show that simple feedback can improve surrogate accuracy (which we anticipate, given past results), this study will help identify *and* address the problem of inaccurate surrogate decisions.

Previous research offers yet another opportunity for further examination. Some past studies (e.g. Ziegler et al., 2012) have manipulated the social distance of surrogate decision recipients and has demonstrated that people choose closer to the recipient’s preferences when the recipient is closer socially (i.e. family members vs. strangers). One recent paper (Clithero et al., in review) provided subjects with short descriptions about the recipients intended to invoke a certain belief about the subject-recipient similarity. The explicit nature of these manipulations may be subject to demand effects; moreover, they are inherently qualitative in nature. Therefore, in this proposal, we present an alternative method in which similarity/distance is both endogenous and quantifiable.

Given this rationale, we have designed two studies to answer the following research questions:

1. When given the chance to observe previous choices, can people learn others’ risk preferences?
2. How are one’s own risk preferences (i.e. the discrepancy between self and other preferences) related to surrogate success?
3. Does the nature of the incentives change surrogate behavior, both in terms of process (i.e. with mouse tracking) and in outcome (i.e. choice)?

**Method**

Much of the research in this area focuses on decisions for others that involve some sort of risk (e.g. Hsee & Weber, 1997; Beisswanger et al., 2003; Faro & Rottenstreich, 2006; Fernandez-Duque & Wifall, 2007; Stone & Allgaier, 2008; Stone et al., 2013) and we will therefore use this highly relevant decision domain. The general idea for each study is to let subjects observe monetary risk choices made by another and then allow them to make incentivized monetary risk choices for this other. Additionally, we will have subjects make incentivized risk decisions for themselves. This will enable us to examine the relationship between personal risk preferences (i.e. how risk averse someone is) and the ability to learn another’s preferences (e.g. people might be more accurate when choosing for someone more similar to themselves). For the decisions, we will use non-loss risk choices between a 50-50 gamble and a sure thing (Sokol-Hessner et al., 2009).

When subjects are observing the other’s choices, we will first show both options on the screen to let the subjects think about the choice alternatives. We will then highlight the chosen option. Subjects will move their mouse and click on the selected option. We will track the movement of the mouse cursor as a measure of learning (sooner, more direct movements might indicate learning). In a similar vein, when subjects make choices for the other, we will utilize mouse tracking as a process measure of the unfolding course of the decision. Mouse tracking has been demonstrated as a useful tool to show the relative speeds at which different choice attributes are processed during a decision (Sullivan et al., 2014). Thus, with mouse tracking, we should be able to disentangle competing influences in surrogate decision-making: what the surrogate would choose vs. what the surrogate thinks the recipient would choose.

Study 1 (N = 40): Before we examine how subjects learn another’s preferences and subsequently choose for this other person, it will be prudent to examine if/how subjects learn fixed, stable preferences (generated by an algorithm). Therefore, in Study 1, subjects will try to learn algorithm-generated preferences by observing several “choices” made by an algorithm (i.e. a standard risk-aversion utility function with a softmax choice function). They will then make new choices for the computer on previously-unseen trials and will be rewarded if they can correctly identify which option the computer chose. Subjects will repeat this process for several different algorithms; each algorithm will be designed to have a different degree of risk aversion (and a fixed level of noise/unpredictability) so that we can examine subjects’ surrogate abilities across a range of risk preferences. Subjects will also make incentivized choices for themselves; the order of choices-for-self and the choices-for-algorithm will be counterbalanced across subjects. The subjects in Study 1 will serve an additional purpose as “recipients” in Study 2, with the potential to earn additional money.

Study 2 (N = 50): Using the data from Study 1, we will select subjects across a wide range of risk preferences to be our recipients in Study 2. Subjects in Study 2 will observe several choices made by each of these chosen recipients and then will make choices on the recipients’ behalves. However, there will be a within-subjects manipulation on the incentives. For some recipients’ choices, subjects will earn a bonus for each “correct” answer (i.e. each time they pick the option chosen by the recipient), similar to the set-up in Study 1. This will serve as a measure of what subjects think the other person *would* do. In other choices — to figure out how subjects make decisions that they think the other person *should* make — we will randomly select one decision and give the outcome to the recipient.

Clearly, these two conditions are not necessarily equivalent because of who stands to earn money as a result of the choices. Therefore, we will also have a condition where the *recipients* will earn a bonus based on the surrogate’s accuracy. That is, for each choice where the subject picks the option chosen by the recipient, the recipient will earn a bonus.

**Hypotheses**

H1) People can learn others’ risk preferences (i.e. there will be a significant correlation between the fitted risk aversion parameters for recipients’ choices and the fitted risk aversion parameters for surrogates choices for these recipients).

H2) People will choose more accurately (i.e. closer to the recipient’s preferences) and less noisily (i.e. more consistently) when the recipient is more similar to the surrogate.

H3) There will be a significant difference in surrogate accuracy and in mouse movements between the incentive conditions (i.e. people will be more likely to choose in line with the recipient’s preferences and mouse movements will be more direct to the option chosen by the recipient when they are personally incentivized to be accurate).

We have conducted power analyses for both studies to determine the number of subjects needed to achieve at least 80% power to detect significance for the hypotheses above, and we estimate 40 subjects for Study 1, 50 subjects for Study 2.

We (Steph Smith, Decision Psych; Ian Krajbich, Decision Psych/Economics) agree to the requirements specified online and our preferred presentation semester would be Spring 2019.

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**Choosing for Others DSC Grant Proposal ($2050)**

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| Description of Transaction | Budgeted Debit |
| Study 1 Participant Payment (40 people x $20) | $800.00 |
| Study 2 Participant Payment (50 people x $25) | $1250.00 |
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| Total | $2050.00 |