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Revealed strength of preference: Inference from response times

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Abstract

Revealed preference is the dominant approach for inferring preferences, but it is limited in that it relies solely on discrete choice data. When a person chooses one alternative over another, we cannot infer the strength of their preference or predict how likely they will be to make the same choice again. However, the choice process also produces response times (RTs), which are continuous and easily observable. It has been shown that RTs often decrease with strength-of-preference. This is a basic property of sequential sampling models such as the drift diffusion model. What remains unclear is whether this relationship is sufficiently strong, relative to the other factors that affect RTs, to allow us to reliably infer strength-of-preference across individuals. Using several experiments, we show that even when every subject chooses the same alternative, we can still rank them based on their RTs and predict their behavior on other choice problems. We can also use RTs to predict whether a subject will repeat or reverse their decision when presented with the same choice problem a second time. Finally, as a proof-of-concept, we demonstrate that it is also possible to recover individual preference parameters from RTs alone. These results demonstrate that it is indeed possible to use RTs to infer preferences.

Keywords: response times, preferences, drift-diffusion model, risky choice, intertemporal choice, social preferences

1 Introduction

When inferring a person's preferences, decision scientists often rely on choice outcomes. This is the standard revealed preference approach (Samuelson, 1938). While very powerful, relying purely on choice data does have its limitations. In particular, observing a single choice between two options merely allows us to order those two options (as less and more preferred); we cannot infer the strength of the preference. That is, we do not know the confidence with which the person made the choice or the likelihood that they would choose the same alternative again.

Choice itself is not the only output of the choice process. We are also often able to observe other features such as response times (RT), which are continuous and so may carry more information than discrete choice outcomes (Loomes, 2005; Spiliopoulos & Ortmann, 2017). The potential issue with RTs is that they are known to reflect many factors, including subject-level traits such as decision strategy and motor latency (Kahneman, 2013; Luce, 1986), as well as features of the choice problems such as complexity, stake size, and option similarity (or attributes) (Bergert & Nosofsky, 2007; Bhatia & Mullett, 2018; Diederich, 1997; Fific, Little & Nosofsky, 2010; Gabaix, Laibson, Moloche & Weinberg, 2006; Hey, 1995; Rubinstein, 2007; Wilcox, 1993).

One useful characteristic of RTs is that they often correlate (negatively) with strength-of-preference. This effect was observed in early studies in psychology and economics (Dashiell, 1937; Diederich, 2003; Jamieson & Petrusic, 1977; Mosteller & Nogee, 1951; Tversky & Shafir, 1992) and has been recently extensively researched using choice models (Alós-Ferrer, Granić, Kern & Wagner, 2016; Busemeyer, 1985; Busemeyer & Rapoport, 1988; Busemeyer & Townsend, 1993; Echenique & Saito, 2017; Hutcherson, Bushong & Rangel, 2015; Krajbich, Armel & Rangel, 2010; Krajbich & Rangel, 2011; Moffatt, 2005; Rodriguez, Turner & McClure, 2014). In other words, choices between more equally-liked options tend to take more time. If this relationship is strong, relative to the other factors that affect RT, then we should be able to infer strength-of-preference information from RTs.[1]

Consider the following example. Suppose we are attempting to determine which of two people, Anne or Bob, has a higher discount factor for future rewards (in other words, is less patient). We ask each of them the same question: "would you rather have $25 today or $40 in two weeks?"

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[1] A similar approach has been adopted in the neuroimaging literature, where it is considered important to go beyond correlations and demonstrate that behavior can be predicted from brain activity (Haxby, Connolly & Guntupalli, 2014).

Suppose that both take the $40. With just this information there is no way to distinguish between them. Now suppose Anne made her choice in 5 seconds, while Bob made his in 10 seconds. Who is more patient? We argue that the answer is likely Anne. Since Anne chose the delayed option more quickly than Bob, it is likely that she found it more attractive. In other words, Anne's relative preference for the delayed option was likely stronger than Bob's; she was farther from indifference (i.e., the point at which she is equally likely to choose either option).

Of course, if Anne and Bob employ different decision strategies (e.g., Anne chooses based on heuristics while Bob chooses based on deliberation) or differ on other relevant characteristics (e.g., Anne is smarter or younger) then we might be misled about their preferences. It is thus an empirical question whether our example is actually feasible, or merely speculation. This is a key question that we tackle in this paper.

The answer to this question has potential practical importance. Consider an online marketplace. A customer might inspect a series of products but reject them all, making the choice data uninformative. However, the customer may linger more on certain items, revealing which ones were most appealing. The online seller could use that information to target related products at the customer. Or returning to an interpersonal example, an overloaded clothes salesman might focus their attention more on customers who hesitate longer before returning items to the rack.

Taking this idea one step further, we might also want to know whether choice data are necessary to infer preferences, or whether RTs alone could suffice. In the example with Anne and Bob, we used both the choice outcome and the RT to rank the two decision makers on patience. While the RT told us how easy the decision was for each person, without the choice outcome we could not know whether Anne faced an easy decision because she was very patient or very impatient. This might lead one to believe that it is still necessary to observe choice outcomes in order to infer preferences. However, in theory, all we need is a second RT.

Suppose that both Anne and Bob take 5 seconds to choose between the $25 today vs. $40 in two weeks, but we do not see their choices. Let us assume, for the sake of this example, that strength-of-preference is the only factor that affects RT. At this point we can use Anne and Bob's RTs to infer their distance from indifference, but we cannot say whether they were on the patient side or impatient side. Now we ask a second question: $25 today vs. $50 in two weeks. Relative to the previous question, we have made the "patient" option more attractive, i.e., we have made the decision easier for a patient person (e.g., someone who chose the $40) and more difficult for an impatient person (e.g., someone who chose the $25). Suppose Anne makes this decision in 6 seconds while Bob makes this decision in 4 seconds. We can then conclude that Bob is on the patient side and Anne is on the impatient side. With just two questions we are thus able to infer their temporal discounting factors (preferences, more generally). Of course, this procedure assumes a noiseless relationship between strength-of-preference and RT. In what follows, we investigate the usefulness of this procedure using more than two decisions (to compensate for noise in the decision process) and show that the preferences inferred from RTs can indeed be reliable.

Our work builds on a growing literature focused on sequential sampling models (SSM) (such as the drift-diffusion model (DDM)) of economic decision making. The idea of applying SSMs to economic choice was first introduced by Jerome Busemeyer and colleagues in the 1980s (Busemeyer, 1985) and further developed into decision field theory in subsequent years (Diederich, 1997, 2003; Roe, Busemeyer & Townsend, 2001). Recent years have seen renewed interest in this work due to the ability of these models to simultaneously account for choices, RTs, eye movements, and brain activity in many individual preference domains such as risk and uncertainty (Fiedler & Glöckner, 2012; Hunt et al., 2012; Stewart, Hermens & Matthews, 2015), intertemporal choice (Amasino, Sullivan, Kranton & Huettel, 2019; Dai & Busemeyer, 2014; Rodriguez et al., 2014), social preferences (Hutcherson et al., 2015; Krajbich, Bartling, Hare & Fehr, 2015; Krajbich, Hare, Bartling, Morishima & Fehr, 2015), food and consumer choice (De Martino, Fleming, Garret & Dolan, 2013; Krajbich et al., 2010; Milosavljevic, Malmaud, Huth, Koch & Rangel, 2010; Polanía, Krajbich, Grueschow & Ruff, 2014), and more complex decision problems (Caplin & Martin, 2016; Konovalov & Krajbich, 2016). The SSM framework views simple binary decisions as a mental tug-of-war between the options (Bogacz, Brown, Moehlis, Holmes & Cohen, 2006; Brunton, Botvinick & Brody, 2013; Fudenberg, Strack & Strzalecki, 2018; Shadlen & Shohamy, 2016; Tajima, Drugowitsch & Pouget, 2016; Usher & McClelland, 2001; Woodford, 2014). For options that are similar in strength (subjective value) it takes more time to determine the winner, and in some cases the weaker side may prevail. In other words, these models predict that long RTs indicate indifference, and that RTs decrease as the superior option gets better than the inferior option.

Here, we estimate individual preferences using subjective value (utility) functions with single parameters and demonstrate the strength of the relationship between preference and RT, using experimental data from three prominent choice domains: risk, time, and social preferences. We show that single-trial RTs can be used to rank subjects according to their degree of loss aversion, that RTs on "extreme" trials (where most subjects choose the same option) can be used to rank subjects according to their loss, time, and social preferences, and that RTs from the full datasets can be used to estimate preference parameters. In every case these rankings significantly align with those estimated from subjects' choices over the full datasets. We also show that trials with longer RTs are less consistent with a subject's other choices, and more likely to be reversed if presented a second time.

These results complement several recent papers that have investigated the relationship between RT and preferences. Chabris et al. (2009) use a structural RT model to estimate time preferences in groups, but they do not attempt the same exercise at the individual level. Alós-Ferrer et al. (2016) demonstrate that preference reversals between choice and valuation tasks are associated with longer RTs. We take this idea a step further by looking at reversals between two instances of identical choice problems. Finally, Clithero (2018) uses the DDM to improve out-of-sample predictions in food choice. We provide a complementary approach where subjective values can be inferred parametrically, and apply the DDM without using the choice data. Considering these results, our main contribution is in demonstrating that, across many decision domains, there are several ways in which RTs can supplement or even replace choice data in individual preference estimation.

2 Methods

We analyze four separate datasets: the last two (Studies 2 and 3) were collected with other research goals in mind, but included precise measurements of RTs, while the first two (Study 1) were collected specifically for this analysis (see Note 1 in the Supplement for summary statistics). For each dataset, we selected a common, single-parameter preference model (i.e., subjective-value function). Our goal here was not to compare different preference models but rather to identify best-fitting parameter values given a particular model that explains the data well. The decision problems in these datasets were specifically designed with these particular models in mind.

In addition to the differing domains, these tasks vary along a couple of dimensions that might affect the relationship between preference and RT. One dimension is time constraint. Time limits are common in binary choice tasks in order to keep subjects focused, but overly restrictive cutoffs may dampen the effect of strength-of-preference on RTs. Here we examine datasets with varying time constraints (3s, 10s, and unlimited) in order to explore the robustness of our results.

2.1 Study 1: risky choice

2.1.1 Participants

This experiment was conducted at The Ohio State University. The experiment had two versions: 61 subjects participated in the adaptive version of the task, earning \$17–20 on average; and 39 subjects participated in the non-adaptive version, earning \$18 on average. In order to cover any potential losses, subjects first completed an unrelated task that endowed them with enough money to cover any potential losses.

2.1.2 Adaptive risky choice task

In each trial, subjects chose between a sure amount of money and a 50/50 lottery that included a positive amount and a loss (which in some rounds was equal to \$0). The set of decision problems was adapted from Sokol-Hessner et al. (2009). Subjects' RTs were not restricted. In the adaptive experiment, each subject's choice defined the next trial's options using a Bayesian procedure to ensure an accurate estimate of the subject's risk and loss aversion within a limited number of rounds (Chapman, Snowberg, Wang & Camerer, 2018). Each subject completed the same three unpaid practice trials followed by 30 paid trials. Each subject received the outcome of one randomly selected trial. Importantly, every subject's first paid trial was identical.

2.1.3 Non-adaptive risky choice task

In the non-adaptive experiment, each subject first completed a three-trial practice followed by 276 paid trials. These trials were presented in two blocks of the same 138 choice problems, each presented in random order without any pause between the two blocks. Subjects were endowed with \$17 and additionally earned the outcome of one randomly selected trial (in case of a loss it was subtracted from the endowment).

2.1.4 Preference model

For both experiments we assumed a standard Prospect Theory value function (Kahneman & Tversky, 1979):

$$U(x) = \begin{cases} x^{\rho} & \text{if} \quad x \geq 0 \\ -\lambda \cdot -x^{\rho} & \text{if} \quad x < 0, \end{cases} \tag{1}$$

where x is the monetary amount, ρ reflects risk aversion, and λ captures loss aversion. For simplicity, we assumed linear probability weighting. Similar to prior work using this task, we found that risk aversion plays a minimal role in this task relative to loss aversion, with ρ estimates typically close to 1. Therefore, acknowledging that varying levels of risk aversion could add noise to the RTs, for the analyses below (both choice- and RT-based) we assumed risk neutrality ($\rho = 1$).

In the non-adaptive experiment, the preference functions were estimated using a standard MLE approach with a logit choice function. We used only trials with non-zero losses (specifically, 112 out of 138 decision problems). Two subjects with outlying estimates of λ (beyond three standard deviations of the mean) were removed from the analysis due to unreliability of these estimates (subjects making choices that are extremely biased towards one of the options). The same exclusion criterion was used for the other datasets.

2.2 Study 2: intertemporal choice

2.2.1 Participants

This experiment was conducted while subjects underwent functional magnetic resonance imaging (fMRI) at the California Institute of Technology (Hare, Hakimi & Rangel, 2014). 41 subjects participated in this experiment, earning a $50 show-up fee and the amount from one randomly selected choice. The payments were made using prepaid debit cards that were activated at the chosen delayed date.

2.2.2 Task

In each round, subjects chose between getting $25 right after the experiment or a larger amount (up to $54) at a later date (7 to 200 days). There were 108 unique decision problems and subjects encountered each problem twice. All 216 trials were presented in random order. Each trial, the amount was first presented on the screen, followed by the delay, and subjects were asked to press one of two buttons to accept or reject the offer. The decision was followed by a feedback screen showing "Yes" (if the offer was accepted) or "No" (otherwise). The decision time was limited to 3 seconds, and if a subject failed to give a response, the feedback screen contained the text "No decision received". These trials (2.6% across subjects) were excluded from the analysis. Trials were separated by random intervals (2–6 seconds).

2.2.3 Preference model

In line with the authors who collected this dataset, we used a hyperbolic discounting subjective-value function (Loewenstein & Prelec 1992; Ainslie 1992):

$$U(x, D) = \frac{x}{1 + kD}, \tag{2}$$

where x is the delayed monetary amount, k is the discount factor (higher is more impatient), and D is the delay period in days. One subject who chose $25 now on every trial was removed from the analysis. Preference parameters were estimated using a standard MLE approach with a logit choice function. Two subjects with outlying estimates of k were also removed from the analysis.[2]

2.3 Study 3: social preference

2.3.1 Participants

This dataset was collected while subjects underwent fMRI at the Social and Neural Systems laboratory, University of Zurich (Krajbich et al., 2015). In total, 30 subjects were recruited for the experiment. They received a show-up fee of 25 CHF and a payment from 6 randomly chosen rounds, averaging at about 65 CHF.

2.3.2 Task

Subjects made choices between two allocations, X and Y, which specified their own payoff and an anonymous receiver's payoff. The payoffs were displayed in experimental currency units, and 120 predetermined allocations were presented in random order. Each allocation had a tradeoff between a fair option (more equal division) and a selfish option (with higher payoff to the dictator). 72 out of 120 decision problems per subject had higher payoff to the dictator in both options X and Y (to identify advantageous inequality aversion), while the rest of the problems (48/120) had higher payoffs to the receiver in both options (to identify disadvantageous inequality aversion). In each trial, subjects observed a decision screen that included the two options, and had to make a choice with a two-button box. Subjects were required to make their decisions within 10 seconds; if a subject failed to respond under this time limit, that trial was excluded from the analysis (4 trials were excluded). Intertrial intervals were randomized uniformly from 3 to 7 seconds. Subjects read written instructions before the experiment, and were tested for comprehension with a control questionnaire. All subjects passed the questionnaire and understood the anonymous nature of the game.

2.3.3 Preference model

To fit choices in this experiment, we used a standard Fehr-Schmidt other-regarding preference model (Fehr & Schmidt, 1999):

$$U_i(x_i, x_j) = x_i - \alpha \cdot \max(x_j - x_i, 0) - \beta \cdot \max(x_i - x_j, 0), \tag{3}$$

where x_i is the dictator's payoff, x_j is the receiver's payoff, α reflects disadvantageous inequality aversion, and β reflects advantageous inequality aversion. Each trial was designed to either measure α or β, so we treated this experiment as two separate datasets. The preference parameters were estimated using a standard MLE approach with a logit choice function. One subject with an outlying estimate of α was removed from the analysis.

2.4 Computational modeling

2.4.1 Choice-based estimations

The three preference functions we selected to model subjects' choices performed well above chance. To examine the number of choices that were consistent with the estimated parameter values, we used standard MLE estimates of logit choice functions (see the Supplement) to identify the "preferred" alternatives in every trial and compared those to the

[2] We also considered an alternative attribute-wise comparison model (Dai & Busemeyer, 2014), but it did not fit the data as well as the hyperbolic model (total log-likelihood of −3148 vs. −3024). Therefore, for the rest of the paper we focus only on the hyperbolic model.

actual choice outcomes. More specifically, we calculated subjective values using parameters estimated purely from choices, and in every trial predicted that the alternative with the higher subjective value would be chosen with certainty. All subjects were very consistent in their choices even in the datasets with a large number of trials: social choice α: 94%, social choice β: 93%, intertemporal choice: 83%, non-adaptive risky choice: 89% (see Figure S5).

2.4.2 Drift-diffusion model (DDM)

We used the simple, most robust SSM variant, which is the DDM with constant thresholds (see Note 2 in the Supplement), where we assumed that drift rate on every trial is a linear function of the difference in the subjective values of the two alternatives. Unlike previous studies, we assume that only RT data are available and use the RT probability densities to estimate the preference parameter for each subject i (θ_i) given the empirical distribution of RTs. Note that we do not use choice-conditioned RT distributions. Instead we maximize the RT likelihood function across both choice boundaries:

$$\begin{aligned} LL \; = {} & \textstyle\sum_n \; \log\big(f(RT_n, a_n = 1|b, \tau, v_n)\big) \\ & + \; \log\big(f(RT_n, a_n = 2|b, \tau, v_n)\big). \end{aligned} \tag{4}$$

Here $f(\cdot)$ is the response time density function, RT is the response time on a specific trial, a is the choice the subject could have made, b is the DDM decision boundary, τ is non-decision time, and v_n is the drift rate on the specific trial n, which depends on the difference in subjective values, which in turn depends on the subject's preference parameter (θ_i) (see Note 2 in the Supplement). Intuitively, the individual parameter is identified due to the fact that longer RTs correspond to lower drift rates and thus smaller subjective-value differences. Please see the Supplement for more detail.

3 Results

3.1 RTs peak at indifference

We first sought to establish the hypothesized negative correlation between strength-of-preference and RT. For this analysis, our measure of strength-of-preference was the difference between the subject's preference parameter (estimated purely from their choices, see Note 2 in the Supplement) and the parameter value that would make the subject indifferent between the two options in that trial (we refer to this as the "indifference point"). When a subject's parameter value is equal to the indifference point of a trial, we say that the subject is indifferent on that trial and so strength-of-preference is zero.

Let us illustrate this concept with a simple example. Suppose that in the intertemporal-choice task a subject has to choose between \$25 today and \$40 in 30 days. The subject would be indifferent with an individual discount rate k^* that is the solution to the equation $\$25 = \$40/(1 + 30k^*)$, or $k^* = 0.0125$. This would be the indifference point of this particular trial. A subject with $k = k^*$ would be indifferent on this trial, a subject with a $k < k^*$ would favor the delayed option, and a subject with a higher $k > k^*$ would favor the immediate option.

We hypothesized that the bigger the absolute difference between the subject's parameter and the trial's indifference point $|k - k^*|$, the stronger the preference, and the shorter the mean RT. This is analogous to how, in decision field theory, the difference in valence between the two options determines the preference state and thus the average speed of the decision (Busemeyer & Townsend 1993). We observe this effect in all of our datasets, with RTs peaking when a subject's parameter is equal to the trial indifference point (Figure 1). Mixed-effects regression models show strong, statistically significant effects of the absolute distance between the indifference point and subjects' individual preference parameters on log(RTs) for all the datasets (fixed effect of distance on RT: dictator game α: t = −7.5, p < 0.001; dictator game β: t = −9.1, p < 0.001; intertemporal choice k: t = −9.9, p < 0.001; non-adaptive risky choice λ: t = −9.6, p < 0.001, adaptive risky choice λ: t = −4.4, p < 0.001).

Having verified the relationship between strength-of-preference and RT, we next asked whether we could invert this relationship. In other words, we sought to test whether one can estimate preferences from RTs. First, we investigated whether RTs can reveal preference information when only a single trial's data is available.

3.2 One-trial preference ranking

In the adaptive risk experiment, all subjects faced the same choice problem in the first trial. They had to choose between a 50/50 lottery with a gain (\$12) and a loss (\$7.5), vs. a sure amount (\$0). Assuming risk neutrality, a subject with a loss aversion coefficient of $\lambda = 1.6$ should be indifferent between these two options, with more loss-averse subjects picking the safe option, and the rest picking the risky option.

Because the mean loss aversion (estimated based on all the choices) in our sample was 2.5 (median = 2.46), most of the subjects (44 out of 61) picked the safe option in this first trial. Now, if we had to restrict our experiment to just this one trial, the only way we could classify subjects' preferences would be to divide them into two groups: those with $\lambda \geq 1.6$ and those with $\lambda < 1.6$. Within each group we would not be able further distinguish between individuals.

However, by additionally observing RTs we can establish a ranking of the subjects in each group. Specifically, we hypothesized that subjects with loss aversion closer to 1.6 would exhibit longer RTs. To test this hypothesis we ranked subjects in each group according to their RTs and then com-

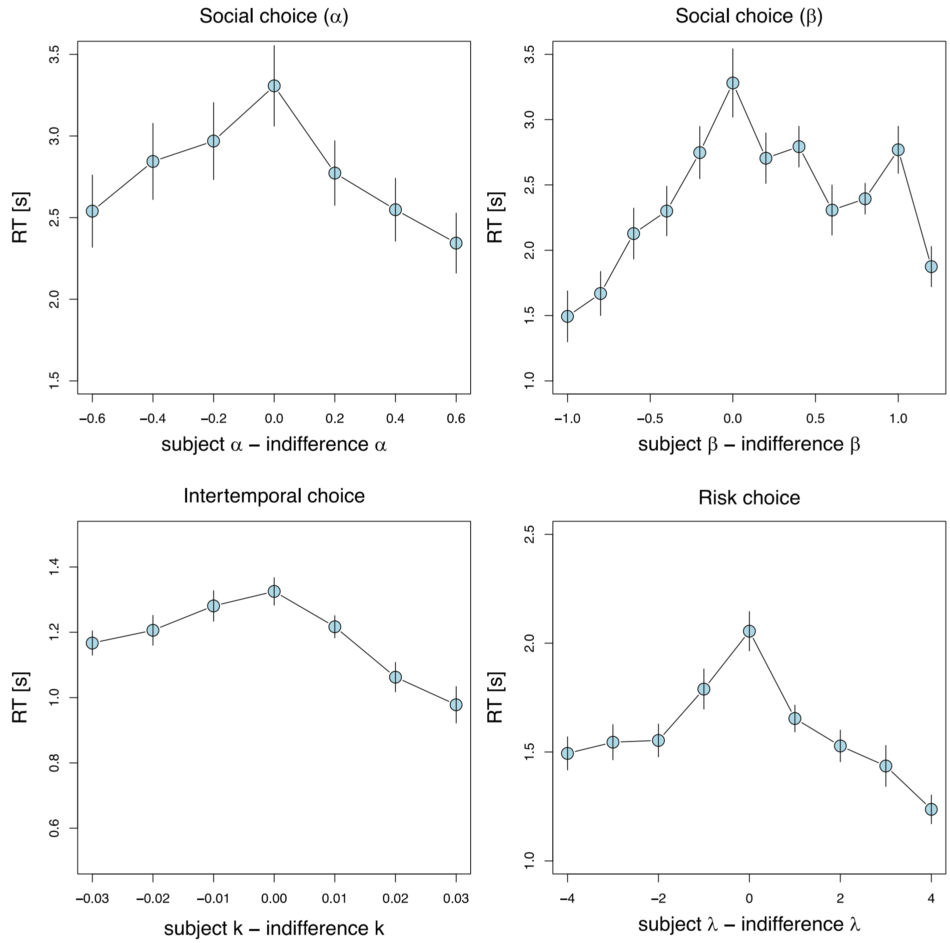

Figure 1: RTs peak at indifference. Mean RT in seconds as a function of the distance between the individual subject's preference function parameter and the indifference point on a particular trial; data are aggregated into bins of width 0.02 (top row), 0.01 (bottom left panel), and 1 (bottom right panel), which are truncated and centered for illustration purposes. Bins with fewer than 10 subjects are removed for display purposes. Bars denote standard errors, clustered at the subject level.

pared those rankings to the "true" loss aversion parameters estimated from all 30 choices in the full dataset (see Figure 2, Note 2 in the Supplement, and Figure S5 for the choice-based estimates).

There was a significant rank correlation (Spearman) between RTs and loss seeking in the "safe option" group (r = 0.43, p = 0.004) and marginally between RTs and loss aversion in the "risky option" group (r = 0.41, p = 0.1). Thus, the single-trial RT-based rankings aligned quite well with the 30-trial choice-based rankings.

3.3 Uninformative choices

A similar use of RT-based inference is the case where an experiment (or questionnaire) is flawed in such a way that most subjects give the same answer to the choice problem (e.g., because it has an extreme indifference point, or because people feel social pressure to give a certain answer, even if it contradicts their true preference (Coffman, Coffman & Ericson, 2017)). This method could be used to bolster datasets that are limited in scope and so unable to recover all subjects' preferences.

To model this situation, for each dataset (non-adaptive risk, intertemporal choice, and social choice) we isolated the 4–10 trials (depending on the dataset) with the highest indifference points, where most subjects chose the same option (e.g., the risky option), and limited our analysis to those subjects who picked this most popular option. Then we iterated an increasing set of trials (just the highest point, the first and the second highest points, the first, second, and third, and so on), took the median RT in this set, and correlated it with the "true" choice-based estimates. We hypothesized that the slower the decisions on these trials, the more extreme the choice-based parameter value for that subject.

The set of trials varied across datasets due to the structure of the experiments. In the risk and intertemporal datasets

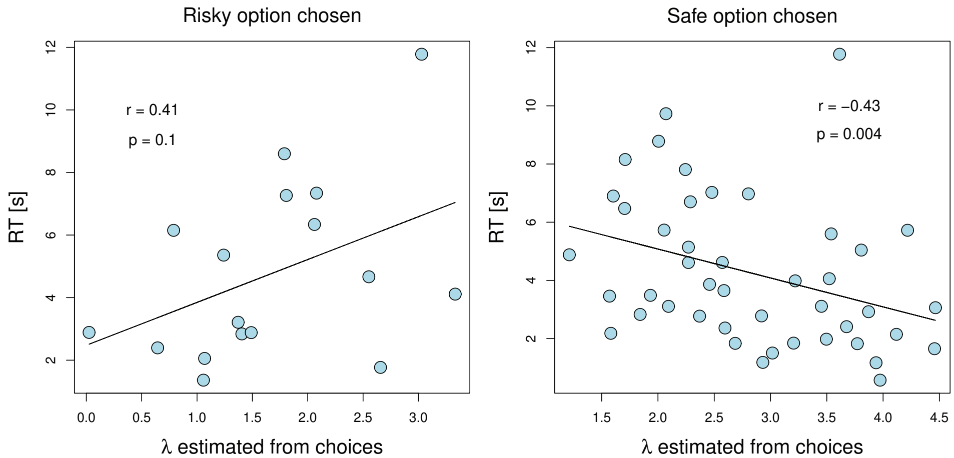

Figure 2: Preference rank inferred from a single decision problem. RTs in the first trial of the adaptive risk experiment as a function of the individual subject's loss-aversion coefficient from the whole experiment; each point is a subject, Spearman correlations displayed. In this round, each subject was presented with a binary choice between a lottery that included a 50% chance of winning $12 and losing $7.5, and a sure option of $0. The right panel displays subjects who chose the safe option, and the left panel shows those who chose the risky option. The solid black lines are regression model fits.

every decision problem was shown twice, so we started with two trials and then increased in steps of two. For the risk task there were several trials with identical indifference points after the first 8 trials, so we stopped there. For the social-preference datasets there were many trials with the same indifference point (8 and 6 for α and β respectively) so we simply used those trials, going from lowest to highest game id number (arbitrarily assigned in the experiment code). Note that we used only the highest indifference points, since trials with indifference parameters close to zero were often trivial "catch" trials, e.g., $25 today vs. $25 in 7 days.

Confirming the hypothesis, we found that the RTs on these trials were strongly predictive of subjects' choice-based parameters in all four domains (Figure 3), with Spearman correlations ranging from 0.37 to 0.84 (for the largest set: risk choice (n = 19): ρ = 0.50, p = 0.03; intertemporal choice (n = 25): ρ = 0.59, p = 0.002; social choice α (n = 26): ρ = 0.50, p = 0.009; social choice β (n = 20): ρ = 0.84, p < 0.001). Thus, we again see, in every domain, that RT-based rankings from a small subset of trials align well with choice-based rankings from the full datasets. These analyses also hint at potential benefits from including more trials, but also suggest that RTs may not be that noisy once we control for the difficulty of the question and subject-level heterogeneity.

3.4 DDM-based preference parameter estimation from RTs

The results described in the previous sections demonstrate that we can use RT to rank subjects according to their preferences on trials where they all make the same choice. A more challenging problem is to estimate a subject's preferences from RT alone. In this section, we explore ways to estimate individual subjects' preference parameters from their RTs across multiple choice problems.

The DDM predicts more than just a simple relationship between strength-of-preference and mean RT; it predicts entire RT distributions. The drift rate in the model is a linear function of the subjective value difference (or in decision field theory the valence difference) and so by estimating drift rates we can potentially identify the latent preference parameters. We hypothesized that the DDM-derived preference parameters, using only RT data, would correlate with the choice-based preference parameters estimated in the usual way.

We used the simple standard DDM, but did not condition the RT distributions on the choice made in each trial (see Section 2.4. and the Supplement). We assumed no starting point bias and, following the traditional approach, assumed that the drift rate is a simple linear function of the difference in subjective values (Busemeyer & Townsend, 1993; Dai & Busemeyer, 2014). Parameter recovery simulations confirmed that the preference parameters could be identified using this method (Figure S6).

First, we estimated the DDM assuming that the boundary parameter b, non-decision time τ, and drift scaling parameter z were fixed across subjects (see Note 2 in the Supplement). We made this simplifying assumption to drastically reduce the number of parameters we needed to estimate. In each dataset, we found that DDM-derived preference parameters were correlated with the choice-based parameters (social choice α: r = 0.39, p = 0.04, t(27) = 2.2; social choice β: r = 0.52, p = 0.003, t(28) = 3.2; intertemporal choice k: r = 0.57, p < 0.001, t(37) = 4.2; risky choice λ: r = 0.36, p =

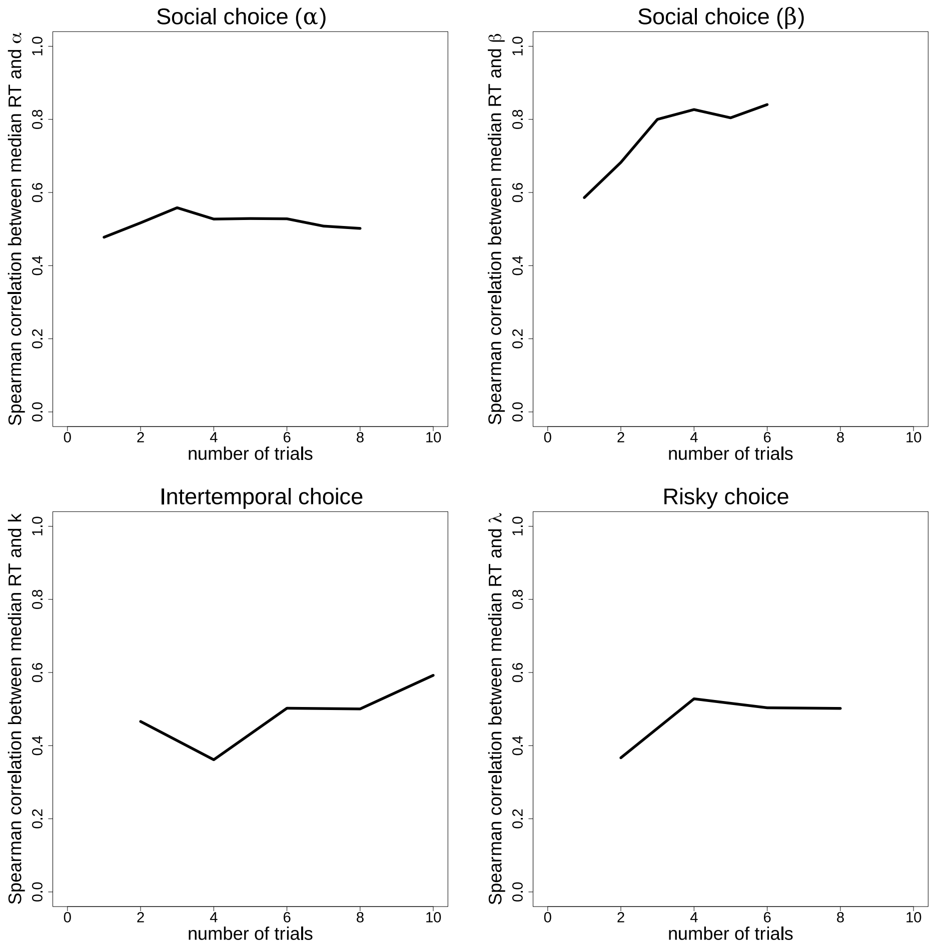

FIGURE 3: Spearman correlations between choice-based parameter estimates and the median RT in the trials with the highest indifference points, for increasing sets of these extreme trials.

0.03, t(35) = 2.26; Pearson correlations, Figure S7).

We did not use the adaptive risk dataset here (or for subsequent analyses) since the adaptive nature of the task means that subjects should be closer to indifference as the experiment progresses. The well-established negative correlation between trial number and RT would thus counteract the strength-of-preference effects and interfere with our ability to estimate preferences.

We also estimated the DDM for each subject separately, assuming individual variability in the boundary parameter b, non-decision time τ, and drift scaling parameter z. In some cases, this causes identification problems for certain subjects (the parameters were estimated at the bounds of the possible range), most likely due to the small number of trials (only 48 trials to estimate 4 parameters in the case of α in the social preference task) and the tight distribution of subjects' indifference points in that task. After excluding these subjects (2/30 and 2/30 in the social choice dataset, 16/39 in the intertemporal choice dataset, and 7/37 in the risk choice dataset), we found that in most cases correlations between DDM parameters and choice-based parameters were stronger than in the pooled estimation variant (social choice α: r = 0.09, p = 0.65, t(25) = 0.45; social choice β: r = 0.74, p < 0.001, t(26) = 5.54; intertemporal choice k: r = 0.63, p = 0.001, t(22) = 3.84; risky choice λ: r = 0.53, p = 0.002, t(28) = 3.33; Pearson correlations, Figure S8).

These results highlight that it is useful to have trials with a wide range of indifference points. This can be inefficient with standard choice-based analyses, since most subjects choose the same option on trials with extreme indifference points. However, when including RTs, these trials can still convey useful information, namely the strength-of-preference.

3.5 Alternative approaches to preference parameter estimation from RTs

The DDM may seem optimal for parameter recovery if that is indeed the data generating process. However, several factors likely limit its usefulness in our settings. The DDM has several free parameters that are identified using features of

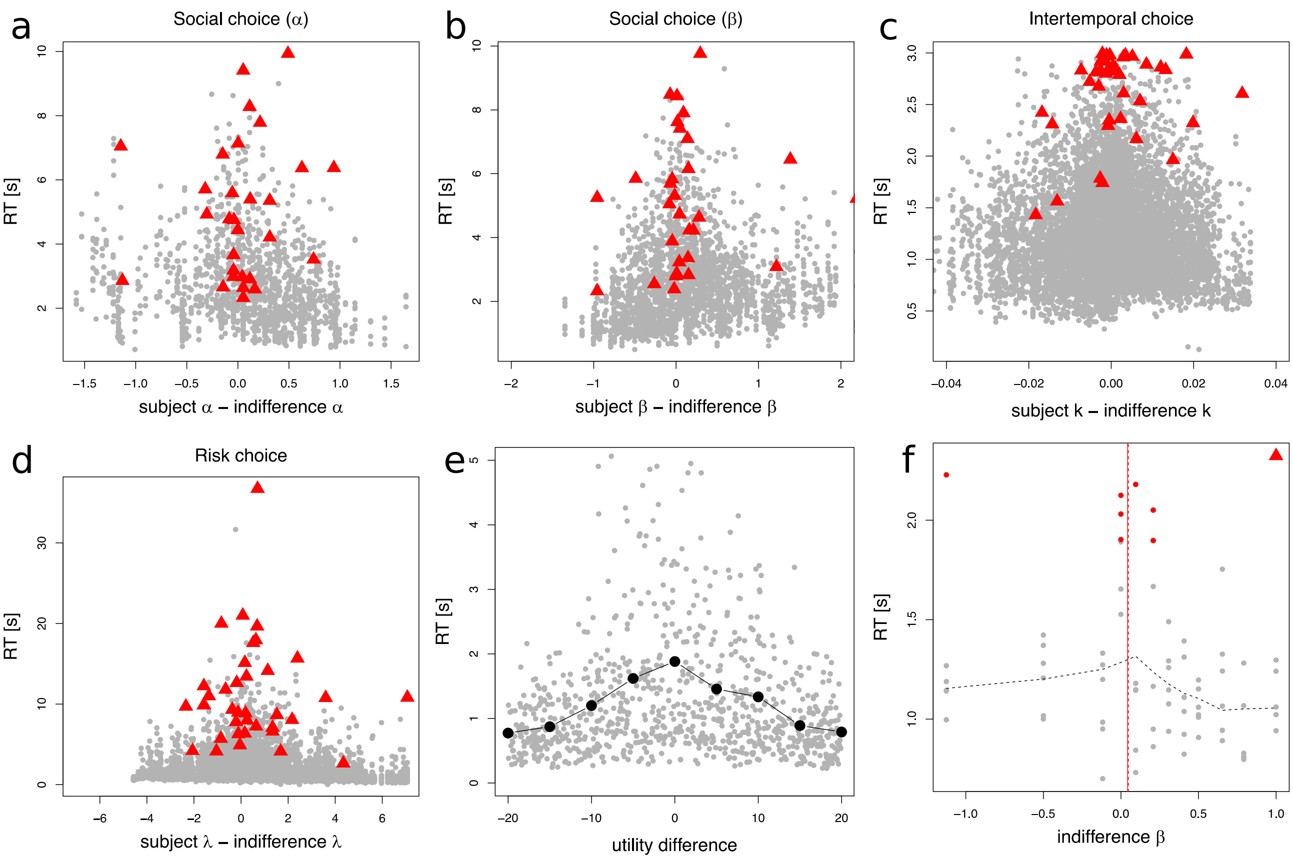

FIGURE 4: Slow decisions tend to occur at indifference. (a-d) Subject data from each task. RT in seconds as a function of the distance between the individual subject preference parameter and the indifference point on a particular trial; gray dots denote individual trials. Red triangles denote trials with the highest RT for each individual subject. (e) Simulation of the DDM. Response times (RTs) as a function of the difference in utilities between two options in 900 simulated trials. The gray dots show individual trials, the black circles denote averages with bins of width 10. The parameters used for the simulation correspond to the parameters estimated at the group level in the time discounting experiment ($b = 1.33$, $z = 0.09$, $\tau = 0.11$). Subjective-value differences are sampled from a uniform distribution between -20 and 20. (f) Example of an individual subject's RT-based parameter estimation. The plot shows RTs in all trials as a function of the indifference parameter value on that trial. Observations in the top RT decile are shown in red. The red triangle shows the longest RT for the subject. The solid vertical red line shows the subject's choice-based parameter estimate. The dotted vertical red line shows the average indifference value for the top RT decile approach. The dotted grey line shows the local regression fit (LOWESS, smoothing parameter = 0.5).

choice-conditioned RT distributions. Identification thus typically relies on many trials and observing choice outcomes. Without meeting these two requirements, the DDM approach may struggle to identify parameters accurately. Thus, we explored alternative, simpler approaches to analyzing the RTs.

One alternative approach is to focus on the longest RTs. Long RTs are considerably more informative than short RTs. Sequential sampling models correctly predict that short RTs can occur at any level of strength-of-preference, but long RTs almost exclusively occur near indifference (Figure 4). With these facts in mind, we set about constructing an alternative method for using RTs to infer a subject's indifference point.

Clearly, focusing on the slowest trials would yield less biased estimates of subjects' indifference points. However, using too few slow trials would increase the variance of those estimates. We settled on a simple method that uses the slowest 10% of a subject's choices, though we also explored other cutoffs (Figure S9).

In short, our estimation algorithm for an individual subject includes the following steps: (1) identify trials with RTs in the upper 10% (the slowest decile); (2) for each of these trials, calculate the value of the preference parameter that would make the subject indifferent between the two alternatives; (3) average these values to get the estimate of the

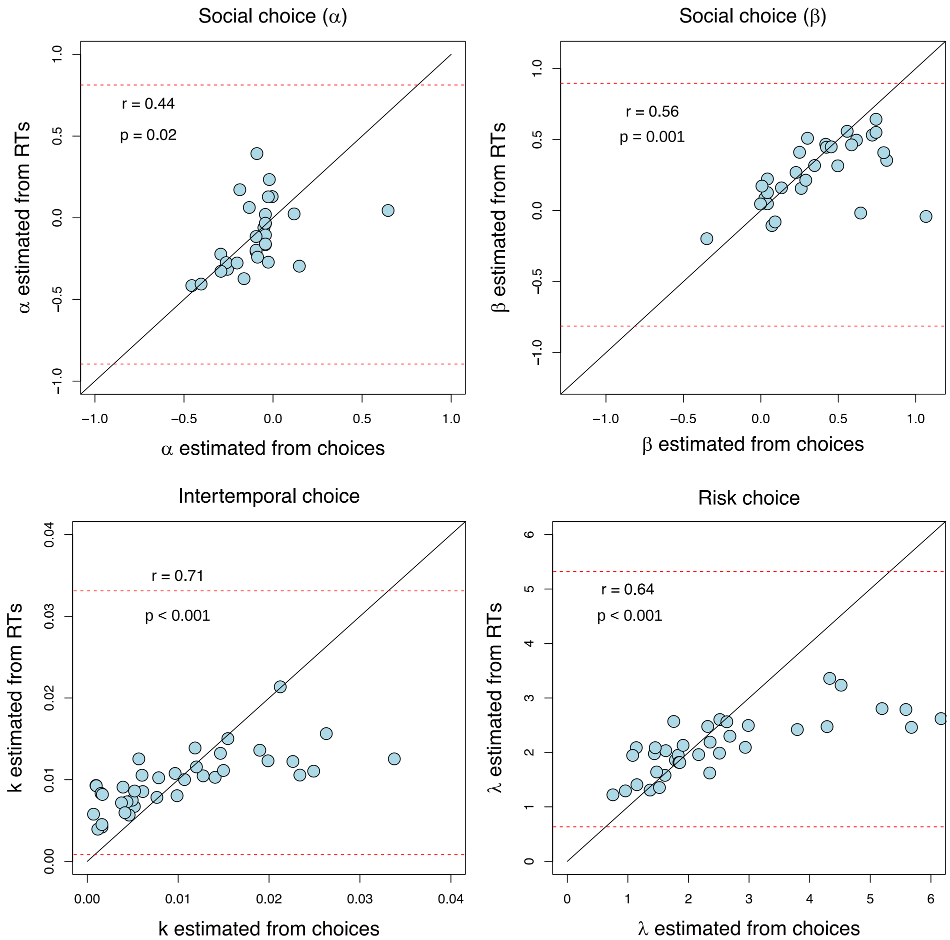

Figure 5: Estimates of subjects' preference parameters, estimated using the top RT decile method. Subject-level correlation (Pearson) between parameters estimated from choice data and RT data. The solid lines are 45 degree lines. The dotted red lines indicate the minimum and maximum parameter values that can be estimated from the RTs.

subject's parameter (see Figure 4f and the Supplement for formal estimation details and Figure S6 for the parameter recovery simulations). It is important to note that this method puts bounds on possible parameter estimates: the average of the highest 10% of all possible indifference values is the upper bound, while the average of the lowest 10% of the indifference values is the lower bound.

Again, the parameters estimated using this method were correlated with the same parameters estimated purely from the choice data, providing a better prediction than the DDM approach (social choice α: r = 0.44, p = 0.02, t(27) = 2.54; social choice β: r = 0.56, p = 0.001, t(28) = 3.57; intertemporal choice k: r = 0.71, p < 0.001, t(37) = 6.17; risky choice λ: r = 0.64, p < 0.001, t(35) = 4.9; Pearson correlations; Figure 5, see the Supplement for estimation details for both methods). Furthermore, these parameters provided prediction accuracy that was better than the informed baseline in three out of four cases (excluding social choice α). In all cases, a random 10% sample of trials produced estimates that were not a meaningful predictor of the choice-based parameter values (since these estimates are just a mean of 10% random indifference points). The RT-based estimations have upper and lower bounds due to averaging over a 10% sample of trials and thus are not able to capture some outliers (Figure 5). Furthermore, the number of "extreme" indifference points in the choice problems that we considered is low, biasing the RT-based estimates towards the middle.

We also explored a method using the whole set of RT data and a non-parametric regression, but its performance was uneven across the datasets (see the Supplement and Figure S6 for the parameter recovery).

3.6 Choice reversals

Finally, we explored one additional set of predictions from the revealed strength-of-preference approach. We know that when subjects are closer to indifference, their choices become less predictable, and they slow down. Therefore, slow choices should be less likely to be repeated (Alós-Ferrer et al., 2016).

In all three datasets, the choice-estimated preference model was significantly less consistent with long-RT choices than with short-RT choices (based on a median split within subject): 80% vs 89% ($p < 0.001$) in the risky choice experiment, 71% vs 79% ($p < 0.001$) in the intertemporal choice experiment, 88% vs 94% ($p = 0.008$) and 90% vs 96% ($p < 0.001$) in the dictator game experiment; p-values denote Wilcoxon signed rank test significance on the subject level.

A second, more nuanced feature of DDMs is that with typical parameter values, without time pressure, they sometimes predict "slow errors", even conditioning on difficulty (Ratcliff & McKoon, 2008). In preferential choice there are no clear correct or error responses, however, we can compare choices that are consistent or inconsistent with the best-fitting choice model. The prediction is that inconsistent choices should be slower than consistent ones.

To control for choice difficulty, we ran mixed-effects regressions of choice consistency on the RTs and the absolute subjective-value difference between the two options. In all cases we found a strong negative relationship between the RTs and the choice consistency (slower choice = less consistent) (fixed effects of RTs: social choice α: $z = -2.62$, $p = 0.009$; social choice β: $z = -3.3$, $p < 0.001$, intertemporal choice: $z = -5.28$, $p < 0.001$, risk choice: $z = -5.35$, $p < 0.001$).

In two of the datasets (intertemporal choice and non-adaptive risk choice) subjects faced the same set of decision problems twice. This allowed us to perform a more direct test of the slow inconsistency hypothesis by seeing whether slow decisions in the first encounter were more likely to be reversed on the second encounter.

In the intertemporal choice experiment, the median RT for a later-reversed decision was 1.36 s, compared to 1.17 s for a later-repeated decision. A mixed-effects regression effect of first-choice RT on choice reversal, controlling for the absolute subjective-value difference, was highly significant ($z = 4.04$, $p < 0.001$). The difference was even stronger in the risk choice experiment: subsequently reversed choices took 2.36 s versus only 1.4 s for subsequently repeated choices. Again, a mixed-effects regression revealed that RT was a significant predictor of subsequent choice reversals (controlling for absolute subjective-value difference, $z = 5.2$, $p < 0.001$).

There are a couple of intuitions for why slow decisions are still less consistent, even after controlling for difficulty. First, the true difficulty of a decision can only be approximated. Even with identical choice problems, one attempt at that decision might be more subjectively difficult than another. In the DDM, this is captured by across-trial variability in drift rate. In other words, one cannot fully control for difficulty in these kinds of analyses. So, slow decisions can still signal proximity to indifference, and thus inconsistency in choice. Second, slow errors can also arise from starting-points that are biased towards the preferred category (e.g., risky options) (Chen & Krajbich, 2018; White & Poldrack, 2014). In these cases, preference-inconsistent choices typically have longer distances to cover during the diffusion process and so take more time.

4 Discussion

Here we have demonstrated a proof-of-concept for the method of revealed strength-of-preference. This method contrasts with the standard method of revealed preference, by using response times (RTs) rather than choices to infer preferences. It relies on the fact that people generally take longer to decide as they approach indifference. Using datasets from three different choice domains (risk, temporal, and social) we established that preferences are highly predictable from RTs alone. Finally, we also found that long RTs are predictive of choice errors, as captured by inconsistency with the estimated preference function and later choice reversals.

Our findings also have important implications for anyone who studies individual preferences.

First, using RTs may allow one to estimate subjects' preferences using very short and simple decision tasks, even a single binary-choice problem. This is important since researchers, and particularly practitioners, can often only record a small number of decisions (Toubia, Johnson, Evgeniou & Delquié, 2013). Since RT data is easily available in online marketplaces, and many purchases or product choices occur only once, these data might provide important insight into customers' preferences. Along the way, the speed with which customers reject other products might also reveal important information. On the other hand, clients who wish to conceal their strength-of-preference, might use their RT strategically to avoid revealing their product valuations.

Second, the fact that RTs can be used to infer preferences when choices are unobservable or uninformative is an important point for those who are concerned about private information, institution design, etc. For instance, while voters are very concerned about the confidentiality of their choices, they may not be thinking about what their time in the voting booth might convey about them. In an election where most of a community's voters strongly favor one candidate, a long stop in the voting booth may signal dissent. Another well-known example is the implicit association test (IAT), where subjects' RTs are used to infer personality traits (e.g., racism) that the subjects would otherwise not admit to or even be aware of (Greenwald, McGhee & Schwartz, 1998). Thus, protecting privacy may involve more than simply masking choice outcomes.

Third, our work highlights a method for detecting choice errors. While the standard revealed preference approach must equate preferences and choices, the revealed strength-of-preference approach allows us to identify choices that are more likely to have been errors, or at the very least, made with low confidence.

There are of course limitations to using RTs to infer strength-of-preference. Other factors may influence RTs in addition to strength-of-preference, such as complexity, stake size, and trial number (Krajbich, Hare, Bartling & Fehr, 2015; Logan, 1992; Moffatt, 2005). It may be important to account for these factors in order to maximize the chance of success. A second issue is that we have focused on repeated decisions which are made quite quickly (1–3 seconds on average) and so the results may not necessarily extend to slower, more complex decisions (but see Krajbich, Hare, Bartling & Fehr, 2015).

More research is required to distinguish between SSMs and alternative frameworks (Achtziger & Alós-Ferrer, 2013; Alós-Ferrer et al., 2016; Alós-Ferrer & Ritschel, 2018; Hey, 1995; Kahneman, 2013; Rubinstein, 2016), where long RTs are associated with more careful or deliberative thought and short RTs are associated with intuition. It may in fact be the case that in some instances people do use a logic-based approach, in which case a long RT may be more indicative of careful thought, while in other instances they rely on a SSM approach, in which case a long RT likely indicates indifference. This could lead to contradictory conclusions from the same RT data; for example, one researcher may see a long RT and assume the subject is very well informed, while another researcher may see that same RT and assume the subject has no evidence one way or the other. More research is required to test whether SSMs, which are designed to tease apart such explanations, can be successfully applied to complex decisions.

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