American Psychological Association

Decision

2019, Vol. 6, No. 1, 77–107
http://dx.doi.org/10.1037/dec0000092

Mechanisms of Deliberation During Preferential Choice: Perspectives From Computational Modeling and Individual Differences

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Computational models of decision making typically assume as people deliberate between options they mentally simulate outcomes from each one and integrate valuations of these outcomes to form a preference. In two studies, we investigated this deliberation process using a task where participants make a series of decisions between a certain and an uncertain option, which were shown as dynamic visual samples that represented possible payoffs. We developed and validated a method of reverse correlational analysis for the task that measures how this time-varying signal was used to make a choice. The first study used this method to examine how information processing during deliberation differed from a perceptual analog of the task. We found that participants were less sensitive to each sample of information during preferential choice. In a second study, we investigated how these different measures of deliberation were related to impulsivity and drug and alcohol use. We found that although properties of the deliberation process were not related to impulsivity, some aspects of the process may be related to substance use. In particular, alcohol abuse was related to diminished sensitivity to the payoff information and drug use was related to how the initial starting point of evidence accumulation. We synthesized our results with a rank-dependent sequential sampling model which suggests that participants allocated more attentional weight to larger potential payoffs during preferential choice.

Keywords: deliberation, preference, reverse correlation, risky behavior, stochastic process

Deliberation plays a critical role in human behavior. It is during deliberation that valuations of options and their attributes like outcomes and probabilities (Kahneman & Tversky, 1979) or time (Dai & Busemeyer, 2014; Dai, Pleskac, & Pahcur, in press; Scholten & Read, 2010) are transformed into a choice. These choices and the speed in making them (response times) govern

This article was published Online First September 13, 2018.

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This research was supported in part by a grant from the National Institutes of Health (R03DA033455). All data and analyses reported in this paper can be found at this repository at the Open Science Framework: https://osf.io/g7a49.

Author contributions: Conceptualization and methodology: Christopher Hopwood, Shuli Yu, Taosheng Liu, and Timothy J. Pleskac; Investigation: Shuli Yu; Formal analysis: Shuli Yu and Timothy J. Pleskac; Writing - Original Draft: Timothy J. Pleskac; Writing - Reviewing & Editing: Christopher Hopwood, Shuli Yu, Taosheng Liu, and Timothy J. Pleskac; Supervision: Taosheng Liu and Timothy J. Pleskac We thank Kyle Bort, Mitchell Uitvlugt, and Patrycja Zdziarska for help in programming the studies and running the empirical studies. We also are grateful for Peter Kvam's input on the reverse correlation analyses.

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whether someone appears risk averse or risk seeking (Weber, 2010), impulsive or cautious (Nigg, 2000), or distracted or focused (Miller, 2000). These choices also help individuals learn about their environment and make better decisions in the future (Pleskac, 2016). Thus, a better mechanistic understanding of deliberation should be revealing in terms of these many vital aspects of human behaviors. A common hypothesis is that deliberation is a sequential sampling process, where people sequentially sample information about the options and accumulate the information as evidence to make a choice. When the quantity of accrued evidence reaches a threshold, the appropriate choice is made, which also determines the response time (Busemeyer & Johnson, 2004; Krajbich, Armel, & Rangel, 2010; Shadlen, Kiani, Hanks, & Churchland, 2008).

There is good evidence that this sequential sampling process provides an accurate characterization of deliberation during perceptual decisions both at the computational (Ratcliff & Smith, 2015) and perhaps even at the neural level (Gold & Shadlen, 2007; Forstmann, Ratcliff, & Wagenmakers, 2016). However, investigations of risky choice have predominantly focused on static models (e.g., Tversky & Kahneman, 1992). Alternatively, they have treated dynamic models as static, testing, for instance, how well the models explain choices but ignoring response times (e.g., Rieskamp, 2008). Either way, it is less clear whether the same or similar process is used during preferential decision making, where people make decisions without objectively correct answers, such as choosing between snack items, investment opportunities, or places to live.[1] Certainly there are strong indications that, like perceptual choice, a sequential sampling process is used for preferential decision making (e.g., Busemeyer & Diederich, 2002; Krajbich & Rangel, 2011; Summerfield & Tsetsos, 2012). Under such a scenario, possible outcomes or consequences from the different alternatives are sampled (i.e., come to mind), evaluated, and compared across alternatives from moment to moment. This comparison is accumulated to form a preference for a particular alternative.

Such a sequential sampling process is inherently dynamic, yet previous studies have largely examined this process using choice options with static, symbolic descriptions of, for example, monetary gambles (Rieskamp, 2008), hypothetical choices between consumer goods (Krajbich et al., 2010; Roe, Busemeyer, & Townsend, 2001), or in some cases decisions based on a relatively large set of past experiences (Busemeyer & Townsend, 1993; Busemeyer, 1985; Diederich & Busemeyer, 1999; Jessup, Bishara, & Busemeyer, 2008). Sometimes the dynamics of information acquisition are inferred via eye tracking (Cavanagh, Wiecki, Kochar, & Frank, 2014; Krajbich & Rangel, 2011) or indirectly via experimental manipulations (Diederich, 2016). As an alternative approach, we adapted a method from studies of perceptual decision making that have used so-called expanded judgment tasks. These tasks make explicit the samples of information that participants need to use to make a decision (i.e., Brown, Steyvers, & Wagenmakers, 2009; Irwin, Smith, & Mayfield, 1956; Newsome, Britten, & Movshon, 1989; Pietsch & Vickers, 1997; Smith & Vickers, 1989; Tsetsos, Usher, & McClelland, 2011; Teodorescu, Moran, & Usher, 2016; Vickers, Burt, et al., 1985; Vickers, Smith, et al., 1985). Thus, we made the stimulus itself dynamic and amenable to a sequential sampling process.

The specific task we used was the Flash Gambling Task (FGT; Zeigenfuse, Pleskac, & Liu, 2014). The FGT uses dynamic dot stimuli where each option is represented by an array of randomly positioned dots. The value of each option at each instant is equal to the number of dots in the display at that time point. For example, a certain option with a value of 130 points has a fixed number of 130 dots, whereas the number of dots in the uncertain option are dynamically updated every 50 ms via draws from an unknown payoff distribution (we used a Gaussian distribution). This dynamic updating allows people to integrate the payoff information over time to form a preference between the two options and thus provides a method to study the deliberation process during preferential choice.[2]

We report two studies that used the FGT to characterize the deliberation process during

[1] Sometimes these types of decisions are called economic decisions (Summerfield & Tsetsos, 2012), or value-based decisions (Rangel, Camerer, & Montague, 2008).

[2] The FGT is a specific type of preferential choice sometimes referred to as decision making under uncertainty where each option does not produce the same outcome when chosen, but instead can produce one of a set of possible outcomes where the probability of any given outcome is not known (Luce & Raiffa, 1957).

preferential choice. In Study 1, we compared the deliberation process during preferential choice to that of perceptual choice. We used the same stimulus in both tasks, but with participants in the preferential task making a choice reflecting a value judgment while those in the perceptual task making a choice based on a perceptual attribute. Crucially, participants' goals in both tasks were aligned such that they should choose the option that showed the highest average number of dots in both tasks. Past studies that have made this perceptual versus preferential comparison have found that the basic deliberation process for both types of decisions can be described as a sequential sampling process (Dutilh & Rieskamp, 2016; Tsetsos, Chater, & Usher, 2012; Zeigenfuse et al., 2014). However, despite the aligned goals in the two tasks, there were also systematic differences which were largely isolated to how the sampled information contributes to the accumulating evidence (Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014; see also Tsetsos et al., 2012). We sought to replicate these results and go beyond these studies by examining the online processing of the sampled information during the two types of decisions. To do so, we developed and validated a method of reverse correlation analysis to characterize the linkage between the sampled information and the ultimate choice.

In Study 2, we investigated individual differences in the deliberation process during preferential choice. Our motivation to do so was partly in response to recent calls for behavioral decision making theories to not just model the choices of the average subject but to better understand and model variability within and between people (Hertwig & Pleskac, 2018; Regenwetter & Robinson, in press). In addition, previous work has suggested a relationship between laboratory-based measures of risk taking and real-world risky behavior like drug abuse (e.g., Bechara et al., 2001; Lejuez et al., 2002; Pleskac, 2008; Rogers et al., 1999; Stout, Busemeyer, Lin, Grant, & Bonson, 2004). Moreover, a close inspection of the facets of impulsivity reveals that at least at the descriptive level there appears to be some relationship with the properties of deliberation (Whiteside & Lynam, 2001). Thus, we evaluated the relationship between our measures of the deliberation process and measures of impulsivity and self-reported measures of drug and alcohol use. Anticipating the results, we found that aspects of the deliberation process and impulsivity were not correlated. However, both uniquely account for substance use, suggesting our understanding of the deliberation process can play an important role in a multimethod approach to understand a person's actions and beliefs (Hopwood & Bornstein, 2014).

Study 1: Characterizing Deliberation During Preferential Choice by Comparing It With Perceptual Choice

Our first study compared deliberation during preferential and perceptual choice. As mentioned earlier, direct comparisons of these decision types have shown that deliberation in both is well described by a sequential sampling process, but that there are also systematic differences (Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014). These differences became apparent when the choice and response times were modeled with a drift diffusion model (DDM; Ratcliff & Smith, 2015), which decomposes choice behavior into meaningful parameters that characterize the deliberation process (see Table 1).[3] In this case, the differences were isolated to the drift rates of evidence accumulation. Zeigenfuse et al. (2014) found that compared with the perceptual condition, in the gambling condition (a) more evidence accumulated in a given time interval for the uncertain alternative (i.e., the drift rate was higher) and (b) evidence accumulation rates were less affected by changes in the expected value of the uncertain option. These two effects worked together so that during preferential choice the average accumulation rate was toward the uncertain option, even when its expected value was below that of the certain option (i.e., risk-seeking). Dutilh and Rieskamp (2016) also found drift rates were less affected by changes in the value of the uncertain option, but did not find drift rates were shifted toward the uncertain option. Similarly, risk-seeking behavior was reported when payoffs are presented

[3] The DDM used was a Wiener process with drift and two absorbing boundaries that includes a non-decision time to account for residual processing time. Trial-level variability in the parameters (e.g., Ratcliff & Rouder, 1998) was not included as the focus was on how the core parameters of the process differ between the tasks. For these reasons, the same model DDM is used in this paper.

Table 1
Main Parameters of the Drift Diffusion Model and Their Substantive Interpretations

Parameter	Description
Threshold separation, α	The separation between the choice thresholds with $\alpha > 0$. With this parameterization the choice threshold for the uncertain option is set at α, and the choice threshold for the certain option set at 0. The threshold separation measures the degree of response caution with lower thresholds permitting faster, but less consistent choices.
Relative start point, β	The location of the starting point for evidence accumulation relative to the two thresholds, with $0 < \beta < 1$. The relative starting point indexes an initial bias for either response, with higher values of β indicating greater bias to choose the uncertain option.
Drift rate, δ	The rate at which evidence accumulates in favor of the uncertain option. The sign of the drift rate indicates the average direction of the evolution, with negative values indicating evidence for the certain alternative and positive values indicating evidence for the uncertain alternative.
Non-decision time, τ	The amount of contaminant time in the observed response times beyond the deliberation time specified by the DDM, with $\tau > 0$. The non-decision time includes the time spent on encoding the stimulus, executing a response, and any other contaminant processes.

sequentially (Tsetsos et al., 2012). In general, these results seem to conflict with the canonical result that people are risk averse in the domain of gains, that is they prefer a certain payoff over a lottery that has a higher expected value (Kahneman & Tversky, 1979). This difference provided further motivation for the study. We thus sought to replicate these results.

We also sought to go beyond past these investigations by better measuring how information was used to make a decision. A limitation of these DDM analyses is that the sampling process is still unobserved. The strength of the FGT is that by explicitly providing participants continuous stimulus samples, it allows a more direct investigation of the online processing of the sampled payoff information. To do so, we adapted a reverse correlation technique from Kiani, Hanks, and Shadlen (2008) and Zyberberg, Barttfeld, and Sigman (2012) to study the time-varying contribution of the stimulus samples to choice. We investigated how differences in the estimated rate of evidence accumulation (from DDM) translates to the relationship between the observed samples of stimulus and choice. Doing so allowed us to identify how sensitivity to the samples of information changes between decision types as well as any possible bias in information usage when choosing the uncertain or certain option.

Method

Participants. We used flyers and online advertisements on social media to recruit 40 native English-speaking participants from the Michigan State University community and surrounding Lansing area. Our sample size target was based on previous studies that also targeted 40 participants (Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014). We lost the demographic data of 3 participants because of a programming error, so the following demographic information applies to 37 participants, consisting of 29 women and 8 men between 18 and 28 years old ($M = 22.0$, $SD = 5.1$). In terms of race and ethnicity, 75.7% described themselves as White, 13.5% as Black or African American, 8.1% as Asian or Southeast Asian, and 2.8% described as having more than one race. Participants were paid \$10 per hour plus a \$0–5 performance bonus. The study protocol was approved by the Institutional Review Board at Michigan State University.

Flash gambling task. The stimuli were generated in MATLAB using Psychophysics Toolbox Version 3 (Brainard, 1997; Kleiner et al., 2007). The stimuli were displayed on a LCD monitor with a resolution of 1280 × 1024 in a sound attenuated booth. To maintain a fixed viewing distance, participants were asked to rest their chin in a head mount that was secured to the desk 48.5 cm from the screen.

In general, we constructed the tasks to resemble a psychophysical discrimination experiment using the method of constant stimuli. In the FGT, participants chose between two options: a certain or an uncertain alternative. Both options were represented by circular displays of white dots on a black background (see Figure 1). Each display had a diameter of 6.1° visual angle, with

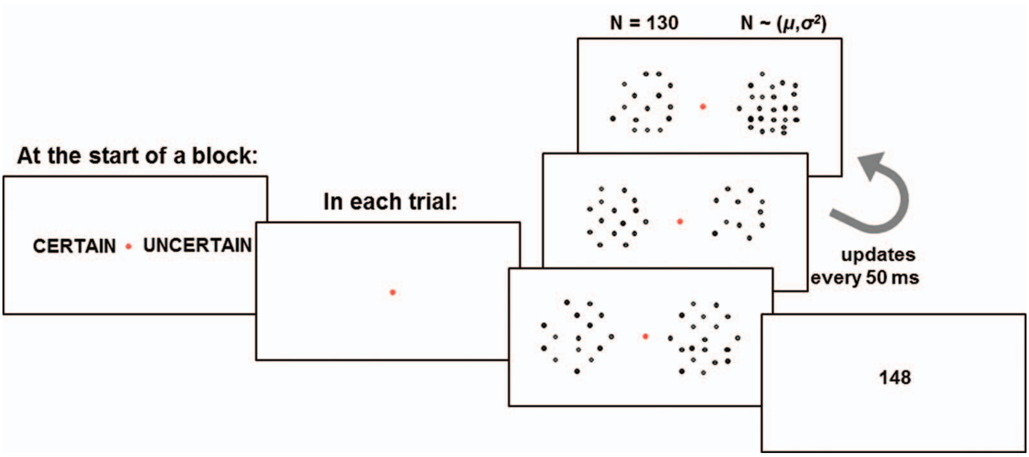

Figure 1. Schematic diagram of FGT stimulus. Participants viewed a fixation point for 500 ms, followed by the two dynamically updating options until they responded with their choice, which was followed by the feedback. See the online article for the color version of this figure.

one located 6.75° to the left of a central fixation and the other 6.75° to the right. Each dot had a diameter of 0.023°. The certain and uncertain alternatives were labeled for the participants at the beginning of each block.

The uncertain alternative had a dynamic display of dots that changed every 50 ms (20 Hz). At each update, the number of dots was drawn from a normal distribution and then shown in random locations in the display. We truncated the normal distribution at ±2 standard deviations. This ensured the uncertain alternative always had at least 30 dots. The certain alternative always had 130 dots that were randomly placed within the respective circular aperture, with their positions also updated every 50 ms (20 Hz).[4]

Participants were instructed that each dot was worth 1 point and that they were to evaluate the certain and uncertain (risky) option to form an impression of each option. They were told to choose between the two options by pressing a left or right key on a computer keyboard. If the uncertain option was chosen, the payoff was a random draw that corresponded to the next sample that would have been shown and that determined the number of points they earned. If the certain option was chosen then the participant earned 130 points. After the choice, the payoff from the chosen option was displayed as feedback. The total number of points participants earned were accumulated across all the trials and not shown. At the end of the experiment, the point totals were scaled to give a bonus between $1–5.

Perceptual task. The perceptual task was identical to the FGT except participants were told to identify the option that had the higher number of dots on average. Technically, we set this to be determined by the observed sample mean. We sought to match the payoff structure of the perceptual task to the FGT. Thus, during the perceptual task they received a payoff equal to the mean number of dots in the distribution for the chosen option (i.e., μ), which was displayed as feedback. With this structure, goals in the FGT are aligned with the perceptual task such that in both cases participants should strive to choose the option with the higher expected value.

Design and procedures. We manipulated the type of decision between participants with half the participants randomly assigned to the FGT and the other half to the perceptual task. At the trial level, we also factorially manipulated (within-participants) the mean and standard de-

[4] This is a deviation from Zeigenfuse et al. (2014), where the randomly placed dots in the certain alternative remained in a fixed position throughout the trial. Here, we made the certain alternative dynamic to help control for differences in visual after–effects between the two alternatives.

viation of the number of dots in the uncertain option. The mean had five levels (μ = 100, 115, 130, 145, and 160) and the standard deviation had three levels (σ = 5, 25, and 45), and we presented 64 trials per experimental condition.

After agreeing to participate in the study, participants received a brief introduction to the task informing them that they would make many decisions about two options represented by arrays of dots. We kept the specific task vague in the introduction to manipulate between subjects whether people were in the gambling or perceptual condition. Following the introduction, participants were seated at a desk in a sound-attenuated booth and instructed how to use and adjust the head rest. Participants then received more precise instructions about the task and completed 30 practice trials of either the FGT or the perceptual task. The practice trials were identical to the actual trials, except that an additional description was used to emphasize the difference between the two options: the descriptive label "Same number of dots" was placed below the certain option and "Changing number of dots" was placed below the uncertain option.

Once participants confirmed they understood the task, they completed a total of 960 trials (in 12 blocks of 80 trials). Figure 1 outlines the general task procedure. The location of the certain and uncertain option (right or left side of the screen) was fixed within a block and counterbalanced across blocks and displayed to participants at the start of each block. In each trial, participants first viewed a fixation point for 500 ms, followed by the two dynamically updating options until they indicated their choice. They then received feedback based on the condition they were in. After completing either the FGT or the perceptual task, participants also completed a set of self-report measures related to risk taking and impulsivity and the Balloon Analogue Risk Taking Task (BART; Lejuez et al., 2002). This last set of measures were collected as pilot testing in preparation for Study 2. They are described in more depth in the method section of Study 2. Because the current study is underpowered for examining correlations with these measures we do not report further on these measures in this study.

Analyses. Our statistical analyses for both the behavioral effects and computational analyses employed a multilevel modeling approach. We fit the models and conducted statistical inference using Bayesian estimation techniques (Gelman, Carlin, Stern, & Rubin, 2014; Kruschke, 2014). In each of the analyses, Markov Chain Monte Carlo (MCMC) methods were used to generate estimates from the posterior distribution of each parameter. All chains were inspected for the representativeness of the posterior distribution both visually and with the Gelman-Rubin statistic. We also inspected the autocorrelation within chains to confirm their ability to provide stable and accurate estimates of the distributions. In reporting results from the models we report the mean of the posterior distribution of the parameter or statistic of interest and the 95% equal tail credible interval (CI) around each value.

General linear model analyses. At the behavioral level, we used a hierarchical general linear model to examine the effect of the experimental manipulations on choice and response times. The mean number of dots in the uncertain option, μ, and the standard deviation in the number of dots in the uncertain option, σ, were within-subject variables, and the task frame (perceptual vs. gambling) was the between-subjects variable. We used a logistic link for choice data and a normal link for response time data. The models were estimated using RStanArm using the standard priors (*RStanArm Version 2.9.0–4*, 2016). The MCMC estimation involved generating 6 chains of 2000 steps estimated from the posterior distribution of each parameter. The predictor variables were unstandardized in regressions for all studies, and we report *b*, the unstandardized coefficient which quantifies the effect of the experimental conditions on the measured criterion values. In simple comparisons between groups we used Kruschke's (2013) Bayesian comparison of two groups.

Drift diffusion analyses. We used a DDM model to decompose choices and response times into meaningful parameters that characterize the deliberation process (see Table 1). To do so, we embedded our DDM analysis within a hierarchical framework (Vandekerckhove, Tuerlinckx, & Lee, 2011; Wabersich & Vandekerckhove, 2014) and used Bayesian estimation techniques (Kruschke, 2014; Lee & Wagenmakers, 2013) to estimate the model parameters. We parameterized the DDM so that the means (and variances) of each of the free parameters (threshold separation, relative start point, drift rate, and nondecision time) at the group level could differ between the preferential and perceptual tasks. This allowed us to characterize what effect, if any, the two tasks have (holding the stimulus constant) on the model parameters. The comparison is not trivial in that in principle the posterior distributions of each of the parameters can completely overlap showing no difference between the task types. This method was verified by model simulation and recovery analysis (see Appendix of Pleskac et al., in press).

The JAGS code with the priors specified for the participant and group level parameters are given in the Open Science Framework repository for this paper. In general, we used vague and uninformative parameters, but the conclusions we report are robust to reasonable changes in the priors. The models were estimated using the rjags package with the JAGS Wiener module (Wabersich & Vandekerckhove, 2014), an extension for the Just-Another-Gibbs-Sampler (JAGS; Plummer, 2003) in *R*. In the MCMC estimation, we generated 3 chains of 5000 steps estimated from the posterior distribution of each parameter. We parametrized the model to examine how the decision frame manipulation impacted the model. Based on past results, only the drift rate was allowed to vary freely between the different means of the uncertain option (Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014). Note in a different model we also examined how the manipulation of the variance impacted the parameters and found no credible effect, just as in the behavioral data, so we focused on a model that collapses across the variance manipulation.

Reverse correlation analysis. We used a reverse correlation technique to investigate the time-varying contribution of the samples of information to choice (Kiani et al., 2008; Zyberberg et al., 2012). The technique is based on the actual samples of dots shown at each time point t for the uncertain option, $y(t)$. Recall these samples were normally distributed with a mean of $\mu = 100,115,130,145$, and 160 and standard deviation $\sigma = 5$, 25, and 45. Across all trials the number of dots in the certain option was set at $c = 130$. For these analyses we focus on the trials where $\mu = 130$, $\sigma = 45$. Although trials from the other conditions lead to the same or similar conclusions, these trials (high variance, equal mean number of dots for the two options) proved clearest in reaching reliable conclusions in how the sampled information impacted choice.

For each trial, we calculated the deviation of each sample from the mean of the uncertain option in that condition μ,

$$d(t) = y(t) - \mu. \tag{1}$$

Note that in the $\mu = 130$ condition, μ is also the number of dots in the certain option. Thus, $d(t)$ is the time-varying difference signal between the uncertain and certain option. We grouped $d(t$; vectors of different lengths) into two groups: (a) when the uncertain option was chosen $d_U(t)$ and (b) when the certain option was chosen $d_C(t)$. We refer to these vectors as *deviation profiles*.

To better understand the properties of this time-varying signal, we simulated a simple sequential sampling model where a decision must be made between a certain option worth $k = 130$ and an uncertain option with a $\mu = 130$ and a standard deviation of $\sigma = 45$. The model implemented a simple accumulate-to-bound process where at each stimulus frame the observed sample information from the uncertain option $y(t)$ was compared with the magnitude of the certain option k, and these values were accumulated to form a preference,

$$P(t) = P(t - \Delta) + [y(t) - k], \tag{2}$$

where Δ is a small increment in time (here, $\Delta = 0.05$ *s*). Once preference $P(t)$ reached the upper or lower threshold (θ or $-\theta$, respectively) then a choice is made accordingly. We simulated this model using a threshold of $\theta = 100$. The model also included a delay between when the response was recorded and when a threshold level of evidence was reached (i.e., nondecision time). In addition, we assumed there was variability between simulated trials in the location of the starting point and the nondecision time delay.

Figure 2 shows, for illustration, the expected deviation profiles time-locked to stimulus onset (A) and response (B), conditioned on the choice. They show that the expected deviation profiles will reflect the chosen option such that when the uncertain option was chosen the deviations will be on average positive, and when the certain option is chosen they will be on average negative. This is observed with the profiles time-locked to

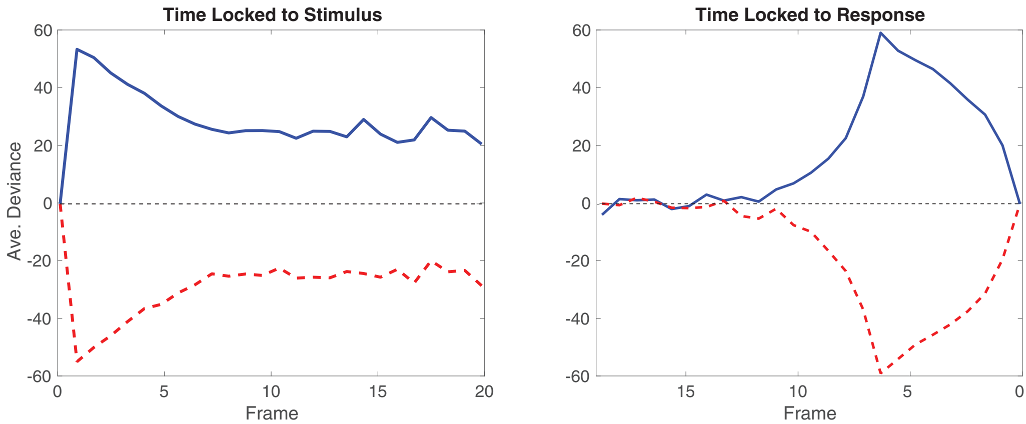

Figure 2. Expected deviation profiles for choices of uncertain option (top/blue) and certain option (bottom/red) for a simulated accumulate to bound model during the FGT time-locked to stimulus onset (A) and response (B). The mean of the uncertain option was set at $\mu = 130$, the standard deviation was set at $\sigma = 45$, the value of the certain option was set a $k = 130$, and the sampling rate was 20 Hz. For model parameters, the threshold was set at 100, the start point was at 0 with trial-level variability (uniform distribution with a width of 90), and the average nondecision time was 0.2 s with trial-level variability (uniform distribution with a width of 0.4 s). Results are based on 50,000 simulated runs. See the online article for the color version of this figure.

stimulus onset and time-locked to response. The latter profiles illustrate a feature of sequential sampling models for two-alternatives, which is that the last sample before choice is consistent with the choice. The early bump in the profiles time-locked to the stimulus onset is attributable to the trial-level variability in start point and nondecision time. These two components lead to different delays in evidence accumulation from trial to trial and thus by averaging across the delays an early bump is created. Similarly, trial-level variability also explains the shark-fin shaped response-locked profiles.

Decision kernel. We derived two additional measures from these profiles to index how the sample information is used. One measure is the decision kernel, defined as the distance between the deviation profiles when the uncertain and certain alternative was chosen,

$$d_{DK}(t) = d_U(t) - d_C(t). \tag{3}$$

A similar measure has been used to measure sensitivity to perceptual information in the random dot motion tasks (Kiani et al., 2008; Zylberberg et al., 2012). The decision kernel d_{DK} measures the total contribution of the samples at each frame to choice. Averaging the decision kernel across time ($\bar{d}_{DK}$) measures the average sensitivity of a participant to the FGT stimulus. The larger the decision kernel the more sensitive to the sample information. We used the decision kernel time-locked to stimulus onset to calculate the average decision kernel per participant.

Decision bias. The deviation profiles can also be used to measure to what extent the samples of information were used in a biased fashion. To do this we calculated the midpoint between the two average levels of evidence,

$$d_B(t) = [d_U(t) + d_C(t)]/2. \tag{4}$$

In the $\mu = 130$ condition, $d_B(t)$ reflects the relative contribution of the information from the uncertain option toward participants' decisions hence we label it *decision bias*. Because both options have 130 dots on average, $d_B(t) = 0$ would indicate unbiased processing, whereas a negative $d_B(t)$ value would indicate a bias for the uncertain option. As with the average decision kernel, we used the decision-bias time-locked to stimulus onset to calculate the average decision bias per participant ($\bar{d}_B$).

Results

Behavioral analysis. As a first step in our analyses, we compared choice and response times for perceptual and preferential decisions. Five participants exhibited choice behavior that was completely insensitive to the mean value of the uncertain option so we removed those participants from any further data analysis. Thus, the results are based on data from 35 participants.

Figure 3 illustrates that participants were sensitive to the difference in mean number of dots between the two options. As expected, the proportion of choosing the uncertain option increased with the mean number of dots in that option ($b = 1.06$, CI = [0.98, 1.15]). Moreover, participants chose the uncertain option less often in the perceptual compared with the gambling frame ($b = -0.64$, CI = [−1.19, −0.12]). Consistent with past comparisons between perceptual and preferential choice, there was a trend for an interaction between decision type and the mean of the uncertain option ($b = 0.11$, CI = [−0.01, 0.24]). The interaction suggests differential sensitivity to the mean number of dots in the uncertain option. In particular, participants were more likely to choose the uncertain option in the gambling condition when the it had 100 dots on average. However, as the mean increased the choice proportions in the gambling and perceptual frames converged.

In Figure 3 we have collapsed across the standard deviation (σ) as there was no credible effect of different levels of standard deviation ($b = 0.07$, CI = [−0.04, 0.18]), nor was there an interaction with the mean of the uncertain option, the decision frame, or a three-way interaction. This lack of an effect of the variance is consistent with our past work with this task (Zeigenfuse et al., 2014), but inconsistent with what is called the payoff-variability effect in risky choice (Busemeyer, 1985; Busemeyer & Townsend, 1993).

The response times (averaging across when participants chose the uncertain and certain option) are shown in Figure 3, which, as expected, exhibited an inverted U-shape, that is, participants responded faster as the difference in the mean number of dots between the two options increased ($b = -0.03$, CI = [−0.06, −0.01]).

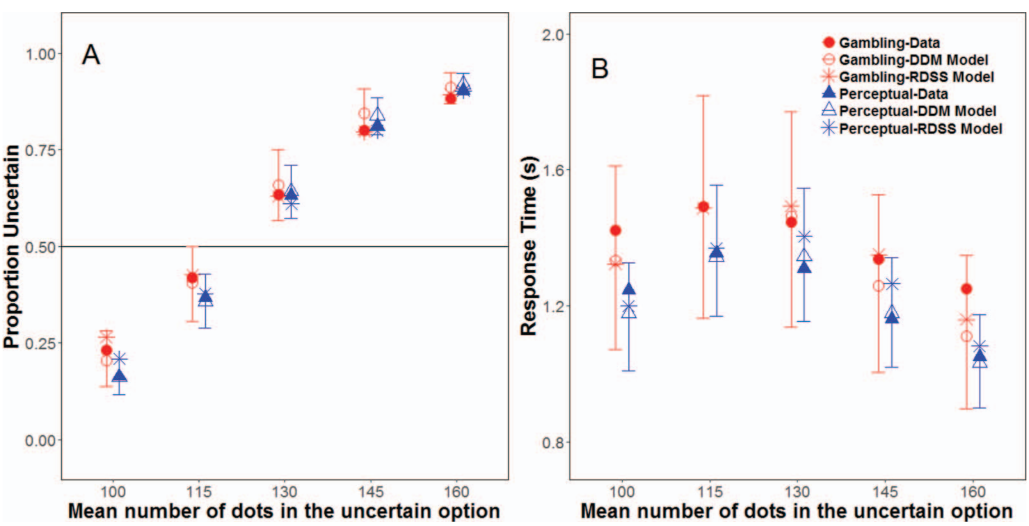

Figure 3. Average choice proportions (A) and response times (B) in the gambling and perceptual conditions. Posterior predictive fits of the DDM to the data at the group level are shown as unfilled markers with corresponding credible intervals, reflecting the uncertainty for a given subject's behavior. The stars are the posterior predicted means from the RDSS Model (see the General Discussion). Note that in both tasks there was a tendency to choose the uncertain option as evidenced by the $\mu = 130$ condition. When the uncertain option was relatively unattractive this tendency to choose the uncertain option was greater in the gambling condition. See the online article for the color version of this figure.

However, the slowest response times were not when the uncertain option had the same number of dots as the certain option (130), but occurred when the uncertain option had a mean of 115 dots. As we will establish shortly with the DDM, this is consistent with a "risk seeking" bias in the drift rates toward the uncertain option. There were no credible differences in response times across the variance conditions ($b = -0.03$, CI = [−0.06, 0.01]) and task frames ($b = -0.13$, CI = [−0.45, 0.20]).

Drift diffusion analysis. To better characterize the deliberation process, we submitted the choice and response time data from both decision frames to a drift diffusion analysis. As described earlier, the DDM is a mathematical formulation of a particular sequential sampling process where participants are assumed to sequentially sample noisy information and accumulate it as evidence until a threshold is reached initiating a response. As a mathematical model, we can fit it to the observed choices and response time distributions to decompose observed choice behavior into four psychologically meaningful parameters (see Table 1). We were particularly interested in whether the observed behavioral-level difference between the perceptual and gambling conditions were isolated to differences in the drift rates, as in our past results. Such a difference would indicate a difference in how the information was processed between the two tasks. An alternative possibility is that the difference between the tasks is due to the start points where it would be closer to the threshold in the gambling condition.

The DDM recreates the choice and response time data reasonably well. The posterior predictive fits at the group level are shown in Figure 3. The estimated DDM parameters at the group level are shown in Figure 4. The initial bias, β, was close to 0.50 in both the gambling and perceptual conditions and did not differ credibly from each other, indicating little bias in the

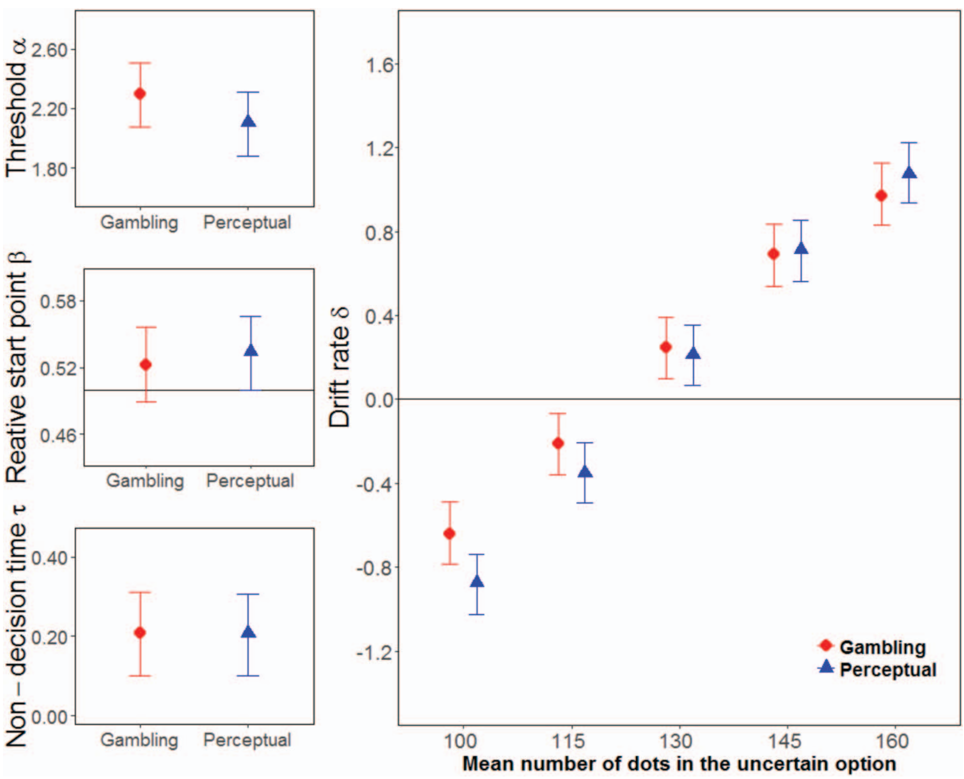

Figure 4. Study 1 posterior means and 95% CI (error bars) for the group-level parameter estimates of the DDM in each condition. See the online article for the color version of this figure.

relative start point between the two conditions. The threshold separation α and nondecision time τ were also similar across the two task frames.

As we would expect, the drift rate δ increased with the average number of dots in the uncertain option (μ). Note that δ was positive in both the gambling and perceptual tasks when the uncertain and certain option were matched in terms of expected value (i.e., $\mu = 130$). This indicates that in general, participants accumulated more evidence for a fixed period of time in favor of the uncertain option than evidence in favor of the certain option. Moreover, when the uncertain option was particularly unattractive ($\mu = 100$), δ was credibly higher in the gambling ($M = -0.64$, CI = [−0.79, −0.49]) compared with the perceptual condition ($M = -0.87$, CI = [−1.02, −0.73]), (contrast of gambling vs. perceptual $M = 0.23$, CI = [0.02, 0.44]).

Although the difference between the decision types was less pronounced compared with the original Zeigenfuse et al. (2014) study, we note that in Study 2 we obtained results much closer to those in Zeigenfuse et al. (2014). Later we show how these differences in drift rates both between studies and between conditions are consistent with differences in the attention allocated to extreme events using a rank-dependent sequential sampling model (RDSS; Zeigenfuse et al., 2014). Next, we use a reverse correlation analysis to characterize the relationship between the behavioral choices and the individual samples of information viewed by participants within a trial. This analysis gives us further insights into the differences between decision types.

Reverse correlational analysis. Figure 5 shows the average time series of the deviation profiles for $d_U(t)$ and $d_C(t)$, time locked to stimulus onset (A) and response (B) for gambling and perceptual conditions, which are similar to those generated by an evidence accumulation process (see Figure 2). We found that $d_U(t)$ is generally above 0 while $d_C(t)$ is below 0, indicating participants were sensitive to the samples of information across time. Note because there were fewer observations that contribute to each profile at later times (due to the optional stopping procedure), the estimates become less reliable and show more fluctuations. Nevertheless they are similar to those generated by an evidence accumulation process (see Figure 2).[5]

Figure 6A plots the decision kernel across time for both the gambling and perceptual conditions. Positive values of $d_{DK}(t)$ highlight that participants were sensitive to the relative number of dots displayed in the uncertain option over and above its mean. Averaging across the kernel shows there was greater sensitivity in the perceptual ($M = 7.75$; $SD = 2.41$; CI = [6.52, 9.02]) compared with the gambling ($M = 4.86$; $SD = 4.38$; CI = [2.51, 7.07]) condition (difference: $M = 2.97$; CI = [0.41, 5.57]; Figure 6B).

Figures 6C also shows that the decision bias $d_B(t)$ was on average negative, implying that participants needed on average less overall evidence to choose the uncertain option. However, once prior uncertainty and variability in the data is accounted for, the average value of the decision bias for the gambling condition ($M = -0.45$; CI = [−1.40, 0.72]) and the perceptual condition ($M = -0.81$; CI = [−1.55, 0.08]) were not credibly different from 0 or from each other ($M = 0.41$; CI = [−0.94, 1.70]; Figure 6D).

Relating the reverse correlation results with behavior and DDM. In seeking to validate the measures of information usage from the reverse correlation analysis, we also investigated to what degree they corresponded with choice behavior and the parameters of the DDM. For the decision kernel, we correlated the mean decision kernel for each participant $\bar{d}_{DK}$ with the proportion of times the option with the larger expected value was chosen $Pr(EV_{max})$. Recall that the decision kernel was calculated using the condition where the uncertain and certain options had the same mean, $\mu = 130$, and the standard deviation was $\sigma = 45$. Thus, to avoid circularity in calculating $Pr(EV_{max})$, we excluded the conditions when the uncertain option had the same mean as the certain option ($\mu = 130$). Figure 7A plots this relationship and shows there was a positive correlation between each individuals' decision kernel and the reward-maximizing choice. However, the strength of this relationship depended on the decision frame ($b = 0.007$, CI = [0.0001, 0.013]). That is, the magnitude of the correlation between $Pr(EV_{max})$ and

[5] The Open Science Framework repository for this paper provides the time series plots for all the offset conditions time-locked to stimulus onset and response as well as the average of the cumulative sum of the deviations.

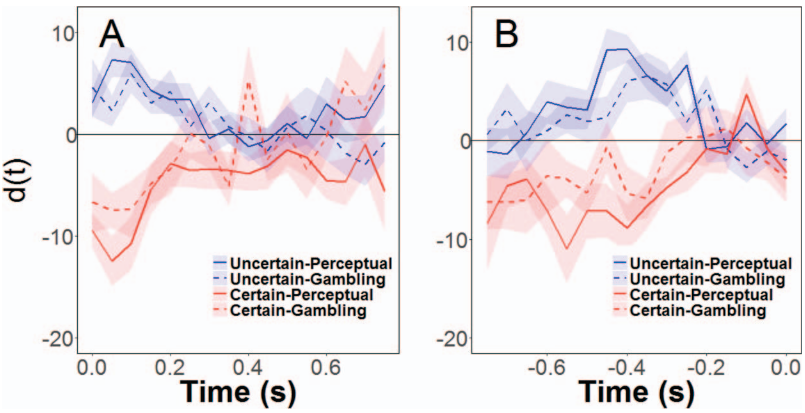

Figure 5. Time series of the deviation profiles from the reverse correlation analysis (Equation 1), time locked to stimulus (A) or time locked to response (B) when $\mu = 130$ and $\sigma = 45$. The top/blue and bottom/red lines represent evidence when choosing the uncertain option ($d_U(t)$) and when choosing the certain option ($d_C(t)$), respectively. See the online article for the color version of this figure.

d_{DK} was stronger in the perceptual than the gambling condition. This difference between decision tasks shows that during preferential decisions participants are less sensitive to individual samples of information during deliberation. This conclusion thus converges with the DDM analyses even though it was based on actual samples of dots in the stimulus.

The decision kernel $\bar{d}_{DK}$ was also related to changes in the drift rates as the mean number of dots μ increased. To see this, for each participant, we calculated the average piecewise linear slope of the drift rates across levels of μ. This slope indexes how much drift rates in the DDM changes with each change in μ. Figure 7B shows the positive relationship between the estimated slopes and the mean decision kernel for each participant across conditions ($b = 0.04$, CI = [0.02, 0.06]).[6]

The average decision bias $\bar{d}_B$ was also meaningfully related to the DDM parameters. Recall the drift rate in the $\mu = 130$ condition for both the gambling and perceptual conditions was positive indicating that the sampled information was interpreted in favor of the uncertain option, even when objectively it was not the favorable option (see Figure 4). At the same time, the $d_B(t)$ measures the difference in the amount of evidence needed to choose the uncertain versus certain option with negative values indicating less evidence is needed to choose the uncertain option. Thus, we would expect a negative relationship between the drift rate in the $\mu = 130$ condition (δ_{130}) and the decision bias from the reverse correlation analysis ($d_B(t)$). As Figure 7C shows, indeed, the average decision bias $\bar{d}_B$ was negatively correlated with the respective drift rate in the $\mu = 130$ condition ($b = -0.04$; CI = [−0.07, −0.01]; though note in this correlation there is a bit of redundancy in that both draw on the same choice data). Figure 7C also shows that this relationship did not depend on the decision type. These results corroborate the conclusion that in both decision tasks the information was on average processed slightly biased toward the uncertain option, but equally so in the gambling and perceptual condition.

Interim conclusion. We showed that deliberation during preferential choice can be well described as a sequential sampling process where individuals accumulate samples of possible payoffs to form a preference between options. When preference reaches a threshold this triggers a choice. To better characterize this process, we compared deliberation during the FGT to a perceptual analog of the task, at the behavioral level, the computational level, and at the level of the actual information usage. These

[6] To test whether $\bar{d}_{DK}$ is related to the noisy process of evidence accumulation as estimated by the DDM, we estimated a DDM that allowed the variability in the drift process (drift coefficient) to vary between conditions. The $\bar{d}_{DK}$ did not correlate with either of these estimates.

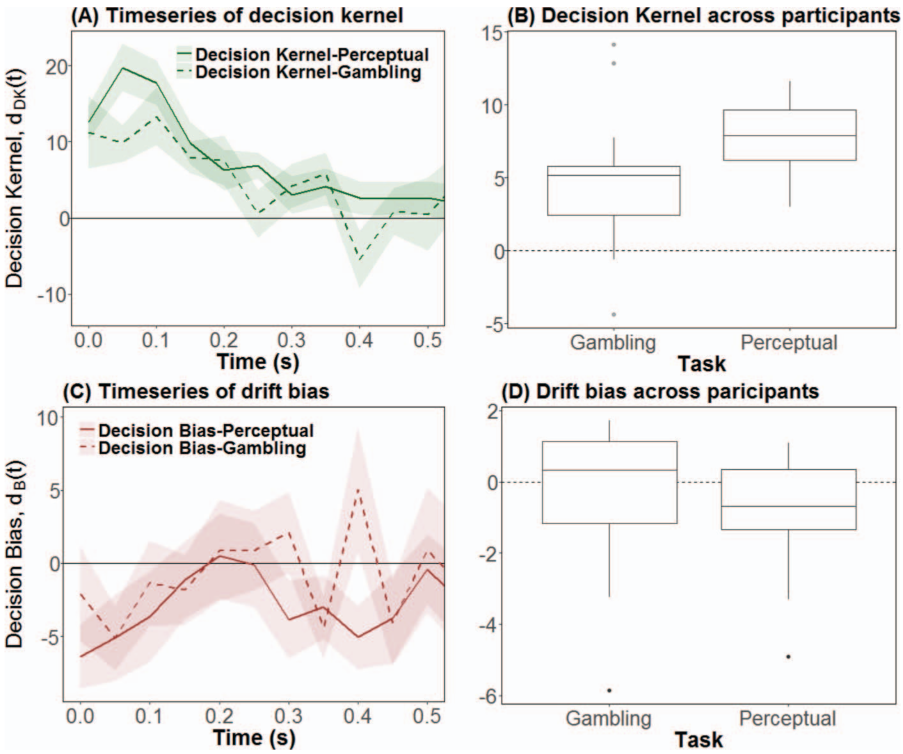

Figure 6. (A) Time series of the decision kernel $d_{DK}(t$[highlight]) ([/highlight]Equation 3) time-locked to stimulus onset. (B) Distributions of the average decision kernel $\bar{d}_{DK}$. (C) The decision bias $d_B(t)$ across participants time-locked to stimulus onset (Equation 4). (D) Distributions of the average decision bias $\bar{d}_B$. See the online article for the color version of this figure.

comparisons showed that a similar sequential sampling process is used in both decision types. In fact, the comparisons showed that part of the risk-seeking behavior we identified in the FGT is attributable to a perceptual bias in processing information, as reflected in both the DDM analysis where there was a positive drift rate for the $\mu = 130$ condition, and the reverse correlation analysis where the decision bias (d_B) was on average negative (though not credibly so).

There were also differences in the processing of information between these two decision types. Most notably, during preferential choice participants were less sensitive to the samples of payoff information. This conclusion is supported by both the DDM analysis showing the drift rates for unfavorable options were more positive, and the reverse correlation analysis showing a smaller decision kernel (d_{DK}). In the next study, we used these measures of deliberation during preferential choice to investigate their relationship to other traits and behaviors like impulsivity and risk taking.

Study 2: Individual Differences in Deliberation During Preferential Choice

The reverse correlation analysis in Study 1 revealed systematic individual differences in how participants deliberate and ultimately make a choice under uncertainty. In the second study, we investigated whether these individual differences uncovered in a laboratory task were related to real-world behaviors and personality traits. One possible connection seems to be substance abuse, as past results suggest a link between substance use and decision making, such as poor learning (Stout et al., 2004; Yechiam, Busemeyer, Stout, & Bechara, 2005), as well as differences in reward processing (Pleskac, 2008; Wallsten, Pleskac, &

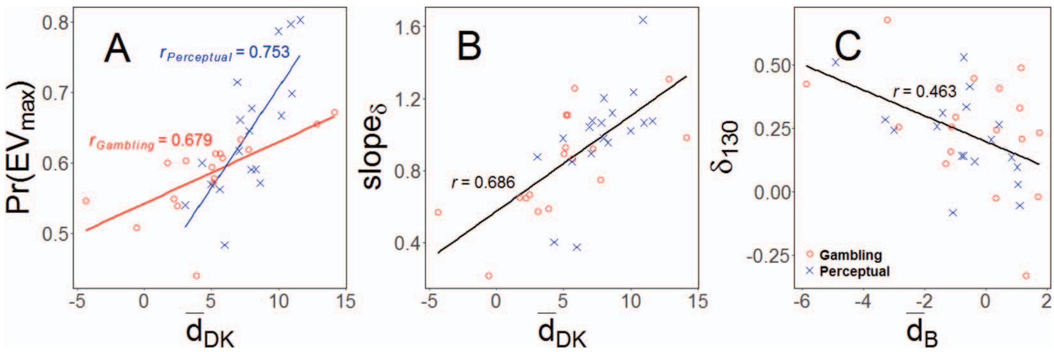

Figure 7. (A) The relationship between the average decision kernel and the proportion of times the higher expected value choice was made for gambling (blue) and perceptual (red) conditions. (B) The relationship between the average decision kernel and the change in drift rates across offset conditions ($slope_\delta$) for gambling (blue) and perceptual (red) conditions. (C) The relationship between average decision bias and drift rates in the $\mu = 130$ condition, δ_{130}. See the online article for the color version of this figure.

Lejuez, 2005). However, as of yet, very little work has established a relationship between deficits in the deliberation process and substance use. There are indications that substance abuse may be associated with differences in the deliberation process. For instance, Rogers et al. (1999) report that individuals with drug abuse problems have longer response times and less extreme choice proportions when choosing between simple monetary gambles. In terms of an evidence accumulation process, these differences are consistent with these individuals showing decrements in the online processing of the payoff information (i.e., lower drift rates δ in the DDM). At the same time, substance use is sometimes understood as a cue-induced urge (Bonson et al., 2002; Ehrman, Robbins, Childress, & O'Brien, 1992), which may be explained by risk-taking-relevant cues leading to differences in the start point of the deliberation process. The FGT allows us to further investigate possible associations between substance use behavior and the deliberation process.

We also investigated to what degree deliberation in the FGT was related to trait-level measures of impulsivity. We focused on impulsivity as some aspects of this trait seem a priori related to deliberation (Whiteside & Lynam, 2001). For instance, one aspect of impulsivity is premeditation, which is described as measuring how much people deliberate over options. Another aspect is urgency, which is described as measuring a tendency to commit rash or regrettable actions. These descriptions seem likely to be related to the quality (indexed by drift rate, δ) or quantity (indexed by threshold separation, α) of accumulated evidence. For exploratory purposes and to assess convergent and divergent validity, we also included measures of risk attitudes in different domains of risk taking behavior (Weber, Blais, & Betz, 2002) as well as the BART (Lejuez et al., 2002) to serve as a measure of risk taking via another laboratory-based decision task.

Method

Participants. We used flyers and online advertisements on social media to recruit participants between the ages of 21 and 40. To determine the sample size, we performed a power analysis in a null hypothesis significance testing framework of a point-biserial correlation. For an expected effect size of $|r| = .3$, a Type I error rate of $\alpha = .05$, and a desired level of power at $1 - \beta = .95$, we determined we needed 134 participants. Because we sought to increase the likelihood of recruiting a representative number of individuals at the upper end of the risk-taking continuum, we included in the advertisement the phrase "Are you a risk taker?" (see also Lejuez et al., 2002). We also sought to recruit beyond the typical student population by posting flyers in the nearby Lansing, MI, community as well as choosing keywords related to drug use when posting advertisements on social media. Participants were paid \$10 per hour plus a performance bonus that averaged about \$3. The study protocol was approved by the Institutional Review Board at Michigan State University.

We ended up with a sample of 126 adults. Eight additional participants were run, but were over the targeted age range of 40. The sample consisted of 61 men and 65 women, ranging in age from 18 to 38 years ($M = 24.8$, $SD = 4.53$). In terms of race and ethnicity, 72.0% described themselves as White, 14.3% as Black or African American, 3.2% as Asian or Southeast Asian, and 4.0% as Hispanic or Latino, 0.8% as Native American or Alaska Native; the remaining 5.6% marked "Other" or chose not to respond to the question.

Self-reported risk taking behaviors. We asked participants to complete several different measures of self-reported risky taking behavior. As a measure of hazardous and harmful alcohol consumption participants completed the 10 item Alcohol Use Disorders Identification Test (AUDIT; Saunders, Aasland, Babor, Delafuente, & Grant, 1993). In the current sample, the Cronbach's alpha for the AUDIT was $\alpha = .77$.

As a measure of drug dependency, we asked participants to complete the Drug Use Disorders Identification Test (DUDIT; Berman, Bergman, Palmstierna, & Schlyter, 2005). The reliability of the DUDIT in the current sample was $\alpha = .90$. To assess illegal/legal drug use, participants reported whether they had ever tried a drug. Eleven different drug categories were cannabis, alcohol, cocaine, MDM (ecstasy), stimulants (e.g., speed), sedatives/hypnotics, opiates, hallucinogens, PCP, inhalants, and nicotine. The sum of the number of categories tried (polydrug) is a validated measure of risky drug use (Babor et al., 1992; Grant, Contoreggi, & London, 2000).

Finally, as a measure of high-risk sexual behavior participants completed the Scale of Sexual Risk Taking (Metzler, Noell, & Biglan, 1992). However, the scale was only moderately reliable ($\alpha = .68$). In looking back at the scale presentation, we found that the scale items were incorrectly presented out of order from the original scale and one question was truncated. For these reasons we chose not to include this scale in our subsequent analyses.

Impulsivity. To measure impulsivity, we used the 40-item UPPS Impulsive Behavior Scale (UPPS; Whiteside & Lynam, 2001). The UPPS measures impulsivity across four different facets (with Cronbach's alpha measures of reliability of each subscale in parentheses): premeditation ($\alpha = .86$), urgency ($\alpha = .95$), sensation seeking ($\alpha = .86$) and perseverance ($\alpha = .85$). Across the facets, in the current sample, the Cronbach's alpha for the UPPS was $\alpha = .94$.

We also asked participants to complete 50 selected items from Form II of the Sensation Seeking Scale (Zuckerman, 1994), which measures the optimal stimulation level an individual seeks. In the current sample, the Cronbach's alpha of the sensation seeking scale was $\alpha = .86$.

Domain specific risk attitudes. Participants also completed the DOSPERT Scale (Weber et al., 2002), which contains 40 items that assess their attitudes (via likelihood judgments) toward risky behavior in six domains: ethics ($\alpha = .74$), investment ($\alpha = .85$), gambling ($\alpha = .80$), health/safety ($\alpha = .64$), recreational ($\alpha = .84$), and social ($\alpha = .61$). Across the subscales, in the current sample, the Cronbach's alpha was $\alpha = .86$.

Balloon Analogue Risk Task (BART). In addition to the FGT, participants also completed the BART, a risk-taking task that has been found to correlate with a range of risk-taking behaviors (Lejuez et al., 2002). We used the BART as implemented in Pleskac and Wershbale (2014). During the BART, a computerized balloon is shown on the screen. Each time participants press the 'v' key on a QWERTY keyboard (labeled with a 'P' for pump) the balloon can inflate. If the balloon stays intact, participants earn 10 points. However, the balloon can also explode, and if it does participants lose the points earned on that trial. To stop and collect the points, participants press the 'n' key on the keyboard (labeled with an 'S' for stop). Doing so ends the trial and transfers the points earned on that trial to a permanent bank. The average number of pumps taken on nonexploding balloons is the common behavioral measure of risk taking (Lejuez et al., 2002).

Procedures. Participants first received 15 practice trials of the FGT, before completing a total of 200 trials (in blocks of 50). The mean of the uncertain option was set at $\mu = 115$, 130, or 145 with a fixed variance of $\sigma = 45$. We used these levels of μ and σ as they proved to promote the greatest variability between participants in Study 1. The number of dots in the certain option was set at $c = 130$. As in Study 1, participants were told each dot equaled 1 point. Half of the participants then completed the UPPS, DUDIT and AUDIT scales (set 1), the BART, and the DOSPERT, Sensation Seeking, drug use, and Sexual Risk Taking scales (set 2). The other half of participants completed the same scales in a counterbalanced order (set 2 first, the BART and then set 1). Finally, at the end of the session, all the participants completed another 200 trials of a perceptual version of the FGT (see Study 1), where participants were instead told to choose the option with more dots on average. We included this version to explore how well the decision type manipulation held up as a within-subject manipulation. This was a purely exploratory manipulation and our a priori plan was to use the preferential task in all of our analysis. In the end, behavior in the perceptual task closely mimicked behavior in the FGT, most likely because at this point participants ignored the perceptual instructions. Because our focus is on preferential choice, we excluded the perceptual task in this study from any further analysis.

The entire session lasted about 90 min. At the end of the session, participants received a monetary bonus based on the total number of points earned in the BART and in the FGT. The typical bonus was between $1–5.

Results

Initial analyses of the data revealed that we needed to exclude 2 participants from the analysis. One participant did not finish the study, and one participant responded faster than 0.250 s on a majority of the trials during the FGT. Thus, all analyses are based on a sample of 124 participants.

Behavioral analysis. Figure 8 displays the choice proportions and RTs at both the average (solid black circles) and the individuals level (small gray circles). The unfilled circles and error bars show the posterior predictive model fits of the DDM to the data, which we will return to shortly. As in Study 1, participants were more likely to choose the uncertain option when the mean number of dots between the fixed reward and risky gamble increased (b = 0.39, CI = [0.35, 0.42]). This risky preference for the uncertain option extended even to the condition where the uncertain option was disadvantageous, which closely tracks our previous results (Zeigenfuse et al., 2014). Response times were relatively insensitive to the mean number of dots in the uncertain option. Trial level analyses of the response times, in fact, suggested a very small (unexpected) increasing

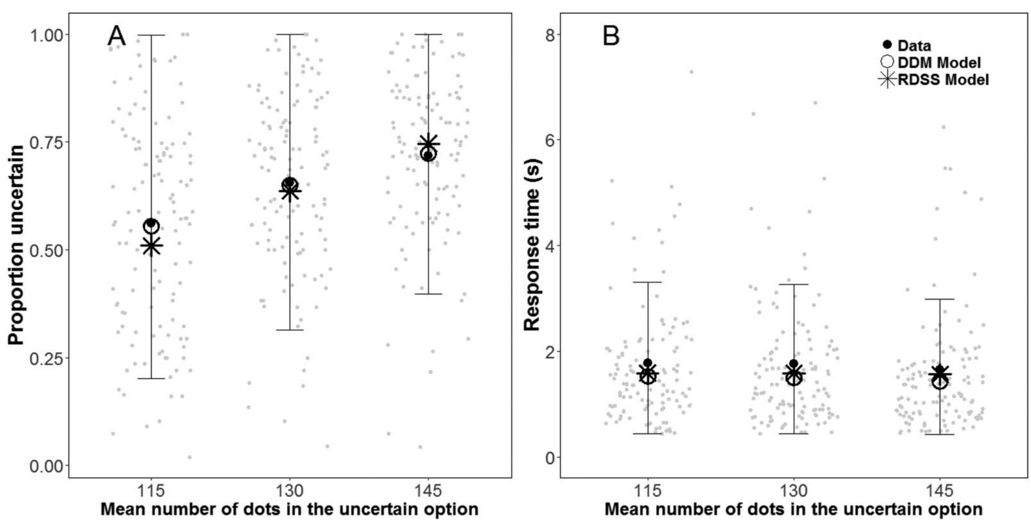

Figure 8. Choice proportions (A) and response times (B) in Study 2. The small solid circles are the average observed values. The gray points depict mean values for each participants. The unfilled circles are the posterior predicted means from the DDM model and the error bars reflect the 95% posterior predicted credible interval accounting for the variability between subjects. The stars show the posterior predicted means from the RDSS Model (see General Discussion).

trend of response time (b = 0.06, CI = [0.02, 0.09]) rather than taking an inverted U shape as in Study 1.

Drift diffusion analysis. We also fit the DDM to the choice and response times using a hierarchical Bayesian estimation framework to model both group level effects as well as individual-level data. The group-level parameters are summarized in Table 2. The fit of the model at the aggregate level is shown in Figure 8. Consistent with Study 1 and our past results, the risk-seeking behavior was isolated to the drift rate δ (see Table 2). That is, instead of exhibiting an initial bias to choose the uncertain alternative, the drift rate on average was positive, indicating information was processed to favor the uncertain option on average. In fact, even when the uncertain option was unattractive (μ = 115), the estimated drift rates were positive, indicating a tendency to accumulate information toward the uncertain option.

Reverse correlation analysis. To characterize the online processing of the samples of reward information, we conducted our reverse correlation analysis (see Figure 9). The average decision kernel $\bar{d}_{DK}$ across subjects was (M = 2.39, SD = 4.54) and credibly different from 0 (CI [1.67, 2.62]). Similar to Study 1, the mean decision kernel $\bar{d}_{DK}$ for each participant was also correlated with both the percentage of choosing the option with the higher expected value (r = .34, CI [.18, .49]; Figure 10A) and the change in the drift rate across the different levels of the mean of the uncertain option (r = .34, CI [.18, .49]; Figure 10B).

The average estimates of decision bias $\bar{d}_B$ reveals that there was no bias in how the sample information from the uncertain option was processed. The average value of $M = -0.01$ was not credibly different from 0 (CI = [−0.13, 0.30]), but unlike Study 1 was not credibly related to the drift rate in the μ = 130 condition ($r = -0.01$, CI [−.19,.17]). The decision kernel and decision bias were not associated with any other parameters of the DDM (see Appendix A).

We note here that participants in Study 2 were overall more risk seeking than in Study 1 in the FGT. Comparing the choice proportions in Study 1 (see Figure 3) with Study 2 (see Figure 8) shows that although choice proportions were similar in the (μ = 130) condition, in Study 2 they tended to still favor the uncertain option when it was less attractive (μ = 115). Note also the proportion of choices for the uncertain option when it was more attractive (μ = 145) were also lower than in Study 1. Together this pattern of results implies that participants in Study 2 were less sensitive to the payoff information. The DDM analysis yielded similar results: the drift rates in the (μ = 130) condition were similar in value, whereas the changes in the drift rates across the μ conditions were smaller in Study 2. Finally, the reverse correlation analysis also provided converging results when comparing the decision kernel $\bar{d}_{DK}$ and bias $\bar{d}_B$ measures. The average decision kernel $\bar{d}_{DK}$ was lower in magnitude in Study 2 compared with Study 1 (Contrast: $M = -2.51$; CI = [−4.76, −0.47]), but the decision bias was in the same range as Study 1 (Contrast: M = −0.44; CI = [−1.29, 0.74]).

Individual difference analysis. With these different measures of deliberation in hand, we examined how they were related to other traits and behaviors. Appendix A provides a complete correlation matrix for the FGT behavioral and reverse correlation measures, DDM parameter estimates, and individual difference measures. Here we focus on the correlations that are relevant to the question we set out to test, that is, to what degree does behavior in FGT correlate with risky behaviors, and other related measures, and does FGT account for unique variance in risky behaviors above and beyond other measures. At the behavioral level, there was little empirical support for a relationship between choice behavior in the FGT and measures of impulsivity and risk attitudes. None of the measures of the deliberation process from the FGT (from the DDM or the reverse correlation analysis) showed credible relationships with the individual facets of impulsivity from the UPPS scale or the risk attitudes from specific domains of risk taking in the DOSPERT. Thus, we have

Table 2
Estimated DDM Group-Level Parameters From the Posterior Distributions in Study 2

Parameter	Mean	95% Credible interval
Threshold, α	2.51	[2.32, 2.73]
Relative start point, β	.46	[.44, .49]
Nondecision time, τ	.11	[.10, .12]
Drift in μ = 115, δ_{115}	.21	[.13, .29]
Drift in μ = 130, δ_{130}	.40	[.32, .48]
Drift in μ = 145, δ_{145}	.56	[.48, .63]

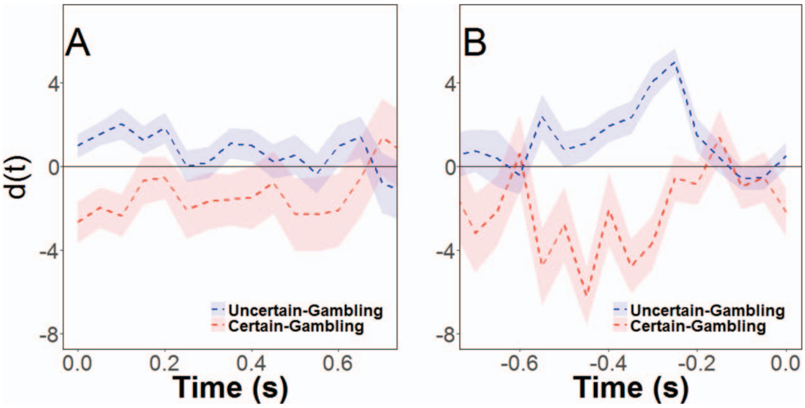

Figure 9. Time series of the deviation profiles (Equation 1) time locked to stimulus (A) or time locked to response (B) when $\mu = 130$ and $\sigma = 45$ for Study 2. The blue and red lines represent evidence when choosing the uncertain option $d_U(t)$ and evidence when choosing the certain option $d_C(t)$, respectively. See the online article for the color version of this figure.

collapsed across all these subscales forming one single measure of impulsivity (UPPS) and risk attitudes (DOSPERT).

The relationship between measures of deliberation from FGT to self-reported individual risk behaviors provided a somewhat different perspective to the individual differences. The mean decision kernel $\bar{d}_{DK}$ measuring sensitivity to the incoming samples of information in the FGT was negatively correlated with engaging in more problematic drinking behavior (AUDIT; Figure 10C; $r = -.22$, CI [−.39, −.05]), that is, individuals who drank more tended to be less sensitive to the displayed samples of payoff information. Furthermore, the start point parameter from the DDM (β) was correlated ($r = .23$, CI [.05, .39]) with the number of different types of drugs (polydrug) participants had tried, that is, participants who tried more drugs tended to have a greater initial starting bias to choose the uncertain option (Figure 10D).[7]

Trait levels of impulsivity as measured by UPPS were related to polydrug ($r = .29$, CI [.12, .45]) as well as AUDIT ($r = .23$, CI [.06, .39]). This raises the question as to what degree do measures of the deliberation derived from FGT account for unique variance in the self-reported measures of risky behavior above and beyond self assessments of trait impulsivity and risk attitudes? In fact, in each case they do. Simultaneously regressing polydrug onto start point bias β ($b = 0.19$, CI [0.03, 0.36]) and UPPS ($b = 0.25$, CI [0.09, 0.42]) showed that both were credible predictors of polydrug. The same is true for the decision kernel ($b = -0.18$, CI [−0.35, −0.01]) and UPPS ($b = 0.18$, CI [0.02, 0.36]) when predicting the AUDIT score. These results suggest that FGT-based measures of deliberation can provide complementary information to standard measures of trait impulsivity and risk attitudes in predicting real-world risky behaviors.

Rank-dependent Sequential Sampling

Together the DDM and the reverse correlation analysis isolate task and individual differences to online processing of dynamic information. To further synthesize these results and provide a more mechanistic framework, we turn to the rank-dependent sequential sampling (RDSS) model developed by Zeigenfuse et al. (2014). This model assumes that preference is formed by accumulating comparisons of the value of the certain option k to the values sampled from the uncertain option $y(t)$,

$$P(t) = P(t - \Delta) + \omega[y(t)] \cdot u[y(t)] - u(k). \quad (5)$$

[7] There was a relationship between estimates of nondecision time τ and problematic drug use as measured by DUDIT ($r = .31$, CI [.13, .45]). However, this correlation is likely spurious as it is largely driven by a few participants with high nondecision times. When we remove seven participants with $\tau > 0.5$ s, the correlation is no longer credible.

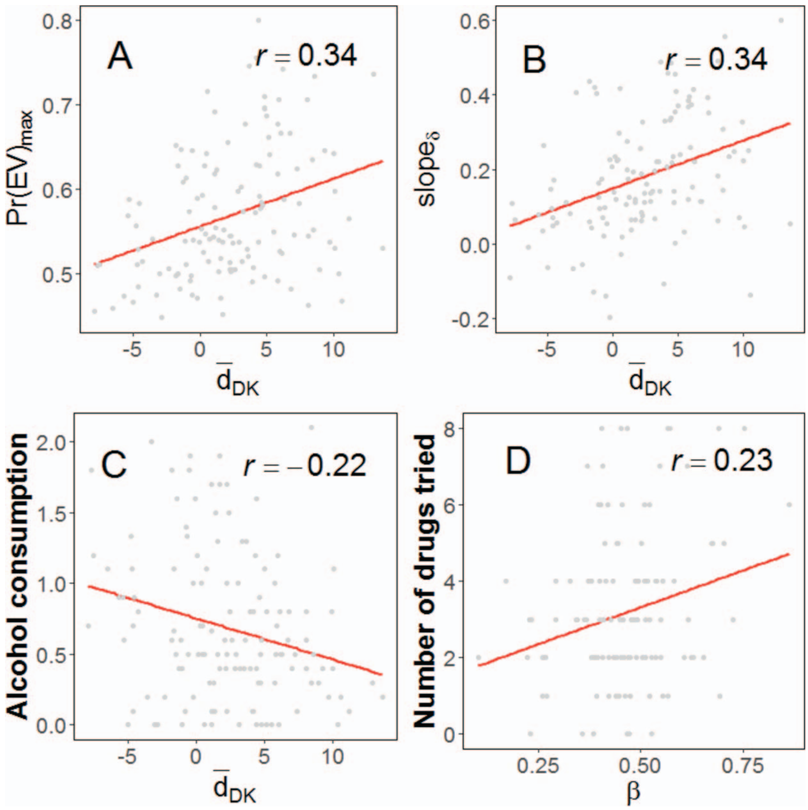

Figure 10. Correlation of behavioral measures, dot metrics, DDM parameters, and individual differences across participants. (A) The relationship between the average decision kernel and the proportion of times the higher expected value choice. (B) The relationship between the average decision kernel and the change in drift rates across offset conditions. (C) The relationship between the average decision kernel and alcohol consumption as measured by the AUDIT score. (D) The relationship between the individual relative start point and the number of drugs tried. See the online article for the color version of this figure.

Compared with the "base" model (Equation 2), Equation 5 adds two components to the accumulation process: a utility function $u(\cdot)$ and attentional weights $\omega[\cdot]$. The utility function captures how people evaluate monetary outcomes based on their subjective value or utility rather than their objective value. People typically exhibit decreasing sensitivity to payoffs as the magnitude of payoffs increases, which is modeled with a power function $u(x) = x^{\theta}$ with $0 < \theta < 1$.

The ω is the weight allocated to each sampled outcome from the uncertain option. In the standard evidence accumulation models each sampled outcome gets the same weight, $\omega = 1$. We allowed differential weights to capture possible fluctuations of attention. In particular, the weight allocated to each sampled value is a function of its likelihood and favorability within the stream (e.g., the normal distribution). This is done by making the sample weight a function of the (de)cumuluative rank from the normal distribution or the probability of obtaining an outcome of equal or higher value from the stream, $q = Pr(Y \geq y)$. The weight ω is approximated with the following function

$$\omega(y) \approx \frac{\gamma\delta}{F(y)}\exp\{-\delta[-ln(F[y])^{\gamma}]\}\{-ln[F(y)]\}^{\gamma-1} \quad (6)$$

where $F(y)$ is the decumulative rank of the outcome in the distribution. Equation 6 is actually the derivative of the Prelec (1998) probability weighting function, which is often used to

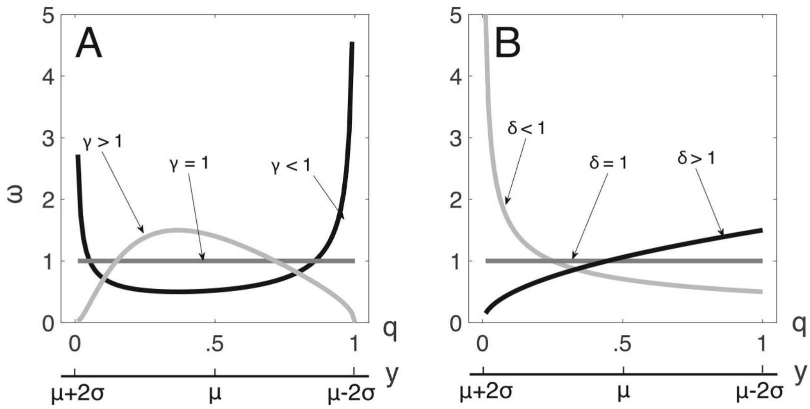

Figure 11. Possible rank-dependent sample weighting functions. The rank-dependent model allows the weight to be determined as a function of its (de)cumulative rank, $q = P(Y \geq y)$. The first horizontal axis denotes this decumulative rank q, and the second horizontal axis identifies the corresponding value y. Thus, for a given stimulus in the FGT the values run from $\mu + 2\sigma$ to $\mu - 2\sigma$. The weight given to each potential outcome are determined by two parameters γ and δ. Panel A illustrates how the parameter γ controls the sensitivity to extreme outcomes for a given value of δ, and Panel B illustrates how the parameter δ controls sensitivity to the magnitude of the outcomes for a given value of γ. In panel A $\delta = 1$ and $\gamma =$ 0.5, 1, or 1.5. In panel B $\gamma = 1$ and $\delta = 0.5$, 1, or 1.5.

capture the nonlinear impact probabilities (and subjective probabilities) have on choice in decisions under risk and uncertainty (Luce, 2000; Wakker, 2010 see Appendix B for a formal derivation). Figure 11 illustrates the properties of this function for different values of γ and δ. Panel A shows that γ controls the sensitivity to different ranges of outcomes. As γ goes below 1 the decision maker becomes more sensitive to extreme events, and as γ goes above 1 the decision maker become sensitive to moderate events. Panel B shows that the δ parameter controls sensitivity to either high magnitude outcomes ($\delta < 1$; optimism) or low magnitude outcomes ($\delta > 1$; pessimism).

We specified the rank-dependent model similarly to the DDM so that preference was accumulated over time until reaching a threshold at which point the appropriate choice was made. We parameterized the RDSS with a relative start point (β), a threshold separation parameter (α), and nondecision time τ (see Table 1), and fit this rank-dependent sequential sampling model at the individual level to the choice and response times from both Study 1 and Study 2 using Bayesian estimation techniques (see Appendix A).[8] The key difference between the RDSS model and the DDM is that the drift rate δ is no longer a free parameter independent from the stimulus. Instead in the RDSS the drift rate is determined at the trial level by the properties of the stimulus, and other parameters characterizing how the participant evaluates and attends to the sampled outcomes. Note also that we have parameterized the RDSS so that when θ, γ, and δ, are all set to 1, the RDSS reduces to a DDM where the drift rates are the standardized mean difference between the uncertain and certain option.

Table 3 lists the mean and standard deviation of the parameters across participants. One thing to note is that the mean parameters for the threshold separation α, and relative start point β correspond closely to the estimates from the DDM analysis (see Figure 4 and Table 2). The close correspondence between posterior predictive fits of the model to the choice and response time data are shown in Figures 3 and 8 (the asterisks). Note, for instance, that the RDSS is able to account for the peak in the response times that occurs not when the uncertain and certain alternative are equally attractive ($\mu =$

[8] In principle, the model can be fit using the actual observed samples. However, model recovery analyses showed that our study designs were inadequate for accurate parameter recovery.

Table 3
Mean (SD) of the Parameters From the Rank-Dependent Sequential Sampling Model

Parameter	Gambling	Perceptual	Gambling, Study 2
Sensitivity to extremes, γ	.97 (.45)	1.19 (.44)	.88 (.31)
Sensitivity to magnitudes, δ	.78 (.31)	.89 (.25)	.67 (.33)
Threshold separation, α	2.17 (.46)	2.04 (.38)	2.39 (.90)
Relative start point, β	.52 (.08)	.53 (.05)	.46 (.12)
Nondecision time, τ	.261 (.093)	.300 (.089)	.190 (.141)

130), but when the uncertain alternative is a bit less attractive. This can be a difficult property for diffusion models that set the drift rate as a function of the mean difference to account for (Teodorescu et al., 2016). However, the greater sensitivity to extremely favorable payoffs in the RDSS gives rise to this peak. In sum, we take this as converging evidence that the model is accurately capturing the choice process.

Figure 12 shows the differences in the sample weights used in the gambling and perceptual conditions. It shows that in the gambling condition participants placed more weight on the extreme favorable events. This explains why the drift rates from the DDM analysis pointed more strongly toward the uncertain alternative, particularly when the uncertain alternative was unfavorable. It also explains why the decision kernel was lower for the gambling conditions as participants in the gambling condition downweighted most of the incoming information.

In terms of parameter estimates, in Study 1 relative to the perceptual condition the gambling condition had a lower (though not credibly so) estimate of $\gamma(M_{\text{diff}} = -0.23$, CI = [−0.55, 0.08]), implying more sensitivity to extreme events. The gambling condition also showed a lower (though also not credibly so) $\delta(M_{\text{diff}} = -0.13$, CI = [−0.29, 0.03]), implying more attention to favorable outcomes. These effects become much more pronounced when comparing Study 2's estimates to Study 1's perceptual condition, with Study 2 having much lower estimates for $\gamma(M_{\text{diff}} = -0.35$, CI = [−0.56, −0.14]), and $\delta(M_{\text{diff}} = -0.23$, CI = [−0.36, −0.10]).[9]

In sum, the RDSS further synthesizes the results from the DDM and reverse correlation analyses by showing that in the gambling condition participants are both less sensitive (particularly to intermediate events) and biased to attend to more extreme positive events. Importantly, the comparison with the perceptual condition helps rule out that these effects are simply attributable to perceptual processing of the stimulus (Kahneman & Tversky, 1984) or how individuals process numerical information (Schley & Peters, 2014).

General Discussion

Across two studies we sought to better understand the deliberation process during preferential choice. We did this using the FGT in which participants made decisions between a certain and an uncertain option. A key feature of the FGT is that it explicitly provides a stream of information that individuals can use to form a preference between the options. In this case, the information is the possible payoffs (indicated by the number of dots in the display) that the uncertain option can generate. Comparing choices in the FGT with its perceptual analog showed that while both decision types (preferential and perceptual) were well described by a sequential sampling process, there were also systematic processing differences. The DDM analysis isolates the differences to the drift rates, which exhibited a biased accumulation of evidence in favor of the uncertain option. These results converge with past studies of a similar

[9] Correlating the RDSS parameters with measures of individual difference in Study 2 showed that the γ parameter measuring sensitivity to different ranges of outcomes was correlated (but not credibly so) with the number of drugs tried (r = 0.17, CI [−0.001, 0.34]), and the correlation between number of drugs tried and initial bias β reduced to (r = 0.14, [−0.03, 0.31]). This implies that some of the risk-seeking tendency captured by the start point in the DDM may be due to other factors. However, a limitation of the RDSS is that individual differences in payoff sensitivity θ is not accounted for. Nevertheless, these potential relationships call for future work in terms of individual differences in deliberation.

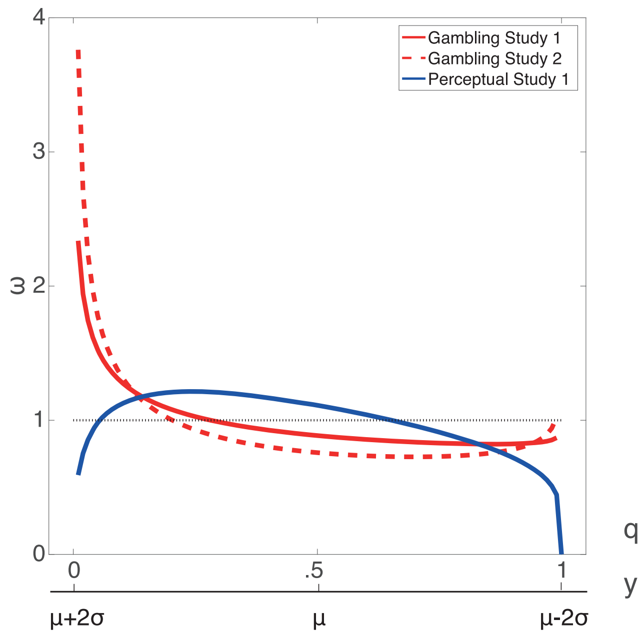

Figure 12. Estimated sample weight function from the average parameter estimates listed in Table 3. See the online article for the color version of this figure.

type (see also Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014).

To go beyond the DDM approach for characterization deliberation, we employed a reverse correlation technique to examine how different choices are related to the observed samples of information, and found that people were less sensitive to the stream of incoming information during preferential choice than perceptual choice. Besides between-task differences, we also investigated how individual differences in the properties of deliberation during FGT were related to real world risky behavior and attitudes. We found that participants' initial starting point of evidence accumulation toward choosing the uncertain option was related to drug use and their sensitivity to the incoming information was related to alcohol use.

Finally, we explained these results in terms of a rank-dependent sequential sampling model that places different attentional weight on the sampled outcomes, which are then accumulated over time to form a preference. The weights are determined by the likelihood and the favorability of the different outcomes, and are analogous to the probability weights used in rank-dependent expected utility models (e.g., Luce, 2000; Quiggin, 1982; Tversky & Kahneman, 1992). This model showed that in the FGT participants placed more weight on high magnitude events as compared with the perceptual condition. Overall, our extensive behavioral and modeling analysis gives rise to a richer and more mechanistic understanding of the deliberation process in preferential choice.

Maximizing Behavior

A question that arises is why preferential choice patterns vary between Study 1 and Study 2 (and in part Zeigenfuse et al., 2014)? One possible explanation is that feedback and experience can lead to greater maximization of expected value (and hence less biased responding; Erev & Roth, 2014; see also Cox & Grether, 1996; List, 2003; List, 2004; Shogren et al., 2001). Indeed, once the practice trials are included, participants in Study 1 completed a higher number of trials (990) than in Study 2 (215) or in Zeigenfuse et al. (2014) (840). To examine whether any learning effects impacted differences in performance between task, we split the trial data in Study 1 into thirds (first 320 trials, next 320 trials, and last 320 trials) and compared the choice proportions for the uncertain option. In the first third of trials, when the uncertain option was least attractive (μ = 100), participants chose the uncertain option in the gambling (M = 0.27, SD = 0.38) more frequently than in the perceptual condition (M = 0.15, SD = 0.32), leading to a mean difference of 0.12 CI = [0.01, 0.24]. This difference between tasks were not credible in later trials, thus consistent with the idea that feedback and experience can lead to greater maximization of expected value. Furthermore, it suggests an intriguing possibility where the FGT and its measures of the deliberation can be used in the future to understand how feedback and experience can change deliberation.

Value-Based Psychophysics

The FGT broadly fits within a methodology that Tsetsos et al. (2012) called value-based psychophysics. This approach seeks to map out how rewards are processed giving rise to a preference and ultimately a choice. For this purpose the comparison with a perceptual analog can be quite informative. In fact, Tsetsos et al. (2012) also compared perceptual and preferential decisions, but did not find a difference between decision types. However, their tasks differed in several ways from ours including a slower rate of sampling (every 0.5 s vs. every 0.05 s), presentation of values with symbolic numbers, and the requirement of a simultaneous comparison of samples from two uncertain options. It is not clear which of these methodological differences are responsible for the discrepant results, though we note that Dutilh and Rieskamp (2016) also found a difference between perceptual and preferential choice when the values were presented as a single static sample of numerical counts of dots (much like the FGT). This implies that it may be easier to identify a difference with values presented in an analog fashion than symbolic numbers.

Despite the differences, there are also some commonalities between our study and Tsetsos et al. (2012). Importantly, both studies observed risk-seeking choices when the two alternatives were matched in terms of expected values. This result conflicts with the canonical finding that people are often risk averse for gains (except for gambles with rare highly desirable payoffs; Kahneman & Tversky, 1979). One reason for the difference may be how individuals learn about the gambles. In our study and in Tsetsos et al. (2012), they learn about the gambles from experience, whereas in other research individuals learn about the properties of the gambles from summary descriptions. Such a difference in presentation format can often lead to systematic differences in how people make choices (Barron & Erev, 2003; Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig, Barron, Weber, & Erev, 2004; Hertwig & Pleskac, 2010; Weber, Shafir, & Blais, 2004). For instance, learning from experience may help highlight possible outcomes (see also Ludvig, Madan, & Spetch, 2014). Indeed Tsetsos et al. (2012) show that participants allocate differential weight to samples based on their local relative rank between options (see also Tsetsos et al., 2016). Our RDSS model has a similar feature, though we determined the rank by the global relative rank within the option.

The RDSS model makes some intriguing progress toward a more complete process level understanding of deliberation. More work is needed though. For instance, in terms of the weighting scheme, a more plausible assumption may be that the weights are based on the rank in the current sample history. However, our model recovery analysis showed limited success in estimating the weights this way. Tasks with controlled response times and longer sample streams appear to do better. Even more promising is to directly manipulate the temporal distribution of samples to better test how particular events impact choice (e.g., Teodorescu & Usher, 2013; Tsetsos et al., 2011). In general, a value-based psychophysics approach combined with process-level modeling offers a promising method to further disentangle the process of deliberation during preferential choice.

Individual Differences

There has been a recent concern that decision-making models do not properly account for heterogenity in preferences (Regenwetter & Robinson, in press). To address this concern, we can start to investigate the sources of this variability (Hertwig & Pleskac, 2018). Thus we sought to investigate to what degree our measures of the deliberation process are associated with individual differences both within the task and with other aspects of decision making in the real world. Although our results indicate that there was little relationship between the deliberation process and self-reports of trait impulsivity and risk attitudes, they did reveal a unique relationship to self-reported substance use.

From a traditional construct-validation perspective, the lack of credible relationships between measures of seemingly similar constructs might be worrisome (Campbell & Fiske, 1959). However, from a process-focused perspective, such results are intriguing, particularly when both measures independently relate to a relevant criterion variable, suggesting that they are capturing different aspects of the complex construct of substance use (Bornstein, 2002). Whereas a questionnaire such as the UPPS assesses a respondent's awareness of their own tendencies toward deliberative or impulsive behaviors, the FGT assesses the underlying cognitive processes that give rise to such behavioral tendencies. Moreover, even within the FGT, not all measures of substance use were associated with the same aspects of the deliberation process. Recall that alcohol abuse was related to decreased sensitivity to the online processing of payoff information whereas drug use was related to the initial start point during deliberation between the uncertain and certain option. These results certainly need to be replicated, but they may reveal potential computational phenotypes for these different behaviors that deserve future investigation (Montague, Dolan, Friston, & Dayan, 2012). For instance, perhaps the association between drug use and the relative start point reflect a sensitivity to cues, like the labels for the uncertain and certain option, which may provide new insights on how substance use could result from cue-induced urge (Bonson et al., 2002; Ehrman et al., 1992). An exciting dimension of the FGT is that the task and the computational model are amenable to functional neuroimaging and other neuroscientific investigations thus providing a possibility to characterize these computational differences at the neural level.

Conclusion

In summary, we conducted two studies to characterize information usage during preferential choice, in situations commonly referred to as decision making under uncertainty. We showed that deliberation during preferential choice can be modeled by a sequential sampling process, but with important differences from the sequential sampling process during perceptual choice. In particular, using a novel reverse-correlation methodology, we found that individuals are less efficient in processing the samples of information when making a preferential choice. At the same time, we also found that not only were there group and task differences in this process but also measurable individual differences in how people deliberate. These differences, in turn, were associated with risky substance use, a relationship that provided complementary information to standard measures of trait impulsivity and risk attitudes. Finally, an extension of the sequential sampling model using rank-dependent utility has the potential to synthesize the behavioral and modeling results while offering a mechanistic account of the decision machinery. Taken together, we believe these results demonstrate the critical role deliberation can play in risk-taking behavior and validate our methodological and computational framework for investigating this process.

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Appendix A

Correlation Matrix for Individual Difference Analysis in Study 2

Table A1
Pearson's Correlation for FGT Behavioral and Reverse Correlation Dot Measures, DDM Parameter Estimates, and Individual Difference Measures in Study 2

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Pr(UA)	.64	.20															
2. $Pr(EV_{max})$	.57	.08	−.27[a]														
3. $\bar{d}_{DK}$	2.28	4.57	.04	.34[a]													
4. $\bar{d}_{B}$	−.01	2.67	−.13	.00	−.47[a]												
5. α	2.40	.78	.06	.24[a]	−.04	−.03											
6. β	.46	.12	.50[a]	.05	.09	.01	.00										
7. τ	.20	.15	−.13	.30[a]	.06	.12	.23[a]	−.06									
8. δ_{130}	.56	.35	.58[a]	−.13	−.01	−.06	−.15	.10	−.07								
9. $slope_{\delta}$	.24	.21	−.12	.76[a]	.34[a]	−.05	.07	.07	.21[a]	−.42[a]							
10. BART	35.63	13.01	.20[a]	.19[a]	.15	−.12	.08	.19[a]	.06	.05	.10						
11. UPPS	2.22	.41	.13	.05	−.13	.09	.03	.08	.00	.05	.02	−.02					
12. SS	.57	.17	.08	.08	−.02	−.01	.04	.06	−.13	.00	.13	−.12	−.07				
13. DOSPERT	2.68	.48	.02	−.10	.00	.11	.00	.06	.00	−.05	−.07	−.11	−.12	−.07			
14. Number of drugs	3.15	2.02	.16	.09	−.09	−.05	.04	.23[a]	−.02	.15	.03	.08	.29[a]	.01	.05		
15. DUDIT	.47	.67	−.04	.18[a]	.05	.05	.08	.11	.30[a]	−.10	.15	.17	.00	.09	.21[a]	−.06	
16. AUDIT	.71	.53	−.04	−.06	−.22[a]	.11	−.07	−.05	−.03	.08	−.03	−.04	.23[a]	.04	.03	.37[a]	.01

[a] Indicates the 95% credible interval did not contain 0.

Appendix B

Rank Dependent Sequential Sampling Model

The RDSS captures the hypothesis that each outcome that is sampled does not have equal contribution to the accumulation, but is weighted as a function of the outcome's likelihood of occurring and overall favorability. This hypothesis is typically captured using rank dependent utility models and their decision weight construct (Luce, 2000; Quiggin, 1982; Tversky & Kahneman, 1992; Wakker, 2010). According to rank dependent utility models, the subjective value of the uncertain option is

$$v = \sum_{i=1}^{n} \pi_i \cdot y_i^{\theta} \tag{B1}$$

where θ is the exponential parameter in the utility function, $y_1 < \ldots < y_n$ are the possible outcomes of the uncertain option ordered by desirability, and each π_i is the decision weight assigned to y_i.[10] The π_i are determined by the probability of obtaining an outcome at least as large as y, $q_i = Pr(Y \geq y_i)$. These decumulative probabilities are transformed by a probability weighting function to capture the nonlinear impact of probabilities on preference. A common function is the Prelec (1998) function

$$W(q) = \exp\left\{-\delta[-ln(q)]^{\gamma}\right\} \tag{B2}$$

[10] As most research in the behavioral decision theory, we will work with discrete gambles. Indeed the FGT uses a discretized normal distribution for stimulus generation. Alternatively one can work with differential calculus to make the derivations in the continuous domain.

(*Appendices continue*)

The parameter γ controls the curvature of the weighting function capturing sensitivity to changes in the ranks, and the δ controls the elevation of the function producing optimistic or pessimistic weights (Gonzalez & Wu, 1999). The probability weights π_i are determined by taking successive differences of the transformed decumulative probabilities,

$$\pi_i = W(q_i) - W(q_{i-1}). \tag{B3}$$

With $\pi_1 = W(q_1) - W(0)$. These decision weights reflect the marginal contribution of each possible outcome to the value of the option. We, however, for the RDSS do not want the marginal contribution but the individual contribution of the sampled outcome. To arrive at those it is useful to multiply Equation B3 by $\frac{p_i}{q_i - q_{i-1}}$ where p_i is the probability of outcome y_i. Note $p_i = q_i - q_{i-1}$ by definition, thus we are multiplying the constant 1 to the right side of Equation B3. Doing the multiplication leads to

$$\pi_i = p_i \times \frac{W(q_i) - W(q_{i-1})}{q_i - q_{i-1}}. \tag{B4}$$

The ratio on the right-hand side of Equation B4 is approximately equal to the derivative of the weighting function when p_i is small (see Equation 6). This factor reflects the sensitivity of the rank dependent value to each individual outcome. It is these factors that we use as outcome weights in the sequential sampling process so that,

$$\omega_i = \frac{W(q_i) - W(q_{i-1}).}{q_i - q_{i-1}} \tag{B5}$$

Zeigenfuse et al. (2014) showed that when the sample weights in rank-dependent sequential sampling process (Equation 5) are set using Equation B5, as the number of observations increases the average preference will approximate the rank dependent utility of the alternative (Equation B1). The average change in preference for each sample in the RDSS will therefore be equal to $d = \Sigma_{i=1}^{n} \pi_i \cdot y_i^{\theta} - k^{\theta} = v - k^{\theta}$. The variability in the change in preference is given by $\sigma^2 = \Sigma_{i=1}^{n} \pi_i (y_i^{\theta} - v)^2$. As a result, to fit the RDSS we can use the standard DDM formulization (see Chapter 4 of Busemeyer & Diederich, 2010) setting the drift rate δ for each gamble problem to $\delta = d/\sigma$.

According to the RDSS, a choice occurs when preference reaches a threshold. The uncertain option is selected when the upper threshold is reached, and the certain option is chosen when preference reaches the lower threshold. The drift rate is determined as above by the mean difference between the uncertain and certain option, the variance of the gamble, and the utility and sample weight functions. α has the same interpretation as the threshold separation in the DDM. Also similar to the DDM, the start point of the process is set by β, and a non-decision time τ parameter accounts for contributions from processes other than the deliberation.

Bayesian Estimation of RDSS

To estimate the model at the individual level, we used Bayesian estimation methods. We used truncated normals for our priors over the parameters,

$$\begin{aligned}
\gamma &\sim TN(1, .3, .01, 1.99)\\
\delta &\sim TN(1, .3, .01, 1.99)\\
\alpha &\sim TN(1, 1, .01, 3)\\
\beta &\sim TN(.5, .2, .1, .9)\\
\tau &\sim TN(.15, .05, .01, \min(RT) - .01).
\end{aligned}$$

Where a $TN(m, s, l, u)$ is the truncated normal with a mean m, standard deviation s, lower bound l, and upper bound u. The term $min(RT)$ refers to minimum observed response time for the subject. These are vague priors. We have explored different specifications of priors and found our estimates to be robust with reasonable changes in the priors.

(*Appendices continue*)

For each participant we estimated the model using the differential evolution Markov Chain Monte Carlo (DE-MCMC) algorithm specified in Matlab to estimate the posterior distributions (Turner, Sederberg, Brown, & Steyvers, 2013). Our estimation method used 24 chains with 3250 iterations for each chain after a burn in of 500 iterations. We excluded observations for which the response time was less than 250 ms.

Preliminary model recovery analyses showed that the event sensitivity parameter γ(Equation 6) and the reward sensitivity parameter θ from the utility function ($u(x) = x^{\theta}$) could not be simultaneously estimated. Thus, we set $\theta = 1$. Preliminary analyses with the model showed that the variability in the uncertain option was insufficient to account for the choice probabilities and response times. Therefore, consistent with Zeigenfuse et al. (2014), we added an additional level of noise to each option. Specifically, we added a normal random variable with a mean of 0 and standard deviation of 30 to each uncertain option, $\epsilon \sim N(0, 30)$.

Received May 21, 2017
Revision received September 5, 2017
Accepted October 14, 2017 ■