Running Head: INFORMATION OVERLOAD OR SEARCH-AMPLIFIED RISK

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BRIEF REPORT

Information Overload or Search-amplified Risk? Set Size and Order Effects on Decisions from Experience

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Abstract

How do changes in choice set size influence information search and subsequent decisions? Moreover, does information overload influence information processing with larger choice sets? We investigated this by letting people freely explore sets of gambles before choosing one of them, with choice sets either increasing or decreasing in number for each participant (from 2 to 32 gambles). Set size influenced information search, with participants taking more samples overall but sampling a smaller proportion of gambles and taking fewer samples per gamble when set sizes were larger. The order of choice sets also influenced search, with participants sampling from more gambles and taking more samples overall if they started with smaller as opposed to larger choice sets. Inconsistent with information overload, information processing appeared consistent across set sizes and choice order conditions, consistently favoring gambles with higher sample means. Despite no evidence for information overload, changes in information search did lead to systematic changes in choice. People who started with smaller choice sets were more likely to choose gambles with the highest expected values, but only for small set sizes. For large set sizes, the increase in total samples increased the likelihood of encountering rare events at the same time as the reduction in samples per gamble amplified the effect of these rare events when they occurred—what we call search-amplified risk. This led to riskier choices for individuals whose choices most closely followed the sample mean.

Keywords: information overload, decisions from experience, risk, choice overload

From what we wear to how we entertain ourselves, we are constantly choosing among sets of alternatives. It is as if our lives are merely extended department store experiences, where we commonly make hundreds of choices before we reach the checkout aisle. Though these decisions often rely on past experience—for which there is ample literature (Hertwig & Erev, 2009; Hertwig, Barron, Weber, & Erev, 2004; Rakow, Demes, & Newell, 2008; Ungemach & Chater, 2009)—they have two important qualities that separate them from the dominant focus of prior research. First, our choices often involve more than two options—sometimes ranging into the hundreds (consider cheeses in French supermarkets)—and therefore potentially lead to choice set size effects predicted to involve information overload (Iyengar & Lepper, 2000; Mick, Broniarczyk, & Haidt, 2004; Schwartz, 2004; Scheibehenne, Greifeneder, & Todd, 2010). Second, our choices are often sequential, with the order of choice set sizes varying from one decision to the next (e.g., there may be more kinds of cheese than bananas). As a result, the order of choice sets may lead to choice set size effects carrying-over from one decision to the next (Levav, Reinholtz, & Lin, 2012; Levav, Heitmann, Herrmann, & Iyengar, 2010), pointing to the need for a more fine-grained and practically-relevant study of information processing under choice overload.

Here we investigate the influence of choice set size and choice order effects on information search and information processing. In particular, we focus on the prospect that information overload may influence search, choice, and the role of infrequent, risky events. This combines two previously independent literatures: consumer choices over multiple options and decisions from experience. Before describing our study in more detail, we briefly review the relevant findings from these two literatures.

Information Overload and Choice Order Effects

Choices with many options have been suggested to lead to *choice overload*. As examples, choices over many options have been shown to lead to foregoing decisions or choosing simpler options (Chernev, 2003; Greifeneder, Scheibehenne, & Kleber, 2010; Iyengar & Kamenica, 2010; Iyengar & Lepper, 2000; Reutskaja & Hogarth, 2009; Schwartz, 2004; Shah & Wolford, 2007). In addition to arguments based on regret and satisfaction (e.g., Iyengar & Lepper, 2000; Schwartz, 2004), the predominant explanation for choice overload effects has been *information overload* (e.g., Jacoby, Speller, & Kohn, 1974; Lee & Lee, 2004; Schwartz, 2004). As options increase in number, efforts to make rational decisions may succumb to the overwhelming amount of information processing required. In such cases, too many options may influence information search, information processing, or both. Indeed, choice overload effects may represent a cognitive limit on models of choice developed for small set sizes.

However, claims regarding choice overload have been equivocal. For example, an attempt to replicate the jam study of Iyengar & Lepper (2000) found no evidence of choice overload (Scheibehenne, 2008). A more recent meta-analysis found that the effect size based on more than 60 studies of choice overload is "virtually zero" (Scheibehenne, Greifeneder, & Todd, 2010). In addition to the studies in the meta-analysis, still further studies have continued to find inconsistent support for choice overload (e.g., Arunachalam, Henneberry, Lusk, & Norwood, 2009; Bundorf & Szrek, 2010). These conflicting results call for a more detailed analysis of the information processing underlying choice over many options.

In addition to choice overload, choice set size can also influence behavior through potential carryover effects. Recent work on *choice order effects* has shown that varying the order of choice environments—e.g., making choices among many options before choices among fewer options—can influence choices even after set sizes have decreased (Levav et al., 2012; Levav et al., 2010). For example, a study by Levav and colleagues (2012) found that when people chose songs among varying sizes of music selections, they listened to fewer songs before choosing a song when set sizes varied from many to few songs than when set sizes varied from few to many. Similarly, in a naturalistic study on car buyers, buyers who saw vehicle options (e.g., engine types and gearshift styles) were more likely to choose the default option if they experienced choices with many (as opposed to few) alternatives first (Levav et al., 2010).

Taken together, the above results suggest the consequences of large choice sets potentially lead to information overload and may, in addition, carry over to smaller choice sets. Unfortunately, finding evidence for information overload at the level of information processing has been difficult because previous research in this area has dominantly looked at choices among items without objective measures of quality (e.g., songs, pens, and chocolates). Subjective choice criteria have also made it difficult to examine other aspects of choices, such as expected value and risk. To answer such questions requires a quantitative decision paradigm.

Decisions from Experience

The *sampling paradigm,* used in research on decisions from experience, provides a well-tested method for independently studying information search, information processing, and subsequent decision making (Hertwig & Erev, 2009). Here, we refer to our paradigm of interest as the sequential sampling paradigm to distinguish it from other sampling paradigms (e.g., Hilbig & Glöckner, 2011). With the sequential sampling paradigm, people sample ad lib from two gambles with initially unknown payoff distributions—exploring them—before choosing the gamble that will determine their final payoff. Sampling involves selecting a gamble and witnessing an outcome sampled from its payoff distribution. For example, one distribution could offer $32 with probability 0.10, or 0 otherwise; the other distribution could offer $3 for sure. Sampling might then lead a participant to experience 0, 0, 32, 0 in the first distribution and 3, 3, 3 in the second, before making a final decision. Thus, like the jam study in Iyengar & Lepper (2000), participants can sample items as much as they like and then choose the one they most prefer. However, the sequential sampling paradigm allows us to investigate not only how decision environments influence information search and subsequent choice, but also how the outcomes of the search influence the subsequent decisions (e.g., Hau, Pleskac, Kiefer, & Hertwig, 2008).

Though studied dominantly with set sizes of two, the sequential sampling paradigm can be scaled to include more gambles available for sampling. This is the approach we take here. Nonetheless, even with two samples, the sequential sampling paradigm provides several observations relevant to our current investigation. First, information search foreshadows decisions (Hau et al., 2008; Hills & Hertwig, 2010). In particular, people who sample more and switch less often between gambles are more likely to choose gambles with higher expected values. Because choice order effects may lead to more sampling for individuals who sample few items first (Levav et al., 2012), it follows that these individuals may also be more likely to choose gambles with higher expected values.

How sampling scales to large choice set sizes is not clear, and leads to the second insight from previous work on the sequential sampling paradigm. In decisions from experience people make choices that suggest they may underweight rare events (Hau et al., 2008; Hertwig et al., 2004; Hertwig & Erev, 2009; Ungemach & Chater, 2009). When presented with two gambles, people often choose as if rare events occur less frequently than their true probability. In part, this is explained by small samples (Hertwig et al., 2004; Rakow et al., 2008), with individuals simply failing to experience rare events due to a paucity of sampling. In other words, the apparent underweighting is not always necessarily a result of biased weighting of observed outcomes, but may reflect proper weighting of small samples. How will this influence choices when set sizes are large? In Levav et al. (2012), increasing set sizes of songs led to less information sampled per song, but more songs sampled in total. If this is the case in the sequential sampling paradigm with many gambles, then we can predict that participants will be more likely to experience a rare event because they will sample more risky gambles. However, they will have sampled less from any individual gamble. Thus, with large set sizes, rare events will be encountered not because of intensive sampling with a single gamble—which would provide good information about the expected value—but because of distributed sampling over many gambles. In part, this will amplify differences between gambles—as predicted by *the amplification effect* (Hertwig and Pleskac, 2008)—but importantly for large set sizes, the gambles with the highest sample mean will often be the riskiest gambles—what we call *search-amplified risk*.

The Present Study

The present study addresses the above issues using a simple manipulation of the sequential sampling paradigm—changing the order of choice set sizes from few-to-many (2, 4, 8, 16, and 32 gambles) or from many-to-few (32, 16, 8, 4, and 2 gambles). Our primary concerns are how choice set size and choice order influence information search, information processing, and the impact on choice quality. This study investigates three predictions that follow directly from the research outlined in the introduction: 1) Choice order and choice size effects will influence information search, leading to more search in the few-to-many condition than in the many-to-few condition, and more samples overall, but fewer samples per gamble as set sizes increase, respectively, 2) Differences in information search induced by choice order effects will lead to choices for gambles with higher expected values in the few-to-many than in the many-to-few condition, especially when set sizes are small. Our last prediction 3) depends on the influence of information overload: If the theory of information overload applies in the sequential sampling paradigm with large choice sets, then this will lead to choices *less* in line with expected value maximization as choice sets grow larger due to failures of information processing; on the other hand, if the theory of information overload does not apply—with decisions for large choice sets appearing to rely on the same information as they do for small choice sets—then we predict that search-amplified risk will lead to choices favoring riskier gambles.

Method

Participants were 64 undergraduates from the University of Warwick, who received course credit and monetary compensation (ranging from £1 to £5) based on their choices. Participants sat in front of a computer and saw the following instructions:

> “Each box is a money machine that pays off a certain amount with a certain probability. You can sample these boxes as many times as you want to try and determine which box you want to choose to receive your payoff. During the sampling phase, you will not receive any payoffs. When you decide to make a final decision, you will get one draw from this gamble 'for real' as your payoff for that set of gambles.”

Following this, participants saw an array of boxes with the instruction to “sample the options until you are ready to choose one.” Clicking on a box sampled and presented an outcome from its probability distribution for 2 seconds. Participants continued sampling until they indicated they were ready to make a final decision. Then they were instructed to “choose the option from which you would like to receive a final payoff” and allowed to click on one of the boxes from the same array. Participants were randomly assigned to either the *many-to-few* or the *few-to-many* conditions, representing choice set sizes of 32, 16, 8, 4, and 2 gambles, experienced in that order, or the opposite, respectively. Thus, we employed a 2 (conditions: few-to-many or many-to-few between subjects) x 5 (set sizes: 32, 16, 8, 4, and 2 gambles within subjects) mixed design.

Payoffs within a choice set were constructed as follows. An initial value, *h*, was randomly sampled for each gamble from a distribution with mean 5 and standard deviation 1. Then payoff probabilities were assigned each gamble by randomly assigning values from an equal spaced grid, with grid size proportional to the number of gambles in the choice set: for two gambles, 0.66 and 0.33; for four gambles, 0.2, 0.4, 0.6, and 0.8; and so on. Finally, the initial value, *h*, was divided by the probability to produce the non-zero payoff, rounded to the nearest integer. For example, a gamble with an *h* of 5.21 and probability of 0.2 would payoff 26 with probability 0.2, otherwise 0. Note that because of the way the choices are created (trading off maximum outcome with probability of payoff), no single choice will dominate the others on maximum value, median value, and expected value simultaneously. Participants in both conditions sampled from the same payoff distributions for each set size.

Results

The Impact on Information Search

Both choice order and choice set size influenced information search for a variety of measures (Fig. 1). Participants took more samples with larger set sizes and took more samples in the few-to-many than the many-to-few condition (Fig. 1a). Predicting total sample size, there is a main effect for set size ($\chi^2(1)=83.63$, $p<.001$) and for condition ($\chi^2(1)=5.41$, $p=.020$)[i]. The proportion of gambles sampled was also affected (Fig. 1b). Proportionally fewer gambles were sampled as set size increased ($\chi^2(1)=24.75$, $p<.001$) and participants in the few-to-many condition sampling proportionally more gambles than those in the many-to-few condition ($\chi^2(1)=5.87$, p=.015).

Participants in the few-to-many condition also sampled each gamble more times, despite sampling from more gambles overall (Figure 1c). Results predicting samples per gamble show a significant main effect for set size ($\chi^2(1)=49.58$, $p<.001$) and for condition ($\chi^2(1)=5.13$, $p=.024$), and a significant interaction ($\chi^2(1)=17.80$, $p<.001$). As shown in Figure 1c, both conditions become more similar as set sizes increased, suggesting that as choice set size increased, the influence of large set sizes overshadowed choice order effects. Finally, participants tended towards switching between gambles less frequently per sample than participants in the many-to-few condition, though this was not significant at a threshold of $p < 0.05$ (Figure 1d, $\chi^2(1)=3.74$, $p=.053$). However, both conditions switched between gambles more often as set sizes increased ($\chi^2(1)=54.37$, $p<.001$). Taken together the above results strongly support our prediction that choice order and choice set size have a systematic influence on information search.

The Impact on Choice Value

Did the above changes in information search also influence participants' choices with respect to the expected value? To evaluate this, we computed for each decision the relative rank of the expected value for the chosen gamble. Here we define the relative rank as equal to $\frac{n-r}{n-1}$, where r equals the rank of the chosen gamble, and n equals the choice set size. Figure 2a shows an influence of choice order and set size on the relative rank of the expected value for the chosen gambles.[ii] Results of a beta regression including both condition and log set size finds a non significant effect for set size ($b=0.11$, $p=.068$), a significant effect for condition ($b=0.74$ $p<.001$), and a significant interaction between condition and set size ($b=-0.26$, $p=.001$). Taking each condition individually, the few-to-many condition shows a significant effect of set size ($b=-0.16$, $p=.005$), whereas the many-to-few condition does not ($b=0.11$, $p=.073$). In comparison with random choice (relative rank = 0.5), one-sample t-tests indicate that only the few-to-many condition differs significantly from random choice and only when there are as few as 2 ($t(30)=5.04$, $p<.001$) or 4 ($t(31)=3.14$, $p<.001$) gambles. For both conditions, with larger set sizes the probability of choosing gambles with ranks higher than 0.5 is no different than would be expected from random choices (using a Bonferroni corrected criteria of $p>.01$).

In sum, choice order influenced decision quality with respect to the expected value as we predicted. In particular, the few-to-many condition chose gambles with higher expected values, consistent with their increased information search. However, during or after making decisions among large set size, participants were no better than random at choosing gambles with higher expected values.

The Impact on Information Processing

Our last prediction depends on whether or not information overload influenced information processing. To evaluate information processing, we used choice models to predict choices based on the outcomes of the information search phase (e.g., Hau et al., 2008). Note that the experiment was not designed to discriminate among the best choice models, as each participant only makes one choice for each set size and samples are small for the largest set sizes. Thus, the most well supported models from prior research are indistinguishable. Instead, our experiment was designed to evaluate whether or not information processing becomes more susceptible to noise with large set sizes, as predicted by the information overload hypothesis. Here we present only a representative model from the best performing of those we tried: the sample mean (i.e., the natural mean or mean of experienced outcomes for a gamble, see Hau et al., 2008).[iii]

To provide a measure of how well outcomes predicted choice, we ranked gambles by the relative means of their outcomes. Figure 2b presents the relative rank of the chosen gamble, with respect to the sample mean, as a proportion of the ranks of other sampled gambles, i.e., $\frac{s-r}{s-1}$, where r equals the rank of the chosen gamble, and s

the number of sampled gambles. The results of a beta regression including both choice order and choice set size show that the two conditions did not differ in their sensitivity to the sample mean (b=0.27, p=.111), but were influenced by the set size (b=0.12, p=.019) with higher ranked gambles chosen for larger set sizes. Because the conditions were not different, we aggregated them to evaluate whether or not the relative ranks were significantly above 0.5. Results of one-sample t-tests comparing the aggregated relative rank with 0.5 for each set size were consistently p<0.001. Because participants chose higher ranked gambles as the number of gambles increased, this indicates that choices became even more systematic in favor of the sample mean as choice set size increased. This result indicates that choices did not become noisier with increased set sizes as predicted by the information overload hypothesis (Schwartz, 2004), but instead appear to have become even more consistent with the sample mean (possibly due to the amplification effect, Hertwig & Pleskac, 2008).

The Impact on Risky Choice

The above results show an effect on information search and choice, but they also reveal that choices did not become less systematic with respect to the information acquired for large set sizes. As we predicted in the introduction, in the absence of information overload, the observed changes in information search—i.e., more total sampling but fewer samples per gamble—should lead to search-amplified risk effects. To investigate this, we examined a measure of riskiness—the coefficient of variation (CV)—of the chosen gambles (Weber, Shafir, & Blais, 2004). Results of a beta regression using choice order and set size finds a significant effect of condition (b=-1.17, p<.001; Fig. 3a), no effect of set size (b=0.05, p=0.58) and a significant interaction effect (b=0.38, p=0.003). When taken individually, only the few-to-many condition shows a significant increase in CV (b=0.27, p<.001), whereas the many-to-few condition does not (b=0.04, p=.510). However, this result mainly reflects the lower coefficients of variation for the highest expected value options available in the smaller choice sets. Looking at the choice set sizes where this is not the case (8 or more options), a beta regression finds no relationship between a participant's sample mean ranking (e.g., Figure 2b) and the probability that their choices will return a zero payoff (i.e., making a riskier choice) for choices with 8 options (b=0.04, p=.92), but finds a positive relationship for choice set sizes of 16 (b=1.62, p=.002)and 32 (b=1.10, p=.043). Moreover, for participants who chose options with sample mean rankings greater than 0.5 in set sizes of 16 and 32, their choices returned zero payoffs 56% of the time, which was significantly above a chance level of 50% (results of a one sample t-test averaging first within participants, $t(25)=-2.17$, p=.039). This supports our prediction of increased risk-taking among users of the sample mean when confronted with the largest set sizes.

Did search-amplified risk contribute to the increase in risky choice for large set sizes? This would be reflected by a disproportionate increase in the sample mean of chosen gambles with respect to their underlying expected value—indicating an influence of rare events. Figure 3b shows that as set sizes increased, the sample means of chosen gambles increased, with a significant main effect for set size ($\chi^2(1)=26.35$, $p<.001$; both condition and interaction effects were not significant, $p>0.1$). However, the expected value of the chosen gambles did not change for either condition ($\chi^2(1)<2$, $p>.2$). This indicates that rare events drove this increase in the sample mean—consistent with search-amplified risk. In other words, as set sizes increased, participants were more likely to sample rare positive events and, for some individuals, this led them to choose these riskier gambles.

Discussion

By combining approaches from consumer choice over many options and decisions from experience, the present research makes contributions to both domains. Foremost, choice set size and choice order influenced information search (as in Levav et al., 2012, 2010), with effects on total samples taken, proportion of gambles sampled, samples per gamble, and propensity to switch between gambles. Information processing, on the other hand, appeared to scale across set sizes, contradicting one of the core explanations for choice overload (discussed in Scheibehenne et al., 2010). Decisions were predicted by the outcomes of information search, with participants consistently choosing gambles associated with higher sample means. Thus, the influence on decisions caused by changes in choice set size and choice order appear to be dominantly mediated by changes in information search. In turn, changes in information search led to systematic changes in risky choice, with participants tending to make more choices for gambles with rare events as set sizes increased.

Why do we not find an effect of information overload? One possibility is that in the sequential sampling paradigm participants can control how much information they sample. Thus, as predicted by Jacoby (1984), individuals may make procedurally rational decisions (Simon, 1978), and limit search, to avoid overwhelming their cognitive capacities. This capacity to control the information is, of course, also possible in many of the choice overload paradigms, and this may explain the absence of a consistent strong effect found in the meta-analysis by Scheibehenne and colleagues (2010). In the present case, individuals made rational and consistent decisions based on the outcomes of their information search, even for large choice sets. This may indicate that choice overload—when it occurs—is not a consequence of changes in information processing, but is instead driven by the meta-cognitive realization that, with many options, things are not always what they seem. If people are aware of the sampling biases they create with large choice sets (e.g., and anticipate regret, Loomes & Sugden, 1982), it may explain the observations associated with choice overload, including hesitation and choosing less complex options (Iyengar & Lepper, 2000; Mick et al., 2004).

Despite consistent information processing, changes in information search had dramatic effects on risky choice as set sizes increased, with participants tending to choose gambles with rarer positive outcomes. This is in contrast to prior research on decisions from experience, which have been interpreted as indicating an underweighting of rare events (e.g., Hertwig et al., 2004; Hills & Hertwig, 2010; Rakow et al., 2008; Ungemach & Chater, 2009). As we noted in the introduction, the impact of rare events as set sizes increase is a predictable outcome of certain changes in information search. With large set sizes, increased sampling overall increased the likelihood of encountering a rare event. However, reduced sampling per gamble reduced the opportunity for these events to be encountered alongside more common outcomes from that distribution. This both amplifies differences in sample means between gambles (Hertwig & Pleskac, 2008) and leads to search-amplified risk—with risky gambles being the gambles most likely to have the highest sample means. Thus, the greater likelihood of choosing gambles with rare events may not be due to a bias in the processing of sampled outcomes, but due to a bias in sampling.

Though this apparent overweighting of rare events appears at first glance to be at odds with previous research (Hau et al., 2008; Hertwig et al., 2004; Ungemach & Chater, 2009), it is nonetheless a consequence of the same phenomenon of limited search scaled to many options. In practice, with large set sizes people may often make the trade-off between information overload and search-amplified risk—risking either too much information to process or information biased in favor of risky choices. Future research will be needed to address this possibility as well as how best to deal with it.

Finally, what may be behind the observed carry-over effects in information search? We can offer two possibilities. First, people may adapt to one search environment by tuning an implicit cognitive search parameter (e.g., giving up times), and then transfer this to subsequent search environments (Hills, Todd, & Goldstone, 2010). In the present case, this may mean that giving up times are tuned to initial choice environments with few or many options, and then when choice set sizes change, participants do not update these parameters. Alternatively, set size may influence explicit maximizing or satisficing mindsets, which then transfer to new environments (Levav et al., 2012). This might lead people to believe they can make optimal choices, even in complex environments, because they have made similar choices in less complex environments. Though our research was not designed to distinguish between these two options, the question of the implicit or explicit nature of the observed carryover effects remains open for future research. As we found significant differences in people's likelihood of choosing gambles with higher expected values when set sizes were small, understanding how choice order and set size influences decision making has clear practical implications for real world decisions, be they consumer or otherwise.

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Figure 1: The influence of choice set size and choice order on information search: (a) total samples, (b) proportion of options sampled, (c) samples per gamble, and (d) switching per sample. Error bars are 95% confidence intervals.

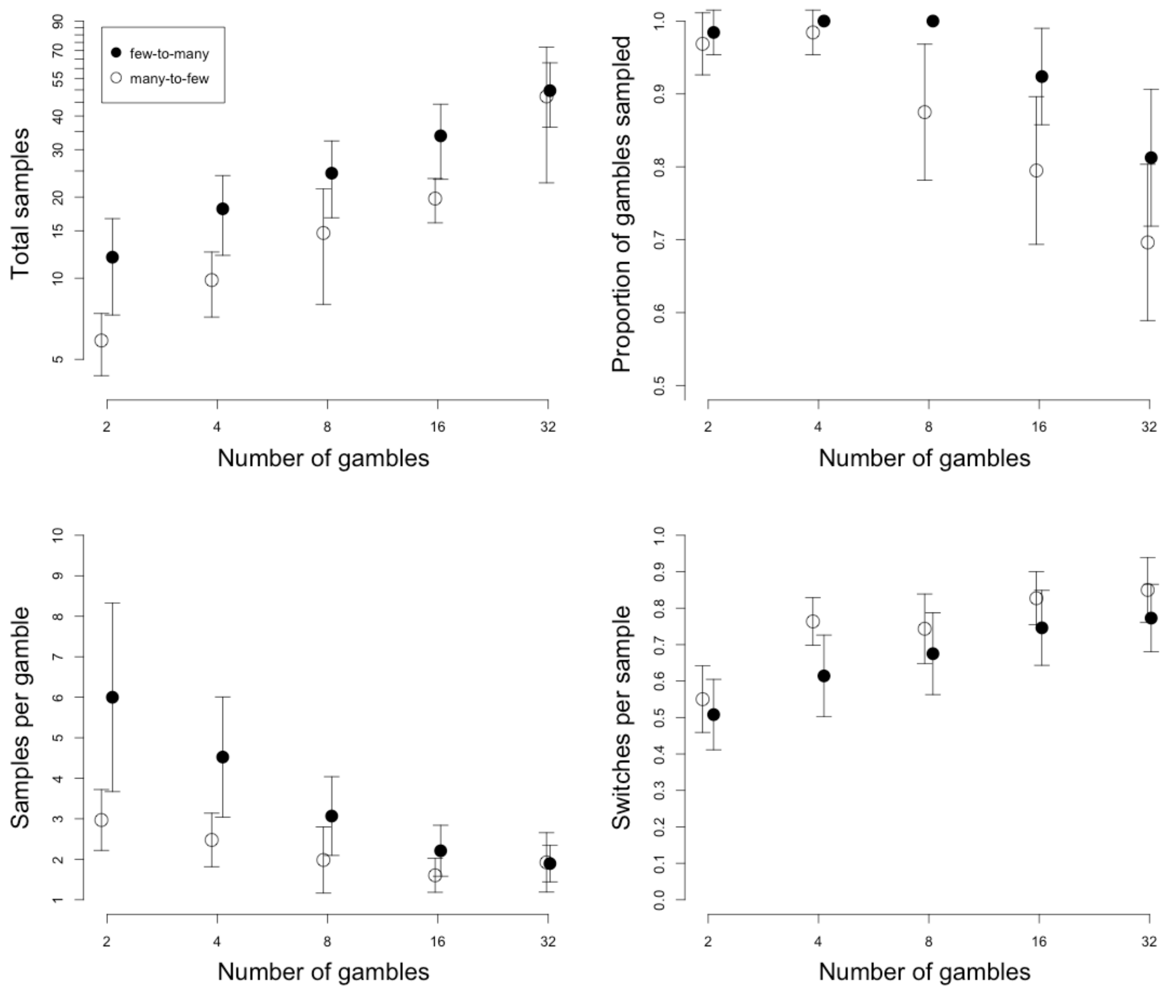


Figure 2: The influence of choice set size and choice order on the expected value and sample mean of the chosen gamble. (a) Relative rank of the expected value. (b) Relative rank of the sample mean. The dotted lines indicate the expected rank if choices were random with respect to the vertical axis. Error bars are the 95% confidence intervals.

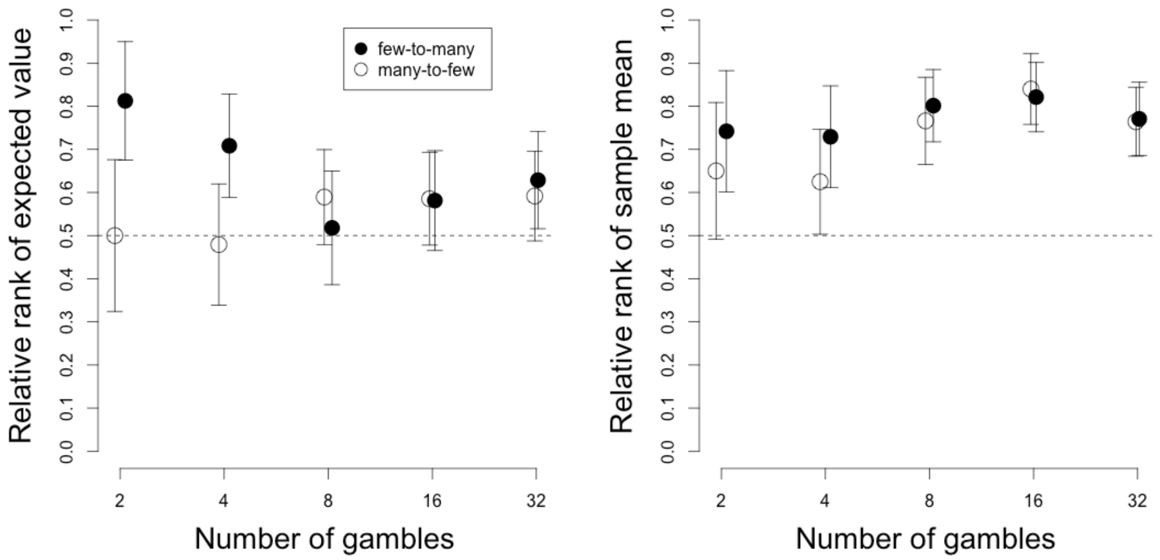
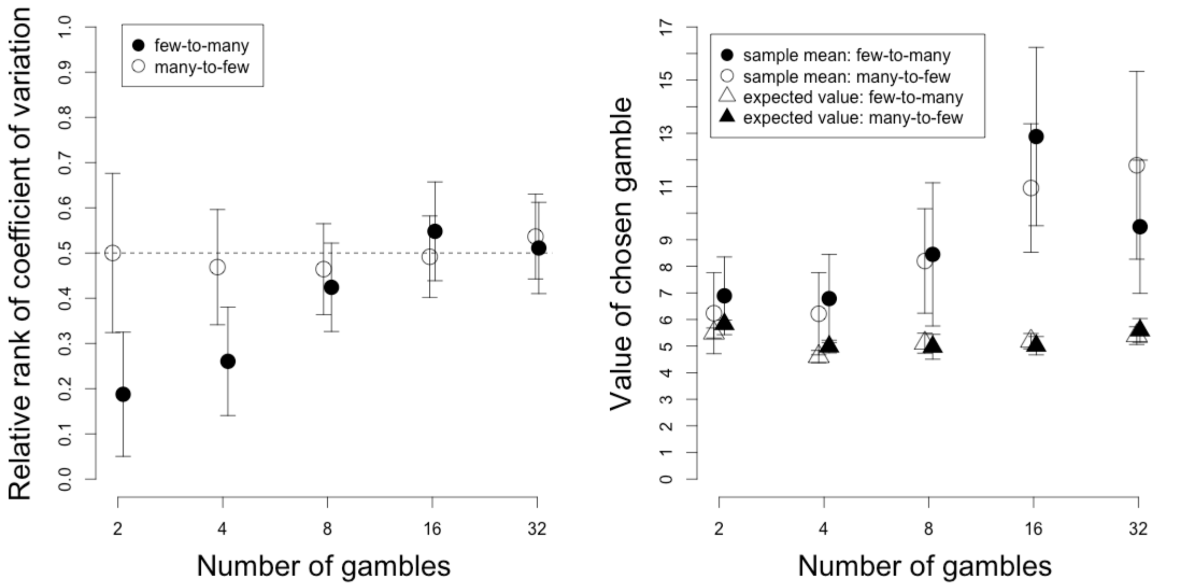


Figure 3: The influence of choice set size and choice order on risk qualities of the chosen gamble. (a) The coefficient of variation of the chosen gamble. (b) Sample mean and expected value of chosen gamble. Error bars are 95% confidence intervals.



Endnotes

[i] Except where noted (e.g., beta regressions), we used general linear mixed effects models with fixed effects for log set size and condition, and random error terms for subject intercept and slopes by-subject for log set size. Results present the likelihood ratio of the full model with a model removing the fixed effect of interest (distributed as a χ^2 statistic with one degree of freedom). Where random effects were highly correlated ($>|.9|$), the slope term was removed from the analysis (Baayen, Davidson, & Bates, 2008; Pinheiro & Bates, 2004). Where repeated measures ANOVAs were appropriate, results led to the same statistical conclusions. Unless reported, all interactions were non-significant ($p>.1$).
[ii] The decision analyses utilized the 303 (out of 320) decisions with more than one option sampled and the final decision among the sampled options. Results lead to the same statistical conclusions if this constraint is relaxed.
[iii] Other effective decision strategies (e.g., maximax and lexicographic, Hau et al., 2008) lead to identical conclusions.