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## **Overall Probability of Winning Heuristic in Decisions Under Uncertainty and Ambiguity**

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We demonstrate how subtle changes in presentation formats can lead to systematic and adaptive changes in decision-making strategies and the use of overall probability of winning heuristic for decisions under uncertainty. These findings also extend to decisions under ambiguity, where probabilities are unknown and need to be learned from experience.

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# “Understanding Uncertainty: The Mechanisms Behind the Adaptive Nature of Decision-making Under Uncertainty”

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## **Paper #1: Development of an Individual Measure of Loss Aversion**

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## **Paper #2: Biases in Using Information to Evaluate Uncertain Financial Prospects**

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## **Paper #3: Overall Probability of Winning Heuristic in Decisions Under Uncertainty and Ambiguity**

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## **Paper #4: Updating Under Ambiguity: Insights from Neuroscience**

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### **SESSION OVERVIEW**

Consumers face uncertainty in a wide range of choices that they encounter daily. Some of these reflect risks, in which people are well informed about the likelihoods of possible outcomes, though those outcomes are uncertain. Others involve ambiguity, in which people have little, or incomplete, information about a situation with uncertain outcomes. It is well known that consumers find many instances of such uncertainty and/or ambiguity aversive, making these decisions difficult and frustrating. This can lead to an array of biases, or even simply avoidance of important choices in uncertain realms. The papers in this session explore the mechanisms underlying uncertain decision-making, how they change with experience, and how they impact real (incentivized) choices. Specifically, we seek to address the following questions: (i) do simple measures of decisions under uncertainty like loss aversion predict real world decisions? (ii) how do consumers use information to reduce uncertainty across various situations, and (iii) how they might learn from their experiences to improve the quality of decisions.

The first paper from Payne and colleagues explores loss aversion as a key construct that predicts how individuals react to uncertainty. They show that a simple measure of loss aversion reliably predicts consumer financial preferences for retirement savings investments, Social Security claiming, and life annuity preferences. In the second paper, Karmarkar and Peysakhovich examine how people incorporate partial or incomplete information as it is added in uncertain situations, depending on its valence. Though loss aversion might suggest that individuals give more weight to unfavorable information, they find that people appear to overweight favorable information when estimating the worth of uncertain financial prospects. Notably, this net behavioral effect arises from a complex set of mechanisms involving how information impacts *feelings* of certainty.

While adding information can be seen as one type of “updating”, Venkatraman and colleagues demonstrate the adaptive nature of decision-making across decision contexts using eye-tracking. They

show that the decision-making strategies are consistent even for decisions under ambiguity, where individuals have to learn the underlying probabilities through experience. In the final paper, Hsu and colleagues take a neural perspective on adaptive types of changes, also focusing on how people behave in dynamic situations where ambiguity can be reduced over time. Using fMRI, they show that the updating process involves more cognitive regions unlike traditional decisions under ambiguity, which have been associated with more emotional processing.

This session will appeal to researchers interested in motivation, goals, situation/context effects, and self-control as well as risk and uncertainty. In accordance with the “Advancing Connections” conference theme, these papers bring together data from a wealth of methodologies including laboratory experiments, eye-tracking, large-scale field surveys, and neuroimaging to better understand the processes involved in decision-making in uncertain situations and the dynamics of how these processes develop and change with experience over time. As such, these findings have important implications for designing choice architecture in used in marketing and public policy. They additionally speak to issues regarding the welfare of individual consumers, particularly in the realm of consumer financial decision-making.

### **Development of an Individual Measure of Loss Aversion**

#### **EXTENDED ABSTRACT**

Many of the complex, and difficult, consumer financial decisions we face such as choices for mortgages, health insurance, and when to collect Social Security benefits involve options that have multiple “mixed” outcomes in the sense that there is both risk of loss and opportunity for gain. A key concept in explaining such decisions is loss aversion. Kahneman (2011) defines loss aversion in terms of the direct comparison of gains with losses - the idea that “losses loom larger than gains” - and makes it clear that individuals will differ in their loss aversion. For marketers of financial services, or public policy experts who may wish to nudge individuals’ risky decisions, having a simple and easy to use individual loss aversion measure is useful for customizing their advice.

Given the importance of loss aversion in explaining behaviors, several approaches for measuring it at the individual level have been developed. Most of the approaches assume an underlying model of decisions under risk (Kahneman & Tversky, 1979), and use simple 50:50 two-outcome gambles. While sophisticated model-based estimation techniques have much to recommend them, we offer an alternative approach that is model-free and based on choices made between slightly more complex mixed three-outcome gambles. In particular, our loss aversion measure is based on ideas presented in Brooks and Zank (2005). They offer several reasons for adopting a more model free approach to measuring loss aversion, including the avoidance of 50:50 gambles; we also note that a choice between two options differing on two dimensions of value (gain versus loss) evokes more System 2 thinking (Kahneman, 2011). Many important “real-world” consumer decisions under risk involve more than simple two-outcome gambles.

To obtain a precise measure of individual differences in degrees of loss aversion we present participants with a series of gamble

choices. Participants are asked at each step to choose between two mixed three-outcome gambles, A and B. Each gamble has one positive outcome at 45% chance, a zero outcome at 10% chance, and one negative outcome at 45% chance. We find, for example, that most respondents (often above 70%) express some degree of loss aversion by preferring a loss averse (LA) gamble (\$400, .45; \$0, .10; -\$400, .45) to a matched gain seeking (GS) gamble (\$600, .45; \$0, .10; -\$600, .45). Building on this base gamble, we go beyond prior literature and systematically change the amounts to be gained (or lost) for either A or B in each pair. The different pairs of gambles with different levels of gain vs. loss tradeoffs are presented to the respondents in random order. The ultimate result is that this series of simple paired comparison choices yields an overall measure of loss aversion per participant.

We report on the results of a meta-analysis that tests this measure of loss aversion with over 7,000 participants from online studies with national survey panel companies. All of the results presented are for respondents whose choices satisfy first-order stochastic dominance. We focus on four main questions: (1) whether the individual measures of loss aversion collected from participants match the typical overall distribution of loss aversion found in other studies; (2) how individual loss aversion measures correlate with other individual differences such as gender, age, and time preferences; (3) whether these measures are predictive of other behaviors and choices, especially within the realm of consumer financial decision-making; and (4) the predictive power of our loss aversion measure relative to traditional measures of risk taking.

To summarize our results, we find that the overall pattern of loss aversion scores we collected is consistent with the results found in other studies. We check robustness by testing the measure with different probability values; the similarity in responses across different probability amounts suggests that respondents are focusing on comparisons between gain and loss amounts and not simply expected value differences. Next, we find that other individual differences are correlated with our loss aversion measure in meaningful ways, such as females indicating higher loss aversion. More importantly, we find that this choice-based loss aversion measure is highly predictive of a range of expressed preferences for financial decisions. For example, we consistently find that higher levels of loss aversion predict individuals' preference for claiming Social Security benefits early. We also find that loss aversion is predictive of decisions about retirement savings, life annuities, and investment preferences, such choices between bond and stock funds.

Lastly, we have studied the predictive power of our loss aversion measure against other traditional measures of risk taking. In an online study with 99 participants, we tested risk likelihood and risk perception for a series of gambles under different choice brackets (narrow, broad) and gamble types (positive EV mixed, negative EV mixed, and strictly negative). We then collected individual measures of loss aversion via our nine-point scale, loss aversion using the DEEP measure (Toubia et al 2013), subjective risk aversion, and a measure of risk aversion from the economics literature (Kapteyn & Teppa 2011). We find that our loss aversion measure is significantly positively correlated with the DEEP loss aversion measure ( $r=.35$ ,  $p<.05$ ). On the other hand, it is not significantly correlated with either subjective risk aversion ( $r=-.04$ ) or economic risk aversion ( $r=-.20$ ) measures, suggesting that loss aversion is capturing a different construct from risk aversion. Importantly, our loss aversion measure has a significant negative effect on choosing to gamble ( $B = -0.07$ ,  $p = 0.03$ ) across all gamble choices, even after controlling for risk perception (the greatest predictor of risk-taking in the extant literature). This finding suggests that our loss aversion measure has predictive

value over and above what risk perception captures; specifically, it suggests that loss aversion measures aspects of risk-taking preference that are not completely captured by subjective beliefs about the level of risk in a financial gamble. Many financial services firms currently employ generic risk perception questions when working with new clients; this new loss aversion measure offers them the ability to gather individual information that is more predictive of actual financial choices.

## Biases in Using Information to Evaluate Uncertain Financial Prospects

### EXTENDED ABSTRACT

Consider a trader contemplating the value of a stock, or an individual choosing where to invest a windfall. Often they have *some* relevant favorable and unfavorable information, but their overall knowledge is incomplete. Unlike risky situations, in which the likelihood of a good vs. bad outcome is known, ambiguous situations like these arise from uncertainty about outcome probabilities (e.g. Ellsberg 1961). Since people are disproportionately averse to losses and negatives in general (e.g. Kahneman and Tversky 1979; Baumeister et al. 2001; Rozin and Royzman 2001) one might predict that a decision-maker would overweight unfavorable information. Instead, across a series of experiments, we show that favorable information is "overweighted" when determining the value of uncertain financial prospects. We find that this bias is driven by the interaction of multiple mechanisms.

In our first study, individuals indicated their willingness-to-pay (WTP) for gambles where one poker chip was randomly drawn from a bag of 100 red and blue chips. Participants read the following: "This bag contains at least  $X$  red chips and at least  $Y$  blue chips," and learned that a red chip resulted in a monetary payout, and a blue chip had no payout. Thus  $X$  represented the amount of favorable information available while  $Y$  represented the amount of unfavorable information, and both could be varied independently ( $X=\{0, 25, 50\}$ ;  $Y=\{0, 25, 50\}$ ). Regression analyses demonstrated that unfavorable information had much less impact on WTP than favorable information (absolute magnitude=5% of favorable, test for equality of regression coefficients  $p<.01$ .) This bias persisted when tested in the domain of losses, that is, even when unfavorable information signaled a distinct monetary loss as opposed to merely absence of a win.

In such "constrained" ambiguity experiments, participants were aware of the limited total number of chips (and thus the total amount of information possibly available). Addressing this, we tested WTP for gambles with more subjectively interpretable, or "unconstrained" situations based on trivia questions. Participants continued to overweight favorable information and even overclassify information as being favorable towards their desired outcome.

Though these findings suggest a bias arising (only) from engagement with favorable information, we hypothesized a second mechanism based on individuals' aversion to feelings of ignorance and ambiguity (e.g. Fox and Tversky 1995). We considered that information can be used both to estimate the probability of winning, and to reduce the uncertainty felt about those estimates. We conducted a study in which participants indicated their WTP, their estimate of the likelihood that a red or blue chip would be drawn, and their certainty in that estimate. This multi-trial, incentive compatible experiment replicated the net bias in WTP. From a mechanistic standpoint, we found that that favorable information increased perceived likelihood of winning, and unfavorable information appropriately decreased it. However, favorable *and* unfavorable information significantly increased felt certainty. And in turn, both likelihood and

certainty variables explained a significant amount of the positive effect of information on WTP. Put another way, we show that people will pay more when they feel more certain, even when that certainty comes from negative information.

Thus we find a complex set of mechanisms driving biases in how favorable and unfavorable information is used to estimate value and make decisions. In financial situations, though unfavorable information decreases the estimated likelihood of a desired outcome, it also increases felt certainty about this estimate. These elements act in opposition, minimizing the effects of unfavorable information, and deepening the asymmetry in information processing. This multi-mechanism framework is supported by preliminary fMRI data showing that valenced information is represented in different ways across multiple neural loci when individuals are making incentive-compatible decisions under uncertainty.

Our findings demonstrate a real and robust role for subjective, or felt certainty in these types of financial decisions. While increasing easily interpretable information can increase certainty in the financial domain, it has been shown to have more complex effects when the information is more complex (Hadar, Sood and Fox, 2013) or when people are choosing romantic partners (Norton, Frost and Ariely, 2007). We discuss how our insights about certainty relate to these findings, and can be extended across various choice domains.

### Overall Probability of Winning Heuristic in Decisions Under Uncertainty and Ambiguity

#### EXTENDED ABSTRACT

Over the past few decades, there has been considerable debate about the role of inherent preferences that are stable and time-invariant versus constructed preferences, which are influenced by the context and cognitive resources. Several studies in behavioral economics, consumer behavior, and judgment and decision-making have shown that people adaptively make judgments and decisions depending on different descriptions and procedures of given tasks or choice options (Tversky & Kahneman, 1986), which seem to support the preference construction framework. However, those adaptive behaviors have been studied mostly with risky decision-making tasks where outcomes and probabilities are known, but relatively less has been investigated under ambiguity where the outcomes and/or probabilities are unknown (Fox & Hadar, 2006; Knight, 1921). Here, we explore further the adaptive nature of preferences under uncertainty and ambiguity by two different decision-making paradigms across three studies (Hertwig, Barron, Weber, & Erev, 2004; Ludvig & Spetch, 2011).

We report findings from three independent studies. All studies were approved by Temple University IRB, and participants received course credit in exchange for their participation. In study 1, 29 participants completed a series of risky-choice problems involving mixed gambles (Venkatraman et al., 2014), while seated in front of a Tobii T60XL eye tracking system. In each trial, three gambles were presented in the form of a 4x4 grid, with the columns rank-ordered from the highest gain to greatest losses. The probabilities occupied the top row. Each gamble consisted of three outcomes (one gain, one loss and one intermediate), each with its own probability. One alternative was associated with the highest gain outcome (Gain maximizing or Gmax), one alternative was associated with the lowest loss outcome (loss minimizing or Lmin) and the third alternative was associated with superior value for the intermediate outcome. Trials were classified as either OP (overall probability) available or OP unavailable. In the OP available trials, the intermediate alternative was associated with a greater overall probability of winning (Pwin) compared to the

other alternatives. In the OP unavailable trials, there was no change in overall probability of winning across all alternatives.

A total of 30 additional participants completed a follow-up Study 2. Here, we varied the presentation formats (fixed, random), such that the columns were no longer rank-ordered in some trials. Therefore, most common attribute-based decision-making strategies (e.g., lexicographic, take the best) were unavailable on certain trials. In Study 3, a total of 47 participants ( $M = 21.75$ ,  $SD = 2.98$ ;  $Male = 16$ ) completed a similar risky-choice task with mixed gambles. However, no probability information was presented for each of the gambles and participants had to learn this information by repeatedly sampling the outcomes from each of the gambles (Camilleri & Newell, 2013; Hertwig et al., 2004). Three boxes (corresponding to the three gamble alternatives) were presented on the computer screen. Participants could sample one gamble at a time by pressing the corresponding button, and a randomly chosen outcome (based on the underlying probabilities) from that gamble was revealed within that box for 500ms. They could sample each gamble as many times as they wanted without any restriction in the sampling order. When participants felt that they had sufficient information to make their decision, they could indicate their choice. In all studies, we were primarily interested in the relative preference for the overall probability of winning option (Venkatraman et al., 2014).

In Study 1, participants showed a strong preference for the intermediate outcome only when it changed the overall probability of winning (53%), but not in the OP unavailable trials (34%). In Study 2, we replicated the findings from Study 1 with participants showing a strong preference for Pwin choices in OP available trials. Crucially, we also found a strong effect of presentation format. In trials where the information was presented in a randomized format, the preference for Pwin choices increased (64%) for OP available trials. Strikingly, the introduction of random trials lead to systematic changes in decision-making strategies as indexed by eye-tracking measures, even for fixed trials when compared to similar trials from Study 1. In Study 3 for decisions under ambiguity, initial analysis indicated that participants showed a reduced preference for Pwin choices when information had to be learned through sampling unlike Studies 1 and 2, but these preferences still adapted with trial types. We next investigated whether the effects could have been masked by the actual samples experienced. We used a conditional logistic regression to determine the effects of predefined overall probability of winning (set-OP) and experienced overall probability of winning (exp-OP) on choice. The result showed that set-OP negatively influenced the choice of an option ( $b = -0.39$ ,  $SE = 0.12$ ,  $p = .001$ ,  $e^b = 0.67$ ), while exp-OP positively influenced the choice of option ( $b = 0.99$ ,  $SE = 0.14$ ,  $p < .001$ ,  $e^b = 2.69$ ), and the effect of exp-OP was significantly greater than the effect of set-OP ( $e^b = 0.25$ ,  $SE = 0.06$ ,  $z = -5.70$ ,  $p < .001$ ). These findings suggest that participants demonstrate a bias for the overall probability of winning even when making decisions under ambiguity.

We show that both preferences and decision-making strategies are systematically influenced by format in which information is presented, consistent with the notion of constructed preferences. Crucially, we extend the recent developments from the decisions-from-experience paradigm for risky choice to show that such adaptivity may also extend to decisions under ambiguity - situations where the probabilities are unknown and need to be learned from experience, but only if information about learning is integrated into the models.

## Updating Under Ambiguity: Insights From Neuroscience

### EXTENDED ABSTRACT

Some of the most important decisions consumers make involve ambiguity where probabilities of potential outcomes are unknown or partially known. Empirically, behavioral experiments have repeatedly shown that in gambling decisions most participants are averse to ambiguous bets involving unknown probabilities, e.g., an urn containing 100 balls with unknown proportions of red and black, compared to risky bets with known probabilities, e.g., an urn containing 50 red balls and 50 black balls (Ellsberg 1961; Slovic and Tversky 1974; Sarin and Winkler 1992).

This aversion to ambiguity has important implications for a number of aspects of consumer decision-making, among others timing of purchase, brand choice (Muthukrishnan 1995). Scientifically, it has resulted in a rich literature on psychological antecedents to ambiguity (e.g., Curley, Yates, and Abrams 1986; Fox and Weber 2002; Trautmann, Vieider, and Wakker 2008). In particular, these studies have suggested the importance of emotional processes associated with consideration of ambiguous options, such as the fear of negative evaluation (FNE) by others (Curley et al. 1986; Trautmann et al. 2008).

More recently, these accounts have received support from neuroscientific studies that allow researchers to directly access psychological processes underlying behavior. In particular, consistent with accounts of bias resulting from emotional systems, these studies have implicated regions involved in emotion processing in decisions under ambiguity, in particular the amygdala and the lateral orbitofrontal cortex (Hsu et al. 2005; Levy et al. 2010).

In contrast, much less is known about how people behave in dynamic situations where ambiguity is reducible over time. Such an understanding is important for developing marketing strategies, such as those involving new brand and product introduction decisions. One possibility is that the same systems involved in choices under ambiguity are also involved in updating, such that updating, like choice, would be colored by emotional processes. An alternative account is that updating will engage analytical regions of the brain, such as frontoparietal circuits engaged in more sophisticated forms of Bayesian reasoning processes (Botvinick, Niv, and Barto 2009; Gläscher et al. 2010) in the form of a reward prediction error (RPE), and that the influence of emotional processes are restricted to choice.

To provide direct evidence of the constructive process behind updating of behavior in ambiguous settings, we conducted a functional neuroimaging study using a series of decisions involving the so-called Ellsberg's Three-Colored Urn problem. In the Three-Color Urn problem, an agent is presented with an urn containing some number balls of three possible colors—yellow, red, and green. Furthermore the agent knows about the exact number of balls in one color (referred to as the “risky color”), but not in the other two colors (“ambiguous colors”). For example, if the yellow ball is risky, it means the green and red are ambiguous. The agent wins some monetary prize if the drawn ball matches a pre-determined “winning” color, for example green. We next introduce updating to this decision problem in the form of an “observed draw”. A ball is randomly drawn from the urn, observed by the agents and returned back, before the gamble is resolved. Valuation for the urn both before and after the observed draw was elicited as willingness to pay to play the gamble (WTP).

A total of 20 participants made 90 decisions over a series of 12 different three-color urns while undergoing functional magnetic resonance imaging (fMRI). Behaviorally, we first examined how participants updated WTP under three types of information condi-

tions in our experiment: (i) “good news” in cases where the observed draw was an ambiguous ball matching the winning color, thereby improving one’s likelihood of winning, (ii) “bad news” where the observed draw was an ambiguous ball that did not match the winning color, therefore lowering one’s likelihood of winning, and (iii) “no news” where the draw was a risky ball. We found that the direction of WTP changes overwhelmingly conformed to prediction (chi-square test of independence,  $\chi^2(4) = 1493.4, p < 10^{-10}$ ), such that WTP values changed positively (negatively) under good (bad) news, and did not change when there was no news.

Next, we investigated how the brain responded to these different types of information. Specifically, we sought to characterize brain regions that responded to (i) updating of information of urn contents and (ii) updating of the value of the urns. We found that a set of frontoparietal regions responded to updating of information of urn contents, in particular bilateral dorsolateral prefrontal cortex and intraparietal sulcus ( $p < 0.001$ ). In contrast, we found that the updating of urn value was correlated with brain activity in the ventromedial prefrontal cortex.

Compared to previous findings involving choice under ambiguity, these results provide striking contrast in the dissociations observed between these processes. That is, unlike *choice* under ambiguity which engages brain regions known to subservise emotion-related processes, *updating* under ambiguity engages an entirely different set of frontoparietal systems thought to subservise sophisticated reasoning processes (Daw et al. 2011). This has potential implications for marketing strategies involving new brand and product introduction decisions. It suggests that although initial introduction are likely to be met with emotion-related ambiguity-averse responses that suppress demand for new brands and products, they may be mitigated by the use of more reason-based strategies in subsequent interactions that allows consumers to overcome the initial aversion. Future studies are needed to assess whether this also holds for real products.

### REFERENCES

- Andersson, O., Holm, H. J., Tyran, J., & Wengstrom, E. (2015, In press). Deciding for Others Reduces Loss Aversion, *Management Science*.
- Botvinick, M. M., Niv Y., and Barto, A.C. (2009), “Hierarchically Organized Behavior and Its Neural Foundations: A Reinforcement Learning Perspective,” *Cognition*, 113, 262–80.
- Baumeister, R., Bratslavsky, E, Finkenauer, C & Vohs, K (2001). “Bad is stronger than good.” *Review of General Psychology* 5(4): 1089-2056.
- Brooks, P., & Zank, H. (2005). Loss averse behavior. *Journal of Risk and Uncertainty*, 31(3), 301-325.
- Camilleri, A. R., & Newell, B. R. (2013). Mind the gap? Description, experience, and the continuum of uncertainty in risky choice. *Progress in brain research: Decision-making: Neural and behavioural approaches*, 55-72.
- Curley, S.P., Yates, J.F., and Abrams, R.A. (1986), “Psychological Sources of Ambiguity Avoidance,” *Organizational Behavior and Human Decision Processes*, 230–56.
- Daw, N.D., Gershman, S.J., Seymour, B., Dayan, P. and Dolan, R.J. (2011), “Model-Based Influences on Humans’ Choices and Striatal Prediction Errors.” *Neuron*, 69(6), 1204–15.
- Ellsberg, D. (1961), “Risk, Ambiguity, and the Savage Axioms,” *Quarterly Journal of Economics*, 75, 643–69.

- Fox, C. R., & Hadar, L. (2006). Decisions from experience= sampling error+ prospect theory: Reconsidering Hertwig, Barron, Weber & Erev (2004). *Judgment and Decision-making*, 1(2), 159-161.
- Fox, C.R. and Weber, M. (2002), "Ambiguity Aversion, Comparative Ignorance, and Decision Context," *Organizational Behavior and Human Decision Processes*, 88, 476-98.
- Fox, C. & Tversky, A (1995). "Ambiguity aversion and comparative ignorance." *Quarterly Journal of Economics* 100(3): 585-603.
- Gläscher, J., Daw, N. Dayan, P. and O'Doherty, J.P. (2010), "States versus Rewards: Dissociable Neural Prediction Error Signals Underlying Model-Based and Model-Free Reinforcement Learning," *Neuron*, 66(4), 585-95.
- Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, 15(8), 534-539.
- Hadar, L., Sood, S., & Fox, C. R. (2013). Subjective knowledge in consumer financial decisions. *Journal of Marketing Research*, 50(3), 303-316.
- Hsu, M., Bhatt, M., Adolphs, R. Tranel, D. and Camerer, C.F. (2005), "Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making.," *Science (New York, N.Y.)*, 310, 1680-83.
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.
- Kapteyn, A. & Teppa, F. (2011). Subjective measures of risk aversion, fixed costs, and portfolio choice. *Journal of Economic Psychology*, 32(4), 564-580.
- Knight, F. H. (1921). Risk, uncertainty and profit. *New York: Hart, Schaffner and Marx*.
- Levy, I., Snell, J, Nelson, A, Rustichini, A & Glimcher, P (2010). "Neural representation of subjective value under risk and ambiguity." *Journal of Neurophysiology* 103(2): 1036-1047.
- Ludvig, E. A., & Spetch, M. L. (2011). Of black swans and tossed coins: is the description-experience gap in risky choice limited to rare events?. *PLoS One*, 6(6), e20262.
- Muthukrishnan, A. V. (1995), "Decision Ambiguity and Incumbent Brand Advantage," *Journal of Consumer Research*, 98.
- Norton, M. I., Frost, J. H., & Ariely, D. (2007). Less is more: the lure of ambiguity, or why familiarity breeds contempt. *Journal of personality and social psychology*, 92(1), 97.
- Rozin, P. & Royzman E. (2006). "Negativity bias, negativity dominance and contagion." *Personality and Social Psychology Review* 5(2): 296-320.
- Sarin, R.K. . and Winkler, R.L. (1992), "Ambiguity and Decision Modeling: A Preference-Based Approach," *Journal of Risk and Uncertainty*, 5, 389-407.
- Slovic, P. and Tversky A. (1974), "Who Accepts Savage's Axiom?," *Behavioral science*, 19, 368-73.
- Toubia, O., Johnson, E., Evgeniou, T., & Delquié, P. (2013). Dynamic experiments for estimating preferences: An adaptive method of eliciting time and risk parameters. *Management Science*, 59(3), 613-640.
- Trautmann, S.T., Vieider, F.M. and Wakker P.P. (2008), "Causes of Ambiguity Aversion: Known versus Unknown Preferences," *Journal of Risk and Uncertainty*, 36, 225-43.
- Tversky, A., & Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of business*, S251-S278.
- Venkatraman, V., Payne, J.W. and Huettel, S.A. (2014). An Overall Probability of Winning Heuristic for Complex Risky Decisions: Choice and Eye Fixation Evidence, *Organizational Behavior and Human Decision Processes*, 125:2, 73-87.