A COMPARISON OF ECOLOGICAL AND EVOLUTIONARY MODELS OF DECISIONS UNDER RISK

by

WILLIAM TREY HILL

B.S., Oklahoma State University, 2007
M.S., University of Louisiana at Monroe, 2009

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Psychological Sciences
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2013

Abstract

Risky decision making occurs in both humans and non-human animals. For a large portion of the history of scientific investigation into human judgment and decision making, risky behavior has been viewed as flawed and irrational. However, the past several decades have seen advances in the view of human rationality. Scientists have suggested that, rather than using probability theory as the metric by which humans are judged as rational or irrational, human minds should be evaluated with respect to specific ecologies (e.g., Gigerenzer & Selten, 2001) with some scientists going further and specifying the ecologies as those which our ancestors evolved; essentially, our minds and their decision processes are adapted to solve specific recurring problems, and to solve those problems in specific environments.

Within the domain of risky decision making there are a number of theories and models which are consistent with the hypothesis that human (and non-human) minds are molded for specific behavioral patterns based on environmental cues. One example is the priority heuristic. The priority heuristic is based in the ecological rationality approach—that heuristics are designed for specific ecologies. However, the ecological rationality of the priority heuristic is underspecified. Studies One and Two of the present dissertation compared predictions made by two models of risk-taking from evolutionary biology and behavioral ecology (dominance theory and risk-sensitive foraging) with a variety of predictions made by the priority heuristic. Data clearly showed that risk-sensitive foraging outperforms the priority heuristic (Study One) and that the priority heuristic cannot account for the motivation to acquire a minimum number of resources. Study Two showed mixed results for the priority heuristic when compared to dominance theory. Specifically, choice patterns were consistent with the priority heuristic, but process data in the form of decision times were not consistent with the priority heuristic. Also, the data pointed to a strong effect for desiring higher status when competing against others of varying status.

Study Three compared four potential models of risky decision making in an attempt to extend the pattern of results from Studies One and Two showing general risk-sensitivity when attempting to achieve a specified need level (Money for Study One; Status for Study Two). Also, Study Three attempted to clarify the scope of the pattern of general risk-sensitivity by

examining differential patterns of results based on whether the models predicted motivations to achieve need levels for money, status, or both. Results from Study Three were consistent with a general model of risk-sensitivity which operated on both monetary need levels and status need levels. This effect was additionally ubiquitous for males and females, contrary to predictions by dominance theory.

The data from three studies showed support for a general model of risk-sensitivity consistent with those proposed by others (Mishra, 2010). The concept and implications of this general risk-sensitivity model are discussed, as well as future directions to understand the finer details and potential scope of this particular general risk-sensitivity model.

A COMPARISON OF ECOLOGICAL AND EVOLUTIONARY MODELS OF DECISIONS UNDER RISK

by

WILLIAM TREY HILL

B.S., Oklahoma State University, 2007
M.S., University of Louisiana at Monroe, 2009

A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Psychological Sciences
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2013

Approved by:

Major Professor
Gary L. Brase, Ph.D.

Abstract

Risky decision making occurs in both humans and non-human animals. For a large portion of the history of scientific investigation into human judgment and decision making, risky behavior has been viewed as flawed and irrational. However, the past several decades have seen advances in the view of human rationality. Scientists have suggested that, rather than using probability theory as the metric by which humans are judged as rational or irrational, human minds should be evaluated with respect to specific ecologies (e.g., Gigerenzer & Selten, 2001) with some scientists going further and specifying the ecologies as those which our ancestors evolved; essentially, our minds and their decision processes are adapted to solve specific recurring problems, and to solve those problems in specific environments.

Within the domain of risky decision making there are a number of theories and models which are consistent with the hypothesis that human (and non-human) minds are molded for specific behavioral patterns based on environmental cues. One example is the priority heuristic. The priority heuristic is based in the ecological rationality approach—that heuristics are designed for specific ecologies. However, the ecological rationality of the priority heuristic is underspecified. Studies One and Two of the present dissertation compared predictions made by two models of risk-taking from evolutionary biology and behavioral ecology (dominance theory and risk-sensitive foraging) with a variety of predictions made by the priority heuristic. Data clearly showed that risk-sensitive foraging outperforms the priority heuristic (Study One) and that the priority heuristic cannot account for the motivation to acquire a minimum number of resources. Study Two showed mixed results for the priority heuristic when compared to dominance theory. Specifically, choice patterns were consistent with the priority heuristic, but process data in the form of decision times were not consistent with the priority heuristic. Also, the data pointed to a strong effect for desiring higher status when competing against others of varying status.

Study Three compared four potential models of risky decision making in an attempt to extend the pattern of results from Studies One and Two showing general risk-sensitivity when attempting to achieve a specified need level (Money for Study One; Status for Study Two). Also, Study Three attempted to clarify the scope of the pattern of general risk-sensitivity by

examining differential patterns of results based on whether the models predicted motivations to achieve need levels for money, status, or both. Results from Study Three were consistent with a general model of risk-sensitivity which operated on both monetary need levels and status need levels. This effect was additionally ubiquitous for males and females, contrary to predictions by dominance theory.

The data from three studies showed support for a general model of risk-sensitivity consistent with those proposed by others (Mishra, 2010). The concept and implications of this general risk-sensitivity model are discussed, as well as future directions to understand the finer details and potential scope of this particular general risk-sensitivity model.

Table of Contents

List of Figures

List of Tables

Acknowledgements

Achieving a Ph.D. is an enormous milestone in my life. Although I am proud of the accomplishment, I know that it would not have been possible without the help of many people along the way. I apologize in advance for the length of this acknowledgement section. However, at the very least, these people deserve a few sentences of commendation.

To Amy

All along I have said that you deserve this degree much more than I do. You, more than anyone else, had to suffer with me through the stress and the heartache. You were also there in the moments of elation such as getting my first publication, and any thereafter; or, when my dreams of being a scientist were finally realized when I received my first job offer. You were there to pick me up when I was down and to tell me how proud you were of me when I had a hard time being proud of myself. Thank you for being the best decision I have ever made. It has been a long journey, but I could not have made it without you. I can't wait to start the next chapter of our lives together. I love you.

To Mom, Dad, Cody, and the rest of my family

Mom and Dad, I truly believe that I am a lucky young man. When you grow up with loving and supportive parents, it is easy to assume that *all* parents are loving and supportive. However, after being out in the world for a while, I quickly realized that both of you were special. There was never a moment in my life where I thought it was an option *not* to attend college. You are probably the reason for that. However, thank you for also allowing me to be my own person, even when you did not fully agree with my decisions (e.g., running cross country instead of playing football). More than anything, I want to thank you both for being so unflinchingly supportive. There have been plenty of times in my life where I have fallen flat on my face. You knew it. I knew it. Everyone knew it. However, rather than feeling alone, I felt like my family was there for me. You have no idea how important those moments have been. I know all too well what it is like to fail, but I also know what it is like to rise back up and prove everyone wrong. I love both of you. You can now finally say that you are finished raising me. I have a job!

Cody. Thank you for being a great brother. One of the nice things about getting older is that it is easier just to be friends with your siblings. I know that it is horrible when one of us is down and the other is doing well. We always get the implied "why can't you just be your brother?" questions and assertions. I'm glad we don't have to worry about that anymore. I want you to know that I'm immensely proud of everything you have accomplished in the last year. No one deserves a little hard-earned success more than you. Soak it up man. Thanks for just being you. I love you.

I also need to thank my aunts and uncles for collectively being a great extended family. Thanks Aunt Nell, Aunt Barbara, Uncle Spud, and the more recent addition to our family, Rick Taylor. I have great aunts and uncles who have always supported me. Also, I need to thank Rick Hinshaw for basically being like an extended family member, and for always being excited about what I'm doing in my life. I have a lot of people who care about me, and it makes me feel full of life. You are all great, and I am blessed to know you.

My two grandmas deserve more than just a few sentences in this dissertation to fully compensate for everything they have done for me. My Grannie and Mema always embodied what it meant to be a grandparent. They went out of their way to help me my entire life. I will never forget the trip that Lezlie and I took with them that led us across the South, looking at Civil War battlefields and appeasing the curiosity of a nerdy little 12 year-old kid interested in history. Grannie, I cannot thank you enough. Mema, I miss you so much.

To my advisor and committee

Graduate school can be an intimidating place. When I came to Kansas State University in the fall of 2009, I had no idea how far from the finish I would be, at least in terms of scientific ability. I can honestly say that the journey was difficult. However, I can also honestly say that I am a better scientist now than I would have ever imagined. I have Dr. Brase to thank for that. For many years now, I have dreamed of getting to do science for a living. Because of great mentorship from Dr. Brase, as well as the help of my committee members—Drs. Eva Horne, Kimberly Kirkpatrick, Les Loschky—I now have a job as an academic. The dream has finally come true. Thank you all for your help.

To my former teachers

It is necessary that I also thank several of my former teachers from my time in Marlow, Oklahoma and also from my college years at The State's University (Oklahoma State University) and the University of Louisiana at Monroe. The people mentioned below helped me and continue to help me. They are shining examples of what a great teacher and scholar should be. (i.e., you should care about your craft and rigorously work to always be improving). All I can hope is that I one day come close to being the teachers and scholars that they currently are.

Bill Ray: I knew before his courses that I loved science, but his courses showed me that a career in science was important and admirable.

Linda Hutson: To me, she will always be *Mrs.* Hutson. She is quite simply the best teacher I have ever had.

Dr. Tim O'Connell: I took college biology and animal behavior with him at OSU. His courses first introduced me to the idea that you could use theories from non-human animal behavior and apply them to human behavioral psychology.

Dr. James Grice: His behavioral statistics course was the first psychology class I took after switching my major. He helped me apply to graduate schools and has been a great mentor during this entire process. In my opinion, Dr. Grice is the perfect embodiment of what a professor should be: a serious scholar who cares about instilling knowledge and wonder in students. Dr. Grice is the primary reason I decided to pursue a Ph.D.

Dr. Jack Palmer: When I moved to Monroe to start working on my master's degree, I was incredibly motivated to do research. Some of my colleagues had their research stifled or restricted by their advisors. Luckily, Dr. Palmer gave me the chance to explore my own ideas. This resulted in the development of a lot of confidence as a scientist, which is something I desperately needed at that time in my life. For that I am very grateful.

To my colleagues

I want to thank Ryan Hinds, Dr. Adam Larson, Stephen Nettelhorst, Lora Adair, Haley Dillon and former graduate students Dr. April Park and Dr. James Daugherty. Some of you sat patiently while I bounced ideas off of you (even the bad ones). Some of you simply accompanied me in partaking of the stress-relieving remedies of Aggieville. Some of you did both. However, all of you have been great friends. Thank you.

To others

I would like to thank Kevin Kenney and Xiangqi Li, the undergraduate research assistants who helped in data collection for the three studies described in this dissertation. Their hard work was, and is, much appreciated. I could not have collected data in such a timely fashion without their help. I wish them luck in their future endeavors.

Dedication

To the individuals in my life whose hard work has helped me reach pinnacles I never dreamed possible. I am forever grateful for the sacrifices you have made. This culmination of my academic training is dedicated to all of you.

Preface

In the summer of 1838, a young Charles Darwin, then only 29, was contemplating a decision which he probably believed to be one of the most important in his life up to that point. The decision was not whether to continue working on the scientific data he had accumulated on his nearly 5-year voyage with the HMS Beagle. It was not to continue working out the theoretical structure of how species could evolve in their phenotypic structure over time. Instead, the decision young Charles Darwin was contemplating was whether or not to marry Emma Wedgwood. Charles, a very detailed young man, approached this difficult problem just as he had with the various naturalistic phenomena experienced over the previous five years in the far reaches of the planet: by scribbling notes in one of his many notebooks. In this particular instance, Charles created a pros and cons list of getting married (two columns below) (adapted from Desmond & Moore, 1991, p. 257).

Marry

Children – (if it Please God) -- Constant companion, (& friend in old age) who will feel interested in one, --object to be beloved & played with. –better than a dog anyhow. –Home, & someone to take care of house – Charms of music & female chit chat. – These things good for one's health. – but terrible loss of time. –

My God, it is intolerable to think of spending ones whole life, like a neuter bee, working, working, & nothing after all. – No, no won't do. – Imagine living all one's day solitarily in smoky dirty London House. – Only picture to yourself a nice soft wife on a sofa with good fire, & books & music perhaps — Compare this vision with the dingy reality of Grt. Marlbro' St.

Marry – Mary Marry Q.E.D.

Not Marry

*Freedom to go where one liked – choice of Society & little of it. – Conversation of clever men at clubs – Not forced to visit relatives, & to bend in every trifle. – to have the expense & anxiety of children – perhaps quarrelling – **Loss of time.** – cannot read in the Evenings – fatness & idleness – Anxiety & responsibility – less money for books &c – if many children forced to gain one's bread. – (But then it is very bad for ones health to work too much)*

Perhaps my wife wont like London; then the sentence is banishment & degradation into indolent, idle fool.

As can be seen at the bottom of the left-hand column in the figure, Darwin did decide to marry Emma Wedgwood, and they were by most accounts happily married until Charles' death in 1882. This simple heuristic technique for making a decision is commonly used when people are trying to make a complex decision. Normative models of decision making would suggest that people calculate the probabilities and decision weights for each of the potential options of a decision, sum those, and then choose the option with the highest value (e.g., the highest subjective expected utility).

For example, if Kahneman and Tversky (1976) were advising Charles on his decision to marry Emma Wedgwood they would have suggested that he assign a decision weight to "Children if it please God" (essentially, how important is this possibility to Charles), and then to estimate the probability that it would happen. These two would then be multiplied. The same procedure would be performed for each of the pros and cons on each side of the argument (i.e., to marry or not to marry). In the end, Charles would simply add the values for each column and choose the column with the highest value. Simple enough, right? Not quite.

Using this technique assumes many things. One basic assumption is that the columns for Marry and Not Marry contain an exhaustive list of the possibilities; all of the possible outcomes have to be listed. But how would Charles possibly know that he would indeed have children and that one of them would tragically pass away from scarlet fever, forever changing his own outlook on religion? In the real world we often do not know the probabilities, the exact importance of certain attributes of a decision, or even have a decent understanding of the possible events in the future. Essentially, we are making decisions on the fly in a dynamic and ever-changing environment. Normative methods of understanding decision making processes often fail to account for these basic facts of the world.

A different way to examine Darwin's decision process shown in the figure is by assuming that he used a simple heuristic method to decide whether or not to marry: by simply tallying the number of pros and cons for each side (e.g., Dawes, 1979; Gigerenzer, 2008). Tallying is anecdotally used often when making decisions. It is easy to use, and does not assume that people use some compensatory strategy whereby they are multiplying decision weights with utility estimates of different possible outcomes. Instead, each possible outcome is given a weight of "1." If you examine Darwin's list in this light, it is easy to see that he thought of far more pros for Marry than for Not Marry. This heuristic not only predicts what Darwin's decision would have been if we would have been able to look at his notes prior to making the decision, but it also explicitly describes the *process* he used when making the decision. The study of processes is important if we want to take a cognitive approach to understanding judgment and decision making.

For many years the psychological study of judgment and decision making has been dominated by normative theories illustrating human biases when compared to the objectively correct solutions derived from probability theory. Often these experimental demonstrations of biases have resulted in the mere labeling of phenomena without any explicit discussion of the mechanisms underlying the phenomena (e.g., representativeness, availability). However, recent research using a fundamentally different approach to research—ecological rationality—has resulted in explicitly described process models of decision making which can be empirically tested and falsified. This dissertation is one example of such research. Perhaps using these methods we can uncover the cognitive processes occurring when Darwin made on of the most important decisions of his life. Enjoy.

Chapter 1 - A New View of the Human Mind

Humans occasionally take risks. Specifically, humans sometimes *choose* riskier options over safer alternative options (Daly & Wilson, 2001; Fuemmeler, Taylor, Metz, & Brown, 2002; Stulp, Kordsmeyer, Buunk, & Verhulst, 2012; Tversky & Kahneman, 1981). This propensity to take risks has historically been given as an example of human irrationality, implicitly suggesting that if we only had more information, more time, and more cognitive capacity, we would not take unnecessary risks and would instead be a much safer species (Delfabbro & Winefield, 2000; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). However, recent research has called into question the claim of irrationality in risky decision making, and if one examines risk taking more closely, it is readily apparent that risk taking is often not random, but instead highly systematic (Brandstätter, Gigerenzer, & Hertwig, 2006; Ermer, Cosmides, & Tooby, 2008; Mishra & Lalumière, 2010; Mishra, Lalumière, & Williams, 2010; Rode, Cosmides, Hell, & Tooby, 1999). Such systematic risk taking seems to further suggest that the behavior of risk taking surfaces in response to implicitly- or explicitly-recognizable variables in the environment, and that the behavior of risk taking may *not* be due to throwaway explanations such as limited cognitive capacity.

Although the term "risk" is colloquially used in reference to many different types of behaviors and characteristics, the definition used throughout this dissertation is that risk is equal to variance. Essentially, if someone is given to lotteries with equal expected values, the riskier lottery can be operationally defined as the lottery with a higher variance in payoffs. This definition can be colloquially returned to typical examples of behaviors often thought of as "risky." For example, people may view skydiving as riskier than standing on the ground and watching someone else skydive. In terms of variance, the skydiver has a high probability of having fun and a relatively low probability of dying, whereas the person on the ground has an almost certain probability of not dying, but will have perhaps less fun. The skydiver's distribution of adrenaline payoffs is much more variable, and therefore the decision to skydive is riskier. This definition of risk is consistent with past literature in areas of foraging behavior in non-human animals (Stephens & Krebs, 1986).

Risk taking is a complex behavior, and it is therefore highly probable that risk taking is the result of complex cognitive architecture. When scientists—including psychologists—discuss the "design" of a complex feature, as psychologists often do when speaking of cognitive architecture, and as biologists often do when speaking of phenotypic structure, there begs the question: "What is doing the designing?" The field of evolutionary biology answers that question promptly and definitively: Evolution by natural selection is currently the only viable scientific theory capable of explaining complex life (Dawkins, 1976/2006), and the umbrella of natural selection does not stop at the species level, but trickles down to the specific adaptations—both physical and psychological—which each species possesses.

For most organisms the world is an unforgiving place. Organisms inevitably produce more offspring than the environment can sustain. Random mutations, while often deleterious, occasionally provide an individual organism with a slight reproductive advantage. Any reproductive advantage, encapsulated at the level of the gene, will have a decent probability of also being present in that particular organism's offspring (Dawkins, 1976/2006). Through many successive generations that phenotype will become widespread in the species due to the reproductive advantage it confers upon its possessors (Darwin, 1859/1976). This general process is the cornerstone of modern biology, and has become a foundational and indispensable idea (Dobzhansky, 1973).

The broad concept of evolution is generally agreed upon within the biological sciences. Instead what is often argued is *how* the process occurs rather than the theoretical certitude that evolution enacts phenotypic changes on organisms over many generations. However, evolution may create more than phenotypic changes alone, but may also act on the psychological structures of human and non-human minds (Barkow, Cosmides, & Tooby, 1992). Darwin (1859/1976) briefly mentioned this in his seminal work *On the origin of species*, and further developed psychological ideas in later works (Darwin, 1871/1971, 1872/1979). It is also apparent that Darwin believed evolution could act on the behavioral patterns of organisms. Indeed, the fields of ethology and behavioral ecology have provided ample evidence in support of Darwin's proto-hypothesis (Lorenz, 1958; Tinbergen, 1951; von Frisch, 1967).

Let us assume that evolution does indeed act on behavioral patterns by favoring those patterns which either directly or indirectly provide some reproductive advantage. The next question is precisely *how* could behavioral patterns be shaped through natural selection? The question becomes more tractable if we think of behavioral patterns as the result of complex information processing systems, similar to the functioning of a computer; a given mechanism (cognitive component) produces a certain output (behavior) in a specified situation (an environment). So, if evolution acts on the behaviors by "rewarding" those which lead to "successful" outcomes, it then indirectly acts on the mechanisms producing those behaviors. If the development of specific types of mechanisms are genetically encoded, then successful behavioral patterns leading to reproductive success over the long term would result in the same mechanisms being carried on to the next generation. This concept of information processing mechanisms as a description of how human and non-human cognition may work is described in the next section.

Modularity versus Generality in Cognition

For decades the computer metaphor of the human mind has been used in cognitive psychological research. This metaphor has propelled research into how the human mind works, and has driven the burgeoning fields of study under the academic umbrella of cognitive science. The realization that what we conceive of as "thought" can be conceptualized as the series of communications between highly specialized modules represented a watershed moment for the science of cognitive psychology (Pinker, 1997), and has had implications for specialized areas of study within many areas of cognitive science (e.g., the study of judgment and decision making). Also, the idea of a computational theory of mind (Fodor, 1983) coupled with advances in evolutionary biology yielded the burgeoning field of evolutionary psychology (Barkow et al., 1992).

Evolutionary psychology developed in response to perceived stagnation and lack of theoretical growth in the social sciences. For many years researchers and scholars in the social sciences (e.g., anthropology, sociology, and psychology) operated under the umbrella of what Tooby and Cosmides (1992) termed the Standard Social Science Model (SSSM). The SSSM concept of the human mind was as a blank slate (e.g., Locke, 1690/1956), perhaps with a few basic innate processes such as associative learning. These mechanisms received input from culture itself, leading to most of the human behavioral spectrum being a result of learned culture. And thus, the consistencies seen in human behavior within cultures and the disparities seen between cultures was easily explainable based on the SSSM. The SSSM framework also divided the social sciences into their respective fields of study, with anthropology studying cultural differences, and psychology studying the “innate” mechanisms for *learning* culture (e.g., associative learning, social learning, etc.).

Paired with the SSSM was the concept of the mind as a content-independent problem solver. Proponents of this content-independent mind believed that content independence (freedom from contextual constraints) allowed for a more flexible mind and the resulting flexibility in human behavior and decision making. In essence, a flexible mind is “good” and a mind constrained by context and content is “bad.” However, as Tooby and Cosmides (1992) point out, the concept of a content-independent mind is very problematic on a few grounds.

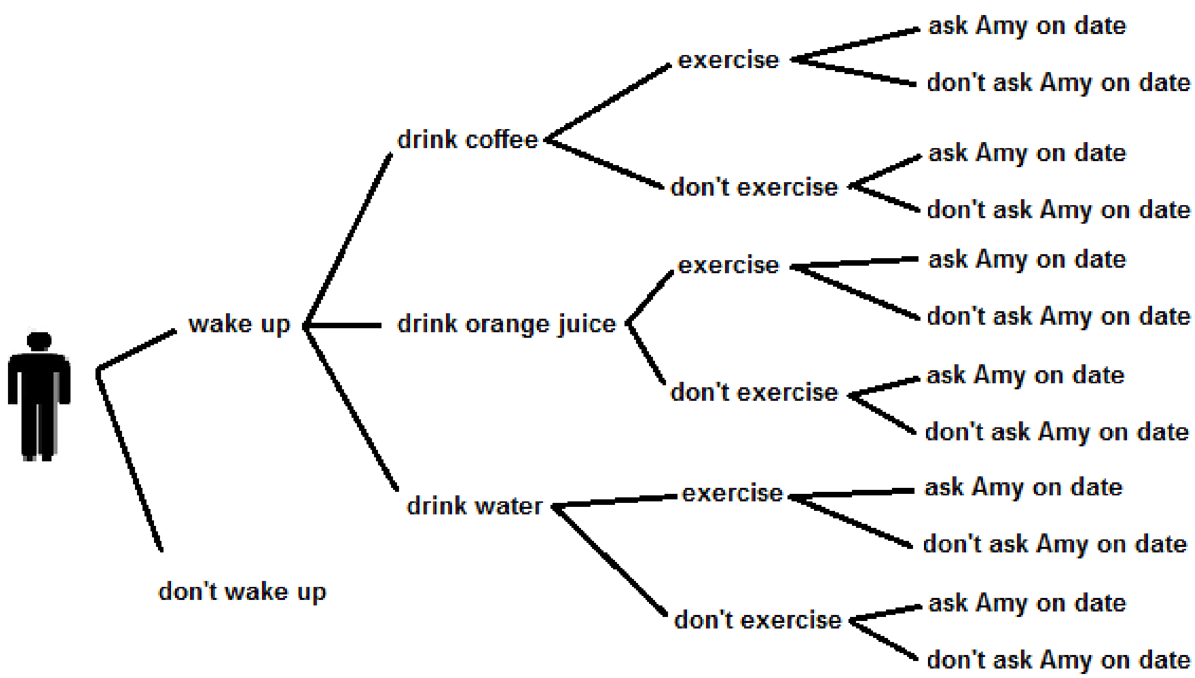
The first issue is that a truly content-independent mind would have no cognitive architecture to solve any of the hundreds of problems our ancestors faced, not to mention the perhaps more cognitively complex tasks modern humans face. The notion that the content-independent mind is shaped and molded by culture is problematic because there would have to be an incredibly complex cognitive architecture to sort and parse the stream of information from a given culture and incorporate it into the cognitive structure of the mind. Content-independent minds do not have such architecture. They have a general problem solving architecture.

The second issue has to do with something much more practical regarding content-independent systems of *any kind*, not just in reference to human cognitive architecture. The issue has been called both the *frame problem* and *combinatorial explosion.* Computer scientists have long observed something known as the “frame problem” (Boden, 1977; Dennett, 1987). Specifically, the frame problem is the observation that, when designing a program or a system, it is rather easy for the problem to become rapidly intractable; the problem the program is trying to solve is too large, and the number of possibilities becomes functionally limitless. To combat this issue, computer scientists create very specialized functions within very specialized programs. Specialized functions and programs solve problems faster and more accurately than more general purpose programs because they come pre-packaged with more information. This pre-packaged information only works at creating more efficient programs because the program is designed to work on specific problems or in specific situations. To conclude, the frame problem is solved in computer science by defining, or “framing” the problem in a very detailed way. Operations are written for the program which contains a rich set of information about the structure of the decision space, the types of options that should be available when making a decision, the goal of the decision, etc. These content-dependent programs contain much more information than content-independent programs. The information is not irrelevant, but directly relates to the problem the program is trying to solve. This allows the program to operate faster and more efficiently because there are fewer options to search in the problem space; mathematically defined, this is also called *combinatorial explosion.*

Combinatorial explosion occurs in any decision algorithm dealing with any number of alternative options. For example if a domain-general, content-independent decision algorithm, such as those which may exist in the mind of your neighbor, is designed to solve the problems which arise every day, we may specify the decision options both graphically and mathematically. Let us assume that your neighbor must first decide to wake up. This is a binary choice with two options: (1) wake up, or (2) don't wake up (see Figure 1-1). So, at this point, the content-independent guidance system in your neighbor's head is only making a choice between two options which may have long term consequences for his reproductive fitness. However, the next step involves something to drink in the morning and this decision involves three different choices: (1) coffee, (2) orange juice, and (3) water. Each of these options may have differing effects on fitness long term, based on caffeine in coffee, vitamins in the orange juice, or the need for basic hydration after sleep. The next decision involves deciding to exercise, either (1) don't exercise, or (2) do exercise. Note that the decision here is greatly affected by the previous decision as well, as both exercising and drinking coffee increase heart rate, while different effects occur after drinking orange juice or water. Finally, your neighbor has to decide whether or not to ask out on a date the attractive female, Amy, from next door. All previous decisions may have an effect her decision to say yes or no to a date.

The point here is that, in order to produce a desirable behavioral outcome—in this instance getting Amy to go on a date—depends on the correct succession of choices. In this example there are a total of 13 combinations of choices. The date with Amy is the successful outcome in this scenario, however, as Tooby and Cosmides (1992) point out, "the issue then becomes, what kind of guidance systems can propel computational systems sufficiently often toward the small scattered islands of successful outcomes in the endless expanse of alternative possibilities?" (p. 102). The answer is most certainly not a domain-general, content-independent one because each variable (e.g., what to drink, whether or not to exercise) multiplies the number of potential decision trajectories. Determining which decision trajectory to take in ancestral environments had very high stakes. A domain-general guidance system with no pre-packaged information helping frame the decision space would have resulted in more (costly) time to make a decision, and potentially guidance down the incorrect path, leading to no food and physical death, or to no mate and genetic death.

Figure 1-1 Example of the Effects of Combinatorial Explosion on the Decision Process



To further explain the importance and practicality of specialization regarding the concept of context-dependent, domain-specificity, let us reflect on the operation of two widely used pieces of software: Microsoft Word and Microsoft Excel. A word processor such as Microsoft Word does not perform the same functions as Microsoft Excel, a spreadsheet program. The two programs perform their specialized tasks very well. They can even share information; tables can be imported into Microsoft Word and text can be copied and pasted into Microsoft Excel. The specialized programs can communicate information back and forth regarding graphs located in a Word document such that, if data is changed in a spreadsheet, it will effectively change the graph in the Word document. Nonetheless, the two programs cannot perform the same functions equally well. Microsoft Word is an effective word processor, but cannot perform spreadsheet functions with the same facility as its counterpart Microsoft Excel.

The caveat of specialization is important not only in reference to the frame problem but also in reference to how evolution works. Evolution is not an ultimate, goal-directed process; there is no absolute end in which the final product is reached and evolution effectively stops. Rather, evolution acts via a one-up process. Although the process of evolution by natural selection is not intentional or goal-directed, it takes what is already present in the organism and, by chance modification, improves on what is already present, similar to overhauling a ship while at sea[1]; modifications can be made plank by plank but each modification must be careful not to sink the ship (Tooby & Cosmides, 1992, p. 60). In terms of behavior, that which is the most effective at leading to reproductive success will spread throughout the population and become widespread, that is, until an even better design appears in the population.

Let us assume that a certain behavior, which leads directly to reproductive success, may be, at first, the result of a simple, general purpose program (hereafter referred to as a module). Through chance mutation, organisms may acquire new features to this module. Most will be less effective, but some will be more effective. One aspect is likely true for all modules that result in more effective behavior: effective modifications tend to be due to a *more* specialized module. Referring back to the frame problem, it is apparent that most modules which have a specialized function will, on average, perform better than their general-purpose colleagues. Thus, it is plausible that over evolutionary history, natural selection has shaped modules—reliably developing patterns of neural connectivity—that solve specific adaptive problems in specific environments, leading to an increase in reproductive success. In essence, these modules and their resultant behavior can explain much about human and non-human psychology. Next, the role of modules in the concept of rationality is explored.

---

[1] It should be noted that chance modification *most often* does not result in a better design. The vast majority of chance modifications are deleterious to the organism to which the modification occurred. However, over deep time, some modifications produce beneficial effects. These effects are retained due to their impact on increased fitness in the specific organism and its offspring.

Massive Modularity and Relevance to Rationality

Modularity—in some degree—as a conceptual framework for how the mind is designed, and for how the mind can guide behavior to desirable outcomes, is well regarded in the cognitive sciences (e.g., Barrett, 2005; Gallistel, 2000; Kashtan & Alon, 2005; Pinker, 1997). However, there remains some disagreement between theorists of both the scientific and philosophical types. The concept of modularity is divided into roughly two streams of thought: (1) Fodorian modularity, derived from Fodor's (1983) original conception of modularity, and (2) massive modularity, the framework derived from evolutionary thought as it relates to modular systems in the mind (Barrett, 2005, 2012; Barrett & Kurzban, 2006; Carruthers, 2005; Coltheart, 1999; Pinker, 1997; Samuels, 1998).

Despite the apparent surface similarities between these two camps of modularity, the differences are theoretically crucial and thus the debate can, and has been, heated (Pinker, 1997; for rebuttal see Fodor, 2000). Further, the debate has unfortunately become lost in inaccuracies which have occasionally derailed scientific progress within the systematic search for how the mind is actually constructed. This debate is vast, intricate, and ongoing. Thus, the details will not be discussed here, as they are not the primary focus of the present studies. However, other scientists have framed the debate quite well, and interested readers are directed to Barrett and Kurzban (2006).

When systems are designed in a modular fashion, they by definition function on more specialized problems. A massive modularity perspective assumes that the mind is composed of modules "all the way down.” Because modules are specialized for specific contexts they also tend to produce proper decisions in those contexts. In short, in specific contexts (e.g., specific environments/ecologies) modular decision processes lead to "rational" decisions. These modules are only useful in certain environments, and environmental cues serve as a triggering mechanism in determining which module should be activated, and thus for which module's decision process should be used. By taking a module out of context it is highly probable that the module and its decision process will lead to an undesirable or "irrational" choice. In short, a decision process—activated by modular organization—is only "rational" when it is evaluated in the appropriate ecology, context, or environment. This philosophical approach has been, more so than any other group, coherently championed by the ABC research group at the Max Planck Institute for

Human Development (Gigerenzer & Selten, 2001; Gigerenzer, Todd, & the ABC Research Group, 1999).

Ecological and Evolutionary "Deep" Rationality

Thus far the idea has been introduced that human phenotypic design and *psychological* design are the products of evolution by natural selection. We have mentioned that evolution may act on psychological processes by enacting changes on the modular structure of the mind. The modular structure—as opposed to a general structure—has been promoted, and given some justification. Some space has been devoted to describing how modular systems can create what might be termed "rational" behavior. Next, the relationship between modularity, as it relates to "deep rationality" (Kenrick et al., 2009), and heuristics is described. The relationship between modules—of the massive type—and heuristics is symbiotic, with each bringing different qualities to the scientific table. However, the relationship would not work if both ideas were not based in a similar theoretical framework: that cognition is inextricably linked to the environment, and should be evaluated as such (Simon, 1957).

Typically in judgment and decision making research a basic tenet of rationality is that individuals attempt to maximize expected utility, and that this is done irrespective of external contextual variables. The concept of ecological rationality is similar, but with respect to context. The concept of deep rationality is that evolutionary utility = fitness. Thus, decision processes are rational in the sense that the process tended to promote genetic propagation either through reproduction or through the rearing of close genetic relatives. However, this should not be confused with what Symons (1992) refers to as Darwinian Social Science (DSS). Specifically, in DSS, researchers examining behavior through the "Darwinian" lens tend to look for the effects of any behavior on *current* fitness (i.e., reproductive viability). This is an incorrect use of evolutionary thought as applied to social science research. Research examining the correlates of behavioral tendencies on current reproductive success is only useful in determining whether a behavior is adaptive—that is, whether it currently leads to reproductive success. However, this research is not by itself capable of determining whether a behavioral pattern is an *adaptation.* Adaptations are created over deep evolutionary time, and for a very specific and recurring feature of an environment. However, the current environment may not be the same as the environment of evolutionary adaptedness (EEA). For example, an adaptation to enjoy and seek food high in sugar content is currently no longer adaptive. The concept of deep rationality frames judgment and decision making as the examination of the current decision processes which were shaped in an EEA. Thus, it is plausible that current decision processes may be adaptations which are no longer adaptive, or may not appear adaptive (i.e., may appear irrational) when examined in context-free economic and judgment and decision making experiments.

Modules, Evolution, and Models of Risky Behavior

The previous discussion has developed the hypothesis that the mind is composed of a large number of modules. These modules are reliably developing patterns of cognition which solve problems. In short, they are they are the machinery by which psychology relates back to behavior. Within the field of evolutionary psychology—including the compatible fields of behavioral ecology, evolutionary biology, cognitive science, and the study of fast-and-frugal heuristics—the primary goal is to discern (1) the existence of these modules, (2) their level of domain specificity, and (3) the pain-staking and elaborate process of providing evidence that a given module is indeed an adaptation, irrespective of whether it is currently adaptive (for review see Barkow et al., 1992).

The guiding philosophy of this dissertation is that the psychological study of risk-taking can be vastly improved by taking the perspective that the mind is composed of many content-dependent modules, each specialized to solve a specific problem. Often these problems were evolutionarily recurrent problems faced by our ancestors over deep time. Rather than approaching risk-taking using normative, or even context-independent processes such as expected utility or prospect theory, it is believed that much more information can be gained by examining risk-taking as a systematic pattern of behavior. To summarize, risk-taking may be "rational" when the behavior is in response to certain environmental cues. Fortunately, various theoretical perspectives have attempted to explain risk-taking behavior in response to precisely such environmental cues. Three of these theoretical perspectives are the focus of the current dissertation. Each will be discussed in more detail in the following chapter.

Chapter 2 - Theoretical Perspectives on Decisions under Risk

The present collection of studies will focus on three theoretical explanations of risk-taking, two from behavioral ecology, and one from the fast-and-frugal heuristics tradition in psychology. Although these three theoretical perspectives on risk taking are different, and, in some scenarios make different predictions, they are all compatible with the meta-theoretical position of massive modularity due to their alignment with either evolutionary studies in behavioral ecology (risk sensitive foraging and dominance theory) or within the framework of ecological rationality (the priority heuristic). While it is believed that all three of these theoretical perspectives are moves in a promising direction, more work is needed to disentangle their proper ranges of explanation, as a theory that can explain everything consequently explains nothing. The perspectives are described in more detail in the sections that follow.

The Priority Heuristic

The priority heuristic is the fast-and-frugal heuristic answer to complex compensatory models of risk taking such as prospect theory (Kahneman & Tversky, 1979), cumulative prospect theory (Tversky & Kahneman, 1992), and a variety of others (e.g., Birnbaum & Chavez, 1997; Lopes & Ogden, 1999). The major difference between the priority heuristic and most other theories of risk taking in psychological or experimental economics research is that the priority heuristic is non-compensatory, that is it takes into account only a few pieces of information at a time, and does not assume that the decision maker combines information during the decision process (Brandstätter et al., 2006).

Background and Development

Brandstätter et al. (2006) entertained a few potential heuristic types before choosing the lexicographic category. Lexicographic heuristics are a set of heuristics which compare the values of two options, one value at a time, until a difference is found (e.g., Gigerenzer & Goldstein, 1996; Tversky, 1972). Then the appropriate option is chosen depending on the goal of the choice being made. Because lexicographic heuristics assume a one-by-one sequential search through cues, perhaps the most important issue for lexicographic heuristics is the ordering of those cues.

The Take the Best heuristic assumes that decision makers order cues based on their validity (i.e., the accuracy of a cue at predicting the target). For instance, in the well-known German Cities problem in which participants are asked to determine which of two German cities has the largest population, people are provided with a number of cues (e.g., whether the city has a soccer team, whether the city has an airport). The validity of each can be determined by selecting the city in each pair which has a given cue as the largest (e.g., selecting Munich as a larger city because it has a soccer team), and then checking the accuracy of those decisions. It is assumed that decision makers are fairly accurate at ordering cues based on their validity, and the heuristic appears to work well in specific situations (e.g., Lee & Zhang, 2012). However, the priority heuristic must rely on very different cues in making decisions between riskier and safer gambles. Two important issues are finding the relevant cues, or, as the priority heuristic refers to them, "Reasons", and determining how these reasons are ordered lexicographically.

Upon examining the standard behavioral economics two option, two outcome gambles, it is clear that there are four pieces of information to which a decision maker could attend: The minimum gains, the maximum gains, the probability of the minimum gains, and the probability of the maximum gains. In two option gambling tasks, people can examine and compare the values of each gamble on those attributes (i.e., reasons).

Regarding the lexicographic order, Brandstätter et al. (2006) cite prior research to pare down all possible permutations of the ordering of reasons. For instance, prior research has shown that payoffs, or gains, are valued more heavily by decision makers than probabilities of their occurrences (Loewenstein, Weber, Hsee, & Welch, 2001). A thorough review of the decision making literature, specifically regarding risky choice behavior, led Brandstätter et al. (2006) to organize the lexicographic order such that minimum gains appeared prior to maximum gains. Thus the ordering of the priority heuristic reflects a pervasive observation in most of the judgment and decision making research that, when in the gain domain as opposed to the loss domain, people tended to be risk-averse. That is, people prefer to choose gambles with the highest minimum gain rather than the gambles with the highest maximum gain because often the highest maximum gain is paired with a lower probability of winning (i.e., it is more variable, and therefore riskier). Lastly, empirical testing demonstrated that decision makers more heavily attend to the probabilities of the minimum gain than the total value of the maximum gain, thus resulting in a finalized lexicographic order (Figure 2-1).

Figure 2-1 Standard Lexicographic Order of the Priority Heuristic.

Order	Reason
1	Minimum Gains†
2	Probability of Minimum Gains‡
3	Maximum Gains†
4	Probability of Maximum Gains‡

Decision Time ⟶

Note. † = Aspiration level is equal to 1/10 of maximum gain between all gambles, rounded to closest prominent number; ‡ = Aspiration level is equal to .10 (i.e., 1/10 of probability scale).

After the order of reasons was set for the priority heuristic, other components of the decision process were established. Specifically, the priority heuristic consists of three rules which are followed in this order: (1) the priority rule, (2) the stopping rule, and (3) the decision rule. The priority rule consists of nothing more than going through the reasons in Figure 2-1 in the designated order. The decision maker compares the properties of each gamble for each reason as he or she moves through the priority rule. At some point the properties for each gamble may be "different enough" to constitute choosing a gamble. This is precisely the function of the stopping rule. The most important issue regarding a stopping rule is determining *when* the magnitude of separation between the properties of two or more gambles constitutes a "big enough" difference.

Drawing from prior work on satisicing (Simon, 1957) the priority heuristic's stopping rule utilizes aspiration levels—amounts or levels that, if met, constitute stopping a search during decision making and proceeding to the decision phase. Because the priority heuristic's reasons contain both probabilities and quantities (e.g., most often monetary amounts), there must be two different types of aspiration levels, and these levels must change with respect to the other properties of the gambles. For quantities (e.g., money) the priority heuristic assumes that decision makers set the aspiration level at 10% of the maximum gain among all gambles, rounded to the nearest prominent number (i.e., 1, 2, 5, 10, 20, 50, 100, 200, 500, 1000)[2]. Gamble properties (i.e., minimum gains or maximum gains) are then compared based upon the aspiration level. If the difference between the relevant quantities of two or more gambles exceeds or is equal to the aspiration level for that reason, then search stops.

The aspiration level for probabilities is much simpler. For probabilities 10% of the probability scale is used as an aspiration level and, since the probability scale remains constant, the aspiration level is not dependent upon properties of any of the gambles. Instead the aspiration level remains at .10. The stopping rule works the same for probabilities of gains as it does for the gains themselves. The probabilities between gambles are compared and if their difference is equal to or larger than .10 then search stops at whichever reason the decision maker was on (Figure 2-1).

Empirical Evidence of the Priority Heuristic

Brandstätter et al. (2006) provided a large portion of the empirical support for the priority heuristic although the 2006 paper was also heavily theoretical in addition to empirical. Brandstätter et al. demonstrated that the priority heuristic can be used to predict majority choice using a large set of data from many different studies. Comparisons of several complex models compared against the priority heuristic revealed that the priority heuristic did as well as, and often much better, in predicting majority choice of participants in the data sets. Other analyses examining decision time supported the prediction that decision time should increase when participants use more reasons to make their decisions (see Figure 2-1).

Despite the support for the priority heuristic in the fast-and-frugal camp of researchers, some third-party psychologists have found shown data inconsistent with the priority heuristic's predictions. For instance, Johnson, Schulte-Mecklenbeck, and Willemsen (2008) examined the priority heuristic using MouseLab, experimental software designed to examine process data. This offered a very suitable environment in which to test the priority heuristic's own predictions about its underlying process. Contrary to the priority heuristic's predictions however, Johnson et al. found that people did not most often compare minimum gains across gambles—a prediction of the priority heuristic—but instead most often made transitions from a gamble's payoffs (either

[2] Brandstätter et al. (2006) define prominent numbers as "powers of 10 (e.g., 1, 10, …), including their halves and doubles. Hence, the numbers, 1, 2, 5, 10, 20, 50, 100, 200, and so on, are examples of prominent numbers" (p. 413).

maximum or minimum) to the probabilities of those payoffs. This particular transition implied to the researchers that participants in their study were using both pieces of information—a gamble's payoffs and probabilities—in order to compute expected values for different gambles. This is of course consistent with expected utility theory (von Neumann & Morgenstern, 1947) and its contemporary variants (e.g., prospect theory; Kahneman & Tversky, 1979) which assume that multiple pieces of information—in the form of probabilities and payoffs—are integrated.

Johnson et al. (2008) did however discover that decisions between gambles could be accurately predicted based on process data derived from transitions between pieces of information and the amount of time spent on a piece of information. This particular type of data offers an important insight into heuristic process models such as the priority heuristic and is one I will return to later in this dissertation (see General Discussion). Using eye-tracking methodology Glöckner and Herbold (2011) demonstrated essentially the same finding: that individuals' decision processes, as operationally defined by eye fixations and movements, are not consistent with predictions made by the priority heuristic.

Other process-based studies have found similar results when examining the priority heuristic. For instance, Ayal and Hochman (2009) used a mixed-factorial design to examine the differential effects of disparity in gambles' expected values, and the number of reasons used by the priority heuristic, on decision time. Although, in certain conditions, the priority heuristic's choice patterns were supported, the decision time process data was not supportive. Specifically, participants took more time to choose between gambles with roughly equal expected values, with the effect of increasing number of reasons examined having very little influence on decision time.

However, some recent research using fMRI techniques to examine the connectivity, and activity, between different brain regions has lent some support for non-compensatory models of risky choice (e.g., the priority heuristic). Rao, Li, Jiang, and Zhou (2012) examined the relative activations of brain areas known to be involved in the processing of payoffs and probabilities. These researchers either explicitly asked participants to perform tradeoffs between probabilities and payoffs when making their decisions, or did not tell them any explicit instructions about how to make their choices. Their results showed that the connectivity between regions involved in payoffs and probabilities was significantly more activated when participants were explicitly told to make tradeoffs as opposed to being given no instruction. The authors suggest that this is evidence that, when not being given explicit instruction, people *may not* use compensatory methods in determining which gamble to choose.

Another claim about the priority heuristic—that it can perform equally well and sometimes better than compensatory models—has fallen under criticism by some researchers (e.g., Birnbaum, 2008). Specifically, Birnbaum made the claim in re-examining the Brändstatter et al. (2006) data that, if the proper parameters (i.e., λ, α, β) are estimated from the data set prior to fitting, cumulative prospect theory (Tversky & Kahneman, 1992) performs quite well. However, Brändstatter, Gigerenzer, and Hertwig (2008) note that there is a key difference between the "accuracy" of models in the sense that Birnbaum means, and the sense that they (Brändstatter et al.) mean. Specifically, there is a difference between data fitting in the case of Birnbaum's re-analysis, and prediction in the case of Brändstatter et al. (2006). The priority heuristic has no flexible parameters. Thus, the data is not needed prior to fitting. Rather, the heuristic can make cold predictions without any prior knowledge of individual differences in the individual making the decisions. This is quite different from cumulative prospect theory, which has five adjustable parameters.

As can be seen by the limited amount of research on the priority heuristic, both its accuracy and hypothesized process are in question. Proponents of the ecological rationality approach to studying judgment and decision making are clearly in support of the priority heuristic's abilities as a process model and as a predictor of choice behavior (e.g., Katsikopoulos & Gigerenzer, 2008). Furthermore, some research outside of that specific group has also shown support for such simple models (McCrea & Bulanda, 2010; Rao et al., 2012). The majority of research has, however, not been in support of the priority heuristic as either a process model or as a predictor of choice behavior (Ayal & Hochman, 2009; Glöckner & Herbold, 2011; Hilbig, 2008; Johnson et al., 2008). Despite this, there is still some utility in modeling cognitive processes as heuristics.

These heuristics make explicit the structure of the decision, revealing the components of importance, and easily allowing for falsification and updating, as can be seen by the number of researchers who *have* falsified the heuristic's predictions. This stands in stark contrast to less explicit models of risky behavior such as prospect theory (Kahneman & Tversky, 1979). A crucial next step for the priority heuristic, before a complete overhaul of the hypothesized process model, is to examine different contexts in which it may perform well. To determine these different contexts, more well-established models of risky choice behavior were drawn from the literature on behavioral ecology and evolutionary biology.

Risk-Sensitive Foraging Theory

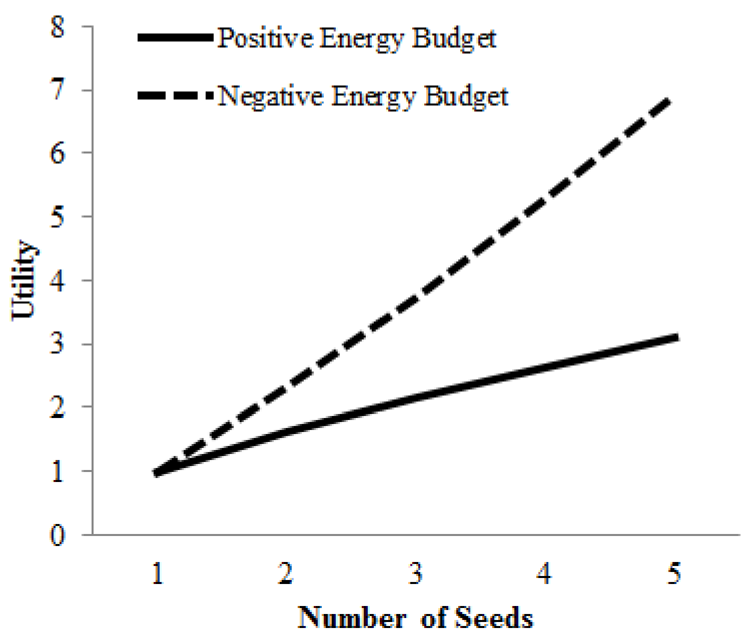
In the realm of animal feeding behavior, payoffs of resources are not arbitrary. The difference between patches of food resources quite literally can mean the difference between life and death. Ultimately, this may have implications for gene propagation since organisms which fail to live forego future reproductive efforts. Thus, the point of the foraging game is to secure enough resources to survive. However, in a variable environment, organisms must often choose between probability distributions of resources, rather than certain amounts on each foraging attempt (Stephens & Krebs, 1986). For instance, if the squirrel on the Kansas State University campus needs 25 acorns per day to survive and has accumulated only 15 up to the point of the last foraging attempt of the day, the last choice matters greatly; choosing the incorrect patch of resources (i.e., choosing the wrong "gamble") may result in survival to the next day, or unfortunate death.

Background and Development

Seminal work by Stephens and Krebs (1986) outlined the scientific philosophy of approaching foraging behavior from the perspective of an economist. Their work also collected and summarized research from foraging theory and interpreted it within the economic framework. Their central thesis on risk-sensitivity in foraging: organisms are not risk-invariant. Rather, their choices are based in both the need level of the resource for which they are foraging, and also in the variability of the distributions of resources from which they are foraging (i.e., "sampling"). In this work Stephens and Krebs define risk as variance, and when they discuss risk-prone and risk-averse, they mean the general tendency to seek or avoid resource distributions of increasing variance. By imagining food resources just as an economist would envision any resource worth pursuing, Stephens and Krebs demonstrated that economic principles could be applied to foraging behavior. One implication of their work (Chapter 6) outlined what would happen if organisms needed a specific amount of a resource to survive. This idea was termed the energy budget rule.

The observation of risk-sensitivity to food rewards appears to have been discovered as early as Leventhal, Morrell, Morgan Jr., and Perkins Jr. (1959). However, a more formal theory referred to as risk-sensitive foraging (as it is in this dissertation), among other names, appears to have first been thoroughly described by Caraco, Martindale, and Whittam (1980) on research with yellow-eyed juncos (*Junco phaenotus*). In this research, Caraco et al. provided juncos with the choice of one of two containers of either (1) a constant amount of millet seeds (safer option) or (2) a variable amount (e.g., 0 seeds or 10 seeds at equal probabilities) with an equal expected value as the option with the constant amount. Caraco et al. examined choice patterns of the juncos when they were in a positive energy budget (i.e., given enough food to satisfy their daily energy requirements) or when they were in a negative energy budget (i.e., *not* given enough food to satisfy their daily energy requirements). Caraco et al. then modeled the utility functions for individual juncos in different energy budgets and discovered vastly different functions depending on energy budget (Figure 2-2). For instance, individual juncos in negative energy budgets displayed convex utility functions indicating risk-proneness, whereas juncos in the positive energy budget displayed concave utility functions indicating risk-aversion.

Figure 2-2 Effects of Energy Budget on Utility of Seeds (Caraco et al., 1980)



Note. This is an adapted version of the results found by Caraco et al. (1980). Readers should refer to the original version for more accurate results.

Following Caraco et al. (1980), other research attempted to model the risk-sensitive foraging patterns of the organisms involved in these studies. Various scientists envisioned the risk-sensitive choice patterns as being the result of a shortfall minimizing organism (e.g., Caraco & Lima, 1987; Stephens, 1981; Stephens & Charnov, 1982); an organism in this sense would seek to minimize the probability of not reaching a specific daily energy requirement[3]. Note that the model of risk-sensitive foraging presented here remains an optimization model of foraging. However, the optimization occurs in minimizing the probability of falling short of an energy requirement, rather than maximizing potential resource gains from a patch of food.

As with most models in optimal foraging theory, risk-sensitivity to resources can be expressed mathematically. Stephens (1981) and Stephens and Charnov (1982) described the *z*-score model in such mathematical terms: $p(S_0 > R) = p$(surviving the night), where p(surviving the night) can be expressed as $1\text{-}\Phi(z)$. This model essentially states that the probability of surviving the night is equal to the probability that an organism's energy budget at the end of the day (S_0) is larger than its energy requirement (R). The probability is then calculated by the formula $1\text{-}\Phi(z)$, where $z = (R - \mu) / \sigma$. The values of μ and σ represent the mean and standard deviation, respectively, of the assumed-to-be normally distributed energy budget at the end of the day (S_0). The value of Φ refers to the cumulative normal distribution, in this case of the value of z, whatever its value.

Using this model, Stephens and Krebs (1986) describe an organism as a z-minimizer, and thus a shortfall minimizer. The z-score model describes *how* choosing risk (variance) makes sense given the assumptions of the model. For example, if we keep μ and R constant, but only vary σ, one can see how it affects $1\text{-}\Phi(z)$, or the probability of surviving the night (Figure 2-3).

---

[3] Stephens and Krebs (1986) note that the use of *daily* energy budgets is primarily a convention which may have started with Caraco et al. (1980). However, the concept of an energy budget could, in theory, be applied to any specified time span.

Figure 2-3 The Effects of Variance (Risk) on the Probability of Survival using the *z*-score model of risk-sensitive foraging (Stephens, 1981)

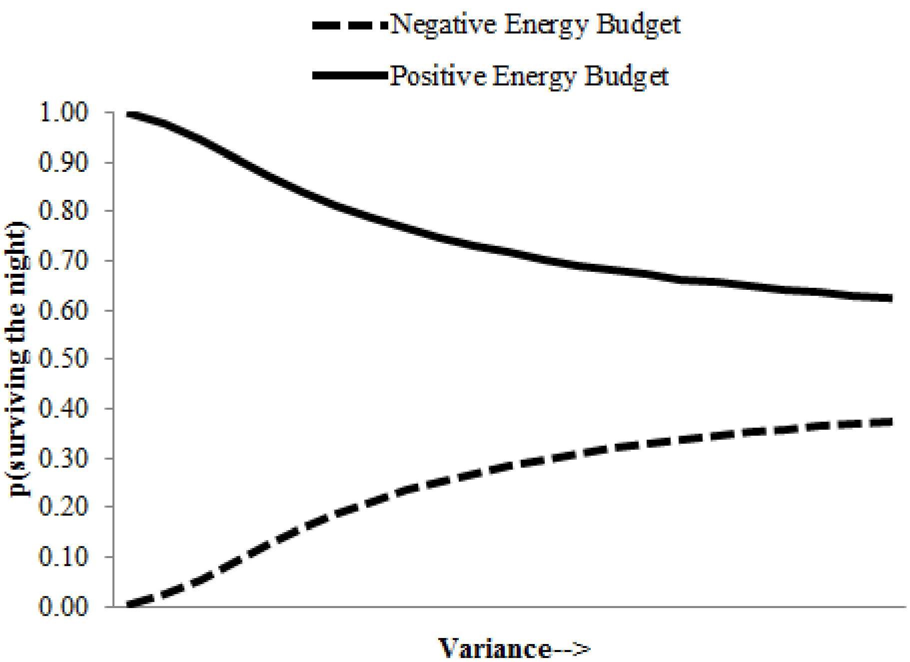


Figure 2-3 shows that, as variance (risk) increases, the probability of surviving the night changes differentially depending on the energy budget of the orgnism making the decision. This also suggests that choosing the maximum possible variance is the optimal solution given a negative energy budget, whereas the minimum possible variance is optimal given a positive energy budget. It also suggests, however, that the outlook is grim for those in a negative energy budget; the payoff of choosing risk has diminishing return in the form of increases in the proability of surviving the night. Perhaps this leads to increased motivation to choose risk; times are truly desparate for those in a negative budget.

Empirical Evidence for Risk-Sensitive Foraging in Humans

Since risk-sensitive foraging was first formalized into a coherent framework there have been numerous studies indicating consistent results: that given a negative energy budget, organisms tend to be risk-prone relative to when they are in a positive energy budget. This effect has been shown for a number of different species. For example, Caraco (1983) extended the results from Caraco et al. (1980) to white-crowned sparrows. Others have shown this general effect of risk-sensitive foraging to apply to common shrews (Barnard & Brown, 1985), rats

(Kirshenbaum, Szalda-Petree, & Haddad, 2000), bumble bees (Cartar, 1991), some species of fish (Young, Clayton, & Barnard, 1990), and even humans (Mishra & Fiddick, 2012; Mishra, Gregson, & Lalumière, 2012; Mishra & Lalumière, 2010; Pietras & Hackenberg, 2001; Rode et al., 1999; Searcy & Pietras, 2011; Winterhalder, Lu, & Tucker, 1999). The focus of risk-sensitive foraging discussion turns next to human examples.

Rode et al. (1999) commented on the nature of a pervasive and perplexing paradox within the judgment and decision making field: the ambiguity effect. The ambiguity effect, also called ambiguity *aversion*, describes the tendency to prefer gambles with known probabilities over gambles with uncertain, or not explicitly given probabilities, thus demonstrating an aversion to ambiguity.

For example, in an example described by Ellsberg (1961), suppose that participants are told that they get to play a lottery. The lottery consists of two boxes, each with a different proportion of black and white balls. In Box A, there are 50 white balls and 50 black balls, whereas in Box B there are a total of 100 black and white balls with an unknown proportion. Participants in psychological studies of this example would then be asked which box they would draw from, after being told that they would win $100 dollars upon drawing a black ball. The observation: most people prefer the box with known probabilities (Box A), which, under normative methods would suggest that the probability of a black ball in Box A (.50) is greater than the probability of the black ball in Box B (< .50; conversely meaning that the probability of the white ball is > .50).

The paradox occurs when participants are then asked which box they would choose if the white ball was rewarded with the $100. Again, most people choose Box A with known probabilities, showing that people are not using normative methods in deciding; choosing Box A in the first round indicates that, for Box B, p(black) < .50, justifying choosing Box A. However, choosing Box A in the second round suggests the decision maker believes p(white) < .50 in Box B, which by completion means they believe p(black) > .50 in the same box. Participants behavior consistent with p(black) being both greater than and less than .50 illustrates the paradox, and the general avoidance of ambiguity. This has been demonstrated many times (e.g., Fox & Tversky, 1995; Keren & Gerritsen, 1999).

However, Rode et al. (1999) suggested one plausible explanation for ambiguity aversion was that ambiguity served as a cue for variability, and people tend to be variance-, or risk-averse.

By showing that people were indeed avoidant to high variance, but not necessarily ambiguity (see Experiment 3), they set the stage to examine theoretical reasons *why* people may be avoidant of variance. Drawing, on risk-sensitive foraging theory, Rode et al. then demonstrated that people would flip their behavioral patterns from ambiguity avoidant to ambiguity seeking when placed in a situation of high need (i.e., a negative energy budget). In their studies, participants had the option to choose from one of two boxes, each containing different proportions of black and white balls, similar to the Ellsberg (1961) example. In one box (e.g., Box A), the proportion of balls were explicitly stated (e.g., 70% white, 30% black), thus participants knew the chances of drawing a black ball. The other box (e.g., Box B) did not have an explicitly stated proportion. However, participants were told that the proportion of white and black balls would be determined by drawing from a container with 101 chips, each with the specific proportions of the black and white balls being determined. The 101 chips corresponded to the 101 possible proportions of the 100 balls (i.e., 100 black balls and 0 white balls, to 0 black balls and 100 white balls). In this example, Box B was known as the ambiguous option.

What was discovered was that when participants had 10 draws with replacement to draw a certain number of black balls, and this number was necessary to move to an actual money earning round, both the amount of black balls needed (the need level) and the variability in the options from which participants could draw mattered. Specifically, when the known risk option did not offer a good chance of reaching the need level (e.g., if they needed 5 black balls, and the proportions of the known risk option were 70% white balls, 30% black balls), participants were more likely to choose the ambiguous option with an unknown probability of black balls. Rode et al. interpreted these data as being consistent with risk-sensitive foraging theory; participants chose what they perceived as high variance when the less ambiguous option did not give them a good chance of reaching a need level.

Mishra and Lalumière (2010) took the decision under risk paradigm used by Rode et al. (1999) and modified it to be more dynamic and ecologically valid by having participants experience the payoffs and probabilities of payoffs through simulation in a dynamic laboratory environment, similar to what an organism would experience in a real-world environment. Specifically, Mishra and Lalumière created a computerized game in which participants were asked to sample from different trees and try to obtain 50 apples during seven trials (described to participants as obtaining 50 apples during a "week"). Prior to the actual game, participants were trained so they could learn the various payoffs and probabilities typically sampled from trees of different colors. Then participants were asked to complete the experiment, during which they would try to earn the 50 apples during the seven trials (i.e., during the "week"). However, participants were unaware that during the first five trials half of them were sampling from lower producing trees than the other half of participants, resulting in having only half as many apples as necessary by the sixth "day." These participants were in a negative energy budget relative to the participants who had higher producing apple trees during the first five "days" of the experiment. Mishra and Lalumière then examined the proportion of choices from the higher risk tree during the last and seventh trial; the sixth trial was not used as a dependent variable. Their conclusions were that participants in the high need (negative energy budget) group were much more likely to choose the riskier tree on the seventh day than the low need (positive energy budget) group. This finding showed that, even in a dynamic environment, humans behave consistent with risk-sensitive foraging theory.

The transition from static environments (e.g., Rode et al., 1999) to dynamic environments (e.g., Mishra & Lalumière, 2010) is important for a few reasons. As pointed out by others (e.g., Hayden & Platt, 2009; Hertwig et al., 2004), the task environment may have important implications for risky choice behaviors. Also, as pointed out by Schuck-Paim, Pompilio, and Kacelnik (2004), great care must be taken when transcending the gap between human economic and judgment/decision making phenomena to biological phenomena, with a major component of the gap being the difference in how these judgment and decision making phenomena are tested (e.g., dynamically or statically). Thus, it is important that the same effect (i.e., risky choice based on the energy-budget rule of risk-sensitive foraging) has been shown in both static task environments (described) and more dynamic experiments (experienced) in a few different studies (e.g., Pietras & Hackenberg, 2001; Searcy & Pietras, 2011).

To some extent, risk-sensitive foraging theory has also been applied to anthropological studies of subsistence societies (for review see Winterhalder, Lu, & Tucker, 1999), and the general framework of risk-sensitive foraging has even been applied to explain the phenomenon of risky choice framing effects (Mishra & Fiddick, 2012; Mishra, Gregson, & Lalumière, 2012). Collectively, these studies show a robust effect of need levels on risky decision making in both humans and non-human animals, in experimental contexts and in their natural environments.

These data suggest that the organisms involved have an evolved mechanism for being sensitive to outcome variance of different decision options, across a wide range of decisions.

Dominance Theory

In humans, it has been documented that cues of relative status are often highly predictive of risky behavior. For example, cues such as socioeconomic status were highly predictive of intrasexual violence, including homicide, in the data gathered by Wilson and Daly (1985). Also, the offender's age and sex were highly predictive of intrasexual violence, with males between 15 and 25 being the biggest violent offenders. This observation sparked their term "the young male syndrome." So, why do young males deem it necessary to take risk associated with violent competition?

Background and Development

Dominance theory—formalized for psychological research by Ermer et al. (2008)—is based in substantial literature from evolutionary biology and psychology showing that human and non-human males engage in risky behavior in an attempt to acquire more resources and/or status, offering the potential of elevating their status in a male hierarchy (Hammerstein & Parker, 1982; Maynard Smith, 1974; Maynard Smith & Price, 1973). This specific example of intrasexual competition is sexually dimorphic, with the behavior being much more prominent in males than females. For example, cross-culturally, females desire higher status men more so than men desire higher status women (Buss, 1989). It then follows that *males of prime reproductive age* should have significant motivation to acquire higher status. Indeed this has been found in many occasions, with the direct result being that risk taking in an attempt to reach higher status increases during the young adult years of a male's life (Wilson & Daly, 1985; Wilson, Daly, & Pound, 2002).

However, this motivation to take risks in male-male competition is also highly systematic, and is modulated by the relative status of the individual with whom one is competing for resources. For instance, it has been shown that a potential evolutionary stable strategy (ESS) for intrasexual conflict consists of examining the competitor for cues of his competitive qualities in order to determine his status relative to yours. The best strategy is then to compete only if you are of equal status to your competitor; if you are clearly lower in status than your competitor it is better to retreat and compete another day (Maynard Smith, 1974; Maynard Smith & Price, 1973). It is also not beneficial to the person higher in status; they have nothing to gain by competing against a lower status individual, but may take an unnecessary risk in competing.

Empirical Evidence for Dominance Theory in Humans

The framework of predictions which Ermer et al. (2008) termed dominance theory is based in mostly non-human animal research and/or mathematical modeling based on known non-human animal research (e.g., Hammerstein & Parker, 1982; Maynard Smith 1974; Maynard Smith & Price, 1973). However, the basic concepts have been applied to a few areas within human competition as well.

For example, Stulp et al. (in press) examined data from different athletic leagues in both German football (American soccer), and American basketball (i.e., the NBA). Stulp et al. examined levels of aggression by using the metric of number of fouls committed by both teams during contests. Stulp et al. operationalized relative rank of each team by using each team's rank at the time of the game. Their findings: When the difference between rankings of teams was small, the number of fouls committed increased, thus suggesting that aggression and risk-taking was elevated between groups of equal status.

Intrasexual competition in nature typically involves some type of prolonged posturing up until a point of actual physical conflict. This is of course different than what can be tested in a laboratory. However, the underlying psychological processes occurring during intrasexual competition likely involve the motivation to be risk-prone rather than risk-averse when being evaluated by someone of perceived equal status, especially when competing with that person for a needed resource. This general case can be evaluated in the laboratory by examining such mundane tasks as choices between risky and safe gambles, and has been demonstrated by Ermer et al. (2008) among others (e.g., Frankenhuis, Dotsch, Karremans, & Wigboldus, 2010; Hill & Buss, 2010).

Ermer et al. (2008) demonstrated that hypotheses about animal intrasexual conflict could be tested using traditional descriptive gambles used in classic judgment and decision making research. In their studies, Ermer et al. told participants that they were being evaluated by students from other universities. The universities were pilot tested for perceived status. Results from their studies showed that, when choosing between two gambles—one risky, one safe—male participants behaved according to the predictions of an asymmetric war of attrition (i.e., low risk taking when competing against lower, or higher status individuals, but high risk-taking against equal status individuals). This trend was not discovered for females however, and it was not discovered when participants (male or female) were choosing between options which provided non-status resources (i.e., medical problem illustrating losses of life).

Other researchers have more directly tied such competitive risk-taking to sexual selection, suggesting that such risky behavior during competition is a signal to females of status, or resource holding potential (e.g., Archer, 2009; Baker & Maner, 2009; Frankenhuis et al., 2010). For instance, Frankenhuis et al. demonstrated that risk-taking behavior in males was most heavily influenced by females. Baker and Maner (2009) found similar results. However, Ermer et al. (2008), as well as Hill and Buss (2010) demonstrated that risk-taking was not dependent upon opposite-sex presence.

Hill and Buss (2010) demonstrated that this desire for higher status was robust. Specifically, they showed that participants would choose the gambles which provided a chance of having more than their peer group, even if the gamble was objectively less desirable; people would take less money if it was more than their peers. However, Hill and Buss did not manipulate perceived status levels as did Ermer et al. (2008), leaving a potential gap in their connection between various research examining risk-taking as a function of the status of competitors and/or onlookers.

It is clear from research that status is an important variable in intrasexual competition. Research has also shown that this phenomenon is not limited to non-human animal research, but applies in experimental lab settings for humans (e.g., Ermer et al., 2008) as well as more real-world contexts (e.g., Stulp et al., in press).

Because both Hill and Buss (2010) and Ermer et al. (2008) were able to demonstrate the effects of status in using paper and pencil, static, described gambles, that method was deemed useful for the studies described in this dissertation. The utility of using paper and pencil described gambles was also consistent with the findings from other studies, testing different theoretical perspectives (e.g., Brandstätter et al., 2006; Rode et al., 1999).

Individual Differences: Numerical Literacy

Despite a growing need to understand basic mathematical and statistical concepts in the modern world, there appears to be a large group of individuals who fail to perform well when presented such tasks (Hanoch, Miron-Shatz, Cole, Himmelstein, Federman, 2010; Hill & Brase, 2012; Lipkus, Samsa, & Rimer, 2001; Peters et al., 2006). The concept of numerical literacy has been defined in different ways by different researchers within the medical, educational, and psychological fields. Lipkus et al. define numeracy as a person's facility with basic probability and mathematical concepts. However, numeracy is often measured in terms of applying these basic probability and mathematical concepts to novel contexts, usually in the form of word problems. Thus, numeracy is not merely mathematical ability, but rather the ability to apply what is known to new and relevant situations in a correct manner (Hill & Brase, 2013).

Although the theoretical construct of numerical literacy remains a somewhat open question (Barwell, 2004; Hill & Brase, 2013; Schapira, Walker, & Sedivy, 2009; Weller et al., 2012), the primary utility of numeracy in judgment and decision making research is as a measure of individual differences in numerical processing (Chapman & Liu, 2009; Hill & Brase, 2012; Peters et al., 2006; Sirota & Juanchich, 2011). This is also the primary importance of numeracy in the current collection of studies.

Brandstätter et al. (2006) mention that one weakness of the priority heuristic is that it does not account for individual differences which may moderate the performance of the heuristic in predicting behavioral patterns. While risk-taking propensity as an individual difference was mentioned by Brandstätter et al., the authors did not mention numerical literacy. However, numerical literacy has been shown to play a role in *how* individuals process choices which vary in payoffs and probabilities (Peters & Levin, 2008).

Peters and Levin (2008) attempted to look into the effect of individual differences in numeracy on the risky-choice framing effect. Specifically, Peters and Levin asked participants to rate the attractiveness of individual options (e.g., 100 lives saved for certain) in isolation and then asked them to rate their preferences for two gambles together, one certain, one risky (e.g., which do you prefer? 100 lives saved for certain, or a 1/3 chance that 300 are saved but 2/3 chance that none are saved). Participants in this study were, of course, randomly assigned to either the positively framed problems or the negatively framed problems.

Results from the study showed that for high numerates (individuals scoring high on the Lipkus et al., 2001 measure), the attractiveness ratings of the individual options were significant unique predictors of the preferences for one option over another in the combined decision tasks. Thus, for high numerates, the framing of the problems was not a significant unique predictor. These results stand in stark contrast to the results for low numerates. Low numerates' individual ratings of options were not unique predictors of overall preferences, but the framing of the problems was a unique predictor.

Peters and Levin (2008) interpreted these results as meaning that there are qualitative differences in how high and low numerates use the information in risky choice paradigms. High numerates rely on the payoffs and probabilities (the numerical information) when forming an opinion about the overall gambles, whereas low numerates do not use such information or at least use such information considerably less. Instead, low numerates rely on other information in the problems such as the whether the problem is framed as positive (saving lives) or negative (losing lives).

A large collection of research on numeracy suggests that this individual difference variable strongly predicts performance on a variety of mathematical tasks (e.g., Chapman & Liu, 2009; Hill & Brase, 2012; Peters et al., 2006). Particularly important to the current studies on risky decision making is the observation made by Peters and Levin (2008) that facility with mathematical and probability concepts may play an important role in predicting whether individuals will utilize the numerical properties of gambles when making their decisions. Because the priority heuristic (1) hypothesizes that individuals perform some basic mathematical operations either implicitly or explicitly, and (2) at this point, lacks any integration with individual differences in decision making, the factor of numeracy is included in the first two studies of this dissertation.

Chapter 3 - Study One

Conclusions about the ability of the priority heuristic to model human risky choice behavior have not yet been empirically settled (Birnbaum, 2008; Johnson, Shulte-Mecklenbeck, & Willemsen, 2008; Reiger & Wang, 2008). However, perhaps of more profound theoretical importance is to return to the issue of *when* the priority heuristic is ecologically rational; that is, under what environmental conditions do people appear to use a process similar to the priority heuristic? Or put simply, in which ecology is the priority heuristic ecologically rational?

The priority heuristic was created as a demonstration that complex models of decision making with many parameters are not needed to explain human decision behavior. For example, Brandstätter et al. (2006) demonstrated that the priority heuristic can predict behavior patterns better than more complex models, such as prospect theory (Kahneman & Tversky, 1979), cumulative prospect theory (Tversky & Kahneman, 1992), the transfer of attention-exchange model (Birnbaum & Chavez, 1997), and the security potential/aspiration level theory (Lopes & Ogden, 1999). However, choices between risky and safe options normally depend on many variables, not simply those of the probabilities and the potential payoffs. It could be argued that the priority heuristic is limited to being a clever demonstration of how other models of decision making should be created: that is, as process models which need not assume averaging, and weighting within the organism's cognitive processes.

So, it may be that the ecology of the priority heuristic is no more than the ecology of standard psychology and economics experiments where the only manipulation is in terms of the probabilities and payoffs of described gambles. Although Brandstätter et al. (2006) demonstrated that there is merit in using process models such as the priority heuristic when predicting risky choice behavior, there may be little validity in the priority heuristic in terms of how our minds were designed, by natural selection, to solve consistent adaptive problems such as when to take risks. The priority heuristic *does not* take into account several potential environmental concerns that may motivate an organism to choose risk over safety (e.g., energy budget, status of competitor). Fortunately, there is a rich literature on risky choice behavior in non-human animals from evolutionary biology and behavioral ecology that *does* take into account many environmental considerations when making decisions under risk. One well-supported theory in behavioral ecology is risk-sensitive foraging (Stephens, 1981; Stephens & Krebs, 1986).

Study One was designed to systematically test whether the priority heuristic's predictions based on its hypothesized process would hold true when put in more ecologically valid environments faced by many organisms (Barnard & Brown, 1985; Caraco, 1981, 1983; Cartar, 1991; Kirshenbaum, Szalda-Petree, & Haddad, 2000; Real & Caraco, 1986; Young, Clayton, & Barnard, 1990), including perhaps humans (Mishra & Lalumière, 2010; Pietras & Hackenberg, 2001; Rode et al., 1999; Winterhalder, Lu, & Tucker, 1999). Specifically, we wanted to see if the priority heuristic would be able to account for behavior in the face of resource need levels[4]. Although the layout of the study is reminiscent of approaches of strong inference (Platt, 1964), the major goal of Study One was to test when the priority heuristic might work well, rather than examining if one model of risky choice was "correct" while the other was not. Indeed this is a major goal of the ecological rationality approach to judgment and decision making (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011; Gigerenzer & Selten, 2001; Todd & Gigerenzer, 2007).

A major goal of any model—or any theory—is to test its range of focus. For instance, Darwinian evolution postulated the modification of species over time. However, Darwin's proposed process "driving" evolution—the process of natural selection—assumed some form of mechanism for inheriting such modifications. Pangenesis, Darwin's own idea for how inheritance could work (Darwin, 1871/1971), was later supplanted by Mendelian genetics and then more advanced models of inheritance (e.g., the Boveri-Sutton chromosome theory), ultimately leading to a revolution in evolutionary thinking during the 20th century known as the "modern synthesis." The modern synthesis led, in turn, to extensive support of Darwin's own evolution by natural selection, despite some of his other idea's being supplanted by better ones along the way. This process is illustrative of an ideal in science, but it also demonstrates how theories and models of observed phenomena are modified through the scientific process. This

[4] Throughout this dissertation I refer to "need levels." Most often in risk-sensitive foraging research these need levels are conceptualized as amounts of tangible resources (e.g., calories) needed to literally survive. However, for this dissertation and all of its studies I refer to need levels as the amount of earned fake money necessary to reach a potential second round, during which participants may earn additional fake money.

process is certainly also true in the behavioral sciences, with the psychology of judgment and decision making being no exception.

The priority heuristic is an example of a fast-and-frugal heuristic for making risky decisions in the tradition of the ecological rationality approach in psychology. However, it is unknown when this heuristic will work; that is, under what conditions does the hypothesized process stop predicting behavior? The goal of Study One was to test a few of the possible conditions.

To summarize, the priority heuristic makes specific predictions about preferences for gambles in risky choice situations. The structure of the priority heuristic's predictions should not change with respect to context (e.g., if money earned through gambling is changed to food consumed through foraging). Although the priority heuristic is in the tradition of ecological rationality, the ecology does not necessarily imply the same thing when speaking in terms of our species' evolutionary history. If fast-and-frugal heuristics such as the priority heuristic are adequate "as-if" models of human cognition then they should also be compatible with the massive modularity thesis—that minds are composed of a large number of context-dependent, domain-specific modules, each specialized to solve recurrent problems that our ancestors faced throughout evolutionary history. However, the priority heuristic does not, on the surface, appear to be capable of handling different contexts. Ultimately, this is an empirical question, and one which is the focus of Study One of this dissertation.

Hypotheses

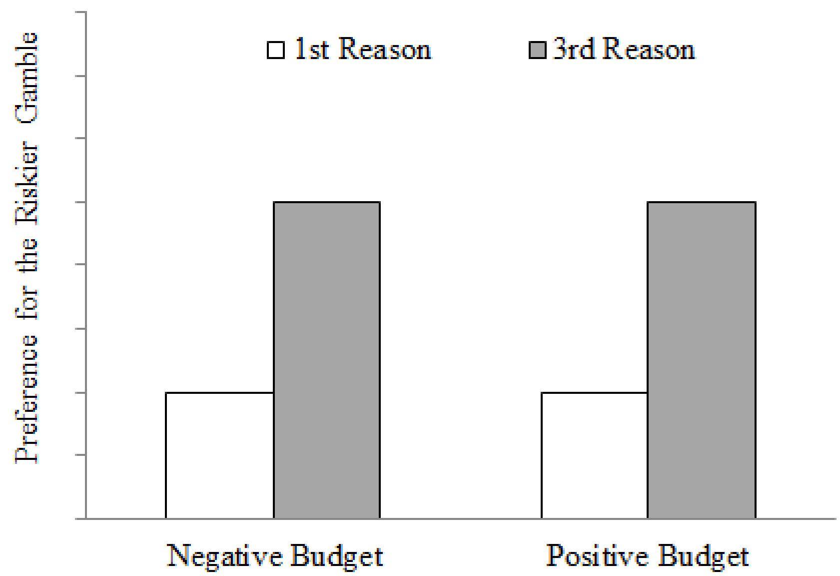
From these two models of risky choice behavior—the priority heuristic and risk-sensitive foraging—specific predictions can be made about overall preferences for risky options depending on specific characteristics of the decision problem (i.e., the probabilities and payoffs of winning and losing each gamble) and the environmental considerations (i.e., amount of money needed to advance to a potential next round).

The Priority heuristic

General predictions cannot be made that would encompass *all* decision problems because the various payoffs and probabilities of each decision problem will affect the prediction made by the priority heuristic. However, the priority heuristic's predicted choices are embodied within the process model itself (Figure 2-1). For the gambles created for Study One (see Decision

Tasks section below), the priority heuristic predicts that gambles labeled as "3rd Reason" tasks should result in higher preferences for the riskier gamble than gambles labeled as "1st Reason" tasks (Figure 3-1). An additional prediction about the priority heuristic would be that decision time, based on the time taken by each participant to make a decision, should increase when problems require more steps of calculation as outlined by the priority heuristic's hypothesized process. For example, decision problems that require only one "reason" should take less time to decide than problems that require two or three reasons.

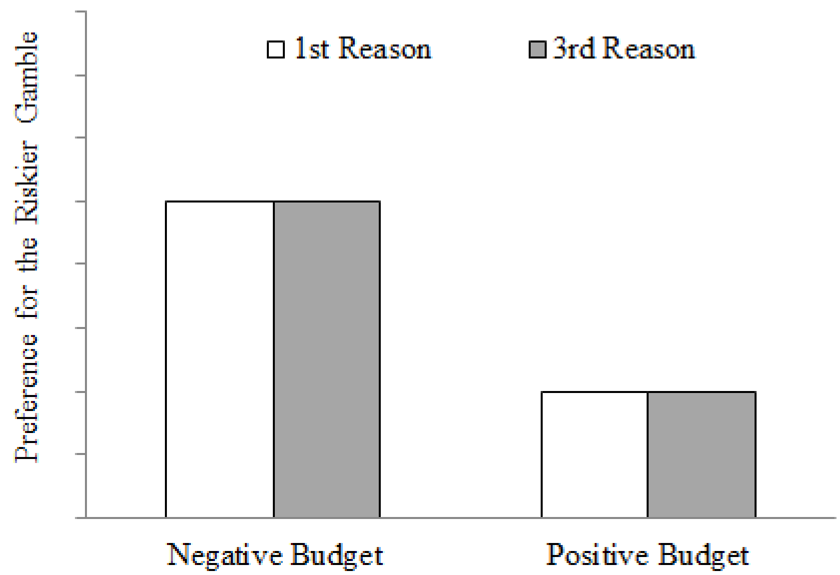
Figure 3-1 Priority Heuristic Predictions for Preferences in Study One



Risk-sensitive foraging

Participants should be risk-averse and choose the safer option when it is enough to reach the need level, characterized in the present experimental methodology as the amount of money needed to reach a potential second round. However, people should be risk-seeking when the riskier option is the only option that gives them a chance to reach the need level (Figure 3-2). Risk-sensitive foraging makes no predictions about decision time in this specific context.

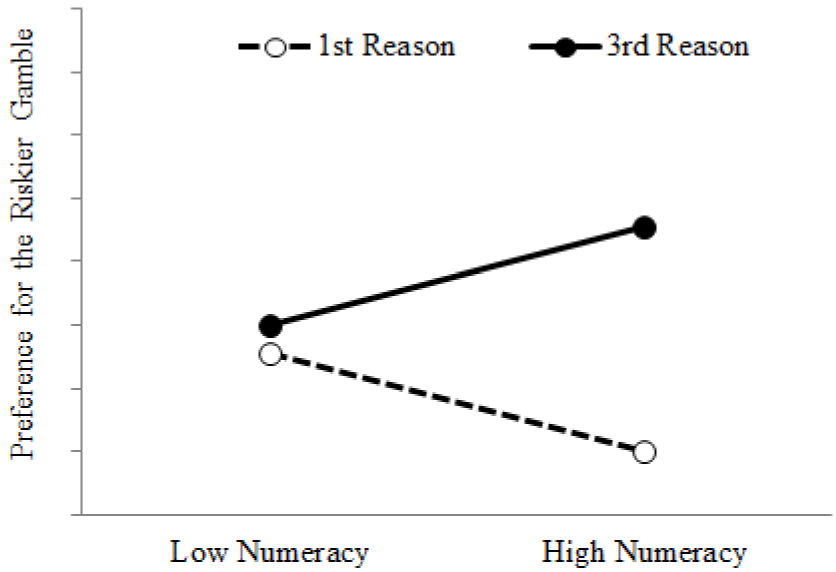
Figure 3-2 Risk-Sensitive Foraging Predictions for Preferences in Study One



Moderating effect of numeracy

Peters and Levin (2008) suggest that high numerates, more than low numerates, use their evaluations of the different numerical options when deciding between two options, one risky and one safe. If this is true, one would expect that models which implicitly assume some numerical processing should better predict decisions for high numerates than low numerates who may be using other types of information to make a decision. Because the priority heuristic implicitly assumes a modest level of numerical processing (e.g., calculation proportions, comparing decimals), it is plausible, given the findings of Peters and Levin, that numeracy should moderate the accuracy of the priority heuristic in predicting risky-choice preferences. Specifically, higher numerates should behave more consistently with the priority heuristic than lower numerates, resulting in high numerates having a high preference for the riskier gamble in 3rd Reason tasks and a lower preference for the riskier gamble in 1st Reason tasks (Figure 3-3). There are no specific predictions regarding potential main effects of numeracy or the direction of the numeracy/risk-proneness relationship.

Figure 3-3 Numeracy-Priority Heuristic Relationship Predictions for Study One



Study One Method

Participants

Data were collected from 60 participants enrolled in introductory psychology courses at Kansas State University. All participants received experimental research credit which went toward a course requirement. Students not wishing to participate in research were given the option of writing short response papers to peer-reviewed psychological research articles. The demographic characteristics of the participants were consistent with typical college-age samples used in psychological research in terms of age (M = 18.88, SD = 2.15), and the ratio of males to females, (Males: n = 14, Females: n = 46). Also typical of human-participant research conducted in the Midwestern United States, the majority of participants were of Caucasian ethnicity (n = 50), with other ethnic groups being less represented: African American (n = 4), Asian (n = 4), and Hispanic (n = 1). One participant identified their ethnicity as "Other."

Design

Research has shown a tendency for participants in human psychological research to be relatively risk-averse, especially when gambles are framed in terms of gains, as they are in Study One and throughout this dissertation (Tversky & Kahneman, 1981; but see Wang & Johnston, 1995). Pilot testing for Study One showed the same tendency for general risk-aversion. To address such risk-aversion, and examine *relative* risk-aversion, two different measures of choice behavior were used in Study One. A binary choice paradigm (Binary Choice; BC) was used in which participants chose between one gamble over another; this is the most ecologically valid decision paradigm, but is also highly susceptible to low variability in choices, with most participants choosing the safe gamble. To provide for more sensitive measurements of choice in Study One, participants were also asked to provide a preference rating for the same gambles on a scale from 1 to 6, with 6 indicating a higher preference for the risky gamble, and 1 indicating a higher preference for the safer gamble (Continuous Preference; CP). This measure provided a more sensitive metric for determining each participant's motivation to choose risky over safe gambles, but it also introduced an additional problem of order effects. To address the potential for order effects—whether providing a continuous preference, or making a binary choice first, have differential effects on decisions—the order was counterbalanced within Study One's design.

The purpose of Study One was to systematically examine a few conditions under which the priority heuristic may, or may not, work well, by introducing variables from risk-sensitive foraging (i.e., the energy-budget rule) (Stephens, 1981; Stephens & Krebs, 1986). To assess the performance of these two different models of risky decision making, while also providing the opportunity to look at potential order effects of different choice paradigms, a 2 (Budget: Negative and Positive) by 2 (Task Order: BC 1st or CP 1st) by 2 (Reason Number: 1st Reason and 3rd Reason) mixed factorial design was utilized. In this design, Reason Number was within-participants while Budget and Task Order were between-participants.

Materials

Study One used novel "decision tasks": problems in which participants were asked to choose between two gambles, each with different buy-in amounts, payoffs, and respective probabilities of winning and losing. Participants also answered questions as part of the General Numeracy Scale (Lipkus et al., 2001) to assess the potential moderator effect on priority heuristic predictive accuracy, and the Domain Specific Risk Scale (Kruger, Wang, & Wilke, 2007) to *control* for individual differences in domain-specific risk-taking. The decision tasks and individual difference measures are described in more detail in the sections that follow.

Decision tasks

To measure performance a total of four different problems were created (Table 3-1). Half of the problems were created so they would correspond to reason number one in the priority heuristic (1^{st} Reason). The other half of the problems were created in a way consistent with decision making at the third reason of the priority heuristic (3^{rd} Reason)[5]. Participants received both the 1^{st} and 3^{rd} Reason problems. Participants were randomly assigned to one of two conditions of Budget. To create experimental environments analogous to varying energy budgets, different "need levels" were created, such that participants would need to earn different amounts of money in order to move to a second round, if a second round occurred. In reality, there was never a second round. All participants only completed a single round. The purpose of telling participants that they may be a potential second round was to create an environment in which there was an uncertain future. Thus, if the future round occurred, there would be a good reason to have the necessary fake money to play that round.

For the purposes of Study One, conditions in which the "safer" gamble *and* the "riskier" gamble offered the possibility of reaching the need level were characterized as being *positive budget*. Participants did not need to take risk in order to reach the need level. The need level in the negative budget conditions was set in a way that *only* the riskier gamble allowed the possibility of reaching the need level. The expected values between the riskier and safer gambles were identical for all decision tasks. This is a requisite for testing the priority heuristic in that decisions need to be "difficult" (i.e., expected values between options need to be similar) (Brandstätter et al., 2006).

---

[5] The standard lexicographic order of the priority heuristic suggests that gambles should be compared first at minimum gains (i.e., the 1^{st} Reason). The decision task labeled 1^{st} Reason in Study One was designed so that the difference between the two gambles would meet the aspiration level and search would stop, resulting in the participant choosing the safer gamble because it had the highest minimum payoff. Similarly, for the 3^{rd} Reason decision task, it was designed to require participants to continue search through the 2^{nd} Reason, resulting in participants stopping search at the 3^{rd} Reason and choosing the gamble with the highest maximum payoff (i.e., the riskier gamble).

Table 3-1 Decision Task Characteristics for Study One

	Decision Task Order					Buy-in Amounts		Winnings (Probabilities)	
Condition	First Task	Second Task	Reason	Budget	Need Level	Safer	Riskier	Safer	Riskier
1	Binary Choice	Continuous Preference	1st	Negative	$300	$25	$100	$250 (.90)	$600 (.50)
			3rd	Negative	$400	$20	$25	$400 (.55)	$450 (.50)
2	Continuous Preference	Binary Choice	1st	Negative	$300	$25	$100	$250 (.90)	$600 (.50)
			3rd	Negative	$400	$20	$25	$400 (.55)	$450 (.50)
3	Binary Choice	Continuous Preference	1st	Positive	$200	$25	$100	$250 (.90)	$600 (.50)
			3rd	Positive	$300	$20	$25	$400 (.55)	$450 (.50)
4	Continuous Preference	Binary Choice	1st	Positive	$200	$25	$100	$250 (.90)	$600 (.50)
			3rd	Positive	$300	$20	$25	$400 (.55)	$450 (.50)

The General Numeracy Scale

The General Numeracy Scale (GNS) (Lipkus et al., 2001) was used to assess participants' levels of numeracy. The GNS is an eleven-item scale consisting of questions assessing participants' understanding of number conversion, risk, and probability concepts (Appendix A). Lipkus et al. developed the GNS primarily for use within medical decision making contexts and, as a result, their scale poses questions framed in medical and disease terminology. However, Lipkus et al. suggest that the GNS assesses a global construct of numerical literacy despite its content focused on medical decision making.

Despite its wide use (e.g., Cokely & Kelley, 2009; Hill & Brase, 2012; Peters et al., 2006), the GNS has been criticized for its undesirable psychometric properties, most prominent of which is a highly negatively skewed distribution of scores, and potential ceiling effects (Liberali, Reyna, Furlan, Stein, & Pardo, 2011; Weller et al., 2012). This creates problems when researchers utilize standard median split techniques for use in ANOVA (MacCallum, Zhang, Preacher, & Rucker, 2002). Despite these issues, many people still use such median split techniques on the GNS (e.g., Chapman & Liu, 2009; Peters et al., 2006; but see Galesic & Garcia-Retamero, 2011 and Peters & Levin, 2008). The GNS was used in Study One primarily due to scientific inertia; despite attempts to create better, more theoretically motivated scales (Cokely, Galesic, Shulz, Ghazal, & Garcia-Retamero, 2012; Weller et al., 2012), the GNS remains the most widely used measure of numerical literacy. As such, it was used in Study One to assess each participant's facility with processing and understanding numerical information.

Domain Specific Risk Scale

Risk taking propensity was measured in Study One due to the potential effect that individuals may have variable levels of general risk taking which may influence the variables of interest in Study One (i.e., need level, priority heuristic reasons). Mishra and Lalumière (2010) demonstrated that, when a need level is present in decisions from experience, individual differences in risk taking propensity do not significantly predict actual risk taking beyond that participant's energy budget at the time of making a decision. This would suggest that there is no merit in assessing individual differences in risk taking propensity. However, Mishra and Lalumière also note that, in conditions where participants had already met their need level, their subsequent choices—either risky or safe—were heavily predicted by general risk taking propensity. These results would suggest that, when there are no environmental constraints such as the need to reach a required need level, individual risk taking propensity is predictive of risky choice behavior. In order to control for risk-taking in Study One, individual tendencies to be risky in domain-specific contexts were measured.

Risk taking propensity may not be a domain general individual difference variable (Weber, Blais, & Betz, 2002). However, because of the evolutionarily-motivated nature of the current research, a domain specific risk taking scale which embodied evolutionarily-important risk taking behavior was used. The Domain Specific Risk Scale (DSRS) (Kruger et al., 2007) consists of 15 likert-response statements corresponding to five evolutionarily-important domains of risk (Appendix B). The domains of risk are: between-group competition, within-group competition, fertility, mating and resource allocation for mate attraction, and environmental.

Study One Procedure

To elicit motivated responding in participants, Study One was presented as a gambling competition between students from all over the Kansas State University campus. Participants were be brought into the lab by a researcher wearing professional clothing and a white lab coat. The appearance of the researcher remained professional in order to make participants believe in the importance of taking the study seriously; some research has demonstrated that professional attire, including lab coats, increases third-party perceptions of power and status toward the person wearing the attire (Brase & Richmond, 2004). Once in the laboratory participants were first told that the study they were participating in was actually designed to be a competition between students from Kansas State University. They were told that they would be participating in a gambling competition in which they would choose between gambles, and at the end of the study they would play out the gambles selected in order to see if they had won fake money. Participants were then told that the student with the most fake money would win the competition, and would be notified after all students had participated in the competition. All participants were then asked if they understood the gist of the competition. Questions by participants were answered by the researcher.

Participants were then instructed to click "OK" on the screen in MediaLab (Jarvis, 2008). Participants first were presented with a "welcome" screen with the text "Welcome to the Decisions about Money Competition." Immediately below this text was the official Kansas State University logo. Participants then automatically proceeded to the informed consent screen. At this time the researcher explained the informed consent to participants and asked them to read the informed consent and ask any questions if necessary. Participants were then directed to the paper copy of the informed consent located at each computer station. Once participants had signed the informed consent sheets and agreed to participate in the competition, they proceeded to the rules section of the study.

Participants learned the rules of the game by clicking through an animated PowerPoint slideshow. The slideshow was designed so that participants could move through at their own pace, one bullet point or animation at a time, by left-clicking the mouse on their respective computers. The rules of the game were that participants would be competing in two separate gambling competitions during the experiment. Participants were told that they would be choosing between two gambles with different odds and payouts, and that they would play out their chosen gambles at the end of each round. Each round consisted of two decision tasks; participants were told the two decision tasks were unrelated. The two decision tasks were said to be independent of each other, similar to having "two horses in a race." We, the researchers, were simply letting the participants have two separate chances of winning the competition. The two decision tasks actually constituted the within-participants independent variable of Reason Number (i.e., 1st Reason, and 3rd Reason).

Participants were additionally told that there would be either one or two rounds of the competition and that each computer would randomly select the number of rounds each participant would be allowed to play, so it could be different for each participant in the competition. Furthermore, in order to reach a potential second round, participants would need to earn a certain amount of fake money to qualify for the second round. Thus, participants were essentially told that they would be placed in an environment in which there is an uncertain future; they knew that there may be a possible future round in which they could earn money, but this was not guaranteed. If they wished to earn money in the potential second round they needed to take steps to ensure their likelihood of making it to the second round (by choosing the gambles that would offer them the best chance of earning the minimum need level in the decision tasks). This amount of money needed to reach the potential second round, hereafter referred to as the "need level", was manipulated between-participants as part of the Budget manipulation. After finishing the rules in PowerPoint, participants were asked if they had any questions about how the game was played. Participants were then asked a series of five questions to assess their understanding of the rules using MediaLab (Jarvis, 2008).

Participants then completed a sample decision task in which it was made clear that their performance on the decision task would not affect their actual performance in the competition; the sample decision task was simply to teach participants how the competition would be structured. In this sample decision task participants were shown the exact same graphical representation of the gambles as they were in the actual decision tasks, however, after the sample tasks, participants then played out their gambles to see if they won fake money (Figure 3-4). The payouts to participants were structured so that each participant, regardless of what gambles they chose, won a single gamble and lost the other gamble. This was done in order to remove any unintended priming effects of winning during the sample decision task on actual decisions in the later, and more important, experimental decision tasks.

Figure 3-4 Example decision task for Study One

After participants completed the sample decision tasks they were stopped and asked if they had any questions about the competition, or the procedure, before the actual competition began. Questions were answered by the researcher prior to beginning the "competition" (the main part of the study). First participants answered the two decision tasks (1^{st} Reason, 3^{rd} Reason). These two decision tasks were presented in a randomized order to participants. These first two decision tasks were either answered in the binary choice format or the continuous preference format depending on the condition to which each participant was randomly assigned. Next, participants answered questions on the General Numeracy Scale (Lipkus et al., 2001). Questions on the GNS were randomized from their normal order for each participant, and so the ordering of questions is not the same as seen in the Appendix A. Following the GNS, participants answered questions from the Domain-Specific Risk Scale (DSRS) (Kruger et al., 2007). The DSRS items were also randomized for each participant and did not appear in the same order as those in the Appendix B. Following the DSRS items participants were asked to recall their answers to the first two decision tasks. They were then told that they would be answering the same decision tasks again, but in a slightly different format. Participants were told that the necessity of this follow-up was because we, the researchers, wanted to match each participant with the gambles he or she absolutely preferred. Once matched with their preferred gambles, they would then be able to, at the end of the round, play the gambles out to (potentially) earn fake money.

Following their answers to the second instantiation of their original decision tasks, participants were asked a series of follow-up questions, including questions on the importance of the need level in making their decisions, as well as the importance of the probability of winning, potential amount won, and potential amount lost. Additionally, participants were asked about their level of suspiciousness with regard to the authenticity of the competition (Appendix C).

When participants completed the follow-up questions their computer automatically proceeded to a dialogue box notifying them that the experiment was finished and that they should notify the researcher present. At this time the researcher told the participants that the competition was not real, and that we (the researchers) used deception in order to get them to respond in a certain way. Participants were all given debriefing forms and asked if they were distressed by being lied to. No participants responded that they were distressed, but the researcher made clear that they could use the contact information provided on the debriefing form (Appendix D) if they felt distressed, or simply had questions after the experiment. If participants had no further questions, they were thanked for their participation and Study One was concluded.

Study One Results

Study One was conducted with the aim of systematically examining one potential scenario in which the priority heuristic may not be able to successfully predict individual risky choice and preference patterns—environments in which there are predetermined need levels, creating motivation for risky preferences (Mishra & Lalumière, 2010; Real & Caraco, 1986; Rode et al., 1999; Stephens & Krebs, 1986); the priority heuristic's model does not explicitly take into account resource need levels. Decision tasks were created and need levels assigned to different conditions, resulting in different predictions for risk preference (both binary choice and continuous preference) for the priority heuristic and risk-sensitive foraging. Further, different predictions were made for the relationship between numerical literacy and risky-preference as it may relate to the priority heuristic. To test the specific hypotheses made, a series of statistical analyses were performed. These hypotheses and their respective analyses are described in the sections that follow.

Preliminary Data Issues

Before the major analyses were performed a series of preliminary data issues were first resolved. Among these issues were (1) cleaning the decision time data, (2) the use of covariates and (3) specific analytic techniques to be used on a variety of data collected in Study One. These issues are addressed in more detail in the following sections.

Preliminary Data Cleaning

Unlike the Likert scale responses for the continuous preference ratings which were limited in range from 1 to 6, decision time data was not limited and thus the data were screened for outliers by using the *z*-score method (Tabachnick & Fidell, 2007). The variables for reaction time of the continuous preference ratings tCP and the reaction time for binary choice task, tBC were converted to *z*-scores and sorted according to size. Any cases with values greater than ±3.29 were removed from the analyses on decision time. Because the priority heuristic is within-participants, each participant had two decision times for each type of decision task (e.g., BC and CP), one for each level of Reason Number. In the case that a participant had only one outlier, that person's data for the remaining decision task was also deleted because it would otherwise result in incomplete within-participant data (i.e., data for one level of Reason Number but not for another). Using this method a single data point was deleted from the tBC ($z = 6.05$) and one other was deleted from the tCP ($z = 5.30$). In the end, the total sample sizes for the analyses on decision times (tBC and tCP) were $n = 59$ for tBC and $n = 59$ for tCP.

Risk Propensity as a Covariate

Prior to Study One it was assumed that general risk taking propensity in the individual participants may have unintended effects on the dependent variables of interest. To control for the individual differences in risk taking the subscales of the Domain Specific Risk Scale (Kruger et al., 2007) were assessed using a Pearson correlation matrix. The correlations demonstrated the relationships between each of the five subscales of the DSRS and the summed continuous preference scores, summed binary choice reaction times, and summed continuous preference reaction times. The summed dependent variables were created to demonstrate the correlations between the subscales of the DSRTS and risk-proneness and reaction time collapsed across Reason Number.

Following the guidelines of Tabachnick and Fidell (2007) the correlation matrix was examined to look for (1) the relationships between all potential covariates (DSRS subscales), and (2) the relationships between the dependent variable and the potential covariates. As suggested by Tabachnick and Fidell, acceptable covariates should not be significantly correlated with other covariates entered into a model, but should be significantly correlated with the dependent variable. Highly correlated covariates entered into the same model result in diminished return in the form of adjusted dependent variables, while also resulting in decreased degrees of freedom. In short, the costs do not outweigh the benefits.

The correlational analyses demonstrated that there were no statistically significant correlations between any of the subscales of the DSRS and any of the continuous dependent variables (Table 3-2). Due to the results of these analyses, it was determined that the use of any of the risk subscales as a covariate was not warranted and would potentially remove degrees of freedom while not providing an increase in statistical power.

Table 3-2 Correlations between potential covariates and dependent variables in Study One

	Potential Covariates				
Depenent Variables	*Fertility*	*Between-Groups*	*Within-Group*	*Mating*	*Environmental*
Sum (CP)	-.06	.22	.11	.08	-.18
Sum (tCP)	-.04	.09	-.03	.07	-.04
Sum(tBC)	.02	-.11	-.01	.16	-.11

Note. CP = Continuous Preference Ratings, tCP = decision time for Continuous Preference Ratings, tBC = decision time for Binary Choice tasks. Statistically significant correlations are denoted by *.

It is odd to discover that none of the subscales of the Domain Specific Risk Scale, designed to measure individual differences in risk-proneness on a variety of evolutionarily important domains, significantly correlated with preferences for risky gambles. However, Mishra and Lalumière (2010) demonstrated that personality differences in risky decision making only predicted risky behavior in situations of low need (analogous to a positive energy budget in Study One). Further examination of the data from Study One revealed the same basic trend; specifically, between-groups risk propensity was positively correlated with risk preferences (CP summed across Reason Number) only when the need was low (i.e., when participants were in a positive budget) (see Table 3-3). No covariates were analyzed in the main analyses due to their lack of an omnibus relationship with any of the dependent variables of interest, and, in the case of continuous preference ratings, a violation of the assumption of homogeneity of regression (Tabachnick & Fidell, 2007).

Table 3-3 Correlations between Potential Covariates and Dependent Variables for Each Level of Budget

		Potential Covariates				
Budget	Depenent Variables	*Fertility*	*Between-Groups*	*Within-Group*	*Mating*	*Environmental*
Negative	Sum (CP)	-.17	-.15	.18	.01	-.44*
	Sum (tCP)	-.08	.27	-.05	-.34	-.02
	Sum(tBC)	.16	-.19	.08	-.09	-.16
Positive	Sum (CP)	.08	.62*	.12	.21	.09
	Sum (tCP)	-.02	-.03	-.01	.30	-.05
	Sum(tBC)	-.18	-.07	-.11	.37*	-.05

Note. CP = Continuous Preference Ratings, tCP = decision time for Continuous Preference Ratings, tBC = decision time for Binary Choice tasks. Statistically significant correlations are denoted by *.

Potential Order Effects

In Study One there was a potential order effect due to the use of two different measures of risk taking. These measures were the Binary Choice (BC) task and the Continuous Preference rating task (CP). Both of these measures were given to all participants but in a different order. The order variable was called Task Order and was divided into two levels (BC 1st and CP 1st) indicating which of the two measures were administered first, with the other measure coming last. To assess the potential order effects a one-way analysis of variance (ANOVA) with Task Order as the independent variable was administered for the three different continuous dependent variables (CP, tCP, and tBC). These three different dependent variables were summed across Reason Number and the analyses were performed on the summed dependent variables. A lack of order effects in these analyses deemed it unnecessary to use the Task Order variable in the primary analyses.

Results from the one-way ANOVA on Continuous Preference ratings (CP) showed no significant order effects for any of the three dependent variables: CP, $F(1, 58) = 0.14$, $p = .709$, $\eta^2 < .01$; tBC, $F(1, 57) = 0.59$, $p = .445$, $\eta^2 = .01$; tCP, $F(1, 57) = 1.78$, $p = .188$, $\eta^2 = .03$. These results suggested that Task Order did not play a significant role in determining behavioral preferences (CP) or the underlying process (tCP and tBC). Because of these results, Task Order was left out of the main analyses.

General Data Analytic Procedures

All analyses utilizing a continuous dependent variable (continuous preference ratings and all decision time analyses) were analyzed using a 2 (Budget: Negative and Positive) x 2 (Reason Number: 1st Reason and 3rd Reason) mixed-factorial ANOVA with Budget as the between-participant independent variable and Reason Number as the within-participant independent variable.

In the case of the binary choice dependent variable nonparametric statistical analyses had to be performed due to the dichotomous nature of the participants' responses. Specifically, to assess the effect of Budget on binary choice a sum score was created by adding binary choice variables across each of the levels of Reason Number (coded as 0=safe choice, 1=risky choice). This resulted in an ordinal dependent variable ranging from 0 to 2 with higher scores indicating higher levels of risky choices. Then, to determine whether negative or positive energy budget conditions resulted in higher levels of risky choice a Mann-Whitney *U* test was performed. This test is the nonparametric equivalent to an independent samples *t*-test. To examine the effect for Reason Number another nonparametric test, McNemar's test was used to assess the difference of risky choice proportions depending upon which reason number was used in the priority heuristic.

Assessment of the relationship between risk-proneness and numeracy was analyzed using sum-difference regression techniques (Judd, Kenny, McClelland, 2001). Those analyses are described in a later section. In addition, a primer on sum-difference regression is provided due to the novelty of the analytic strategy. Specific analyses and results are discussed in the sections that follow according to the research questions they answer.

Preference Ratings and Binary Choices for Risky Gambles

The primary analysis of concern for Study One was conducted to assess which model best explained the data: the priority heuristic or risk-sensitive foraging. Although research design and data analysis were structured in the fashion of strong inference (Platt, 1964), it was always a possibility that risk-sensitive foraging and the priority heuristic would both be partially supported. Indeed, the two variables of interest (Budget and Reason Number) provided four different discrete conditions, each with a specific data pattern predicted by risk-sensitive foraging and the priority heuristic. Prior to data analysis it was highly plausible that there would be some interactive effect between the independent variables of interest and preferences and choices for risky gambles.

Continuous Preference Ratings

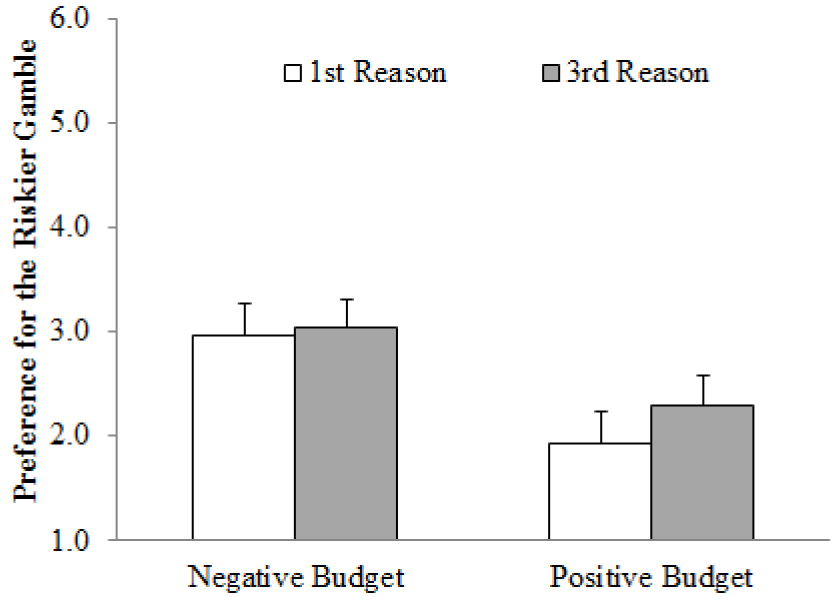
For this analysis, risk-sensitive foraging predicted a main effect for Budget with higher risk-preference ratings for gambles in the negative budget condition. Risk-sensitive foraging makes no predictions regarding any main effect for Reason Number or any predictions regarding an interaction between Budget and Reason Number.

Recall that decision tasks were created that would elicit specific response patterns if the process hypothesized by the priority heuristic was correct. From the rationale involved in creating the decision tasks, it was thus hypothesized, consistent with the priority heuristic, that there should be a main effect for Reason Number with higher risk-preference ratings for gambles in the 3rd reason condition. No main effect for Budget and no Reason Number x Budget interaction were predicted by the priority heuristic's hypothesized process because the heuristic does not explicitly take into account such environmental characteristics.

Statistical analysis of the continuous preference ratings in the two-way mixed-factorial analysis of variance yielded a main effect of Budget, $F(1, 58) = 9.32$, $p = .003$, partial $\eta^2 = .14$, with participants in the negative energy budget conditions ($M = 3.00$, $SD = 1.71$) reporting significantly higher levels of preference for the riskier gamble than participants in the positive energy budget conditions ($M = 2.12$, $SD = 1.44$) (Figure 3-5).

There was no significant main effect for Reason Number, $F(1, 58) = 0.57$, $p = .455$, partial $\eta^2 = .01$. Participants reported similar continuous preference ratings for both the 1st reason decision tasks ($M = 2.45$, $SD = 1.73$) and the 3rd reason decision tasks ($M = 2.67$, $SD = 1.53$). There was no statistically significant interaction in the analysis: Reason Number x Budget, $F(1, 58) = 0.27$, $p = .605$, partial $\eta^2 = .01$, suggesting that there was no moderating relationship between the independent variables with respect to continuous preference ratings for the gambles in Study One.

Figure 3-5 The Effects of Budget and Reason Number on Continuous Preference Ratings



Relationship between Binary Choices and Continuous Preference Ratings

Recall that continuous preference ratings were utilized in Study One due to pilot testing and past research which suggested that there may be widespread risk-aversion in the present study. This was potentially problematic for any task involving a binary choice between gambles because it was possible that participants would overwhelmingly choose the safer option, providing little or no variance with which to test the pressing research questions. Indeed, data from the continuous preference ratings further imply such risk aversion; on a 1 to 6 scale with 6 indicating an absolute preference for the riskier gamble and 1 an absolute reference for the safer gamble, the average continuous preference rating was 2.55 (on the side of the safer gamble).

Binary choice data were also collected in Study One. One point of interest is whether or not people are consistent with regard to their choices; that is, whether people who choose the safer option also provide lower continuous preference ratings indicating risk-aversion, and vice versa. To assess consistency in responding two separate point biserial correlations were calculated: one to assess the relationship between continuous preference ratings and binary choices for the 1^{st} Reason decision tasks, and one to assess that same relationship with the 3^{rd} reason decision tasks.

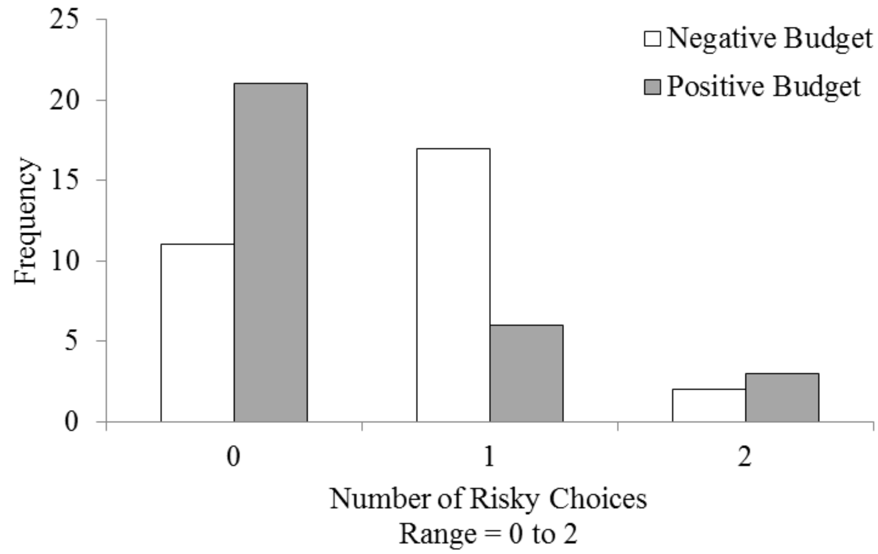
Point biserial correlation coefficients are typically suppressed due to the restricted range of the dichotomous variable—in this case the binary choice variable (Kemery, Dunlap, & Griffeth, 1988). Nonetheless, the correlation coefficients between binary choices and continuous preference ratings in Study One indicated a high level of consistency. Specifically, for 1st Reason decision tasks, the relationship was strong and positive between participants' continuous preference ratings and their binary choice decisions, r_{pb} (58) = .40, p = .001. The same pattern was true for 3rd Reason decision tasks, r_{pb} (58) = .46, p < .001. Collectively these strong correlation coefficients suggest that participants who report a higher preference for the riskier gamble in the continuous preference rating (indicated by a higher value) will also tend to choose the riskier gamble in a binary choice task (riskier gamble coded as 1, safer gamble coded as 0).

Binary Choice

Although it can be argued that continuous preference ratings are a better measure for testing the differences in risky choice behavior, there remains some utility in assessing binary choice data. Most choices in nature are binary, all-or-nothing decisions rather than a preference on some continuum ranging from one option to another. However, due to the nature of the data (binary) and the experimental design (mixed), different statistical procedures had to be used to analyze the data in a way that would produce the same variety of answers as analysis of the continuous preference ratings.

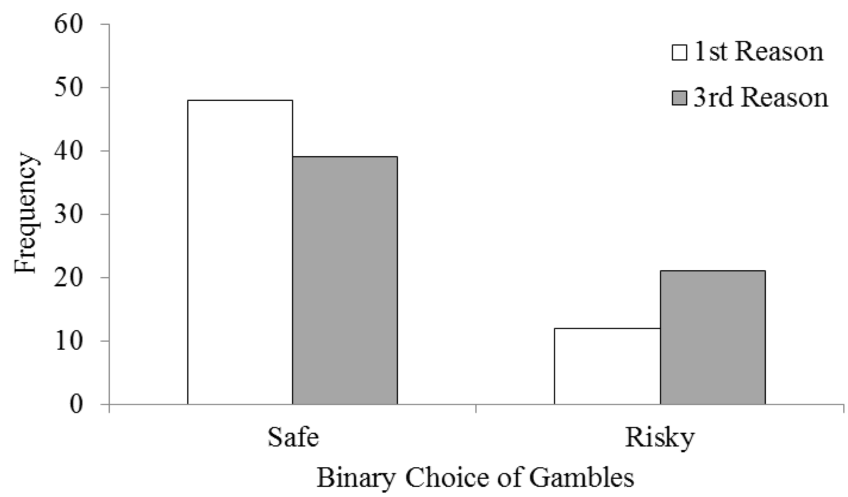
To test for an effect of Budget on discrete, all-or-nothing risky choices, a Mann-Whitney *U* test was performed on the sum of risky choices across Reason Number. This variable was ordinal ranging from 0 to 2 and thus it was inappropriate to use a parametric comparison such as a *t*-test. However, the Mann-Whitney *U* test is the nonparametric equivalent of an independent-samples *t*-test. Results from the Mann-Whitney *U* test showed that participants in the negative budget had a higher average rank (34.85) than participants in the positive budget condition (26.15), suggesting that, on average, participants in the negative budget condition chose the risky gambles more often than participants in the positive budget condition (Figure 3-6). This difference was statistically significant, U = 319.50, p =.030.

Figure 3-6 The Effects of Budget on Binary Choice in Study One



To assess the significance of Reason Number in eliciting differential risky choice behavior, a McNemar's test was performed on the within-participants variable. Results of the test showed that the number of risky choices for 3rd Reason problems (n = 16) was not statistically greater than the number of risky choices for 1st Reason problems (n = 7), collapsing across Budget, χ^2 (1, N = 60) = 2.78, p = .093 (Figure 3-7).

Figure 3-7 The Effects of Reason Number on Binary Choice in Study One



Decision Time for Preference Ratings and Binary Choices

Recall that additional predictions were made regarding the priority heuristic in relation to the amount of time necessary, on average, to make a decision. Referring back to Figure 2-1, it is clear that the priority heuristic predicts that decisions requiring a larger number of reasons (3rd reason decision tasks in the present study) should take longer to arrive at a decision than decisions requiring a fewer number of reasons (1st reason decision tasks in the present study). Because the present study utilized two different methods of choice behavior (continuous preference and binary choice) reaction time data were collected for both decision paradigms.

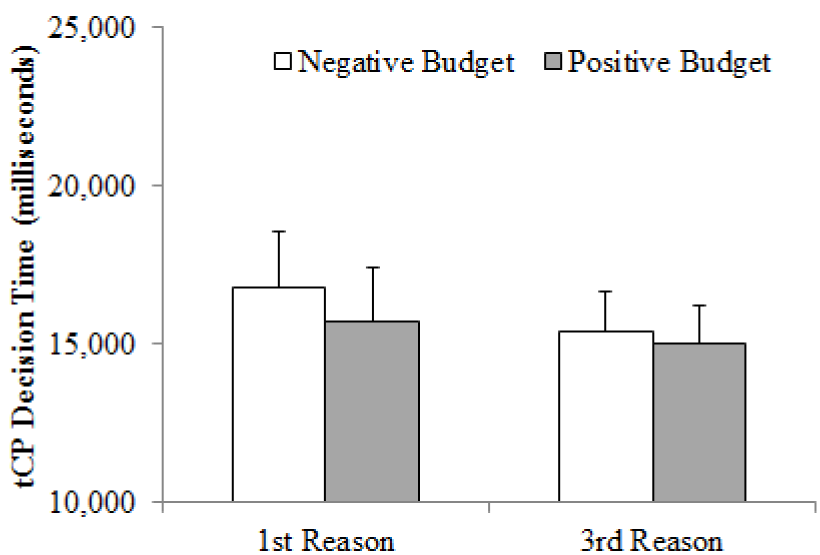
Continuous Preference Decision Time

Results from the analysis of reaction times for the continuous preference ratings showed no statistically significant main effect for Budget, $F(1, 57) = 0.18$, $p = .678$, partial $\eta^2 < .01$, suggesting that, despite significant differences in actual reported decision tendencies (see previous analyses), the participants' Budgets did not seem to affect their time needed to make a decision, with negative budget decisions (M = 16,116.38, SD = 7,149.82) no different than positive budget decisions (M = 15,371.07, SD = 8,834.20) (Figure 3-8).

Of primary concern for this analysis was the prediction made by the priority heuristic that 1st Reason decision tasks should require significantly less time to arrive at a decision than 3rd Reason decision tasks. Data from continuous preference rating decision times did not support this prediction, $F(1, 57) = 0.81$, $p = .371$, partial $\eta^2 = .01$. Specifically, 1st Reason decision tasks (M = 16,258.73, SD = 9,375.34) did not take less time to make a decision on than 3rd Reason decision tasks (M = 15,216.08, SD = 6,625.93) in Study One when participants were providing continuous preference ratings. Additionally, the interaction between Reason Number and Budget, $F(1, 57) = 0.08$, $p = .773$, partial $\eta^2 < .01$, failed to reach statistical significance. In sum, no significant effects were found with respect to decision time for the continuous preference ratings (Figure 3-8).

The lack of a statistically significant main effect for Reason Number on decision time for the continuous preference ratings is perplexing. Using standard Fisherian statistical analysis it is not possible to say with any degree of confidence that the null hypothesis is true in these data (i.e., that there truly exists no effect of Reason Number on decision time). However, using Bayesian approaches a degree of confidence in the null hypothesis can be calculated from the data. Statistical techniques described by Rouder, Speckman, Sun, and Morey (2009) were used to calculate the JZS Bayes factor for the effect of Reason Number on decision time. Consistent with their methods, the *t* statistic of 0.90 calculated using a paired-samples *t*-test was used in conjunction with the sample size ($N = 60$) and a Scale r value of 1 (recommended by Rouder et al.)[6]. The resulting JZS Bayes factor from the analysis was $B_{01} = 6.64$. According to Rouder et al., this value can be interpreted as the null hypothesis (i.e., no effect of Reason Number on decision time) being 6.64 times more likely than the alternative hypothesis (i.e., Reason number has an effect on decision time). According to Rouder et al., this falls within the categorical range of "some evidence" in support of the null hypothesis.

Figure 3-8 The Effects of Budget and Reason Number on Continuous Preference Decision Time (tCP)



Binary Choice Decision Time

Data from the binary choice tasks were analyzed using the same analytic technique as decision time data for the continuous preference ratings (tCP). Consistent with those findings,

---

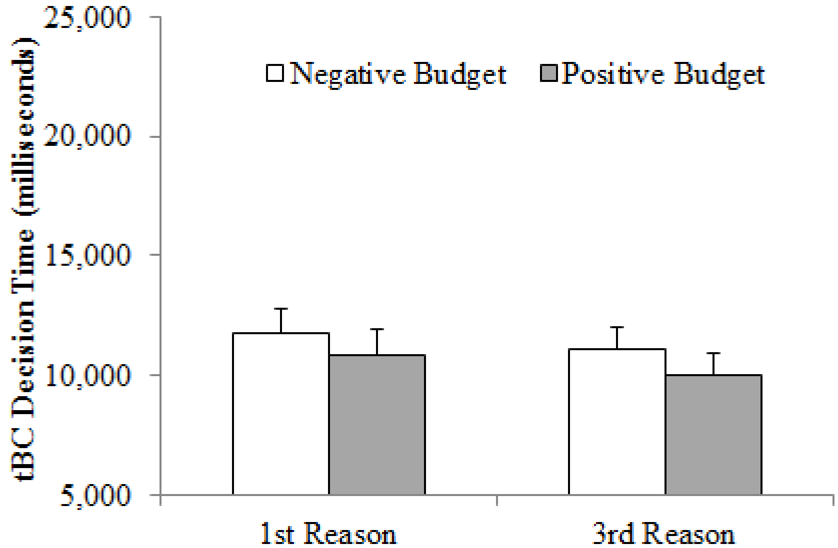
[6] The JZS Bayes factors reported in all studies were calculated using the web-based applets found at pcl.missouri.edu/bayesfactor

there was no statistically significant main effect for Budget, $F(1, 57) = 1.11$, $p = .297$, partial $\eta^2 = .02$. Specifically, binary choices took approximately the same amount of time whether the participant was in a negative budget ($M = 11{,}447.88$, $SD = 5{,}136.10$) or a positive budget ($M = 10{,}416.52$, $SD = 5{,}642.97$).

The within-participant main effect of Reason Number was also not statistically significant, $F(1, 57) = 0.50$, $p = .482$, partial $\eta^2 = .01$. The interaction between Reason Number and Budget, $F(1, 57) = 0.01$, $p = .919$, partial $\eta^2 < .01$, also failed to reach statistical significance. For the priority heuristic, the lack of a main effect for Reason Number is the most troubling since the heuristic predicts increases in decision time based on the number of reasons utilized; thus, 3rd Reason decision tasks should take significantly more time than 1st Reason decision tasks. Regarding these data, it was shown that problems which should require only the 1st Reason to decide ($M = 11{,}300.29$, $SD = 5{,}759.51$) did not actually take less time to make a decision than problems which should require participants to move to the 3rd Reason ($M = 10{,}581.59$, $SD = 5{,}025.36$) (Figure 3-9).

Because of the null results for decision time with respect to Reason Number, the JZS Bayes factor was computed for binary choice decision time as well. The same methods were utilized as described in the previous analysis using JZS Bayes factors. A paired-samples *t*-value of 0.71, a sample size of $N = 60$, and a Scale r of 1.0 were used in the analysis. The JZS Bayes factor was computed as $B_{01} = 7.70$. This suggests that the null hypothesis of no effect of Reason Number on decision time is 7.70 times more likely as the alternative hypothesis that Reason Number does have effect on decision time. This is consistent with “some evidence” of support for the null hypothesis.

Figure 3-9 The Effects of Budget and Reason Number on Binary Choice Decision Time (tBC)



The Role of Numeracy

A Primer on Sum-Difference Regression

Regression was chosen as the analytic technique to examine the role of numeracy on priority heuristic-consistent decision making. Because numeracy as measured by the General Numeracy Scale (Lipkus et al., 2001) is a continuous score ranging from 0 to 11, and it is highly negatively skewed, it seemed appropriate to use regression techniques.

However, because the independent variable of Reason Number in Study One was within-participants, normal regression techniques used to test for moderating relationships between variables (e.g., Baron & Kenny, 1986) could not be used to test the relationship between Reason Number and preference for the riskier gambles. Instead, a sum-difference regression approach (Judd, Kenny, & McClelland, 2001; for a brief, but clear description see Giancola, Saucier, & Gussler-Burkhardt, 2003, p. 1949) was used to test for moderation in the mixed design (GNS score = between-participants, Reason Number = within-participants).

Sum-difference regression is performed by creating two separate dependent variables, one by summing across the two (or more) levels of the within-participant variable, and the other by subtracting scores between the levels of the within-participant variable. If there are more than two levels of the within-participant variable then specific comparisons will need to be made. The comparisons can either be planned in advance or an exhaustive list of comparisons can be made. However, in the case of the current study, there were only two levels of the within-participant variable. This allowed for the use of only a single difference score to assess the within-participant variable of Reason Number. It is also important to remember the direction of the subtraction in interpreting regression coefficients after analysis.

When the separate dependent variables are created, separate regression analyses are then performed, one for each dependent variable. In cases where there are only two levels of the within-participant independent variable, there will only be two analyses, one for the summed dependent variable and one for the differenced dependent variable. The results and coefficients for analyses using the summed dependent variable constitute all between-participant effects and fully-between-participant interactions (if there are any). The differenced dependent variable's results constitute any within-participant interactions with the variables in the output. For instance, regression results when the differenced dependent variable is regressed onto a between-participant independent variable represent the interaction between the within-participant and between-participant independent variables. This is the test of moderation for sum-difference regression. Additionally, to examine the main effect for the within-participant independent variable, one would examine the statistical test for the constant. If the constant is statistically significant it suggests that it is statistically different from zero. Because the dependent variable is a difference score, it means that the difference between within-participant conditions is significantly different from zero when other independent variables are set at zero. The summative conclusions drawn from the two regressions constitute the same conclusions that can be drawn from a mixed-factorial analysis of variance. The benefit here is that there is no need to break numeracy into artificial discrete groups.

Numeracy as a Moderator

The sum-difference regression technique was used to analyze the potential moderator effect of numeracy on the effect between Reason Number and continuous preference ratings for gambles. Numeracy, as assessed by the GNS, was centered by subtracting the mean from each score, thus resulting in a new mean of zero. This technique was chosen over standardizing because it allowed for conclusions drawn from the unstandardized regression coefficients (*b*s) to be interpreted with respect to actual scores on the GNS.

The summed dependent variable was calculated by adding 1st Reason continuous preference ratings to 3rd Reason continuous preference ratings (1st Reason CP + 3rd Reason CP). The differenced dependent variable was calculated by subtracting 3rd Reason continuous preference ratings from 1st Reason continuous preference ratings (1st Reason CP – 3rd Reason CP). Thus, negative values on the differenced variable reflected a higher preference for the riskier gamble in 3rd Reason decision tasks.

Two simultaneous regression analyses were then performed. First, the summed dependent variable was regressed onto the centered GNS scores. The differenced dependent variable was also regressed onto the centered GNS scores. Results for the summed dependent variable model were not statistically significant [$F(1, 58) = 2.95$, $p = .091$, $R^2 = .05$]. Numeracy was also not a unique predictor of continuous preference ratings summed across Reason Number, $t(58) = -1.72$, $p = .091$, $b = -0.26$)[7]. Results from the differenced dependent variable model were also not statistically significant [$F(1, 58) = 3.31$, $p = .074$, $R^2 = .05$]. The main effect of Reason Number, assessed by examining the regression equation's constant, was not significantly different from zero, $t(58) = -0.77$, $p = .444$, $b = -0.22$. The *b* can be interpreted as there being only a 0.22 difference between the mean continuous preference ratings for 1st Reason and 3rd Reason problems, with 3rd Reason problems having slightly higher ratings for the riskier gamble, although this difference is not statistically significant.

Of most importance is the role of numeracy as a potential moderator. Results from the difference scores regressed onto numeracy would reflect whether the difference between continuous preference ratings for 1st and 3rd Reason problems (reflected in the dependent variable) depends on a person's numeracy level. The Peters and Levin (2008) hypothesis about processing differences being reflected through numeracy would be supported by results

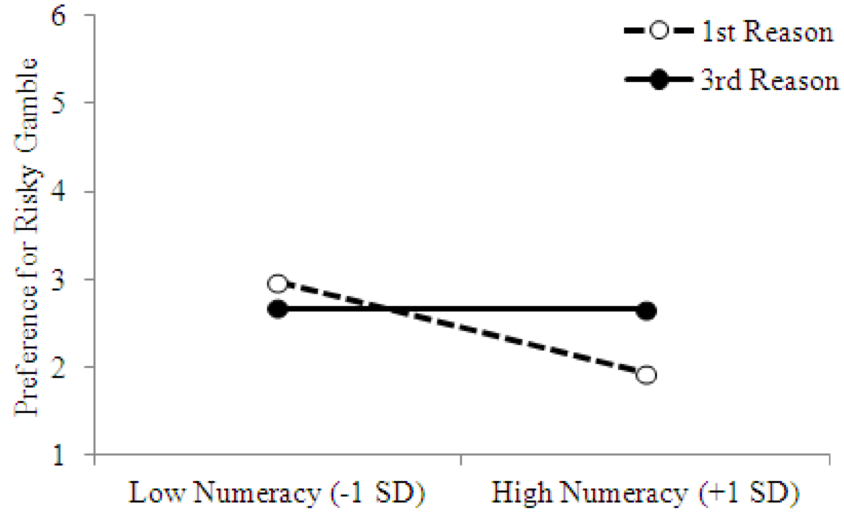
---

[7] Regression coefficients displayed in the sum-difference regression results, and discussed in later sections are unstandardized *b*s. These weights were chosen over standardized versions for two reasons: (1) the main effect for Reason Number is interpreted through the constant in the regression equation, and the constant only has an *unstandardized b*. (2) Interpretation of unstandardized *b*s is more intuitive, especially when comparisons are not made across different variables with different scales. In those cases it is more appropriate, and easier to use standardized rather than unstandardized *b*s.

indicating that numeracy was a strong, unique predictor of difference scores on continuous preference ratings. Further, the estimates of this relationship would need to be negative (i.e., negative beta weights), showing that higher numerates have a tendency to prefer the riskier gamble in 3rd Reason decision tasks, but the safer gamble in the 1st Reason decision tasks. However, this relationship was not statistically significant, suggesting that the interactive relationship is not a unique predictor of continuous preference ratings, $t(58) = -1.82$, $p = .074$, $b = -.25$.

Using the parameters from the simultaneous regressions for continuous preference scores for each separate Reason Number, the effect of numeracy on the relationship between Reason Number and CP can be plotted. Data were plotted along numeracy by creating high and low numeracy groups (Figure 3-10). These groups were created by using one standard deviation above and below the mean ($SD = 2.04$). The slopes were determined performing separate regressions, one for each of the two different Reason Numbers. The numeracy-risky preference relationship was negative for 1st Reason problems ($b = -.26$) and almost zero for 3rd Reason problems ($b = -.003$).

Figure 3-10 The Effect of Numeracy on the Relationship between Reason Number and Continuous Preference Ratings in Study One



Study One Discussion

Study One was conducted to examine if the priority heuristic (Brandstätter et al., 2006) could predict participants' behaviors regarding risky choice when novel environmental variables were introduced. These novel variables were the amounts of money necessary to move to a potential next round. Risk-sensitive foraging (Stephens & Krebs, 1986) predicts that participants should be sensitive to necessary amounts, and therefore be risk-prone when only riskier options provide a chance of reaching a specified need level. Although the theory's background is in non-human animal research, with need levels most often conceptualized as caloric intake needed to survive, psychological research has also shown people to be sensitive to need levels for gaining monetary rewards (Mishra & Lalumière, 2011; Rode et al., 1999). By designing decision tasks with certain features Study One was able to systematically examine if the priority heuristic could work well, regardless of a participant's need level. Additionally, individual differences in numerical literacy were examined in order to determine whether the priority heuristic may be a more accurate model of risky decision making in high numerates.

Can the priority heuristic handle need levels?

In short, it appears the answer is no, at least not very well. Participants consistently preferred the riskier gamble more than the safer gamble when participants were in a negative energy budget, that is, when only the riskier gamble offered a chance of reaching the need level. This was true regardless of Reason Number for the priority heuristic, and was consistent with the predictions of risk-sensitive foraging. Decision tasks were designed so that 1st Reason decision tasks should result in risk-aversion, and 3rd Reason tasks in risk-proneness, if indeed the priority heuristic is an adequate as-if model of the human decision process. Data did not support the priority heuristic's predictions. Participants were not significantly more likely to choose the riskier option, or have a higher preference for it, in 3rd Reason decision compared to 1st Reason decision tasks.

Perhaps even more compelling evidence is provided by decision times for participants in the different conditions of Study One. The priority heuristic predicts increases in decision time when decision tasks require an increased number of reasons to reach a conclusive decision. This prediction was supported by Brandstätter et al. (2006). However, data from Study One did not support the prediction and found results inconsistent with those of Brandstätter et al. There were in fact no significant differences in decision time based on different levels of the independent variables; even Budget, which did have an effect on risky preference ratings, did not appear to have an effect on decision time.

Results from Study One suggest that, although the priority heuristic has been shown to be a viable heuristic for predicting majority choice in a large set of decision problems (Brandstätter et al., 2006) it does not appear to supersede risk-sensitive foraging in terms of predictions about preferences for riskier or safer gambles. In fact, the pattern of data does not require any integration of the priority heuristic and can be explained entirely in terms of the risk-sensitive foraging framework.

Are high numerates' decisions more consistent with the priority heuristic?

In short, it depends. Following the conclusions from Peters and Levin (2008) it was hypothesized that there may be a relationship between numeracy and decisions consistent with the priority heuristic. The priority heuristic appears to assume some basic level of numerical processing on the part of the individual, and Brandstätter et al. (2006, p. 425) mention that a weakness of their heuristic is a lack of accountability for individual differences (e.g., numeracy).

Following the logic of the findings from Peters and Levin (2008) and the process model from the priority heuristic, it was hypothesized that highly numerate participants, more so than low numerates, would prefer gambles consistent with the predictions of the priority heuristic: (1) low preferences for 1st Reason decision tasks, and (2) high risky preferences for 3rd Reason decision tasks. Ideally this would have statistically been revealed by way of a statistically significant interaction between Reason Number and numerical literacy score. This was not the case. However, there was a negative relationship between numeracy and preference for the riskier gamble on 1st Reason decision tasks, consistent with what was expected. There was however almost no statistical relationship (e.g., $b = 0$) between numeracy and preference for the riskier gamble on 3rd Reason decision tasks when there should have been a significant positive relationship.

Chapter 4 - Study Two

The results of Study One offered support for a general theory of risk-sensitivity associated with risk-sensitive foraging theory, at the expense of predictions made by the priority heuristic. These conclusions held for binary choice, preference ratings, and decision time measurements. In essence, the previous results provided empirical evidence in support of a superordinate role of risk-sensitive foraging mechanisms over simple lexicographic heuristics. In light of this evidence, the purpose of Study Two was to examine how the priority heuristic would perform in other environments which have, up to this point, been explained from the perspective of biological theories of risky behavior in the context of intrasexual competition; Study Two sought to examine how well the priority heuristic would perform against dominance theory.

Despite the observation that the priority heuristic does not seem to perform well in environments containing need levels, this evidence does not preclude the possibility that the heuristic will work well in other ecologically valid environments experienced by human and non-human organisms. One characteristic of such an environment is the relative status of individual organisms competing for resources, when the status of the individual is related to how it will perform during the competition in question. Ermer et al. (2008) term rational behavior in such contexts *dominance theory* and base it on work from behavioral biology research examining competitive behavior. Often this competitive behavior escalates in the amount of risk taking, with participants competing against one another moving in a sequential step-by-step process in which they evaluate one another; if they are similar on a given trait then they proceed to the next step in competition which is often riskier (Maynard Smith, 1974; Maynard Smith & Price, 1973). This incremental process of competition results in escalated risk taking when both participants are relatively close in status, but lowered risk taking when there is a discrepancy between status levels of the two competing individuals (usually males for theoretical reasons; see Wilson & Daly, 1985).

As with the premises in Study One, the priority heuristic is created in the tradition of fast-and-frugal, ecologically rational heuristics. This should mean that the heuristic has a very specific "ecology" in which it will predict *both* the decision process (i.e., decision time; tBC and tCP) and the outcome of that process (i.e., the choice behavior; CP and BC). As with all ecologically rational heuristics, the primary scientific goal is to systematically determine when and where they work best. Study Two represents another sequential step in the process of fine tuning and narrowing down on the proper ecology of the priority heuristic. It has already been empirically shown that dominance theory can predict choice behavior in certain experimental (Ermer et al., 2008; Rosati & Hare, 2012) and "real-world" scenarios (Stulp et al., 2012); however, it has not been determined whether the priority heuristic can also predict choice behavior in similar situations, where individuals are competing against same-sex others who are perceived as being higher, lower, or equal in status to the individual making the decision. If the priority heuristic is capable of predicting risky choice behavior in situations of same-sex competition, it offers not only a new environment in which the priority heuristic may explain behavior but it also offers previously tested scenarios (e.g., Ermer et al.) an adequate process model describing the choice behavior (i.e., the priority heuristic).

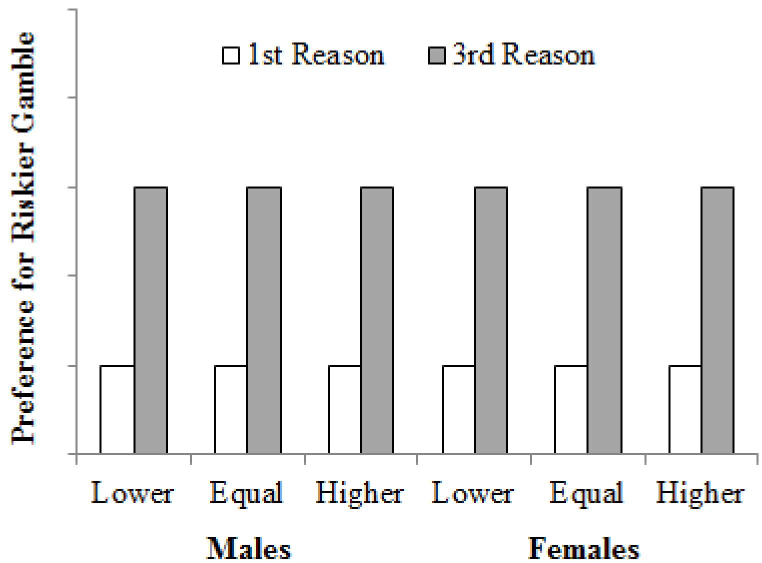
Hypotheses

As with Study One the different models of decisions under risk assessed in Study Two also make specific predictions regarding which gambles to choose (the riskier or safer). Also, as with Study One, the predictions made by the priority heuristic are embodied within the hypothesized heuristic. Despite data from Study One suggesting that the priority heuristic's model may not hold in situations of resource need levels, the model's viability has not been tested in situations of competition between same sex individuals varying in levels of perceived status. In conclusion, the hypotheses offered here are justified.

The Priority Heuristic

The priority heuristic's predictions are embodied within the hypothesized process model shown in Figure 2-1. This standard lexicographic order described by Brändstatter et al. (2006) is depicted in Figure 2-1 which shows that people should, if the process is correctly described, attend to the minimum gains, probability of minimum gains, maximum gains, and probability of maximum gains, and in that specific order. If the priority heuristic is an accurate descriptive model of choice behavior then participants should follow the model. Specifically, like Study One, participants should prefer the riskier option in 3rd Reason tasks and prefer the safer option in 1st Reason tasks (Figure 4-1). An additional prediction is made, much like Study One, that decision time should increase as the number of reasons examined increases (i.e., as participants fail to stop search at each reason in the priority heuristic's model).

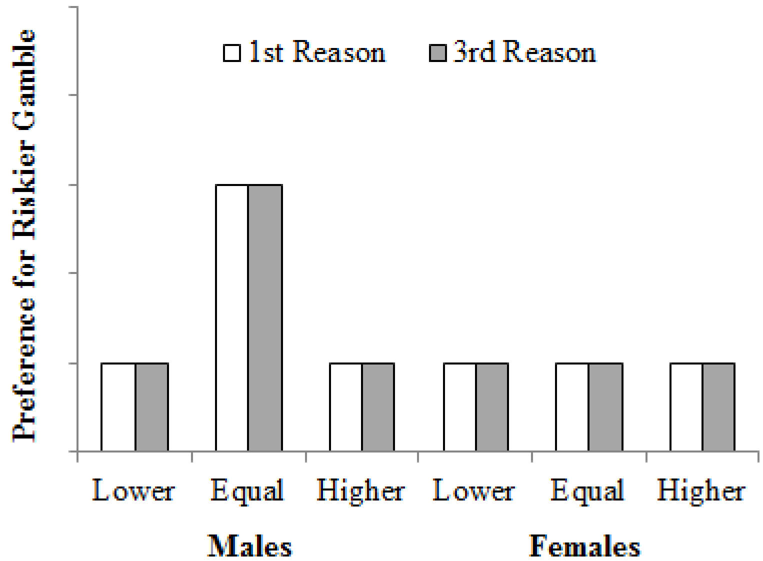
Figure 4-1 Priority Heuristic Predictions for Preferences in Study Two



Dominance Theory

Consistent with the psychological formulation of dominance theory by Ermer et al. (2008), the theory should predict that, when competing against others of the same sex over resources, participants should be more risk-prone when their competitor is perceived as being close to the same status. However, participants should be risk-averse when competing against same-sex others perceived as being higher or lower in status than themselves (Figure 4-2). An additional hypothesis regarding dominance theory that was supported by Ermer et al. is the prediction that the motivation to take risks when competing against same-sex individuals of a similar status is sex-specific. That is, the effect should be limited to male participants.

Figure 4-2 Dominance Theory Predictions for Preferences in Study Two



Moderating Effect of Numeracy

As with Study One's hypotheses regarding the relationship between numerical literacy and evaluating gambles, the same predictions are made in Study Two. Specifically, it is hypothesized that high numerates' decision patterns should be more consistent with process models that assume some level of numerical processing. For instance, because the priority heuristic assumes that individuals may implicitly be computing proportions for a specific aspiration level, it follows that high numerates—who are by definition better at such calculations—may be more likely to follow such a decision process more accurately than their lower numerate counterparts. This hypothesis is based on findings by Peters and Levin (2008) which suggested that high numerates base their choices, when deciding between two options, on the outcomes and their respective probabilities, whereas lower numerates base their decisions more on "unimportant" contextual factors (e.g., the frame of the decision).

In sum, high numerates should behave more consistently with the priority heuristic than lower numerates (see Figure 3-3). Because dominance theory does not assume any implicit calculations there are no specific predictions made about the relationship between numerical literacy and behavior consistent with dominance theory's predictions in Study Two.

Study Two Method

Participants

Data for Study Two were collected from 120 undergraduate students enrolled in an introductory psychology course at Kansas State University. Of these 120 students, exactly half were male and half were female (i.e., n = 60 each). This was a calculated decision on the part of the researcher, and was made due to the theoretical importance of gender in some predictions made by dominance theory.

The average age of participants was consistent with typical undergraduate research samples drawn from introductory psychology courses (M = 19.11, SD = 2.15). Also, although of no theoretical importance to the study, ethnicity of participants was consistent with demographics in this region of the United States (Caucasian: n = 92; African-American: n = 12; Asian: n = 6; Hispanic: n = 8). Two of the participants identified their ethnicity as "Other."

Design

Consistent with Study One, decision problems in Study Two were framed in terms of gains rather than losses. The same two-measure protocol of assessing risky choice behavior was also used in Study Two. Specifically, the binary choice paradigm (BC) and the continuous preference paradigm (CP) were both used to assess risk preferences.

The design of Study Two included the two dependent variables (BC and CP) as well as five independent variables. Two of the independent variables were implemented to assess potential order effects. These independent variables were Status Order and Task Order. Task Order, just as in Study One, was a between-participants independent variable used to examine if there were systematic differences in risk preference based on whether a participant answered the BC or CP dependent measure first or second. Status Order was implemented for Study Two because of the within-participant nature of the Competitor Status independent variable. Participants sequentially competed against three separate fictitious students from other universities who varied in status. This created a potential issue of order effects based on the order in which each participant competed against the fictitious students from other universities. For example, it is possible, although not predicted, that competing against a lower status individual may result in different risk preferences depending on whether the previous competition was with a person of higher, or lower status. The Status Order independent variable consisted of three levels which described the order by which each participant would encounter each of the fictitious competitors. These levels were: (1) Lower→Equal→Higher (LEH), (2) Equal→Higher→Lower (EHL), and (3) Higher→Lower→Equal (HLE).

The remaining three independent variables are of theoretical importance. These independent variables are Gender, Reason Number, and Competitor Status. Gender (by definition) and Reason Number (by design) were both between-participant independent variables. Reason Number (1^{st} Reason and 3^{rd} Reason) as an independent variable was implemented by creating one decision task that would result in stopping search at the 1^{st} Reason and choosing the safer gamble. The 3^{rd} Reason condition was created with characteristics that would result in search stopping only after the 3^{rd} Reason and then choosing the riskier gamble. Both decision tasks were created and assigned to their respective conditions based on the decision process outlined in the priority heuristic. More detail is offered in the Materials section regarding the construction of these decision tasks.

The last independent variable of theoretical interest was Competitor Status. Specifically, Competitor Status was a within-participant independent variable consisting of three levels (Lower, Equal, and Higher), with each denoting the *relative* status of the fictional student competitor in comparison to the participant. For example, the Lower status indicates that the fictional student is "lower" in status than participant. To manipulate the status level of different fictional students, each student was said to attend a specific school, with the different schools being of varying relative rank when compared to Kansas State University. More detail regarding the pilot-testing phase for determining schools and their status levels is discussed in the Materials section to follow.

Materials

Study Two also used novel decision tasks—different from those in Study One. The decision tasks were similar to those in Study One in terms of the types of features but differed in terms of specific probabilities and payoffs. One major difference between the decision tasks in Study One and those in Study Two is that the latter decision tasks did not contain a need level as part of their structure. This is because Study Two was not interested in examining the effect of need levels on risk taking since it had already been examined in Study One.

In addition to the decision tasks, participants were asked to complete the General Numeracy Scale (Lipkus et al., 2001), and the Domain Specific Risk Scale (Kruger et al., 2007). One additional component of Study Two was the use of status priming—material which was read by all participants that has been shown to elicit status-related motives (e.g., Griskevicius et al., 2009; Griskevicius, Tyber, & Van den Bergh, 2010).

Decision Tasks

Two different decision tasks were created for Study Two. These decision tasks were created such that one decision task had properties that, if they followed the priority heuristic, a person would stop search at the first reason and would choose the safer gamble. The other decision task was created such that, if the priority heuristic was used, people should only stop search at the third reason and should choose the riskier gamble[8]. Additionally, these two decision tasks were crossed with the Competitor Status variable (i.e., the status of the person with whom they were competing). This resulted in six different decision tasks, although, for the sake of simplification when displaying the variables of theoretical interest, Table 4-1 shows two decision tasks, with Reason Number as a between-participant variable and Competitor Status as a within-participant variable.

---

[8] In the standard lexicographic order of the priority heuristic Bramdstätter et al. (2006) suggest that gambles' minimum gains should first be compared (i.e., the 1st Reason). Decision task number 1 in Table 4-1 is designed so that the difference between the minimum gains is higher than a threshold (i.e., losing $25 and losing $100 is a difference of $75; that difference is greater than 1/10 of the maximum possible winnings of $600). Thus, search should stop and the participant should choose the gamble with the highest minimum earnings (i.e, the safer gamble). For decision task number 2, Reasons 1 and 2 do not meet the threshold for stopping, thus search stops at the 3rd Reason, which is maximum gains. Thus, participants should choose the gamble with the highest maximum gain (i.e., the riskier gamble).

Table 4-1 Decision Task Characteristics for Study Two

Decision Task	Reason	Competitor Status (Earnings)	Buy-in Amounts Safer	Buy-in Amounts Riskier	Winnings (Probabilities) Safer	Winnings (Probabilities) Riskier
1	1st	Lower ($100)	$25	$100	$300 (.95)	$600 (.60)
		Equal ($275)				
		Higher ($350)				
2	3rd	Lower ($145)	$30	$50	$350 (.80)	$400 (.75)
		Equal ($320)				
		Higher ($335)				

Note. This table displays the characteristics for the two main independent variables of interest (Competitor Status and Reason Number). For the design of Study Two these variables were additionally crossed with order controls and participant gender.

The General Numeracy Scale

The General Numeracy Scale (Lipkus et al., 2001) (Appendix A) was also used in Study Two, just as it was in Study One, to assess any potential moderator effects with priority heuristic-consistent risky choice decisions.

Domain Specific Risk Scale

The Domain Specific Risk Scale (Kruger et al., 2007) (see Appendix B) was used in Study Two to measure individual differences in risk taking propensity in five different evolutionarily relevant domains. The primary reason for assessing risk taking propensity was to treat it as a covariate in the primary analyses of Study Two's data.

Status Manipulation

The status manipulation was very important for the theoretical interpretation of results from Study Two. In order to systematically test whether participants adhered to principles outlined in dominance theory—risk aversion against lower and higher status, risk proneness against equal status—we had to accurately put each student against competitors which he or she believed were lower, equal, and higher in status. Ermer et al. (2008) performed pilot testing on their participant pool's impressions of the status of different universities (and their students) to determine which universities to use and assign to specific status levels. A similar process was used for Study Two to determine universities of varying status.

As part of an independent pilot sample, a total of 39 participants (17 females, 22 males) were given a series of questionnaires (see Appendix E) containing free response items regarding attitudes toward 30 different universities of varying size, and their respective students. These universities ranged from top tier private universities (e.g., Princeton University), to research intensive public universities (e.g., Ohio State University), to regional, public universities (e.g., Georgia Southern University).

The universities were evaluated on (1) how much better or worse participants believed students from a given university were, compared to the average student from Kansas State University[9], (2) each participant's familiarity with a given university, and (3) how intimidated each participant would be by a student from each university.

Results from this pilot study to determine status manipulations in the form of universities revealed that Kansas State University students were most intimidated by students from Harvard University (M = 6.26, SD = 1.14), as indicated by a rank ordering of values. The lowest ranking university in terms of intimidation was Emporia State University (M = 2.33, SD = 1.20). The middle two universities (rankings of 15 and 16) were Oregon State University (M = 3.15, SD = 1.25) and Idaho State University (M = 3.08, SD = 1.20). Ultimately, Oregon State University was chosen as the equal status university because it was more familiar (2.77 for Oregon State compared to 2.23 for Idaho State) and because it was rated as closer to the midpoint of the scale (i.e., 4 on the 7 point scale). Thus, the status manipulation was decided to be Harvard University, Oregon State University and Emporia State University for the Higher, Equal, and Lower Status universities, respectively.

In addition to choosing specific universities for different status levels, each university—and it's fictional student was paired with an ACT score representing the relative status of the average student at that particular university. To find accurate ACT scores for students at each university, the scores were taken from www.ed.gov. This site contained the average ACT score for the bottom 25th percentile and top 75th percentile of enrolling freshmen. The middle score between these two figures was taken as the ACT score for the fictional student from each university. This resulted in the fictional Harvard University student having an ACT score of 33,

---

[9] Although data were collected asking participants to rank the average student from each university relative to the average student from Kansas State University, these data were not used because of what appeared to be a regional bias in reporting. Specifically, the University of Kansas—an athletic rival of Kansas State University—received the lowest scores on this item indicating that participants viewed KU students as the most inferior students relative to KSU students, on the list of all possible universities. This was problematic due to the observation that KU received much different scores on other items, such as the intimidation item.

the fictional Oregon State University student received a 24, and the fictional Emporia State University student received a 22 ACT score. Conveniently, these scores were consistent with the perceived status of average students from these universities by those Kansas State University students we used in pilot testing of university status.

Status Priming Vignette

In order to get participants to think about status during the experiment when viewing different decision tasks against different students from the universities previously mentioned, we used a status priming technique common in the social evolutionary psychology literature (e.g., Griskevicius et al., 2009; Griskevicius, Tyber, & Van den Bergh, 2010). The specific vignette used for Study Two was adapted from the "competition" condition used by Griskevicius et al. (2009) (Experiment 1). This vignette (see Appendix F), including the directions, consisted of 376 words. The vignette asked each participant to imagine being in a situation where they are hired at a new, high-status job. The participant then is asked to read that the boss invites all three new hires into his office and says that only one of the three will be promoted to a fast-track position with a corner office, and that one of the two remaining will be fired. Participants are asked to imagine feeling the emotions they would feel if they were in a similar situation as the one provided in the vignette. Griskevicius et al. (2009) used this status manipulation to attempt to elicit intrasexual direct aggression (e.g., violent acts toward a same-sex individual), and they succeeded in doing so, showing that the competition priming story—referred to here as status priming—induced status-related motives in participants.

Study Two Procedure

Participants were brought to the lab and tested in groups ranging from 1 to 8. Just as in Study One, participants in Study Two were told that the research was actually a gambling competition. The researcher, who wore professional clothing and a white lab coat with a clip board, notified participants that the researchers who were organizing the gambling competition were collaborating with other scientists at three different universities. These three universities were, of course, the three universities varying in status (i.e., Harvard University, Oregon State University, and Emporia State University). The researcher then explained to the participants that they would be competing against *same sex* students from the three different affiliated universities in three separate one-on-one gambling competitions, and that the student—the KSU student or the student from the other university—who earned the most fake money in the gambling competitions, would effectively win. Participants were asked if they understood the gist of the competition, and were told that more detailed instructions would be provided prior to playing the competition. Questions were answered prior to asking for informed consent.

Participants were instructed to click “OK” on the opening screen in MediaLab (Jarvis, 2008). Upon clicking “OK” participants first were presented with a “welcome” screen with the text “Welcome to the Decisions about Money Competition.” Below this greeting were the logos of the four “participating” universities. This portion of the study was designed and implemented using PowerPoint slideshows, so at the end of the welcome screen the slideshow automatically proceeded to the informed consent screen.

Participants were next directed to individual folders containing paper copies of the informed consent sheets. The informed consent sheets were inside these folders, while, on the outside, there was text with “Decisions about Money Competition” in bold type. Also, below the title, were the four university logos for the universities “participating” in the competition. The logos and their arrangement were identical to those used for the welcome screen in MediaLab. Participants were told that, although they were participating in a competition, it was still technically research, and the researchers were required to provide them with enough information so that they, the participants, could make an informed decision regarding whether they wanted to compete in the inter-university gambling competition.

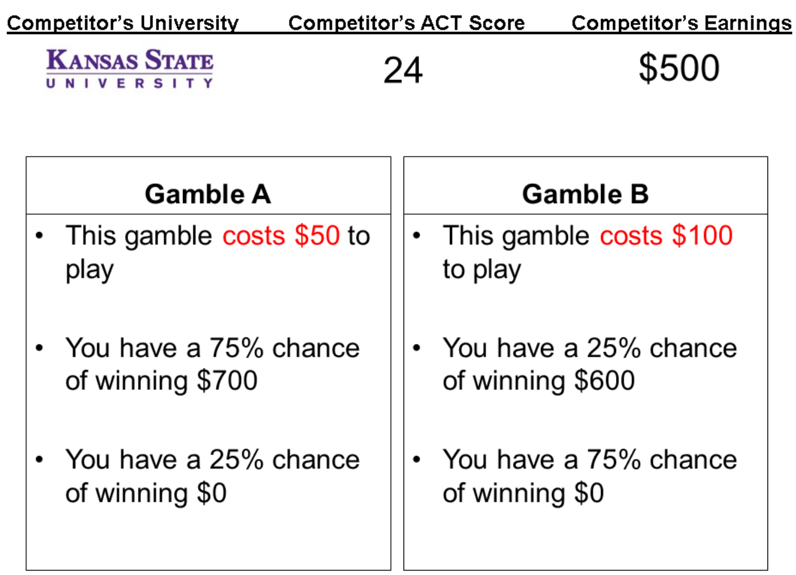
After participants signed the informed consent forms the researcher directed them to begin the rules section of the competition. Similar to Study One, the rules section of the experiment was set up on a PowerPoint slideshow. This allowed participants to move through the rules of the competition one bullet point at a time, and at their own pace. During the rules section participants learned that they were playing against three randomly chosen students of the same sex, one from each of the different universities participating in the inter-university competition. Participants were shown that the competitions were completely independent, “similar to running three separate races.” Participants read that at the end of their third decision task against the third student, which would constitute the end of a round. To introduce uncertainty regarding the decision tasks, participants read that there would be either one or two rounds, but that the number of rounds would be randomly chosen by the computer. It was stressed that the individual with whom they were competing in the decision tasks was allowed the *same* number of rounds, and that there would not be an unfair advantage in favor of the competitors from other universities.

Participants were then told that, similar to what they were currently doing, students from the other universities involved in the competition had, in the weeks prior, come into labs at their respective universities and participated in the gambling competition. However, students at those universities simply chose which gambles they preferred and then played out the gambles at the end, resulting in some accumulated amount of fake money. Participants were told that we the researchers at Kansas State University had taken the data from their participation and put all of it onto the computers at which they the KSU students were currently sitting. The participants were told that the primary purpose of the computers was to randomly select a same sex student from each university for them to compete against in the competition. Importantly, participants were shown a graph illustrating "empirical" relationship between ACT score and typical performance on the gambling competition in which they were about to participate. This was used to establish in the minds of the participants a relationship between ACT score and affiliated university, and performance in the gambling competition. After finishing the rules section PowerPoint slideshow participants were asked a series of five questions to determine whether or not they understood the basic rules of the competition. This was used to determine if participants were attentive to the study.

After answering questions about the rules of the competition participants were presented with the demographic questions. Participants reported their age, ethnicity, and their ACT score. Next, participants read the status priming vignette (Griskevicius et al., 2009) (Appendix F). This vignette was displayed on two separate screens within MediaLab. The first screen contained the main component of the story used by Griskevicius et al. Once participants had finished reading the vignette they were asked to click "Continue" and move to the next screen. This next screen (Appendix F) asked participants to select which of the different strategies they would employ in an effort to obtain the job promotion referenced in the status priming vignette. This additional component, although not used by Griskevicius et al., was used in Study Two in order to further engage participants in thinking about status motives. Thus, to this point in the study, participants (a) were aware that they were competing against students from different universities which they (according to pilot testing) viewed as having students who varied on levels of intimidation, (b) were aware that ACT score was related to performance in the gambling competition, and (c) were primed to think about status motives using priming material which has been successfully used in a variety of situations (e.g., Griskevicius et al., 2009; Griskevicius, Tyber, & Van den Bergh, 2010).

Participants then completed one sample decision task. It was stressed that this decision task was simply for teaching purposes and did not count toward the actual competition. In this sample competition, participants were allowed to become familiar with the structure of the decision tasks as well as the look of them (Figure 4-3). Participants were asked to look over the gamble options and make a choice. After making a choice, participants then proceeded to a screen in which they played out the gambles they had selected. This consisted of participants being reminded of the gamble they had chosen, and being re-informed of the probabilities and payoff potential of the gamble. Participants played out the gamble by clicking a small button located in the middle of the screen. This virtual slot machine button was designed so that every participant, regardless of their choice of gamble during the sample task, ended up winning. This was done in order to remove any unintended effects during the actual competition due to winning or losing in the sample decision task.

Figure 4-3 Example decision task for Study Two



After participants completed the sample decision task, they were then stopped and asked if they had *any* questions about the procedure or gambling competition before the actual competition began. If there were questions, the researcher promptly and clearly answered them to the best of his or her ability.

The main part of the study began with participants immediately beginning the competition portion. Participants were shown the decision task (for example Figure 4-3) and were asked to either choose which gamble they preferred (Binary Choice) (BC) or to provide a rating on a scale from 1 to 6 (Continuous Preference) (CP). The specific dependent measure used first was counterbalanced such that half of the participants answered decision tasks in the BC format first and the CP format at the end of the study, whereas the other half answered in the CP format first and the BC format at the end of the study. During this first competition portion, participants competed in three sequential decision tasks, each against a different fictional same-sex student from one of the three "participating" universities. The specific gamble's properties remained the same across the three different one-on-one competitions because Reason Number (the priority heuristic) was a between-participant independent variable. However, the Competitor Status (dominance theory) was within-participant, and each participant competed against every level of status (i.e., the different students from Harvard, Oregon State, and Emporia State). Going back to the Design section of Study Two, recall that the ordering of different status competitors in the within-participant design was treated as an order variable: Status Order. This was added in order to look for potential order effects and will be discussed in the Results section of Study Two. Because there were two dependent variables (BC and CP), and thus two opportunities for Status Order to play a role, the Status Order variable remained constant across each individual's experience. For example, if the participant competed against fictional students in the order of Lower→Equal→Higher for the BC portion of the experiment then that same order was used for the CP portion of the experiment.

After participants finished the first group of decision tasks they then answered a series of individual difference measures. These measures were implemented in MediaLab from their paper and pencil versions, and the ordering of the questions was randomized for each participant. Thus, the specific order of questions presented in Appendices A and B is not what each participant consistently viewed. First, participants answered the 11-item General Numeracy Scale (GNS) (Lipkus et al., 2001). After completing this measure, participants then completed the 15-item Domain Specific Risk Scale (DSRS) (Kruger et al., 2007).

After participants completed the DSRS they were reminded of the decision tasks they completed at the beginning of the competition. They were then told that they were going to answer the same exact decision tasks as before, just in a slightly different way. This second answering of the decision tasks constituted the second dependent variable (either the BC or CP task depending on each participant's condition). This was justified to participants by telling them that we, the researchers, wanted to make certain that we matched them with the gambles they absolutely preferred so that they could play those out at the end of the competition.

When participants finished this second group of decision tasks they were asked a series of follow-up questions (Appendix G). After answering these follow-up questions the experimental software provided a message to each participant that he or she should notify the experimenter that they had completed the study. When all participants had finished the study, the researcher told all participants as a group that there was no real competition, and that deception was used in order to get participants to respond in a certain way to the decision tasks. Participants were asked if they were distressed by being deceived. Although none of the participants responded as being distressed, they were encouraged to contact the researchers if they became distressed later on after leaving the study. Contact information, as well as a description of the research goals, was provided on the debriefing form (Appendix D) which was provided to each participant upon completing the study. Participants were thanked for their participation and Study Two was concluded.

Study Two Results

The goal of Study Two was to systematically test an additional ecology in which the priority heuristic may not successfully predict individual risky choices and preferences: ecologies in which the decision maker is primed to compete against same-sex others of varying levels of perceived status (Ermer et al., 2008; Maynard Smith, 1974; Maynard Smith & Price, 1973; Stulp et al., 2012; Rosati & Hare, 2012); the priority heuristic does not contain an explicit step which takes into account status levels of others with whom one is competing. For Study Two, decision tasks were created in such a way that different patterns of predictions could be forecast depending on the ability of either dominance theory or the priority heuristic to explain data in our experimental paradigm (similar to the paradigm used in Study One). In addition, predictions were made for the relationship between numerical literacy and risky-preference as it may relate to the priority heuristic, just as in Study One. To test the many specific hypotheses, a host of statistical analyses were performed, each of which are described in the sections that follow.

Preliminary Data Issues

Prior to the main data analyses for Study Two, covariates were tested for their potential use in removing theoretically unimportant explained variance. These covariates were the five subscales of the DSRS (Kruger et al., 2007) and the self-reported ACT composite score of each participant. ACT composite score was analyzed as a potential covariate because of the nature of the status priming; participants with higher ACT score may not feel as intimidated by the Harvard University student operationally defined as the higher-status student competitor. Additionally, a plan was made for specific types of data analysis in answering the primary theoretical questions of Study Two. These issues are further discussed in the sections that follow.

Preliminary Data Cleaning

Decision time data were screened for outliers using the *z*-score method described by Tabachnick and Fidell (2007), and also used in Study One. Decision time variables (tBC and tCP) were first standardized to z-scores in SPSS. Next, cases with values greater than ±3.29 were removed from all subsequent analyses. Because of the within-participant independent variable of Competitor Status, participants each had three decision times for each of the two decision task formats (CP and BC). Because of this, in the event that a single outlier was discovered for one level of Competitor Status, cases for the other two levels of Competitor Status were also removed so there would not be incomplete within-participant data for the Competitor Status independent variable.

By using the z-score method (Tabachnick & Fidell, 2007) a total of six data points were deleted from the tBC (*z*s: 7.36, 7.27, 5.68, 3.50, 3.47, 3.40), and three other data points were deleted from the tCP (*z*s: 10.64, 4.39, 4.03). None of the data points deemed to be statistical outliers belonged to the same individual, thus the total sample sizes for the analyses using decision time data were n = 114 for tBC and n = 117 for tCP.

Risk Propensity and ACT Composite Score as Covariates

Although Study One's analyses did not use risk propensity in the form of the DSRS subscales (Kruger et al., 2007) as covariates due to a lack of the appropriate relationships between them and the dependent variables, that lack of relationship did not preclude the existence of a relationship for Study Two. For Study Two it was again assumed that risk taking propensity, as measured by the DSRS, in participants may have theoretically unimportant effects on the dependent variables of interest. Additionally, ACT composite score was thought to be a potential covariate for Study Two because of the way that status was framed and manipulated in the experimental procedure. For instance, it was plausible that individuals with high ACT composite scores may view students from higher universities as their equals rather than the intended case of viewing the "equal" status college as their equal.

Three participants did not take the ACT and thus had no composite score to report. Because of the potential use of participants' ACT composite scores in the statistical analyses for Study Two these missing values were replaced using mean substitution. This technique was used over more sophisticated methods such as regression because mean substitution offers a more conservative estimate, whereas regression, for example, can lead to over fitting (Tabachnick & Fidell, 2007).

To control for these potential effects of risk propensity and individual ACT composite score, Pearson correlations were performed to assess relationships, and the viability of each variable as a potential covariate in the main analyses of Study Two. The Pearson correlations showed the relationships between the five subscales of the DSRS and ACT composite scores, and the summed dependent variables of CP, tCP, and tBC. The summed dependent variables were created to demonstrate the correlations between the covariates of interest—DSRS subscales and ACT composite scores—and general risk preference (CP) as well as reaction times in decisions (tCP and tBC) when collapsed across the status of the person with whom they were competing (Competitor Status).

Correlational analyses demonstrated that there was only a single statistically significant correlation between a dependent variable of interest and a potential covariate (Table 4-2). This relationship was between ACT composite score and the summed continuous preference ratings (Summed CP).

Table 4-2 Correlations between potential covariates and dependent variables in Study Two

	Potential Covariates					
Depenent Variables	*Fertility*	*Between-Groups*	*Within-Group*	*Mating*	*Environmental*	*ACT Score*
Sum (CP)	.04	.01	.09	-.09	.16	.25*
Sum (tCP)	.20*	.08	.16	.01	.23*	.05
Sum(tBC)	-.03	-.08	-.02	-.09	.15	.22*

Note. CP = Continuous Preference Ratings, tCP = decision time for Continuous Preference Ratings, tBC = decision time for Binary Choice tasks. Statistically significant correlations are denoted by *.

However, further analysis of the relationship between ACT composite score and Summed CP at different levels of Reason Number showed that this covariate relationship violated the assumption of homogeneity of regression (Tabachnick & Fidell, 2007). Specifically, although there was a significant positive relationship between ACT score and Summed CP at the 3rd Reason decision task, this relationship was not statistically significant at the 1st Reason decision task (Table 4-3). Due to this serious issue, neither ACT composite score, nor any of the other domain specific risk subscales, were used as covariates in the main analyses of Study Two.

Table 4-3 Correlations between Potential Covariates and Dependent Variables for Each Level of Reason Number

		Potential Covariates					
Reason Number	Depenent Variables	*Fertility*	*Between-Groups*	*Within-Group*	*Mating*	*Environmental*	*ACT Score*
1st Reason	Sum (CP)	.16	.18	-.03	.04	.17	.16
	Sum (tCP)	.18	.25	.39*	.09	.32*	.10
	Sum(tBC)	.03	-.01	.04	-.09	.32*	.24
3rd Reason	Sum (CP)	-.10	-.05	.17	-.23	.16	.32*
	Sum (tCP)	.25	-.15	-.15	-.06	.14	-.01
	Sum(tBC)	-.10	-.14	-.12	-.10	-.03	.20

Note. CP = Continuous Preference Ratings, tCP = decision time for Continuous Preference Ratings, tBC = decision time for Binary Choice tasks. Statistically significant correlations are denoted by *.

Potential Order Effects

For Study Two there were two possibilities for order effects (Status Order and Task Order) for each of the three continuous dependent variables (CP, tCP, and tBC). The potential order effects were examined prior to any of the main, theoretically important analyses in order to remove these variables from the analyses if they had no effect.

For Task Order—whether participants completed the BC or CP decision task first—a series of three separate one-way analyses of variance were performed, one for each of the three continuous dependent variables. Results from these analyses demonstrated that for CP, there was not a main effect for Task Order, $F(1, 118) = 0.68$, $p = .413$, $\eta^2 = .01$. This suggests that Task Order did not have an impact on continuous preference ratings of risky choice for Study Two's data. However, there were statistically significant order effects for both tCP, $F(1, 115) = 37.05$, $p < .001$, $\eta^2 = .24$, and for tBC, $F(1, 112) = 88.15$, $p < .001$, $\eta^2 = .44$. Regarding decision time for continuous preference ratings (tCP), this suggests that decisions take significantly longer to make when the CP task is first, than when it is second. The pattern is reversed for tBC. Specifically, the decision time for BC decision tasks was significantly longer when BC was first than when it was second. Reflection upon these order effects for decision time reveals that the order effect is easily explained. Decision time for the continuous preference decision tasks is faster after participants have already made a previous choice between the gambles (in the BC task). The same pattern is true for the decision time on the binary choice decision tasks. Specifically, decision time is much faster if participants have already made a preference rating for the gambles. Nonetheless, the significant order effect resulted in Task Order being used as an independent variable in the analyses of decision time in the main analyses.

For Status Order—the order in which participants viewed different fictional competitors—an additional three one-way analyses of variance were performed, one for each of the continuous dependent variables. Results of these analyses showed that there were no statistically significant order effects for CP, $F(2, 117) = 0.11$, $p = .899$, $\eta^2 < .01$, for tCP, $F(2, 114) = 2.21$, $p = .114$, $\eta^2 = .04$, or for tBC, $F(2, 111) = 0.12$, $p = .890$, $\eta^2 < .01$. Thus, Status Order as an independent variable was left out of subsequent analyses due to the lack of theoretical importance and the lack of any statistically significant order effects on any of the continuous dependent variables.

General Data Analytic Procedures

Study Two was designed such that specific predictions from dominance theory could be compared against specific predictions from the priority heuristic. One area in which these two different theoretical positions make different predictions is in choice behavior: which option do people most often choose (Binary Choice) or which option do people prefer (Continuous Preference).

Continuous preference ratings (CP) were analyzed by using a 2 (Gender) by 2 (Reason Number) by 3 (Competitor Status) mixed-factorial analysis of variance, with Gender and Reason Number as the between-participant independent variables and Competitor Status as the within-participant independent variable.

Binary choices (BC) were analyzed using a combination of McNemar's test and Mann-Whitney *U* test on nonparametric data. To assess the impact of Reason Number on binary choices, the Binary Choice data was summed (0 = safer choice, 1 = riskier choice) which gave the dependent variable an ordinal structure with values ranging from 0 to 3 risky choices. A Mann-Whitney *U* test was performed on this data, essentially the nonparametric equivalent of the independent-samples *t*-test. To analyze the within-participant variable of Competitor Status, a McNemar's test was performed to examine if there were statistically significant deviations from proportions of risky and safe choices between different levels of Competitor Status.

Both of the decision time dependent variables were analyzed using a 2 (Gender) by 2 (Reason Number) by 2 (Task Order) by 3 (Competitor Status) mixed-factorial analysis of variance with Reason Number, Task Order, and Gender as the between-participant independent variables, and with Competitor Status as the within-participant independent variable. Recall that Task Order had a statistically significant effect on decision time, and thus was included in the primary analyses.

Numeracy, as calculated by the General Numeracy Scale (Lipkus et al., 2001), was used to determine each participant's level of numeracy ranging from 0 to 11. Preliminary examination of the distribution of numeracy scores revealed that the distribution of scores was negatively skewed (*Skew* = -0.89, *SE* = 0.22), with a mean (*M* = 8.39, *SD* = 2.16) closer to the maximum possible score than the minimum. However, this distribution is consistent with what has previously been seen in other research using numeracy as an individual difference variable (e.g., Peters et al., 2006; Hill & Brase, 2012; Liberali et al., 2011), with the authors in those studies using different analytic techniques such as simple regression and median splitting numeracy and performing an analysis of variance. For the purposes of assessing the potential moderating effect of numeracy on the effect between Reason Number and Continuous Preference ratings for gambles a 2-step hierarchical regression was performed on the summed CP ratings (summed across Competitor Status).

Preference Ratings and Binary Choices for Risky Gambles

Continuous Preference ratings and Binary Choices were analyzed in order to determine which pattern of choice behavior was consistent with the different models of behavior, be it dominance theory or the priority heuristic. Just as in Study One, the experimental design was structured in a fashion consistent with strong inference (Platt, 1964). However, there remained a possibility that a mixture of results could occur (e.g., main effects for both Competitor Status and for Reason Number). In the event of mixed results indicating partial support for both theoretical perspectives, the data from the decision time analyses was hoped to illuminate the underlying process. For instance, in the event that both Competitor Status and Reason Number yielded main effects on continuous preference ratings, the decision time data for continuous preference ratings (tCP) could then be used to estimate which conditions took longer in making a decision. This exploratory observation of the difference in decision time could then be used to approximate the underlying cognitive process for future empirical testing.

Continuous Preference Ratings

For this specific analysis on Continuous Preference ratings (CP), the hypothesis consistent with dominance theory predicts that there should be a main effect of Competitor Status on preference ratings. However, the specific pattern is also very important. Dominance theory predicts that people should be more risk-prone when competing against someone they perceive as equal in status, whereas people should be more risk-averse when competing against those who are perceived as higher and lower in status. Further, consistent with the findings of Ermer et al. (2008), it was predicted that this pattern of results would only hold for male participants. Thus, a significant Competitor Status by Gender interaction should be found. Dominance theory makes no predictions regarding Reason Number.

Just as in Study One, decision tasks were created so that specific patterns of choice behavior and preference ratings should be found if the priority heuristic is correct. Based on the decision tasks created, the priority heuristic predicted a main effect for Reason Number such that decision tasks labeled 3rd Reason tasks should elicit higher preferences for the riskier gamble than the 1st Reason tasks which were designed to elicit risk-aversion. The priority heuristic makes no predictions regarding Gender or Competitor Status.

Results from the three-way mixed factorial analysis of variance showed a statistically significant main effect for Competitor Status, $F(2, 232) = 3.24$, $p = .041$, partial $\eta^2 = .03$. There was also a statistically significant main effect for Reason Number, $F(1, 116) = 7.25$, $p = .008$, partial $\eta^2 = .06$. The two-way interaction between Competitor Status and Gender was not statistically significant, $F(2,232) = 0.74$, $p = .480$, partial $\eta^2 = .01$.

Further examination of the main effect for Competitor Status showed that the main effect was due to the much lower preference for the riskier gamble when competing against someone lower in status ($M = 2.73$, $SD = 1.83$), compared to competing against fictional students perceived as higher in status ($M = 3.18$, $SD = 1.93$), $t(119) = -2.24$, $p = .027$, $d = .20$. There was not a statistically significant difference between lower status and equal status ($M = 3.11$, $SD = 1.87$), $t(119) = -1.97$, $p = .051$, $d = .18$. The difference between equal status competitors and higher status competitors was not statistically significant, $t(119) = -0.43$, $p = .671$, $d = .04$, and more importantly, was not in the hypothesized direction as predicted by dominance theory (Figures 4-4 and 4-5). The main effect for Reason Number was produced by the statistically significant difference between 1st Reason tasks ($M = 2.66$, $SD = 1.25$) and 3rd Reason tasks ($M = 3.36$, $SD = 1.55$), with the latter receiving higher preference ratings for the riskier gamble. The direction of this main effect was consistent with predictions made by the priority heuristic.

There was not a statistically significant main effect for Gender, $F(1, 116) = 0.64$, $p = .427$, partial $\eta^2 = .01$, nor were there statistically significant interactions between Gender and Reason Number, $F(1, 116) = 0.06$, $p = .813$, partial $\eta^2 < .01$, Competitor Status and Reason Number, $F(2,232) = 1.18$, $p = .308$, partial $\eta^2 = .01$, or the three-way interaction between Reason Number, Competitor Status, and Gender, $F(2,232) = 0.97$, $p = .382$, partial $\eta^2 = .01$.

Figure 4-4 The Effects of Competitor Status and Reason Number on Continuous Preference Ratings in Males

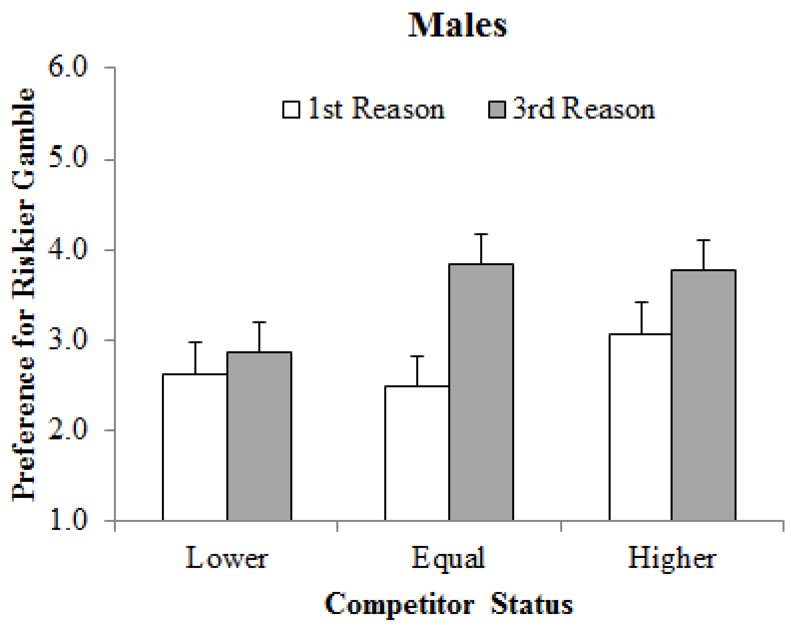
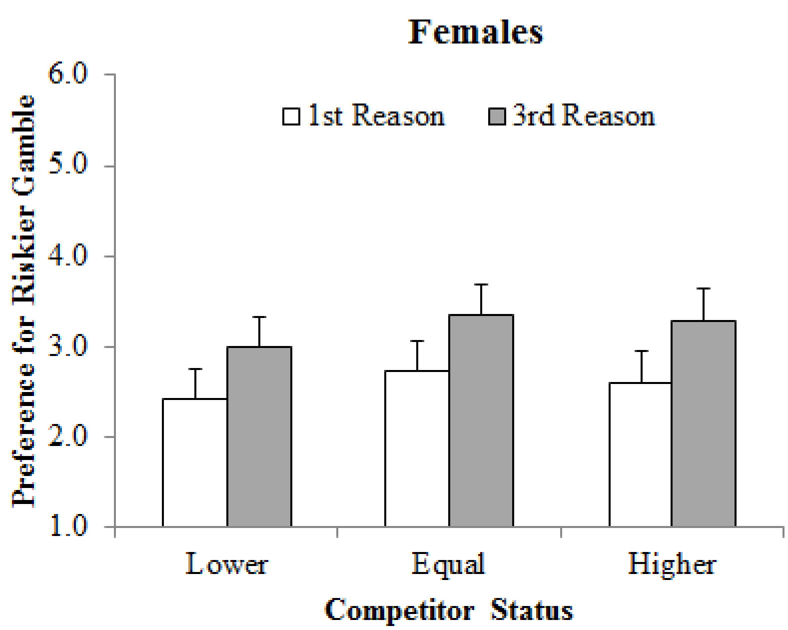


Figure 4-5 The Effects of Competitor Status and Reason Number on Continuous Preference Ratings in Females



Relationship between Binary Choices and Continuous Preference Ratings

Continuous Preference ratings were used in Studies One and Two due to the observation that participants are generally risk-averse, all else being equal. This was true for the data in Study Two as well: CP ratings (M = 3.01, SD = 1.44) were on the bottom half of the 1 to 6 scale with 6 indicating the highest possible preference for the riskier gamble. Nonetheless, Binary Choice data were also analyzed due to their high ecological validity; people make discrete choices rather than choices of degree (e.g., preference ratings).

To determine a level of consistency in participants' responding on the two different formats of decision tasks—Binary Choice and Continuous Preference—point biserial correlations were performed for each level of the Competitor Status within-participants independent variable. Recall that point biserial correlation coefficients typically are suppressed due to the restricted range of the binary or dichotomous variable being assessed (Kemery, Dunlap, & Griffeth, 1988). The binary variable in these analyses was the Binary Choice dependent variable coded as 0 for the safer choice and 1 for the riskier choice. The Continuous Preference ratings ranged from 1 to 6 with higher scores indicating a stronger preference for the riskier gamble and lower scores a stronger preference for the safer gamble.

Results from these separate correlation analyses indicated quite strong positive relationships between Binary Choices and Continuous Preferences regardless if the participants were competing against fictional students perceived as lower, r_{pb} (118) = .57, $p < .001$, equal, r_{pb} (118) = .64, $p < .001$, or higher in status, r_{pb} (118) = .65, $p < .001$. This indicates a high level of consistency with regard to participants' choices and preferences, which lends credence to the use of the more sensitive, but perhaps less ecologically valid, continuous preference ratings.

Binary Choice

A Mann-Whitney U test was conducted to examine the effect of Reason Number (1^{st} or 3^{rd}) on discrete risky choices collapsed across the Competitor Status independent variable. The risky choice dependent variable was created by calculating the sum of risky choices across the within-participant independent variable of Competitor Status; risky choices were coded as 1, and safe choices were coded as 0. This summed dependent variable was ordinal in nature, and ranged from 0 to 3, with a score of 3 meaning that the participant chose the riskier gamble in all three decision tasks, one against each of the three fictional competitors. The Mann-Whitney U test was used because of the ordinal, rather than interval or ratio, nature of the data. The Mann-

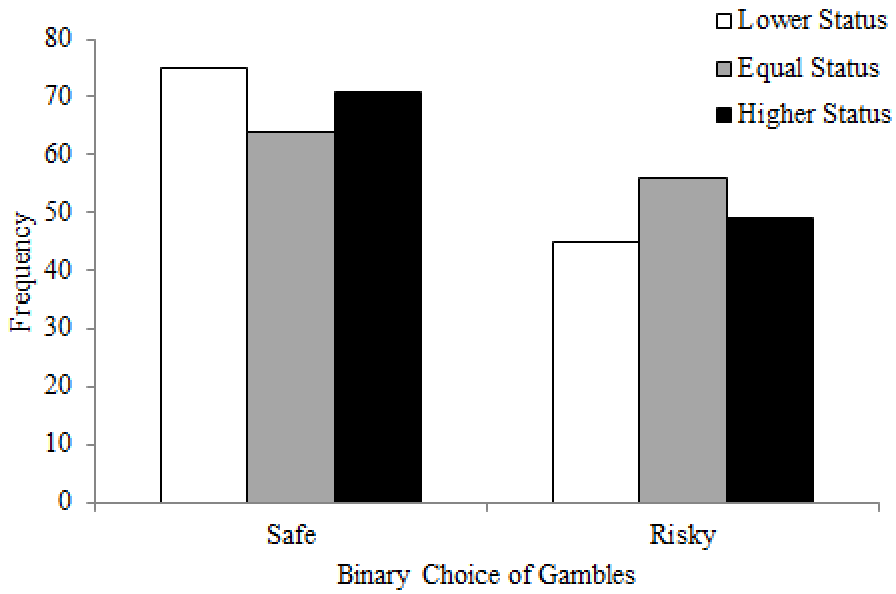
Whitney U test is essentially the nonparametric equivalent of the independent-samples t-test though.

Results from the Mann-Whitney U analysis showed that participants receiving the 1st Reason decision task, designed to elicit risk-averse choices, did make fewer risky choices (Mean Rank = 52.95) than the participants who were randomly assigned to receive the 3rd Reason decision tasks (Mean Rank = 68.05) which were designed to elicit risk-prone decisions. This difference in mean rank of the ordinal data proved to be statistically significant, $U = 1347.00$, $p = .013$ (Figure 4-6).

Figure 4-6 The Effects of Reason Number on Binary Choice in Study Two

To examine the impact of Competitor Status on eliciting risky choice behavior in participants, a McNemar's test was performed on the within-participant independent variable of Competitor Status. Three separate paired comparisons were made. Results of these tests revealed that there was not a significant difference between the number of risky choices in terms of the differences between Lower Status ($n = 45$) and Equal Status ($n = 56$), χ^2 (1, $N = 120$) = 2.33, $p = .127$, Equal Status and Higher Status ($n = 49$), χ^2 (1, $N = 120$) = 0.19, $p = .665$, or Lower Status and Higher Status, χ^2 (1, $N = 120$) = 0.88, $p = .349$ (Figure 4-7).

Figure 4-7 The Effects of Competitor Status on Binary Choice in Study Two



Decision Time for Preference Ratings and Binary Choices

Because the priority heuristic is a *process model*, additional predictions were made regarding the amount of time it should take participants to choose between options (Binary Choice) or to indicate a preference (Continuous Preference) based upon the number of reasons necessary before search stops (Figure 2-1). Specifically, because Study Two assumed that participants were utilizing the standard lexicographic order of reasons for the priority heuristic—as outlined by Brändstatter et al. (2006)—decision problems which should, based on their construction, require participants to proceed to the reason of maximum payoffs (i.e., the 3rd Reason), should also take longer to complete. This would be reflected in differences in reaction time data between 1st and 3rd Reason conditions. Because two different measures of choice behavior were recorded for Study Two (i.e., Binary Choice and Continuous Preference), two different arrays of decision time were analyzed. Also, recall that there were order effects for Task Order. Although the most parsimonious explanation for the order effects is theoretically inimportant, the independent variable was included in all analyses on decision time data.

Continuous Preference Decision Time

Results from the analysis of Continuous Preference decision times (tCP) showed a statistically significant main effect for Task Order (previously shown in the Preliminary Data

Issues section), $F(1, 109) = 35.82$, $p < .001$, partial $\eta^2 = .25$. These data showed that, when participants completed the CP decision task first ($M = 17{,}624.68$, $SD = 5{,}785.45$) they were much slower in making decisions than if they completed the BC decision task first and the CP decision task second ($M = 11{,}454.91$, $SD = 5{,}173.48$). As previously was mentioned, this is an intuitive finding. When people have answered decision task once, it should take less time to make a decision about the same gambles again, even if the decision task format changes (e.g., from Binary Choice to Continuous Preference).

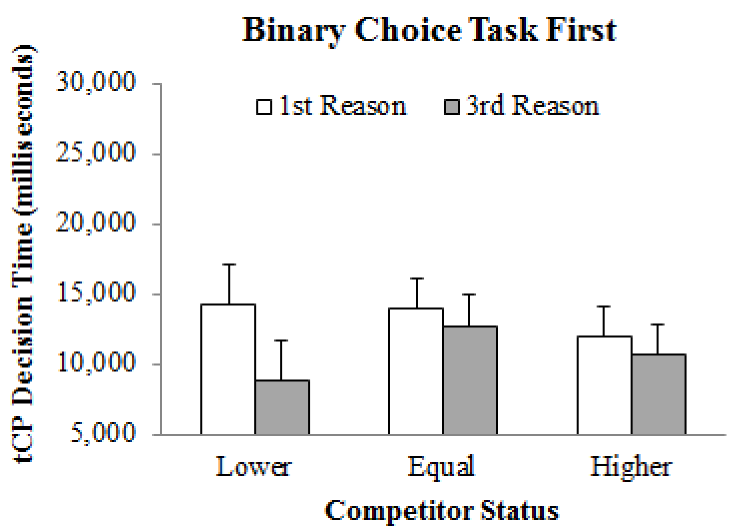
There were no main effects for Gender, $F(1, 109) = 1.06$, $p = .305$, partial $\eta^2 = .01$, Competitor Status, $F(2, 218) = 0.05$, $p = .947$, partial $\eta^2 < .01$, or of paramount theoretical importance, Reason Number, $F(1, 109) = 0.61$, $p = .438$, partial $\eta^2 = .01$. Specifically, males ($M = 15{,}005.57$, $SD = 6{,}800.76$) and females ($M = 13{,}906.43$, $SD = 5{,}694.53$) had similar decision times for the Continuous Preference decision tasks. Decision times were similar irrespective of whether participants were competing against lower ($M = 14{,}230.91$, $SD = 11{,}015.95$), equal ($M = 14{,}540.80$, $SD = 9{,}120.15$), or higher ($M = 14{,}610.37$, $SD = 9{,}189.54$) perceived status students (Figures 4-6 and 4-7). And finally, contrary to the priority heuristic, 1st Reason decision tasks ($M = 14{,}873.12$, $SD = 6{,}714.51$) did not take less time to reach a decision than 3rd Reason decision tasks ($M = 14{,}041.16$, $SD = 5{,}820.52$).

The two-way interactions all failed to reach statistical significance: Competitor Status by Task Order, $F(2, 218) = 0.94$, $p = .393$, partial $\eta^2 = .01$; Competitor Status by Reason Number, $F(2, 218) = 0.66$, $p = .519$, partial $\eta^2 = .01$; Competitor Status by Gender, $F(2, 218) = 0.69$, $p = .505$, partial $\eta^2 = .01$; Task Order by Reason Number, $F(1, 109) = 0.03$, $p = .862$, partial $\eta^2 < .01$; Task Order by Gender, $F(1, 109) = 0.01$, $p = .922$, partial $\eta^2 < .01$; Reason Number by Gender, $F(1, 109) = 0.52$, $p = .473$, partial $\eta^2 = .01$.

The three-way interactions also all failed to reach statistical significance: Task Order by Reason Number by Gender, $F(1, 109) = 0.78$, $p = .379$, partial $\eta^2 = .01$; Competitor Status by Task Order by Reason Number, $F(2, 218) = 0.25$, $p = .779$, partial $\eta^2 < .01$; Competitor Status by Task Order by Gender, $F(2, 218) = 0.84$, $p = .434$, partial $\eta^2 = .01$; Competitor Status by Reason Number by Gender, $F(2, 218) = 0.89$, $p = .412$, partial $\eta^2 = .01$. Additionally, the four-way interaction between Competitor Status, Reason Number, Gender, and Task Order failed to reach statistical significance, $F(2, 218) = 0.03$, $p = .972$, partial $\eta^2 < .01$.

The lack of statistically significant main effect for Reason Number was further examined using the Rouder et al. (2009) Bayes factor score method. An independent-samples t-value of 0.72, a sample size of $N = 120$, and a Scale r of 1.0 were used in the calculation. The resulting JMZ Bayes factor was $B_{01} = 10.71$. This is consistent with what Rouder et al. describe as "strong evidence" in support of the null hypothesis, with the null hypothesis of Reason Number having no effect on decision time being approximately ten times more likely than the alternative hypothesis of Reason Number having an effect on decision time.

Figure 4-8 The Effects of Competitor Status, Reason Number, and Task Order on Continuous Preference Decision Time (tCP) in Male Participants



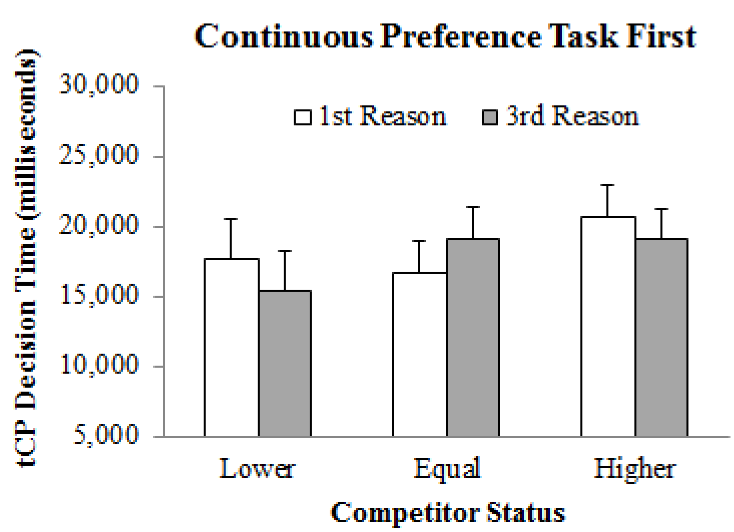
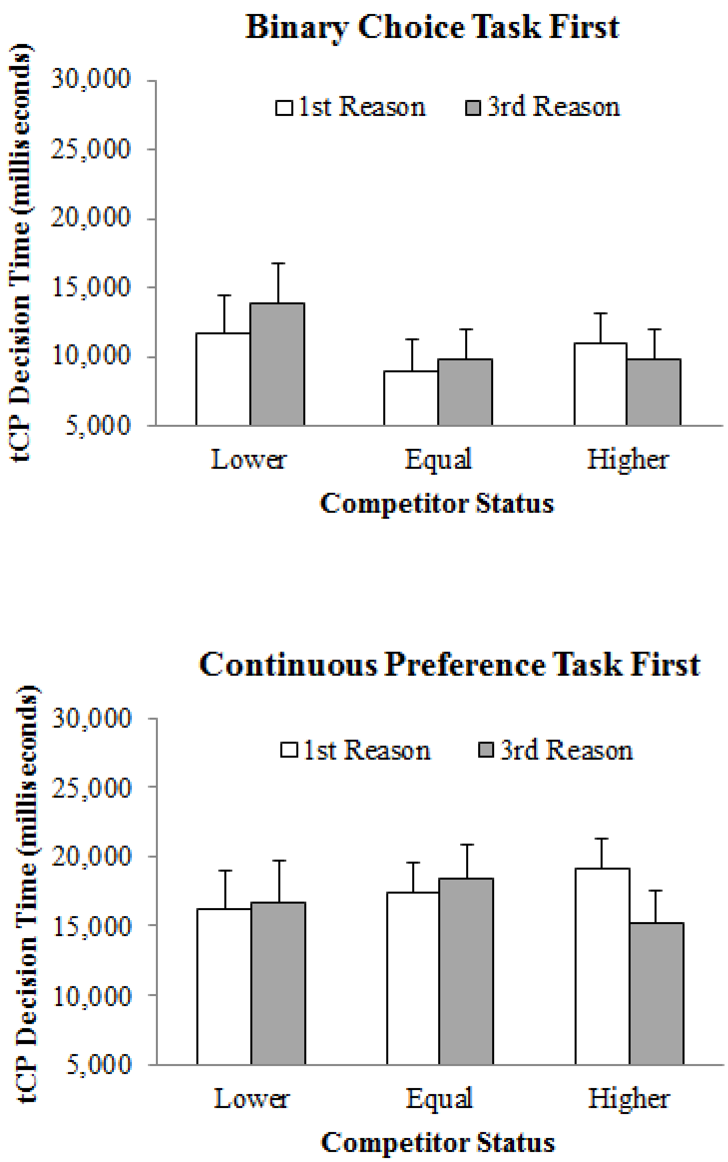


Figure 4-9 The Effects of Competitor Status, Reason Number, and Task Order on Continuous Preference Decision Time (tCP) in Female Participants



Binary Choice Decision Time

Results from the analysis on decision times for the Binary Choice tasks (tBC) revealed a statistically significant main effect for Task Order, $F(1, 106) = 89.54$, $p < .001$, partial $\eta^2 = .46$. This was consistent with results from the preliminary analyses examining potential order effects. This result also suggested that participants took significantly longer to make a decision between the two gambles in the BC task when they performed the BC task first (M = 16,269.54, SD = 6,107.33) compared to when they performed the BC task last (M = 7,603.29, SD = 3,530.03). Additionally, there was a statistically significant main effect for Gender, $F(1, 106) = 4.89$, p = .029, partial $\eta^2 = .04$, with females (M = 10,702.19, SD = 6,004.67) responding to Binary Choice tasks faster than males (M = 12,714.51, SD = 6,959.14), irrespective of Task Order.

The main effect for Competitor Status failed to reach statistical significance, $F(2, 212) = 0.60$, $p = .550$, partial $\eta^2 = .01$, indicating that the relative status of the fictional student competitor had no impact on the time to make a decision in the Binary Choice tasks. Importantly, there was also not a statistically significant main effect for Reason Number, $F(1, 106) = 0.88$, $p = .351$, partial $\eta^2 = .01$, suggesting that decision tasks which should have resulted in decisions after the 1st Reason took equally long as decision tasks that should have resulted in decisions after the 3rd Reason (i.e., after an additional two decision steps) (Figures 4-8 and 4-9). This is inconsistent with predictions made by the priority heuristic about the positive correlation between decision time and number of reasons used to make a decision.

All of the two-way interactions failed to reach statistical significance: Competitor Status by Task Order, $F(2, 212) = 0.89$, $p = .413$, partial $\eta^2 = .01$; Competitor Status by Reason Number, $F(2, 212) = 0.19$, $p = .831$, partial $\eta^2 < .01$; Competitor Status by Gender, $F(2, 212) = 1.96$, $p = .144$, partial $\eta^2 = .02$; Task Order by Reason Number, $F(1, 106) = 0.27$, $p = .602$, partial $\eta^2 < .01$; Task Order by Gender, $F(1, 106) = 0.39$, $p = .534$, partial $\eta^2 < .01$; Reason Number by Gender, $F(1, 106) = 0.02$, $p = .888$, partial $\eta^2 < .01$.

Also, all of the three-way interactions failed to reach statistical significance: Task Order by Reason Number by Gender, $F(1, 106) = 1.17$, $p = .281$, partial $\eta^2 = .01$; Competitor Status by Task Order by Reason Number, $F(2, 212) = 0.05$, $p = .951$, partial $\eta^2 < .01$; Competitor Status by Task Order by Gender, $F(2, 212) = 1.24$, $p = .292$, partial $\eta^2 = .01$; Competitor Status by Reason Number by Gender, $F(2, 212) = 0.35$, $p = .706$, partial $\eta^2 < .01$. Also, the four-way interaction of Competitor Status by Task Order by Reason Number by Gender failed to reach statistical significance, $F(2, 212) = 0.77$, $p = .466$, partial $\eta^2 = .01$.

The lack of a significant main effect for Reason Number was additionally assessed using the JZS Bayes factor method (Rouder et al., 2009). The independent-samples t-value of -0.59, the sample size of $N = 120$, and the Scale r of 1.0 were used in the analysis. The resulting JZS

Bayes factor was B_{01} = 11.64. This is consistent with "strong evidence" in support of the null hypothesis that Reason Number does not have an effect on decision time.

Figure 4-10 The Effects of Competitor Status, Reason Number, and Task Order on Binary Choice Decision Time (tBC) in Male Participants

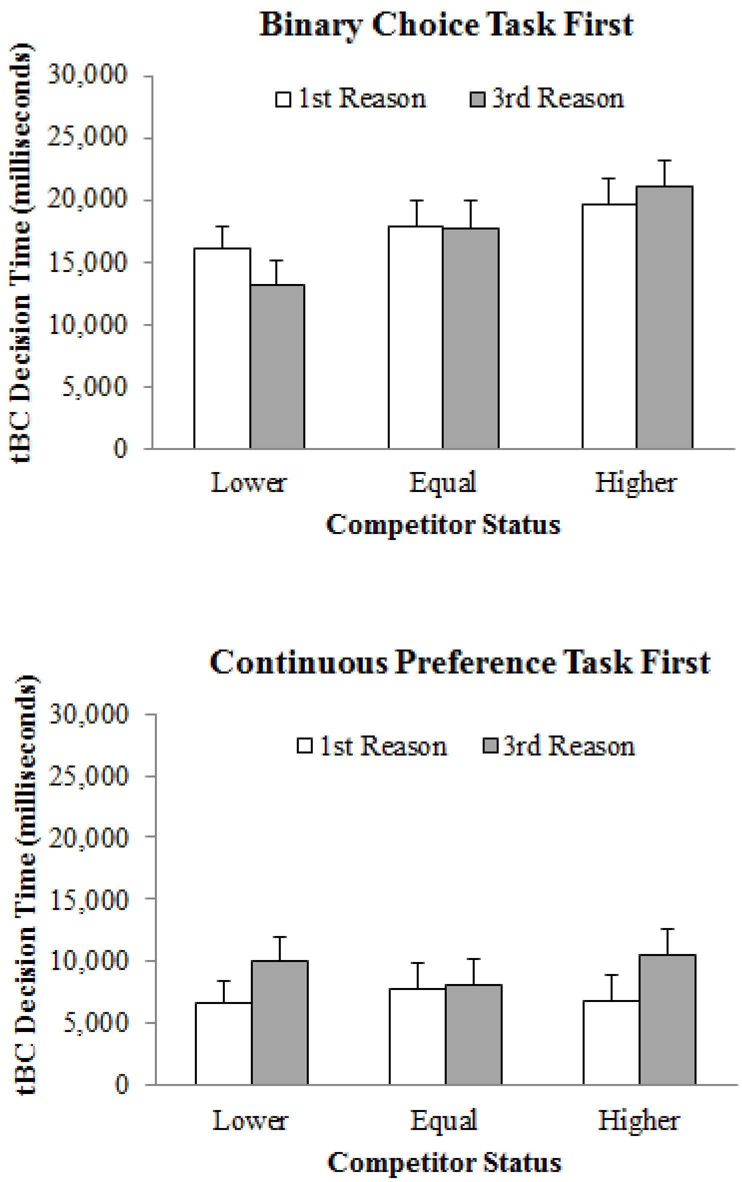
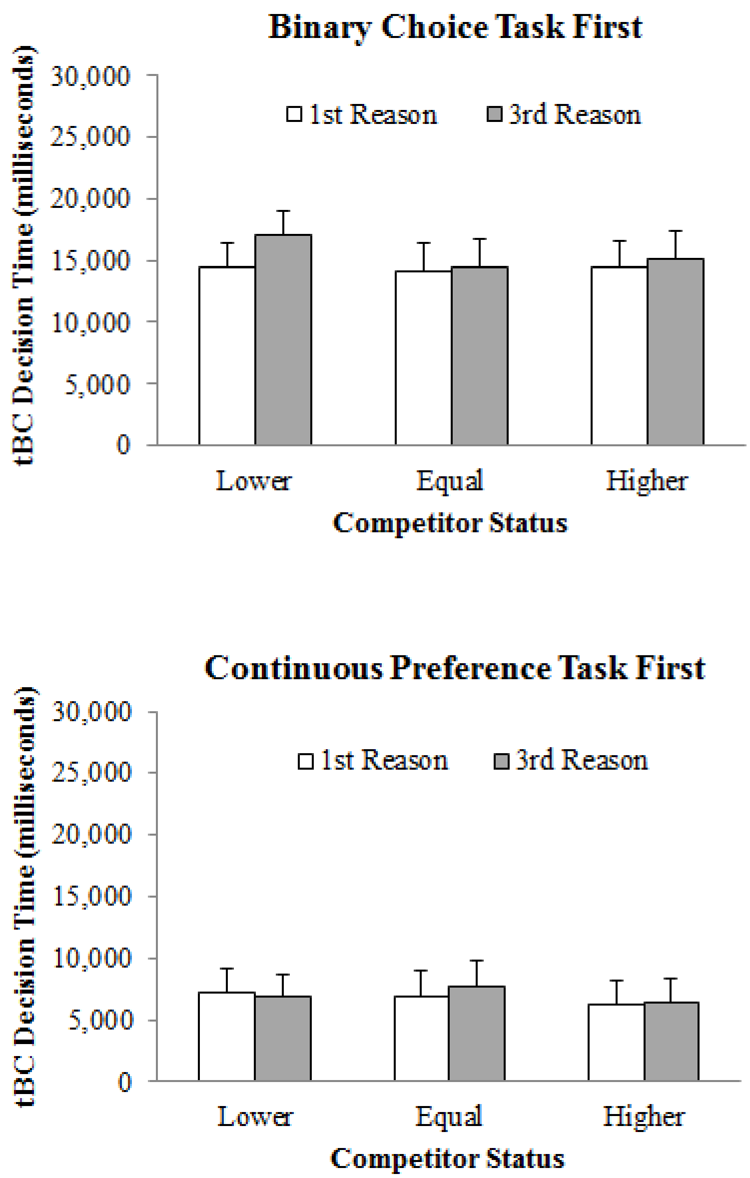


Figure 4-11 The Effects of Competitor Status, Reason Number, and Task Order on Binary Choice Decision Time (tBC) in Female Participants



The Role of Numeracy

To assess the potential relationship between numerical literacy and consistency with the priority heuristic and risky choice behavior a 2-step hierarchical regression was performed using participants' numeracy scores (centered to reduce multicollinearity with interaction term), Reason Number, and their interaction term as the predictors, and summed CP scores as the criterion. This method, as opposed to the sum-difference regression used in Study One, was possible due to the fact that Reason Number was between-participants in Study Two, rather than within-participants as in Study One.

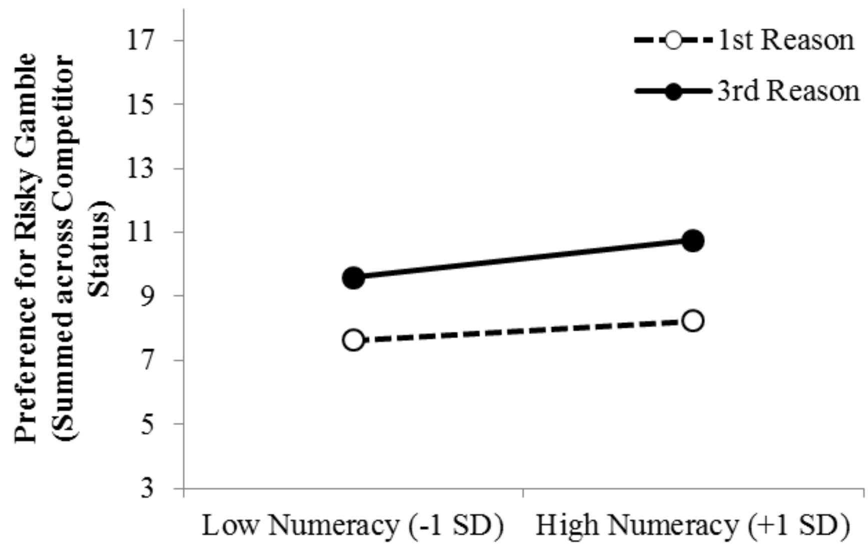
Centered numeracy scores and Reason Number were added to the model in Step 1, and the interaction term of Numeracy by Reason Number was added to the model in Step 2. Statistical significance on the part of the interaction term was assessed in Step 2, while main effects for Reason Number and Numeracy were assessed at Step 1.

Results from the 2-step hierarchical regression showed that the model was a statistically significant predictor at Step 1, $F(2, 117) = 4.31$, $p = .016$, $R^2 = .07$. Assessing the individual predictors composing the Step 1 model revealed that, although Reason Number was a unique predictor of summed CP ratings, $t(117) = 2.88$, $p = .005$, $b = 2.25$, Numeracy (centered) was not a unique predictor, $t(117) = 1.13$, $p = .262$, $b = 0.21$.

Results from Step 2 of the model showed that the change in predictive power past that of the Step 1 model was not statistically significant, $\Delta F(1, 116) = 0.12$, $p = .729$, $\Delta R^2 < .01$. This suggested that that introduction of the interaction term did not add unique predictive power to the model beyond what was previously accounted for by the individual predictive power of Numeracy and Reason Number alone. These results suggest that, in Study Two's data, numeracy did not moderate the effect of Reason Number on CP ratings.

Using the regression parameters from the hierarchical regression, the relationship between Numeracy and Reason Number could be plotted. Numeracy data were plotted using two groups (Low and High Numeracy), created by subtracting (Low) or adding (High) one standard deviation (i.e., $SD = 2.16$) from the mean of 0; numeracy was mean centered, which meant it retained properties consistent with the scaling of the GNS (Lipkus et al., 2001), but had a mean of 0. Probing of the relationships showed that the slope of the Numeracy line for 1st Reason tasks ($b = 0.14$) was only slightly lower than the Numeracy slope for 3rd Reason tasks ($b = 0.27$) (Figure 4-12).

Figure 4-12 The Effect of Numeracy on the Relationship between Reason Number and Summed Continuous Preference Ratings in Study Two



Study Two Discussion

The purpose of Study Two was to determine if the priority heuristic (Brandstätter et al., 2006) could still sufficiently predict participant's gamble choices (BC) and preferences (CP) when they, the participants, were competing against students perceived as having different status levels. Human risky behavior in the context of status competition had previously been predicted by dominance theory (Ermer et al., 2008). Specifically, *males* of equal status should choose riskier behavior when competing against one another, but should be risk-averse when competing against other males perceived as being either higher or lower in status. Ermer et al. found data consistent with those predictions. Also, just as in Study One, the current study tested a hypothesis derived from Peters and Levin (2008) suggesting that high numerates use numerical information in risky decision making contexts more than their less numerate brethren. From this hypothesis the following prediction was made for Study Two: High numerates should be more consistent with priority heuristic predictions than low numerates due to the assumed numerical nature of the priority heuristic decision process (Figure 2-1). The results are discussed in detail below.

Can the priority heuristic account for competitor status?

Although there is nothing within the hypothesized process model of the priority heuristic which would precisely account for competitor status, the preference and choice data collected in Study Two very clearly showed that the priority heuristic's predictions were supported, irrespective of the status of the fictional competitors. This choice and preference data lends support to the lexicographic order hypothesized by the priority heuristic. Participants in the 1st Reason task consistently chose, and preferred, the safer gamble, whereas participants in the 3rd Reason task consistently chose, and preferred, the riskier gamble. This is important because these tasks were designed to elicit that exact pattern of choice and preference, if indeed the priority heuristic's process was an accurate account of our participants' cognitive processes.

However, despite strong support for the priority heuristic as a model of decision behavior in terms of preferences and choices, the decision time data for those choices and preferences did not support the hypothesized underlying process (i.e., the lexicographic order outlined in Figure 2-1). Specifically, the 3rd Reason decision task did not take significantly longer to choose, or prefer, than the 1st Reason decision task. In fact, the 3rd Reason decision task took less time, on average, to choose and prefer, than did the 1st Reason decision task, although the difference was not statistically significant.

In sum, the priority heuristic predicted behavioral outcomes quite well, even when compensating for different statuses of fictional student competitors. However, the underlying process assumed by the priority heuristic was not supported by the decision time data, suggesting that the actual process may (a) not apply when participants are in contexts of same-sex competition with others of varying perceived status, or (b) that the process is generally incorrect. These two options are not exhaustive, but do illustrate the implications of these data on the potential scope of the priority heuristic's hypothesized process. The scope of the heuristic refers to its ecological rationality. Recall that, in Study One, neither the behavioral outcomes, nor the decision time data, were consistent with the priority heuristic. So, in two separate studies, with two separate samples of participants, the process data (tBC and tCP) did not fit with the priority heuristic's predictions. These data call for a potential reconceptualization of the priority heuristic's decision process (i.e., perhaps it is not lexicographic in nature), or perhaps a limiting of the heuristic's valid ecology to context-free, described gambles; i.e., gambles without the additional contexts of need levels (Study One) or competition against others of varying status (Study Two).

Are high numerates' decisions more consistent with the priority heuristic?

Brändstatter et al. (2006) noted that one of the limitations of the priority heuristic, at least when the heuristic was first formulated, was that it does not account for individual differences within the decision maker. Brändstatter et al. explicitly mention individual differences in risk taking as a potential "wrench" in the heuristic. However, results from Peters and Levin (2008) suggested another possible individual difference: numerical literacy, or "numeracy."

Numeracy was shown in Peters and Levin (2008) to be predictive of risky choice framing effects. Specifically, numeracy did not predict the framing effect per se, but it did predict *how* the individual's decision process. More specifically, it predicted what types of information the participants used to make their decisions. Whereas highly numerate individuals used the probabilities and payoffs of the options in making their decisions, the low numerates relied more heavily on non-mathematical information such as the frame (losses or gains) of the problem.

In line with the results from Peters and Levin (2008), it was predicted that individuals high in numeracy would use the probabilities and payoffs more when making their decisions about which of the two gambles they preferred. Because the priority heuristic assumes that individuals perform some type of calculation using exactly the types of information (probabilities and payoffs) that high numerates have been shown to use, that these individuals (high numerates) would behave more consistent with the priority heuristic's predictions. In contrast, the opposite was predicted for those lower in numeracy.

However, data from Study Two did not support the predictions derived from the results of Peters and Levin (2008). Specifically, participants' numeracy levels were not indicative of differential preferences for the 1st Reason and 3rd Reason decision tasks as was hypothesized. This suggests that numerical literacy did not, in Study Two, play a major role in moderating the effect of problem characteristics, embodied in the Reason Number variable, on choice preferences. And, more importantly, the lack of moderation was not consistent with what would be expected if the Peters and Levin conclusions could be extrapolated to priority heuristic-consistent behavior patterns.

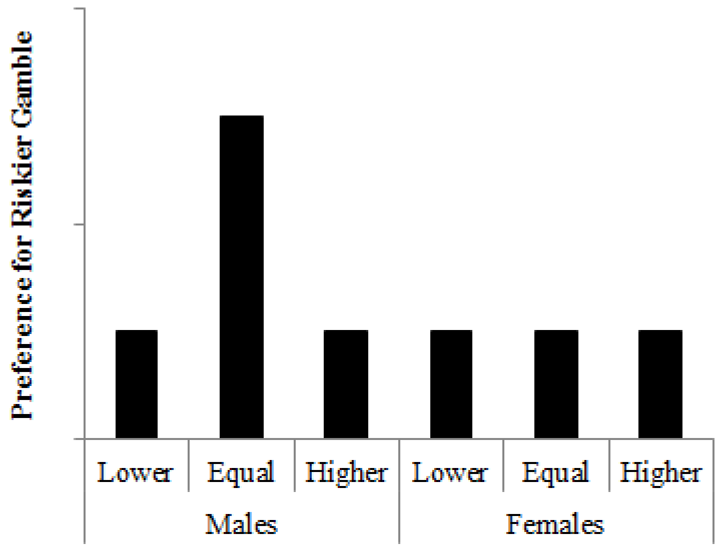
These data from Study Two are somewhat consistent with the results from a similar analysis in Study One. Data from Study One indicated that indeed numeracy was not a moderator in the Reason Number-Risky Preference relationship. However, in Study One, numeracy did have a negative relationship with preference ratings (CP) in the 3rd Reason decision tasks, a finding consistent with the hypothesis. Unfortunately, due to the lack of a statistically significant interaction, the simple slopes analysis technically has no meaning; simple slopes should only be examined if there is a *significant* interaction.

To conclude, across two studies attempting to assess the potential moderating effect of numeracy in the priority heuristic's process, no substantive evidence was found to support the notion of numeracy as a moderator. At this point it appears that numeracy does not need to be accounted for when determining the utility of the priority heuristic, at least in terms of its accuracy as a process model. Brändstatter et al. (2006) were concerned about the potential limitations of the priority heuristic due to it not taking into account individual differences. From these data it appears that numeracy as one of the potential individual differences may be crossed off the list of possible individual difference "wrenches" threatening the predictive power of the priority heuristic.

On the role of competitor status in risk taking

Recall that dominance theory, as made explicit by Ermer et al. (2008), predicts that, when males are competing in intrasexual competitions for resources, the relative status of the individuals participating makes a difference with regard to risky behavior. Specifically, if you are a male competing for resources against another male, then individuals perceived as being higher in status should not be competed against because they are higher in status for a reason: they are higher in status because they are good at *something* and will likely beat you at that *something*, resulting in substantive loss on your part. Likewise, individuals perceived as lower in status should not be competed against because they are lower in status for a reason: they are bad at *something* and therefore have not won frequently enough to acquire any resources. Thus, a win against them would be worthless. However, competitors perceived as equals are worth the risk of competition because they have something to compete for, and they are similar to you in ability. The factor of relative competitor status was hypothesized by Ermer et al. to be a primary motivator to engage in risk. Such motivational patterns would result in a pattern of results similar to Figure 4-13. Indeed, this pattern of results is what Ermer et al. found in their studies.

Figure 4-13 Continuous Preference Pattern of Results Predicted by Dominance Theory



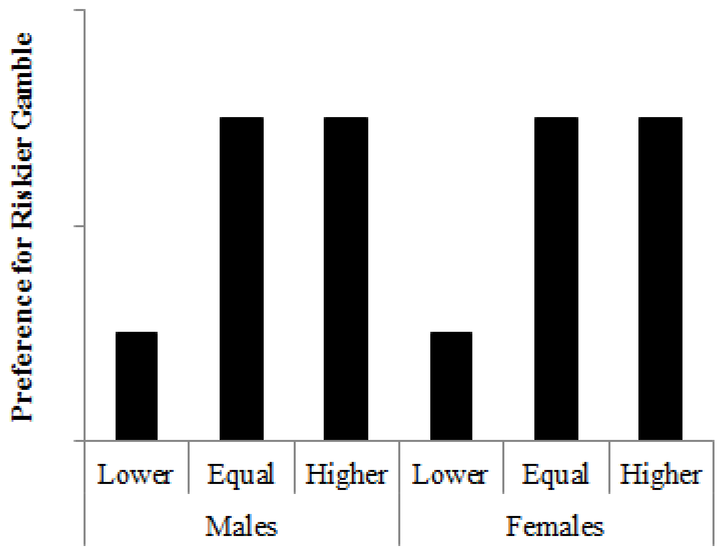
Although there was a statistically significant main effect for Competitor Status in Study Two, further examination of the data showed that the pattern of results was not consistent with dominance theory, or the pattern displayed in Figure 4-13. Instead, irrespective of gender, participants tended to be relatively risk-averse when competing against students perceived as lower in status, but were relatively more risk-prone when competing against students perceived as either equal, or higher in status. Again, this pattern was consistent for both males and females.

The pattern of continuous preference results from Study Two is, at first, somewhat perplexing since the pattern does not match with dominance theory. However, Ermer et al. (2008) offered the exact same pattern of results as an alternative hypothesis for their 2008 studies. This hypothesis was based on work by Rode et al. (1999) which showed that risk-sensitive foraging could explain ambiguity aversion, or a risk-aversion to uncertain variation. Applied to competitor status, Ermer et al. posited that a general theory of risk-sensitivity would entail the following: Humans have a general risk-sensitivity based on need levels, or aspiration levels, and this risk-sensitivity mechanism operates on any physical (e.g., money) or psychological (e.g., status) resource. This general risk-sensitivity model of risk taking behavior posits that humans have need levels for both physical and psychological resources. If humans are below the need level, then people should behave consistent with the standard model of risk-sensitive foraging and take the risk that will get them to the need level. Essentially, this is risk-sensitive foraging, but it is modeled to operate on psychological constructs such as perceived status as well as physical resources.

The crucial differences between dominance theory's account of risk taking behavior and a general model of risk-sensitivity is that the latter would assume a need level for status. A large amount of research has demonstrated that happiness is relative and that people would prefer normatively less if it meant they would have more than their neighbors (e.g., Blanchflower & Oswald, 2004; Luttmer, 2005; McBride, 2001; Veenhoven, 1991). Metaphorically, owning a cheap car on a block full of bus-riders feels better than owning a Cadillac when your neighbors all have Porches. In fact, Hill and Buss (2010) demonstrated that people will shift from a safer option to a riskier option when the riskier option allows for the possibility of having more than those in their peer group. This is true even when the mean payoff for the riskier option is quantitatively less than the mean payoff for the safer option.

So, if a general model of risk-sensitivity has a need level similar to that in risk-sensitive foraging, it appears that the need level is not a fixed amount (e.g., 300 calories, $400). Rather, based on past research it appears that the need level for status is dynamic: Always try to be the highest in status in your group. In terms of risky preferences this would translate into risk-aversion against anyone that is lower in status than yourself, but risk-proneness against anyone else (i.e., equal status and higher status others) (Figure 4-14). Indeed, this is the precise pattern of results which Ermer et al. (2008) suggested would be consistent with risk-sensitive foraging when applied more generally to status competition. This idea of a general risk-sensitivity with need levels for both psychological and physical resources is explored in more detail in Study Three.

Figure 4-14 Idealized Continuous Preference Pattern for a General Model of Risk-Sensitivity Applied to Status Acquisition



Chapter 5 - Study Three

Through two studies it was shown that the priority heuristic, when considered in its entirety (behavioral predictions and decision time process data included), does not perform well when having to account for contextual variables such as competitor status and resource need levels. However, from the results of Study Two, it was shown that, despite results inconsistent with dominance theory, the data *were consistent* with a more general model of risk-sensitivity.

Study One provided support for risk-sensitive foraging theory (Stephens & Krebs, 1986). Study Two provided support for the *behavioral* predictions of the priority heuristic, but more importantly, it also provided support for the idea of a more general risk-sensitivity mechanism of risky decision making which could be applied to the resource of status. This general risk-sensitivity was posed as an alternative hypothesis by Ermer et al. (2008; Experiment 1, hypothesis ii-a):

> If men's [and women's; my addition] risk-taking motivations result from an aspiration for higher status plugging into general risky decision-making mechanisms, as on the risk-sensitive foraging account, then relative status will up-regulate men's willingness to take risks when their aspiration for higher status has not been met (i.e., when their relative status is lower than or equal to that of their potential evaluators) (p. 109).

This hypothesis is an extension of the risk-sensitive foraging model into domains other than physical resources (e.g., status). However, if humans have a general risk-sensitivity mechanism which guides decisions between options of different payoff variance then this mechanism must also require some need level, or aspiration level. The need level is important because its value determines the relative need of a resource. This relative need, in turn, dictates the individual's motivations to choose riskier options; when being risky is the only way to get to the need level, choose the risky option. The next issue is determining what a need level would look like for a construct such as status.

Various research has shown that relative status matters when it comes to self-reported happiness (e.g., Blanchflower & Oswald, 2004; Luttmer, 2005; McBride, 2001; Veenhoven, 1991). This collection of research is in agreement that it generally feels better to have more than your peer group. Thus, people should prefer to have more than their peer group, and any cognitive mechanism consistent with pursuing the goal of a higher status should guide people toward decisions which would result in having more than those of the peer group, and obtaining a higher status. Hill & Buss (2010) showed empirically that this is indeed true; that people choose options that provide them with a chance of having more than their peer group, even if the mean expected outcome is inferior (i.e., the expected value is smaller than a safer alternative). Relating this research back to the idea of a need level for status, this would mean that individuals should have a dynamic, moving need level. Specifically, the need level should reside at the level of the highest status person in the peer group. The goal: obtain the highest level of status.

This is precisely how Ermer et al. (2008) describe the hypothesis of risk-sensitive foraging as applied to status (what I refer to as general risk-sensitivity):

> By positing an aspiration level for status, this approach can be applied to the current research. Social status is always relative: having a high or low level depends on the current comparison group. Thus, one might expect men to have a relatively constant aspiration for higher status relative to others. If men seek resources to gain higher relative status, this model predicts they will seek risk when their status is lower than or equal to the status of the men observing and evaluating their actions (because their status aspiration level has not been met) and avoid risk when their won status is higher (because their status aspiration level has already been satisfied) (p. 108).

Graphically, when applied to the resource of *status*, this hypothesis would look like the pattern of results depicted in Figure 4-14. Participants, both male and female, should have high risk preferences when competing against a competitor of equal or higher status than themselves. Similar to dominance theory, this general model of risk-sensitivity suggests that people will choose less risk when competing against someone of lower status, although for potentially different reasons. This idea of a general model of risk-sensitivity is tested in Study Three, by comparing predictions of four separate potential models in a paradigm both similar to that of Studies One and Two, and similar to what was done in Ermer et al. (2008).

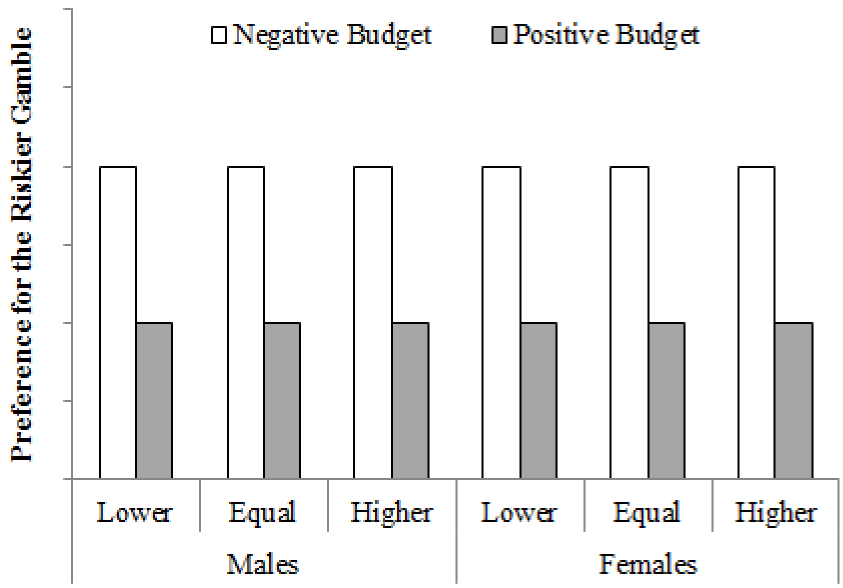
Hypotheses

Study Three was designed to test risk-sensitive foraging against dominance theory in the same way as Ermer et al. (2008). Study Three was composed of a combination of features from Studies One and Two: (1) need levels in the gambling task to study risk-sensitive foraging, and (2) competing against other fictional students to test dominance theory. However, based on the results of Studies One and Two, two additional hypotheses were constructed: general risk-sensitivity applied to status only, and general risk-sensitivity applied to both status and money. Like Studies One and Two, numeracy was also measured in Study Three. However, unlike Studies One and Two, numeracy as a potential moderator *was not analyzed* in Study Three due to the lack of any explicitly known theoretical importance; whereas, the priority heuristic assumed that individuals perform calculations when making decisions about two gambles, none of the proposed models tested in Study Three assume numerical processing ability. The mathematical models of risk-sensitive foraging (Stephens & Krebs, 1986) are used to predict behavioral patterns, not to describe the mental processes occurring in the mind of the forager, be it human or non-human. The hypotheses are described in detail below. Also, to allow for easier comprehension of the differences between various hypotheses, idealized graphical representations accompany each hypothesis.

Risk-sensitive foraging

Participants, both male and female, should be relatively risk-averse when the safer option will allow them the amount of money needed to reach a potential second round (Positive Budget). However, participants should be relatively risk-seeking when only the riskier option allows for the possibility of reaching the amount of money needed to reach a potential second round (Negative Budget) (Figure 5-1). This model of risk taking behavior is limited to monetary amounts for the purposes of Study Three, and makes no predictions regarding the effects of competitor status, as was the case with risk-sensitive foraging applied to status by Ermer et al. (2008) (see previous block quotes). Their hypothesis is re-labeled as *general risk-sensitivity applied to status only*, and is discussed in a following section.

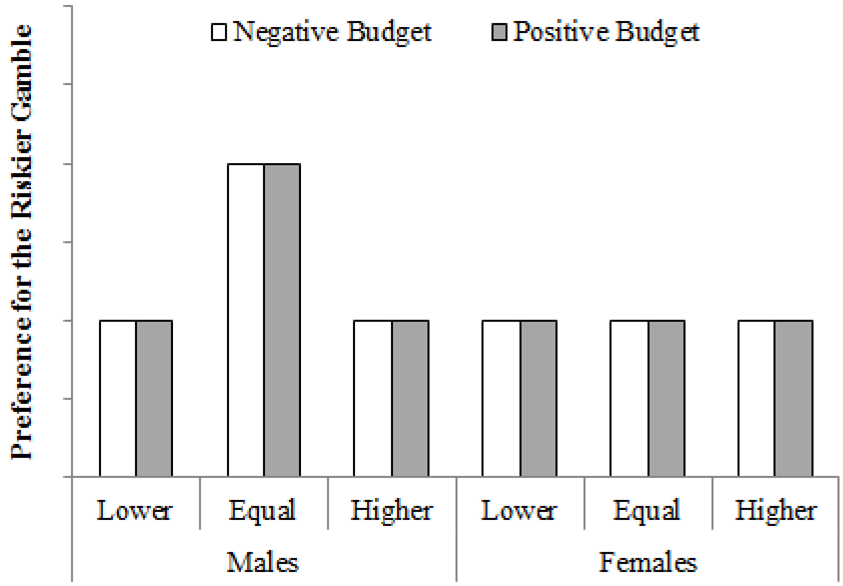
Figure 5-1 Risk-Sensitive Foraging Predictions for Study Three



Dominance theory

Dominance theory as laid out for psychological research by Ermer et al. (2008) predicts that, when *males* compete for resources with other males, the relative status dictates risk taking behavior. Specifically, males should be risk-taking in situations where the individual with whom they are competing is perceived as relatively equal in status. This is because there is both something to gain, and because the individual has a fair chance to win the competition. This also illuminates why dominance theory predicts risk-aversion against individuals perceived as both lower and higher in status; there is nothing to gain against someone lower in status, and there is a greater chance of losing against someone higher in status. This effect is predicted to be limited to male-male competition. Research has shown that females perceive higher status males as being more attractive; however, for men, status is not as important factor in determining the attractiveness of females (Buss, 1989). The graphical pattern of results is depicted in Figure 5-2.

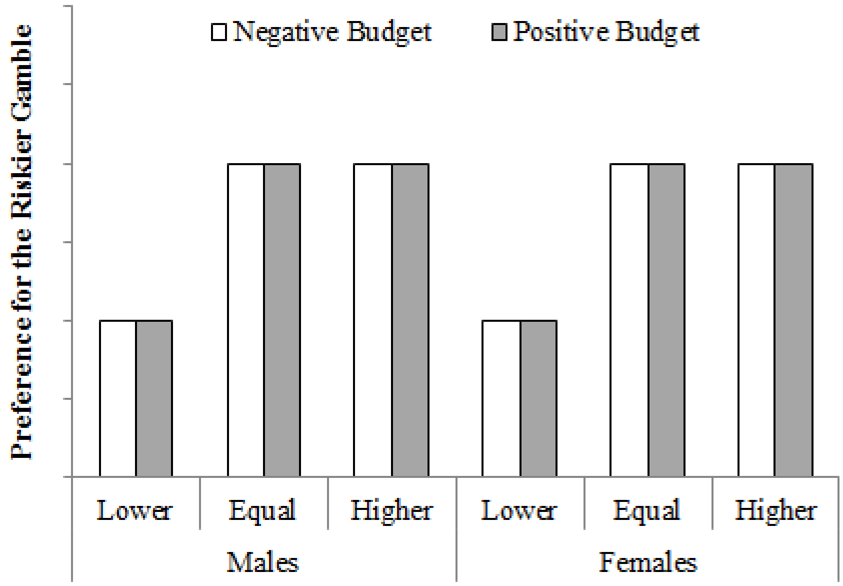
Figure 5-2 Dominance Theory Predictions for Study Three



General risk-sensitivity for status only

General risk-sensitivity applied to status only is conceptualized as the general risk-sensitivity mechanism, but only being applied to the resource of status, at least in terms of the results. This is similar to the alternative, risk-sensitive foraging hypothesis applied to status which Ermer et al. (2008) conceived (Figure 4-14). The key difference is that this hypothesized model would neglect the monetary amount needed to move on to a potential next round in the experimental procedure, a feature not tested by Ermer et al. Instead, it would focus on the status need level: the monetary amount greater than that of the person with whom one is competing. This model predicts that people would be risk-seeking against those individuals perceived as equal and higher in status, but risk-averse against those individuals perceived as lower in status (Figure 5-3). Further, the model predicts no sex differences in risk taking.

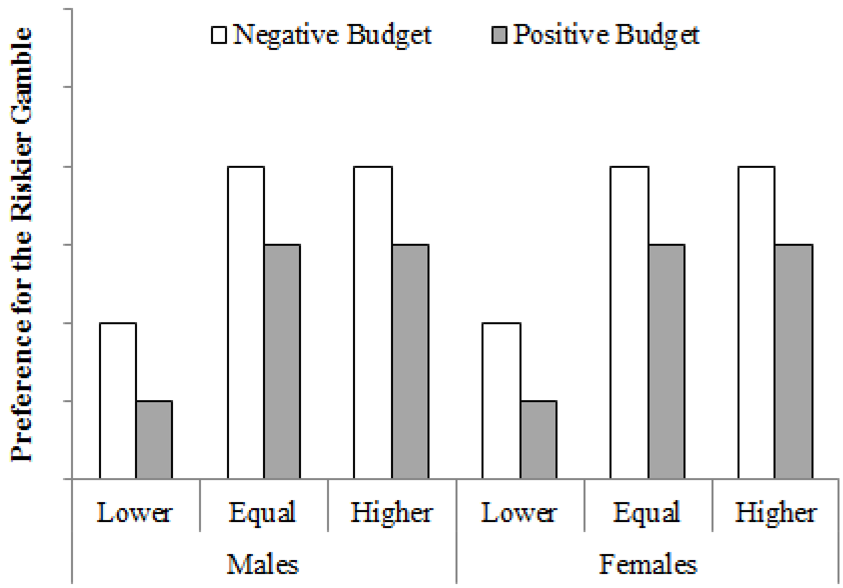
Figure 5-3 General Risk-Sensitivity (Status Only) Predictions for Study Three



General risk-sensitivity for status and money

As opposed to the status-only version of the general risk-sensitivity model, the status *and* money version takes into account both potential motivations to take risk: (1) the motivation to earn enough money to reach a potential second round, and (2) the motivation to earn more than the person against whom participants are competing. Essentially, this is a mixture of the risk-sensitive foraging model and the general risk-sensitivity for status only model. The key difference between the combined model and its constituents is that it assumes individuals will be motivated to reach *both* need levels: (1) enough money to reach the second potential round, and (2) enough money to have more than the person against whom the participant is competing (Figure 5-4). In this model, both need levels are important. Additionally, no sex difference is predicted.

Figure 5-4 General Risk-Sensitivity (Status and Money) Predictions for Study Three



Study Three Method

Participants

The data for Study Three were collected from 120 undergraduate students enrolled in introductory psychology at Kansas State University. Consistent with the design of Study Two, the gender split for Study Three was completely even (i.e., n = 60 males and n = 60 females). This equal split between males and females was purposeful due to the inclusion of Gender as an independent variable necessary for the predictions of dominance theory.

Participant age was consistent with both Studies One and Two, and was consistent with typical research samples drawn from undergraduate courses (M = 18.95, SD = 1.41). The distribution of ethnicities was also typical of research conducted in this specific region of the United States with a vast majority reporting themselves as Caucasian (Caucasian: n = 103; African-American: n = 4; Asian: n = 4; Hispanic: n = 5). Additionally, four of the participants identified their ethnicity as "Other."

Design

Just as the decision tasks in Studies One and Two, the tasks in Study Three were also framed as gains rather than losses. Also, the dual-measure methodology used in the two previous studies was utilized for Study Three. Specifically, participants were assessed using Binary Choice tasks (BC) and also Continuous Preference tasks (CP); these tasks were counterbalanced between participants, and each decision task was answered in both measurement formats.

Study Three's design included the two dependent variables mentioned in the previous paragraph (BC and CP decision tasks). Study Three was also composed of five total independent variables, two of which were control variables used to assess potential order effects. These two order variables were Task Order and Status Order. Task Order, a between-participants independent variable, was defined as the ordering of the different dependent variables in terms of which format of decision task was completed first and which decision task was completed last. There were two levels of Task Order: BC 1^{st} and CP 1^{st}. Status Order was a between-participants independent variable used to describe the order in which participants competed against different fictional student competitors. There were three levels of Status Order: Lower→Equal→Higher (LEH), Equal→Higher→Lower (EHL), and Higher→Lower→Equal (HLE).

The last three independent variables were Gender, Budget, and Competitor Status. These three independent variables, and their interrelationships, were of primary theoretical importance for each of the four proposed models of risk taking (see Study Three Hypotheses). Gender is inherently between-participants. However, Budget was designed to be a between-participant independent variable. Budget was composed of two levels: Negative Budget and Positive Budget. This independent variable was conceptually identical to the Energy Budget independent variable described in Study One. Specifically, decision tasks were categorized as Negative Budget if the riskier option was the only option which provided a chance of reaching the pre-specified need level. However, if both the riskier *and* safer options offer the chance of reaching the need level, then it was categorized as Positive Budget. This is consistent with the energy-budget rule (Stephens & Krebs, 1986) and their conception of positive and negative energy budgets in relation to sampling between resource patches of differing variance. Last, the independent variable of Competitor Status was a within-participants independent variable composed of three levels (Lower, Equal, and Higher) of competitor status relative to the participant. The same universities and manipulations as used in Study Two for Competitor Status were used in Study Three.

Materials

The statistical properties of Decision Task # 1 from Study Two were used for all of the decision tasks in Study Three. However the need levels of money required to reach a potential second round were manipulated in order to create the different levels of Budget. Also, these decision tasks were coupled with information for the different fictional competitors similar to the way materials were constructed for Study Two.

Also, participants answered questions on a variety of individual difference measures. These measures included the Domain Specific Risk Scale (Kruger et al., 2007) and the General Numeracy Scale (Lipkus et al., 2001), although the numeracy scale was only used in an exploratory fashion, and no theoretical predictions were made regarding its relationship to risky preference. The DSRS was measured in order to use as a potential covariate in the main analyses, despite not being used in Studies One and Two due to inappropriate statistical relationships with the dependent variables, and a violation of the assumption of homogeneity of variance. Also, participants were primed to think about status motives by using the status priming material which was also used in Study Two (Griskevicius et al., 2009; Griskevicius et al., 2010).

Decision Tasks

Two decision tasks were created (Table 5-1) to study risky preference behavior in Study Three. Both decision tasks had the same probabilities and payoffs; however, the need level varied between the two decision tasks. This variation in the need level was the manipulation for Budget, and allowed participants to be in a Negative or Positive Budget. Further, as can be seen by the construction of Table 5-1, each participant competed against all three of the fictional student competitors who varied in perceived status. The decision tasks were created such that, in a Negative Budget, only the riskier gamble offered the possibility of reaching the need level required to move to a potential second round. However, in the Positive Budget decision task both the riskier *and* safer gambles offered the possibility of reaching the need level.

Regarding Competitor Status, participants had to choose whether or not to try and earn more money than the fictional student competitor based on that fictional student's perceived status. When competing against lower status individuals the participant did not have choose the riskier gamble in order to earn more money than the lower-status individual. When competing against someone perceived as equal in status the participant could choose the safe option with a high probability of earning the same amount as the equal-status fictional student, or the participant could choose the riskier gamble to try and earn more than the fictional student. When competing against the higher status fictional student, the only option providing a chance to beat the fictional student was the riskier option.

Table 5-1 Decision Tasks Characteristics for Study Three

				Buy-in Amounts		Winnings (Probabilities)	
Decision Task	Budget	Need Level	Competitor Status (Earnings)	Safer	Riskier	Safer	Riskier
1	Negative	$300	Lower ($200)	$25	$100	$300 (.95)	$600 (.60)
			Equal ($275)				
			Higher ($350)				
2	Positive	$200	Lower ($200)				
			Equal ($275)				
			Higher ($350)				

Note. This table displays the characteristics for the two main manipulated independent variables of interest (Competitor Status and Budget). For the design of Study Three these variables were additionally crossed with controls for order effects as well as participant gender.

The General Numeracy Scale

Just as in Studies One and Two, the General Numeracy Scale (Lipkus et al., 2001) (Appendix A) was also used in Study Three. However, in Study Three it was primarily measured for the sake of consistency, and comparison with Studies One and Two. Data from the GNS were used in an exploratory post-hoc fashion since there were no theoretically motivated hypotheses regarding the proposed models and individual differences in numerical processing. Also, because these analyses are not theoretically motivated, they are not included in this dissertation. The inclusion of the GNS is mentioned here to provide full disclosure to the methodology used in Study Three, including the measures used to assess individual differences (e.g., the GNS).

Domain Specific Risk Scale

The Domain Specific Risk Scale (Kruger et al., 2007) (see Appendix B) was also used in Study Three as a potential covariate to control for individual differences in domain specific risk taking.

Status Manipulation

The same universities as were used in Study Two were also used in Study Three. These universities were pilot tested, and their use in Study Two yielded theoretically interesting and meaningful patterns of results. Therefore, there was no apparent reason to perform an additional pilot test to determine new universities for the low, equal, and high status levels of Competitor Status. In sum, the universities and their corresponding ACT scores used in Study Two were used in their entirety for Study Three as well.

Status Priming Vignette

In order to prime participants to think about status-based motivations, Study Three used a status priming procedure utilized in some social evolutionary psychology research (Griskevicius et al., 2009; Griskevicius, Tyber, & Van den Bergh, 2010). This vignette was the same as the one used for Study Two (Appendix F), and consisted of 376 words, including the directions. The vignette described a story about recently being hired at a high-status job and then being told that you (the participant) will have to compete for the job. The vignette then closes by asking participants to indicate the ways in which they would vie for the higher-status, corner office job. This vignette was used with good results in Study Two, and also has a long list of research by Griskevicius and colleagues showing that it is capable of successfully priming participants to think about status-based motivations.

Study Three Procedure

All participants in Study Three were tested in a computer lab in groups ranging from 1 to 8. The researchers wore white lab coats and carried clip boards to present an appearance of professionalism and authority. Essentially, the purpose of the researchers' attire was to influence participants to take the study seriously. Just as in Study Two, the participants in Study Three were told that they would be competing in an inter-university gambling competition against students from Emporia State University, Oregon State University, and Harvard University.

The researcher explained to students participating in the study that they would be competing against three separate, randomly selected same-sex students in one-on-one gambling games. Participants were told that researchers at Kansas State University were collaborating with scientists from the other three universities to examine gambling behavior in students at different universities. Participants were told that they would compete in one-on-one games with other same-sex students, and that, if they earned more money than the student against whom they were competing, they would win the competition. It was made clear that no monetary awards would be actually distributed based on their performance in the gambling tasks. Participants were asked if they understood the gist of the competition. If there were questions the researcher did his or her best to answer those questions. Once all questions were answered the participants were instructed to click "OK" on the MediaLab screen and proceed to the informed consent page.

After clicking "OK" participants were presented with a welcome screen with the logos of the four universities affiliated with the "competition": Kansas State University, Emporia State University, Oregon State University, and Harvard University. Accompanying these logos was the text "Welcome to the Decisions about Money Competition" in bold type. Immediately following the welcome screen was an electronic version of the informed consent sheet. Participants were then directed to individual tan folders in front of each computer monitor. These folders had cover art similar to that of the welcome screen presented on MediaLab. Participants were told to open their folders and find the paper copies of the informed consent sheets. Each folder contained two forms, one for them to sign and one for them to keep for their own records. The researcher then explained that, although the participants were competing in a gambling competition, they were still technically participating in research. Due to this fact, the researcher explained that they the researchers were required to provide students with adequate information about the study such that they could make an informed decision about whether or not they wanted to participate. Participants were then asked to read the informed consent, either the electronic version or the paper version, and sign the form if they wished to participate.

Once participants had signed the informed consent sheets the researcher directed participants to begin the rules section of the competition. Just as Studies One and Two, the rules for Study Three were implemented using a PowerPoint slideshow. This allowed participants to proceed through the rules section at their own pace. This was important because understanding how the competition worked was crucial to the manipulations such as Budget (whether participants understood that they needed to earn a certain amount to move to a potential next round).

In the rules section of the study, participants learned that they would be competing against three randomly chosen same-sex students from each of the universities collaborating in the gambling competition. Participants learned that, similar to what they were currently doing, students at those universities had come into labs on their own campuses in the weeks prior and had made selections about gambles they would like to play. They then played out those gambles and earned (or did not earn) fake money toward the gambling competition. The data from each of those students on all of the universities involved was then uploaded onto the computers at which they (the participants) were currently sitting, and the role of the computer was to randomly select a same-sex student from each university for them to compete against.

Participants learned that the competitions were completely independent of one another. Specifically, participants were told that money earned in one competition did not go toward money totals from other competitions. This was explained as being similar to running in three separate races.

It was explained that a single round would conclude at the end of the third one-on-one competition with a student from a different university. In order to introduce the idea of an uncertain future, participants were told that the computer would randomly select whether or not there would be a second round in which participants could earn additional money. Participants were told that this potential second round was not automatic however, even if the computer randomly determined that there would be a second round. It was then explained that, in order to reach this potential second round participants would have to earn a minimum amount of money in the first round (i.e., reach a need level).

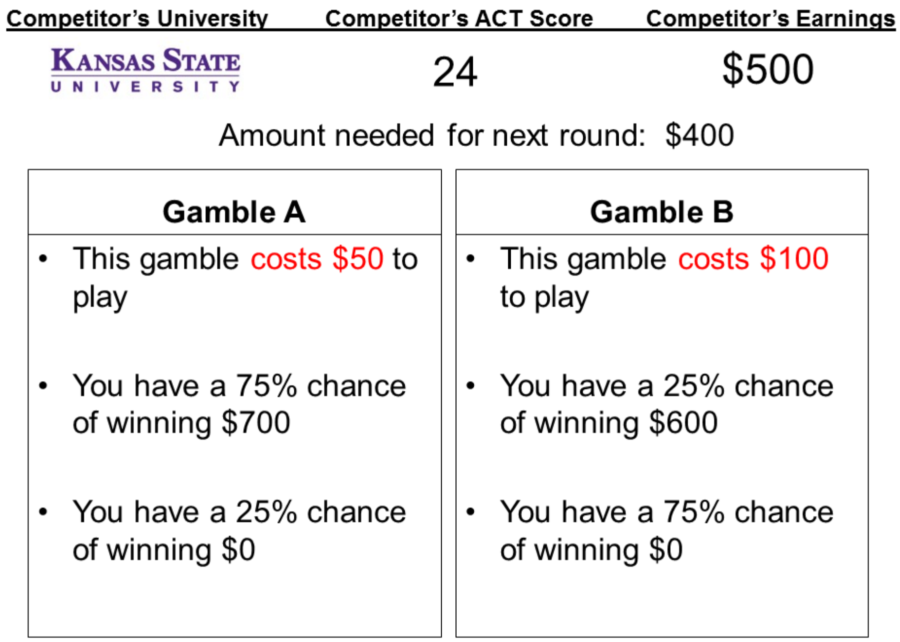
Participants were then shown a line graph demonstrating the "empirical" relationship between competitors' ACT scores and typical performance on the gambling competition. This fictional relationship was given to participants in order to establish a relationship between status associated with each university and performance in the competition in which they were going to be performing. When participants finished the rules section they were then asked a series of follow-up questions about the rules section. This was done in order to test participants' knowledge and comprehension of the rules of the competition, and to test whether participants were paying attention or simply clicking through the slides without reading the content. If participants answered a question incorrectly they were notified that their answer was incorrect, and the correct answer was displayed.

After answering the follow-up questions participants were asked to answer basic demographic questions about their age, gender, ethnicity, as well as their ACT composite score. After completing the demographics portion of the study participants proceeded to the status priming vignette. Participants were asked to read the vignette consisting of approximately 350 words (Appendix F). The vignette was displayed on two separate screens. The first screen contained the main text of the vignette. Participants were asked to carefully read the vignette and click "Continue" when they had finished reading. On the next screen participants were asked to select different strategies they would take to increase their chances of receiving the promotion at the high-status job described in the vignette. This additional screen and its required responses were used with the goal of increasing thinking about the status priming vignette.

At this point in the study participants were aware of, or were exposed to, several key pieces of information: (1) they were aware that they would be competing in one-on-one competitions with same-sex students from universities which they perceived as varying in status, based on pilot testing, (2) they were aware that ACT scores were positively correlated with performance on the gambling competition, and (3) they were primed to think about status-based motivations.

After the status priming vignette participants were asked to complete a sample decision task. It was made clear that the decision task in no way was related to the actual competition, but was rather a chance to familiarize competitors with the format of the competition's structure (Figure 5-2). Participants were asked to study the information on the decision task and make a choice about which gamble they preferred. After making a choice, participants were directed to the payoff screen. On this screen participants were reminded of the gamble they had selected to play. They were then shown a button which, when pressed, told them if they had won or lost the gamble. The results of the button-press were manipulated so that each participant won money. This was done in order to remove any unintended effects of winning or losing the sample task on actual risk preferences in the more theoretically important part of the study.

Figure 5-5 Example Decision Task for Study Three



When participants finished the sample decision task they were presented with a "stop screen" telling them to stop and notify the researcher. When all participants tested in a group (ranging from 1 to 8) had made it to the stop screen, all participants were again asked if they had any questions about the competition, rules, or other things related to the competition. The researcher answered any questions.

Participants were then wished good luck and were told to continue to the main part of the study. First participants were shown a decision task (see, for example Figure 5-2) which was the first of the three one-on-one competitions against a fictional student competitor. The ordering of the fictional student competitors in the sequential one-on-one competitions was accounted for by the Status Order independent variable. Additionally, the format of this first decision task, either Binary Choice (BC) or Continuous Preference (CP), was counterbalanced and captured by the Task Order independent variable. Also, because Study Three, just as Studies One and Two, used this two dependent measure system, the Status Order was kept constant across both decision task formats (CP and BC). For example, if a participant in the BC 1st condition competed in one-on-one competitions in the order of Higher→Lower→Equal the same order would also be used when the participant reached the Continuous Preference portion of the study near the end.

When participants completed the first grouping of decision tasks they were then presented with a series of questionnaires used to assess individual differences in risk-taking propensity (DSRS) (Kruger et al., 2007) and numerical processing ability (GNS) (Lipkus et al., 2001). First, participants completed the GNS (Appendix A) and then participants completed the DSRS (Appendix B), both of which were re-formatted from a paper/pencil questionnaires to MediaLab questionnaire files. Question order for both questionnaires was randomized and thus, each participant saw a different question order. This means that the question orders appearing in Appendices A and B are not indicative of what each individual participant viewed.

After participants completed both the GNS (Lipkus et al., 2001) and the DSRS (Kruger et al., 2007) they were reminded of the decision tasks they had completed previously. Participants were then told that, in order to make certain of which gambles they preferred, they would be presented with those decision tasks again but would be asked to respond in a slightly different format depending on how they responded in the initial task. Participants were then explained the difference between the Binary Choice and Continuous Preference decision formats.

After completing the second grouping of the same decision tasks participants were asked to answer four follow-up questions (Appendix H). Once participants had answered these follow-up questions the MediaLab software displayed a message telling participants to notify the researcher that they had completed the experiment. When all of the participants had finished the study, the researcher debriefed the entire group. Specifically, participants were told that there was not a real competition between students from different universities. Instead, participants were told the nature of the experiment and its hypotheses. Participants were given a debriefing form (Appendix D) and were asked if any of them felt distressed as a result of being deceived by the researchers. No students responded as being stressed. Participants were nonetheless directed toward the contact information on the debriefing form, and were told to contact one of the researchers if they became distressed in the days and weeks following the study. Questions asked by participants were answered, and when finished, all participants were thanked. This concluded the procedure for Study Three.

Study Three Results

Study Three was designed to test four separate models of risk taking in a single experiment (Figures 5-1 through 5-4). Several statistical analyses were used to test the risk preferences (CP) and the discrete choices (BC). Additionally, because MediaLab collected decision time data, this was analyzed in an exploratory fashion; none of the hypothesized models tested in Study Three make clear predictions about relative differences in decision time based on different levels of the important independent variables. The analyses are described in detail in the sections that follow.

Preliminary Data Issues

Data for Study Three were first examined for any potential issues. This was done by examining the decision time data (tBC and tCP) for potential outliers; continuous preferences (CP) on a scale from 1 to 6 were limited in responses, thus extreme outliers were not possible. Additionally, DSRS scores and self-reported ACT composite scores were examined for their potential influence as covariates on the dependent variables of interest. Last, potential order effects – Status Order and Task Order – were statistically examined in order to determine if they should be included in the main analyses. The general data analytic techniques used to answer different research questions are also described in the sections that follow.

Preliminary Data Cleaning

Data from the decision time measures were screened for outliers using the z-score method (Tabachnick & Fidell, 2007). This method was used in Studies One and Two as well. First, the decision time data (tBC and tCP) were standardized to z-scores using SPSS. Values for the z-scores were then examined. The criterion of ±3.29 was used to determine if a value was a statistical outlier. Since the Competitor Status variable was within-participants, and thus decision time was also within-participants, any deletion of a decision time on a specific level of Competitor Status meant that there would be incomplete data across a participant's decision time values. Thus, if an outlier was found for one level of Competitor Status, the other values were also removed from the data set. This method was consistent with the method used in Studies One and Two.

The z-score method located a total of three outliers from the tBC (*z*s: 10.57, 9.41, and 3.74). The z-score method located eight outliers for the tCP though (*z*s: 9.68, 7.56, 4.77, 3.96, 3.51, 3.45, 3.31, and 3.30). None of the data points determined to be outliers belonged to the same individual. The total sample sizes for the analyses using decision time data were $n = 117$ for tBC and $n = 112$ for tCP.

Risk Propensity and ACT Composite Score as Covariates

Studies One and Two did not utilize any of the subscale scores of the DSRS as covariates due either to (1) the lack of relationships between the subscale scores and the continuous dependent variables (CP, tCP, and tBC), or (2) a violation of the homogeneity of regression assumption. However, the same individual difference measures (DSRS scores) and self-reported intelligence measures (ACT scores) were assessed as potential covariates in Study Three. Just as in Study Two, ACT composite scores were thought to have unintended consequences on the primary theoretically-motivated analyses because ACT score was used as part of the status manipulation; students who have a high ACT score may not be as intimidated by Harvard students. Four participants did not take the ACT. All of these students were international students and self-reported their ethnicity as "Asian." However, to compensate for this missing data point, the mean substitution technique was utilized instead of regression (Tabachnick & Fidell, 2007).

To help control for the possibility of unwanted, and theoretically unimportant, covariate effects, ACT composite scores and the five subscale scores of the DSRS were correlated with the three continuously measured dependent variables (CP, tCP, and tBC) to assess the strength of the relationships. The dependent variables were summed across Competitor Status, thus the correlation matrix seen in Figure 5-6 is based on summed scores for the dependent variable.

Analyses showed that there were no relationships between any of the potential covariates and the dependent variables of interest. Because of this lack of statistically significant relationships across the entire range of variables, no tests for the homogeneity of regression were performed.

Table 5-2 Correlations between potential covariates and dependent variables in Study Three

	Potential Covariates					
Depenent Variables	*Fertility*	*Between-Groups*	*Within-Group*	*Mating*	*Environmental*	*ACT Score*
Sum (CP)	.11	.04	-.02	.14	-.04	.04
Sum (tCP)	-.01	-.10	-.08	.02	.03	.01
Sum(tBC)	-.11	-.17	.16	-.10	-.11	.05

Note. CP = Continuous Preference Ratings, tCP = decision time for Continuous Preference Ratings, tBC = decision time for Binary Choice tasks. Statistically significant correlations are denoted by *.

Potential Order Effects

There were two potential order effects for the data in Study Three. These order effects were described in the data by Status Order and Task Order. Status Order described the ordering of the fictional student competitors in the sequential one-on-one competitions for each individual participant. The levels were LEH, EHL, and HLE, with L, E, and H standing for Lower, Equal, and Higher, respectively. The ordering of those status levels is determined by moving from left to right (i.e., LEH means the order was Lower→Equal→Higher). Task Order was used as a way to describe order effects based on the two different dependent variables. Task Order described whether participants completed the CP task first or the BC task first. These order effects were analyzed prior to the main analyses. If no significant relationships were found, per each continuous dependent variable (CP, tCP, and tBC), then the order variables were not utilized in the main analyses described in later sections.

For Status Order, a series of three one-way analyses of variance were performed on the three summed dependent variables of interest. The dependent variables were summed across the Competitor Status independent variable. Results from the analyses showed that there was not a statistically significant effect of Status Order on Continuous Preference ratings (CP), $F(2, 117) = 0.31$, $p = .731$, $\eta^2 = .01$, or on decision time for Continuous Preference ratings (tCP), $F(2, 109) = 0.04$, $p = .966$, $\eta^2 < .01$, or on decision time for Binary Choices (tBC), $F(2, 114) = 0.11$, $p = .892$, $\eta^2 < .01$.

For Task Order another series of three separate one-way analyses of variance were performed on the summed dependent variables of interest. Again, these dependent variables had previously been computed by summing across Competitor Status; they were the same dependent variables used in the previous analysis on Status Order. Results from these analyses suggested that Task Order did indeed have a significant relationship with Continuous Preference ratings (CP), $F(1, 118) = 3.92$, $p = .050$, $\eta^2 = .03$, decision time for Continuous Preference ratings (tCP), $F(1, 110) = 58.23$, $p < .001$, $\eta^2 = .35$, and also with decision time for Binary Choices (tBC), $F(1, 115) = 62.78$, $p < .001$, $\eta^2 = .35$.

The order effects for Task Order on decision time are consistent with what was observed in prior results, and most likely is explained in this way: It should take longer to make a decision on the Continuous Preference task (tCP) if the Continuous Preference task is the first decision task the participant completes (CP 1^{st}: $M = 20{,}064.61$, $SD = 7{,}053.95$). However, if the

Continuous Preference task is the second decision task, the participant has already answered the task and has a preference. Thus, it should take less time to determine which gamble he or she wishes to prefer (BC 1st: $M = 11{,}476.16$, $SD = 4{,}773.10$). The opposite pattern should be true for decision time on Binary Choice tasks (tCP). Indeed this is the pattern we see in the data (CP 1st: $M = 9{,}622.96$, $SD = 4{,}356.99$; BC 1st: $M = 16{,}598.87$, $SD = 5{,}150.90$).

The Task Order effect for Continuous Preference ratings (CP) however is not as easily explained. Based on the data it appears that average preference ratings are higher when the Binary Choice task (BC) is completed first ($M = 3.00$, $SD = 1.43$) rather than second ($M = 2.51$, $SD = 1.27$). This may suggest that those participants who receive a binary all-or-nothing choice at first are more likely to state their preferences on the extremes of the scale when given the continuous preference task later. However, this could also result in no difference, or lower ratings for those who complete the BC task first. It is unclear what the Task Order effect means in terms of the behavior of the participants. Nonetheless, Task Order was included in all of the main analyses in Study Three.

General Data Analytic Procedures

Study Three was designed with the intentions of being able to illuminate which of the four hypothesized models (Figures 4-1 through 4-4) most accurately described choice patterns. The models were evaluated on choice patterns, both in terms of Binary Choices (BC) and in terms of Continuous Preferences (CP). However, different data analytic techniques were performed for both of these metrics.

Continuous Preference ratings (CP) were analyzed using a 2 (Gender) by 2 (Budget) by 2 (Task Order) by 3 (Competitor Status) mixed-factorial analysis of variance. Gender, Budget, and Task Order were between-participant independent variables, and Competitor Status was the within-participants independent variable.

Binary choice data (BC) were analyzed using both the Mann-Whitney *U* test on nonparametric data for the between-participants variable of Budget, and the McNemar's test on nonparametric data for the within-participants variable of Competitor Status. Similar to Study Two, the data on binary choices were coded as 0 = safer choice and 1 = riskier choice. The choices were then summed across Competitor Status and used as the dependent variable, with a range from 0 to 3 riskier choices. This dependent variable was utilized for the Mann-Whitney *U* test, which is essentially the nonparametric equivalent of the independent-samples *t*-test. To analyze the effect of Competitor Status on binary choices (BC), a McNemar's test was performed on the proportions of risky and safe choices between the three levels of Competitor Status.

Although decision time was not a primary analysis in Study Three due to the lack of explicit predictions about decision time made by the four proposed models, decision time was still analyzed in an exploratory fashion. To analyze both the tBC and tBC variables a 2 (Gender) by 2 (Budget) by 2 (Task Order) by 3 (Competitor Status) mixed-factorial analysis of variance was performed on both of the decision time variables independently. Competitor Status was the within-participant independent variable, whereas the other three independent variables were between-participants.

Preference Ratings and Binary Choices for Risky Gambles

Data from Continuous Preference ratings and Binary Choices were analyzed to determine choice and preference behavioral outcomes based on the different manipulations in Study Three. Unlike Studies One and Two in which patterns of data, other than those predicted by the models tested, were possible, Study Three contained a more exhaustive list of proposed models. This more exhaustive list of models concurrently allows for a more complete method of strong inference (Platt, 1964). The methodological concern of strong inference is designed to allow for incremental advances in knowledge, despite results inconsistent with the researcher's expectations. Thus, as a way of designing experiments, it is highly desirable.

Continuous Preference Ratings

The main analysis of Continuous Preference ratings (CP) should result in specific patterns of main effects, interactions, and paired-comparisons for each of the specific proposed models of risk taking. For *risk-sensitive foraging* (RSF), there should only be a main effect for Budget and nothing else. For *dominance theory* (DT), there should be a main effect for Competitor Status, with paired comparisons showing a significant difference between lower- and equal-status levels, and equal- and higher-status levels, but no difference between lower- and higher-status levels. Further, there should be a significant interaction between Competitor Status and Gender such that the specific paired comparison pattern previously described is only consistent with male participants, but not for female participants. For *general risk-sensitivity (status only)* (GRS-Status), there should be a main effect for Competitor Status with paired comparisons showing only differences between the lower- and equal-status, and lower- and higher-status levels but not between the equal- and higher-status levels. Further, there should not be an interaction between Competitor Status and Gender with regard to the pattern of risk taking relative to Competitor Status. This is because it is a model of *general* risk-sensitivity. Last, for the model of *general risk-sensitivity (status and money)* (GRS-Status & Money), there should be a pattern of results precisely similar to the GRS-Status model, with the addition of a main effect for Budget. The exact results of the analyses are described below.

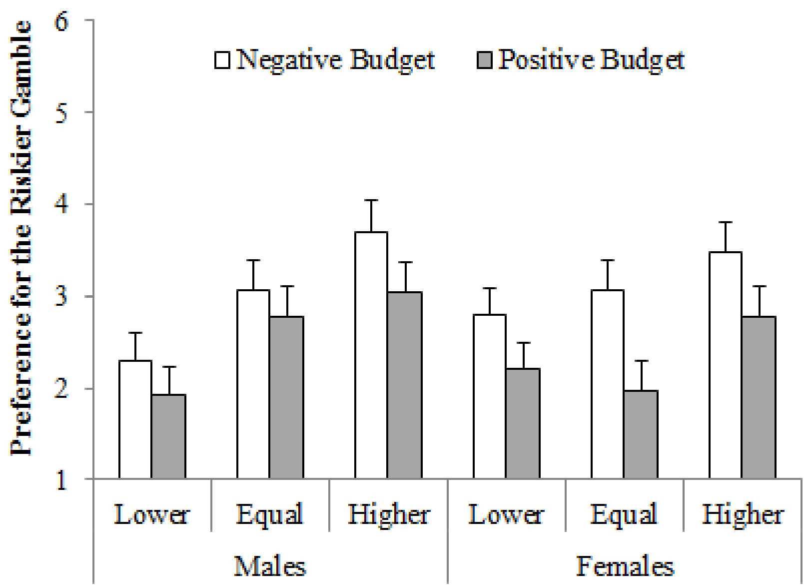
The results from the four-way mixed-factorial analysis of variance revealed a statistically significant main effect for Competitor Status, $F(2, 224) = 14.06$, $p < .001$, partial $\eta^2 = .11$, suggesting that status matters to participants when making preference ratings about gambles varying in risk (i.e., variance). Paired-comparisons of the three Competitor Status levels were performed using paired-samples *t*-tests. These analyses showed that there were statistically significant differences between the lower ($M = 2.31$, $SD = 1.61$) and equal status levels ($M = 2.72$, $SD = 1.83$), $t(119) = -2.23$, $p = .027$, $d = .20$, the lower and higher status levels ($M = 3.24$, $SD = 1.86$), $t(119) = -4.95$, $p < .001$, $d = .45$, and between the equal and higher status levels, $t(119) = -3.36$, $p = .001$, $d = .31$ (see Figure 5-6).

Results additionally showed a main effect for Budget, $F(1, 112) = 6.67$, $p = .011$, partial $\eta^2 = .06$. Examination of the effect showed that individuals in a negative budget ($M = 3.07$, $SD = 1.56$) indicated a higher preference for the riskier gamble than did individuals in a positive budget ($M = 2.44$, $SD = 1.07$). Also, consistent with the preliminary data analysis on order effects, Task Order showed a main effect, $F(1, 112) = 4.12$, $p = .045$, partial $\eta^2 = .04$. This effect is described in more detail in previous sections.

There was not a statistically significant main effect for Gender, $F(1, 112) = 0.14$, $p = .713$, partial $\eta^2 < .01$, nor were there statistically significant interactions between Gender and Budget, $F(1, 112) = 0.55$, $p = .462$, partial $\eta^2 = .01$, Gender and Task Order, $F(1, 112) = 2.18$, $p = .143$, partial $\eta^2 = .02$, or Competitor Status and Gender, $F(2, 224) = 2.78$, $p = .065$, partial $\eta^2 = .02$. There was not a Budget by Task Order interaction, $F(1, 112) = 1.92$, $p = .169$, partial $\eta^2 = .02$, nor were there interactions between Competitor Status and Budget, $F(2, 224) = 0.23$, $p = .792$, partial $\eta^2 < .01$, or Competitor Status and Task Order, $F(2, 224) = 0.60$, $p = .550$, partial $\eta^2 = .01$.

All of the three-way interactions failed to reach statistical significance: Competitor Status by Budget by Gender, $F(2, 224) = 0.64$, $p = .531$, partial $\eta^2 = .01$; Competitor Status by Budget by Task Order, $F(2, 224) = 1.82$, $p = .164$, partial $\eta^2 = .02$; Competitor Status by Gender by Task Order, $F(2, 224) = 0.07$, $p = .930$, partial $\eta^2 < .01$; Budget by Gender by Task Order, $F(1, 112) = 0.69$, $p = .408$, partial $\eta^2 = .01$. Also, the four-way interaction failed to reach statistical significance, $F(2, 224) = 0.67$, $p = .511$, partial $\eta^2 = .01$.

Figure 5-6 The Effects of Competitor Status, Budget, and Gender on Continuous Preference Ratings



Relationship between Binary Choices and Continuous Preference Ratings

Consistent with procedures used in Studies One and Two, Continuous Preferences were used as a more sensitive measure of risky choice than the Binary Choices alone. Continuous Preferences were primarily utilized to combat widespread risk-aversion in the experimental procedure. Nonetheless, it could be argued that the most ecologically valid metric for choice behavior is all-or-nothing binary choice.

In order to see if participants were generally consistent in their Binary Choices and Continuous Preference ratings, the two metrics were correlated at each level of Competitor Status. Because one of the variables is binary (i.e., the Binary Choice variable) and one of the variables is continuous (i.e., Continuous Preference variable), the correlation coefficient is a point-biserial coefficient. Research has shown that point-biserial correlations can be suppressed due to a restricted range of variability in the binary variable (Kemery et al., 1988). Binary Choice was coded as 0 = safer choice and 1 = riskier choice. The Continuous Preference ratings were scored on a scale from 1 to 6 with higher scores indicating a stronger preference for the riskier option.

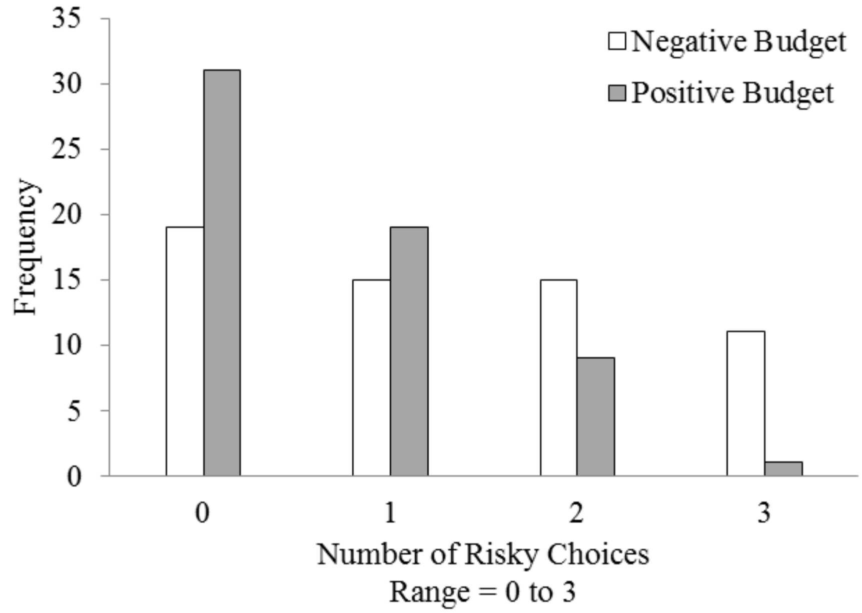
Results from these correlational analyses showed that, despite the limitations of point-biserial correlations, the effects were quite large. Specifically, the correlations between BC and CP decision tasks were large and positive when participants were competing against someone lower in status, r_{pb} (118) = .56, $p < .001$, equal in status, r_{pb} (118) = .72, $p < .001$, and higher in status, r_{pb} (118) = .66, $p < .001$.

Binary Choice

To examine the effect of Budget on binary choices between a riskier or safer gamble in the experimental task a Mann-Whitney *U* test was conducted. To calculate the effect of Budget on risky choices, the binary choice data (coded as 0 = safer, 1 = riskier) were added across the levels of Competitor Status such that there was a summed dependent variable of risky choice. This variable was ordinal and ranged from 0 to 3, indicating the number of risky choices made across the levels of Competitor Status.

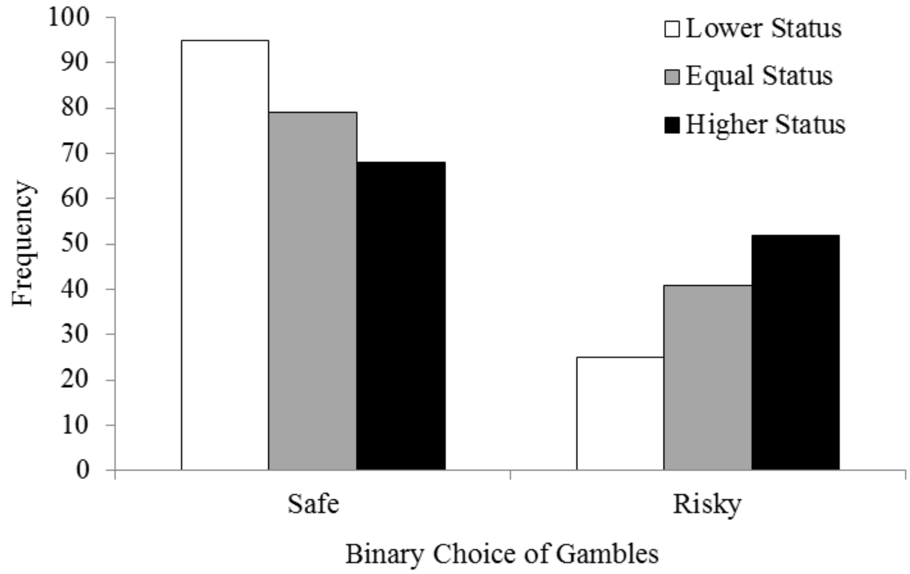
The Mann-Whitney *U* test showed that participants in a Negative Budget (Mean Rank = 70.07) chose the riskier option significantly more than participants in the Positive Budget (Mean Rank = 50.93). This difference in mean rank of the ordinal data was statistically significant, U = 1226.00, p =.001 (Figure 5-7).

Figure 5-7 The Effects of Budget on Binary Choice in Study Three



The effects of Competitor Status on risky choices in the Binary Choice task were assessed using McNemar's test on within-participant nonparametric data. Specifically, three separate paired comparisons were made between the three levels of Competitor Status. Results of these tests showed that there was a significant difference in the proportions of risky choices between Lower Status (n = 25) and Equal Status (n = 41), χ^2 (1, N = 120) = 5.63, p = .018, and between Lower Status and Higher Status (n = 52), χ^2 (1, N = 120) = 14.38, p < .001. However, there was not a significant difference between Equal Status and Higher Status levels, χ^2 (1, N = 120) = 3.45, p = .063 (Figure 5-8), showing support for both of the general risk-sensitivity models (Status, and Status and Money), but not for dominance theory or risk-sensitive foraging.

Figure 5-8 The Effects of Competitor Status on Binary Choice in Study Three



Decision Time for Preference Ratings and Binary Choices

Decision time was analyzed in Studies One and Two because those studies tested the priority heuristic (Brändstatter et al., 2006). The priority heuristic made predictions about decision time because it is an explicit process model with a hypothesized ordering of input and manipulation. However, the models tested in Study Three (RSF, DT, GRS-Status, and GRS-Status and Money) did not make explicit predictions about decision time. Despite this, decision time data were collected for both Continuous Preference and Binary Choice decision tasks. The logic for collecting decision time data was that, if there were any significant effects, it may provide some illuminating information regarding the underlying cognitive processes causing the behavioral outcomes observed in the Continuous Preference ratings and the Binary Choice data.

Continuous Preference Decision Time

Aside from Task Order, which was already shown to be statistically significant, $F(1, 104) = 58.52$, $p < .001$, partial $\eta^2 = .36$, there were no statistically significant main effects for decision time on the Continuous Preference ratings (tCP): Budget, $F(1, 104) = 0.56$, $p = .454$, partial $\eta^2 = .01$; Gender, $F(1, 104) = 0.01$, $p = .915$, partial $\eta^2 < .01$, Competitor Status, $F(2, 208) = 1.94$, $p = .147$, partial $\eta^2 = .02$.

There were no statistically significant two-way interactions: Competitor Status by Budget, $F(2, 208) = 0.47$, $p = .629$, partial $\eta^2 < .01$; Competitor Status by Gender, $F(2, 208) = 0.18$, $p = .840$, partial $\eta^2 < .01$; Competitor Status by Task Order, $F(2, 208) = 0.73$, $p = .484$, partial $\eta^2 = .01$; Budget by Gender, $F(1, 104) = 1.36$, $p = .246$, partial $\eta^2 = .01$; Budget by Task Order, $F(1, 104) = 2.03$, $p = .157$, partial $\eta^2 = .02$; Gender by Task Order, $F(1, 104) = 2.37$, $p = .127$, partial $\eta^2 = .02$.

Additionally, there were not any statistically significant three-way interactions: Budget by Gender by Task Order, $F(1, 104) = 0.62$, $p = .434$, partial $\eta^2 = .01$; Competitor Status by Budget by Gender, $F(2, 208) = 0.01$, $p = .994$, partial $\eta^2 < .01$; Competitor Status by Budget by Task Order, $F(2, 208) = 0.65$, $p = .526$, partial $\eta^2 = .01$; Competitor Status by Gender by Task Order, $F(2, 208) = 0.72$, $p = .489$, partial $\eta^2 = .01$. Also, the four-way interaction failed to reach statistical significance, $F(2, 208) = 0.67$, $p = .515$, partial $\eta^2 = .01$ (Figure 5-9).

Binary Choice Decision Time

Decision time data for the Binary Choice decisions (tBC) was analyzed in the same way as decision time data for Continuous Preferences (tCP). Results from the analysis showed that, other than Task Order, $F(1, 109) = 62.76$, $p < .001$, partial $\eta^2 = .37$, there were no statistically significant main effects: Budget, $F(1, 109) = 3.89$, $p = .051$, partial $\eta^2 = .03$; Gender, $F(1, 109) = 0.18$, $p = .671$, partial $\eta^2 < .01$; Competitor Status, $F(2, 218) = 1.61$, $p = .203$, partial $\eta^2 = .02$.

The two-way interactions in the analyses all failed to reach statistical significance: Competitor Status by Budget, $F(2, 218) = 1.05$, $p = .351$, partial $\eta^2 = .01$; Competitor Status by Gender, $F(2, 218) = 0.08$, $p = .924$, partial $\eta^2 < .01$; Competitor Status by Task Order, $F(2, 218) = 1.50$, $p = .225$, partial $\eta^2 = .01$; Budget by Gender, $F(1, 109) = 0.20$, $p = .653$, partial $\eta^2 < .01$; Budget by Task Order, $F(1, 109) = 0.05$, $p = .833$, partial $\eta^2 < .01$; Gender by Task Order, $F(1, 109) < 0.01$, $p = .980$, partial $\eta^2 < .01$.

The three-way interactions also failed to reach statistical significance: Budget by Gender by Task Order, $F(1, 109) = 1.98$, $p = .162$, partial $\eta^2 = .02$; Competitor Status by Budget by Gender, $F(2, 218) = 1.78$, $p = .171$, partial $\eta^2 = .02$; Competitor Status by Budget by Task Order, $F(2, 218) = 2.84$, $p = .061$, partial $\eta^2 = .03$; Competitor Status by Gender by Task Order, $F(2, 218) = 0.44$, $p = .643$, partial $\eta^2 < .01$. Also, the four-way interaction failed to reach statistical significance, $F(2, 218) = 1.85$, $p = .160$, partial $\eta^2 = .02$ (Figure 5-10).

Figure 5-9 The Effects of Gender, Budget, Competitor Status on Continuous Preference Decision Time (tCP)

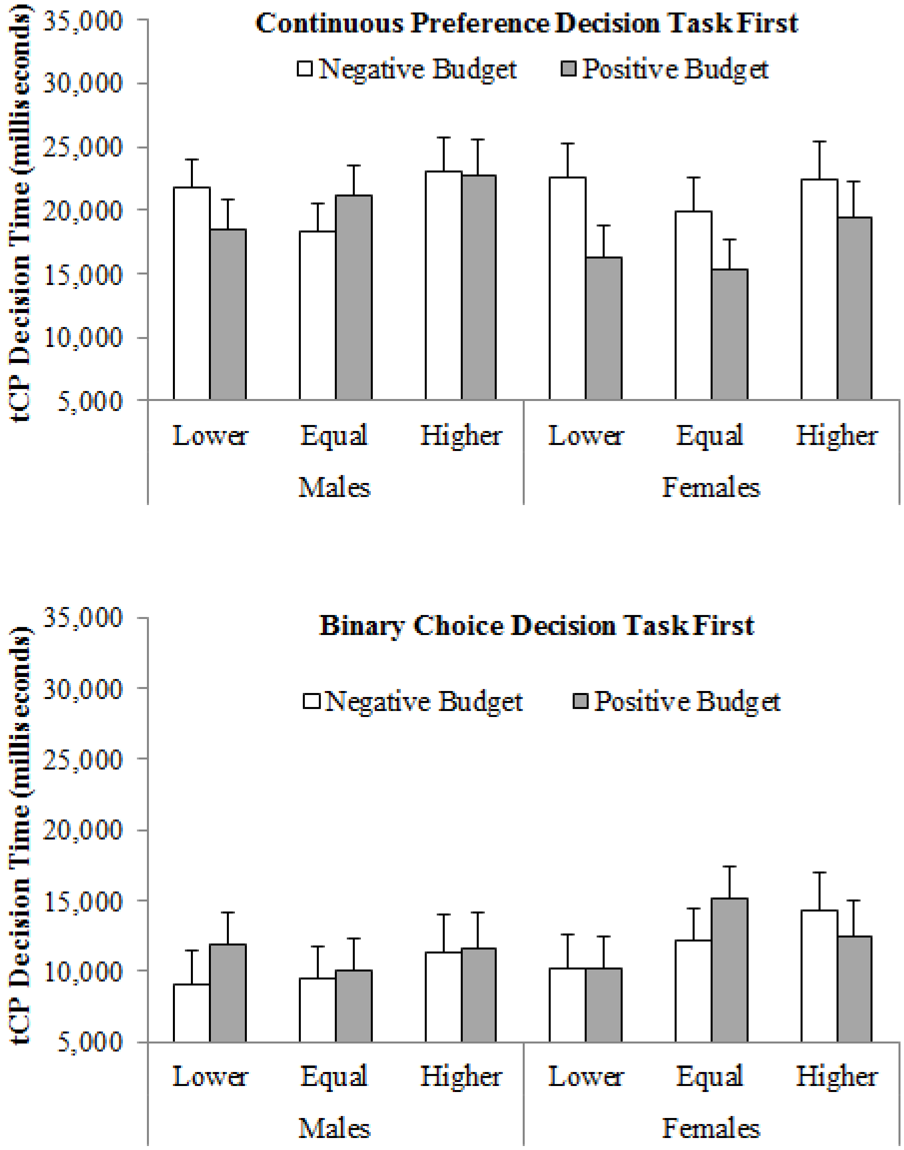
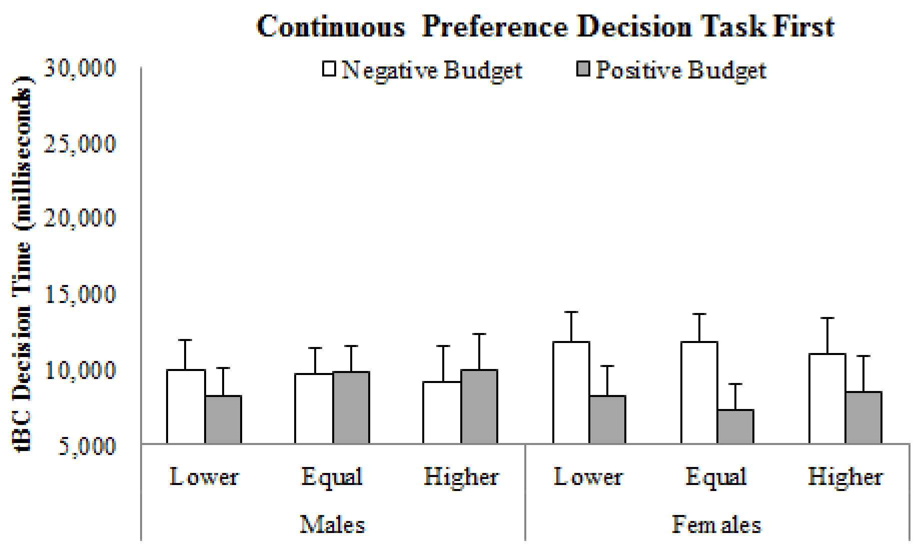
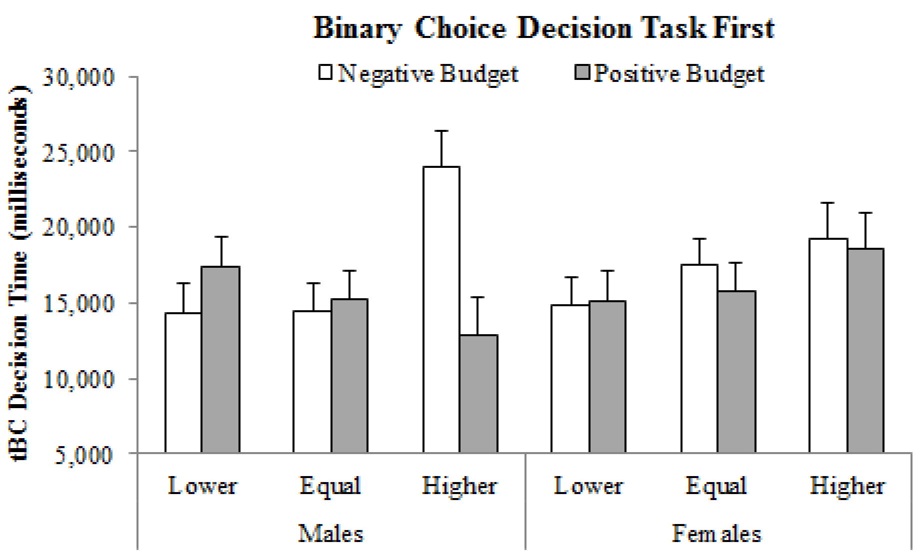


Figure 5-10 The Effects of Gender, Budget, Competitor Status on Binary Choice Decision Time (tBC)





Study Three Discussion

Study Three was designed to test four different hypothesized models of risk-taking. Two of the models were based in the literature and had previously been tested by Ermer et al. (2008): risk-sensitive foraging, and dominance theory. However, in response to the data collected in Studies One and Two, and based in literature on happiness (e.g., Blanchflower & Oswald, 2004; Luttmer, 2005; McBride, 2001; Veenhoven, 1991) as well as alternative hypotheses by Ermer et al., two additional models were tested: General risk-sensitivity (Status), and General risk-sensitivity (Status and Money). Each of the four models made different but fairly explicit predictions about choice patterns, but not necessarily about decision time, or decision processes as was the case with the priority heuristic. Implications of Study Three's results are discussed in the sections to follow.

Which model best accounts for the data?

To be explicit, each model and its predictions will be discussed, as well as whether the predictions were supported by the data from Study Three. Risk-sensitive foraging (Stephens & Krebs, 1986) predicted a main effect for Budget, but no main effects for Competitor Status, or Gender, and no interactions. Dominance theory (Ermer et al., 2008) predicted a main effect for Competitor Status with a specific pattern of Lower status equal to Higher status, and Equal status higher than both Lower and Higher status levels (Figure 5-2). Further, dominance theory predicted no main effect for Budget, but did predict an interaction between Competitor Status and Gender, such that the effect of Competitor Status was limited to male participants. The General risk-sensitivity (status) model predicted main effect for Competitor Status similar to dominance theory, however the pattern of paired comparisons differed: lower status is less than equal status and higher status, equal status and higher status are not different. Further, the general risk-sensitivity (status) model predicted no main effect for Budget, and no interactions (the same pattern of results were predicted for males and females). Last, the general risk-sensitivity (status & money) model predicted a main effect for Competitor Status with the same pattern as that of the status-only version of general risk-sensitivity, but it also predicted a main effect for Budget, similar to risk-sensitive foraging. Also, no interactions were predicted for this model.

Results showed that there was a main effect for Budget, consistent with risk-sensitive foraging and also consistent with the general risk-sensitivity (status & money) model. However, there was also a main effect for Competitor Status, which risk-sensitive foraging did not predict, but which the general risk-sensitivity (status & money) model *did* predict. Thus, it appears from the pattern of data that the general risk-sensitivity (status & money) model's predictions fit better than the other proposed models. The only troubling aspect is that, in Continuous Preference ratings (CP) paired comparisons showed that there was a significant difference between risk ratings in the higher- and equal-status levels of Competitor Status. The model predicted no difference, and this deviation from prediction should not be ignored.

One explanation could be that the preference to take risk appears as more elevated against participants who are perceived as higher in status than the participant because they *are* higher in status. This would mean that there would have to be a greater motivation to take risk against someone higher in status than yourself as opposed to someone equal in status than yourself. However, this would only appear in continuously measured metrics such as the Continuous Preference (CP) ratings. Real choices are typically discrete, all-or-nothing decisions such as those in the Binary Choice (BC) tasks.

In fact, examination of the nonparametric results for the paired comparisons using nonparametric statistical analyses showed that, despite an absolute difference in the number of risky choices between the equal- and higher-status levels, the difference failed to reach statistical significance. At least in terms of inferential statistical analysis, the proposed explanation fits the data. However, as is the case with any HARKing (hypothesizing after the results are known) (Kerr, 1998), these explanations should be tested empirically. They are merely offered here as a potential explanation for the data patterns deviating from predictions made by the best fitting model (general risk-sensitivity (status & money)).

The role of decision time, and implications for process models

Decision time data were collected in Study Three primarily for exploratory purposes since none of the models made explicit predictions about differences in decision time based on different levels of the utilized independent variables. It was thought that any significant effects of different variables on decision time may provide some stepping stone to future work examining the underlying cognitive process driving the behavioral outcomes seen in Continuous

Preference (CP) and Binary Choice (BC) data. Unfortunately, for both of the decision metrics (CP and BC), their decision time data did not show a single theoretically meaningful statistically significant effect. The issues of (1) decision time in relation to the three studies discussed here, and (2) the implications for these data on future research into process models using decision time, are discussed in more detail in the General Conclusions section of this manuscript.

Chapter 6 - General Conclusions

Risk-taking happens. This has been well-documented. The psychological literature on risk-taking has historically attempted to understand *why* humans (and non-human animals) take risk, with the guiding normative philosophy being that risk-taking is irrational or not consistent with utility maximization. However, recent research using fast-and-frugal heuristics, as well as research incorporating models of risk-taking from the literature on foraging and intrasexual competition has suggested that indeed it may be "rational" to choose risk over certainty, if rationality is redefined in terms of evolutionarily adaptive behavior (Brandstätter et al., 2006; Ermer et al., 2008; Mishra & Fiddick, 2012; Mishra, Gregson, & Lalumière, 2012; Mishra & Lalumière, 2010; Rode et al., 1999; Wang & Johnson, 2012).

This definition of rationality is based in the notion that a behavior—including a decision to take risk—is ultimately judged by whether the resultant outcome of the behavior leads, over deep evolutionary time, to a fitness advantage, either by spreading one's own genes or by helping to spread the genes of one's kin.

The results of three studies examining the priority heuristic, dominance theory, risk-sensitive foraging theory, and two proposed models of general risk-sensitivity, suggested that the participants in these studies behaved as if context truly mattered. However, the contextual importance of the decisions was keyed to aspiration or need levels, irrespective of whether the resource one was aspiring to reach was status (Studies Two and Three) or money (Studies One and Three), thus supporting a general model of risk-sensitivity applying to both status and money resources.

The fast-and-frugal priority heuristic underperformed in predicting choice patterns (Study One) and in the decision process (Studies One and Two), suggesting that the heuristic's proper ecology may not extend to domains in which need levels are an important factor (e.g., those tested in Studies One and Three). Also, despite some support for decision *preferences* in Study Two, the decision *process* was not supported, as evidenced by a lack of the predicted decision time patterns. These data suggest a narrowing of the heuristic's ecology, or at least a reconceptualization of the heuristic's actual process.

The lack of consistency with respect to the priority heuristic's predictions about decision time is troubling for the heuristic's claim as a process model of decision making under risk. This lack of consistency raises questions about why the results were not found in the present collection of studies. It is possible that reading time required for the decision tasks perhaps affected the overall decision time to respond, masking any effects of increased number of priority heuristic reasons on actual decision time. However, due to the relatively limited amount of reading required of participants and the average time observed in making a decision (15-20 seconds), it is unlikely that reading time had any effect. One additional possibility is that reasons flip (see Directions for Future Research) based on cues of resource scarcity or competitor status. This would alter the predictions made about the specific decision tasks in Studies One and Two. However, to fully articulate accurate hypotheses about decision times in response to the flipping of priority heuristic reasons, one would have to first know under which conditions those reasons would reliably flip, and also the exact ordering of reasons once they have been flipped. This work is currently underway.

Dominance theory did not explain the patterns of choice preferences for Studies Two or Three. Specifically, participants generally were risk-prone for both equal *and* higher status individuals, a finding inconsistent with some sequential methods of increasing aggression proposed by various theorists (Hammerstein & Parker, 1982; Maynard Smith 1974; Maynard Smith & Price, 1973). In these models, one useful strategy is to systematically assess the relative status of the other competitor, and only increase escalation (risky behavior) if the competitor is of a similar status to yourself. Results from Studies Two and Three suggested that individuals did not curtail their motivation to take risk when they noticed that the other competitor was higher in status.

Also, the predicted gender difference in response to competitors of different status was not supported in Studies Two or Three. Males *and* females responded to competitor status in statistically equal ways. This finding is inconsistent with dominance theory and a wide array of research showing that individual status should not theoretically be as important to females as males (e.g., Buss, 1989). Eagly (1987) suggests that traditional gender differences in behavioral patterns (e.g., risk-taking in the face of status competitors) are largely the result of learned social roles. It could be argued that, because all of our participants were college students that the social roles of the male and female students were roughly equivalent. Most of them could be status-seeking individuals which is why they have chosen college; the assumption here being that our students chose college in order to acquire a higher-status career than would be possible given no college education. Essentially, it is possible that our sample is more homogenous with respect to the status motivations of the respective males and females in the studies. However, it should be noted that Ermer et al. (2008) also used college-age males and females in their study. In their studies they showed data consistent with the gender difference predicted by dominance theory.

The model of general risk-sensitivity as applied to status and money appeared to best fit the data collected from Study Three, while also being consistent with the data from Study Two; however, the model was developed in response to Study Two's results, so that data cannot be used as evidence for the model's predictive ability. Specifically, it appears that the human participants in Study Three were choosing options of varying risk based on motivations to reach multiple need levels. These results were consistent with the hypothesis that two need levels existed: one for money necessary to reach a potential second round, and one for desiring to have the highest status level, determined by having more money than the fictional student competitor.

Implications for the Concepts of Modularity and Domain-Specificity

The findings consistent with a general risk-sensitivity mechanism may appear to call into question the hypothesis that the mind is composed of many content-dependent modules, each used to solve specific adaptive problems which our ancestors faced throughout deep evolutionary time. However, the results from Studies One through Three *do not* suggest that the mind is content independent. They do support the notion that the mind *may* contain at least one relatively generalized risk-sensitivity mechanism which can operate on both monetary amounts and psychological constructs such as perceived status. The extent to which the use of a general risk-sensitivity mechanism on multiple domains is currently adaptive is an open question, but does not preclude the hypothesis that it is an adaptation. Within that line of thought, it is also quite possible that what is being observed in Study Three is the existence of a risk-sensitive foraging mechanism operating (incorrectly) on status levels as well as monetary amounts; this is theoretically plausible given Sperber's (1996) distinctions between *actual* and *proper* domains of a cognitive module designed by evolutionary selection pressures. The answers to some of these open questions will require many more theoretically motivated experiments.

Alternative Accounts and Potential Limitations

With regard to dominance theory, it is possible that participants did not perceive the fictional students as higher or lower in status. In short, perhaps our manipulation did not work.

This is doubtful since pilot testing of the same general population of students indicated these preferences, and this pilot testing is the reason why specific schools were used in Studies Two and Three.

It is also possible that the GRS model is not always used when competing against others of varying status. Specifically, if participants felt as though they could lose something by competing against others of higher status, the results may have differed for Studies Two and Three. Recall that the original conception of the dominance theory's mechanisms is based in intrasexual competition, whereby competition implies the possibility of losing something when you compete against the other individual of varying status. If our participants did not recognize the situation in that way, then dominance theory's proposed cognitive mechanism may not have been activated, leading to the results which were contrary to its own predictions. It should be noted, however, that a similar methodology as was used in Studies Two and Three, was used by Ermer et al. (2008), and those authors found support for dominance theory. Clearly, more research is needed to build on the specific cognitive mechanisms which are at play when choosing between options of varying risk (i.e., variance), and scientists need to work toward elucidating the contextual factors which call each of the cognitive mechanisms into action.

Ermer et al. (2008) cite research by Daly and Wilson (2001) suggesting that participants' beliefs that others of different status are actually watching and evaluating the participants' behaviors, may play a very important role in the regulation of motivational systems designed to up-regulate risk taking in response to cues of varying status. Thus, in Studies Two and Three, participants' status-based mechanisms may not have been activated since their competitors were not explicitly said to have been watching each participant's decision making. This is questionable however, since participants did behave as if status was important, just not in the specific way predicted by dominance theory.

As is the case with any research using static, descriptive examples of risk-taking, in order to move toward more comfortable claims about evolutionarily-designed mechanisms, one has to move the experimentation to more ecologically valid methodology. Specifically, Studies One through Three used the traditional static, described gambles, where the probabilities and payoffs were explicitly available for participants to make informed decisions. This is what Knight (1921) referred to as decisions under risk, rather than decisions under uncertainty. It is likely that most decisions are, at least initially, decisions under uncertainty. Thus, this avenue of research should be implemented in more dynamic, experience-based experimental paradigms (e.g., Mishra & Lalumière, 2010; Hertwig et al., 2004).

Directions for Future Research

Future research should examine the true viability of the priority heuristic. These fast-and-frugal heuristics are very elegant scientific models of decision choice, and while their explicit structure allows for clear falsification under experimental evidence, it also allows for easy modification to improve on the heuristic's ability to account for both behavior and process. Specific future directions should include: looking into this heuristic process as it accounts for decisions from experience (Hertwig et al., 2004). This could be used to assess the difference between what was studied in this collection of research (risk) and what is in the larger world (uncertainty) (Knight, 1921; Volz & Gigerenzer, 2012).

Also, in personal communication with Gerd Gigerenzer[10] about how such a heuristic would account for differences in resource availability (as in risk-sensitive foraging) he noted that one possibility is that individuals are capable of reordering the standard lexicographic order of the priority heuristic (Figure 2-1). This would lead to the conceptualization of the priority heuristic's reasons as moveable tiles, easily rearranged based on contextual cues in the environment. Such a conception could alleviate some concerns with the heuristic's inflexibility (Fiedler, 2010, p. 27-28). These cues could be in the form of cues of scarcity. This would suggest that individuals examine different orders of reasons, potentially resulting in entirely different decisions. This is also consistent with Rieskamp's (2008) priority model—an extension of the priority heuristic. Thus, a technique similar to those used to test the priority heuristic's processes (i.e, Mouselab) could be used, in conjunction with varying energy budget manipulations to determine if, under a negative budget, for instance, people focus on the maximum gains first, as opposed to the minimum gains. This work is currently being conducted. Results are forthcoming.

Other research is looking into the general model of risk-sensitivity as outlined in Studies Two (results section) and Three (a hypothesized model). If there exists a general risk-sensitivity mechanism which is activated in environmental situations containing need levels, it is plausible

[10] July 10, 2013 at the Summer Institute on Bounded Rationality; The Max Planck Institute for Human Development, Berlin, Germany

that such a mechanism would be responsive to less explicit cues of such need levels. An open question regarding the risk-sensitivity mechanism is just *how sensitive* it is to cues of scarcity in the environment. For instance, will the present results hold without setting up explicit situations in which a variable gamble will reach a need level whereas a less variable gamble will not? Similarly, if people are primed to think about a (monetarily) resource scare environment (see Griskevicius et al., 2013), will they behave as if they were in an explicitly framed negative budget? Such priming effects would suggest that the system is very sensitive to cues of a negative budget (i.e., cues of a resource-scarce environment).

The general risk-sensitivity mechanism may be primed by status as well. The status priming story used in Studies Two and Three (Appendix F) has been used by other researchers to elicit different forms of economically motivated decision making behaviors (Griskevicius et al., 2009; Griskevicius et al., 2010). In the present collection of studies, however, it was not used as a manipulation, and thus may have primed all participants to behave according to an environment where status has real consequences. This was indeed the motivation for using the status priming in Studies Two and Three. However, to assess the sensitivity of the general risk-sensitivity mechanism for cues of status, a between-participants manipulation may be necessary.

References

Archer, J. (2009). Does sexual selection explain human sex differences in aggression? *Behavioral and Brain Sciences, 32*, 249-311. doi: 10.1017/S0140525X09990951

Ayal, S., & Hochman, G. (2009). Ignorance or integration: The cognitive processes underlying choice behavior. *Journal of Behavioral Decision Making, 22*, 455-474. doi: 10.1002/bdm.642

Baker, Jr., M. D., & Maner, J. K. (2009). Male risk-taking as a context-sensitive signaling device. *Journal of Experimental Social Psychology, 45*, 1136-1139. doi: 10.1016/j.jesp.2009.06.006

Barkow, J. H., Cosmides, L., & Tooby, J. (Eds.) (1992). *The adapted mind: Evolutionary psychology and the generation of culture.* New York: Oxford University Press.

Barnard, C. J., Brown, C. A. J. (1985). Risk-sensitive foraging in common shrews (*Sorex araneus* L.). *Behavioral Ecology and Sociobiology, 16*, 161-164. doi: 10.1007/BF00295150

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173-1182. doi: 10.1037/0022-3514.51.6.1173

Barrett, H. C. (2005). Enzymatic computation and cognitive modularity. *Mind and Language, 20*, 259-287. doi: 10.1111/j.0268-1064.2005.00285.x

Barrett, H. C. (2012). A hierarchical model of the evolution of human brain specializations. *Proceedings of the National Academy of Science, 109*, 10733-10740. doi: 10.1073/pnas.1201898109

Barrett, H. C., & Kurzban, R. (2006). Modularity in cognition: Framing the debate. *Psychological Review, 113*, 628-647. doi: 10.1037/0033-295X.113.3.628

Barwell, R. (2004). What is numeracy? *For the Learning of Mathematics, 24*, 20-22. http://www.jstor.org/stable/40248441

Birnbaum, M. H., & Chavez, A. (1997). Tests of theories of decision making: violations of branch independence and distribution independence. *Organizational Behavior and Human Decision Processes, 71*, 161-194. doi: 10.1006/obhd.1997.2721

Birnbaum, M. H. (2008). Evaluation of the priority heuristic as a descriptive model of risky decision making: Comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review, 115*, 253-262. doi: 10.1037/0033-295X.115.1.253

Blanchflower, D. G., & Oswald, A. O. (2004). Money, sex, and happiness: An empirical study. *Scandanavian Journal of Economics, 106*, 393-415. doi: 10.1111/j.0347-0520.2004.00369.x

Boden, M. (1977). *Artificial intelligence and natural man.* New York: Basic Books.

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The Priority Heuristic: Making choices without trade-offs. *Psychological Review, 113*, 409-432. doi: 10.1037/0033-295X.113.2.409

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2008). Risky choice with heuristics: Reply to Birnbaum (2008), Johnson, Shulte-Mecklenbeck, and Willemsen (2008), and Rieger and Wang (2008). *Psychological Review, 115*, 281-290. doi: 10.1037/0033-295X.115.1.281

Brase, G. L., & Richmond, J. (2004). The white coat effect: Physician attire and perceived authority, friendliness, and attractiveness. *Journal of Applied Social Psychology, 34*, 2469-2481. doi: 10.1111/j.1559-1816.2004.tb01987.x

Buss, D. M. (1989). Sex differences in human mate preferences: Evolutionary hypotheses tested in 37 cultures. *Behavioral and Brain Sciences, 12*, 1-14. doi: 10.1017/S0140525X00023992

Caraco, T. (1981). Energy budgets, risk and foraging preferences in dark-eyed juncos (*Junco hyemalis*). *Behavioral Ecology and Sociobiology, 8*, 213-217. doi: 10.1007/BF00299833

Caraco, T. (1983). White-crowned sparrows (*Zonotrichia leucophrys*): Foraging preferences in a risky environment. *Behavioral Ecology and Sociobiology, 12*, 63-69. doi: 10.1007/BF00296934

Caraco, T., & Lima, S. L. (1987). Survival, energy budgets, and foraging risk. In M. L. Commons, A. Kacelnik, and S. J. Shettleworth (Eds.), *Foraging: Quantitative analyses of behavior (Vol. 6)* (pp. 1-21). New York: Psychology Press.

Caraco, T., Martindale, S., & Whittam, T. S. (1980). An empirical demonstration of risk-sensitive foraging preferences. *Animal Behavior, 28*, 820-830. doi: 10.1016/S0003-3472(80)80142-4

Cartar, R. V. (1991). A test of risk-sensitive foraging in wild bumble bees. *Ecology,* 72, 888-895. http://www.jstor.org/stable/1940590

Carruthers, P. (2005). The case for massively modular models of mind. In R. Stainton (Ed.), *Contemporary debates in cognitive science* (pp. 205-225). Oxford, England: Blackwell.

Chapman, G. B., & Liu, J. (2009). Numeracy, frequency, and Bayesian reasoning. *Judgment and Decision Making, 4*, 34-40. http://journal.sjdm.org/8708/jdm8708.pdf

Cokely, E. T., Galesic, M., Shulz, E., Ghazal, S., & Garcia-Retamero, R. (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making, 7*, 25-47. http://journal.sjdm.org/11/11808/jdm11808.pdf

Cokely, E. T., & Kelley, C. M. (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation. *Judgment and Decision Making, 4*, 20-33. http://journal.sjdm.org/81125/jdm81125.pdf

Coltheart, M. (1999). Modularity and cognition. *Trends in Cognitive Sciences, 3*, 115-120. doi: 10.1016/S1364-6613(99)01289-9

Daly, M., & Wilson, M. (2001). Risk-taking, intrasexual competition, and homicide. *Nebraska Symposium on Motivation, 47*, 1-36.

Darwin, C. (1976). *On the origin of species, or, the preservation of favored races in the struggle for life.* Westport, CT: Easton Press. (Original work published 1859)

Darwin, C. (1971). *The descent of man and selection in relation to sex.* Adelaide, Australia: Limited Editions Club. (Original work published 1871)

Darwin, C. (1979). *The expression of emotions in man and animals.* New York: St. Martin's Press. (Original work published 1872)

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist, 34*, 571-582.

Dawkins, R. (2006). *The selfish gene.* New York: Oxford University Press. (Original work published 1976)

Delfabbro, P. H., & Winefield, A. H. (2000). Predictors of irrational thinking in regular slot machine gamblers. *The Journal of Psychology, 134*, 117-128. doi: 10.1080/00223980009600854

Dennett, D. C. (1987). Cognitive wheels: The frame problem of AI. In C. Hookaway (Ed.), *Minds, machines, and evolution* (pp. 129-151). Cambridge, England: Cambridge University Press.

Desmond, A., & Moore, J. (1991). *Darwin.* New York: Warner Books.

Dobzhansky, T. (1973). Nothing in biology makes sense except in the light of evolution. *The American Biology Teacher, 35*, 125-129. doi: 10.2307/4444260

Eagly, A. H. (1987). *Sex differences in social behavior: A social-role interpretation.* Hillsdale, NJ: Erlbaum.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics, 75*, 643-669. http://www.jstor.org/stable/1884324

Ermer, E., Cosmides, L., & Tooby, J. (2008). Relative status regulates risky decision making about resources in men: Evidence for the co-evolution of motivation and cognition. *Evolution and Human Behavior, 29*, 106-118. doi: 10.1016/j.evolhumbehav.2007.11.002

Fiedler, K. (2010). How to study cognitive decision algorithms: The case of the priority heuristic. *Judgment and Decision Making, 5*, 21-32. http://journal.sjdm.org/10/91006/jdm91006.pdf

Fodor, J. A. (1983). *Modularity of mind: An essay on faculty psychology.* Cambridge, MA: MIT Press.

Fodor, J. A. (2000). *The mind doesn't work that way: The scope and limits of computational psychology.* Cambridge, MA: MIT Press.

Fox, C. R., & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *The Quarterly Journal of Economics, 110*, 585-603. doi: 10.2307/2946693

Frankenhuis, W. E., Dotsch, R., Karremans, J. C., & Wigboldus, D. H. J. (2010). Male physical risk taking in a virtual environment. *Journal of Evolutionary Psychology, 8*, 75-86. doi: 10.1556/JEP.8.2010.1.6

Fuemmeler, B. F., Taylor, L. A., Metz, A. E., & Brown, R. T. (2002). Risk taking and smoking tendency among primarily African American school children: Moderating influences of peer susceptibility. *Journal of Clinical Psychology in Medical Settings, 6*, 323-330. doi: 10.1023/A:1020743102967

Galesic, M., & Garcia-Retamero, R. (2011). Do low-numeracy people avoid shared decision making? *Health Psychology, 30*, 336-341. doi: 10.1037/a0022723

Gallistel, C. R. (2000). The replacement of general-purpose learning models with adaptively specialized learning modules. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (pp. 1179-1191). Cambridge, MA: MIT Press.

Giancola, P. R., Saucier, D. A., & Gussler-Burkhardt, N. L. (2003). The effects of affective, behavioral, and cognitive components of trait anger on the alcohol-aggression relation. *Alcoholism: Clinical and Experimental Research, 27*, 1944-1954. doi: 10.1097/01.ALC.0000102414.19057.80

Gigerenzer, G. (2008). Why heuristics work. *Perspectives on Psychological Science, 3*, 20-29. doi: 10.1111/j.1745-6916.2008.00058.x

Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science, 1*, 107-143. doi: 10.1111/j.1756-8765.2008.01006.x

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology, 62*, 451-482. doi: 10.1146/annurev-psych-120709-145346

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review, 103*, 650-669. doi: 10.1037/0033-295X.103.4.650

Gigerenzer, G., & Selten, R. (Eds.). (2001). *Bounded rationality: The adaptive toolbox.* Cambridge, MA: MIT Press.

Gigerenzer, G., Todd, P. M., & the ABC Research Group (1999). *Simple heuristics that make us smart.* New York: Oxford University Press.

Glöckner, A., & Herbold, A. –K. (2010). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*, 71-98. doi: 10.1002/bdm.684

Griskevicius, V., Tybur, J. M., Gangestad, S. W., Perea, E. F., Shapiro, J. R., & Kenrick, D. T. (2009). Aggress to impress: Hostility as an evolved context-dependent strategy. *Journal of Personality and Social Psychology, 96*, 980-994. doi: 10.1037/a0013907

Griskevicius, V., Tybur, J. M., & Van den Bergh, B. (2010). Going green to be seen: Status, reputation, and conspicuous conservation. *Journal of Personality and Social Psychology, 98*, 392-404. doi: 10.1037/a0017346

Griskevicius, V., Ackerman, J. M., Cantú, S. M., Delton, A. W., Robertson, T. E., Simpson, J. A., Thompson, M. E., & Tybur, J. M. (2013). When the economy falters, do people spend or save? Responses to resource scarcity depend on childhood environments. *Psychological Science, 24*, 197-205. doi: 10.1177/0956797612451471

Hammerstein, P., & Parker, G. A. (1982). The asymmetric war of attrition. *Journal of Theoretical Biology, 96*, 647-682. doi: 10.1016/0022-5193(82)90235-1

Hanoch, Y., Miron-Shatz, T., Cole, H ., Himmelstein, M., & Federman, A. D. (2010). Choice, numeracy, and physicians-in-training performance: The case of Medicare Part D. *Health Psychology, 29*, 454-459. doi: 10.1037/a0019881

Hayden, B. Y., & Platt, M. L. (2009). Gambling for Gatorade: Risk-sensitive decision making for fluid rewards in humans. *Animal Cognition, 12*, 201-207. doi: 10.1007/s10071-008-0186-8

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*, 534-539. doi: 10.1111/j.0956-7976.2004.00715.x

Hilbig, B. E. (2008). One-reason decision making in risky choice? A closer look at the priority heuristic. *Judgment and Decision Making, 3*, 457-462. http://journal.sjdm.org/8325/jdm8325.pdf

Hill, S. E., & Buss, D. M. (2010). Risk and relative social rank: Positional concerns and risky shifts in probabilistic decision making. *Evolution and Human Behavior, 31*, 219-226. doi: 10.1016/j.evolhumbehav.2010.01.002

Hill, W. T., & Brase, G. L. (2012). When and for whom do frequencies facilitate performance? On the role of numerical literacy. *The Quarterly Journal of Experimental Psychology, 65*(12), 2343-2368. doi: 10.1080/17470218.2012.687004

Hill, W. T., & Brase, G. L. (2013). *What do numeracy tests measure? An analysis and theoretical examination of the General Numeracy Scale.* Manuscript in preparation.

Jarvis, B. G. (2008). MediaLab (Version 2008.1.22) [Computer software]. New York: Empirisoft Corporation.

Johnson, E. J., Shulte-Mecklenbeck, M., & Willemsen, M. C. (2008). Process models deserve process data: Comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review, 115*, 263-273. doi: 10.1037/0033-295X.115.1.263

Judd, C. M., Kenny, D. A., & McClelland, G. H. (2001). Estimating and testing mediation and moderation in within-subjects designs. *Psychological Methods, 6*, 115-134. doi: 10.1037/1082-989X.6.2.115

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica, 47*, 263-291. http://www.jstor.org/stable/1914185

Kashtan, N., & Alon, U. (2005). Spontaneous evolution of modularity and network motifs. *Proceedings of the National Academy of Science, 102*, 13773-13778. doi: 10.1073/pnas.0503610102

Katsikopoulos, K. V., & Gigerenzer, G. (2008). One-reason decision-making: Modeling violations of expected utility theory. *Journal of Risk and Uncertainty, 37*, 35-56. doi: 10.1007/s11166-008-9042-0

Kemery, E. R., Dunlap, W. P., & Griffeth, R. W. (1988). Correction for variance restriction in point-biserial correlations. *Journal of Applied Psychology, 73*, 688-691. doi: 10.1037/0021-9010.73.4.688

Kenrick, D. T., Griskevicius, V., Sundie, J. M., Li, N. P., Li, Y. J., & Neuberg, S. L. (2009). Deep rationality: The evolutionary economics of decision making. *Social Cognition, 27*, 764-785. doi: 10.1521/soco.2009.27.5.764

Keren, G., & Gerritsen, L. E. M. (1999). On the robustness and possible accounts of ambiguity aversion. *Acta Psychologica, 103*, 149-172. doi: 10.1016/S0001-6918(99)00034-7

Kerr, N. L. (1998). HARKing: Hypothesizing After the Results are Known. *Personality and Social Psychology Review, 2*, 196-217. doi: 10.1207/s15327957pspr0203_4

Kirshenbaum, A. P., Szalda-Petree, A. D., & Haddad, N. F. (2000). Risk-sensitive foraging in rats: The effects of response-effort and reward amount manipulations on choice behavior. *Behavioral Processes, 26*, 9-17. doi: 10.1016/S0376-6357(00)00088-7

Knight, F. H. (1921). *Risk, uncertainty and profit.* New York: Houghton Mifflin.

Kruger, D. J., Wang, X. T., Wilke, A. (2007). Towards the development of an evolutionarily valid domain-specific risk-taking scale. *Evolutionary Psychology, 5*, 555-568. www.epjournal.net/wp-content/uploads/ep05555568.pdf

Lee, M. D., & Zhang, S. (2012). Evaluating the coherence of take-the-best in structured environments. *Judgment and Decision Making, 7*, 360-372. http://journal.sjdm.org/11/111109a/jdm111109a.pdf

Leventhal, A. M., Morrell, R. F., Morgan, Jr., E. F., & Perkins, Jr., C. C. (1959). The relation between mean reward and mean reinforcement. *Journal of Experimental Psychology, 57*, 284-287.

Liberali, J. M., Reyna, V. F., Furlan, S., Stein, L. M., & Pardo, S. T. (2011). Individual differences in numeracy and cognitive reflection, with implications for biases and fallacies in probability judgment. *Journal of Behavioral Decision Making, 25*, 361-381. doi: 10.1002/bdm.752

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General performance on a numeracy scale among highly educated samples. *Medical Decision Making, 21*, 37-44. doi: 10.1177/0272989X0102100105

Locke, J. (1956). *An essay concerning human understanding* (Abr. ed.). Oxford, England: Clarendon Press. (Original published 1690)

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin, 127*, 267-286. doi: 10.1037//0033-2909.127.2.267

Lopes, L. L., Oden, G. C. (1999). The role of aspiration level in risky choice : A comparison of cumulative prospect theory and SP/A theory. *Journal of Mathematical Psychology, 43*, 286-313. doi: 10.1006/jmps.1999.1259

Lorenz, K. (1958). The evolution of behavior. *Scientific American, 199*, 67-78.

Luttmer, E. F. P. (2005). Neighbors as negatives: Relative earnings and well-being. *The Quarterly Journal of Economics, 120*, 963-1002. doi: 10.1093/qje/120.3.963

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychological Methods, 7*, 19-40. doi: 10.1037//1082-989X.7.1.19

Maynard Smith, J. (1974). The theory of games and the evolution of animal conflicts. *Journal of Theoretical Biology, 47*, 209-221. doi: 10.1016/0022-5193(74)90110-6

Maynard Smith, J., & Price, G. R. (1973). The logic of animal conflict. *Nature, 246*, 15-18. doi: 10.1007/BF02837640

McBride, M. (2001). Relative-income effects on subjective well-being in the cross-section. *Journal of Economic Behavior and Organization, 45*, 251-278. doi: 10.1016/S0167-2681(01)00145-7

McCrea, K. T., & Bulanda, J. J. (2010). Caregiving heuristics: Valuable practitioner knowledge in the context of managing residential care. *Qualitative Social Work, 9*, 343-363. doi: 10.1177/1473325010367818

Mishra, S. (2010). *The motivational effect of need on decision-making under risk.* (Doctoral dissertation, University of Lethbridge). Retrieved from http://www.sandeepmishra.ca/MishraDissertation2010.pdf

Mishra, S., & Fiddick, L. (2012). Beyond gains and losses: The effect of need on risky choice in framed decisions. *Journal of Personality and Social Psychology, 102*, 1136-1147. doi: 10.1037/a0027855

Mishra, S., Gregson, M., & Lalumière, M. L. (2012). Framing effects and risk-sensitive decision making. *British Journal of Psychology, 103*, 83-97. doi: 10.1111/j.2044-8295.2011.02047.x

Mishra, S., & Lalumière, M. L. (2010). You can't always get what you want: The motivational effect of need on risk-sensitive decision-making. *Journal of Experimental Social Psychology, 46*, 605-611. doi: 10.1016/j.jesp.2009.12.009

Mishra, S., Lalumière, M. L., & Williams, R. J. (2010). Gambling as a form of risk-taking: Individual differences in personality, behavioral preferences for risk, and risk-accepting attitudes. *Personality and Individual Differences, 49*, 616-621. doi: 10.1016/j.paid.2010.05.032

Peters, E., & Levin, I. P. (2008). Dissecting the risky-choice framing effect: Numeracy as an individual-difference factor in weighting risky and riskless options. *Judgment and Decision Making, 3*, 435-448. http://journal.sjdm.org/8407/jdm8407.pdf

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science, 17*, 407-413. doi: 10.1111/j.1467-9280.2006.01720.x

Pinker, S. (1997/2009). *How the mind works.* New York: W. W. Norton and Company.

Pietras, C. J., & Hackenberg, T. D. (2001). Risk-sensitive choice in humans as a function of an earnings budget. *Journal of the Experimental Analysis of Behavior, 76*, 1-19. doi: 10.1901/jeab.2001.76-1

Platt, J. R. (1964). Strong inference. *Science, 146*, 347-353. http://www.jstor.org/stable/1714268

Rao, L. –L., Li, S., Jiang, T., & Zhou, Y. (2012). Is payoff necessarily weighted by probability when making a risky choice? Evidence from functional connectivity analysis. *PLoS One, 7*, e41048. http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0041048

Real, L., & Caraco, T. (1986). Risk and foraging in stochastic environments. *Annual Review of Ecology and Systematics, 17*, 371-390. doi: 10.1146/annurev.es.17.110186.002103

Reiger, M. O., & Wang, M. (2008). What is behind the priority heuristic? A mathematical analysis and comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review, 115*, 274-280. doi: 10.1037/0033-295X.115.1.274

Rieskamp, J. (2008). The probabilistic nature of preferential choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*, 1446-1465. doi: 10.1037/a0013646

Rode, C., Cosmides, L., Hell, W., & Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition, 72*, 269-304. doi: 10.1016/S0010-0277(99)00041-4

Rosati, A. G., & Hare, B. (2012). Decision making across social contexts: Competition increases preferences for risk in chimpanzees and bonobos. *Animal Behaviour, 84*, 869-879. doi: 10.1016/j.anbehav.2012.07.010

Rouder, J. N., Speckman, P. L., Sun, D., & Morey, R. D. (2009). Bayesian *t* tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*, 225-237. doi: 10.3758/PBR.16.2.225

Samuels, R. (1998). Evolutionary psychology and the massive modularity hypothesis. *The British Journal for the Philosophy of Science, 49*, 575-602. doi: 10.1093/bjps/49.4.575

Schapira, M. M., Walker, C. M., & Sedivy, S. K. (2009). Evaluating existing measures of health numeracy using item response theory. *Patient Education and Counseling, 75*, 308-314. doi: 10.1016/j.pec.2009.03.035

Schuck-Paim, C., Pompilio, L., & Kacelnik, A. (2004). State-dependent decisions cause violations of rationality in animal choice. *PLoS Biology, 2*, e402. http://www.plosbiology.org/article/info%3Adoi%2F10.1371%2Fjournal.pbio.0020402

Searcy, G. D., & Pietras, C. J. (2011). Optimal risky choice in humans: Effects of amount of variability. *Behavioral Processes, 87*, 88-99. doi: 10.1016/j.beproc.2011.01.008

Simon, H. A. (1957). *Models of man: Social and rational.* New York: Wiley.

Sirota, M., & Juanchich, M. (2011). Role of numeracy and cognitive reflection in Bayesian reasoning with natural frequencies. *Studia Psychologica, 53*, 151-161.

Sperber, D. (1996). *Explaining culture: A naturalistic approach.* Oxford, England: Blackwell.

Stephens, D. W. (1981). The logic of risk-sensitive foraging preferences. *Animal Behaviour, 29*, 628-629. doi: 10.1016/S0003-3472(81)80128-5

Stephens, D. W., & Charnov, E. L. (1982). Optimal foraging: Some simple stochastic models. *Behavioral Ecology and Sociobiology, 10*, 251-263. doi: 10.1007/BF00302814

Stephens, D. W., & Krebs, J. R. (1986). *Foraging theory.* Princeton, NJ: Princeton University Press.

Stulp, G., Kordsmeyer, T., Buunk, A. P., & Verhulst, S. (2012). Increased aggression during human group contests when competitive ability is more similar. *Biology Letters, 8*, 921-923. doi: 10.1098/rsbl.2012.0591

Symons, D. (1992). In J. Barkow, L. Cosmides, and J. Tooby (Eds.), *The adapted mind: Evolutionary psychology and the generation of culture* (pp. 137-159). New York: Oxford University Press.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston: Allyn and Bacon.

Tinbergen, N. (1951). *The study of instinct.* London: Oxford University Press.

Todd, P. M., & Gigerenzer, G. (2007). Environments that make us smart: Ecological rationality. *Current Directions in Psychological Science, 16*, 167-171. doi:10.1111/j.1467-8721.2007.00497.x

Tooby, J., & Cosmides, L. (1992). The psychological foundations of culture. In J. Barkow, L. Cosmides, and J. Tooby (Eds.), *The adapted mind: Evolutionary psychology and the generation of culture* (pp. 19-136). New York: Oxford University Press.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79*, 281-299. doi: 10.1037/h0032955

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*, 453-458. http://www.jstor.org/stable/1685855

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*, 297-323.

Veenhoven, R. (1991). Is happiness relative? *Social Indicators Research, 24*, 1-34. doi: 10.1007/BF00292648

Volz, K. G., & Gigerenzer, G. (2012). Cognitive processes in decisions under risk are not the same as in decisions under uncertainty. *Frontiers in Neuroscience, 6*, 1-6. doi: 10.3389/fnins.2012.00105

von Frisch, K. (1967). *The dance language and orientation of bees.* Cambridge, MA: Harvard University Press.

von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior* (2nd ed.). Princeton, NJ: Princeton University Press.

Wang, X. T., & Johnson, J. G. (2012). A tri-reference point theory of decision making under risk. *Journal of Experimental Psychology: General, 141*, 743-756. doi: 10.1037/a0027415

Wang, X. T., & Johnston, V. S. (1995). Perceived social context and risk preference: A re-examination of framing effects in a life-death decision problem. *Journal of Behavioral Decision Making, 8*, 279-293. doi: 10.1002/bdm.3960080405

Weber, E. U., Blais, A.-N., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*, 263-290. doi: 10.1002/bdm.414

Weller, J. A., Dieckmann, N. F., Tusler, M., Mertz, C. K., Burns, W. J., & Peters, E. (2012). Development and testing of an abbreviated numeracy scale: A Rasch analysis approach. *Journal of Behavioral Decision Making.* doi: 10.1002/bdm.1751

Wilson, M., & Daly, M. (1985). Competitiveness, risk taking, and violence: The young male syndrome. *Ethology and Sociobiology, 6*, 59-73. doi: 10.1016/0162-3095(85)90041-X

Wilson, M., Daly, M., & Pound, N. (2002). An evolutionary psychological perspective on the modulation of competitive confrontation and risk-taking. In D. Pfaff (Ed.), *Hormones, brain, and behavior* (Vol. 5), (pp. 381-408). San Diego, CA: Academic Press.

Winterhalder, B., Lu, F.., & Tucker, B. (1999). Risk-sensitive adaptive tactics: Models and evidence from subsistence studies in biology and anthropology. *Journal of Archaeological Research, 7*, 301-348. doi: 10.1007/BF02446047

Young, R. J., Clayton, H., & Barnard, C. J. (1990). Risk-sensitive foraging in bitterlings, *Rhodeus sericus*: Effects of food requirement and breeding site quality. *Animal Behavior, 40*, 288-297. doi: 10.1016/S0003-3472(05)80923-6

Appendix A - General Numeracy Scale

Directions: Answer the following questions to the best of your ability.

1. Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die will come up even (2, 4, or 6)?
2. In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize are 1%. What is your best guess about how many people would win a $10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?
3. In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000. What percent of tickets of ACME PUBLISHING SWEEPSTAKES win a car?
4. Which of the following numbers represents the biggest risk of getting a disease? 1 in 100, 1 in 1000, or 1 in 10
5. Which of the following represents the biggest risk of getting a disease? 1%, 10%, or 5%
6. If Person A's risk of getting a disease is 1% in ten years, and Person B's risk is double that of A's, what is B's risk?
7. If Person A's chance of getting a disease is 1 in 100 in ten years, and Person B's risk is double that of A, what is B's risk?
8. If the chance of getting a disease is 10%, how many people would bet expected to get the disease out of 100?
9. If the chance of getting a disease is 10%, how many people would be expected to get the disease out of 1000?
10. If the chance of getting a disease is 20 out of 100, this would be the same as having a ___% chance of getting the disease.
11. The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected?

Appendix B - Domain Specific Risk Scale

Directions: Rate each of the behaviors below according to how likely you would be to engage in each behavior or activity. Use the following scale: (1) Very Unlikely to (5) Very Likely.

1. Getting sterilized so you cannot have children but have more leisure time and more financial flexibility. ______
2. Exposing yourself to chemicals that might lead to birth defects for a high-paying job. ______
3. Participating in medical research that pays $10,000 but has some chance of making you sterile. ______
4. Adamantly defending the honor of your local team against a fan from a different sporting team even if it might cause a fight. ______
5. Sitting in the section for fans of the opposing team with a group of friends while wearing your team's colors. ______
6. Driving to a rival university at night and stealing the school's flag from the flagpole at the center of campus. ______
7. Standing up to your boss in front of coworkers when your boss is being unfair. ______
8. Trying to take a leadership role in any peer group you join. ______
9. Physically intervening between two friends who are aggressively pushing each other, to prevent a fight. ______
10. Spending a large portion of your salary to buy a sporty new convertible. ______
11. Engaging in unprotected sex during a one-night stand. ______
12. Maintaining long-term romantic relationship with more than one partner. ______
13. Chasing a bear out of your wilderness campsite area while banging pots and pans. ______
14. Swimming far out from shore to reach a diving platform. ______
15. Exploring an unknown city or section of town. ______

Appendix C - Follow-Up Questions for Study One

1. When making your decisions, how important was the amount of money needed to qualify for Round 2?

1	2	3	4	5
Not at all Important				Very Important

2. When making your decisions, how important was comparing Gambles A and B based on the chances of winning the minimum amount?

1	2	3	4	5
Not at all Important				Very Important

3. How important was comparing the possible minimum winnings between Gambles A and B when making your decisions?

1	2	3	4	5
Not at all Important				Very Important

4. How important was comparing the possible maximum winnings between Gambles A and B when making your decisions?

1	2	3	4	5
Not at all Important				Very Important

5. How suspicious were you about the authenticity of the competition?

1	2	3	4	5
Not at all Suspicious				Very Suspicious

Appendix D - Debriefing Form

Debriefing Form
Decisions about Money

Thank you for your participation in today's study. The goal of the experiment was understand the conditions necessary for you to make a risky decision during the gambling task. You were told that the study was actually a competition involving yourself, other students from Kansas State University, and potentially students from other universities. **This is not true.** There is no competition. You were told about a competition in order to provide motivation to respond in a certain way to the gambling task. Research has shown that status and competition can make people behave in a riskier way (Ermer paper cited below). Today we also examined your level of numerical literacy—how well you understand and reason with numbers, and your general level of risk-proneness.

Because this was not a real competition between yourself and other students there is not an actual correct answer to the gambling task, which you answered. Thus, you did not perform better or worse than anyone else in the study. Further, your data will be used only as a component in an average and your name will in no way be tied directly to any of your information, including your reported ACT score.

Your participation today has helped the research team take a small step in answering some important research questions. Again, thank you for your participation. Below I have listed a few citations for material related to this study. Also, if you are interested in this line of research—either as a research assistant or just general interest—feel free to contact us.

<u>Related Works</u>

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The Priority Heuristic: Making choices without trade-offs. *Psychological Review, 113*, 409-432. doi: 10.1037/0033-295X.113.2.409

Ermer, E., Cosmides, L., & Tooby, J. (2008). Relative status regulates risky decision making about resources in men: Evidence for the co-evolution of motivation and cognition. *Evolution and Human Behavior, 29*, 106-118. doi: 10.1016/j.evolhumbehav.2007.11.002

Rode, C., Cosmides, L., Hell, W., & Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing from predictions from optimal foraging theory. *Cognition, 72*, 269-304.

Stephens, D. W. (1981). The logic of risk-sensitive foraging preferences. *Animal Behaviour, 29*, 628-629.

<u>Contact Information</u>

W. Trey Hill	wthill@ksu.edu	(405) 714-0044
Dr. Gary Brase	gbrase@ksu.edu	(785) 532-0609

Appendix E - Status Manipulation Pilot Testing Material

What is your age? __________

What is your gender? (Circle one) Male Female

Directions: Listed below are the same universities. To the right of each university please circle whether you believe *students from that university are better or worse than students from Kansas State University.*

School	**Much Worse than KSU Students**				**Much Better than KSU Students**		
Stanford University	1	2	3	4	5	6	7
University of Kansas	1	2	3	4	5	6	7
University of Nebraska	1	2	3	4	5	6	7
New Mexico State University	1	2	3	4	5	6	7
Cornell University	1	2	3	4	5	6	7
Ohio State University	1	2	3	4	5	6	7
Harvard University	1	2	3	4	5	6	7
Wichita State University	1	2	3	4	5	6	7
Princeton University	1	2	3	4	5	6	7
Georgia Southern University	1	2	3	4	5	6	7
University of North Texas	1	2	3	4	5	6	7
West Virginia University	1	2	3	4	5	6	7
University of Arkansas	1	2	3	4	5	6	7
Oklahoma State University	1	2	3	4	5	6	7
University of Wyoming	1	2	3	4	5	6	7
University of Mississippi	1	2	3	4	5	6	7
University of Cincinnati	1	2	3	4	5	6	7
Oregon State University	1	2	3	4	5	6	7
University of Akron	1	2	3	4	5	6	7
Texas Tech University	1	2	3	4	5	6	7
University of Missouri	1	2	3	4	5	6	7
Portland State University	1	2	3	4	5	6	7
Idaho State University	1	2	3	4	5	6	7
University of Louisville	1	2	3	4	5	6	7
University of Southern Mississippi	1	2	3	4	5	6	7
Brown University	1	2	3	4	5	6	7
University of California, Berkeley	1	2	3	4	5	6	7
University of Memphis	1	2	3	4	5	6	7
Emporia State University	1	2	3	4	5	6	7
Mississippi State University	1	2	3	4	5	6	7

Directions: **Listed below are the same universities. To the right of each university** **<u>please circle how familiar you are with that university.</u>**

School	Not at all familiar						Very familiar
Wichita State University	1	2	3	4	5	6	7
Brown University	1	2	3	4	5	6	7
Texas Tech University	1	2	3	4	5	6	7
University of Nebraska	1	2	3	4	5	6	7
Oklahoma State University	1	2	3	4	5	6	7
Ohio State University	1	2	3	4	5	6	7
Portland State University	1	2	3	4	5	6	7
University of Akron	1	2	3	4	5	6	7
Oregon State University	1	2	3	4	5	6	7
Georgia Southern University	1	2	3	4	5	6	7
University of Memphis	1	2	3	4	5	6	7
Cornell University	1	2	3	4	5	6	7
West Virginia University	1	2	3	4	5	6	7
University of Arkansas	1	2	3	4	5	6	7
Princeton University	1	2	3	4	5	6	7
Stanford University	1	2	3	4	5	6	7
University of Cincinnati	1	2	3	4	5	6	7
Emporia State University	1	2	3	4	5	6	7
University of Kansas	1	2	3	4	5	6	7
University of California, Berkeley	1	2	3	4	5	6	7
University of Southern Mississippi	1	2	3	4	5	6	7
Mississippi State University	1	2	3	4	5	6	7
University of Mississippi	1	2	3	4	5	6	7
Idaho State University	1	2	3	4	5	6	7
University of North Texas	1	2	3	4	5	6	7
University of Louisville	1	2	3	4	5	6	7
New Mexico State University	1	2	3	4	5	6	7
University of Missouri	1	2	3	4	5	6	7
University of Wyoming	1	2	3	4	5	6	7
Harvard University	1	2	3	4	5	6	7

Directions: **Listed below are again the same universities. Imagine that you are in an intellectual competition with a random student from each university. To the right of each university please circle how intimidated you would be by a student from that university.**

School	Not at all intimidated						Very intimidated
University of Wyoming	1	2	3	4	5	6	7
Stanford University	1	2	3	4	5	6	7
University of Southern Mississippi	1	2	3	4	5	6	7
Harvard University	1	2	3	4	5	6	7
Oregon State University	1	2	3	4	5	6	7
University of Akron	1	2	3	4	5	6	7
Portland State University	1	2	3	4	5	6	7
West Virginia University	1	2	3	4	5	6	7
Emporia State University	1	2	3	4	5	6	7
University of Arkansas	1	2	3	4	5	6	7
Wichita State University	1	2	3	4	5	6	7
Texas Tech University	1	2	3	4	5	6	7
Ohio State University	1	2	3	4	5	6	7
University of Cincinnati	1	2	3	4	5	6	7
Cornell University	1	2	3	4	5	6	7
Idaho State University	1	2	3	4	5	6	7
University of Missouri	1	2	3	4	5	6	7
University of California, Berkeley	1	2	3	4	5	6	7
University of Memphis	1	2	3	4	5	6	7
University of Mississippi	1	2	3	4	5	6	7
University of Louisville	1	2	3	4	5	6	7
University of Kansas	1	2	3	4	5	6	7
University of Nebraska	1	2	3	4	5	6	7
Princeton University	1	2	3	4	5	6	7
Mississippi State University	1	2	3	4	5	6	7
Oklahoma State University	1	2	3	4	5	6	7
Georgia Southern University	1	2	3	4	5	6	7
Brown University	1	2	3	4	5	6	7
New Mexico State University	1	2	3	4	5	6	7
University of North Texas	1	2	3	4	5	6	7

Appendix F - Status Priming Vignette

Directions: Before you begin the competition we want to first know how you normally would handle competition. Please carefully read the following story. As you read, try to imagine yourself in the scenario and try to feel the emotions and feelings that the person is experiencing.

Imagine you have recently graduated from college and are arriving for your first day of work at a high-status job. You arrive at the spacious marble and glass reception area, remembering how intimidating it was when you first arrived for your interview. Getting to your new office requires going through the company's oak-paneled research library and passing a number of the large offices that senior partners occupy, but you find that your office is smaller and windowless. There are two other offices near yours that are similar in size, and soon you realize that the people arriving to these offices are also new employees. There are three of you that are all here on your first day of work. All three of you are called to your boss's office about an hour into the day. Your boss welcomes you to the company, confirms that you have all done your personnel paperwork, and then explains what will happen over the course of the next year. Specifically, the three of you will be in competition with each other. The boss explains to the three of you that one of the three will be fired, and one of you will not only be promoted to a luxurious corner office but will also get a large bonus. That person will basically be put on the fast track to a partnership in the company. The third person will continue to work for the company but will remain at their current position, their current office, and likely not get promoted. Think about how you would feel as you look forward to your new job and all that it involves. Imagine raising your levels of enthusiasm and motivation to perform as well as you can, impress your boss, and get the fast-track promotion. On the next screen are several things that you might consider in your efforts to be the best of the three new employees. Click Continue and examine those options.

(New Screen)

In reference to the story you previously read, carefully think about each option, consider the implications for each one, and then decide which things you would be most likely to actually do. Select all the options that you believe you would do.

- Ask a lot of questions about how things work at the company
- Be outspoken about how things are done at the company
- Bring in food for other employees
- Develop new projects on your own initiative
- Find out about all the office gossip and politics
- Host after-work activities
- Identify and develop a mentor for your career
- Invest in nicer clothes for a more professional appearance
- Memorize the names of every co-worker in the company
- Keep as quiet as possible and try not to be noticed
- Start a blog about your job
- Stay at work late and come in to work on the weekends

Appendix G - Follow-Up Questions for Study Two

1. When making your decisions, how important was your competitor's ACT score?

1	**2**	**3**	**4**	**5**
Not at all Important				Very Important

2. When making your decisions, how important was comparing Gambles A and B based on the chances of winning the minimum amount?

1	**2**	**3**	**4**	**5**
Not at all Important				Very Important

3. How important was comparing the possible minimum winnings between Gambles A and B when making your decisions?

1	**2**	**3**	**4**	**5**
Not at all Important				Very Important

4. How important was comparing the possible maximum winnings between Gambles A and B when making your decisions?

1	**2**	**3**	**4**	**5**
Not at all Important				Very Important

5. How suspicious were you about the authenticity of this competition?

1	**2**	**3**	**4**	**5**
Not at all Suspicious				Very Suspicious

6. When making your decisions, how important was the status of your competitor's university?

1	**2**	**3**	**4**	**5**
Not at all Important				Very Important

Appendix H - Follow-Up Questions for Study Three

1. When making your decisions, how important was your competitor's ACT score?

1	2	3	4	5
Not at all Important				Very Important

2. When making your decisions, how important was the amount of money needed to qualify for Round 2?

1	2	3	4	5
Not at all Important				Very Important

3. How suspicious were you about the authenticity of this competition?

1	2	3	4	5
Not at all Suspicious				Very Suspicious

4. When making your decisions, how important was the status of your competitor's university?

1	2	3	4	5
Not at all Important				Very Important