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Incorporating Complexities into the Explanation of Decision Making:

Strategy Simulations and an Empirical Test

by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Arts
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ABSTRACT

This investigation of risky decision making models the standard forced-choice two outcome lottery task by incorporating elements of complexity present in real-world decision making. Potential decision criteria such as current wealth and quality of life information were made available to examine the influence of time-dependent contextual cues on decision strategy selection, since previous investigations of decision making have not included specific contextual cues that would allow for people to use complex or "dynamic" decision strategies.

Two studies explored simulated decision strategies requiring more or less complexity. Results suggest that strategies using dynamic, time-dependent criteria provide important advantages over simpler strategies. Also, as 'aspirations' become closer to the most likely outcome and as trajectories include a larger margin of previous experiences, there is more control over improvements to the likelihood of ending up in an extremely good place over an extremely bad place. Certain changes to the decision environment seem to affect the accuracy of dynamic decision strategies, which in turn can help or hinder their effectiveness.

As a test of convergence, an empirical test was conducted to compare actual decision strategy use with simulated decision strategies. Two distinctly different decision tasks were used: one required only passive choices between two lotteries and the other required active changes to a given lottery situation. Information about lottery outcomes, current wealth, and quality of life were provided to participants to provide additional context to the decision environment.

Participants seemed to be using a variety of different strategies, including strategies that focus on dynamic information. Simple risk policies were often very good at describing risk preferences, though a subset of participants were relying on a complex decision strategies. There were also systematic differences in dynamic decision strategy usage. The combination of simulations and the empirical investigation elucidate the advantages to exploring risk preferences with attention to different decision strategies in specific environments, especially including more complex or "dynamic" decision strategies.

Introduction

Over the past several years, explanations of decision making have been predominantly utility-based. Some advancement has been made by Prospect Theory, which incorporates several psychological phenomena such as reference dependence and loss aversion, though still ultimately using a utility-type curve to explain many risky choice phenomena. Other recent advances in the study of decision making have provided for deviations from the prediction of a utility-based theory through a compartmentalized application of various heuristics or biases. Research from this "heuristics and biases" perspective has become particularly narrow, generally focusing on singular deviations from the standard utility-based models.

This study takes a broader approach to the understanding of decision making. Instead of relying predominantly on utility-based explanations, it may be worthwhile to also take into account the more complex elements from the real world. There are several fundamental complexities to the study of decision making in the real world. After decades of research, three of the most obvious or important fundamental complexities that arise repeatedly are vantage point dependencies, goal dependencies, and aspirations. Several models have made attempts to account for some or all of these complexities, including the Prospect Theory model (Kahneman & Tversky, 1979), Aspiration Level and Goal Trajectory models (Schneider & Lopes, 1986; Lopes, 1987, 1996), and models

using a dynamic systems approach (Busemeyer, 2004). These models have various ways of accounting for the three fundamental complexities.

The purpose of this thesis is to analyze these fundamental complexities in contextually rich environments by synthesizing several different elements of existing models. Two different approaches were taken to better understanding the role of complexities in decision making. First, simulations were created to look at the idealized or statistical aspects of hypothesized decision strategies. Using a Monte Carlo approach, the simulations yield outcome distributions with properties that are helpful in understanding the potential impact of different strategies. A second approach used an experimental decision environment enhanced with contextual information, including time-dependent or "dynamic" context. In addition, a convergent methods approach comparing the simulations with empirical tests is used to look for common patterns and explanations in the behavior of actual participants.

In order to better understand the fundamental complexities mentioned previously and how they relate to the larger question of decision-making, a brief overview of vantage point dependency, goal dependency, and aspiration levels will be provided, as well as a discussion of how they relate to current approaches to understanding risky decision making. A thorough explanation of the current study will then be introduced, along with the findings and implications reached.

Vantage Point Dependency

In the context of this project, "vantage point" dependency refers to reference dependence as it relates to a reference point. The term "reference dependence" is the

notion that a participant's response to a given problem varies due to the perspective of the participant. The simplest utility models (Bernoulli, 1738/1954) predict that people will evaluate risks differently depending on how far away the outcomes are from the reference point of zero on a utility curve (shown in Figure 1).

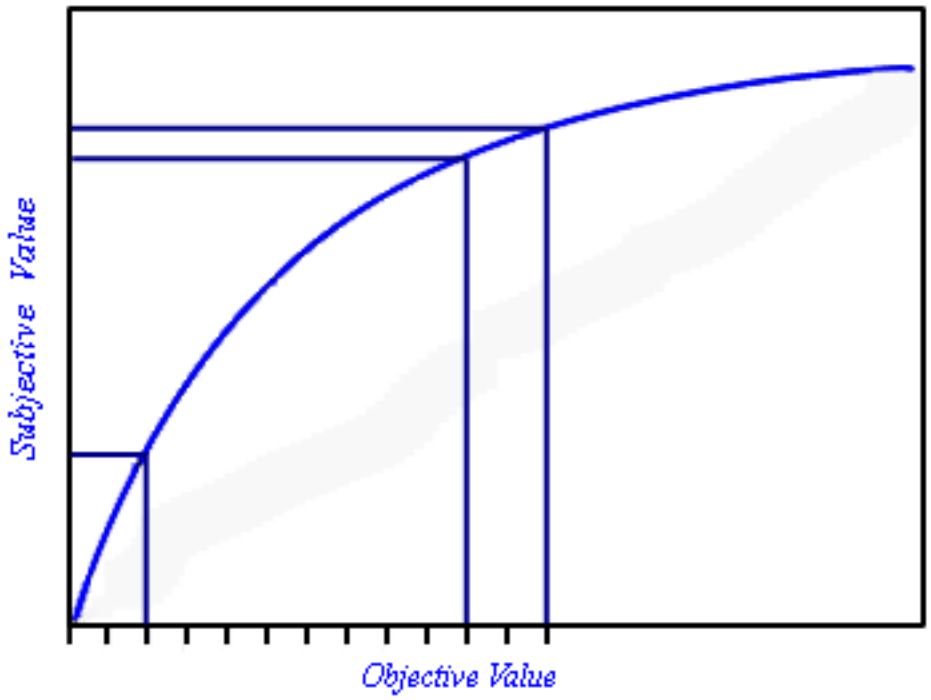

Figure 1: An example of Bernoulli's (1738/1954) simple utility curve.

These models work by assuming a systematic relationship between the actual value of a commodity/lottery and the subjective experience that lottery elicits. Typically, the presumed relationship, as shown in Figure 1, is that a given increase in objective value is experienced as smaller the farther away the values are from zero. For instance, when presented a 50/50 chance of $0 or $100, the difference in objective value between the two options ($100) elicits a larger 'subjective value' than the difference between a 50/50 chance of $500 or $600. This notion of a marginally decreasing relationship

between objective and subjective value is important in that it introduced a way for Bernoulli to explain why people are not neutral to things with the same change in expected value. This helps to illustrate the importance of a reference point for explaining behavior.

However, with the Prospect Theory model and the creation of the S-shaped utility function (Kahneman & Tversky, 1979) shown in Figure 2, participants can evaluate choices differently depending on the valence of the decision, or direction (positive of negative) from the reference point, in addition to the distance from the reference point. In Prospect Theory, the individual first converts the values in the decision problem into valences: either gains, which are choices that result in a "good" or better state than the current reference point; or losses, which are choices that result in a "bad" or worse state than the current reference point. These gains or losses are then weighted by their "subjective value." This allows the valence of the decision problem to have an impact on the outcome of the decision.

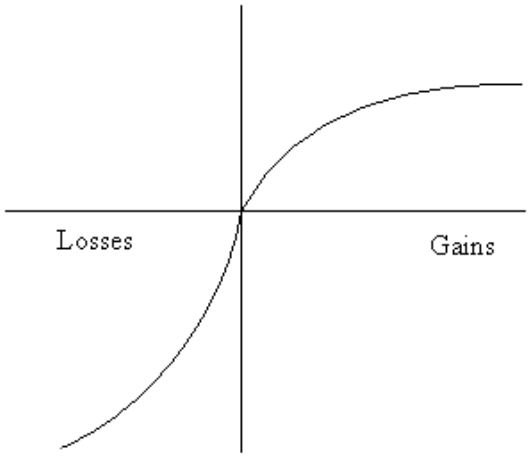

Figure 2: S-shaped Utility Curve (Tversky & Kahneman, 1981).

Reference dependence is commonly demonstrated in phenomenon known as "framing effects." Tversky and Kahneman (1981) proposed that decision makers use the valence of information as a critical reference point. Framing effects are predicted when a decision maker is presented with a choice between a riskless option and a risky option under circumstances that could be considered a loss (e.g., people dying, losing money) versus a gain (e.g., people being saved, gaining money). Tversky and Kahneman (1981) found that participants are likely to choose the riskier option when they adopt a loss perspective and are likely to choose the riskless option when facing what seems like a gain. Reference dependence suggests that the subjective experience elicited by a lottery depends on the perception of the individual, and as a result, a model built on only these simple utility-type curves can gauge subjective experience as it relates to the reference point of the participant. Reference dependence is important in the explanation of decision-making because it requires that the reference point being taken into account be used to make distinctions depending on the direction of the choice outcomes from a neutral point.

Goal Dependency

Vantage point dependencies of distance and direction from zero represent static versions of reference dependence. "Goal trajectories" provide an additional dynamic dimension of the reliance on reference points when making decisions. The reference point can be similar to those previously stated, but in addition to evaluating risky choices based on distance from zero (as with Utility theory) and direction from zero (as with Prospect theory), decision makers may also take into account the experience of previous

outcomes over time as they relate to the expectancy of future outcomes. People are influenced by previous successes and failures, such that previous successes create a tendency to view the current goal as continuing their successes by approaching a more positive state, whereas previous failures create a tendency to view the current goal as preventing their future failures by avoiding a more negative state. From this perspective, goals are formed based on information about previous outcomes as well as information about the outcome trajectory from the previous decisions to the current decision. This explanation would operate consistent with the promotion and prevention focus described by Regulatory Focus theory (Higgins, 1998). The goal trajectory approach takes into account the decision maker's previous experiences as well as their future expectations. Goals are set with respect to whether the decision maker has recently experienced improvements or decrements in outcomes. In short, when people make decisions, goal trajectories are using 'where they are' with respect to 'where they were' to make inferences about 'where they want to be.'

The construct of goal trajectories is inspired by a clever study developed by McKenzie and Nelson (2003). McKenzie and Nelson investigated framing effects using a glass of water at half capacity that was described as having just previously been either empty or full. They found that a majority of the participants interpreted a filling glass as "half full" and an emptying glass as "half empty." McKenzie and Nelson conclude that frames and framing effects are useful in providing additional contextual information about the situation. Participants evaluate glasses differently by using the inferences about the trajectory of the water in the glass. Apparently, this information led participants to

believe the glass was either filling or emptying until it was at half capacity. Hence people interpret events based on outcome trajectories.

Schneider and colleagues (2005) elaborated on this idea by incorporating outcome trajectories into a risky decision making task. They hypothesized that people's goals would be highly sensitive to outcome trajectory information. She devised a task that makes outcome trajectory and goal related information more obvious. Participants start off in a risky situation and are given the opportunity to try to improve the situation, and in doing so either decrease or increase the amount of risk they are facing. Schneider argued that this is a more ecologically valid paradigm than the standard risky choice paradigm, wherein participants behave counter intuitively by taking risks when they are in loss situations but playing it safe for gains. Because the new paradigm places the decision within an ongoing dynamic context, preferences should be more intuitive as a result (e.g., not taking big risks when facing losses). Indeed, Schneider and colleagues found that preferences were very different from the standard risky choice paradigm. Instead, Schneider and colleagues found that people tend to play it safe for both gains and losses, but *especially* for losses.

Schneider and colleagues (2006) then later used her new paradigm to determine if and how outcome trajectories affect the experience of decision-making. She argued that people's affective reactions would differ predictably given the overall valence of experiences across a series of decisions. She argues that basic adaptive mechanisms may lead to negative affect when losing and positive affect when winning as a functional way to assess and respond to longer-term consequences. Specifically, when one is losing over

a period of time, protective measures are in order; however, when one is winning over a period of time, one can afford to be more open to a variety of options.

People have often argued that framing effects should be ignored, but Schneider argues that it is reasonable for people to respond differently to starting with nothing and winning up to a given value versus starting off with a lot and losing down to the same value. This is exactly what Schneider and colleagues (2006) found; affect changed markedly as participants continued through a series of lotteries depending on whether they experienced a positive or negative trend across the entire series (e.g., how much money they received at the beginning of the task + how much they earned [positive trend] or lost [negative trend] during the task). These affective differences in this context seem to operate in a fashion consistent with Damasio's (1995) somatic marker hypothesis. The somatic marker hypothesis focuses on somatosensory reactions to stimuli over a period of time as a means for gauging a choice option's usefulness. All else equal, changes in affective response are likely to signal improvements or declines in one's position and are thus adaptive in more natural scenarios. Goal trajectories pose a problem for decision researchers because trajectory information varies depending on the participants' evaluation of the lottery scenario, previous lotteries in a series, etc. As a result, individual participants' decision patterns may vary depending on their different interpretations of the current lottery state relative to previous *lotteries* and, perhaps more importantly, previous *outcomes*.

Aspirations about the Future

In the same vein as the previously mentioned goal trajectories, Lopes (1981) and others have argued that making a series of decisions can have different meanings and consequences than making a single decision with the same expected value. Lopes addressed a comment by Samuelson (1963) in which he argued with a colleague that if one play of a lottery was not desirable, then multiple plays of that lottery also couldn't be rationally considered preferable. Lopes (1981) argued that lotteries could be interpreted differently depending on the number of plays given. When given a large number of chances to play, people are much more likely to end up close to the expected value of outcomes. For example, if given a 50/50 chance between $0 and $5, after a single play, there is no chance of ending up with the average value $2.50, only either $0 or $5; after ten plays however, there is a relatively good chance of ending up at or near the expected value of $25. The central limit theorem would dictate that the greater the number in the series of games, the higher the likelihood that the experienced cumulative outcome will be close to the expected value. Hence, a single play does not capture the change in outcome distributions associated with a series of events. In short, a large number of chances to play a particular gamble yield a higher likelihood to arrive at some multiple of the expected value such that the standard deviation of outcomes is smaller compared to fewer plays of the same gamble.

Lopes (1981) goes on to argue that it is reasonable for people to base their decisions on something other than expectations, given this difference in experienced outcomes between long run and short run gambles. While vantage point dependencies

and goal dependencies reflect the importance of the reference point for encoding the size of values, their valence, and their impact with respect to recent outcomes and current goals, there may be individual differences that cannot be explained relative to the reference point, but further depend on the implicit goals of participants. Lopes and Schneider have long argued that decision strategies are based less on momentary considerations such as the expected values of gambles and more on the future implications of an increasingly time-dependent decision environment. To that end, Lopes (1987) proposed a dual criterion strategy to address how aspirations serve as threshold values.

SP/A theory (Lopes, 1987) involves two decision criteria in formulating a decision: the first is the security/potential component, which suggests that motivations correspond with how influential the good or bad outcomes are. Specifically, the 'security' modality instantiates that the worse outcome is more influential than the better outcome, while the 'potential' modality instantiates that the better outcome is more influential than the worse outcome. This component functions in a dispositional way, dissimilar to the s-shaped utility function suggested by the Prospect Theory model (Tversky & Kahneman, 1981). Instead of each valence representing a different evaluation of objective value, the particular motivation to remain secure to avoid large losses (as with the "negative" realm) or achieve some large potential gain (as with the "positive" realm) exist with relative simultaneity, wherein the most prevalent motivation is adopted.

The second component of the SP/A theory is the aspiration level component. This is a situational variable, such that the environment introduces opportunities or constraints, which in turn influence choices. Lopes (1987) presents three potential sources of aspiration levels; direct assessment of what is reasonable to look forward to, direct contextual influence of other alternatives in the choice set, and outside contextual influences, such as the rules of a particular decision task. Lopes (1987) suggests that as people make decisions in the real world, often relative to some persistent goal, (e.g., making enough to pay the rent; other financial, often noncompensatory goals) they may change their fiscal strategy depending on how they perceive themselves to be doing relative to that goal. This should be an important aspect of decision modeling because it suggests that an effective model must account for strategy changes as a result of longer-term goals and aspirations. The aspiration level phenomenon is important because it extends the evaluation of risky decision-making beyond a comparison of expected values.

For the purpose of this investigation, we are interested in the noncompensatory processing which can result from the aspiration level phenomenon. Noncompensatory decision criteria are non-additive, all-or-nothing determinants of choice that relate to distinctions people make in their environment (Paine, 1975). While compensatory criteria allow for other criteria to tradeoff such that being good with one characteristic (great miles per gallon in a car) can compensate for being bad with another characteristic (a smaller interior), noncompensatory decision criterion do not consider other criteria if the conditions of the noncompensatory criteria are not met. Noncompensatory criteria work like a gateway, determining whether one needs to consider the other criteria; if the

conditions for a noncompensatory criterion are met for a given subset of choices, then those choices are evaluated using the remaining criteria. The choice subset that does not meet the conditions of the noncompensatory criterion is ignored. Nonlinearity can often arise from situations involving noncompensatory processing, which can create problems for linear models of decision-making.

For example, if the decision problem involved buying a car, one noncompensatory decision strategy would be to not buy a car if it were red. Regardless of the other criteria that can be used in the act of choosing a car, if it is red, it will not be purchased. When a participant changes their strategy by ignoring all of the other characteristics of a choice for a given lottery, that is considered a noncompensatory decision strategy, because the "other criteria" (e.g., the valence of the lottery, previous outcomes, etc.) cannot affect the participant's choice when they are in the given situation. When decision strategies are attached to aspiration levels, the aspiration threshold influences the strategy by creating a discontinuity or nonlinearity. As a result, additive linear models can not account for changes in strategy for situations that "do" versus "do not" meet the aspiration, because these models would require unwieldy "heuristics," addendums, and exceptions to explain why one chose from a limited subset of choices given one's aspirations as they relate to the particular environmental information.

Modeling Decision Complexity: Dynamic systems

Partly in an attempt to account for nonlinear and noncompensatory criteria and partly to explain the problem associated with how simple processes and entities can operate dynamically, (e.g., depending on their initial criterion values and current criterion

values) dynamic systems approach to decision-making was created. Aspects of these systems have been used in research on judgment and decision-making in a number of different ways including the Decision Field Theory model (Busemeyer & Townsend, 1993), explanations of capital investment (Rapoport, 1975), and models of managerial behavior (Sternman, 1989).

The important aspects that make a particular system "dynamic," as laid out by Busemeyer (2001), are as follows:

1. Actions occur in a series over time in order to achieve a goal;
2. Said actions are "interdependent," e.g., later actions depend on previous actions;
3. And the system environment must change spontaneously, as a consequence of earlier actions, or both.

Busemeyer (2001) and later Gonzalez (2005) point out several characteristics found in dynamic systems tasks that are particularly useful when studying decision-making. 'Dynamic systems' models offer advantages in testing for differences related to the fundamental complexities discussed earlier. Dynamic systems modeling address goal dependencies due to the existence of a goal-oriented time series, allowing for time-dependent stimuli in the short term and the long term to be introduced and analyzed. In addition, the dynamic systems methodology includes a contextual environment with specific implicit (e.g., avoiding zero) and explicit (e.g., making money) aspirations.

However, by necessity, these dynamic decision making tasks are generally oversimplifications of real-world situations and as a result require some additional real-world knowledge of the decision environment. In addition, the exact stimulus presented

to each participant is not under the complete control of the experimenter, due to the interaction of previous information with current information. As a result, making comparisons by averaging across individual decisions or participants no longer suffices as an analytical tool. Therefore, dynamic decision making tasks have to be carefully planned and executed, and different analytical tools are required.

There have been previous forays into extending dynamic systems into decision-making. Dynamic systems models are often used with respect to complex multi-attribute decision-making (e.g., Decision Field Theory (Busemeyer & Townsend, 1993)). Dynamic decision-making has also been used to model decision behavior with respect to task rules. This is accomplished by using implicit task-specific goals/aspirations along with explicit task instructions. An example is a firefighting task given by Brehmer (1992) and later adapted by Omodei and Wearing (1995). In this task, participants were given a hypothetical situation of managing resources to fight a fire. Participants were put through a computer simulation that included things like feedback delays and implicit goal contingencies (e.g., don't let the firehouse burn down). These dynamic systems models often use this type of "micro-world," which is broadly defined as a complex computer task which, though relatively simple, allows researchers to evaluate and control a larger set of decision-making characteristics essential in real world dynamic decision-making environments.

'Dynamic systems modeling' often relies on mathematical simulation as a type of analysis. First, simulations allow for easy and controlled addition of dynamic system variables. For example, in a simulation, the addition or removal of certain decision

strategy constraints (compensatory or noncompensatory) from the micro-world can emphasize the impact of different decision criteria under different circumstances. Second, simulations can extract the distributional characteristics of combining participant experiences with given strategy criteria (and criteria interactions) by isolating those specific criteria. Third, simulations remove the individual differences and individual error normally found between participants by determining the actions taken by each "participant" *a priori*. As a result, a simulation provides a distribution of possible outcomes and the relative likelihood for what might occur if participants were to operate using only a particular decision criterion or set of criteria within a specified environment.

While many previous investigations of risk preferences have taken into account vantage point criteria, relatively few have attempted to account for the more complex elements of goal dependency and aspirations. Of those previous investigations which included complex elements, none have included a thorough analysis of the statistical properties associated with time-dependent decision criteria, nor have there been systematic attempts to determine whether these more complex decision criteria are evident in the decision making of study participants. This investigation entails two methodologies: a series of decision strategy simulations to compare and contrast the distributional and statistical aspects of vantage point dependency, goal dependency, and aspiration levels; and an empirical manipulation to compare what we learn using simulations to actual human decision-making behavior in a dynamic decision-making environment. This study will then attempt to provide a richer understanding of the implications associated with vantage point dependency, goal dependency and aspirations

by comparing the effectiveness of each level of complexity under simulated ‘optimal’ conditions, as well as the effectiveness of each at prediction of how real people make decisions.

Study One: Investigate Decision Strategy Simulations

The purpose of using simulations in this investigation was to address the differences in outcomes between a variety of decision strategies that depend to a greater or lesser extent on vantage point dependency, goal dependency, and aspiration levels. In previous work, Schneider and colleagues (2006) developed a series of simulations to compare the longer-term implications of several different models of decision-making. This previous work will be described, followed by an explanation of the extensions to the simulation methodology which is currently utilized, followed by an evaluation of the results from the current simulation.

Pilot Simulations

Our approach in this project is to apply Monte Carlo simulation methodology addressed as an analysis tool by dynamic systems modeling to investigate the relationship between different kinds of decision-making models (risk policies, valence-dependent, and aspirations-based). In order to lay the groundwork for the investigation into decision-making in a dynamic decision making environment, mathematical simulations were performed for the purposes of this experiment in three phases. The first phase was to simply capture the baseline distributional information about risk preferences. The second phase was to compare and evaluate the distributional aspects of several decision strategies that embody the models of late. The third phase was to compare and evaluate the distributional aspects of decision strategies that use contextual information to form an

aspiration criterion in determining choice. For this mathematical simulation, "virtual participants" were created to use a specific decision strategy that resembled either baseline conditions, decision-making models that only use local intra-lottery characteristics as criteria for determining risk preference (Prospect Theory: Kahneman & Tversky, 1979; Risk as threat and opportunity: Highhouse & Yuce, 1996, Lopes, 1987, Schneider & Lopes, 1986; Risk as variance: Savage, 1954) or aspiration level models which use extra-lottery contextual information as criteria for determining risk preference; that is, criteria which used the "cumulative total" value (the concatenation of their starting value and their outcomes so far) as a means for deciding when to be risky or safe. In order to look at vantage point dependency and larger contextual effects, several sets of virtual participants were created to make decisions across a series of 36 lotteries. Each set of virtual participants was ascribed with a particular strategy that fit one of three major groups.

Decision Policies

The Decision Policy strategies include the most basic strategies that represent a constant policy that operate independent of lottery characteristics or environmental constraints. These strategies differ exclusively with respect to the presumed shape of their utility curve. The risk-averse strategy can be said to have a concave utility function, similar to the utility curve supported by Bernoulli (1738/1954), and always leads to selecting the less risky option. The risk-seeking strategy presumes a convex utility function, and opposite to the risk-averse strategy, always leads to the selection of riskier options. The random strategy can be said to imply a straight utility relationship between

objective and subjective value, which produces indifference in the choice between options of equal expected value. As a result, option selection is randomly determined.

Lottery-based Strategies

The lottery-based strategies are dependent on static characteristics of the lottery options for strategy selection. This set emulates the risk preference patterns of several popular models of decision-making. The first strategy presented represents the Prospect Theory Model (Tversky and Kahneman, 1981). In this strategy, lotteries that have positive outcomes are evaluated as gains and therefore are met with risk aversion and lotteries that have negative outcomes are evaluated as losses and therefore are met with risk-seeking behavior, similar to the predictions of the Prospect Theory S-shaped subjective value function (Kahneman & Tversky, 1979). When the choice is between mixed lotteries (containing both positive and negative outcomes), they are met with risk aversion, based on the loss aversion phenomenon suggested by the Prospect Theory model.

The next strategy is meant to represent the Security/Potential component of the SP/A model (Lopes, 1987; Schneider & Lopes, 1986), or is otherwise often described as Cautious Optimism or "Risk as threat and opportunity" (Highhouse & Yűce, 1996). In this strategy, lotteries that have all negative outcomes lead to risk being interpreted as a threat and therefore the safer option is chosen, while lotteries that have all positive outcomes lead to risk being interpreted as an opportunity and therefore the riskier option is chosen. When lotteries have mixed outcomes, they are met with loss aversion, due to the typical tendency to prioritize security over potential, or threat over opportunity.

The next strategy is meant to represent the Risk as variance or modest risk tolerance model, which is similar to a model presented by Savage (1954). This model favors modest amounts of risk on low variance gambles and differentiates lotteries with riskless or "sure thing" options by selecting the riskier option, while in all other cases, the riskier option is rejected. This model still involves a reference point that incorporates both distance from zero and direction. However, instead of direction from zero in terms of objective values, the risk as variance model adjusts risk preference relative to the amount of variability (size differences) between outcomes.

Contextual or Aspiration-based Strategies

The aspiration-based set of strategies combines contextual information and goals as criteria for decision strategies. Specifically, they define goal-direction as a decision criterion, namely the cumulative value across the series of simulation outcomes is the focus for changing risk preference. This incorporates the Aspiration component of the SP/A model with the dispositional tendencies. Specifically, when a virtual participant is above a certain desired wealth threshold or 'aspiration level,' they focus on potential and are willing to take risks, while when a virtual participant is below a certain wealth threshold, they focus on security and are not willing to take risks. Security-focused individuals will set their aspiration levels higher so that they only take a risk when they are substantially well off. Potential-focused individuals will set their aspiration level lower in order to take advantage of the opportunities possible with the riskier options.

Procedure

These 3 sets of strategies were evaluated using Monte Carlo style simulations. 36 lottery pairs were presented in one of four different counterbalanced orders. 10,000 virtual participants were used for each order, for a total of 40,000 per strategy. These virtual participants were assigned to pick the more risky or less risky option based on their given strategy. The results of the simulations were evaluated by examining characteristics for each strategy comparing final outcome distributions, central tendency, variability, and skew within the final outcome distributions, as well as showing the percentage of participants that are consolidated into either the high (denoted "richer") and low (denoted "poorer") extremes of the final outcome distribution. The expected value for the series of 36 lotteries was $1000 in all cases, and hence all distributions had the same mean.

Preliminary Results of the Initial Investigation

For the Risk Policy strategies, we tested the baseline conditions for always choosing the more risky of two options (denoted "Risk-seeking"), always choosing the less risky of two options (denoted "Risk-averse"), and a condition in which risk preference was determined completely randomly (denoted "Random").

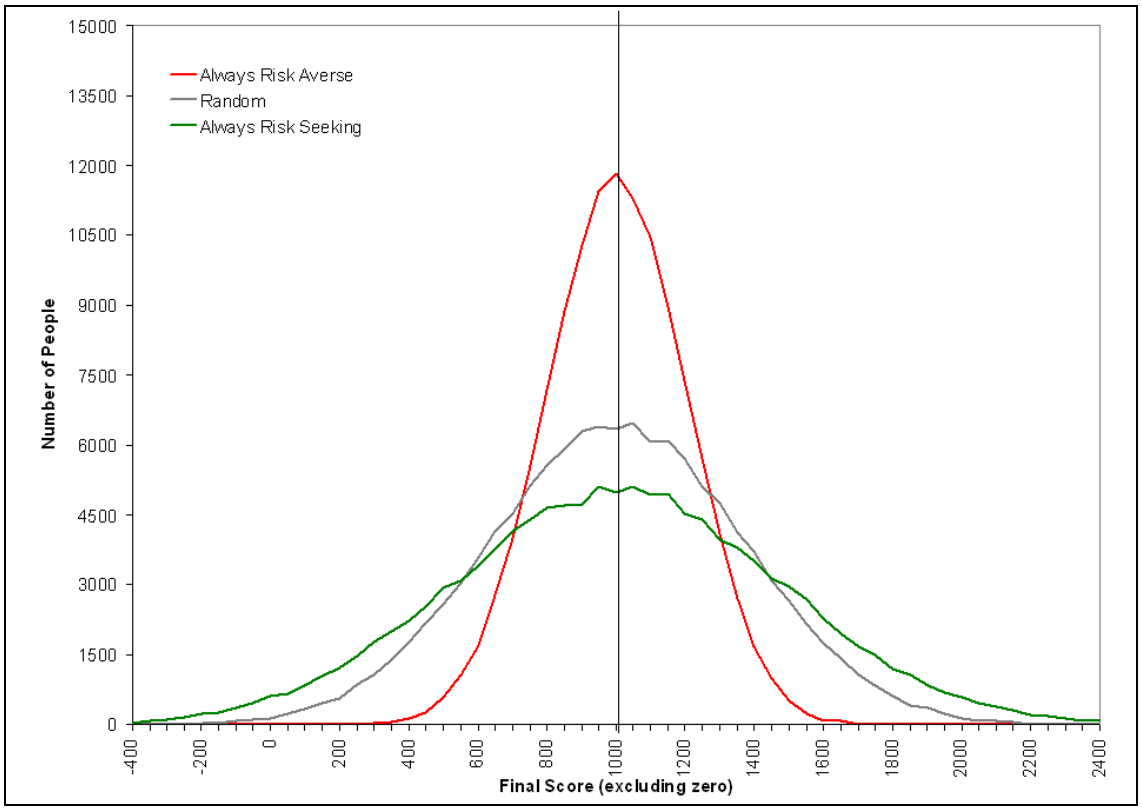

Figure 3: The final outcome distributions for the baseline strategies. "SimLo" designates an entirely risk-averse strategy, "SimHi" designates an entirely risk-seeking strategy, and "Random" designates an entirely random strategy.

As shown in Figure 3, we found that decision strategies involving only risk-seeking choices have a final outcome distribution with a large amount of variance, meaning there are fewer participants at or around the mean and more participants who ended up at the extremes (e.g., very "rich" or ended up very "poor"). Conversely, a decision strategy that involves only risk-averse moves has a final outcome distribution with a small amount of variance, meaning there are more participants at or around the mean and fewer participants at the extremes. Also, a decision strategy that involves only random choices has a final outcome distribution that is intermediate to the risk-averse and risk-seeking strategy.

For the lottery-based strategies, we tested the strategies based on the Prospect theory model (Tversky and Kahneman, 1981), the Risk as Threat and Opportunity or Security/Potential component of the SP/A model (Lopes, 1987; Schneider & Lopes, 1986), and the Risk as variance model (Savage, 1954). We found that decision strategies that are based on these models of decision-making which happen to only use local, static characteristics of individual lotteries (shown in Figure 4) are similar to Risk Policy strategies in that they differ systematically in distributional variability.

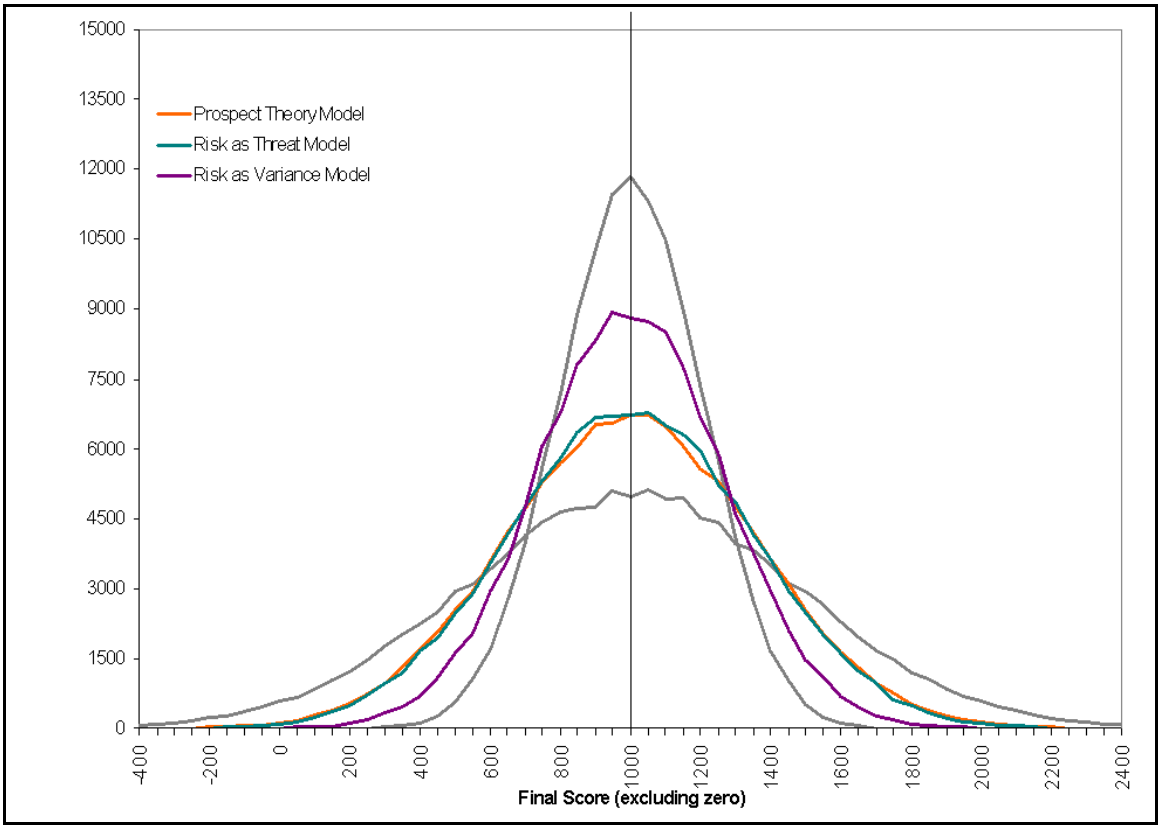

Figure 4: The final outcome distributions for the strategies based on models of decision-making. Risk policies from the previous Figure are included.

These local, lottery-based strategies were symmetrical just like the baseline strategies, but differed in the amount of variance. The amount of variance in a particular

final outcome distribution was completely determined by the number of risky moves that a particular strategy makes for a given series of lotteries. The more risky choices that a strategy demands throughout the series of lotteries, the higher the variance or the more the final outcome distribution looks like the "always risk-seeking" strategy. The more risk-averse actions, the lower the variance or the more the final outcome distribution looks like the "always risk-averse" strategy.

The percentages of participants in the extremes for the final outcome distribution are shown in Figure 5. This illustrates the difference that strategies make in determining the likelihood of ending up at the extremes. The likelihood of ending up in the extremes is very low for strategies that include more risk-averse choices, while the likelihood of ending up in the extremes increases as a number of riskier choices increases. In addition, there is relative symmetry found in both lottery-based and baseline strategy conditions. For the most part, there is the same percentage of participants in the higher outcome groups as the lower outcome groups.

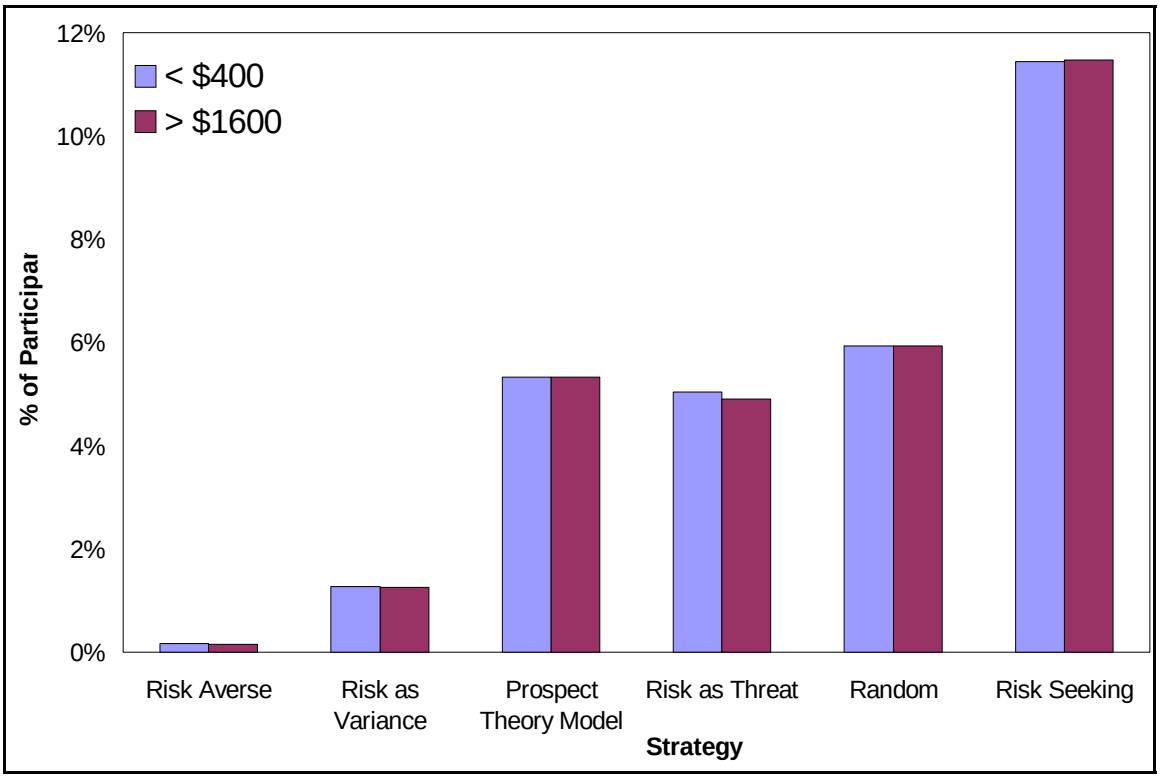

Figure 5: The percentage of the virtual participants for a given strategy found in the extremes of the final outcome distribution. The names of the strategies follow the same naming conventions discussed earlier.

From comparing these strategies, we found that there were systematic differences in strategies based on linear models, and those differences were limited to the amount of variance in the final outcome distribution. The means of these final outcome distributions were all identical, as was the likelihood of ending up in a good place as a bad place within a given strategy. Some of the strategies shared a near identical amount variance, namely the Prospect Theory model, the Risk as Threat model, and the Random baseline condition. However, the similarities between the Risk as Threat model, the Prospect Theory model, and the Random baseline condition existed because the stimulus set had approximately the same number of negative lotteries as positive lotteries. If there were more negative lotteries than positive lotteries, then the Risk as Threat model would

have exhibited more risk-averse behavior and would hence have had a distribution that looked more like the risk-averse strategy's final outcome distribution, while the Prospect theory model would have exhibited more risk-seeking behavior and would hence have a distribution that looked more like the risk-seeking strategy.

For the aspiration-based set, we tested strategies that used an aspiration criterion in determining choice by comparing the current wealth with a specific aspiration. Unlike other strategies, we demonstrated that decision strategies using this, noncompensatory, longer-term aspiration based strategy (shown in Figure 6) created skew in the final outcome distribution, increasing the likelihood of ending up in one tail of the distribution while simultaneously decreasing the likelihood of ending up in the other tail of the distribution.

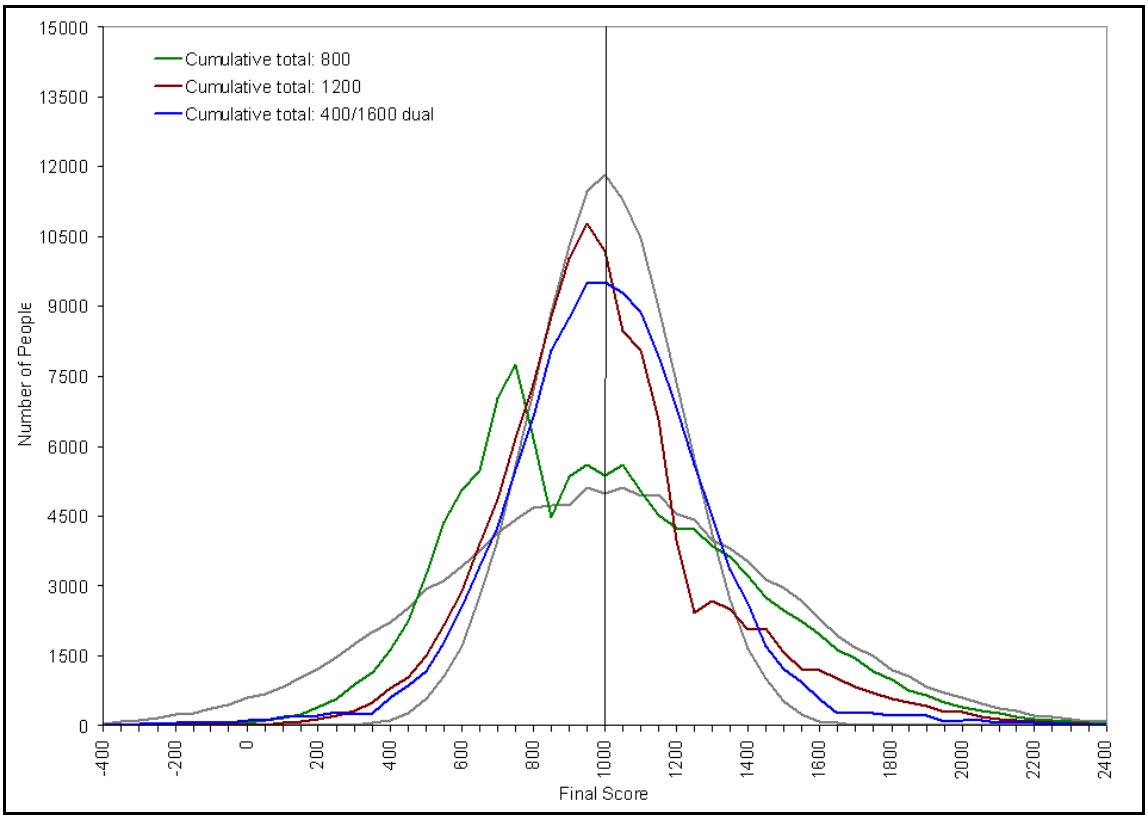

Figure 6: The final outcome distributions for the strategies based on aspiration level criteria. The names of the strategies follow the same naming conventions discussed earlier.

Specifically, for the single aspiration level strategies (denoted 'Cumulative total: 800' and 'Cumulative total: 1200'), when a virtual participant has less than the specific aspiration level (800 or 1200 respectively) as their current total, the decision strategy dictated to act risk-averse until the specific aspiration level was reached, then for as long as that specific aspiration level was exceeded, the strategy dictated to act risk seeking. This causes final distributions to look like the risk-averse strategy distribution on the left side but like the risk-seeking strategy on the right side. Final outcome distributions for these strategies are skewed to the right, such that there were fewer people who ended up very poor and more people who ended up very wealthy. Of course, the positive skew also offsets the median and the mode to the left, meaning that these strategies also

increase the likelihood that you will end up slightly below average. In other words, for a small increase in the likelihood of being slightly less than average, one can substantially decrease chances of being extremely poor and increase chances of being extremely rich. The dual criterion strategy operated such that as long as a virtual participant was between the two specific aspiration values (400 and 1600), the decision strategy dictated risk aversion, and if those values were exceeded, the decision strategy dictated risk seeking.

The comparison of these groups can be seen in Figure 7, which depicts the percentage of virtual participants who ended up at the tails of the final outcome distribution.

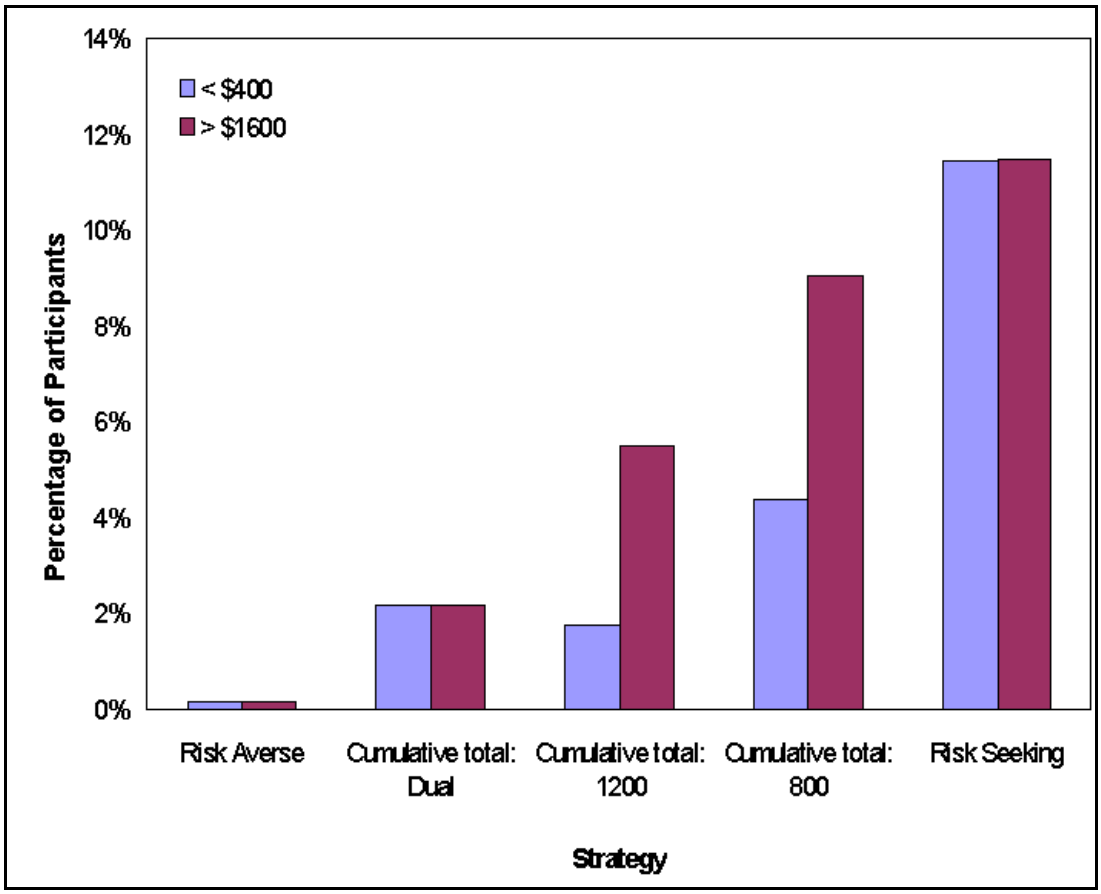

Figure 7: The percentage of the virtual participants for a given strategy found in the extremes of the final outcome distribution. The names of the strategies follow the same naming conventions discussed earlier.

From comparing these strategies, we learn that asymmetries can be created in a final outcome distribution if a long-term aspiration level is used as a criterion in the decision strategy. Of the strategies tested, only those that rely on aspirations can differentially manipulate the long run probabilities of ending up rich or poor.

From the pilot work, we learned that the final outcome distributions for Risk Policy and Lottery-based strategies that use static criteria can only be symmetrical, such that users of those strategies were equally likely over time to end up very rich or very poor, though their risk preferences provided some control over the combined likelihood of landing in the extremes. However, given the use of the long-term aspirations as a

decision criterion, there is the capacity to create an asymmetry in the final outcome distribution. Decision strategies that use decision policies or local, lottery-based criteria as the determining factors for risky choice are limited in their ability to change the likelihood of ending up in a good place over a bad place. However, decision strategies that use contextual or aspiration-based criteria have the benefit of differentially controlling the likelihood of ending up in a relatively good place over a relatively bad place. This pilot work lends itself to the importance of time-dependent criteria, as well as the dynamic systems modeling, which is used to test for time-dependent criteria.

Figuring out precisely how and why an aspiration level decision strategy works is important because finding a point at which there is the "most" skew or the "most" long run benefit may help us figure out when and how actual people might use these strategies. In addition, we expect trajectory-based decision strategies to make an impact in the long run beyond simple lottery-based strategies because trajectory based decision strategies satisfy the conditions of dynamic criteria: They are time-dependent and preferences change dynamically.

Current Simulation Study One Methods

For the current project, the previously outlined simulation methodology has been revamped in a number of ways so as to further investigate the influence of time-dependent criteria that take into account the contextual, historical, and goal-related information of the decision maker. These changes are as follows:

(1) Aspiration levels were more thoroughly manipulated, so as to identify the "optimal" levels of skew for a given simulation environment. In addition, aspiration

levels that occur between two possible current total values were used to reduce distributional "lumps" that are artifacts of our stimuli.

(2) A new phase of strategies that use outcome trajectories as their basis were created and compared. These strategies allow us to evaluate how the dynamic reference points mentioned earlier operate in our simulation. These strategies use information about the previous outcomes to determine their current choice, similar to goal dependency. These outcome trajectory strategies come in two forms.

The first form looks at the previous seven lotteries and makes a distinction with respect to risk preference depending on the number of the outcomes that are good vs. bad.[1] For example, if of the previous seven lotteries, four are the "worse" outcome and three are the "better" outcome, a trajectory strategy would make a choice based on the fact that there is a 'majority' of worse outcomes. This strategy operates without using distance from zero or direction from zero in determining risk preference, and is important because it gives a crude measure for individual effect of outcome trajectory on the final outcome distribution separate from the other influences of reference points.

The outcome trajectory strategies are named based on the virtual participant's inferred interpretation of the future directions for the trajectory. The virtual participants who are using the *Continuation* strategy are inferring from their trajectory that if they are *currently* doing "well" (the trajectory has more "wins" than "losses) that they will *continue* to do well and they attempt to take full advantage by exhibiting risk seeking

[1] Because our simulation uses two-outcome lotteries, one outcome is usually better than the other. Hence "better" outcomes are 'good' relatively speaking insofar as they are better than "worse" outcomes, even though in the absolute sense they may be positive, negative, or zero.

behavior, while if they are currently doing "poorly" (the trajectory has more "losses") they infer that they will continue to do poorly and they attempt to diminish potential future losses by exhibiting risk aversion.

The *Discontinuation* strategy exhibits the opposite inference from the trajectory information. For example, if a virtual participant using the Discontinuation strategy is *currently* doing "well," they infer that they will *not continue* to do well and they attempt to diminish potential future losses by exhibiting risk aversion, while if the same virtual participant is currently doing "poorly," they infer that they will not continue to do poorly and they hence attempt to take advantage of the future gains by exhibiting risk seeking behavior.

The second form of goal-dependent strategies make a distinction with respect to risk preference depending on whether a participant has won or lost money over the previous seven lotteries. Specifically, since each lottery has a specific outcome, the outcomes for the previous seven lotteries are summed, and then risk preference is determined by whether that sum is positive or negative. This is important because it includes the additional reference point information that is left out of the previous incarnation of goal trajectories, so as to allow a direct comparison of the interaction between static and dynamic reference point information.

Using the new decision environments, additional final-outcome likelihood distributions, measures were created and compared for central tendency, variability, and skew, and the percentage of participants that dropped out or "died," or ended up in the high and low extremes of the final outcome distribution.

Materials/Stimuli

Each virtual participant 'saw' a set of 36 monetary two-outcome lotteries. Each virtual participant began the experiment with 200, 1000, or 1800, and the final adjusted expected value for the series of lotteries is 1000. Outcomes of the lotteries accumulate as the virtual participant continues through the study. The lotteries can be positive or negative, and each will have an expected value that ranges from +400 to -400.

Design

This study involves testing strategies using a series of two-outcome lotteries in a Monte-Carlo-style simulation. Each virtual participant is created to follow an assigned algorithm derived from the strategies in Table 1. The measures of interest are the outcomes that virtual participants received based on each trial, the cumulated earnings from trial to trial, and the distribution of final outcomes across a given strategy. In addition, to reduce order effects, four lottery orders were used across all strategies.

Strategies. All the strategies addressed in the preliminary investigation were redone. In addition, the strategies regarding outcome trajectories described in Table 1 were performed and compared.

Table 1: List of Strategy Types used in Pilot Simulations.

Strategy	***Explanation***
Risk-averse	Virtual participants exhibit risk-averse behavior across all lotteries by choosing the less risky option, which reduces variance.
Risk-seeking	Virtual participants exhibit risk-seeking behavior across all lotteries by choosing the more risky option, which increases variance.
Non-systematic, or "Random"	Virtual participants used a non-systematic method to determine risk preference. Randomly chose between riskier and less risky options.
Modest Variance	Virtual participants are willing to accept some but not all of risk. When faced with lotteries that start with a high initial variance, they choose the less risky option, and when faced with lotteries that start with a low or moderate initial variance, they choose the riskier option.
Prospect Theory	Virtual participants act in accord with the S-shaped value function described in Prospect Theory. When facing a 'loss' lottery, participants chose the riskier option. When facing a 'gain' lottery, participants choose the less risky option. When facing a lottery with mixed outcomes, participants exhibit loss aversion and thus choose the less risky option.
Risk As Threat	Virtual participants avoid risks when they are a threat, and only exhibit risk-averse behavior when faced with a potential loss. When facing a 'gain' lottery, participants choose the riskier option. When facing a 'loss' lottery, participants choose the less risky option. When facing a lottery with mixed outcomes, participants exhibit loss aversion and thus choose the less risky option.
Cumulative Total: Aspiration	Virtual participants act based on the amount of money they have accumulated so far. If the virtual participant's cumulative total is below the aspiration value, they choose the less risky option, whereas if the virtual participant's cumulative total is above the value, they choose the riskier option. Proposed aspiration values: 775, 975, 1025, 1225. In addition, we will include one asymmetric dual aspiration, where if a participant has less than 375, they exhibit risk seeking. The reverse, in which a participant's cumulative total being below a given aspiration value elicits risk seeking behavior and a participant's cumulative total being above a given aspiration level elicits risk aversion, will also be evaluated at all of the proposed aspiration values.

Strategy	***Explanation***
Goal Trajectories, Number of Outcomes	Based on the number of better or worse outcomes for the previous seven lotteries, if there are more of the better than worse outcomes received, one of the risk policies is exhibited, while if there are more of the worse than better outcomes received, the other risk policy is exhibited. "Sure thing" outcomes, in which both outcomes of a given lottery are the same, were randomly attributed as either better or worse. *Continuation* infers that if things are going well (a majority of better outcomes), they will continue to go well and so risk-seeking should be employed, while *Discontinuation* infers that if things are going well, they will not continue to go well, and so risk-aversion should be employed.
Goal Trajectories, Cumulative Values of Outcomes	If the overall change in current total for the previous seven lotteries is positive, the higher option is improved simulating risk-seeking behavior while if it is negative, the lower option is improved, simulating risk-averse behavior. If equal to zero, the participant exhibits risk aversion.

Note. Strategies were named based on their similarity to current theories and ideas in human decision making literature. Prospect theory was developed by Kahneman and Tversky (1979).

Orders. Two randomized orders of 36 two-outcome lotteries were created. Then these two orders were reversed (the first lottery in the initial order became the last lottery in the new order, the second lottery in the initial order became the second to last in the new order, etc.) to create two completely new orders, making a total of 4 orders.

Measurements. Using Excel, two databases were created for each simulation strategy: The first database logs the outcome value of each virtual participant at each lottery and the second database shows the accumulation of outcome values across the lotteries completed thus far.

Participants

Forty thousand virtual participants were created to simulate each strategy condition. Ten thousand participants were run through each of the 4 orders for each of the 12 strategies for a total of 480,000 virtual participants.

Procedure

The procedure applied to the current simulation methodology is the same as the procedure used in the pilot simulation discussed earlier.

Study One Analysis of Simulations

The simulations were analyzed by comparing the outcome distributions after 36 trials, including: measures of central tendency, variability, and skew; the percentage of participants that end up in the high and low extremes of the final outcome distribution; and, where applicable, the percentage of participants who "went broke." First, additional findings pertaining to aspiration level strategies are addressed. Then, any novelty that can be attributed to the outcome trajectory strategies is addressed, followed by a step-by-step explanation of how specific changes to the decision environment affect different types of strategies (risk policy, static lottery-based, aspiration level-based, and trajectory-based).

The Aspiration level Criterion: A Thorough Investigation

While investigating aspiration-based or 'cumulative total' strategies, we looked to answer two distinctly different questions with the current simulations: (1) Why does skew occur when using a cumulative total strategy? and (2) How can we 'set' and aspiration level so as to achieve the maximal level of skew?

The answer to question one may be most easily answered by recognizing that the cumulative total functions over time as the current measure of success. In this sense, the cumulative total can be seen as a running tally of a virtual participant's progress thus far in the task. As a result, making decisions based on cumulative wealth allows participants

to manipulate variability differently based on where they consider themselves doing comparatively good or bad with respect to the "average" or expectation. However, participants do not necessarily have to use what they *expect* as their aspiration level, they may just as well use some external constraint (e.g., "my rent is $500, so regardless of what I expect, I need *at least* that much.")

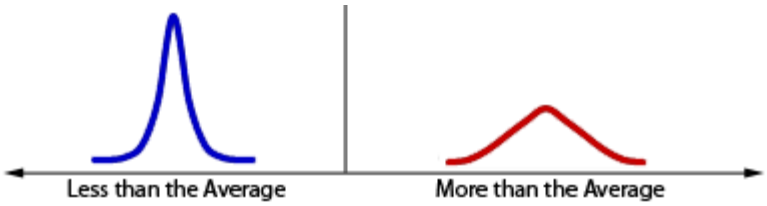

Figure 8: Theoretical Example of how distributional variability is manipulated with respect to current progress.

For instance, if thus-far in the task, your "current total" is comparatively quite low, you might consider that because you want the highest opportunity of getting at least the mean, you would decide to taking fewer risks, or exhibiting the risk-aversion strategy (represented by the blue line in figure 8). When doing comparatively well with a high current total, you might try to take advantage of the potential to achieve a very high amount by taking more risks, or exhibiting the risk seeking strategy (shown in red). *Hence, a sort of "skew" is created as a result of manipulating distributional variability depending on the rough estimate of current position on the final outcome distribution.*

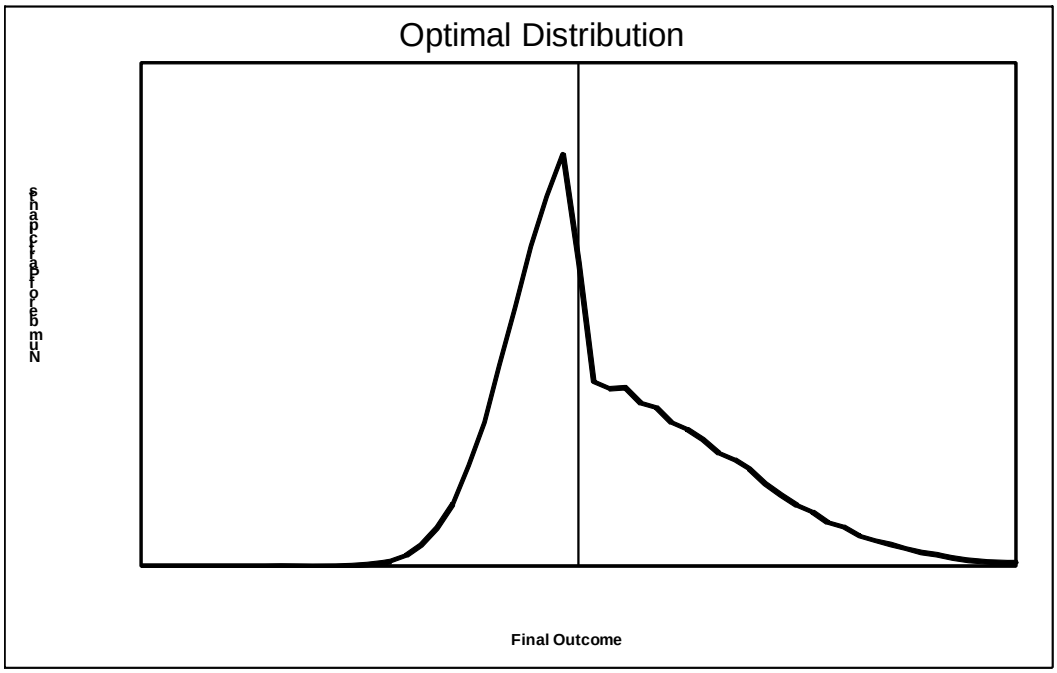

Figure 9: Rendering of the "optimal" skewed distribution. Variability is minimized when you consider yourself to have less than average and maximized when you consider yourself as having more than average based on the goals asserted by Schneider and colleagues (2007) to be the focus of real world decision making.

Schneider and colleagues (2007) suggests that if people knew they were going to do worse than the average, they would form a goal that attempts to increase the likelihood of getting as close to the average as possible. In addition, if people knew they were going to do better than the average, Schneider asserts that they would form a goal that attempts to maximize the potential to get as far away from the average as possible. As a result, a pattern emerges such that one minimizes risk when one would interpret themselves as doing worse than the average (risk aversion) and maximizes risk when one would interpret themselves as doing better than the average (risk seeking). Because the risk averse and risk seeking strategies each represent a particular risk manipulation technique (always safe choices or always risky choices respectively) within the constraints of the

decision environment[2], combining half of each together across the mean should create a representation of the optimal skewed distribution that would satisfy both of these goals.

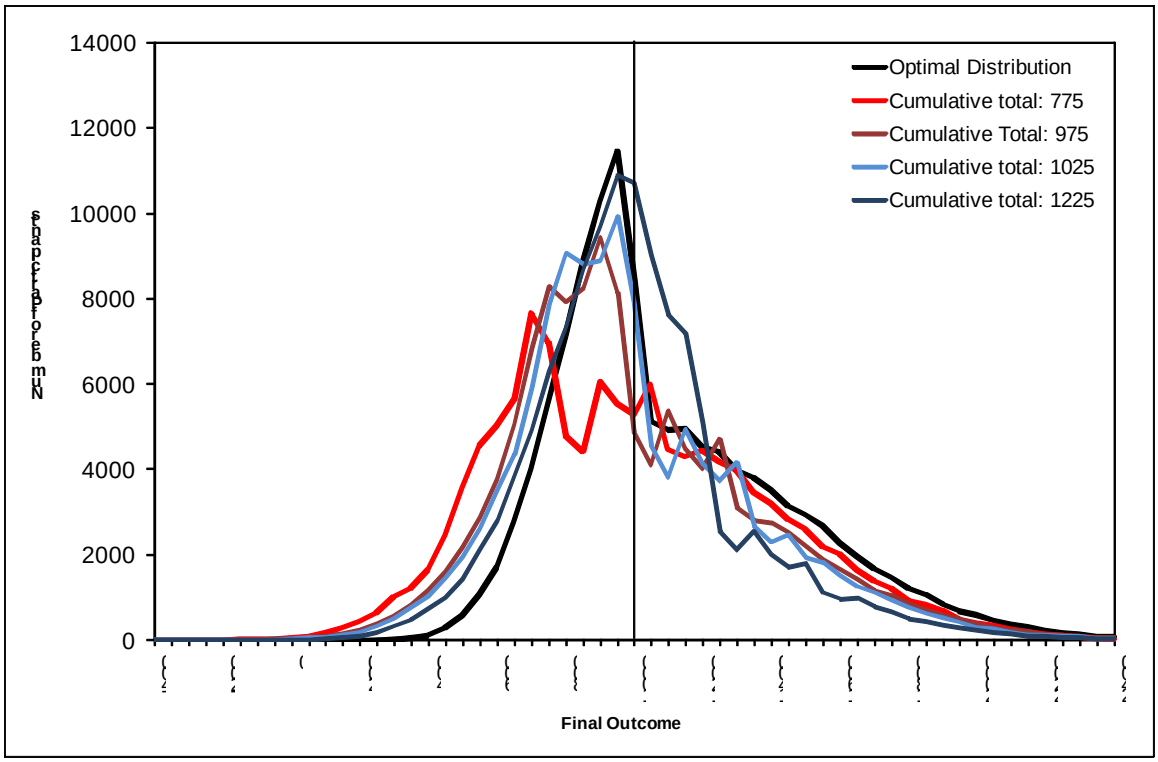

Figure 10: Comparison of different aspiration level strategy final outcome distributions with the optimal skewed distribution under pilot (36 trials) conditions. The aspiration level strategies are named after the cutoff point used to switch from risk aversion (when current total is less than the given value) to risk seeking (when current total is more than the given value).

As shown in Figure 10, the aspiration level strategies are found to look similar to the optimal distribution (also shown). In addition, if one uses the mean or overall expected value of the lottery series (in our simulations, 1000) as one's aspiration level, a distribution of final outcomes is formed that is comparatively the most similar to the

[2] Total lottery distributional variability is determined by a multitude of factors, such as the range of expected values for individual lotteries, the range of differences in the size of ticket values, the total number of lotteries, etc.

optimal skewed distribution. This does not suggest that using the expected value as the aspiration level is necessarily optimal in its own right, since individual preference may still dictate overall tendencies toward risk, in additional to external goals playing an integral role in aspiration formation.

For instance, even though using the expected value as the aspiration level "cutoff" creates the most skew for the distribution, an individual might set their aspiration level "cutoff" as a small margin more than what's expected so as to still tend towards risk aversion, since the larger the aspiration level is compared to the expected value, the more the distribution of outcomes tends toward the risk averse strategy. As an aspiration level becomes unattainably large, a participant would always have a current total that is less than their aspiration level, and hence the final outcome distribution would become the risk aversion final outcome distribution, whereas if the aspiration level is set as always attained (or otherwise unreasonably low), the distribution of final outcomes becomes the risk seeking strategy distribution.

As a result, having information about "what is expected" in the decision environment is helpful in achieving the most effective use of the aspiration level strategy. Without a reasonable expectation, an aspiration level may end up having been set too high, which would result in a predominance of risk averse behavior, or too low, which would result in a predominance of risk seeking behavior. If your goals coincide with those posited by Schneider and colleagues (2007), then you should use an aspiration level as we have described it, as it will create distributional asymmetry in a manner that is consistent with those goals.

New Phase of Strategies: Outcome and Cumulative Trajectories

Even though aspiration levels can generate asymmetry and achieve an outcome distribution that looks similar to the optimal skewed distribution, they are limited in their scope when it comes to the real world. A fixed aspiration level cannot account for changes in the overall direction of experiences. For example, if one sets an aspiration level, and then one's environment systematically fluctuates between doing well for a while (better than average), then doing poorly for a while (worse than average), then doing well for a while again, one's aspiration level strategy would only suggest risks be taken with respect to how much one *has*, not to the fluctuations in the environment. While this is still perfectly reasonable, it is not necessarily optimal, as the main goal is to take risks when one's situation is evaluated as better than average, and there is obviously something systematic going on in a time-dependent manner not accounted for by aspiration levels. The problem is that aspiration levels are "fixed"; they aren't sensitive to changes in environmental *trajectory*, only changes in *cumulative outcomes*.

In part to account for the fixed nature of aspiration levels, outcome trajectory strategies, which do not have a fixed value for risk preference distinctions, and cumulative trajectory strategies, which focus on changes to the cumulative total instead of the actual value, were investigated. A trajectory focuses on directly experienced information from the recent past to make choices about the immediate future (Schneider & Barnes, 2003). This differs from aspiration level strategies because in most cases there is no fixed cumulative value being used by the participants; only recent salient information about the direct past few events. The criterion for action with respect to risk

in an outcome trajectory relies only on outcomes evaluated as “good”, “bad”, “better,” or “worse” over a particular interval. As a result, information about all of the previous performance is not necessarily required.

Refer to p. 26 and 27 to see the specifics of how outcome trajectory strategies and cumulative trajectories work.

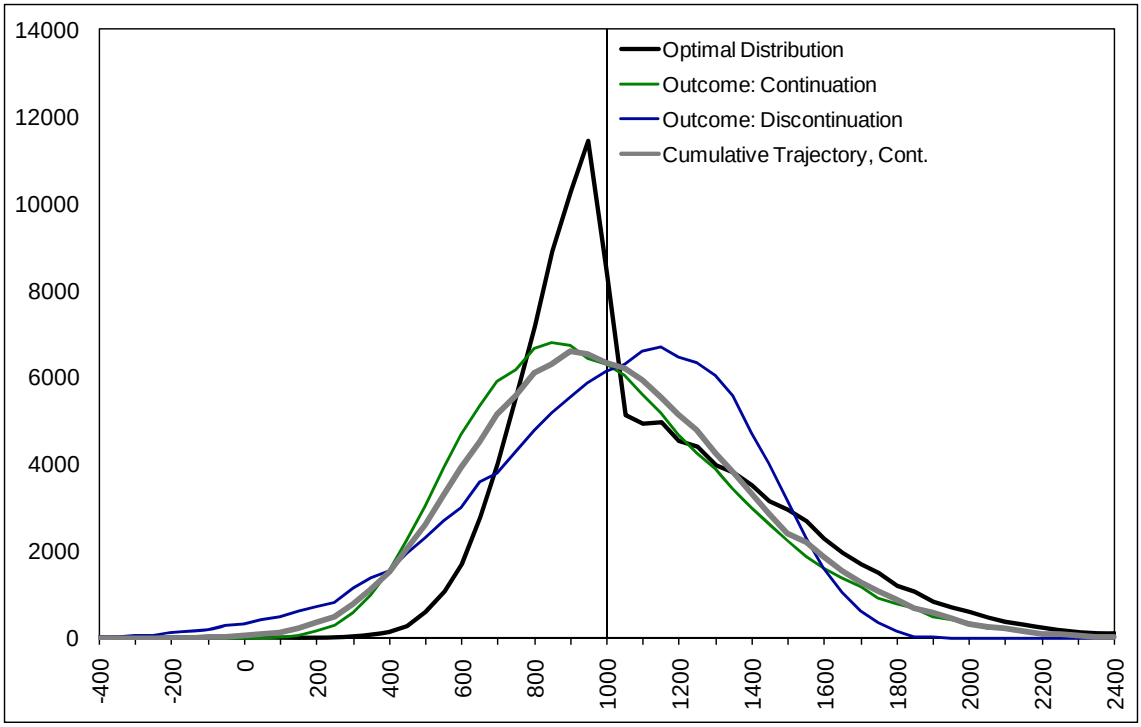

Figure 11: Comparison of different outcome and cumulative trajectory final outcome distributions with the “optimal” skewed distribution under pilot conditions. The number of previous trials used is seven unless otherwise stated.

As can be seen in figure 11, using an outcome trajectory strategy or a cumulative trajectory strategy can generate skew in the final outcome distribution such that one is more likely to end up at one end of the final outcome distribution over the other. The shape of these trajectory strategies is mesokurtic (similar shape as a normal distribution) while the shape of the aspiration levels is leptokurtic (higher probability of ending up at the mean and at extreme values compared to the normal distribution).

Why there is Skew and the Insensitivity to Expected Value. Trajectory decision strategy outcome distributions are skewed because, by evaluating a subset of previous outcomes as "better" than average or "worse" than average and then looking for a majority, one is provided a rough estimate of progress thus far in the task, much like the current total provides a rough estimate of progress as it is used with the aspiration level criterion.

Outcome trajectory strategies do not require that you be able to add up all the previous outcomes into a statistic that represent all the previous outcome information (current total), unlike aspiration level decision strategies. As previously stated, the final outcome distributions for aspiration level decision strategies become more or less skewed as the aspiration level cutoff point becomes closer or further away from the overall expected value of the lottery series (1000). These trajectory strategies do not use the actual current total as the determinant for risk preference, but rather *changes* or *perceived changes* in performance as the determinant for risk preference, so the expected value does not need to be known to effectively use a goal-trajectory based decision strategy.

The Direction of Skew for a Trajectory Strategy. The direction of skew (left or right) depends on the behavior exhibited by the decision maker when a majority of better/worse outcomes is acquired. When a majority of better outcomes is experienced and risk seeking is exhibited, skew follows the same direction as the aspiration level criterion. However, when risk aversion is exhibited during a majority of better outcomes being experienced, skew goes in the opposite direction. In addition, cumulative trajectories can be seen here as less skewed than outcome trajectories.

The skew changes direction between the two outcome trajectory strategies because behavior with respect to "how well you are doing so far" is different between the two strategies. For example, if when using the Continuation strategy, a decision maker experienced a majority of "better" outcomes, the strategy suggests that since the decision maker would consider themselves as doing well and therefore suggest risk-seeking behavior, which follows similarly to the goals laid out by Schneider and colleagues (2007); the skew for the Continuation strategy follows in the same direction as the aspiration level strategies, since risks are being taken at similar times relative to one's evaluation of current progress (e.g., "when I evaluate my progress as above average, I am risk seeking"). However, if you were using the Discontinuation strategy and you experienced a majority of "better" outcomes, you would then exhibit risk aversion, and hence skew goes in the opposite direction.

Why Cumulative Trajectories differ from Outcome Trajectories. For cumulative trajectory strategies, a similar evaluation of situated progress in the task is taking place, however the element being evaluated (change to cumulative total) is heavily influenced by the fluctuation in the values of the individual lotteries. For instance, if one of the five previous lotteries had an extremely low expected value (for example, if the previous five outcomes were -50, -450,150, 50, 0) or if the expected values for the previous five lotteries were all of a similar direction from zero (for example, if the previous five outcomes were 100, 50, 150, 0, 50), then the changes in cumulative total are not necessarily representative of changes in relative success in the task. Skew seems to only present itself when a decision strategy uses an accurate measure of performance, not

simply overall changes in cumulative value due to changes in the static task environment. Cumulative trajectory strategies are problematic because they are overly sensitive to order effects and extreme expected values in certain specific instances like the above mentioned examples. However, that is not to say there won't be instances where cumulative trajectory accurately gauges relative progress in the task, and hence skew is still present, however it is reduced compared to outcome trajectories.

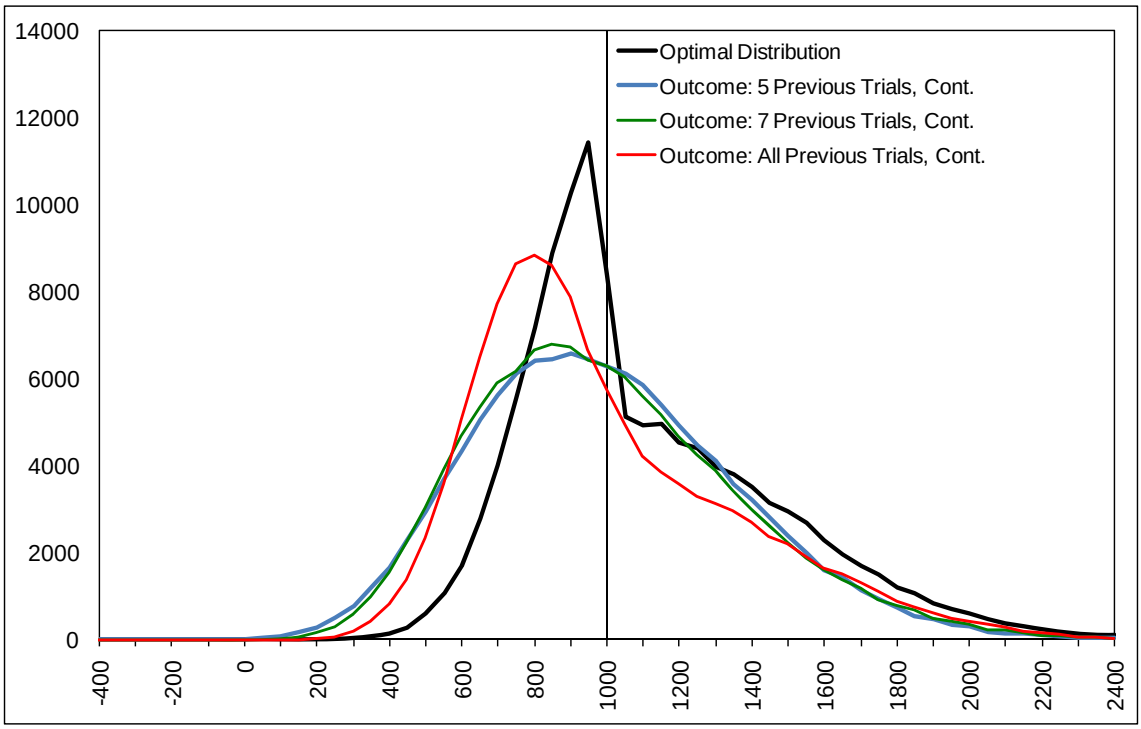

Figure 12: Outcome Trajectories using different number of previous outcomes as determinants for risk preference.

The number of Previous Outcomes being Evaluated. Figure 12 compares different versions of the Continuation outcome trajectory strategy. Each version of the Continuation strategy uses a different-sized subset of previous outcomes from which it attempts to determine a majority. For the strategy labeled "5 previous trials," the

decision strategy only evaluated the five trials that immediately preceded the current trial to search for a majority (so in this case, if there were 3 or more of the "better" outcomes). "7 previous trials" only used the immediately-preceding 7 trials, and all previous trials used all the previous trials. As can be seen in figure 12, the skew in the final outcome distribution is greater for the decision strategies that use more of the previous outcome information. For example, if instead of only looking at the majority of the previous seven outcomes, I were looking at the majority of the previous nine outcomes, the final outcome distribution would be further skewed. If one were to use fewer of the previous outcomes to establish a majority of "better" over "worse" outcomes, one would see a reduction in the amount of distributional skew.

In addition, by looking at all the previous outcomes (shown in figure 12 above), the distribution becomes maximally skewed, because all the previous outcomes are being taken into account. As with the aspiration level decision strategies, the more *accurate* the information about previous and current performance (e.g., closer approximation to what's expected[3]), the more effectively a decision maker can choose to be risk-seeking or risk averse consistent with their goals about where they end up relative to what they expect (e.g., Schneider, 2007).

[3] The accuracy of previous information for outcome trajectories is relative to the "expectation" of receiving the "better" of the two outcomes equally often as receiving the "worse" of the two outcomes.

Study One Results Summary

After further investigation of the aspiration level decision strategies, we established an aspiration level's sensitivity to the expected value of the series of lotteries. Aspiration levels require information about "what is expected" at the end of the lottery series (overall expected value). The more accurate the information about "what is expected" is to the overall expected value for the lottery series, the more skew can be generated in the outcome distribution.

In addition, we have created decision strategies that use the previous outcomes and changes in cumulative total as determinants for risk preference, which are insensitive to expected value, but are also sensitive to one's ability to remember previous events. Outcome trajectory strategies, which establish a majority from a subset of previous outcomes evaluated as "better" or "worse" compared to the alternative outcome, can skew the distribution of outcomes, though less-so compared to aspiration level strategies. Cumulative trajectory strategies, which use the changes in cumulative total across a subset of previous lotteries, can also skew the distribution of outcomes, though less-so compared to outcome trajectory strategies and aspiration level strategies.

As the subset of previous outcomes being used in a trajectory strategy is made larger, the amount of skew that can be generated in the distribution becomes larger as well. Aspiration level decision strategies and trajectory decision strategies are in essence using a similar means to impact the outcome distribution; some measure of performance relative to "what is expected" is used to switch between risk-seeking and risk-averse

behavior when current performance is evaluated as either “better than expected” or “worse than expected.”

Study Two: Test for Parameters of the Decision Environment

It is presumable that by changing the environment in which decisions take place, the effectiveness of certain decision strategies may change. For example, how will different decision strategies be affected by increasing the number of lotteries in the series, removing certain kinds of lotteries, or introducing a real-world noncompensatory component? In an attempt to address these concerns, we present several variations on the previously presented methodology to investigate how the effectiveness of decision strategies may change under certain circumstances.

Study Two Methods

We suggested three specific adaptations to the decision environment used in the previous simulation study to investigate how subtle changes to the decision environment might affect the performance of different decision strategy types.

(1) 72 trials were used instead of 36 in an attempt to eliminate anomalies in the final outcome distributions. Also, the effectiveness of trajectory-based strategies is investigated.

(2) In an attempt to introduce a non-compensatory real-world component, all of the decision strategies were re-tested under the constraints that if a participant fell below a certain wealth threshold (went broke), they no longer accumulate any more wealth (equivalent to dying).

(3) In order to examine the effects of each strategy in an environment similar to the experimental conditions in which Prospect theory model and other models have been tested, a version of the decision environment was simulated using decisions that were either entirely riskless or very risky.

Unless otherwise explicitly stated, all materials, orders, valences, series lengths, simulations types, and procedures are the same as in Study 1.

Study Two Analysis of Simulations

An Examination of Trial Series Length

When the total length of the trial series was increased from 36 trials to 72 trials, there was little change in any of the strategies. This parameter for decision simulations can be thought of similarly to increasing the 'n' for a sampling distribution in inferential statistics. By increasing the number of trials each participant goes through and holding all else equal, it is a transition from one sampling distribution to another more representative sampling distribution. The more representative sampling distribution makes decision strategies more normally distributed. As a result, risk policies and static lottery-based strategies remained relatively unchanged, aside from appearing more normally distributed in shape.

However, should a decision strategy use the number of previous outcomes (as with the trajectory strategies) or make some other calculation based on overall distributional variability (as with aspiration level strategies), there are likely to be other changes in distributional shape.

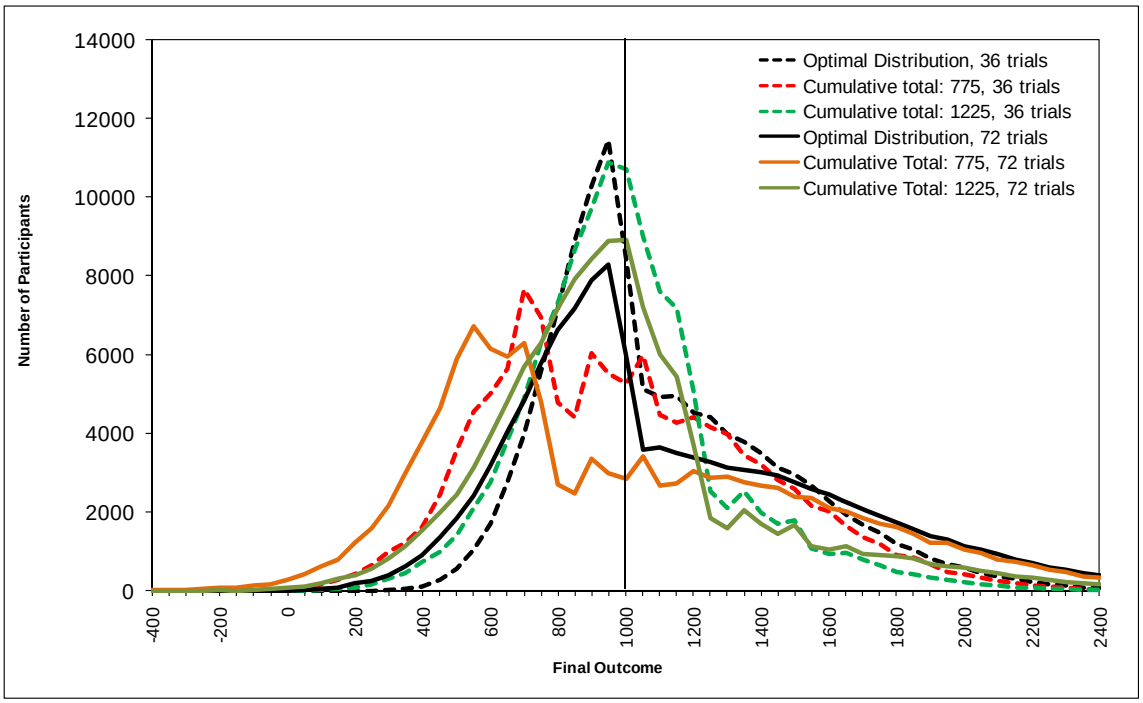

Figure 13: Comparison of 36 trial lottery distributions and 72 trial lottery distributions for aspiration level strategies.

The median and mode values for the aspiration level strategy final outcome distributions were further skewed roughly $150 more to the right compared to 36 trials. Aspiration-based strategies with 72 trials are also much more leptokurtotic, resulting in a higher likelihood at the mean and in the extremes. Even though there were more opportunities for virtual participants to reach intermediate final outcomes, the distributions for the 72 lottery series do not appear to be much smoother. Because there are more trials with which to vary distributional variability based on cumulative total, the skew is likely to increase just as a result of the afforded opportunities. However, the skew that is added based on increasing this parameter is limited. If trial length was extended infinitely (as with a continuous probability distribution), the aspiration level

strategies would look like some variant of the optimal final outcome distribution, with different amounts of skew depending on their "cutoff" values.

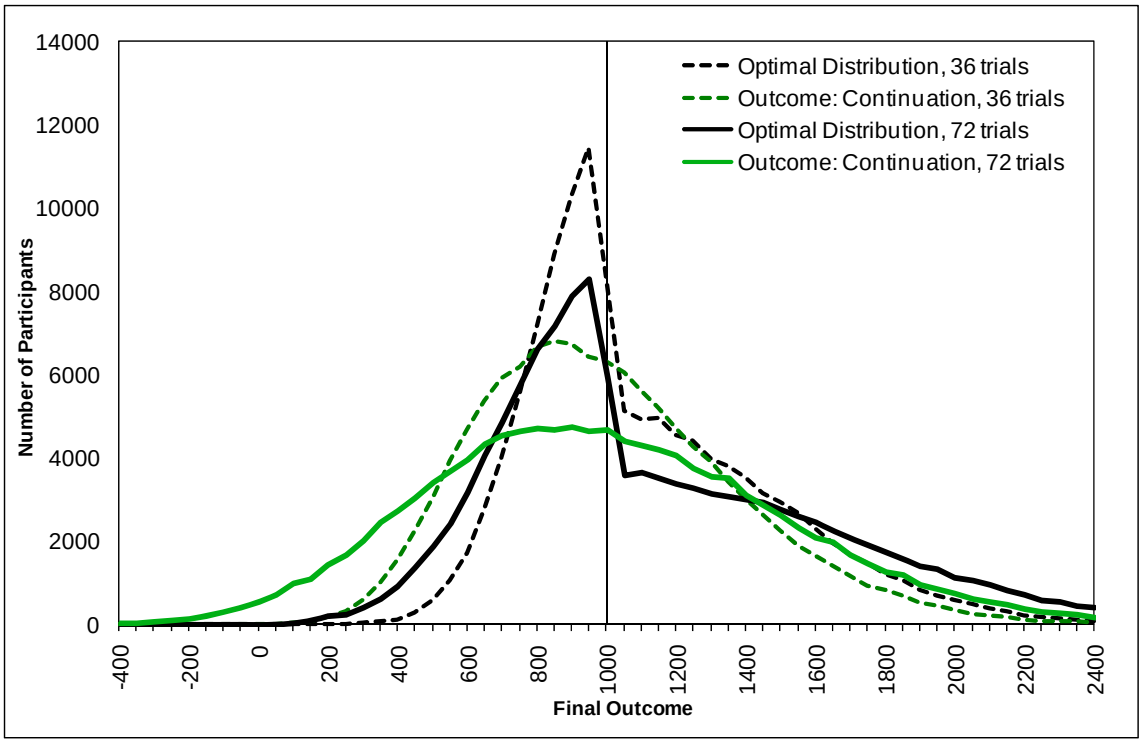

Figure 14: Comparison of 36 trial lottery distributions and 72 trial lottery distributions for trajectory strategies.

However, goal-dependent/trajectory strategies, shown in Figure 14, lost a substantial portion of skew, mainly because the subset of seven previous lotteries which were used to evaluate progress now represented a smaller percentage of the total trials, and hence were less reflective of total progress in the task. The functionality of a trajectory strategy with limited information about previous outcomes (e.g., limited to only the previous seven outcomes) is such that the more previous information you can evaluate (your limit) compared to the total amount of previous information (the lotteries series length) the more accurate your derived evaluation of your current progress relative to the "mean" or average participant.

The Implications of "Going Broke"

The percentage of participants who "went broke" is shown in Figure 15. The risk aversion policy had the fewest number of participants drop out and the risk seeking policy had the largest number of participants drop out. Other static strategies had participants drop out relative to their overall riskiness. Because the random, Prospect Theory, and Risk as Threat strategies all have roughly the same amount of final outcome distributional variability in this instance, it only makes sense that roughly the same percentage of participants would drop out of the study for those three strategies. There are, however, slight differences between the random, Prospect Theory, and Risk as Threat as the result of simple order effects.

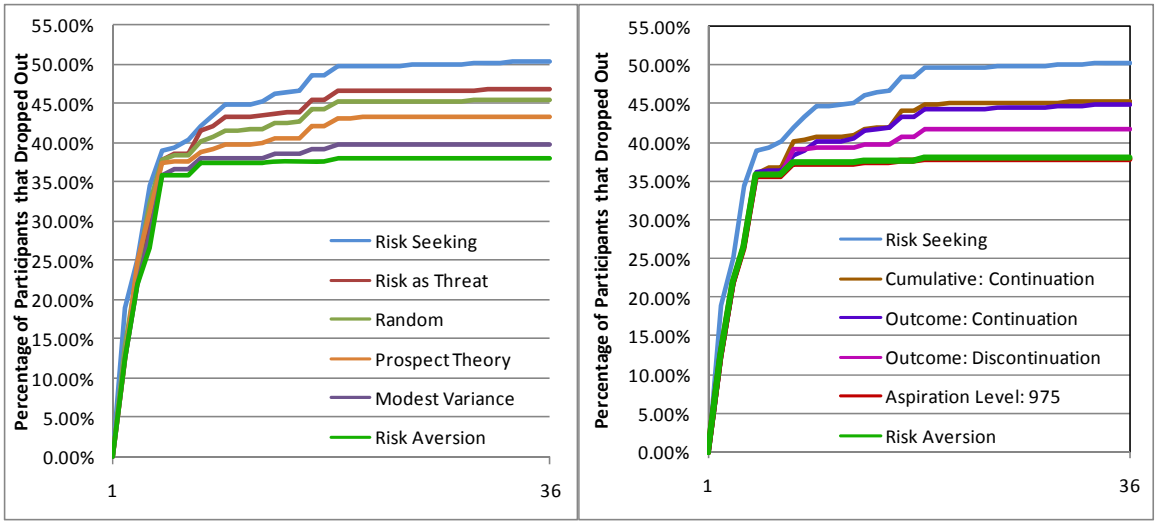

Figure 15: Percentage of participants who dropped out of the study (via reaching zero) for each static strategy (left) and dynamic strategy (right).

However, aspiration level strategies show a strong benefit in this decision environment, with a large reduction in the percentage of participants who drop out, as shown in figure 15. It is important to note that the aspiration level criterion as a measure of progress is sensitive to the distance of the current total to zero, while outcome

trajectory strategies are insensitive to one's current total. Hence, outcome trajectory strategies showed no benefit over static strategies under these conditions. Also, cumulative trajectory strategies use *changes* in cumulative total as the criterion, and hence cannot take into account information about what the actual cumulative total *is*, but only how it has *changed*. As a result, it is understandable that the cumulative trajectory strategy shows no improvement compared to other trajectory strategies or static strategies.

Riskless versus Very Risky Lotteries

The next change in the decision environment involved removing from the choice set all the lottery pairs that did not include a "sure thing" option, in addition to doubling the difference in the ticket separation values. This was done in an attempt to approximate the "riskless" choice options used when for the initial proposition of Prospect Theory (Tversky & Kahneman, 1981).

For example, if the lottery pair included a 50/50 chance between $100 and $200 or a 50/50 chance between $50 and $250, it was excluded from this manipulation. However, if the lottery pair included a 50/50 chance between $100 and $200 or a sure thing of $150, all values were doubled, making the new lottery choice between either a 50/50 chance of $200 and $400 or a sure thing of $300. Because there were both positive and negative lotteries being doubled, the expected value remained the same.

When the lottery choice set was limited to a choice between lotteries that were either riskless or very risky as explained previously, risk policies showed a vast change. For the risk averse strategy, all virtual participants ended with a final outcome that was

equal to the mean of the distribution (since they always selected the riskless choice) and for the risk seeking strategy, virtual participants' final outcomes were more spread out, due to the increase in total variability to the decision environment. Lottery-based strategies based on valence showed relatively no change, while the decision strategy that uses the amount of ticket separations (modest variance) became akin to a risk policy, since there was only one type of inter-lottery variation.

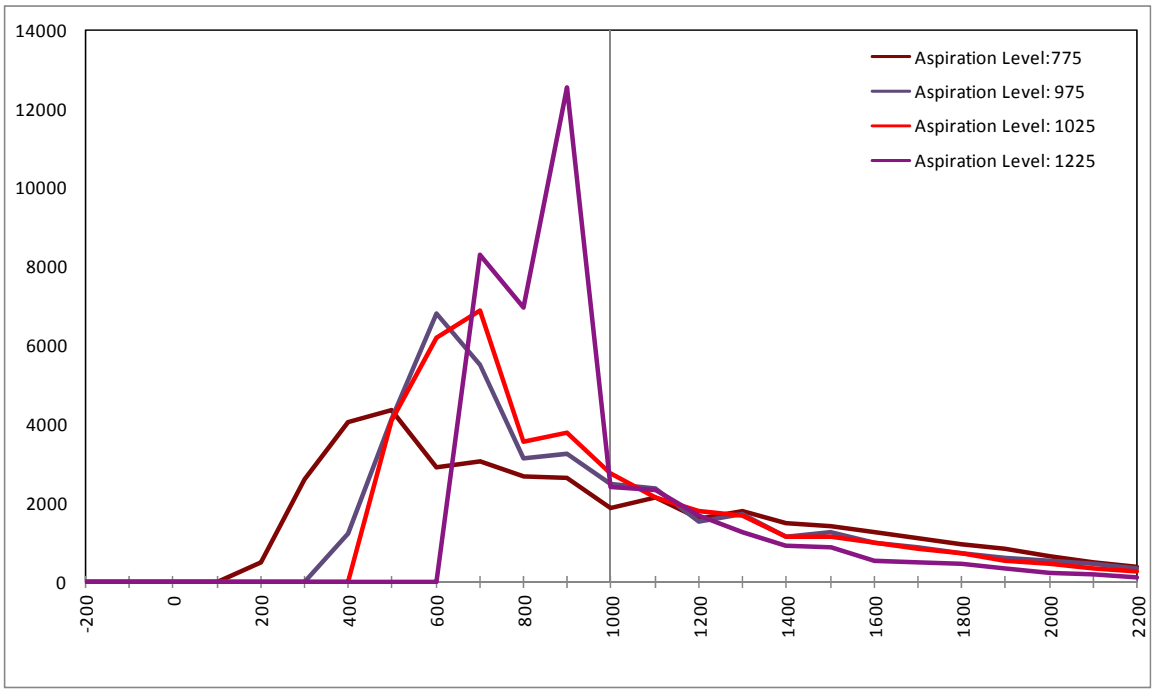

Figure 16: Aspiration level strategies for riskless v. very risky lottery set. Note that there are only 40,000 virtual participants per strategy, one-third the participants compared to previous outcome distributions.

Aspiration-based strategies showed an increase in skew, since an increase in inter-lottery variability (lotteries were made to be more risky) meant that changes in to the cumulative total were more meaningful as a gauge of progress in the task.

Outcome trajectories, however, are ineffective in the face of riskless outcomes, because there is no way to extrapolate meaningful information. For instance, if I am

offering you a choice between two sets of two outcomes with equal probability, the first set consists of 5 dollars or 15 dollars while the second set consists of 10 dollars or 10 dollars, if you choose the second set, there is no meaningful way to differentiate getting one of the 10 dollar outcomes as better or worse than the other 10 dollar outcome. As soon as a majority of riskless options has been chosen, the decision strategy has no way of distinguishing a majority of better-worse outcomes, unless there is a stochastic method (flipping a coin) which would lead one to tend back towards risk seeking behavior.

Study Two Results Summary

Under decision environments with different characteristics or conditions, such as longer trial lengths, non-compensatory dropping out conditions, and changes in the availability of intermediate risk (as in the riskless v. very risky environment), there are advantages and disadvantages for each type of decision strategy, but especially for dynamic decision strategies like the aspiration level strategies or the goal trajectory strategies. When a lottery series of 72 trials is used instead of 36 trials, static decision strategy outcome distributions are found on the whole to appear more normally distributed, while aspiration level decision strategy outcome distributions are more leptokurtotic.

When a non-compensatory drop-out component (dropping out of the study) is introduced, the advantage of one static strategy over another is directly related to the amount of overall final outcome distributional variability (less variability leads to fewer virtual participants "going broke"). However, by skewing the final outcome distribution via a dynamic decision strategy, it is possible to capitalize on the advantages of static

strategies under different non-compensatory constraints. Dynamic strategies such as aspiration level strategies show advantages for this non-compensatory component without simple differences in final outcome distributional variability; the same number of participants drop out of the study for the aspiration level decision strategy as the risk averse strategy.

Under conditions similar to the initial evaluation of Prospect Theory (Tversky & Kahneman, 1981), where no intermediate risks are present but all risks are markedly larger, risk-averse behavior leads to certainty with respect to the final outcome, risk-seeking behavior leads to a spread out final outcome distribution, and other static strategies still appear entirely symmetrical. Aspiration level strategies capitalize on the advantages of having markedly larger risks. Outcome trajectory strategies are limited in their effectiveness without intermediate risks.

In the real world, decision-making takes place under a myriad of different contexts; it becomes increasingly difficult to understand which aspects of the decision environment are most important in determining strategy formation. Based on our observations of simulated environments, aspiration levels show a clear advantage in many of the contexts where static strategies show no influence on final outcomes. Hence we used an empirical test to determine if one aspect in particular (cumulative wealth) would be used as a determinant for risky choice by actual participants.

Study Three: Empirical Investigation of Interaction between Situation and Context

In addition to the simulations, this project includes an empirical investigation to elucidate which strategies might come closest to what people actually do. First, I will address previous empirical work pertinent to the current approach. Then, the current empirical test is outlined, followed by a discussion of the various analyses and comparisons used for the empirical test.

Pilot Empirical Work

In addition to the simulations on risky choice, Schneider and colleagues have looked at two different tasks to examine how people's risk preferences differ. Schneider (2002) designed a decision paradigm mentioned earlier that may be preferable to the standard risky choice paradigm because it makes goal trajectory information more available to the participant. To see how actual strategies may differ, the standard risky choice paradigm and the new goal-trajectory paradigm (ticket transfer task) are directly compared.

In the passive "Choice" task, participants are shown two static lotteries and are asked to simply choose which of the two lotteries they prefer to play. In the active goal-trajectory paradigm (called the "Move" task from here on), participants are given a single lottery and are instructed that they are about to play the lottery. Before playing, their task is to improve the lottery in one of two ways, both of which ultimately lead to the same choices in the Choice task. In this paradigm, participants are either instructed to actively

increase or decrease the amount of risk they are exposed to (Figure 12) if they are in the move condition, or they are subjected to the standard passive choice task in which participants choose between two lotteries that vary in the amount of risk (Figure 13).

The active goal seeking paradigm was invented by Schneider to "situate" decision makers in a given decision environment. With passive choice, people are just looking at two different options, and there is no context with respect to how these lotteries relate to their goals or activities. However using the Move task, participants are given context about the choice, and are asked to make a change in their current situation to influence future outcomes. Schneider's Move task combines aspects of situated cognition by attributing a decision context and then allowing participants to exert some control over the potential outcomes.

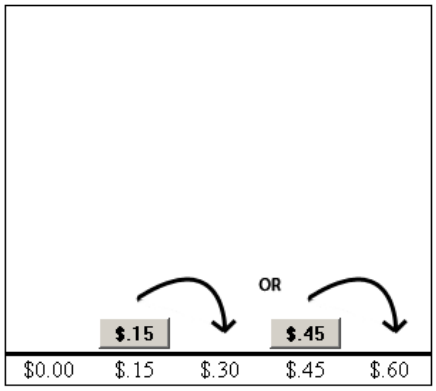

Figure 17: Ticket Transfer Paradigm-Move Example Diagram. In Ticket Transfer paradigm, participants are asked to actively change the amount of risk in a given lottery. The arrows are meant to represent the possible ticket moves.

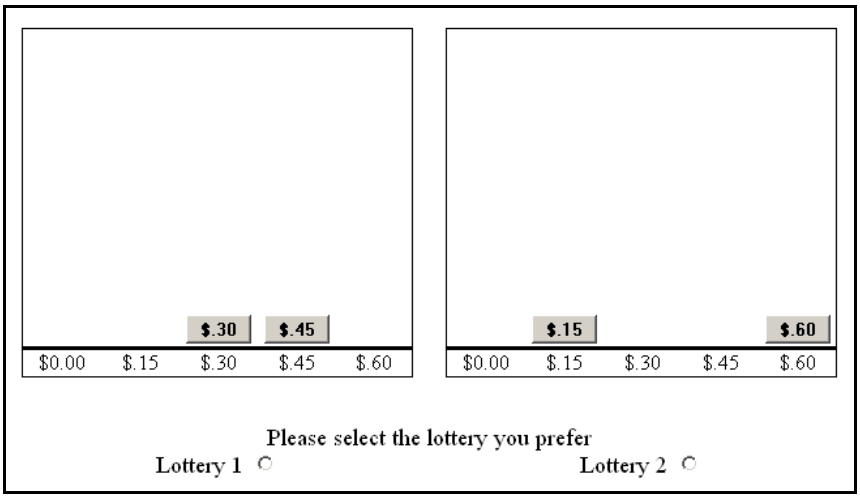

Figure 18: Ticket Transfer Paradigm-Choice Example Diagram. This is an example of the Ticket Transfer paradigm task that calls on participants to passively choose one of the two possible lotteries for a given lottery pair.

In her first investigation of the Ticket Transfer paradigm phenomenon, Schneider and colleagues (2005) compared risk preferences for lotteries that were positive and negative using the Choice and Move tasks. Using the Choice task, Schneider replicated the preference patterns predicted by the S-shaped value function of Prospect Theory. Specifically, when both possible outcomes were monetary gains, participants were more likely to choose the less risky choice option, and when both possible outcomes were monetary losses, participants were more likely to choose the more risky choice option (shown in Figure 14).

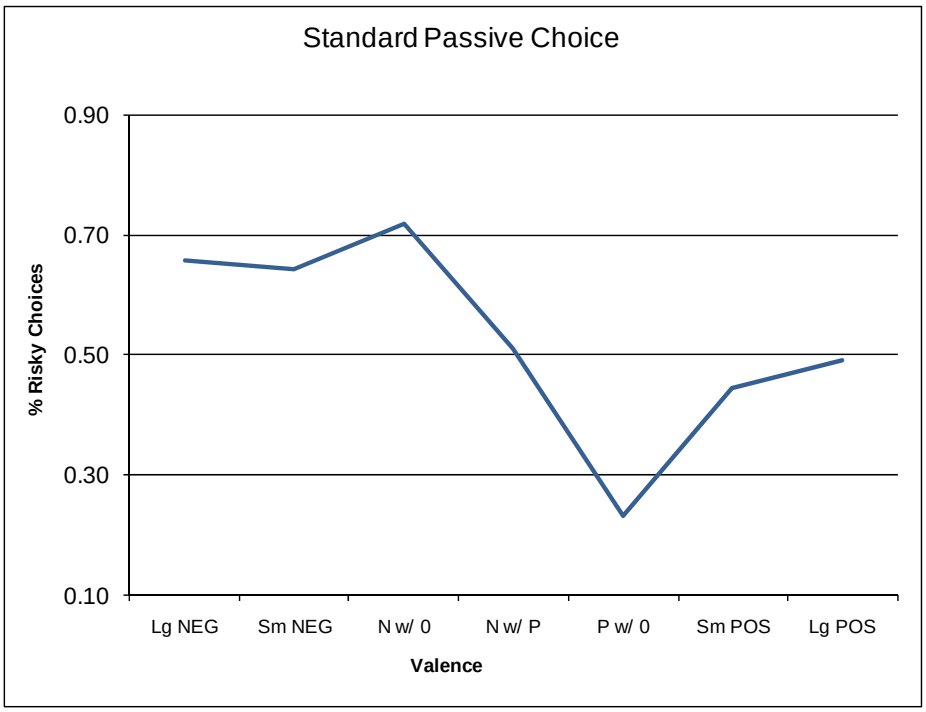

Figure 19: Risk preference by Valence for the Choice task in Previous Research. The higher on the Y-axis, the more participants there were who exhibited risk-seeking behavior in that valence.

However, when participants were given the Move task, their responding was not consistent with the S-shaped value function. Specifically, participants were predominantly risk averse throughout (shown in Figure 15). Schneider and colleagues argue that by providing the decision maker with a situated decision task involving outcome trajectory information, the decision makers are in a better position to understand the meaning of risk and to deal with it in a manner characteristic of other goal-related activities. This enhanced understanding leads to preference patterns that are markedly different from Prospect Theory predictions and more consistent with standard intuitions of how to deal with risk.

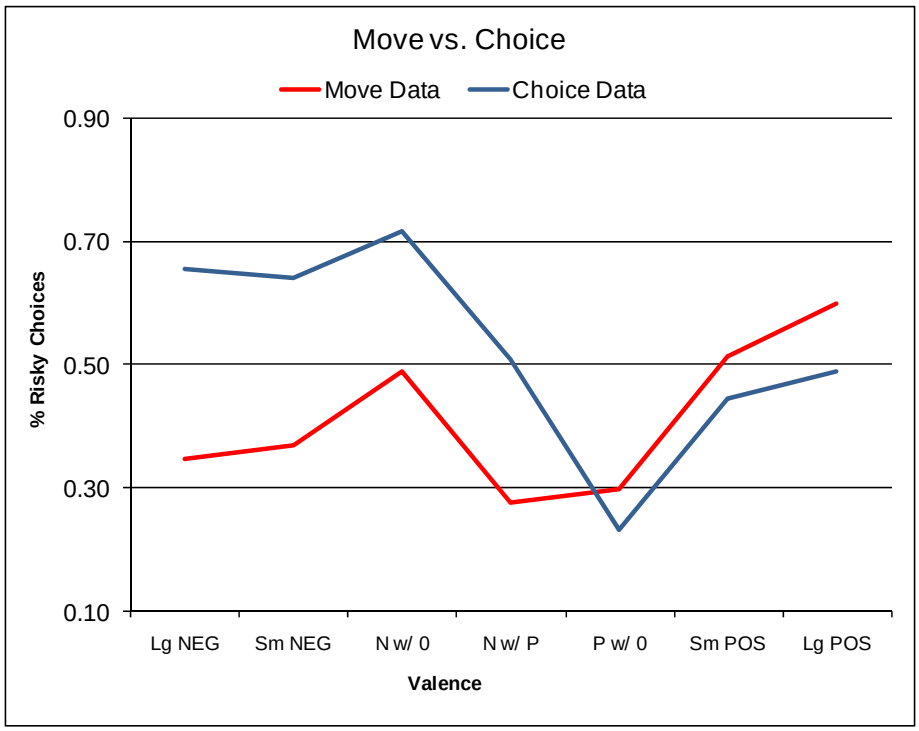

Figure 20: Risk preference by Valence comparison of Move vs. Choice tasks from Previous Research. The higher on the Y-axis, the more participants there were who exhibited risk-seeking behavior in that valence.

In an extension of this study to non-monetary outcomes, Schneider and colleagues (2005b) used "health units" as lottery outcomes, and told participants that these units are meant to represent decisions about improvements or detriments to current health. This adaptation using "health units" was meant to contextualize the Ticket Transfer task beyond the use of simple monetary outcomes. Schneider and colleagues (2005b) found the same pattern of preference reversal for the Choice task, and the same lack of preference reversal for the Move task.

In a third manipulation, Schneider and colleagues (2006) added a component to the Ticket Transfer tasks (both Move and Choice) such that the lotteries actually played and participants were paid some multiple of their winnings. Given this new capability, Schneider and colleagues (2006) developed what is essentially a "trajectory"

manipulation, such that half of the participants would start off with less in their initial "capital," but would have an overall positive experience up to the status quo, while the other half of the participants would start off with more, but would have an overall negative experience down to the status quo.

From this goal trajectory manipulation, Schneider and colleagues (2006) found that there were no substantive differences in risk preference given the different trajectory conditions (though the standard choice versus move differences were replicated); however, participants were asked affect questions about how they were feeling at the beginning of the study and about how they were feeling at the end of the study. The responses to these affect questions showed an overall improvement in mood for the positive trajectory condition, and an overall deterioration in mood for the negative trajectory condition. This shows the importance of long-term considerations such as "trajectories" are important because they impact individual participant experiences. Because these long-term considerations are often overlooked in standard risky choice tasks, we plan to extend the usage of accumulation and experiential outcomes into the more fully contextualized micro-world described previously.

In summary, participants seem to have different patterns of risk preference depending on whether they are shown a task which requires only passive choices between two static options or are shown a task which engages them in self-initiated action to improve the value of the outcomes in a given situation. This suggests participants are sensitive to being 'situated' in risky environments as opposed to simply being provided with static choices.

Methods for Empirical Study

The purpose of our current empirical study is to examine the importance of various decision criteria across these two different decision tasks (the passive Choice task and the active Move task) with respect to risk preferences. Participants completed either the Move task or the Choice task. In addition, to incorporate the inclusion of time-dependent contextual information, several dynamic contextual cues were made available, specifically (a) results of each of the plays of the selected lottery, (b) current actualized wealth and (c) wealth reflected as "social status" at various intervals. These dynamic contextual cues exist to provide additional information for participants to potentially use in guiding their decisions, as this type of dynamic information is often available in the real world. Also, participants were provided with noncompensatory elements, namely the requirement of keeping one's current wealth above zero to avoid "going broke."

Participants

202 undergraduate psychology students received extra credit toward their course grade for participating in this laboratory session; 111 were shown the choice version, while 91 were shown the move version. Due to our participant pool, the majority were female and between the ages of 18 and 22. Of those, several participants were dropped from the analysis (16 from the Choice version and 17 from the Move version), as they failed to pass a short quiz, designed to test if they understood the task.

Stimulus

Participants were provided with lotteries that look the similar to the lotteries shown in figure 17 (excluding the arrows and the "OR") and 18. As discussed

previously, for the "Choice" task, participants passively choose between 2 two-outcome lotteries (figure 18), while for the "Move" task, participants start with a two-outcome lottery and improve one of the two outcomes (figure 17). Each two-outcome lottery consists of outcomes which were either both positive (e.g., 50 & 100), both negative (e.g., -50 & -100), or mixed (some combination of positive values, negative values, or zero). The two outcomes were separated by discrete intervals of '50'. The largest disparity between any two outcomes was 3 intervals ('150').

Design

There were 4 orders in each condition, and all participants began with the same initial score. This score served as a stand in for currency. A higher score represent more currency. Also, the expected value for the series of lotteries was kept consistent between all orders and with the simulation study. There were 38 unique lotteries (from an expected value of '-250' to '325') and each lottery type was presented twice with a few exceptions[4] for a total of 75 lotteries in each order.

Each order consisted of 3 practice lottery pairs, 8 quiz questions, and 75 two-ticket lotteries or lottery pairs, followed by several questions about the participant's strategies regarding the lotteries and their status in the micro-world (to be discussed later). In addition several questionnaires were used to gauge individual differences in risk preferences, namely Higgins's Regulatory focus survey and Elke Weber's risk tolerance survey.

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[4] So as to achieve a slight positive trajectory from the initial score of '600' to the overall expected value of '1000', two of the most positive lotteries were not duplicated, and one of the negative lotteries was seen three times.

The Micro-world

The task consists of a micro-world designed as an oversimplification of real-world decision-making with respect to risk preferences. Participants were provided with a series of forced-choice two-outcome lotteries, and the outcomes of those lotteries accumulated into a displayed value referred to as their "current wealth." This current wealth value or "score" represents the participant's current socio-economic status in the micro-world. Based on the simulation results[5], we set an initial score of 600. Current wealth was adjusted after each lottery was played based on the randomly determined outcome, similarly to the simulation study.

In order to further contextualize the lottery playing task, a variety of information about quality of life relative to a participant's current wealth was provided to participants at occasional intervals. This information included a brief summary of the participant's current living conditions as proportional their amount of current wealth (This information is outlined in Table 2). The larger the participant's current wealth, the richer that participant was considered to be. As mentioned previously, participants receive feedback about their standing in the micro-world incrementally after every 5 lotteries throughout the experiment.

The characteristics for the different levels of social status in the simulated micro-world are designed to represent important real-life human concerns. These characteristics include availability of nourishment, the quality of housing, social influence, level of monetary wealth and capital, and access to medical care. Based on a participant's current

[5] We decided on 600 as an initial score in order to have *some* participants who would "go broke" in the study, but no so many as to negatively impact our results.

wealth, these characteristics changed at specific "milestones" or cutoff points. Also, if one of these milestones was reached and a participant had zero or less than zero in their cumulative total, the participant was notified that they "died" in the simulated micro-world, and they were directed to answer any final questions and leave the room early.

Procedure

A desktop computer was used to run the program, which consisted of either a series of pairs of lotteries as in the Choice task or a series of singular lotteries as in the Move task. Participants were in one of two conditions; either they were asked to choose one of the lotteries to play (for the Choice task) or they were asked to choose one of the two 'tickets' (outcomes) to improve before the lottery played (for the Move task). Once a selection had occurred, a random drawing took place, and the 'winning' outcome was displayed on screen before continuing to the next lottery. After every 5 lotteries, participants were provided with the contextual feedback discussed earlier (an example is provided in Appendix B), or if their current wealth was at or below zero, they were informed of their demise and no more lotteries were provided. Once participants finished all the lotteries, either by completing them or by "going broke," they were asked several questions regarding their overall decision strategy, as well are their reasoning for why they would choose a particular type of lottery (for Choice) or ticket to improve (for Move).

Table 2: Summary of Social Status Indicators.

	Residence	Availability of Nourishment	Method of transportation	Monetary capital	Medical coverage
Destitute	Subsidized in an unsafe neighborhood	Severely limited	Walk or public transit	Limited to survival	No medical coverage
Lower	Forced to share an apartment with others in mostly unsafe neighborhood	Can maintain healthy eating but cannot afford restaurants	Bike or moped, cannot afford car	Most spent on living expenses, but some money can be saved	Limited emergency medical coverage
Lower middle	Can afford own apartment, or share nicer house with a roommate in moderately safe neighborhood.	Maintain healthy eating and restaurants a couple of nights a week	Can afford Economy Car	About half of money earned is spending money	Partial medical coverage /HMO
Upper middle	Can afford own house or apartment in safe neighborhood	Can eat at restaurants any time	Can afford a nice car	A large portion of money can be saved or invested in the future	Full medical coverage
Very Rich	Can afford any house in completely safe neighborhood	Personal chef and nutritionist	Luxury vehicle	Almost all of money can be saved or invested in the future	Top notch health coverage and personal trainer

Note: These were provided to participants in the empirical portion of the experiment.

Results of Empirical Study

For the empirical investigation, the goal was to understand what types of contextual information people might be using when forming their personal risk preferences. To do this, we present an analysis of the data starting from the simplest of possible risk strategies (Risk Policies) and investigate progressively more complex risk strategies. After simple risk policy strategies, the next level of complexity focuses on static lottery characteristics, such as valence and variability. The most complex strategies include aspiration levels and dynamic goal trajectory strategies. We also explore differences between the Choice task and the Move task conditions at each level of complexity, as well as the implications that arise from participants "going broke."

Participants Who "Went Broke"

For participants who were risk-seeking more than half of the time, the rate at which they "dropped out" of the study was 33%, while for participants who were risk-averse more than half of the time, the rate at which they dropped out of the study was only 28%, which demonstrates that being risk-averse helps your chances to avoid going broke (confirming what was already shown definitely using the statistical simulations). Also, for participants who went broke using the risk-averse policy, the minimum number of trials or "life experiences" was 15 and the maximum number of trials was 65, whereas for the participants who were reliably risk seeking, the minimum was 10 and the maximum was 45. Thus, participants who were predominantly risk averse generally outlived participants who were predominantly risk seeking.

Decision Strategy Comparison

In addition to a comparison across different lottery characteristics (e.g., valence) and interpersonal characteristics (e.g., current wealth), tests were conducted to compare each participant's risk preferences with simulated risk strategies. This project uses the decision strategies simulated previously to work backwards and see if "actual" participants are making the same choices as an idealized "virtual" participant might respond under the same conditions. This was done to get a better understanding of whether participants are reacting to specific contextual information from the decision environment at each of the different levels of complexity (basic risk policy differences, static lottery-dependent, wealth-focused/aspiration-based, goal trajectories).

Strategy comparisons were conducted as follows: For basic risk policy decision strategies, we simply had to look at the number of times a participant was risk-averse or risk seeking. Static, lottery-dependent decision strategies focused on the valence of each lottery and the amount of risk in each lottery to determine their choices. We just look at how the characteristics of the lotteries affect preferences. For dynamic decision strategies such as the aspiration level strategies or the trajectory strategies, which require more robust contextual information, an analysis was done for each individual based that participant's complete "decision environment." This "decision environment" included information specific to that individual (including which lotteries were presented, what previous outcomes they received, their current total at each trial, etc.); aspiration level decision strategies used the information about current wealth at each trial, and the goal

trajectory decision strategies used a running tally of information about previous outcomes at each trial.

This analytical technique takes the same basic principle behind creating virtual participants from decision strategies. However, instead of putting the virtual participants into their own unique environment (as with a randomly generated outcome), "virtual" participants are placed in the environment experienced by "actual" participants. Therefore, if an actual participant is *using* a particular decision strategy, then the risk preferences of the "virtual" participant would be the same as the risk preferences of the accompanying "actual" participant.

The number of participants who were best predicted by a particular decision strategy type is presented at each level of complexity, and comparisons between difference strategies are discussed with reference to Table 3. In the case of a tie (two or more strategies predicting a participant with the same accuracy), we used parsimony and credit was attributed to the simpler of the two decision strategies. The samples for each task type only reflect participants who had complete decision environments (i.e., participants who "went broke" were not included).

Table 3: Percentage of Participants Predicted by each Decision Strategy Type.

		Risk Aversion	Risk Seeking	Prospect Theory	Risk As Threat	Modest Variance	Asp. Levels	Goal Trajectories
% Best Predicted	Choice (n = 63)	32%	18%	11%	10%	3%	14%	13%
	Move (n = 53)	43%	9%	2%	21%	11%	4%	9%
Avg. Best Prediction	Choice (n = 63)	79%	80%	69%	61%	67%	66%	69%
	Move (n = 53)	82%	73%	65%	69%	72%	66%	76%

Note: % Best Predicted represents the proportion of participants (excluding those who 'went broke') whose preferences were most accurately predicted by the given decision strategy. The average best prediction represents the proportion of actual responses that were accurately predicted for participants who were best predicted for the given decision strategy.

Simple Differences in the Amount of Risk

There was an overall tendency towards risk aversion for both the Move and Choice task. For the Choice task, participants took risks an average of 45% of the time and for the Move task, participants took risks an average of 36% of the time. As shown in Table 3 (p. 62), when the risk preferences of actual participants were compared to simulated risk policies for the Choice task, 32% of participants were best predicted by the risk-averse strategy while 18% were best predicted by the risk-seeking strategy. For Move, 43% of participants were best predicted by the risk-averse strategy, while 9% were best predicted by the risk-seeking strategy. In addition, on average for both Move and Choice, risk policy strategies predicted roughly 80% of actual responses, compared to the other decision strategies which all predicted roughly 65-70% of actual responses, with the exception of risk seeking in the Move task. This shows that simple risk policy strategies have the largest margin of prediction for actual participant responding, likely due to their simplistic nature. In addition, risk aversion tends to be a more predominant strategy for the situated Move task than for the passive Choice task.

Risk Preferences as a Function of Lottery-Dependent Characteristics

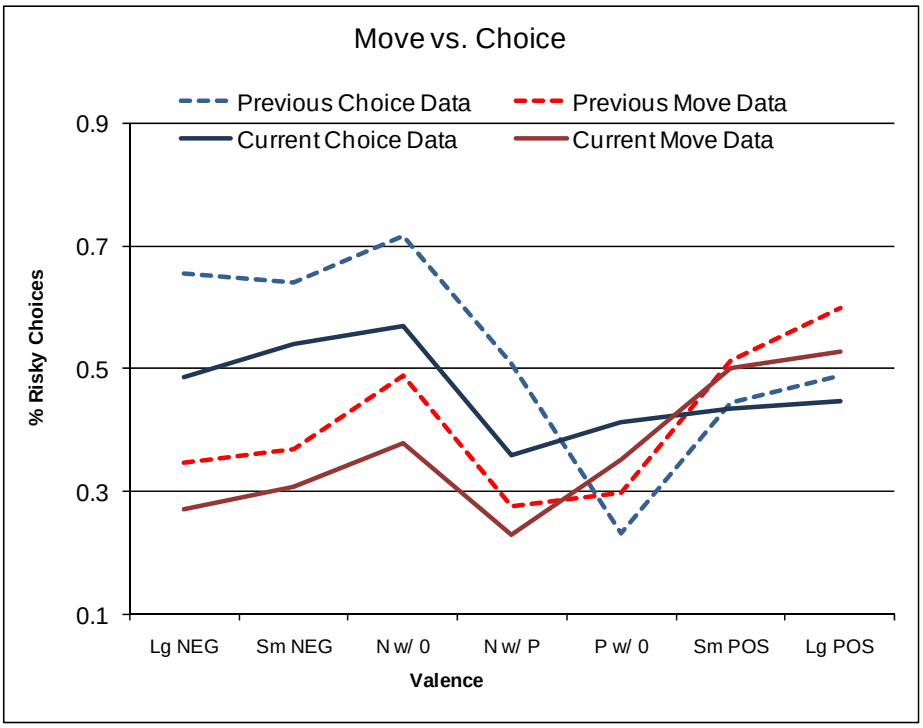

Figure 21: Comparison of previous and current Move v. Choice data.

To look for differences with respect to valence, and to see if our results are consistent with previous findings, Figure 21 shows the comparison of the current data from the Move task and Choice task with previous versions of the Choice task and Move task. Note that for both Choice and Move, there appears to be a substantial reduction in the number of risks taken for the negative lotteries, as well as a general 'middling' of risk preferences effect across all the valences (fewer risks taken/avoided where there used to be a large majority). The substantial reduction in the number of risks taken may have had something to do with the potential for participants to "go broke," as avoidance of this noncompensatory element would suggest an increase in risk-averse behavior and was not included in previous manipulations.

The simulation comparison for decision strategies that use static lottery characteristics (specifically, decision strategies similar to the Prospect Theory model or Risk as Threat model) allowed us to see if different individuals were using a consistent strategy that focused on the valences of the lotteries or the amount of variability between the outcomes in the lotteries. As discussed in Study 1, the Prospect Theory decision strategy produces risk-seeking behavior for lotteries with all negative outcomes and risk-averse behavior for lotteries with either all positive outcomes or a mix of positive and negative outcomes. The Risk as Threat decision strategy exhibits risk-seeking behavior for lotteries with all positive outcomes and risk-averse behavior for lotteries with either all negative outcomes or a mix of positive and negative outcomes. The Modest Variance decision strategy exhibits risk-seeking behavior when there is the potential for a riskless or "sure thing" outcome, otherwise exhibiting risk-aversion. The percentage of participants who were best predicted by these strategies is shown in Table 3 (p. 62).

For Choice, the effectiveness of the Prospect Theory-based decision strategy at predicting actual participant responding for choice is the same as the predictive effectiveness as the Risk As Threat-based decision strategies (10%). For Move, Prospect Theory only predicts 2% of the participants, while the Risk as Threat decision strategy predicts 19% of the participants. This suggests the differences articulated in Schneider (2002, 2005) are indeed correct; Prospect Theory does not adequately account for decision making with respect to risk when under Choice task conditions and Prospect Theory does even worse at attempting to account for decision-making with respect to risk when dealing with the active Move task. In addition, the Modest Variance decision

strategy was a worse predictor for Choice than for Move. This suggests that passively choosing between two options when one of them is riskless (e.g., Choice) does not have the same impact on avoiding riskless options as being forced to actively configure a riskless option (e.g., Move).

Risk Preferences as a Function of Current Wealth.

Because participants may be using information related to their individual current wealth, we investigated individual risk preferences at each wealth level in both Move and Choice. Instead of simply averaging across each wealth level for all participants, we wanted to reflect patterns of behavior at each wealth level, and so first made sure that a participant spent a substantial amount of time at a particular wealth level before their risk preferences contributed to the analysis. This was to account for the fact that not all individuals saw all the wealth levels for a prolonged period of time; it wouldn't make sense to compare people's risk preferences about particular wealth levels if they weren't spending a significant amount of time there.

First, the amount of time a participant spent at each wealth level was tabulated. Then for all the participants who spent a large enough amount of time at each particular wealth level (more than 5 trials), their individual ratios of risk preferences (percentage of risk-seeking behavior) were averaged within each participant and then across each wealth level. The amount of risk seeking behavior at each wealth level is shown in Figure 22.

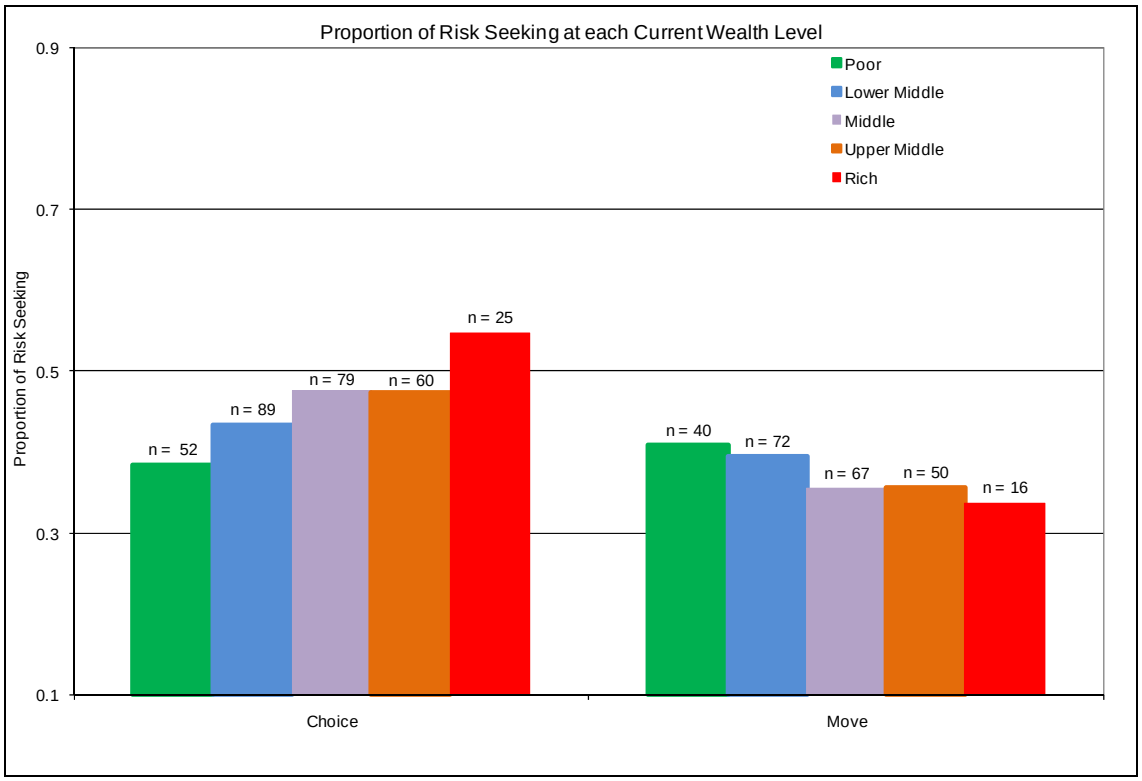

Figure 22: Individual Risk Attitudes at each Wealth Level. 'N' is the number of participants who had more than 5 responses at the given wealth level.

Figure 22 shows that when individual risk preferences are evaluated across wealth levels, the pattern of risk seeking for Choice steadily increases as participants have a higher current wealth level, whereas the pattern of risk seeking for Move steadily decreases as participants have a higher current wealth level. Because there are a different number of individuals at each wealth level and different individuals spent different amounts of time at each wealth level, the variances are not homogenous, so a statistical comparison of these groups would not be prudent.

To better capture the potential individual usage of current wealth levels, a comparison of actual participants' risk preferences and virtual participants imbued with decision strategies focused on current wealth was analyzed. As discussed in Studies 1

and 2, an aspiration level strategy predicts that a participant exhibits risk-averse behavior until their current wealth exceeds a particular goal or "cutoff" point, whereupon that participant exhibits risk-seeking behavior until the current wealth falls below their goal. To see if participants were focused on specific current wealth levels, several different "cutoff" point values were utilized. The percentage of actual participants who were found to be best predicted by the aspiration level decision strategies across all of these various cutoffs are shown in Table 3 (p. 62).

There were several participants for Choice (and many fewer for Move) who were best predicted by aspiration level strategies, which suggests that something is going on in Choice that makes current wealth more salient as a decision criterion than for Move. There were other participants whose preferences resemble with both aspiration level decision strategies and risk policies. As an aspiration level decision strategy had a progressively lower cutoff value (e.g., 775), the participants who were consistent with it were also consistent with the risk seeking risk policy. The same held true for higher cutoff values (e.g., 1225) and the risk-averse risk policy. This makes establishing whether a participant was using current wealth as a criterion or just a simple risk policy quantitatively difficult to differentiate.

To provide for the notion that participants formed their individual risk preferences using current wealth and not just a simple risk policy, the self-report style questions asked directly to participants about their overall strategy were analyzed. Participants were asked direct confidential questions at the end of the lottery series about their individual decision strategy. When participants were asked, "What was your overall

strategy?" 19% of participants for the Move task responded with some mention of a cumulative total or current status as a predominant factor, while 52% responded with a similar strategy answer for the Choice task.

Despite the overlap between risk policies and more complex dynamic decision strategies, aspiration level decision strategies that use specific "cutoff" values to switch between risk policies may not be the way participants are using current wealth. Participants are not told about the total range of current wealth states or the range of possible scores, so it would not be possible to effectively set cutoffs based on particular expectations. However, for our simulations, accurate expectation information for the lotteries was known *a priori* to the design of the decision strategy. The stochastic nature of the simulation procedure allowed us to optimize an aspiration level decision strategy in the general sense, since we knew what the overall expected value was; however, each participant is limited in the actual outcomes they will experience, and the range of values they have previously experienced is changing dynamically throughout the task. Therefore aspiration levels may be changing over time or they may be set with other factors in mind. Trying to match their performance with fixed aspirations having cutoff points relative to information not explicitly given to participants isn't a fair 'litmus test' of whether participants might have been using their current total in their decision-making.

Instead of using a "cutoff point" to utilize current wealth, participants may, in the general sense, be taking more or less risks as their cumulative total increases. To account for this potential utilization of current wealth, a point biserial correlation was performed for each participant to investigate potential within-subject relationships between current

wealth and risk preferences. Participants who were entirely risk averse or entirely risk seeking were not included for obvious reasons. Table 4 shows the pattern of results for these biserial correlations with positive correlations suggesting greater risk seeking at higher wealth levels.

Table 4: Number of Participants for Point Biserial Correlation

	Positive Significant	Positive Non-significant	Negative Non-significant	Negative Significant
Choice (n = 89)	12*	37	35	5*
Move (n = 72)	1*	22	36	13*

While the vast majority of participants have non-significant correlations, there are many more positive significant correlations for Choice and many more negative significant correlations for Move. The relationship between risk seeking behavior and current wealth explained here are consistent with the patterns shown in Figure 22. This suggests that for Choice, when people are using current wealth in their decision-making, they do so by taking more risks as their current wealth increases, while for Move, when people using current wealth in their decision-making, they do so by taking fewer risks as their current wealth increases.

Risk Preferences as a Function of Wealth X Valence

Although we have shown there is evidence to suggest that current wealth plays a role in forming risk preferences, most of the research over the last several decades regarding risk preference patterns focuses on the importance of lottery valence. As such, the interaction between wealth levels and valence for Choice is shown in Figure 23a, while the interaction between wealth levels and valence for Move is shown in Figure 23b. Each point represents the total proportion of risky choices across all the participants at

each particular wealth level for each valence. No limiting procedure was used because all participants saw the same number of each type of lottery valence; so, in this context, wealth level is a byproduct of experience and homogeneity of variance across wealth levels cannot be assumed.

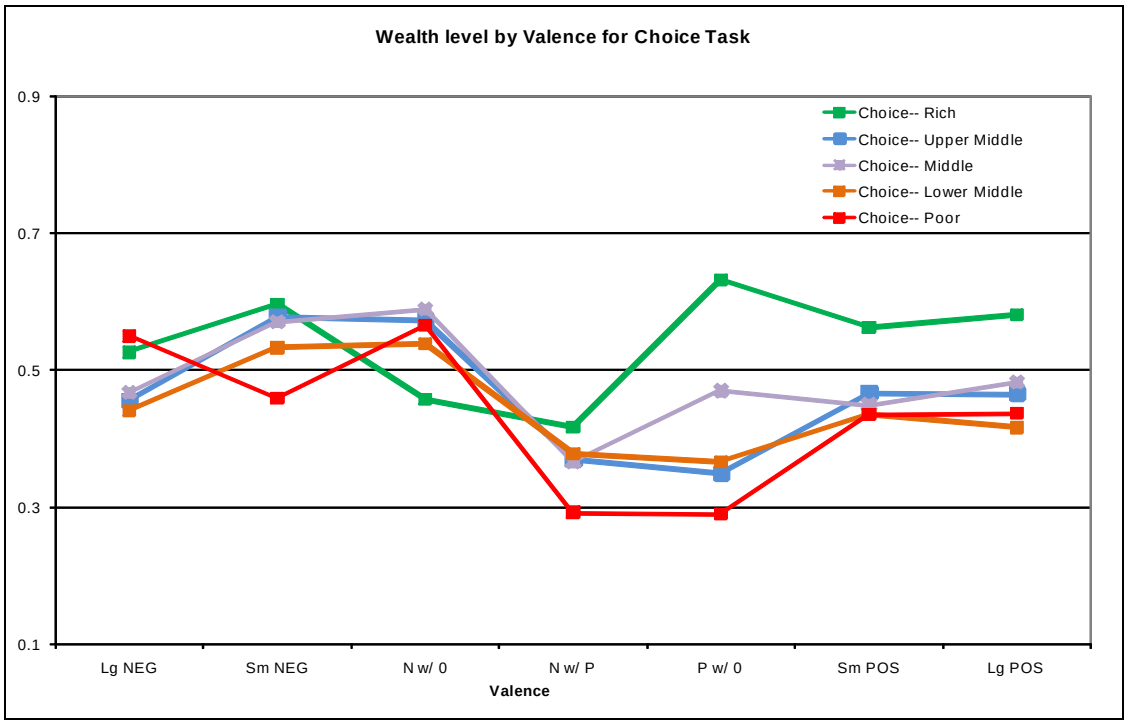

Figure 23a: Wealth Level by Valence for Choice Task. The X axis indicates the proportion of risk-seeking behavior for each wealth level at each valence.

There are three noted points of interest for the Choice by Wealth level by Valence interaction (Figure 23a); First, risk preferences for negative lotteries appear inconsistent/pattern-less, in that they fluctuate between risk aversion and risk seeking across all wealth levels; Second, when participants are 'poor', they exhibit strong risk aversion when faced with a mixed lottery (*N w/ P*) or a choice between a sure gain and a risk that includes zero (*P w/ 0*); Third, when participants are at the "Rich" wealth level, they are compelled to take more risks when facing any of the lotteries which contain positive outcomes (*N w/ P*, *P w/ 0*, *Sm POS*, *Lg POS*) than another other wealth levels.

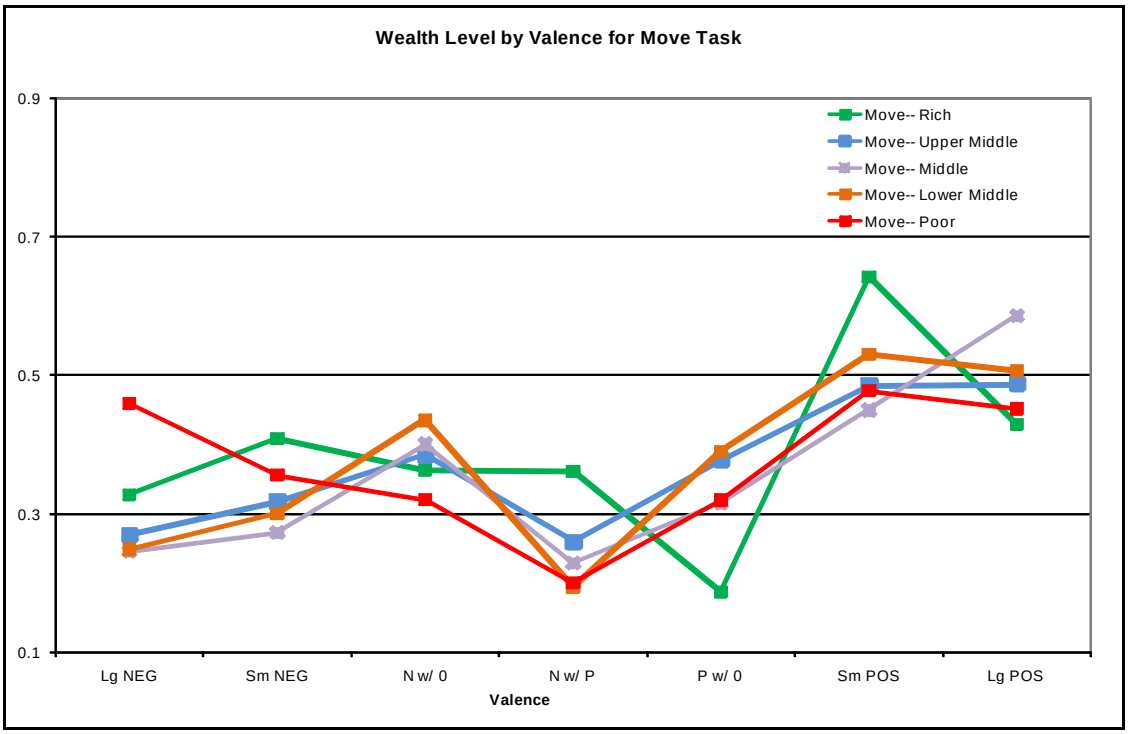

Figure 23b: Wealth Level by Valence for Move Task. The X axis indicates the proportion of risk-seeking behavior for each wealth level at each valence.

Notable points of interest for the Move by Wealth level by Valence interaction (Figure 23b) are that preferences between valences seem relatively consistent across different wealth levels, with the potential exception of the "Rich" wealth level. When comparing Figures 23a and 23b, it should be noted that the differences between wealth levels across valences are not the same for the Move task as the Choice task.

Risk Preferences as a Function of Trajectory Information

Another potential explanation for how participants may still be using dynamic information in a way that isn't captured by the aforementioned comparisons of aspiration level strategies is that participants are sensitive to the overall changes in the *trajectory of previous outcomes*, but not necessarily in their *current wealth* value. As shown in Study

1, trajectory decision strategies provide an analysis of "relative progress" based on sensitivity to subtle changes in outcomes over the short term and/or long term.

The trajectory decision strategies compared with "actual" participants work the same way they were described in Study 1 (p. 26 and 27), inferring a risk preference from a majority of previous outcomes evaluated as the "better" outcome or the "worse" outcome. "Continuation" type trajectory strategies infer that a majority of "better" outcomes leads to the conclusion that outcomes will continue to be good, and hence exhibits risk-seeking behavior, while "Discontinuation" type trajectory strategies infer that a majority of "better" outcomes leads to the conclusion that outcomes will no longer continue to be good, and hence exhibits risk-averse behavior. Each participant had their own "trajectory" depending on their individual previous outcomes. The information for the comparison of these trajectory decision strategies as predictors of actual participant responding can be found in Table 3. Only the "Continuation" version of the trajectory decision strategies was compared to actual participants because the "Continuation" version is fundamentally consistent with the goal-directed behavior of the aspiration level decision strategies. Comparing only this version of trajectory strategies makes the predictability of aspiration levels and goal trajectories directly comparable. Also, trajectory strategies that required a 'super' majority of previous outcomes (e.g., 5 out of 7) as "better" to insight risk-seeking behavior were included in addition to the 'weak' majority (e.g., 4 out of 7) addressed in study 1 and 2, because actual participants may require a larger margin of previous outcomes be "better" before they are willing to take risks.

The effectiveness of trajectory decision strategies at predicting actual participant responding is comparatively high for both Move and Choice given the underlying assumptions that participants were using either the previous 7 outcomes or all of the previous outcomes. Consequently, there are also more participants who are best predicted by trajectory strategies that use all previous outcomes than the trajectory strategies that use a limited number of previous outcomes, which suggests that participants may not overtly sensitive to subtle changes in trajectory over time, but may be sensitive to changes in long-run trajectory information. Also, the comparatively high prediction of actual responses for the Move task (76%) suggests that participants who are using goal trajectory strategies do so more in a consistent manner. This may occur because there is less outcome information being displayed throughout the Move task, as there are only at most two values being shown in the task at any one given point in time.

Discussion of Empirical Study

For the purpose of this investigation, we compared the results of the Move vs. Choice tasks with respect to risk preferences in the dynamic task environment. We further compared those participant results to the patterns of responding found in simulations, taking into consideration the Move v. Choice task distinction. When comparing Move v. Choice tasks, we investigated differences in responding depending on several levels of complexity in the decision environment: basic overall risk policy differences, risk preferences with respect to valence, risk preferences with respect to when the lotteries were presented in time, risk preferences with respect to current wealth, and risk preferences as they related to goal trajectories.

Because the Choice task has a slightly higher tendency for risk seeking behavior than the Move task, it could be argued that something about the Move task and situating participants in the decision environment has an overall effect on their actions with respect to risk. However there may very well be more complex factors mitigating those differences.

Risk preferences with respect to valence in large part replicated the findings of Schneider and colleagues (2005). Group differences indicated that the passive Choice task approximated the preference pattern outlined by Tversky and Kahneman (1981), while the active 'Move' task did not follow the pattern of preference. The strength of the Prospect Theory pattern was less pronounced in our study than in previous manipulations, and may have been influenced by the addition of the noncompensatory "going broke" condition, which was not present in previous manipulations. In addition,

when actual participants were compared to static, lottery dependent decision strategies, the Prospect Theory model was underwhelming in its ability to predict actual participant responding for both Move and Choice, while the Risk as Threat model performed relatively well especially for Move.

Risk preferences at each wealth level had different patterns depending on task type; the Move task showed a weak tendency to decrease in risk-seeking behavior as wealth increased while the Choice task showed an overall tendency to increase in risk seeking behavior as wealth increased. One interpretation is that participants under the Move task, who are actively improving the values of the outcomes, have feelings of more 'control' over their situation, and attribute the increase in cumulative total to 'dispositional' factors (e.g., they acquired a good score based on their skill at improving outcomes). As a result, when they achieve a high current wealth state, they attempt to skillfully "hold on" to that high current wealth state by reducing risk.

Choice, on the other hand, is the act of passively choosing between two lotteries, and may not necessarily lead participants to attribute their high score to dispositional factors, but rather to 'situational' factors (e.g., they acquired a good score based on random luck, a rigged game, etc.). As a result, when they achieve a high current wealth state, they presume it must be some manner of random chance that got them to the higher current wealth state, or that they are lucky, and that continuing to take risks will supply them with even more wealth. This is all speculative however, and more investigation is required to understand participants' explicit reasoning, particularly with respect to

whether there are differences in situational/dispositional attribution for the Choice/Move tasks.

In addition, there are problems associated with assuming participants know more about what to "expect" from the lotteries than they actually do. Participants have no contextual cues to give them a sense of the overall range of possible values in the short term, nor do they have accurate information about what they should expect in the longer term. For future investigations, this problem might be solved by providing participants with information about what they can expect in the short term and long term *before* they begin to make decisions, or alternatively giving them more contextual information about a particular goal, to see if they set an aspiration level as a result. This is because in the real world, people often have information about what to expect in the short term and long term (e.g., weekly salary) and have particular goals or noncompensatory requirements (e.g., cost of living expenses).

For the purpose of this investigation, however, correlations were performed between individuals' risk preferences and their current totals to see if participants generally change their risk preferences with respect to an overall increase or decrease in current wealth. We found that several participants for the Choice task had a positive correlation between risk-seeking behavior and current total (e.g., as current wealth increased, participants were more risk-*seeking*) and several participants for the Move task had a negative correlation between risk-seeking behavior and current total (e.g., as current wealth increased, participants were more risk-*averse*). This suggests the differences between the Choice and Move tasks may be meaningful within individuals

and are not just a byproduct of overall current wealth differences between individuals (e.g., people who were "doing well" the whole time exhibiting risk-seeking behavior while people who were "doing poorly" the whole time exhibiting risk-averse behavior).

The self-report data suggests that several participants were identifying that their own decision strategies include a current wealth component. Both tasks (Move and Choice) had a substantial percentage of participants respond using some reference to their "current state" in their explanation of their overall strategy. The choice version shows more participants offering up this self-report response, which is actually consistent with the results found when comparing the task by wealth level by valence interaction (Figures 23a/b).

Specifically, when wealth level is aggregated within valences for both Move and Choice, differences between wealth levels seem to persist most strongly for the Choice task and further differences between the higher (Rich) and lower (Poor) wealth levels seem to apply almost entirely when participants are facing positive lotteries. When participants are rich, they make more risky choices, and when participants are poor, they make more risk-averse choices. This suggests participants are adopting a criterion similar to the Security-Potential/Aspiration strategy of Lopes (1987). When poor, participants might be interpreting risks as security threats, and hence avoiding them, whereas when rich, participants might be interpreting risks as potential opportunities, and hence adopting them. However, in the Move version, wealth levels aggregated within valences show no strong consistent differences. This suggests that for Move, the risk preference pattern across valence is consistent at each current wealth level, which would

provide a reason for the overall effectiveness of lottery-dependent strategies, particularly the Risk as Threat decision strategy.

The current wealth level analyses as a whole suggest that the Choice and Move tasks present decision information to participants such that current wealth is interpreted to mean two different things. The Move task, which has been hailed by Schneider and colleagues (2005, 2006) as a way to situate participants into improving outcomes in an active, goal-seeking manner, may invoke additional contextual information (e.g., situated risk) which influences risk preferences, potentially to the detriment of other more important contextual factors (e.g., current wealth as a measure of long-run progress). The passive Choice paradigm, on the other hand, is one in which wealth levels were able to make an impact on risk preferences.

The data also suggests that without provocation or manipulation, the participants in the Choice condition who did end up using the wealth levels as a criterion for risky choice, did so in a manner such that the long run outcomes would be skewed to the right, resulting in an increase to the likelihood of ending up in the extreme higher end of the spectrum, a decrease to the likelihood of ending up in the extreme lower end of the spectrum. The problem still exists, however, that lotteries in the negative valence were largely unaffected by the wealth level manipulation, and hence the usage of cumulative total as a criterion is seemingly limited.

When instead of current wealth, participants were analyzed with respect to goal trajectory information (which consequently does not use specific fixed cutoff points), a moderately sized portion of participants were consistently predicted as using one of these

strategies for both Move and Choice. The usefulness of trajectory strategies in circumstances where the overall range of values is not known was discussed in Studies 1 and 2, and it is surprising that participants were found to be consistent with this type of decision strategy, given the number of assumptions required to assert it.

General Discussion

Vantage point dependencies, aspirations, and goal dependencies were investigated in a number of different ways to provide insight into how people make decisions in heavily contextual external world. Study 1 used statistical simulations to investigate how each of these contextual factors from the external world might affect long run outcome distributions. Overall, these simulations provided us with a means to find out about idealized strategies for making risky choices. We investigated if and how decision strategies that use dynamic and time-dependent criteria such as aspiration levels and goal trajectories are advantageous in the probabilistic sense. We found that aspiration levels and goal trajectories are advantageous because they provide some way of gauging one's current position relative to the "average" or expected position.

The ability to skew the long-run distribution (in either direction) is something "static" strategies simply cannot do. In many real-world contexts, using a dynamic strategy can provide an advantage over a static strategy. In fact, there is no case in which a dynamic strategy is suboptimal to a static strategy if used appropriately, because every dynamic strategy is at its core essentially the concatenation of two or more static strategies using some dynamically-acquired value that is a rough measure of progress-thus-far in the decision environment.

Study 2 placed the decision strategies from Study 1 and from the pilot simulation into several variations on contextualized decision environments. We showed that under

different contexts, the effectiveness of different decision strategies may change, but that the core reasons why dynamic decision strategies can be advantageous over static decision strategies still persist.

Study 3 was designed to find out which types of decision strategies people are actually using. As a result of the overwhelming long-run benefits from using dynamic criteria found in studies 1 and 2, we hypothesized there would be evidence that participants use the provided dynamic criterion (cumulative total) in strategic way. We found that while participants appear to have systematic differences in risk preferences with respect to dynamic and time-dependent criteria, there is not an overwhelming usage of dynamic decision strategies over other decision strategies. Nevertheless, our results may underestimate the use of dynamic criteria, as it is much more difficult to specify exactly how these criteria might be used and how the criteria may be changing over time.

Risk Policy strategies are the simplest possible decision strategy, where either risk-averse behavior or risk seeking behavior are predominant throughout. Differences between simulated risk policy decision strategies are limited to differences in variability for the outcome distribution; risk-aversion has a narrow distribution and risk-seeking has a spread out distribution. Simple risk policies were the most commonly used decision strategy for both Move and Choice, particularly the risk-averse decision strategy.

Lottery-based strategies use lottery-dependent *vantage point* information, specifically the valence of the potential outcomes (as with the Prospect Theory and Risk as Threat decision strategies) or the respective difference between the potential outcomes (as with the Modest Variance decision strategy). For simulated lottery-based decision

strategies, there were no differences in the long run outcome distributions aside from different amounts of spread. In the empirical study, the efficacy of Prospect Theory as a predictor of actual behavior was extremely poor. The Modest Variance strategy and the Risk as Threat strategy didn't do much better, especially in the Choice task.

Aspiration level strategies and goal trajectory strategies each use contextual cues from the decision environment that are time-dependent and constantly-updating. Simulations of these dynamic decision strategies showed a specific change in the shape of the outcome distribution via the addition of skew. The skew in the outcome distribution articulates that these strategies have the capacity to influence one's long-run results in ways static lottery-dependent decision strategies cannot. Also, the predictive strength of these dynamic decision strategies is somewhat surprising, considering the large number of assumptions required to assert them. Also, there are substantial task differences, with the Choice task having a larger portion of participants who used an aspiration level decision strategy as consistent with the goals addressed in Schneider and colleagues (2007) compared to the Move task.

The usage of current wealth as a criterion was more pronounced in the Choice version of the task possibly because the elements of the Move version that appear to require skill outweigh any other strategic planning. By asking participants to improve outcomes for each lottery, participants are presumably led to believe that risky choice can be skillfully mastered, and current wealth isn't used as a measure of progress in the task, but as a measure of skillful mastery at the task. The Choice version, however, does not

include elements which might be interpreted as requiring ‘skill’, and is perhaps more open to allowing current total to be used as an inference about future goals.

These task differences have been shown to influence which types of contextual information from the environment are being used to formulate decision strategies. This experiment studied these task differences in isolation, but the two tasks described herein have strong implications for the real world. Decisions that are presented in the passive form of static choice have markedly different real world implications than decisions that are presented in the active form of initiating progress.

So the pros associated with presenting a decision in its passive form is that participants are likely to be more receptive to the external context, with the downside that they are not as situated in the individual risky environments. Presenting a decision in its active form has the benefit of providing a realistic context for each individual decision, even though some external context may not be as salient.

It has also been shown that people are in fact using dynamic information when making decisions, and by comparing different decision strategies, we provide evidence for which strategies make better predictors. Risk aversion is the best predictor of decision making, which is consistent with the most fundamental principles of utility theory from Bernoulli (1738/1954). Aside from that, lots of different decision strategies are being used for both Move and Choice; although some are used more in the Choice task and others are more frequent in the Move task. Trying to establish a single best predictive decision strategy was not accomplished, nor necessarily should it.

Nevertheless, it appears as though the interpretation of "risk" as something to be avoided is highly predictive among actual participant responding, especially when risk corresponds to everyday notions like "danger" or "threat." Thinking of safety from risk is a commonality in this respect. One could consider that decision strategies which exhibit entirely risk-averse behavior throughout or include a component of risk-aversion when one's current vantage point or future outlook are poor or negative as this type of "avoiding" risk. The risk-aversion policy, the Risk as Threat strategy, Aspiration Level decision strategies and "Continuation" Goal Trajectory strategies all exhibit this notion of avoiding risk. When all those are taken into account, over 75% of participants' strategies are accounted for by the notion of avoiding risk.

Of those decision strategies, several include an additional component for taking risks when one's vantage point or future outlook are good. The Risk as Threat strategy, the aspiration level strategies, and the "Continuation" goal trajectory strategies all include this notion of seeking risk as well as avoiding risk. Of the 75% of participants who predominantly avoid risk, about half were also riskier when their vantage point or future outlook was good.

By comparing different decision strategies, we have shown that there are long-run statistical advantages and disadvantages to using different types of contextual information in the environment (static vs. dynamic). It may seem reasonable to base one's decision making on the lottery environment (e.g., valence); however, strategically speaking, if one's goal is to give oneself a long-run advantage, focusing on where one is and where one wants to go from there (e.g., dynamics) is the best way to go, as long as the options

your are provided with have the same monetary expected value. How one comes to know their "current status" can be achieved either by cues provided about one's current status or by observing outcomes to see one is doing well relatively speaking. In addition, the exhaustive investigation of aspiration level simulations and goal trajectory simulations provides evidence that having a meaningless or uneducated 'goal' will not provide one with the same type of long-run advantage as having a meaningful or accurate goal might. We found that as an 'aspiration' becomes more appropriate to what can be best expected and as a trajectory includes a larger margin of previous experiences, there is better control over the long-run probability distribution, specifically the amount and direction of skew in the long-run outcome distribution. However, if one's implicit goals are to tend towards a specific risk policy (e.g., remain predominantly risk-averse), aspiration level decision strategies can use an adjusted cutoff point to reflect a general tendency towards a risk policy (e.g., increasing the cutoff point for one's aspiration level strategy tends towards risk-aversion), and goal trajectory decision strategies can require a stronger or weaker majority to reflect a general tendency towards a risk policy (e.g., requiring a stronger majority of "better" outcomes before one is willing to take risks tends towards risk-aversion).

More research is required to determine the driving force between the differences in the Move and Choice tasks. Though our study provided additional insight into differences with respect to Move and Choice, we have yet to provide a systematic explanation of why those differences exist. In addition, our study was limited in its investigation of the potential influence on decision-making by dynamic criteria because

of the large number of assumptions regarding cutoff points and implicit goals. Future studies will do well to develop additional potential methods for investigating the impact of current wealth levels on risky choice using a more systematic manipulation. Also, the empirical results suggest that the dynamic decision making perspective might provide some additional insight in understanding risk preferences for choices that require actual skill or ability that can improve over time by using the Choice v. Move task manipulation.

Most importantly, since the predictability of actual participant preferences is spread out across multiple decision strategies and different levels of decision complexity, attempting to evaluate all decision making with respect to risk through a single contextual cue or piece of the decision environment is shortsighted. More research is required to determine what types of cues are commonly used by individuals, but not necessarily for the purpose of finding a single unifying decision strategy that predicts all behavior.

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Appendices

ID Number:_____ _____ _____

-$50				
-$50				
-$50				
-$50				
-$50	**$0**			
-$50	**$0**			
-$50	**$0**	**$50**		
-$50	**$0**	**$50**	**$100**	
-$50	**$0**	**$50**	**$100**	**$150**

Do you have a better chance of drawing a ticket worth $0 or $100? _____

If you played this lottery over and over, on average, what ticket value would you draw only 3 out of every 20 times? _____

If you were given the chance to randomly draw a ticket from this lottery, which ticket value would you be **least likely** to draw? _____

In this lottery, do you have a better chance of drawing a winning ticket or a losing ticket? _____

-$100				**$100**
-$100				**$100**
-$100				**$100**
-$100	**-$50**		**$50**	**$100**
-$100	**-$50**	**$0**	**$50**	**$100**
-$100	**-$50**	**$0**	**$50**	**$100**

In this lottery, what value is the **least likely** outcome? _____

In a single play of this lottery, do you have a better chance of drawing a ticket with the value of $100 or -$50? _____

What is the best possible outcome that you could expect in playing this lottery one time? _____

How many tickets would result in your losing money? _____

Appendix B: Social Status Example

THIS IS YOUR CURRENT CONDITION

Your current total of $600 means you are in the lower middle income bracket.

You are forced to share an apartment with roomates in a mostly unsafe neighborhood.

You can maintain healthy eating but cannot afford restaurants.

Travel is limited to a bike or moped, because you cannot afford a car.

The money you earn is mostly consumed by living expenses, but some money can be saved.

You can afford limited emergency medical coverage.

Next