ESSAYS ON DECISION MAKING AND THE ROLE OF HUNGER IN RISKY CHOICE BEHAVIOR

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Decision making is an integral part of human life. It encompasses different domains (e.g., risky choice, intertemporal choice, etc.), and is affected by numerous factors (visceral factors, emotions, representations, etc.). Following a thorough review of the evolution of decision making as a field of study, this dissertation studies the effect of experimentally manipulated hunger – a typical drive state – on choices in the context of decision making under risk for both food and money. Using a risky-choice framing task, the effect of hunger was tested to assess its influence on: (a) choice consistency ("rational choice behavior") as reflected by the degree of framing bias exhibited by the participants, (b) risk preferences, and (c) sensitivity to midpoint probabilities. Furthermore, a number of theoretical hypotheses were driven from three distinct models — two traditional dual-system models and fuzzy-trace theory – and compared with participants' actual choice behavior. Results from the experiment show that being in a drive state of hunger increased risk aversion for food and money but did *not* generate a stronger framing bias, or significantly alter the sensitivity to midpoint probabilities. Particularly, this pattern of risk preferences was robust across both gain and loss-framed decisions. In addition, this work provides some evidence for oversensitivity to midpoint probabilities in the context of risky-choice framing task. These findings pose a challenge to the two traditional dual-system models, contradicting some of their formal predictions, while providing some support to fuzzy-trace theory. Future directions for theoretical research are discussed.

BIOGRAPHICAL SKETCH

Yuval Erez was born and raised in a small city near Tel-Aviv, Israel, where he graduated Shimon Ben-Zvi high school. He then attended Tel-Aviv University where he received his B.A. in Management and Economics (double-major; cum laude), and M.A. in Economics (cum laude). After college, he continued working in Tel-Aviv University as an adjunct lecturer as well as a managing director in Taub Center for Social Policy Studies – a research institute based in Jerusalem. He then returned to school to pursue a Ph.D. in Economics at Cornell University where he also joined as a graduate researcher to Prof. Valerie Reyna's Laboratory for Rational Decision Making at the College of Human Ecology.

עבודת מחקר זו מוקדשת באהבה לאמי היקרה, בתיה דובז'ינסקי ז"ל, אשר הלכה לעולמה בטרם עת, וכן לאבי (החורג), זאב דובז'ינסקי ז"ל, אשר גידל אותי כבנו שלו. תודה על הכל. אני אוהב אתכם!

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THE HISTORY OF DECISION MAKING

Background

In the movie '*Next*', Nicolas Cage (an American actor) plays a man with a unique ability – he can see a few minutes into his future. Thus, knowing what would be the ensuing outcomes of his own choices, within this time frame, he can easily pick the one that maximizes his well-being. Thus, a straightforward decision rule should dictate his choices – choose the best outcome. In the nonfiction world, however, people do not have certainty about future outcomes. They often choose between outcomes that vary in known (e.g., the spin of a roulette wheel) and unknown (e.g., the effectiveness of experimental medical treatments) probabilities.

Despite the uncertainty regarding future events, people still need to make plenty of choices, in various domains, every day. Some choices entail significant, long term, implications (e.g., deciding what to study, which house to buy, whether to start a business, who to get married to). Other choices may sound less dramatic, yet they do carry the potential to either cause or prevent unwanted, and even disastrous, consequences (e.g., having unprotected sex, buying apartment insurance, or passing a vehicle on a two-way road), or to facilitate high-stakes benefits (e.g., purchasing a lottery ticket or investing in a risky but potentially high-return stock). Also, there are choices with mild to low impact over one's lifetime (e.g., carrying an umbrella on a cloudy day, purchasing a new toothpaste brand, or betting $20 on red in a roulette game).

The field of *judgment and decision making* (JDM) classifies this sort of choices, when outcomes are contingent upon whichever state of the world transpires, as *decision making under uncertainty*. Importantly, it constitutes the heart of this field. It should be noted that uncertainty about future events can sometimes be measurable and sometimes immeasurable. That is, in

some cases, we can accurately translate available information into numbers that indicate the likelihood to observe uncertain events. When rolling a (fair) die, for example, we cannot tell for sure which number will come up, but we do know for certain the *probability* to obtain the number six, an even number, or any other related event. In other cases, which apply to most real life situations, the likelihood of uncertain events is incalculable. What is the probability of an economic crisis next year? To find a cure for cancer in the next decade? That the Los Angeles Lakers will win their next NBA game? In his 1921 book, *Risk, Uncertainty, and Profit*, the economist Frank Knight made a formal distinction between the two types of uncertainty mentioned above. He called the measurable one *risk* and the immeasurable one *true uncertainty*, which later has been termed in the literature as *Knightian uncertainty*. However, in order to keep things plain, in this chapter we will use both *risk* and *uncertainty* interchangeably to convey the same theoretical meaning.

There are multiple disciplines comprising the field of JDM (such as Psychology, Economics, Mathematics, and Philosophy), with a staggering number of works striving to account for the processes by which people make, or ought to make, choices in various circumstances. The purpose behind these efforts is not just to satisfy the whimsical curiosity of researchers in the field. In fact, the value of learning how people reason and make decisions stems from its real-life implications. Such knowledge enables policy makers to design better policies and legislate laws to improve public welfare in different areas of life such as health, employment, transportation, insurance, pensions, and many more. It also allows executives in the private sector to devise suitable marketing and other business strategies. By learning the mechanisms of decision making, we can avoid cognitive biases and "irrational" choices, which will be discussed later in this chapter.

In this chapter we explore how the topic of decision making under uncertainty has intellectually evolved over time. However, before plunging into some of the main models and theories of this field, it is useful to discuss three fundamental types of analyses. Each study of decision making can be classified as *normative*, *descriptive*, or *prescriptive*.[1] The normative approach is a "rational" one. It seeks to demonstrate how people ought to make choices in a coherent, logical way. The key assumption underlying this approach is that the decision maker is a logical, deliberative creature, who obeys some basic rules of sound choice behavior formulated in what are called "axioms" (Von Neumann & Morgenstern, 1944). For example, an axiom called "transitivity" means that if a decision maker prefers a red car to a blue car, and the blue car to a yellow one, she will prefer the red car to the yellow car. Similarly, the *Independence of Irrelevant Alternatives* (IIA) axiom posits that if an individual prefers a trip to Rome over Paris, she would not reverse her preference with the introduction of another alternative, say Barcelona (Rome should still be preferred to Paris whether Barcelona was eventually chosen or not).[2] This ideal creature is further assumed to have the capacity to process all available and relevant information, and is fully capable of performing any level of calculation required in order to reach an optimal (best) decision.

Descriptive analysis focuses on how real, imperfect human beings make choices in practice, how they reason, and why they behave the way they do. In particular, it examines different patterns of behavior that systematically deviate from axioms of decision theory. Furthermore, unlike the normative approach, it is mostly based on empirical methods and statistical analysis conducted on observed choice behavior. For instance, in one of their experiments, Simonson and Tversky (1992) found that the proportion of subjects who, from a set

[1] For a thorough discussion on this topic see Bell, Raiffa, & Tversky, (1988)
[2] IIA is sometimes referred to as Chernoff condition or Sen's property alpha.

of two different cameras, preferred to purchase the one that is more expensive grew larger when an even more expensive camera was introduced as a third alternative.[3] Clearly, this study falls under the descriptive category as it shows a situation in which the IIA axiom is violated using empirical data.

In short, normative theories draw upon philosophical standpoints about how the ideal decision maker *ought to* choose, whereas descriptive analyses are the product of empirical findings showing how real people *do* make choices.

Finally, the prescriptive approach can be thought of as a mixture between normative and descriptive analyses. Its main goal is to help people make better and more coherent choices while taking into account that "human cognition is non-optimal, non-rational and non-probabilistic", as argued by Tversky and Kahneman (1983). To this end, prescriptive models typically provide people with decision-aiding tools in the form of specific rules and step-by-step guidelines to help navigate their choice behavior in a normative fashion, i.e., away from the human tendency to make inconsistent and illogical choices, or other cognitive biases, as shown in many situations. Assume, for example, a married couple (with the same set of preferences) who are looking to buy a new house and are considering two alternatives. In order to ensure their choice is indeed rational, at least from a normative perspective, they can apply various prescriptive models to aid their decision. One such model, for instance, can suggest the married couple to expand their set of alternatives to include more options, and if necessary adjust their choices to maintain consistent behavior. This prescription will help them adhere to the IIA axiom. But how should these decision makers handle choosing between options that differ in probability? The following section tackles that topic.

[3] This pattern of behavior is known in the literature as the *Compromise Effect*.

Expected Value and Expected Utility Theory

To think about how decision makers cope with options that differ in probability, imagine that you have been given the opportunity to choose between two alternatives:

- A: Win $5 for sure.
- B: Roll a fair die 4 times. If it lands on six at least one time you win $10, otherwise you win nothing.

Which option would you choose? Arguably, there is no universal right or wrong answer to this choice problem. Each of the two alternatives can be a good fit for different types of people, or even for the same type of people under different circumstances. Normally, the choice to this question is determined by factors such as an individual's skills or traits (e.g., numeracy skills or impulsiveness), values (e.g., gambling is bad), and beliefs (e.g., I am a winner) held by the decision maker, as well as his or her financial state, experience, emotional and physical state (e.g., happy and tired), and attitude towards risk (e.g., I do not like taking chances or *risk intolerance*). In addition, prevailing social norms, from which the decision maker operates (e.g., taking chances is cool), and other environmental or external factors can influence the decision.[4] But is there a more precise mathematical approach to this problem as well?

Evidently, a version of the abovementioned choice problem and other similar games of chance (which were quite popular during the 17th century) led to the emergence of modern probability theory as a branch of study. In the year of 1654, Blaise Pascal and Pierre de Fermat, two of the most influential mathematicians of their time, sought to formulate a proper solution to a challenging, longstanding problem. The problem had arisen from a game of dice known as *The*

[4] Note that the factors mentioned here need not be independent of each other. In fact, there are situations in which one feeds the other (e.g., risk intolerance may trigger a feeling of stress when one is being posed with a risky choice; the sight of a rainbow may reinforce a feeling of optimism).

Points, where two players contribute equally to a prize pot and then play several rounds against each other. The first to win a certain number of rounds is declared as the victor and gets to collect the entire pot. The problem was with concocting a *fair way* to divide the pot between the two contenders in the event that unexpected circumstances compelled them to end the game prematurely, before a victor could be properly declared. Hence, it was also called the problem of *division of the stakes*. Pascal rose to the challenge and began discussing this problem with Fermat through a series of letters. Soon enough, they both came up with a similar mathematical solution that accounted for the chances that each player had to win the pot if they had continued playing from the stopping point. Essentially, their reasoning for a fair solution to the problem introduced a new and fundamental principle in probability theory, which was later referred to as *expected value*.

The expected value (EV) of a random variable calculates the average across all possible outcomes weighted by their probabilities. Formally, if X is a random variable with n possible outcomes, $x_1, x_2, \dots, x_n$, and p_i denotes the probability to obtain x_i for every $i = 1, \dots, n$, then $EV(X) = \sum_1^n p_i x_i$. Imagine, for example, a lemonade stand whose daily revenue from selling lemonades depends on the weather. On a sunny day, total revenue sums up to \$400; when it is cloudy and gray outside, the revenue drops to \$100; and when it rains, people prefer to stay home and the lemonade stand winds up selling nothing (no revenue). Assume now that, according to the weather forecast for tomorrow, there is a 50% chance for pure sunshine, 30% chance of clouds, and 20% chance of heavy rain. While future weather is uncertain, it is still possible to calculate the EV of the revenue the lemonade venture will experience (if open tomorrow): $EV = 0.5 \times \$400 + 0.3 \times \$100 + 0.2 \times \$0 = \$230$.

Furthermore, based on the principle of the *law of large numbers*, EV represents the value to which the average outcome of the random variable converges when the choice is made

repeatedly. That is, if you roll a six sided die a thousand times, for example, and average across the observed outcomes you will almost surely get a number very close to 3.5, which is indeed the expected value obtained from a given roll of a standard die.

With its ability to accurately predict the average outcome of uncertain events, EV soon was recognized as a prominent criterion for guiding rational choice behavior (mostly, but not exclusively, for financial choices). Basically, the theory of expected value argues that rational decision makers should choose the alternative that maximizes their expected value. Thus, when facing a decision problem such as: win $3 for sure or flip a coin and win $8 if it comes up heads or $0 otherwise, an *expected value maximizer* would pick the coin flip over the sure prize. In other words, $3 X 1.0 = $3 and $8 X .5 = $4; the maximizer would choose the coin flip because it has higher expected value ($4) than the sure thing ($3). In a similar fashion, we can now employ the EV theory to reexamine the choice problem posed at the beginning of this section – take $5 for sure or roll the die four times and win $10 if a six comes up at least once (nothing otherwise). A simple calculation shows that the expected value of the risky option (i.e., rolling the die) is just under $5.2. This means that, on average, the return from rolling the die is higher than that of the safe alternative, thus making it a better option for rational EV maximizers.

But as much as this theory may seem plausible from a rational standpoint, people in the real world do not seem to apply the EV principle so avidly in their risky choice behavior. A high proportion of American households, for example, refrain from investing their money in financially risky assets despite being an actuarially favorable gamble (i.e., the stock market provides high average return). This phenomenon is known as the "*stock market participation puzzle*" (Haliassos & Bartaut, 1995). Other evident examples for risky behavior that deviates from the EV maximization rule are gambling at a casino, where the odds are always tilted in favor of the house, purchasing lottery tickets, and even getting cell phone insurance. What is

common to these examples – and many others like them – is that in the long run people will most likely lose money (or earn less) by not following the EV rule.

Occasionally, however, the long run averages themselves are, at least prima facie, immaterial to the decision – particularly when facing a single, non-repeated choice problem. Assume that the daily costs of running the lemonade stand from the example above are $150 and recall that, based on tomorrow's weather forecast, a revenue of $230 is expected on average. Clearly, an EV maximizer would choose to take a risk and open the stand the next day since the expected value of the revenue is higher than the costs ($230 > $150). But note that $230 is merely the result of a theoretical concept and not an attainable outcome. That is, by repeating the same day, with the same weather forecast over and over again, the revenue will ultimately approach $230, yet the actual choice to open the stand concerns only the next day, in which $230 is not a feasible outcome. Why, then, should a choice be driven by the EV principle – even from a normative perspective? Scholars soon criticized the EV principle for this and other reasons.

The first formal challenge to the EV paradigm arose in 1738 when Daniel Bernoulli, a Swiss mathematician and physicist, published a paper in the *Commentaries of the Imperial Academy of Science of Saint Petersburg*. In his paper, Bernoulli proposed a resolution to a problem – known today as the *St. Petersburg Paradox* – which questioned the EV principle as a rational decision rule. The paradox is illustrated by a game of chance that was discovered by Daniel's cousin, Nicolas Bernoulli, in 1713. The game is played as follows: A fair coin is flipped repeatedly until the first time it comes up tails; then the game stops (so there is a 50% chance the game will end after just one toss). The player gets $2 after the first toss and then the prize is doubled with every coin flip until the game ends. Thus, if the game ends after one toss ('tails') the player wins $2, if it ends after two coin tosses ('heads', 'tails') the prize is $4, with three tosses ('heads', 'heads', 'tails') the prize grows exponentially to $8, and so on. What is,

then, the maximal price a rational individual would pay to enter this game? Would you pay $100? How about $100,000?

A decision maker who obeys the EV maximization rule should enter the game for any price lower than the expected payoffs. But apparently, the mathematical expectation of this game is unbounded; namely, the game's long run average win is an infinite number of dollars! Thus, no matter how high the entry price is, a rational EV maximizer will readily pay it. Clearly, however, no rational human being will enter the St. Petersburg game at any cost, and hence the paradox. In fact, as Ian Hacking (1980) argues, the majority of people would not take part in this game even for as little as $25.

Bernoulli's solution to this problem distinguishes between the numerical value of the prize (i.e., number of dollars) and the level of satisfaction, or utility, obtained by the amount of money received. A rational decision maker, then, is said to make choices based on satisfaction gained by the payoffs rather than their monetary value. Furthermore, Bernoulli argued that the level of utility goes up with money but in a nonlinear fashion, particularly as a concave function, such that every additional dollar increases the overall utility by less than the dollar before. Roughly speaking, ten dollars added to an initial prize of $100 seem more satisfying than the same ten dollars when added to a $10,000 prize.[5] Bernoulli proposed a logarithmic function to mathematically represent people's utility (log-utility function), which solves the St. Petersburg problem. A rational individual with a log-utility function characterizing his or her level of satisfaction from wealth will likely pay no more than $4 (the expected utility of the gamble using log-utility function) to participate in the St. Petersburg game.

[5] This has become a key property in the field of economics known as the '*law of diminishing marginal utility*'.

The pioneering work of Bernoulli was the first to provide a formal explication of the notion of utility and diminishing marginal utility – bringing it to the forefront of decision-making research. His solution to the St. Petersburg paradox shifted the focus from expected value to expected utility as the key principle that underlies rational choice behavior, which inspired generations of researchers who embraced this principle in their work.

However, it took over 200 years for the idea of expected utility to evolve into a full-blown theory. In 1944, John von Neumann and Oskar Morgenstern provided a set of four axioms of rational choice behavior that are necessary and sufficient to be able to represent preferences over risky outcomes (gambles) using the expected utility model. We have discussed two of these axioms already: *independence* and *transitivity*. Transitivity is an axiom that entails consistency, as our earlier example with three cars suggests. It states that if an alternative A is preferred to B, and B preferred to C, then A must also be preferred to C. Another axiom, known as *completeness*, states that for every two alternatives, A and B, a decision maker should either prefer A to B, B to A, or be indifferent between A and B. That is, inability to compare any two alternatives is not a viable possibility for a rational decision maker. (The fourth axiom of *continuity* is beyond the scope of this chapter, but see (Von Neumann & Morgenstern, 1944)) Von Neumann and Morgenstern proved mathematically that decision makers whose preferences obeyed these basic rules of consistency--the axioms--would maximize their outcomes. Following von Neumann and Morgenstern's formulation, the expected utility (EU) theory has become the dominant, most influential economic theory for analyzing choices under uncertainty.

Rational models of decision making, such as EV and EU theory, rest on the premise that when making choices people are well informed regarding the available alternatives relevant to their decision as well as every possible outcome for each of these alternatives. Furthermore, it is assumed that their preferences over the set of choice elements are well defined and coherent

(e.g., complete and transitive) and that they are endowed with high enough cognitive capacity to allow them to solve the problem of value maximization through which they could pick the best alternative available. However, it is quite doubtful that a rational individual of this sort has ever existed. The question whether, and to what extent, people behave as rational decision makers was mostly left to psychologists to explore and to suggest alternative models of choice behavior.

Although many economists realized that rational models had some unrealistic assumptions about human information processing, these were considered trivial for most practical purposes. But psychologists became fascinated with the powerful expected utility model: The son of an economist, Ward Edwards, introduced the model to psychologists in 1954, asking whether people actually behave as economists had assumed, balancing the desirability of an outcome against its chance of occurring. Meanwhile, psychologists were identifying substantial limitations in human information processing, notably, George A. Miller in his influential 1956 paper, The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. The central idea of this paper—still believed by most psychologists today—is that people cannot think about alternatives exhaustively. Instead, decision makers can remember and think about only a few chunks of information (seven according to Miller, four according to some recent theorists) at a time, which limits or bounds their ability to make decisions. Miller influenced his friend Herbert Simon, who then assumed people were limited but still "rational" in a scaled-down way: They did not pick the best option possible (maximizing), but, rather, chose options that were good enough, called "satisficing," as we discuss below (Simon, 1957).

Challenging Rationality

Trying to acquire the relevant knowledge to make a rational decision as outlined above, including all available alternatives, probabilities, and outcomes, and then using that information to solve an optimization problem is both time consuming and mentally taxing. Generally, we even lack the cognitive capacity to execute the level of computation required by rational choice models. Thus, in a world where people make numerous choices every day, it is actually inefficient to be entirely rational. Instead, it is essential for us to reduce the vast amount of available information and to be able to rely on some mental shortcuts and more practical decision rules – known as *heuristics* (or rules of thumb) – in order to reach a decision within a reasonable time frame.

Bounded Rationality and Satisficing

Among the earliest scholars who recognized the fact that people's rationality is limited, and thus cannot be represented by the ideal decision maker as portrayed in standard models of rational choice, was Herbert Simon, the 1978 Nobel laureate. He referred to this principle as *bounded rationality* (Simon, 1957) and argued that in general it results in people settling for a cognitive heuristic, labeled *satisficing*, which significantly simplifies the decision-making process. That is, instead of maximizing across all available alternatives, using all the information they can gather, decision makers aim at satisficing by setting aspiration levels, or "good enough" criteria, and then choosing the first alternative whose attributes, or value, exceed the minimum threshold set by these criteria. The chosen alternative is, thus, satisfactory by design but need not be the optimal one.

Consider a situation in which you are looking to buy a birthday present to your 7 years old nephew. Clearly, the number of alternatives you can choose from is enormous and the

amount of relevant information to consider is exponentially higher: Would you buy a board game, a book, tickets to a circus show, or maybe a pet? What color? How much money to spend on the gift? Those are just a few of the questions you can ask yourself. If you try to pick the ultimate gift by solving an optimization problem, you will probably miss your nephew's birthday altogether (maybe his 8th birthday too...). Satisficing, then, is a common course of action in these situations. You can decide to focus on items relevant to your nephew's favorite movie, for example, and set a range of prices you are willing to consider. This will reduce the complexity of the problem allowing you buy a satisfying gift in time for that birthday.

"Errors" in Probabilistic Reasoning

Probabilities are one of the key building blocks of rational models of risky choice (e.g., EV and EU). It is assumed, therefore, that the decision maker is capable of judging the precise likelihood that each possible outcome will occur. But how good are we really at translating given information about events into the exact probabilities that those events will actually occur?

The Monty Hall problem

To exemplify this point, consider the following game: There are 3 doors, A, B, and C, from which you have to choose one. Behind one of the doors lies a prize of one million dollars, nothing lies behind the other two doors. The host of this game, who knows exactly where the prize is, asks you to make your choice. Suppose that you pick door A. At this point, your chance to win the prize is 1/3. Before revealing what awaits you behind door A, the host opens another door and shows you that nothing is there, say door B (remember that he knows where the prize is). He, then, gives you the option to change your initial choice and switch to door C. Would you keep door A or would you choose door C now? Most people believe that there is a

50-50 chance now to find the prize behind either one of the two doors, and they typically stick with their initial choice. Surprisingly, though, they are wrong. By moving from door A to C you actually double your chances to win the prize from 1/3 to 2/3. Thus, counterintuitively, switching doors is an advantageous strategy. Note, that changing the initial choice is equivalent to choosing where the prize is NOT, since effectively you are moving your choice to include both of the remaining two doors (and hence the 2/3 chance to win) – one of which is opened by the host and the other door is the one you moved your choice to. In contrast, by sticking with the original choice you have no control over which two doors will eventually be opened.

This game is known as the *Monty Hall problem*. It is based on a television game show from the early 1960s whose host's name was Monty Hall. In one experiment with this problem, for example, only 12% of all participants chose to switch (Granberg & Brown, 1995). This game, thus, provides a convincing evidence of our difficulty to derive intuition for probabilities from given information.

Conservatism Bias

Starting in the early 1960s, Ward Edwards introduced the idea of Bayesian probability inference into the field of psychology. A statistical formula, known as *Bayes theorem* (or *Bayes rule*) lies at the heart of this idea. This statistical tool allows us to accurately update prior belief regarding the probability of some random event when being presented with new evidence. Edwards, along with his colleagues, had conducted a number of experiments to assess whether people were indeed Bayesian in their probability judgment behavior. That is, how well do people revise their prior beliefs when new information is presented?

Here is a typical Edwards' experiment: There are two book bags, each with 1,000 poker chips. One has 700 red chips and 300 blue chips and the other one has 700 blue chips and 300

red chips. A subject is asked to pick one of the bags, sample few chips one by one (with replacement) at random, and then estimate the likelihood that he picked the book bag that contains mostly red chips. Suppose that a sample of 12 chips has been drawn, 8 of which were red. What is, then, the likelihood this is the bag with the 700 red chips? The majority of subjects believed it is somewhere around 70% chance. However, the correct answer, using Bayes rule, is in fact closer to 97%.

It seems, then, that people do update their prior in the right direction (from 50-50 chance for each bag to around a likelihood of 70% to have the mostly-red-chips bag), but they do so insufficiently when compared to properly applied Bayesian inference. Given his findings, Edwards concluded that people tend to overestimate the prior and underestimate new evidence, or, in his own words, they are "conservative processors of fallible information" (Edwards, 1968). This effect is known as the *conservatism bias*.

Base Rate Neglect

We just discussed how people can be prone to processing new information in a conservative way, giving too much weight to prior belief. However, interestingly, people can also exhibit the exact opposite bias, this time underweighting the prior. This bias is known as the *base-rate neglect* (or *base-rate fallacy*). The base rate of a certain event is defined as its prior likelihood, or unconditional prevalence. People are susceptible to this bias when they shift their attention away from the base rate information and focus mainly on some new acquired data.

A classic example that demonstrates this bias was originally introduced in 1973 by the two celebrated psychologists, Amos Tversky and Daniel Kahneman.[6] Amos Tversky was a student of Ward Edwards, and was joined at University of Michigan by Daniel Kahneman. They

[6] See also: Lyon & Slovic (1976), and Bar-Hillel (1980).

were intrigued by the exceptions to expected value and expected utility theory. Here is a slightly modified version of that base-rate problem:

> A taxi-cab was involved in a hit-and-run accident one night. Of the taxi-cabs in the city, 85% belonged to the Green company and 15% to the Blue company. an eyewitness had identified the cab as Blue. The court tested the reliability of the witness under the same circumstances that existed on the night of the accident and concluded that the witness was able to make correct identifications 80% of the time (failing to identify only 20% of the time). What is the probability that the taxi-cab involved in the accident was Blue rather than Green?

The answers given by the vast majority of respondents ranged between 0.5 to 0.8 probability that a Blue cab was involved in the accident, with 0.8 being the most typical answer to this question. This answer coincides perfectly with the data regarding the witness's credibility, while neglecting the base rate information about the relative frequencies of the two taxi-cab companies. The correct probability obtained by using Bayes rule is actually 0.41. It is very likely, then, that the witness was wrong despite having good observation skills, which may seem counterintuitive. Importantly, the potential consequences of neglecting the base rate can be quite perturbing. Kahneman and Tversky expressed their concern regarding the taxi-cab problem as follows: "Much as we would like to, we have no reason to believe that the typical juror does not evaluate evidence in this fashion." (Daniel Kahneman & Tversky, 1973).

Other practical implications of the rate-base bias on decision making can also be found in the field of medical diagnosis. As Eddy (1982) and others have noted, it is not at all uncommon for physicians, for example, to overly rely on specific test results and disregard the prevalence rate of the actual disease they are trying to diagnose (e.g., Gigerenzer, Hoffrage, & Ebert,1998;

Gigerenzer et al., 2007; Reyna, 2004). To counteract this bias, medical students are sometimes told, when you hear hoof beats (symptoms), think horses not zebras (common not rare diseases).

(In)consistent Choice Behavior

Normative models of decision making are typically founded upon axioms of rational choice, such as completeness, transitivity, and so on. These axioms are designed to ensure consistency of the decision maker's preferences and, at least from a philosophical standpoint, they are arguably sound. For example, it would be considered illogical for a person to strictly prefer some alternative A over B but then, in a similar situation, having no additional relevant information, choose B over A. Normally, the axioms will prevent this form of inconsistency.

But to what extent do real people exhibit coherent choice behavior as predicted by the rational models (such as EU theory)? We highlight here cases in which consistency seems to be violated.

Preference Reversals

In 1971, the psychologists Sarah Lichtenstein and Paul Slovic (also students at University of Michigan) documented a pattern of human choice behavior that challenged the supposition that human preferences are consistent. The researchers designed an experiment in which the stimuli consisted of a number of paired binary gambles. Each pair had roughly the same monetary expected value with one gamble structured as a high-probability, low-stakes payoff (the so-called 'P-bet'), while the other gamble offered low probability to win a relatively large payoff (the so-called '$-bet'). Subjects were asked to choose one bet from every pair of gambles. Generally, the P-bet was chosen more frequently than the $-bet indicating a preference for the lower risk gambles. However, when asked to state their bidding price for every gamble,

the subjects typically placed a higher value on the $-bet, which reflects a reversal in their preference order – a phenomenon known as *preference reversal*.

This pattern of "inconsistent" behavior has been replicated many times since (e.g., Lichtenstein & Slovic, 1973; Grether & Plott, 1979; Tversky, Slovic, & Kahneman, 1990). One common explanation found in the literature for preference reversals is that different types of preference elicitation methods tap into different attributes of the gamble. This is known as *scale compatibility* (Tversky, Slovic, & Kahneman, 1990). That is, when bidding their prices, subjects weighted the gamble's monetary payoffs more heavily than they did when directly choosing between the gambles. This clearly poses a violation to a fundamental principle of rational decision making, which states that preferences should be invariant to the elicitation mode.

The Certainty Effect

During the 1970s, Daniel Kahneman and Amos Tversky continued to search for behaviors that systematically deviated from core principles of rational choice models (e.g., EU theory). In one of their experiments, 95 respondents were asked to give their choices for each of the following binary decision problems:[7]

Problem 1: Choose between

A: 3,000 pounds for certain

B: 4,000 pounds with probability of 0.8 (0 pounds otherwise)

Problem 2: Choose between

C: 3,000 pounds with probability 0.25 (0 pounds otherwise)

D: 4,000 pounds with probability of 0.2 (0 pounds otherwise)

[7] These pair of gambles are based on a problem constructed by the French physicist and economist, Maurice Allais (1953), which was the first major challenge to expected utility theory (calling into question the independence axiom). It is known today as the *Allais paradox*.

Note that if you multiply the probabilities of both, options A and B, by 25% you get options C and D respectively, so that choice problem 2 is merely a 25% version of problem 1. Nevertheless, in the first problem, the majority of respondents (80%) opted for the riskless option, the 3,000 pounds for certain (option A) – although the gamble offers a higher expected value, while in problem 2 a reversed pattern was observed, where this time the riskier option of 4,000 pounds with probability 0.2 (option D) was chosen more frequently (65%). According to Kahneman and Tversky (1979), a significant reduction in the desirability of a prospect occurs when a riskless positive outcome is altered to a probable one. Thus, this bias is referred to as the *certainty effect*.

The Reflection Effect

As part of the same experiment listed above, the 95 respondents were given another decision problem, this time with negative prospects (i.e., losses), in which they needed to choose between two options:

Problem 1': Choose between

A': –3,000 pounds for certain

B': –4,000 pounds with probability of 0.8 (0 pounds otherwise)

Note that this problem is a precise reflection of problem 1 above, only in the negative domain. It is a reflection the way an image is reflected in a mirror—everything is the same except in the opposite direction. However, while in problem 1 the majority chose the safe option (option A), this time 92% of all respondents chose the risky option (option B'). Essentially, they accepted the risk of losing more money (i.e., 4,000 pounds) over a sure loss of 3,000 pounds. The incongruent behavior obtained from problems 1 and 1' follows a consistent pattern in which

people exhibit risk aversion with gains and risk seeking behavior with losses. Kahneman and Tversky (1979) labelled this pattern the *reflection effect*.

To further test this effect, they also presented the following two decision problems:

Problem 3: In addition to whatever you own, you have been given 1,000 pounds. You are now asked to choose between

A: 1,000 pounds with probability of 0.5 (0 pounds otherwise)

B: 500 pounds for certain

Problem 4: In addition to whatever you own, you have been given 2,000 pounds. You are now asked to choose between

C: –1,000 pounds with probability of 0.5 (0 pounds otherwise)

D: –500 pounds for certain

In accordance with the reflection effect, the riskless option B was chosen by the majority (84%) in problem 3, yet most respondents (69%) chose to take a risk with option C in problem 4. That is, people (again) showed a tendency to avoid risk with positive payoffs but were willing to accept it with negative prospects. Importantly, note that by combining the bonus in each problem with the prospects (i.e., the options), problems 3 and 4 are collapsed into the same choice problem with the same final consequences (1,500 for certain vs. 50-50 chance for either 1,000 or 2,000). However, the disparate choice behavior between the two problems is strikingly evident, which puts a big question mark on rationality as defined by standard models of decision making.

Framing Effect

The notion of a *framing effect* is possibly the most striking demonstration of incoherent risky choice behavior. A framing effect is being referred to when a shift in preferences is caused

by the way outcomes of a prospect are described (i.e., *framed*). The popularity of this concept goes back to 1981 when Amos Tversky and Daniel Kahneman published the results of an experiment they had run, which illustrated the effect of variations in framing. In one example, the researchers presented the following two problems to two groups of roughly 150 respondents each, such that every group received one problem:

Problem 1: Imagine that the U.S. is preparing for the outbreak of an unusual disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:

- If Program A is adopted, 200 people will be saved.
- If Program B is adopted, there is a 1/3 probability that 600 people will be saved and a 2/3 probability that no people will be saved.

Which of the two programs would you favor?

While both programs have the same expected value of lives saved, the majority of respondents (72%) chose the riskless option, that is to save 200 people for certain (Program A). The outcomes in problem 1 were framed as gains (lives saved). Problem 2, on the other hand, was described in terms of lives lost (loss frame) as follows:

Problem 2:

- If Program C is adopted, 400 people will die.
- If Program D is adopted, there is a 1/3 probability that nobody will die and a 2/3 probability that 600 people will die.

Which of the two programs would you favor?

Note that the (probabilistic) results from both Programs C and D are identical to those presented in Programs A and B (respectively) in terms of the number of people who will live and

die. However, the majority of respondents (78%) presented with problem 2, chose the risky option (Program B). This is a clear evidence for the effect of framing. Particularly, it shows that people tend to be *risk averse* with prospects when outcomes are framed as gains and *risk seeking* when framed as losses.

The framing effect bias, which has been replicated many times, seems to be driven by context and, thus, poses a real challenge to the proponents of rational choice models since it demonstrates a serious violation of the invariance axiom. In addition, its effect on people's decision making has real-life implications in many different areas (e.g., law, politics, medicine, marketing, etc.). By framing a situation as either the half-full or the half-empty part the glass, one can manipulate our choice behavior. When we react differently to a cash discount and a credit-card surcharge that amount to the same thing, we are demonstrating framing effects.[8]

Loss Aversion and the Endowment Effect

The shift in preferences illustrated by the example of the 'dread disease' problem is a testament to the idea that people react differently to losses than they do to gains. In particular, the negative psychological effect experienced from losing a sum of money outweighs the positive one obtained from gaining the same amount. Hence, people will usually find a gamble that offers a 50-50 chance of losing $10 or winning $11 unattractive, despite the positive expected payoff. In other words, "losses loom larger than corresponding gains" (Tversky & Kahneman, 1991), which best describes the notion of *Loss Aversion*.

Loss aversion is one of the most widely used constructs in descriptive decision research. It was first introduced as a feature of risky choice behavior in *prospect theory* – a model of

[8] For more practical examples of the effect of framing on choices, see Thaler (1980, 1985), a winner of the Nobel prize in 2017 for this work confirming that people are irrational.

decision making under uncertainty formulated by Daniel Kahneman and Amos Tversky in their seminal paper from 1979 in order to characterize the asymmetry between the level of aggravation and pleasure obtained by losses and gains of the same magnitude. Note that since gains and losses carry changes to some absolute value (e.g., overall wealth) they have to be defined relative to a *reference point* (e.g., the status quo), which makes it an integral part of every decision-making model that wishes to incorporate loss aversion. Any changes in the reference point may cause a shift in preferences and, accordingly, alter the observed choices (similar to the pattern we saw in the framing example).

In addition to accounting for the specific pattern of risky choice behavior with mixed prospects, that contain both gains and losses, there is also a riskless manifestation of loss aversion, in which people often demand more to part with a valued object in their possession than they would be willing to pay in order to acquire it. The 2017 Nobel laureate, Richard Thaler, called this phenomenon the *endowment effect* (Thaler, 1980), which highlights the idea that out-of-pocket costs are weighted more heavily than forgone gains of the same magnitude. A number of examples were given by Thaler (1980) to illustrate this effect. According to one such example: "Mr. H mows his own lawn. His neighbor's son would mow it for $8. He wouldn't mow his neighbor's same-sized lawn for $20."

The endowment effect was successfully tested in a series of experiments conducted on college students by Kahneman, Knetsch, and Thaler (1990). In one such experiment, half of the students in a classroom received decorated Cornell coffee mugs (with a price tag of $6), and were assigned to be *sellers*, while the other half were *buyers*. Then, the experimenters elicited the minimum price each seller was willing to accept (WTA) in exchange for the mug and the maximum price each buyer was willing to pay (WTP) to acquire the mug. The results of the experiment showed a significant discrepancy between WTA and WTP in the hypothesized

direction. The WTA median was approximately twice the size of the WTP median. That is, the students who randomly received the mug valued it twice as much as those who did not. The endowment effect was also found in a successive experiment, in which the experimenters used ballpoint pens instead of mugs.

The Fourfold Pattern of Risk Attitudes

As demonstrated by the reflection effect, for example, a person can be both risk averse and risk seeking at the same time. That is, risk attitudes constitute another aspect of inconsistent human behavior. It is not uncommon, then, to see people buy an insurance policy (risk aversion) while also purchasing a lottery ticket (risk seeking). Tversky and Kahneman (1992) generalized this pattern of behavior by organizing the different types of attitudes towards risks according to four distinct domains, which they refer to as the *fourfold pattern of risk attitudes*. Particularly, they noticed that people are risk averse for gains with moderate-to-high probability and losses with low-probability, and risk seeking for gains with low-probability and losses with moderate-to-high probability. The fourfold pattern is illustrated in Table 1.1 using an example adapted from Tversky and Kahneman (1992).

Prospect Theory

After conducting a countless number of experiments to study human choice behavior and derive preferences among various risky prospects, Daniel Kahneman and Amos Tversky decided to put forth an alternative model to standard theories of rational choice (particularly the EU theory), intended to account for their many "irrational" observations. The model was referred to as *Prospect Theory* (Kahneman and Tversky, 1979), and has become the most widely used

behavioral model of human risky choice – rapidly expanding across the multiple disciplines of JDM research.

Prospect theory was built around the many biases and "errors" that characterize both probability judgment and choices, some of which discussed earlier in this chapter. The model consists of two functions designated to capture the underlying psychological process of human decision making: (a) a value function that encodes the level of satisfaction (or dissatisfaction) associated with the possible payoffs and (b) a probability weighting function that assigns decision weights (psychological interpretations of the size of the probability) to the different consequences based on the objective probabilities of occurrence. According to the model, preferences over prospects are determined by their overall valuation – calculated as the sum of all values obtained by multiplying the possible payoffs by their respective decision weights.

Three fundamental features distinguish the value function from a standard utility function (see Figure 1.1). (1) *Reference dependence*: whereas standard utility function represents the satisfaction obtained by the *final* amount of wealth, the values in prospect theory are a function of *changes* in wealth – gains and losses relative to a natural reference point – positive for gains and negative for losses. (2) *Loss aversion*: the value function is steeper for losses than it is for equivalent gains. This feature captures the idea discussed earlier that losses loom larger than corresponding gains. (3) *Diminishing sensitivity*: the higher the size of a given gain or loss, the smaller the marginal change to the value function. This feature generates an S-shape, where the positive domain of the value function is concave and the negative one is convex. The S-shape implies risk aversion for gains and risk seeking for losses due to its mathematical properties (which can account for the reflection effect, for example).

The other major component of prospect theory is the probability weighting function, which reflects the idea that probabilities are often distorted in a predicted way (see Figure 1.2).

Thus, by converting the probabilities into decision weights, it generally captures the psychological impact of probabilities on the desirability of the prospect. For example, people tend to overestimate a 2% chance to win $10,000, and might buy such a lottery ticket; they assign a higher decision weight to this consequence (say 3%), relative to its actual likelihood. The two main characteristics of the probability weighting function are overweighting of low probabilities (but greater than zero) and underweighting high probabilities (but less than one).[9]

In 1992, Kahneman and Tversky extended their theory in order to allow for more flexibility in predicting choice behavior with risky prospects, and to address some other technical issues that were prevalent in the original prospect theory (specifically in the probability weighting function). The updated model was referred to as *Cumulative Prospect Theory* (CPT; Tversky & Kahneman, 1992). In particular, they modified the probability weighting function, while retaining the psychological aspects of the original one (see Figure 1.3).[10] The new function has an inverse S-shape form, which suggests that people tend to be more sensitive to changes in probabilities near the end points (i.e., zero and one) than in the mid-range.[11]

The predictive power of prospect theory is quite remarkable, especially in light of the tractability, and rather simple structure that characterize the model. A combination of the features listed above can account for many of the risky decision making patterns that deviate from the standard models of rational choice, including the certainty effect, reflection effect, framing effect, loss aversion, the four-fold pattern, and so on. However, the predictions derived from prospect theory hinge on the idea of psychophysics and the perception of numbers (e.g.,

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[9] Decision weights are assumed to coincide with probabilities for the edge values of zero and one.

[10] The new functional form of the probability weighting function eliminates some possible violations of a central property of rational decision making known as *first order stochastic dominance*.

[11] See, for example, Camerer & Ho (1994), Wu & Gonzalez (1996), and Gonzalez & Wu (1999).

probabilities and payoffs), which as we see next, fail to actually predict some key findings, such as framing effects and the Allais paradox.

Fuzzy-Trace Theory

The cognitive process behind the act of decision making implicates memory and reasoning – namely, making sense of the available information and consequently reaching a conclusion that facilitates a choice between alternatives. Findings from psycholinguistics, JDM, and memory were integrated into the modern version of *Fuzzy-Trace theory* (FTT) in the 1990s. (see Reyna, 2012, for an overview of the theory)

FTT is a model of memory, reasoning, judgment, and decision-making that was first proposed in 1991 by the two psychologists, Valerie F. Reyna and Charles Brainerd, in an attempt to provide an adequate account for the line of results, which challenged earlier, conventional approaches to cognition. The model distinguishes between two mental representations of informational inputs: *verbatim* and *gist*. Verbatim representation encodes the exact, surface details of a given problem or event, whereas gist representation is fuzzier in nature, extracting the patterns and meaning implied by the information. Furthermore, the verbatim and gist traces of information are encoded and stored in the brain simultaneously (rather than sequentially). For example, when presented with the following data: "Farmer Brown owns 12 cows, 7 sheep, and 3 horses," one can encode and store verbatim traces, such as "12 cows," or "3 horses," concurrently with gist traces in the form of "cows are most," more cows than horses, and "horses are least," (Reyna & Brainerd, 2008).

When facing a choice problem, stored information fuels the decision-making process. According to FTT, relying on gist representations of the available information leads to a type of reasoning which is inherently different than reasoning based on verbatim representations. This

can often lead to different conclusions and choices for the same decision problem. Consider, for example, a choice problem between $50 for sure and a 50% chance to receive $100 and 50% chance to receive nothing ($0). The precise, surface details of this problem entail an equivalence between the expected value of the riskless option and the expected value of the gamble, whereas the bottom line meaning of this problem yields a categorical distinction of the sort: "something" (the riskless option) vs. "a chance of something and a chance of nothing" (the gamble). Thus, reliance on verbatim representations will generate indifference between the alternatives (equal expected value), while reliance on gist promotes risk aversion (i.e., picking the $50 because something is better than a chance of nothing). Note that the gist version of the options is not just any interpretation: the simplest interpretation of outcomes (here, as categorically something or nothing) is favored in decision making, according to FTT.

Given its distinctive properties, FTT can provide an alternative explanation to the observed biases and other anomalies in risky choice behaviors as discussed earlier in this chapter (e.g., framing effect, reflection effect, base rate neglect, etc.). For instance, recall the dread disease example, which is expected to kill 600 people. Table 1.2 presents word by word the two alternative programs proposed in each frame (the verbatim information) as well as the extracted gist representations.

Note that regardless of how the programs are framed, the expected value of the risky option is equal to the number of people who will be saved (or die) by applying the "riskless" program. However, reliance on the simplest gist (called a "fuzzy-processing preference" that most adults have) highlights the categorical distinction between the two programs instead of the exact details. Consequently, program A is favored in the gain frame (it is better to save some than risk saving no one), whereas in the loss frame the pattern is flipped and program D is the one chosen (accepting a chance that no person will die is preferred to the alternative, in which

some people will surely die). Furthermore, choice behavior based on gist representations, with qualitative information only, can produce a nonnumerical framing effect. For example, in one experiment, Reyna and Brainerd (1991) presented a version of the dread disease problem to a group of participants, in which the numerical values were substituted with vague terms such as 'some'. Thus, the options in the gain frame, for example, became: 'some people will be saved' versus 'there is some probability that many people will be saved and a higher probability that no people will be saved'. A similar alteration was made in the loss frame. Results from this experiment showed a strong framing effect (i.e., participants chose the safe option in the gain frame and the gamble in the loss frame). This shows that behavioral anomalies, such as the framing effect, need not be the product of psychophysics of presented numerical information. That is, numbers are *not necessary* to observe the classic effects.

In addition, FTT poses a major challenge to prospect theory and similar utility-based models by demonstrating that numerical values may *not be sufficient* to produce the framing effect. In particular, according to prospect theory consequences that generate no change relative to the reference point (e.g., "no one will be saved"; "no one will die") are valued as zero and, therefore, carry no valuable information to the decision maker. Thus, omitting the zero complement from a framing problem (e.g., the "2/3 chance that no one will be saved" is omitted from the presentation) should have no impact on the framing effect. In FTT, however, those zero outcomes contain qualitative information ("none"), which supports categorical reasoning and produces framing effects. A large number of experiments supported the FTT hypothesis by demonstrating that the framing effect disappears when the zero complement is omitted from the dread disease problem and other decision problems (e.g., Kühberger & Tanner, 2010).[12]

[12] with both monetary and non-monetary outcomes.

Similarly, FTT can explain the certainty effect (e.g., Allais paradox), in which a sure (positive) outcome is disproportionately more attractive than a probable outcome. Recall that most respondents preferred 3,000 pounds for sure over an 80% chance to receive 4,000 pounds (and nothing otherwise), but when the likelihood of each option was multiplied by 0.25, the choice pattern flipped, namely, a 20% chance to win 4,000 pounds was chosen more frequently than 3,000 pounds with 25% probability. This sort of inconsistent behavior poses one of the most fundamental challenges to the idea that people are rational. The certainty effect (that people prefer the sure option) is accounted for by Prospect theory, for example, by using a non-linear probability distortion function (the inverse s-shaped probability function), which captures the idea of psychophysics of numerical information – people tend to overweight small probabilities and underweight large probabilities. Instead, FTT provides an underlying cognitive process that accounts for the reasoning that leads to this phenomenon.

In the first choice problem (comparing a sure 3,000 pounds to 80% chance to receive 4,000 pounds), reliance on the simplest gist representation contrasts "winning something" (3,000 pounds for sure) against "a chance of winning something and a chance of winning nothing" (4,000 pounds with 80% chance), which renders the riskless option more attractive than the gamble, despite having a lower expected value than the risky option (3,000 < 0.8 X 4000 = 3,200) – again, something is better than nothing. Using gist reasoning in the second choice problem leads to an impasse as both options (25% chance to win 3,000 pounds or 20% chance to win 4,000 pounds) are probable with a bottom line meaning of "a chance of winning something and a chance of winning nothing." Thus, in order to reach a decision one needs to go higher on the gist-verbatim reasoning hierarchy and rely on increasingly precise comparisons, ultimately processing the exact numerical data presented. Consequently, based on verbatim reasoning, the riskier gamble (20% chance to win 4,000 pounds) is chosen as it has a higher expected value (0.2

X 4,000 = 800) than the expected value of the other gamble (0.25 X 3,000 = 750) (for more details on FTT and the Allais paradox see: Reyna & Brainerd, 1994; Reyna & Brainerd, 2011; Broniatowski & Reyna, 2017).

Another aspect of FTT posits that decision makers calibrate the specific mental representation – that is, whether to reason based on gist or verbatim – according to the demands of the task (e.g., Reyna, 2012). This can explain the preference reversal phenomenon discussed earlier, in which people respond differently when they are asked to make a choice between two options compared to how much they value (what they are willing to pay for) each option. For example, one may choose apartment A over apartment B but be willing to pay higher rent for apartment B than apartment A. We use the following example to show how FTT explains this mystery. People tend to prefer a 0.75 chance of winning $1.10 and 0.25 chance of losing $0.10 (low-risk gamble) over a riskier gamble of 0.25 chance of winning $9.20 and 0.75 chance of losing $2 (high-risk gamble) with the same expected value ($0.80). While technically both gambles entail winning something and losing something, people often perceive the $0.10 as nothing (see Stone, Yates, & Parker, 1994), which renders a qualitative contrast between the two gambles. Hence, FTT predicts that, based on the simplest gist representation, winning something or nothing is better than winning something or losing something. However, when asked to separately assess the WTP for each gamble, people gave a higher dollar value to the high-risk gamble – exhibiting, thus, preference reversal. The elicitation procedure of the WTP task requires a more detailed, accurate representation (i.e., verbatim representation) of the given information in order to extract an exact number that represents the subjective value of the gamble. In short, the choice between the two gambles is driven by gist reasoning, which promotes risk avoidance and, thus, making the low gamble *more* attractive (due to the categorical

contrast), whereas the assessment task is driven by verbatim representations – trading off risks and benefits – making the low gamble relatively *less* attractive (Corbin et al., 2015).

Finally, a central characteristic of FTT can explain a counterintuitive phenomenon, in which behavioral biases, such as the framing effect, are more prevalent in adults than in children and adolescents, despite the fact that reasoning develops with age. This phenomenon is called *developmental reversal* and was initially predicted by FTT. According to FTT, while both verbatim and gist processes consistently improve from childhood to adulthood (e.g., Reyna & Brainerd, 2011), developmental reversal is the product of a shift from relying mainly on verbatim to relying mainly on gist, which increases with age and expertise (see Reyna et al., 2011; Reyna et al., 2014).

A large number of studies have applied the constructs of FTT to test its predictions in various real-life situations that involve choice behavior under uncertainty, particularly in areas such as law, health (e.g., HIV prevention), and medical decision making. In one such study, a group of researchers, led by Valerie F. Reyna and Valerie P. Hans, conducted an experiment in which 173 subjects were asked to each play the role of a juror and arrive at a dollar value to compensate the plaintiff for pain and suffering caused by a car accident (based on a scenario from a real trial; Reyna et al., 2015). The experimenters systematically varied the size, context, and meaningfulness of numerical comparisons or anchors (i.e., an initial piece of numerical information that need not be related to the subsequent judgment or decision making) to manipulate the bottom line meaning of the perceived award magnitude, which resulted in large and predicted differences in the size of award judgments across the subjects (for the same incurred damage). If people already have a precise idea of a number they wouldn't be as affected by comparisons to other numbers. Instead, their judgments of damage awards should be driven by the severity of the damage caused to the plaintiff. Hence, this result provides another

evidence for the tendency to rely on gist reasoning to drive the processes of judgment and decision making ("fuzzy-processing preference"). That is, people seem to have vague ordinal judgments of damages (mentally represented as qualitative gists) that they map onto vague ordinal judgments of dollar amounts.

In association with the principle of *encoding specificity* (Tulving & Thomson, 1973) – stating that recollection of stored information is related to the conditions present while encoding that information (e.g., it is easier to remember a happy event when one is happy) – FTT predicts that the specificity of retrieval cues in questions can affect the types of representations (gist or verbatim) retrieved from memory. This idea was supported by several studies (e.g., Bigman, 2014; Brown & Morley, 2007; Brown, Nowlan, Taylor, & Morley, 2013; Mills, Reyna, & Estrada, 2008; Reyna et al., 2011). One experiment, for example, used two methods to assess perceived risk of smoking among smokers and non-smokers (Baghal, 2011) – one method cued retrieval of verbatim by asking participants to estimate the risk of smoking using a numerical (verbatim-like) scale, and another cued retrieval of gist representations using an ordinal (gist-like) measure. Findings from this experiment showed negative correlations between perceived risk and the likelihood of smoking for both methods (i.e., greater perceived risk was associated with a lower likelihood of smoking). However, a significantly stronger relationship was produced by the method that cued the retrieval of gist. Furthermore, predictions of current smoking status using the "gist" method were better among adults than adolescents, which supports the FTT's key principle of developmental reversal (see Blalock & Reyna, 2016).

FTT, as mentioned above, also predicts that gist-based reasoning will often be associated with risk avoidance for rewards (when there is the presence of a categorical distinction between some and none; something is better than nothing), and verbatim-based (or more precise) reasoning will be associated with risk taking (trading off between risks and benefits may lead to

risk taking). In other words, people often choose between smaller sure rewards and larger uncertain ones, the latter offering potentially no rewards or bad outcomes; gist promotes risk avoidance under these conditions. A number of studies focused on risky behaviors (i.e., adolescent sexuality, drinking, smoking, speeding) lent support for this prediction. In particular, both Mills et al. (2008) and Reyna et al. (2011) found that measures designed to cue retrieval of gist representations relevant to adolescent sexuality were associated with greater risky sexual behavior avoidance, whereas measures designed to cue retrieval of verbatim representations were associated with greater risk taking. Similarly, Reyna et al. (2013) found that first-year college students who endorsed the categorical gist principle: "I have a responsibility to myself to wait until I am legal to drink" were less likely to drink and, as a result, be harmed (e.g., experience an injury). In addition, studies that examined issues involving patient decision making found that gist reasoning is associated with improved decision making and adoption of behaviors to reduce health risks (e.g., Hawley et al., 2008; Smith et al., 2014).

Because FTT provides insights into how choices under uncertainty are made, interventions can be developed that take advantage of these principles. Hence, the theory offers innovative approaches designed to facilitate gist-based reasoning in order to effectively reduce unhealthy risk behaviors (specifically for adolescents). For example, in a randomized experiment, Reyna and Mills (2014) created a "gist-enhanced" version of an existing sexual education program known as *Reducing the Risk* (RTR; Hubbard, Giese, & Rainey, 1998; Kirby, Barth, Leland, & Fetro, 1991). On top of the topics covered in the original RTR program, the "gist-enhanced" version (RTR+) emphasized framing sexual decisions in categorical ways (e.g., even small risks add up over time) in order to promote the extraction of bottom-line meaning (the gist) associated with each class activity. The experiment randomized 734 adolescents into one of three groups: RTR, RTR+, or unrelated control. Results from this study showed that the positive

effect of RTR+ on self-reported measures such as sexual behavior, behavioral intentions, attitudes, self-efficacy, knowledge, and so on, was significantly greater than that achieved for both the RTR program and the control group. Importantly, at the end of the 12-month follow-up period, 9.5% of participants in the RTR+ group reported having initiated sexual activity since baseline, compared to 18.9% and 15.9% in the control and RTR groups, respectively.

Emotions and Decision Making

Traditionally, models of decision making – both normative and descriptive – focused mainly on logic and cognition processes when modeling and accounting for human choice behavior. Deviations from rational decision making (such as inconsistent choice behavior) were often attributed to humans' *bounded rationality* (the limited capacity of the brain to process information and perform complex calculations needed to maximize our well-being), and the use of mental shortcuts (cognitive heuristics) in order to reach a decision. The role of feelings and emotions was rarely recognized in these models as an underlying component of decision making. The psychologist George Loewenstein described this oversight as follows: "*With all its cleverness, however, decision theory is somewhat crippled emotionally, and thus detached from the emotional and visceral richness of life.*" (Loewenstein, 1996).

Over the past few decades, however, this trend has dramatically changed. The relation between emotions and choice behavior gained a lot of traction in the field of judgment and decision making – mostly by psychologists who increasingly acknowledged its importance and have begun to incorporate the role of feelings and emotions in their theories of choice behavior.

In the early 1990s, Antonio Damasio proposed a theoretical account for the role of affect in decision making, the so called the *somatic marker hypothesis*. According to this theory, positive and negative feelings, which are acquired through a lifetime experience of realized

outcomes, are associated with different kind of bodily signals (e.g., rapid heartbeat, muscle tone, etc.) – namely, *somatic markers*. These changes in body and brain states, which occur in response to some situational stimuli, help guiding the decision-maker's behavior to quickly and efficiently reach a favorable choice (Damasio, 1994). Seeing a big spider, for example, may induce a physiological marker – a warning sign – associated with the feeling of anxiety, which can facilitate a quick responsive behavior. Damasio also showed in a laboratory experiment that emotionally impaired people (due to some brain damage, for example) were repeatedly choosing the riskier, less favorable financial option (at least in the long run) over a safer one, even to the point of bankruptcy.

Another theory that links emotions with decision-making was proposed by Paul Slovic and colleagues and is known as the *affect heuristic* (e.g., Finucane et al., 2000; Slovic et al., 2002). This hypothesis asserts that emotions can influence people's judgment and decision making. Affect-based choices are quick positive or negative emotional responses to stimuli (rooted in past experience), which are easier and more efficient than those guided by deliberative judgments (hence, it is labeled as *heuristic*). It helps people reach a quick and automatic decision, especially when facing complex decision problems. The affect heuristic theory explains, for example, a phenomenon by which people tend to inversely judge the benefits and risks (i.e., high-benefit and low-risk or vice versa) of different activities, medical treatments, and technologies (e.g., smoking, antibiotics, X-rays, nuclear power, etc.). That is, items that trigger negative/positive emotional responses (such as pesticides or cellular phones, for example) are perceived as risky/safe with low/high benefit (e.g., Fischhoff et al., 1978; Alhakami & Slovic, 1994; Slovic et al., 2007). In contrast to this largely misconception, the risk and benefit of many of these items are in fact positively correlated (high-risk / high benefit, or low-risk / low benefit). Generally, "*activities that are low in benefit are unlikely to be high in risk (if they were, they*

would be proscribed)" (Finucane et al., 2000). Naturally, the relationship between risks and benefits varies across domains of decision making.

Other notable and closely related models that incorporate the effect of emotions are: the *risk-as-feeling* framework (Loewenstein et al., 2001), the *determinants and consequences of emotions* model (Loewenstein & Lerner, 2003), and the *affect integrated model of decision-making* (Lerner et al., 2015). Emotions in these models are integrated into decision making in two distinct ways, *expected emotions* and *immediate (current) emotions*. Expected emotions are the predicted feelings a decision maker is thought to experience with each possible outcome of his or her choice. In this case, emotions influence decisions in a similar fashion to standard rational choice models (e.g., EU). That is, decision makers choose alternatives that maximize anticipated positive emotions and minimize anticipated negative emotions. The expected feelings of regret from an unsuccessful investment in the stock market, for example, may promote risk avoidance behavior – seeking safer alternatives to invest one's money. Immediate emotions are feelings decision makers experience at time of decision. The models distinguish between two types of influences that constitute current emotions – *anticipatory influences* and *incidental influences*. Anticipatory influences capture the effect of anticipated emotional reactions, from the decision at hand, on immediate emotions. Reflecting on the possible outcomes (and the associated emotional reactions) of a risky choice, for example, can cause an immediate feeling of anxiety. Incidental influences are current feelings, completely unrelated to the decision at hand, that can influence choice behavior. This is an idea that falls outside the scope of traditional models of decision making (although emotions have been integrated into FTT; Rivers, Reyna, & Mills, 2008). Such influences include people's mood, weather conditions, motivational factors (e.g., hunger, sexual arousal, etc.), and so on. Numerous

experiments have been conducted to test the effect of expected and immediate emotions on decision making. We list some of them here.

Several studies showed, for example, that people are reluctant to exchange lottery tickets (where each had the same probability to win a prize) – even when they are offered a small monetary incentive to do so – and that this reluctance is stronger the more aversive it would be if the exchanged ticket did in fact win (see Bar-Hillel & Neter, 1996; Risen & Gilovich, 2007). The authors generally concluded that regret plays a prominent role in this behavior. That is, the exchange aversion is driven by the desire to avoid the anticipated feeling of regret associated with the act of giving up on a possible winning ticket. (It is important for future research to measure regret to be sure about this interpretation of the results.)

Furthermore, Christopher K. Hsee and Yuval Rottenstreich examined the effect of *affect-rich* outcomes (such as kisses, vacations, music, etc.) versus *affect-poor* outcomes (e.g., money, tuition, etc.) on decision making and its implications on people's sensitivity to changes in reward magnitudes and probabilities (see: Rottenstreich & Hsee, 2001; Hsee & Rottenstreich, 2004). They found that for affect-rich stimuli people tend to exhibit a more invers S-shaped probability weighting behavior (similar to the one proposed in cumulative prospect theory discussed earlier in this chapter). That is, high sensitivity to small and high probabilities (particularly for departure from certainty and impossibility), and relatively low sensitivity to intermediate probabilities. In addition to that, the researchers showed that people's subjective valuation of affect-rich outcomes is less sensitive to the scope of the stimulus (e.g., the reward magnitude) than that of affect-poor outcomes.

Similarly, the effects of incidental feelings on decisions were also thoroughly investigated. Lerner and Keltner (2000, 2001), for example, studied the effect of dispositional fear and anger (unrelated to the decision) on risky choice behavior. They showed that while fear

and anger are both negative feelings, they influence risk perceptions and decisions differently. Fearful people made pessimistic judgments and exhibited risk averse choices, whereas angry people were more optimistic, taking more risks. Lerner, Small, and Loewenstein (2004) tested the impact of incidental sadness and disgust (induced in a laboratory experiment by showing the participants different emotional film clips prior to the task) on the endowment effect – where people value an object in their possession higher than their willingness to pay in order to acquire it. The researchers found that the feeling of disgust eliminated the endowment effect whereas the feeling of sadness revered it. That is, the willingness to pay for an object (a highlighter set) was actually higher than the price set by sellers who were endowed with this object.

Finally, there is abundant empirical evidence showing a substantial relation between different motivational drives (such as hunger, thirst, and sexual arousal) and decision making. Ariely and Loewenstein (2006), for example, conducted an experiment to test the effect of sexual arousal on judgment and decision making with sex-relevant choices. They found that subjects under the "hot" (aroused) state were willing to engage in a risky behavior more than those in the "cool" state. Furthermore, Levy, Thavikulwat, and Glimcher (2013) tested in a laboratory the effect of food and drink deprivation on risk attitude for gambles with monetary, food, and water outcomes. They found that, on average, subjects under the deprivation state exhibited more risk tolerance with all types of reward. That is, they were willing to take more risks than satiated subjects.

Summary

The emergence of decision making as a formal field of study was intertwined with the birth of modern probability theory back in the 17th century and has evolved significantly ever since. The evolution of the field can be divided into two distinct time periods – before and after

the 1950s. The dominant paradigm in decision making during the first period was a normative one. That is, the focus was on how a rational individual *should* make choices. This approach began with the introduction of Pascal's expected value theory in the middle of the 17th century and culminated with von Neumann and Morgenstern's expected utility theory in 1944, which has become the most widely used model of rational choice. However, it has become more and more apparent that people do not follow an optimization process when making decisions, as prescribed by these rational models.

Herbert Simon (1957) was one of the first scholars to build on the idea that human mental capacity is limited. He argued that people behave as "satisficers" instead of maximizers, choosing alternatives that are "good enough" for them, which he referred to as bounded rationality. This was the kick-off of the second period. The focus during that time period has shifted towards a descriptive analysis, namely how people *do* make choices. A very large number of studies have begun to explore the different ways in which people's behavior deviates from models of rational choice. As a result of the growing evidence of systematic cognitive biases, including errors in probability judgment (e.g., base rate neglect) and inconsistent choice behavior (e.g., framing effect), descriptive theories have started to emerge in an attempt to account for such anomalous behaviors.

In 1979, Daniel Kahneman and Amos Tversky introduced their prospect theory, which has become one of the most prominent descriptive models for human risky choice behavior. Prospect theory can account for many of the observed cognitive biases by using a relatively simple mathematical formulation, which captures the idea that people often perceive values in a non-linear way (e.g., they overweigh small probabilities and underweight large probabilities).

Fuzzy trace theory, proposed in 1991 by Valerie F. Reyna and Charles Brainerd, is another model that accounts for prior effects, such as framing effects and the Allais paradox, as

well as new effects by explaining the underlying cognitive reasoning that drives the decision making process. The model posits that adults tend to rely on the simplest gist (bottom line meaning) representations of the information (e.g., winning something; losing nothing) when making decisions, which promotes healthy behaviors, and that this tendency to rely on gist increases with age and expertise. Fuzzy trace theory has lots of real-life implications in areas such as law, health, and medical decision making. Fuzzy trace theory integrates cognition, emotion, personality, and social values to predict decision making (see Reyna, Wilhelms, McCormick, & Weldon, 2015).

Another important landmark in the history of decision making has transpired in the last few decades. Until the 1990s, the majority of the models of decision making focused mainly on cognitive aspects to explain human behavior. However, an affect revolution that started in the early 1990s has shifted the focus away from solely cognitive reasoning to include emotional reactions. A growing number of theories began to recognize the role of emotions in decision making, arguing that affective processes are quick and automatic and, thus, can guide choices efficiently with very little mental effort. Finally, numerous experiments have been conducted to test the effect of emotions on decision making. Findings from these experiments showed that feelings such as anger, sadness, fear, and even hunger and sexual arousal have a systematic effect on choice behavior.

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Table 1.1. *The Fourfold Pattern of risk attitudes.*

	Gains (amounts in $)	Losses (amounts in $)
Low-probability	A: 5 for sure	A: –5 for sure
	B: 100 with probability .05	B: –100 with probability .05
	Risk seeking: B is chosen over A	*Risk aversion*: A is chosen over B
High-probability	A: 95 for sure	A: –95 for sure
	B: 100 with probability .95	B: –100 with probability .95
	Risk aversion: A is chosen over B	*Risk seeking*: B is chosen over A

Table 1.2. *Verbatim and gist representations of the dread disease problem.*

	Verbatim information	Gist representation
Gain frame	A: 200 people will be saved. B: 1/3 chance that 600 people will be saved and a 2/3 chance that no people will be saved.	A: Some people will be saved. B: Some people will be saved or no one will be saved.
Loss frame	C: 400 people will die. D: 1/3 chance that nobody will die and a 2/3 chance that 600 people will die.	C: Some people will be die. D: Some people will die or no one will die.

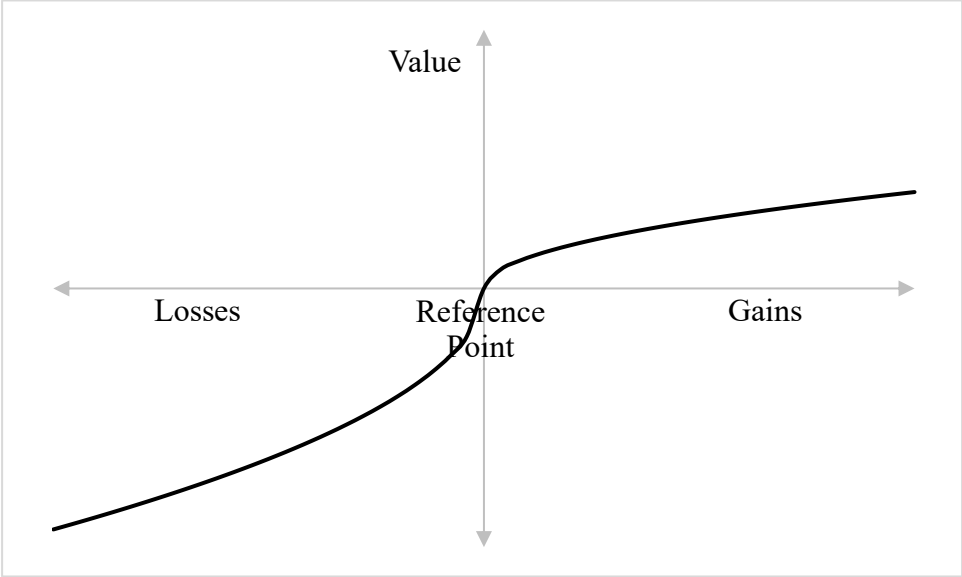

Figure 1.1. The Prospect Theory Value Function.

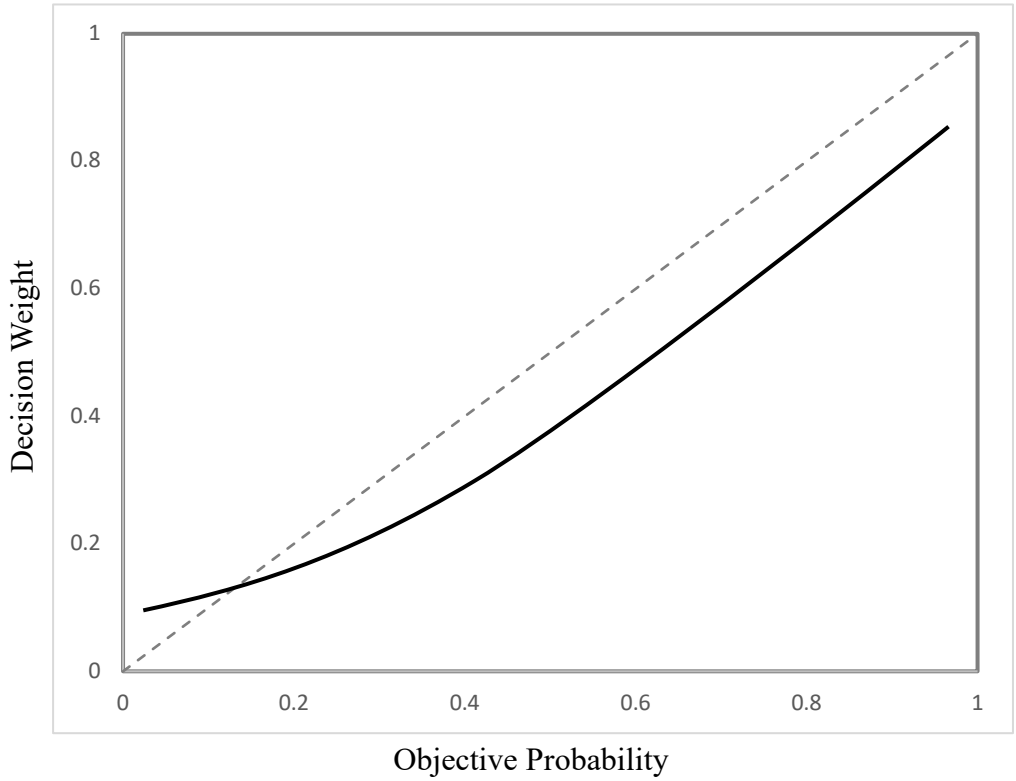

Figure 1.2. The Probability Weighting Function.

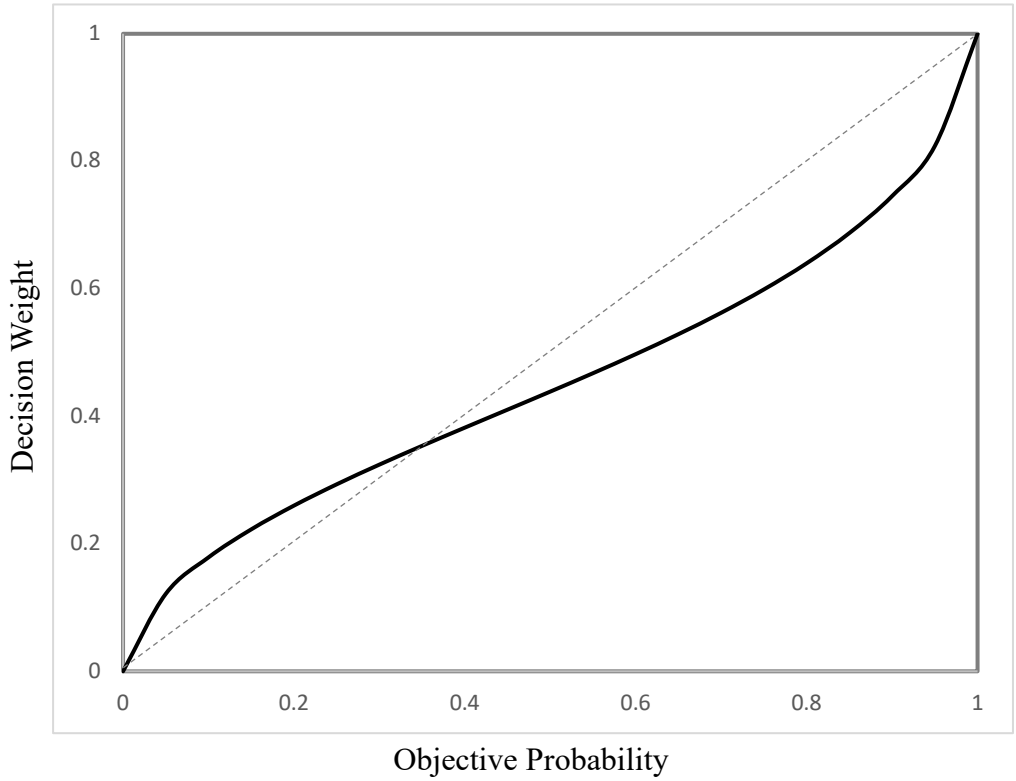

Figure 1.3. Cumulative Prospect Theory's Probability Weighting Function.

CHAPTER 2

WHEN DRIVE DRIVES RISKY CHOICES: THE EFFECT OF HUNGER ON RISK-TAKING BEHAVIOR FOR FOOD AND MONEY

Introduction

Hunger is defined as a physiological need for food. It is a drive state that produces a discomforting physical sensation (e.g., contractions of the stomach) that motivates hungry individuals to attain satiation (Loewenstein, 1996). Furthermore, the feeling of hunger can presumably influence cognitive and emotional processes that are, directly and indirectly, related to choice behavior, such as attentional allocation, perception, impulsiveness, etc. (Bhatia & Loewenstein, 2013). Since many of our choices as human beings are made under various degrees of hunger, it is important to understand the systematic role of such feelings (as well as of other drive states) in decision making. In this work our goals are twofold: to draw a connection between hunger and risk-taking behavior (with both monetary and food related choices), and to examine the extent to which rational decision making is sensitive to such effects. Accordingly, a randomized experiment was designed in which hunger was manipulated by requesting subjects in the treatment group to refrain from eating for at least four hours prior to engaging in the experiment. We also asked the participants to self-rate their current level of hunger on a nine-point Likert scale, and used this subjective measure as a robustness check for the influence of hunger.

A growing body of empirical evidence suggests that hunger has a profound impact on choice behavior in a variety of domains, such as risky decision-making, intertemporal choice, consumer behavior, and even social preferences. Danziger, Levav, and Avnaim-Pesso (2011), for example, studied the effect that food breaks have on judicial rulings made by experienced judges.

They found that favorable rulings gradually dropped from about 65% to near 0% prior to a break, and increased back to around 65% almost immediately after the break.[13] Loeber, Grosshans, Herpertz, Kiefer, and Herpertz (2013) have shown that hunger is associated with a tendency to allocate more attention towards food-associated stimuli. Other investigators have found that stock markets in the Muslim world tend to be less volatile, while yielding higher returns, during the holy month of the Ramadan, in which Muslims abstain from eating and drinking during daylight hours (e.g., Białkowski, Etebari, & Wisniewski, 2012; Seyyed, Abraham, & Al-Hajji, 2005). Hunger is also shown to have an effect on self and social predictions of one's feelings. Respondents' predictions of how much they themselves, as well as others, would be bothered more by thirst than hunger in a predicament, such as getting lost during a hike, was negatively correlated with their actual feeling of hunger (Van Boven & Loewenstein, 2003).

In addition, hunger has specific implications on consumer behavior. Hungry people have been found to spend more money on both food and non-food items (Nisbett & Kanouse, 1968; Xu, Schwarz, & Wyer, 2015) as well as to purchase food products higher in caloric content (Tal & Wansink, 2013). It seems that the typical advice to *avoid (grocery) shopping on an empty stomach* is not at all an impractical one. The connection between hunger and pro-social behavior has also been explored. Several laboratory experiments manipulated either hunger (using food deprivation procedures) or the desire to eat (using the scent of freshly baked cookies to induce appetite) and found that under the influence of the manipulated drive state people were less likely to donate to charity and to allocate money to their opponent in a *give-some game* (Briers, Pandelaere, Dewitte, & Warlop, 2006), and that results obtained from a standard *ultimatum game* were moderated by the degree of hunger (Shabat-Simon, Shuster, Sela, & Levy, 2018).

[13] The authors note that the effect of food breaks on the judges mental resource replenishment may be attributed to both eating and resting, and that they cannot disentangle these effects given their data.

In the current paper we focus on the risky decision-making domain. As mentioned, one of the main goals of this work is to study the impact a moderate level of hunger has on risk-taking behavior with both financial and food related decision problems, and to test whether it is modulated by age, different frame conditions, and other theory-based variations on the presentation of information. Previous studies have already confirmed the prevalence of a hunger effect (and other visceral factors) within a choice-under-uncertainty framework, though with some conflicting results. In some cases, a positive correlation between hunger and risk seeking behavior was found for either monetary or food reward (e.g., Levy, Thavikulwat, & Glimcher, 2013; Shabat-Simon et al., 2018), yet opposite findings (at least on average) have also been observed (e.g., Symmonds, Emmanuel, Drew, Batterham, & Dolan, 2010). In another study, Ditto, Pizarro, Epstein, Jacobson, and MacDonald (2006) induced appetite using the scent and sight of chocolate chip cookies (the visceral group). Every subject had the option to play a game of chance where they could win chocolate chip cookies (as many as they wanted) at a risk of completing an extra 30 minutes of boring task at the lab. Half of the subjects from each group faced a high winning chance (80%) and the other half faced a lower winning chance (60%). While participants in the control group chose the gamble more frequently when the winning chance was higher (80% versus 60%), participants in the visceral group were as likely to choose the gamble regardless of the risk level, thus exhibiting lower sensitivity to risk information. They also exhibited higher risk seeking behavior (in order to attain the food reward) when risk was high – relative to subjects in the control group. (However, appetite is not the same thing as hunger.) Festjens, Bruyneel, and Dewitte (2018) tried to replicate these results but failed. Instead, they found that hungry (not appetite) subjects were more risk averse in their financial decisions in the presence of an external food cue.

It seems that there is no clear-cut evidence for a directional effect of hunger on risk taking behavior (with both related and unrelated goods), which may raise some questions as to the nature of hunger and the methods taken to measure it.[14] Interestingly, when it comes to the effect of sexual arousal (a drive state on its own) on decision-making with sex-relevant choices, findings from different studies were quite consistent, showing that sexually aroused subjects were willing to engage in a more risky behavior than those who were not aroused (e.g., Ariely & Loewenstein, 2006; Ditto et al., 2006).

Another objective of this work is to determine the extent to which rational choice behavior is affected by the feeling of hunger. According to standard economic theory, rational behavior entails the maximization of one's expected utility in a consistent way given the available information. In that sense, there is no substantial evidence that hunger compromises the notion of rationality — but quite the contrary. Hungry participants in a laboratory experiment, for example, were found to make more favorable decisions (compared to sated participants) involving uncertain outcomes in an *Iowa Gambling Task*, which led them to obtain higher monetary payoffs (De Ridder, Kroese, Adriaanse, & Evers, 2014). (Note that expected value is not equal in the Iowa Gambling Task, which makes a difference in fuzzy-trace theory.) Furthermore, in a budget-set choice task (in each trial subjects allocated an endowment of tokens between two lotteries with equal probabilities (50–50% chance of winning)) designed to test economic consistency by testing the *generalized axiom of revealed preference* (GARP) – an axiom of rational choice behavior that is consistent with EU theory, hungry subjects did not demonstrate any significant choice inconsistency over non-hungry subjects (Shabat-Simon et al., 2018). These results may seem counterintuitive to the common view that being in a "hot" state

[14] See Shabat-Simon et al. (2018) for a discussion on some of these questions.

(such as hunger, sexual arousal, etc.) drives the decision maker towards a more impulsive, less deliberative behavior, which is deemed detrimental to rational behavior.[15]

Consistent choice behavior is also known to be fundamentally challenged by the *framing effect*, a phenomenon by which people tend to be risk averse with prospects when outcomes are framed as gains and risk seeking when framed as losses. Perhaps the most classic example of this phenomenon is the *dread disease problem* (Tversky & Kahneman, 1981), whereby two alternative programs are proposed to combat an unusual disease that is expected to kill 600 people. The first set of offers two options to choose from: (1) 200 people will be saved with certainty versus (2) a 1⁄3 chance of saving 600 people and a 2⁄3 chance of saving no one. The second set of programs also consists of two options: (1) 400 people will die with certainty versus (2) a 1⁄3 probability that nobody will die and a 2⁄3 probability that 600 people will die. Note that the two programs are essentially equivalent and differ only by whether outcomes are framed as gains (first program) or losses (second program). However, people typically exhibit choice inconsistency, picking the sure option in the first program (gain frame) and the risky option in the second program (loss frame).

The framing effect is possibly the most striking demonstration of incoherent preferences — violating the invariance axiom (i.e., preferences should be insensitive to different ways the same information is being described), which is one of the most fundamental principles of normative choice behavior. Framing bias has been recorded many times in the literature (e.g., De Martino, Kumaran, Seymour, & Dolan, 2006; Kühberger, 1995; Reyna & Brainerd, 1991; Tversky & Kahneman, 1981, 1986), with some papers testing it in conjunction with a variety of other individual characteristics, such as age

[15] Conflicts of such nature with one's self interest have been found and reported in many studies before (e.g., Ariely & Loewenstein, 2006; Ditto et al., 2006; Read & Van Leeuwen, 1998; Van den Bergh, Dewitte, & Warlop, 2008).

(Reyna et al., 2011), level of expertise (Reyna, Chick, Corbin, & Hsia, 2014), working memory (Whitney, Rinehart, & Hinson, 2008), fear and anger (Lerner & Keltner, 2001), and level of numeracy (Peters & Levin, 2008). There are several different theoretical explanations accounting for this phenomenon, most of which are based on either the notion of psychophysics of numerical information as in *prospect theory* (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) or an underlying cognitive reasoning as in *fuzzy-trace theory* (Kühberger & Tanner, 2010; Reyna, 2012; Reyna & Brainerd, 1995). Another common explanation to this is based on the *two-minds* core principle of traditional dual process models, asserting that two distinct types of thinking are involved in the process of decision-making: (1) an intuitive, automated, fast, and often affective-based processing — defined as *Type 1* process (or more traditionally, 'System 1'), and (2) a more reflective, conscious, and rule-based processing — defined as *Type 2* process ('System 2') (Evans, 2008; Evans & Stanovich, 2013; Kahneman & Frederick, 2002). Thus, given that sure gains are attractive and sure losses are aversive, the intuitive and often impulsive nature of System 1 is most likely to trigger an affective heuristic leading to a framing bias — that is unless System 2 steps in and intervenes by imposing a more reflective mental operation to correct this bias (Kahneman & Frederick, 2007). The mechanisms for these predictions are somewhat unclear, but they are formalized in Loewenstein, O'Donoghue, & Bhatia (2015), and Mukherjee (2010); see below.

Consequently, in the present work we adopt the framing effect as a measure of choice inconsistency and ask whether it is moderated by the feeling of hunger. If, for example, the experience of a drive state suppresses the cognitive abilities of the deliberative system to override the quick and automatic behavior underwritten by the affective system, then we would expect to see higher rates of incoherent preferences committed by hungry people — particularly,

taking fewer risks when outcomes are framed as gains and more risks when framed as losses. We, therefore, devised a risky choice framing task, where in every trial participants were asked to make a choice between a riskless payoff (either money or food) and a simple binary gamble (with zero as one of its outcomes) that carried an expected value equal to the sure option. This also allows us to separately examine the specific effect of hunger on choices with negative outcomes (losses) — a direction, which to the best of our knowledge, has never been tested in the literature on hunger before.

Furthermore, we test our results against some formal theoretical predictions derived from two specific traditional dual system models that can account for the effect of hunger in the context of risky choice, as well as from fuzzy-trace theory, which provides a cognitive account for different types of violations of the invariance principle. (For formal models of fuzzy-trace theory, see Reyna & Brainerd, 2011, and Broniatowski & Reyna, 2018.) As a robustness check, we tested our research questions using both an objective and a subjective measure of hunger, namely a manipulated hunger binary variable (hungry vs. non-hungry, based on 4 hours of food deprivation), and a nine-point self-reported hunger scale — thus utilizing the variations in hunger intensity across subjects, on top of the group mean results obtained with the binary variable. Our framing results are consistent with fuzzy-trace theory. The framing effect was modulated based on whether the emphasis was placed on the zero versus nonzero complement. When the nonzero complement was removed from the gamble (which makes the categorical difference between safe and risky options more apparent), the framing effect increased. When the zero complement was removed from the gamble (which de-emphasizes the categorical difference between options), the framing effect was eliminated. The framing effect did not interact with hunger. Hunger led to risk-aversion for food and money. Hungry participants were risk-averse for *both*

gains and losses, which contradicts traditional dual-system theories. We discuss the implications of our findings.

Theoretical Framework

The accumulation of empirical evidence mentioned earlier points to the undeniable role drive states play in humans' decision-making under uncertainty. Nevertheless, the theoretical literature is largely silent about this phenomenon. Indeed, Loewenstein (1996) was one of the first and few who proposed a theory that formally incorporates the effect of visceral factors as parameters into a normative expected utility formulation. However, his theory underlines the notion of *hot-cold empathy gap* (i.e., the incongruence between preferences in a non-aroused state and actual behavior in the presence of a visceral influence), for both inter- and intrapersonal behavior, and its implications for intertemporal choice, yet it lacks a discussion about its impact in the context of risky decision-making. Of the few models that do account for the effect of various drive states within a risk preference framework, there are two similar dual system models proposed separately by Loewenstein, O'Donoghue, and Bhatia (2015) [hereinafter, LOB], and Mukherjee (2010). The two models integrate the idea of two cognitive systems, a deliberative (cold) system and an affective (hot) system, along with a few key properties from prospect theory, which allows them to offer rigorous theoretical predictions for the extent to which motivational drives modulate risky choice behavior. This provides us with an opportunity to test our empirical findings against some formal hypotheses. Furthermore, we compare some of those findings with formal predictions provided by fuzzy-trace theory (hereinafter, FTT). FTT is a dual-process model that explains how we encode and process information on a continuum of mental representations, in which the "fuzziest" bottom-line gist of information is at one end, and the most precise, verbatim representation of information is at

the other. According to FTT, gist and verbatim representations are encoded simultaneously, but there are differences in reliance on gist versus verbatim-based processing across development. Adults and experts tend to rely on the fuzziest, least precise representation of information when possible, gradually becoming more granular as needed to solve a given problem or complete a task (Reyna, 2012). FTT can explain how reliance on the bottom-line gist leads to choice inconsistencies including the framing effect, common consequence (e.g., the Allais paradox), etc., as well as how these biases are moderated by age. FTT predicts that cognitive biases actually *increase* with development (which can be explained by an increased reliance on gist-based processing with age), despite improved performance on cognitive tasks from childhood to adulthood (Reyna & Ellis, 1994). Importantly, it can also predict a type of systematic violation of the invariance axiom, whereby risk preferences are modulated by the different truncations under which the information of a certain decision problem is described. This quality is particularly relevant to our experiment since we have manipulated the way information of the decision at hand is presented in each trial in accordance with the principles of the theory.

LOB's Dual-System Model

The LOB's model is based upon a traditional dual system model. It asserts that the interplay between two distinct cognitive processes, the deliberative (cold) system and the affective (hot) system, determines the individuals' choice behavior. According to the model, the deliberative system represents the "voice of reason," where choices are evaluated in a cold and deliberative fashion. Thus, it takes the form of standard expected utility model. The authors further assume a linear utility function for small to moderate outcomes (that is, $u(x) = x$). The affective system captures different motivational and affective states. It is formulated on the basis of two key features of prospect theory: (1) loss aversion (relative to some natural reference point)

and (2) insensitivity to probabilities. Furthermore, the tendency to rely on either of the two systems depends on the mental resources available to the decision maker, and the intensity of the affective reaction triggered by the decision at hand. If, for example, the cost to exert sufficient willpower, necessary for the cold system to resist an affect-driven behavior, is high (i.e., not enough mental resources), then the affective system will carry out the decision. Similarly, an affect-rich decision problem (e.g., when lives or pain are at stake) is more likely to shift cognitive control over to the hot system.

The two systems are assumed to be additively separable. Let X be a choice set of lotteries, with $x \in X$ being a lottery (a choice option), such that $x \equiv (x_i, p_i; ...; x_N, p_N)$, where outcome x_i occurs with probability p_i. Thus, the decision maker will choose the option x that maximizes:

$$V(x) = \sum p_i u(x_i) + h(W, \sigma) * [\sum w(p_i) v(x_i, a)] \quad (1)$$

Where $h(W, \sigma) > 0$ is a scaling factor that represents the cognitive cost of exerting willpower needed for the deliberative system to be dominant. That is, a lower cost increases reliance on the cold system. According to the model, this cognitive cost is a factor of both current reserves of willpower, which is denoted by W (with higher W implies a lower cost), and other competing cognitive demands represented by the σ parameter, such as stress or unrelated cognitive tasks (where higher σ produces a higher cost). In addition, the hot system is characterized by relative insensitivity to probabilities and loss aversion properties, represented by a probability weighting function, $w(p)$, and a value function, $v(x_i, a)$, respectively. To reflect the notion of probability insensitivity, it is assumed that $dw/dp < 1$ for $p \in (0, 1)$, which is conceptually closer to the functional form described in the original Kahneman and Tversky's 1979 prospect theory paper. The value function has a linear shape for both positive and negative

small-to-moderate outcomes with a steeper slope for losses to reflect the loss aversion property. That is, $v(x_i, a) = ax_i$ if $x_i \geq 0$, and $v(x_i, a) = a\lambda x_i$ if $x_i < 0$, where $\lambda > 1$ is a parameter that represents the degree of loss aversion, and the intensity of the motivational state is denoted by the affective parameter a — a higher a will increase reliance on the affective system.[16]

Based on the described formulation, and by employing a number of simplifying assumptions, LOB have arrived at some key predictions, some of which are relevant to our work. The authors showed, for example, that for prospects with monetary outcomes, the *certainty equivalence* (CE) of a gamble that offers $|Z| > 0$ with probability p and nothing otherwise, where Z can be positive (gain) or negative (loss), and $p \in (0, 1)$, is determined by: $CE + h(W, \sigma)\,[\,\tilde{a}_M CE] = pZ + h(W, \sigma)\,[w(p)\,\tilde{a}_M Z]$, with $\tilde{a}_M = a_M$ if $Z > 0$, and $\tilde{a}_M = \lambda a_M$ if $Z < 0$, where a_M denotes the affective intensity for money.[17] By rearranging the equation we get the following expression for CE:

$$CE = \frac{p + h(W, \sigma)\tilde{a}_M w(p)}{1 + h(W, \sigma)\tilde{a}_M} Z$$

The expression above yields a number of important inferences (assuming that $h(W, \sigma)a_M > 0$). First, we get risk neutrality (i.e., $CE = pZ$) when $w(p) = p$; risk aversion for gains and risk seeking for losses (i.e., $|CE| < |pZ|$) when probabilities are underweighted ($w(p) < p$); and risk seeking for gains and risk aversion for losses (i.e., $|CE| > |pZ|$) when probabilities are overweighted ($w(p) > p$). (Overweighting occurs for lower probabilities and underweighting occurs for higher probabilities.) Not surprisingly, this pattern is essentially a manifestation of the

[16] Note that in the current work, our risky choice framing task does not include mixed gambles with both gains and losses.
[17] Note that the same example can also work with different goods other than money, such as food quantities, by assuming a relevant good-specific affective parameter instead of a_M.

fourfold pattern of risk attitudes (Tversky & Kahneman, 1992). Second, when facing a gain framed version and a loss framed version of a specific decision problem (e.g., the dread disease problem), then — following the first interpretation — a framing behavior is obtained whenever $w(p) < p_G, p_L$, where p_G and p_L denote the probability to win/lose in the gain/loss frame respectively, irrespective of the fact that similar "final asset position" is offered in both versions.[18] Third, by using simple math, it is possible to show that for $w(p) < p$ (probability underweighting) $|CE|$ decreases (i.e., a higher risk aversion for gains and higher risk seeking for losses) as either h or a_M increases. The opposite pattern occurs when $w(p) > p$.

In order to derive hunger-specific hypotheses on the basis of the above inferences, we invoke a convention by which no model can deterministically predict humans' choice behavior (due to unobserved individual or environmental factors, for example). That is, incorporating a random component to model behavior — a *noise* — is a common practice in the empirical literature (Gul & Pesendorfer, 2006). Employing this idea that choices are characterized by some degree of noise permits us to formally discuss about the likelihood of observing a certain trend of risk attitude (especially in light of our extensive use of equal expected value setting as explained later). Furthermore, we assume that the influence of hunger is captured by the affective system through either h (the cost to deliberative system of exerting willpower), or a (the affective parameter), or both, so that hunger increases reliance on the affective system, and it does so to a greater extent when outcomes involve food. (Note that this prediction applies when amounts of food and money are comparable, i.e., all else equal.) Consequently, we list here three main hypotheses for the effect of hunger using the above expression for CE and its consequential inferences.

[18] In our experimental design, for example, $p_G \leq p_L$.

H1^{LOB}: For $w(p_G) < p_G$ and $w(p_L) < p_L$, the likelihood of observing a pattern of framing behavior increases as hunger intensifies.

H2^{LOB}: For the special case, in which $p_G \leq p_L$, the likelihood of observing a risk averse behavior for *both* gains and losses decreases as the intensity of hunger increases.

H3^{LOB}: The likelihood of observing the patterns of behavior specified in H1 and H2, is more sensitive to the feeling of hunger for decisions made over food than money.

According to the theory, since hunger is a drive state that operates through the affective system, it amplifies any affect-driven choices carried out by the hot system. Thus, H1 states that a baseline framing behavior for an individual in a state of satiety, should intensify as the aversive feeling of hunger grows. In addition, the statement in H2 is true simply because otherwise, in order to obtain a higher likelihood for risk averse behavior for both gains and losses it has to be the case that $w(p_G) < p_G$ (underweighting of the winning probabilities) *and* $w(p_L) > p_L$ (overweighting of the losing probabilities), and given the special case of $p_G \leq p_L$, this implies that $w(p_L) - w(p_G) > p_L - p_G$, or equivalently, $\frac{w(p_L)-w(p_G)}{p_L-p_G} > 1$, which clearly violates the principle of insensitive probability weighting function. Finally, H3 is based upon the idea that, as the feeling of hunger grows, choices over food increase the intensity of the affective state relatively more than choices that involve money do. Put differently, hunger draws attention and motivation to food (Loewenstein, 1996). This premise is embedded in the model through a good-specific affective parameter, *a*.

Mukherjee's Dual-System Model

Mukherjee's model, similar to that of LOB's, is built upon the fundamental characteristics of traditional dual-process theories, in which cold, and deliberative processing (System 2) is often decoupled from a rapid, automatic, and more affect-driven behavior (System 1). The model additively integrates the deliberative and affective systems to form a parsimonious theoretical framework that can account for a variety of behavioral phenomena in the context of decision making under risk and uncertainty (e.g., violation of stochastic dominance, fourfold pattern of risk attitudes, ambiguity aversion, common consequence effect, etc.). It does so by applying key properties from prospect theory to describe System 1, yet the details of how prospect theory is represented in this system differ from LOB's model as we see below. The deliberative system is characterized by a simple expected value function. The affective system is formulated on the basis of the insights drawn from Hsee and Rottenstreich (2004) and Rottenstreich and Hsee (2001), whereby the subjective value function exhibits a stronger diminishing sensitivity, and the probability weighting function adopts a flatter inverse S-shaped functional form (suggesting insensitivity to intermediate probabilities), the more affect-rich the nature of the decision is. Hence, the hot system is assumed to be entirely insensitive to probabilities (i.e., every possible outcome less than one is equally weighed) and is represented by prospect theory type value function — a reference dependent function that is monotonically increasing, concave in the gain frame, convex in the loss frame, and is characterized by the loss aversion property. An individual, then, is assumed to choose the prospect x that maximizes:

$$V(x) = \gamma \frac{1}{n} \sum V_A(x_i) + (1-\gamma) k \sum p_i x_i \tag{2}$$

Where $0 \leq \gamma \leq 1$ is a weighting parameter that determines the relative involvement of each system (a higher γ increases the reliance on the affective system), V_A is the prospect theory type value function, and k is a scaling factor (a constant).[19] Evidently, equation 2 resembles in many aspects to equation 1 (described in LOB's model), as both equations are founded on the same theoretical principles. However, there are some distinctive conceptual differences between the two models. We name two such differences here. (1) According to LOB, the tendency to rely on the deliberative system is a factor of how costly it is to exert sufficient will power to override an affective reaction, whereas in Mukherjee's model such reliance mostly depends on individual thinking dispositions, and the nature of the outcomes — affect-rich outcomes will enhance the relative involvement of the affective system. (2) The formulation of the hot system in LOB's model reflects the idea that motivational states are the main drivers in determining the subjective valuation of a good (which is captured by the affective parameter a), such that hunger, for example, will enhance the valuation of a meal (Loewenstein, 1996). This, however, is not the case in Mukherjee's model. A feeling of hunger in the presence of potential food outcomes, for example, will simply modify the weight placed on the affective system accordingly.

Furthermore, the treatment of the affective system in this model highlights slightly different psychological principles — namely, diminishing sensitivity to scope, and equal decision weights for every possible outcome (i.e., complete insensitivity to probabilities). This, in turn, yields somewhat different predictions as well as psychological accounts for patterns of risk attitudes. To demonstrate, assume as before a simple two-outcome gamble (with 0 as one of its outcomes) that offers a payoff $Z > 0$ with some probability p_G, and another gamble that offers $-Z$ with probability p_L. Note that for such gambles the hot system equally weights all probabilities as 0.5. Thus, in the special case of $p_G = p_L = 0.5$, for example, where probability distortion is

[19] The value function is assumed to have a power functional form for both gains and losses.

absent, a standard framing effect can only be explained by the diminishing sensitivity property embedded in the value function of the affective system. In addition, for p_G, p_L < 0.5 the affective mind experiences a conflict between two forces — diminishing sensitivity and probability overweighting — that operate in opposite directions. For gains (losses), the gamble becomes less (more) attractive because of the curvature of the value function, but more (less) attractive due to relative high decision weights. So that in this case the strength and direction of risk attitudes is ambiguous — depending not only on which system is in control, but also on the degree of curvature that describes the hot system's value function. Nevertheless, this source of ambiguity disappears when p_G, p_L > 0.5, since both forces in the affective system pull the attractiveness of the gamble in the same direction, producing risk averse behavior for gains and risk seeking behavior for losses. This enables us to formulate a concrete hypothesis about the relation between hunger and risk attitudes on the basis of this model, that is relevant to our work.

H4^{M}: For all binary gambles with zero as one of the possible outcome, if p_G > 0.5, then the likelihood of observing a risk averse behavior for gains increases as hunger intensifies. Similarly, if p_L > 0.5, the likelihood of observing a risk seeking behavior for losses increases as hunger intensifies.

Intuitively, since hunger increases reliance on the affective system (that is, γ increases), the likelihood of observing a rational, risk-neutral behavior goes down, leaving the stage for the hot system to drive risk attitude in the predicted direction.[20]

[20] See the Appendix section in Mukherjee (2010) for a formal proof.

Fuzzy-Trace Theory

Fuzzy-trace theory is a dual process model of memory, reasoning, judgment, and decision-making. The theory proposes a psychological mechanism that operates within our brains and can account for many behavioral phenomena and cognitive biases. In that sense, it goes one step beyond the "as if" approach (a general practice of behavioral economics, by which psychology enters into utility-based theories by adding parameters that can account for biases and facilitate a better fit to observed patterns of decision behavior)[21] by directly attacking the 'why question': why do we behave the way we do?

According to the theory, information that describes decision problems is encoded and processed along a continuum of mental representations with *gist* being on one end and *verbatim* on the other. Verbatim representations encode the exact numerical and verbal information of the problem, whereas gist representations are fuzzier in nature, extracting the patterns and meaning implied by the information. In the context of risky decision-making, when evaluating risks and rewards, the simplest gist representation is a categorical one (e.g., *some* versus *none*), a finer distinction (placed in the middle of the continuum) would include an ordinal gist (e.g., *less* versus *more*), and so on towards a precise representation (verbatim). Furthermore, the verbatim and gist traces of information are encoded in the brain simultaneously. For example, when presented with the following data: "Farmer Brown owns 12 cows, 7 sheep, and 3 horses", one can encode and store verbatim traces, such as "12 cows", or "3 horses", concurrently with gist traces in the form of "cows are most", "more cows than horses", and "horses are least" (Reyna & Brainerd, 2008).

Consequently, biases such as the framing phenomenon can be accounted for by the type of cognitive processes underlined above. According to FTT, adults (on average) have a "fuzzy

[21] See Berg and Gigerenzer (2010) for a discussion on this topic.

processing preference" in which they will start with the simplest type of processing necessary to solve a given problem. If the fuzziest, bottom-line, gist-based representation of the information is not sufficient for completion of the task at hand, the decision maker will move to the next level of precision (see Reyna, 2012). Reliance on fuzzy (gist) representations of the informational inputs, coupled with the retrieval of cued social and moral values (called "gist principles") held by the decision maker (which depends on the context of the decision problem, e.g., 'some people saved is better than none saved' in the context of life when life is at stake), emphasizes the categorical distinction between the safe option and the gamble in the respective gain/loss frame. This can be illustrated using the dread disease problem, for example, in which the lives of 600 people are at stake. Table 2.1 presents word by word the options in the two alternative programs (the verbatim information) as well as the extracted gist representations. Note that the implied bottom line meaning of each option in the gain-loss frames highlights the categorical distinction between the sure outcome and the gamble. As a result, a gist based reasoning will promote risk averse attitude in the gain frame, favoring the sure outcome over the gamble (it is better to save some than risk saving no one), whereas in the loss frame this pattern is flipped (accepting a chance that no person will die is preferred to the alternative, in which some people will surely die).

Extracting the bottom line meaning of the information is central to applying gist reasoning. Over the years and through experience, the tendency to rely mainly on gist increases with age and expertise (e.g., Reyna et al., 2014). According to FTT, the framing bias can be explained by the tendency to derive the gist of the options (e.g., the gist of the safe versus risky option becomes *saving some* versus *saving none*) and apply our values to that gist (e.g., "I value saving lives"). Thus, people are risk-averse for gains (*saving some* is better than *saving none*) and risk-seeking for losses (*losing none* is preferable to *losing some*). Framing effects increase across

development, which can be explained by a developmental shift in reliance on verbatim-based versus gist-based processing. That is, the age of the individual can predict how precise the representation of the options is. In making a decision, it is the way an individual thinks about the options that matters, as per FTT. In developmental studies of cognitive biases, children and adolescents are more likely than adults to show smaller framing effects or reverse frame (i.e., choose a risky option in the gain frame and a sure option in the loss frame; Reyna & Ellis, 1994; Reyna et al., 2011). FTT can, therefore, explain a counterintuitive phenomenon, known as *developmental reversal*, in which cognitive control and inhibition improve with age, but cognitive biases, such as the framing effect, are more prevalent in adults than in children and adolescents (e.g., Reyna et al., 2011). This is one of the main features that distinguishes FTT from classic dual-system models — particularly given the common view that adolescence is a stage in life of being in a "constant" drive state. However, despite being subject to more biases, gist-based intuition is a more advanced cognition that can protect against unfavorable decisions such as taking unhealthy, and even life-threatening risks (e.g., Reyna, 2012; Reyna & Farley, 2006).[22] For example, experts show a greater reliance on gist-based processing, and thus, larger framing effects, than novices (Reyna et al., 2014). The FTT predictions about gist-based processing are counterintuitive, as gist is associated with *both* increased cognitive biases and advanced cognition. Gist-based interventions have had positive outcomes with empirical evidence suggests that gist-based interventions lead to fewer risky decisions about sex in adolescents (Reyna & Mills, 2014).

Furthermore, according to the theory, cognition can be oriented towards a more quantitative (verbatim) or qualitative (gist) based processing by making relevant information more (or less) salient. Thus, by emphasizing or de-emphasizing categorical differences in

[22] Note that the theory distinguishes between intuition based decisions and mere impulsiveness.

framing decisions, a respective increment or decrement to the size of framing effect is anticipated. Omitting the zero complement from the gambles in the dread disease problem, for example, obscures the categorical gist, despite being mathematically redundant (i.e., it has no effect on the overall information of the problem and adds nothing to utility based calculations), and consequently reduces and even eliminates the framing bias (Kühberger & Tanner, 2010; Reyna et al., 2014).[23]

Finally, there are two points that connect hunger to FTT framework. First, based on the economic interpretation that hunger affects the utility by increasing the subjective value of the reward, especially for food (Loewenstein, 1996), hungry people should exhibit higher sensitivity to changes in reward magnitudes. Previous studies using framing decisions have shown that as payoffs increased from small to moderate levels (producing greater differences between the outcomes), a reversed framing pattern (i.e., choosing the gamble in the gain frame and the sure loss in the loss frame) was obtained. Essentially, people assimilated the different reward magnitudes (as in gist based intuition) less frequently, demonstrating instead a more analytical processing by trading off risks and payoffs in a verbatim fashion — particularly at young ages, where reward sensitivity is relatively high (Reyna & Ellis, 1994; Reyna et al., 2011). Thus, given that hungry people better discriminate between different sizes of rewards, they are expected to follow a more verbatim based reasoning.

The second point is related to the fact that, according to FTT, negative feeling states are more conducive to verbatim processing. That is, "When experiencing negative affect, the specifics of the stimulus are more likely to be encoded, and processing is more likely to be effortful, analytical, and vigilant, which has been associated with verbatim processing" (Rivers,

[23] A common criticism that this effect may be driven by a sense of possible ambiguity regarding the omitted information was ruled out in the literature (e.g., Chick, Reyna, & Corbin, 2016; see also Reyna, 2012).

Reyna, & Mills, 2008). Thus, given that hunger is an aversive feeling, then by combining the predictions of these two points we derive the following formal hypothesis:

H5^{FTT}: The likelihood of observing a pattern of framing behavior decreases as hunger intensifies.

Note that this hypothesis is contradictory to the first hypothesis derived from LOB's model in a situation where probability underweighting in both gains and losses is taking place. A direct comparison between the predictions of the two models is thus possible on the basis of the empirical findings.

The theoretical predictions of the above three theories (as well as of prospect theory) regarding the effect of framing, hunger, and risk preferences are summarized in Table 2.2.

Method

Participants and Design

A total of 132 right-handed subjects (83 women) from two different age groups (adolescent and adult) participated in the study. Adolescents were 69 high-school students (ages 14-18; M = 16.83, SD = 1.350) from central New-York. The adult group included 63 subjects, (ages 26-49; M = 34.21, SD = 6.577) from the same area. Hunger was manipulated by random assignment to treatment (hungry) and control (non-hungry) groups in order to examine its effect on risk taking behavior and rational decision making. Participants in the hungry group were instructed to abstain from any food consumption at least four hours prior to participating in the experiment. No special food restrictions (e.g., when or what to eat) were imposed on those in the non-hungry group.

The experiment included a risky choice framing task with money (US dollars) and food reward (M&M's) in return for monetary compensation (described below), which took place in the laboratory at Cornell Magnetic Resonance Imaging Facility, at the Human Neuroscience Institute.[24] Four subjects that could not be scanned (two were not in compliance with MRI safety procedure, one subject did not fit in the MRI scanner, and one subject was removed from the scanner due to persistent cough) and nine subjects with systematic missing data (due to human error by the experimenter) were excluded from all subsequent analyses (six adolescents and seven adults). Thus, we obtained analyzable choice data for 119 subjects (62% female; 72.3% Caucasian, 14.2% Asian, 4.2% African American; 8.4% of this group was Hispanic). Table 2.3 displays the age-hunger subgroups distribution for the framing task.

Materials and Procedure

Participants were asked to complete an online survey before arriving to the laboratory. The survey included a 15-item objective numeracy scale (ONS; e.g., "The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected?"), designed to determine the subjects' ability to comprehend and apply numerical and statistical concepts (see Peters, Dieckmann, Dixon, Hibbard, & Mertz, 2007), and 59-item self-report impulsive behavior scale (e.g., "I like to stop and think things over before I do them."), rated on a four-point scale ranging from "strongly agree" (coded as 1) to "strongly disagree" (coded as 4). The scale was designed to assess impulsive disposition along five dimensions: (negative) Urgency, (lack of) Premeditation, (lack of) Perseverance, Sensation Seeking, and Positive Urgency, or in short UPPS-P (see Lynam, Smith, Whiteside, & Cyders, 2006).

[24] As part of the experiment neuroimaging data were collected which will be reported in future work. In this study we focus on the behavioral aspect of decision making.

Demographic characteristics and other measures and background information were also included in the survey.

Upon arriving to the laboratory participants self-evaluated and reported the intensity of their current feeling of hunger on a nine-point Likert scale, where 1 was labeled as "Not hungry at all" and 9 was labeled as "As hungry as I ever felt". Then, they engaged in a risky choice framing session and fulfilled a series of 216 trials presented on a monitor by using a hand-held controller to communicate their responses. Each trial began with a short preamble displayed for 4 seconds (see Figure 2.1). The preamble was designed to set the stage for a subsequent framing decision problem and to clear away any ambiguity that might have been emerged from introducing different fuzzy-trace theory based truncated variations of the problem. Following the preamble, a decision problem was displayed for seven seconds. During this time frame subjects were required to choose between a riskless reward outcome (either money or food) and a binary gamble with zero as one of its outcomes, that carried an expected payoff equal to that of the sure option. Next, a five-point scale ranging from 1 (very low) to 5 (very high) was presented for 4 seconds prompting participants to rate the level of confidence in their decision. The trial ended with an inter-trial screen that included a fixation cross in the middle and was displayed for either 4, 6, or 8 seconds before the next trial has begun.

The framing task included a set of 108 decisions, consisting of the different levels of five different factors: reward type, decision frame, FTT truncation condition, reward magnitude, and probability. The set was presented twice (i.e., two repetitions). Within each repetition the decisions were randomly ordered.[25] US dollars and M&M's were the two types of rewards offered in each trial (either one or the other). Additionally, every decision problem was framed as

[25] We utilized the high choice consistency rate across the two repetitions (80%) to replace the few non-systematic missing observations with the choice made for the same exact decision problem in the opposite repetition.

either ‘gain’ or ‘loss’, such that for any given gain-framed decision there was a loss-framed counterpart generating the same possible net outcomes (in terms of final assets), where the preamble serves to adjust the appropriate endowment accordingly. The three (net) payoff levels, offered as the riskless option for each type of reward (dollars/M&M’s), were small (1), medium (6), and large (20). The three probabilities employed for the gambles were 50%, 60%, and 67%. They represent the likelihood of the worse outcome (i.e., gain nothing in the gain frame; lose everything in the loss frame) whenever the gamble is chosen over the sure option. Each riskless payoff was crossed with three binary lotteries (corresponding to the three probabilities).[26]

Finally, based on fuzzy-trace theory’s paradigm, the information of the gamble presented in each trial was manipulated according to three different truncation conditions — gist, mixed, and verbatim. In the mixed condition both the zero and nonzero complements of the gamble were shown in the traditional way (all the informational inputs were present). The nonzero complement was removed from the gamble in the gist condition, while the opposite was true for the verbatim condition, where the zero complement was omitted (Reyna & Brainerd, 1991; Reyna et al., 2014). Note that this truncation method only removes redundant information while keeping the overall decision problem unaffected (Instructions made clear that truncated outcomes were known by subjects, verified by quizzes) (see also Chick et al., 2016). Table 2.4 presents an example for fuzzy-trace theory manipulation (the 3 FTT truncations) on arbitrary decision problem (gain frame, $20, 67%) with the following preamble: "You have entered a raffle and $60 are at stake. Which would you choose?".

In return to their participation in the framing task, subjects received a payoff of $30. Additionally, to render this task incentive compatible, one of the decision problems was

[26] Note that the nonzero outcome of every gamble is governed by its probability and the magnitude of the sure outcome to ascertain equality of the expected values.

randomly selected at the end of the experiment and its outcome was given to the subject based on their choice made to this decision during the task. Thus, participants could have won an additional payoff ranging from 0 to 60 of either M&M's or US dollars.

General Analysis Method

We analyzed the effect of hunger on response choices in two alternative ways. The main analysis compared group means using a repeated measures ANOVA. Hunger, in this analysis, was measured objectively based on our food deprivation protocol, in which subjects were randomly assigned to treatment (hungry) and control (non-hungry) groups. The between-subject factors included 2 hunger group (hungry, non-hungry) × 2 age group (adolescent, adult). The within-subject factors were 2 repetition × 2 reward type (US dollars, M&M's) × 2 decision frame (gain, loss) × 3 FTT truncation (gist, mixed, verbatim) × 3 reward magnitude (small(1), medium(6), large(20)) × 3 probability (50%, 60%, 67%).[27]

The second analysis capitalized on the variations in the degree of hunger across subjects, as recorded by the nine-point self-report hunger (SRH) scale, and served as a robustness check to the results obtained by our main analysis. To assess the effect of SRH on risky choice and framing bias (while controlling for other between- and within-subject measures) we pooled the data of all sampled subjects, treating each subject as a cluster. Then, a logistic regression model was fitted on the pooled dataset using generalized estimating equations (GEE) analysis with robust standard errors and exchangeable working correlation structure to account for the within-subject clustering effect. The same analysis was then performed separately on each type of reward.

[27] In cases where the assumption of sphericity was violated, we used the Greenhouse-Geisser correction.

Finally, we explored the relation between framing bias with money and with food for both hunger and age groups, by utilizing the intrinsic heterogeneity in framing patterns among the participants.

Results

Manipulation Check

In order to test whether our hunger manipulation protocol was indeed successful, a two-way ANOVA was conducted with scores from the self-reported hunger (SRH) scale serving as the dependent variable, and hunger group (non-hungry, hungry – based on random assignment) and age group (adolescent, adult) as factors.[28] We found that main effect of hunger group was the only one significant, $F(1, 113) = 41.05$, $p < .001$, $\eta^2 = .266$. Age group and the interaction between age and hunger were not significant. A pairwise test revealed that the SRH scores in the hungry group ($M = 5.786$, $SE = .246$) were significantly higher compared with the non-hungry group ($M = 3.585$, $SE = .239$); $p < 0.001$. As expected, food deprived subjects reported feeling hungrier relative to subjects in the control group (non-hungry group), which lends support to the success of our hunger manipulation.

The Framing Effect

In the context of our decision task, in which response choices were coded as 0 (choosing the sure option) or 1 (choosing the gamble), the difference between the proportion of risky choices made in the loss frame and the gain frame defines a framing index pointing to the direction and strength of the framing effect for each subject. The framing index is bounded between −1 and +1, where a positive value denotes standard framing behavior, zero denotes no

[28] Two subjects who failed to report their level of hunger were excluded from this analysis.

framing, and a negative value indicates reverse framing (i.e., choosing the sure option in the loss frame and the gamble in the gain frame).

Findings from a repeated measures ANOVA conducted on the response choices show a significant main effect of decision frame, F (1, 115) = 113.83, $p < .001$, $\eta^2 = .497$. Subjects took fewer risks in the gain frame ($M = .397$, $SE = .026$) compared with the loss frame ($M = .535$, $SE = .025$), demonstrating a standard framing bias. Frame did not interact with reward type. That is, the marginal means of framing effect obtained for both monetary and food choices were not significantly different. However, the main effect of framing was qualified by a two-way interaction with age, F (1, 115) = 7.251, $p < .01$, $\eta^2 = .059$, and with FTT truncation, F (1.448, 166.539) = 125.202, $p < .001$, $\eta^2 = .521$. A three-way interaction between frame, age, and FTT truncation was also found significant, F (1.448, 166.539) = 7.161, $p = .001$, $\eta^2 = .059$, and is illustrated in Figure 2.2.[29] As can be seen in the graph, the framing effect is clearly modulated by the truncation condition. In the mixed condition (the traditional way of presenting risky choice framing problems) a framing bias is prevalent for both adults and adolescents (slightly stronger for adults). This effect vanishes in the verbatim condition, where the zero complement is truncated from the gamble, and becomes larger in the gist condition. Furthermore, the impact of the gist condition on framing is stronger for adults than it is for adolescents.

The Effect of Hunger

Results from Analysis of Variance. The objective measure of hunger state (based on our food deprivation protocol) was found to have a significant main effect on risky choice behavior as revealed by the repeated measures ANOVA, F (1, 115) = 5.995, $p = .016$, $\eta^2 = .050$, showing

[29] All other significant interactions with decision frame are reported in the Appendix. They do not alter the qualitative effect of framing reported here.

a significant lower proportion of risky choices for food-deprived subjects (M = .406, SE = .035) relative to those in the non-hungry group (M = .526, SE = .034). Importantly, hunger did *not* interact with any other variable in a significant two-way interaction. This implies that the main effect of hunger held irrespective of whether the decision was framed as a gain or as a loss ($p < .05$; see Figure 2.3), and that this trend largely prevailed at any reward type and FTT truncation condition, as illustrated in the exploratory Figure 2.4 (significant for candy in each truncation condition, and for money-gist-lost frame, and money-verbatim-gain frame, $p < .05$. The effect in the remaining conditions was qualitative evident but did not reach statistical significance, $p < .1$).

Another significant effect we found was a three-way interaction between hunger group, age group, and reward type, F (1, 115) = 3.316, $p < .05$, $\eta^2 = .035$. Adults in the non-hungry group took more risks with food than they did with money (M_{Diff} = .068, SE = .022, $p < .01$), whereas adults in the hungry group were pretty consistent in their risk-taking behavior between the two types of reward (M_{Diff} = .007, SE = .024, p = .754). Adolescents, similar to the hungry adults, did not show significant inconsistency in their preferences between food and monetary rewards irrespective of their hunger state. This three-way interaction was further qualified by a four-way interaction of hunger group, age group, reward type, and reward magnitude, F (1.99, 228.848) = 5.539, $p < .01$, $\eta^2 = .046$, indicating that the relative risk seeking behavior of non-hungry adults with food compared to money was obtained mainly due to medium and large sized rewards (M_{Diff} = .069, SE = .032, $p < .05$, and M_{Diff} = .134, SE = .031, $p < .001$, respectively) but not small outcomes (M_{Diff} = .001, SE = .022, p = .967). All the other significant interactions with hunger

are reported in the Appendix.[30] Nevertheless, the overall effect of hunger remained qualitatively consistent pointing, again, to a more risk averse behavior for hungry individuals.

Results from Regression Analyses. A binary logistic regression analysis was conducted, using the subjective measure of hunger (SRH) as a predictor, to assess its effect on risk-taking behavior and framing bias. Age group, ONS, and UPPS-P were employed as predictors to control for age and individual differences in impulsivity and level of numeracy as alternative moderators of risk preferences. ONS was measured as the percentage of correct answers in the numeracy test ($M = .82$, $SD = .141$ in our sample population; a higher score implies higher numerate skills). Each of the five UPPS-P subscales (Urgency, (lack of) Premeditation, (lack of) Perseverance, Sensation Seeking, and Positive Urgency) was scored by averaging the ratings across the relevant items (a high score indicates high impulsiveness along the specific dimension).

In order to establish to what extent each subscale of the UPPS-P is related to the overall mean proportion of risky choices (MRC) as well as to theoretically relevant subsets of this measure (MRC for money, food, gains, and losses), we performed a Pearson correlation analysis between the two groups of variables. Results are reported in Table 2.5. As can be seen in the table, (lack of) Premeditation was the only subscale that correlated significantly with the subjects' choices, suggesting that higher disposition to act without much thinking (that is, less reliance on the deliberative system according to traditional dual system models) is largely connected to higher risk taking behavior. Hence, we used this subscale ($M = 1.99$, $SD = .394$) in our subsequent regression analyses.

[30] Additionally, significant effects with a particular focus on objective probabilities will be reported in a future work.

Two subjects who did not rate their level of hunger, and five subjects with missing answers on the numeracy test, were removed from all regression analyses. For the remaining 112 subjects, we regressed the overall MRC on the following predictors: age group (0 = adolescent, 1 = adult), SRH, Frame (0 = gain, 1 = loss), ONS15, and Premeditation, as well as the two-way interaction with age and SRH, and the four two-way interactions with Frame.[31] In order to also address some of the theoretical hypotheses mentioned earlier, we repeated the same exercise separately for money and food stimuli. Table 2.6 summarizes the results of the three regressions.

In concurrence with the results from the repeated measures ANOVA, frame predicted a more risk taking behavior in the loss frame compared with the gain frame in all three cases. Notably, the subjective measure of hunger (SRH) was also found to have a significant main effect for money and food (and in general) — hungrier subjects picked the sure outcome more frequently. Furthermore, for monetary choices SRH interacted with frame ($B = -.056$, $p = .05$), suggesting that hunger was associated with *less* framing bias with money (taking the gamble less frequently in the loss frame). Age group was statistically insignificant as a main effect but significantly interacted with frame in all three analyses, indicating that adults are more susceptible to framing bias. Finally, lack of premeditation and high numeracy corresponded to stronger propensity to pick the gamble (significant in all three cases for premeditation, and in the candy condition only for ONS), yet this proneness was reduced in the loss frame, as evident by the relevant interaction terms (significant for Frame * ONS15 in all cases and for Frame * Premeditation in the money condition and general case only), which implies a reversed framing pattern.

Heterogeneity in Framing Bias. As explained above, the size of the framing effect was calculated by subtracting the proportion of risky choices made in the gain frame from those made

[31] All Independent variables were mean centered.

in the loss frame. Following this technique, we calculated a framing index (FI) separately for each type of reward, which reflects the extent of the framing bias each subject committed with both monetary and food choices. Descriptive statistics of the two framing indices are presented in Table 2.7. Recall that based on group mean analysis, using a repeated measures ANOVA, no significant difference between the two indices was found. However, by exploiting the heterogeneity in magnitude and direction of the framing effect among subjects we could further investigate whether stronger framing biases with money corresponded to stronger biases with food, and if such correlation was modulated by hunger state (as suggested by third hypothesis derived from LOB's model) or by age group.

We first calculated the (Pearson) correlation coefficients between FI money and FI food for both the non-hungry group ($r_{NH} = .535$, $N = 62$, $p < .001$) and the hungry group ($r_H = .841$, $N = 57$, $p < .001$). The results point to a highly significant relation between food and monetary framing bias even when a feeling of hunger was absent. A scatter plot illustrating these correlations with fitted linear trend lines are shown in the left panel of Figure 2.5. Next, we tested the null hypothesis that $r_H - r_{NH} = 0$ by employing both Fisher's z-transformation method, which enables to perform a two-tailed Z-test by converting the correlation coefficients into normally distributed z-scores, as well as Zou's method to derive a 95% confidence interval (CI) for the difference between the two coefficients (Zou, 2007). We found that $r_H - r_{NH} = .306$ was significantly different from zero ($p < .001$), with 95% CI [.121, .521]. That is, the baseline correlation between the two framing indices was enhanced in the presence of hunger. Finally, we repeated the same procedure with the two age groups: adolescent ($r_{ADO} = .671$, $N = 63$, $p < .001$) and adult ($r_{ADU} = .716$, $N = 56$, $p < .001$). The corresponding scatter plot is shown in Figure 2.5 (right panel). In this case, however, $r_{ADU} - r_{ADO} = .045$, with 95% CI [−.151, .241], and thus we could not reject the null hypothesis ($p = .646$).

Discussion

Consistent with the evolving literature on decision making under the influence of various drive states (and hunger in particular), our results provide yet additional empirical evidence showing that the aversive feeling of hunger plays a significant role in the domain of risky choice behavior. More importantly, though, by employing a risky-choice framing task, we could (1) explore novel facets of this phenomenon, and (2) compare our findings against some formal, theory-driven hypotheses. Thus, these findings help expand the overall knowledge on this subject.

First, as expected, our results replicate the previously found joint effect of framing and FTT truncation condition, whereby a standard framing bias is substantially enhanced or completely eliminated (and even reversed) when emphasizing or de-emphasizing categorical distinctions between options in framing decision problems (e.g., Kühberger & Tanner, 2010; Reyna & Brainerd, 1991; Reyna et al., 2014; see also Reyna, 2012; Reyna & Brainerd, 1995). This lends support to the cognitive paradigm of fuzzy-trace theory while at the same time poses a serious challenge to utility based models (e.g., prospect theory). In addition, adults were more susceptible to framing than adolescents (particularly in the gist condition), following a pattern known as developmental reversal. This pattern goes against a fundamental view held by traditional dual system models asserting that the ability to apply interference control by inhibiting System 1 from operating on bias-prone heuristics increases with age. Contrary, the concept of developmental reversal is in fact a key feature underpinning fuzzy-trace theory. It is explained by the increased reliance on gist based intuition as people mature (e.g., Reyna et al., 2014; Reyna & Ellis, 1994; Reyna et al., 2011).

Similarly to the framing results, and perhaps less intuitively, our hunger related findings show an unambiguous directional effect of hunger on risk taking behavior. Hungry subjects exhibited a relatively strong tendency of risk aversion compared with non (or less) hungry individuals, as confirmed by the analyses with both the objective measure of hunger (based on random assignment to treatment and control groups) and the subjective one (derived from self-rated hunger). Interestingly, this pattern was robust across the different factors that were included in our experimental design. That is, hunger did not interact with age group, type of reward, frame, FTT truncation, etc.[32] These findings roughly correspond to Symmonds et al. (2010) who, based on a controlled randomized experiment, found that participants made fewer financial risks on average after a night's fasting than they did immediately after consuming a high-calorie breakfast (although, this effect was attenuated by the extent of the satiating impact of the meal).

However, other empirical studies found an opposite trend, namely that visceral influences resulted in an increased risk-taking behavior (e.g., Ariely & Loewenstein, 2006; Ditto et al., 2006; Levy et al., 2013; and to some extent also Shabat-Simon et al., 2018). Particularly, Levy et al. (2013) examined the effect of hunger (induced by four hours of food deprivation) on participants' risk attitude towards monetary, food, and water rewards. Using both parametric and non-parametric methods the authors found that, on average, participants under deprivation conditions were more risk tolerant with both food and water rewards, and to some extent with money as well, than under satiation. Notably, there is a crucial methodological difference that distinguishes their study from the current one which may explain the conflicting results. In each trial of the experiment Levy and his colleagues offered a choice between a fixed and relatively small riskless outcome (e.g., two dollars; two small crackers), and a gamble with an average

[32] Although some higher order interactions with hunger were significant, they did not influence the directional effect of hunger. The effect was mostly varying in magnitude, but remained qualitatively stable (see the Appendix for the full list of significant effects).

expected value much higher than the sure option (e.g., 7.05 dollars; 6.1 crackers), whereas in the current study we varied the amounts of the riskless option (1, 6, 20 dollars/M&M's) and probabilities of the gamble (50%, 60%, 67% of getting the worse outcome), while keeping an equal expected value in each trial. Arguably, the possibility to win a large reward with much higher expected value relative to a small, sure outcome, may render the gamble quite attractive — especially when feeling hungry and more sensitive to changes in reward magnitude. Put differently, a hungry individual may prefer to take a chance getting a satisfying prize than settling for unsatisfactory, sure gain.[33]

Furthermore, the fact that we obtained no significant interaction between hunger and frame from our repeated measures ANOVA suggests that the baseline framing bias was not sensitive to food deprivation conditions. It also serves as a connection point to the theory discussed earlier. That is, in the context of incoherent preferences across frames, we have no evidence that hunger compromises rational choice behavior, as entailed by the first hypothesis derived from LOB's model ($H1^{LOB}$), nor do we have evidence that it boosts rational choice behavior as may have been expected by FTT ($H5^{FTT}$). Thus, although this statistical finding does not bolster the predictive power of these two models, it does not undermine it as well. However, our regression analysis shows that, for monetary choices, the subjective measure of hunger (SRH) does, in fact, interact with frame ($B = -.056$, $p = .05$). The coefficient's negative sign suggests that hungrier subjects exhibited a reversed framing pattern, demonstrating less incoherent preferences, which lends some support to the formal hypothesis of FTT.

Based on both the ANOVA and the regression analysis, it is also evident that hungry subjects inclined to take fewer risks in *both* the gain and the loss frame. This finding, in

[33] See Caraco, Martindale, and Whittam (1980) for a similar type of behavior with animals operating in a negative expected net energy budget environment.

concurrent with the specific range of probabilities employed in this experiment (the likelihood of the better outcome in the gain frame and the worse outcome in the loss frame varies between 33% to 50% and between 50% to 67% respectively), is clearly incongruent with the theoretical predictions of the two dual system models. More specifically, the increased risk averse behavior of hungry subjects in the loss frame directly contradicts the second part of the hypothesis derived from Mukherjee's model ($H4^{M}$), while the overall directional effect challenges the second hypothesis derived from LOB's model ($H2^{LOB}$). Importantly, as confirmed by the ANOVA, the main effect of hunger is not qualified by any three way interactions of hunger, frame, and another factor such as age group, reward type, or FTT truncation condition, which makes this pattern of behavior across frames quite robust, holding under various conditions.

This finding is similar in spirit to that found in Whitney et al. (2008) who studied the role of working memory in the context of risky choice framing. By manipulating the intensity of the cognitive load using a working memory task, the authors found that people made fewer decisions to accept the risky option in *both* frames under conditions of high cognitive load. Clearly, though, working memory and hunger affect choices through distinct psychological processes (i.e., one modifies the available mental resources while the other is a visceral drive), yet under the dual system framework, both are presumed to increase the reliance on the affective system, which should lead to a different pattern than the one observed.

One way for this framework to reconcile the apparent dissonance between the above empirical finding and the theory is by invoking Matthew Rabin's argument. According to this argument, risk aversion over small-stakes gambles stems from loss aversion (relative to a reference point) (Rabin, 2000; see also Rabin & Thaler, 2001). Thus, if the expected reference point is the riskless outcome in both the gain and the loss frames, a risk averse behavior will follow (e.g., see Kőszegi & Rabin, 2007). However, this approach fails to account for the

framing effect itself, which is undoubtedly prevalent as well. Accordingly, it may seem a bit odd that a dual system model, which aims at explaining risky choice behavior using an integrative model of hot and cold systems, can successfully predict a wide array of observed biases (and even offers predictions that go beyond the scope of prospect theory, for example), yet it does relatively poorly when trying to account for risky decision making under "hot" conditions, such as hunger.

Finally, according to the third LOB-based hypothesis ($H3^{LOB}$), an increased framing bias on the account of hunger should be even more sensitive to food related choices simply because, relative to money, food stimuli are expected to yield a stronger affective reaction when one is hungry than sated. Although, as discussed above, such pattern was not detectable in our ANOVA or regression analysis, the framing heterogeneity examination we conducted does provide some support for this idea. The much stronger correlation between framing with money and framing with food calculated for hungry than non-hungry subjects, suggests that food rewards aroused the affective system almost as much as money did, such that hungry people whose framing bias with money was high were most likely to "sin" by committing a high framing bias with food as well.

Conclusions

The relevance of hunger to our daily lives as decision makers cannot be overstated. During a typical day people experience hunger at different levels of intensity due to various reasons (e.g., the normal biological cycles of hunger-regulating hormones, a strict diet routine, poverty-based malnutrition, anorexia, etc.). It is, therefore, critical to understand the implication hunger has on the way we make choices.

In this work we set out to study the role of hunger in risky decision making, with a special emphasis on risk attitudes and rational choice behavior with both food and monetary related

choices. For this purpose, we used a risky choice framing task (which has never been tested in the context of hunger drive before) and compared our findings against some formal hypotheses derived from two traditional dual-system models and from fuzzy-trace theory — which are among the very few theories that can formally account for the effect of drive states within the framework of decision making under uncertainty.

Our results demonstrate that hunger yields fewer risk-taking decisions, and that this pattern holds across many different conditions including monetary and food stimuli, different age groups, and across gain-framed and loss-framed decisions. Furthermore, the magnitude of the framing effect, which indicates a bias from rational choice behavior, was largely insensitive to the influence of hunger, with the exception of one analysis with money, whereby the framing effect *reduced* as the feeling of hunger intensified. These findings provide some (but not strong) support for fuzzy-trace theory, yet they pose a challenge to the theory formulation underpinning the two dual system models.

There is, however, an important point which may suggest a caveat to our conclusion with respect to the dual system models. Recall that in our framing task, the expected value of the gambles in each trial is equal to the sure outcome. The predicted choice between the two options by these two models will, therefore, remain the same regardless of the hunger state, and will dissociate only due to unexplained, random behavior. As a result, our assessment of the adequacy of these models to fit the data is based entirely on the stochastic noise component (error term) instead of the structural one. While true, our findings clearly show a systematic choice pattern, unlikely to be driven by a random behavior alone, which corroborates our claim despite the absence of decisions with unequal expected value.

Consequently, a natural step forward in the evolution of this field of research calls for the emergence of new and modified theories on the basis of empirical evidence, in order to reliably

account for the observed systematic patterns of behavior. The attempt to formulate dual-process based models using psychophysical principles is a step in the right direction, which may simply require some proper modifications. Another promising option is to employ the core principles of fuzzy-trace theory in a slightly different setting, by allowing gist-based intuition to go beyond the payoff dimension. Particularly, one may assume that gist processing can operate along other (activated) motivational dimensions (e.g., hunger), so that bottom line representations of the decision will revolve around the implication to the relevant drive state (e.g., being satiated vs. a chance of being hungry). This can explain, for example, risk averse behavior under hunger conditions and may serve as a good starting point for future research.

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Table 2.1. *Verbatim and gist representations of the dread disease problem.*

	Verbatim information	Gist representation
Gain frame	A: 200 people will be saved. B: 1/3 chance that 600 people will be saved and a 2/3 chance that no people will be saved.	A: Some people will be saved. B: Some people will be saved or no one will be saved.
Loss frame	C: 400 people will die. D: 1/3 chance that nobody will die and a 2/3 chance that 600 people will die.	C: Some people will die. D: Some people will die or no one will die.

Table 2.2. *Theoretical predictions for framing effect, risk preferences, and the hunger effect.*

	Framing Bias ($33\% < P_G \leq 50\%$; $50\% \leq P_L < 67\%$)	**Risk Preferences**
Prospect Theory	Can explain framing bias (does not predict an increased bias with age and expertise)	Risk-taking behavior depends on the structure of both the value function and the PWF
Mukherjee (dual system model)	Framing bias should increase as hunger intensifies (does not predict an increased bias with age and expertise)	Preference for gamble in the loss frame **increases** as hunger intensifies (more **risk seeking**) (Preference for gamble in the gain frame depends on the structure of the value function)
LOB (dual system model)	Framing bias should increase as hunger intensifies (does not predict an increased bias with age and expertise)	Preference for gamble in either the gain frame or the loss frame (or both) **increases** as hunger intensifies (more **risk seeking**) (That is, it is not likely to observe risk seeking behavior for both the gain and the loss frame as hunger intensifies)
Fuzzy-Trace Theory	Accounts for framing bias Framing bias increases with age and expertise No bias when relying on verbatim reasoning Framing bias not the same cause as affective bias: Hunger is distinct from framing	As reliance on gist grows: Risk-averse behavior in the gain frame; risk-seeking behavior in the loss frame Hunger is distinct from risk preferences

Table 2.3. *Age-Hunger distribution for the risky-choice framing session.*

	Adolescents	Adults	Total
Non-hungry (control)	32	30	62
Hungry (treatment)	31	26	57
Total	63	56	119

Table 2.4. *Fuzzy-trace theory manipulation.*

Condition	Riskless option	Gamble
Gist	Win $20 for sure	2/3 probability you win nothing
Mixed	Win $20 for sure	1/3 probability you win $60 and 2/3 probability you win nothing
Verbatim	Win $20 for sure	1/3 probability you win $60

Note: Presentation of the three truncation conditions is based on the same exact information given in the preamble ("You have entered a raffle and $60 are at stake. Which would you choose?").

Table 2.5. *Correlations between different measures of mean proportion of risky choices (MRC) and the five UPPS-P subscalses.*

	MRC General	MRC Money	MRC Food	MRC Gain	MRC Loss
Negative Urgency	0.088	0.112	0.061	0.109	0.061
Premeditation	0.206*	0.226*	0.177†	0.212*	0.186*
Perseverance	0.065	0.075	0.053	0.084	0.042
Sensation Seeking	0.104	0.131	0.073	0.109	0.093
Positive Urgency	0.082	0.091	0.07	0.1	0.059

*$p < .05$, †$p < .06$

Table 2.6. *Regression results for mean proportion of risky choices in general, for money, and for food stimuli.*

	General		Money		Food	
Variables	B	SE	B	SE	B	SE
(Intercept)	−0.082	0.105	−0.161	0.103	−0.035	0.106
Age Group	−0.077	0.230	−0.1	0.213	−0.108	0.219
SRH	−0.165**	0.053	−0.119*	0.049	−0.188***	0.053
Frame	0.572***	0.053	0.604***	0.059	0.543***	0.057
ONS15	1.341	0.838	1.635*	0.749	1.287	0.832
Premeditation	0.790**	0.278	0.760**	0.261	0.852**	0.258
Age Group * SRH	−0.142	0.112	−0.050	0.101	−0.184	0.109
Age Group * Frame	0.363**	0.112	0.393**	0.122	0.332**	0.122
SRH * Frame	−0.035	0.024	−0.056†	0.028	−0.013	0.028
Frame * ONS15	−1.541**	0.458	−1.720**	0.533	−1.419**	0.462
Frame * Premeditation	−0.284*	0.139	−0.429*	0.170	−0.144	0.154

Note: The reported coefficient estimates were obtained using generalized estimating equations (GEE) with logit link for binary outcomes. SE: Cluster-robust standard errors (clustered by subject). †$p = .05$, *$p < .05$, **$p < .01$, ***$p < .001$.

Table 2.7. *Descriptive statistics of the framing indices for monetary and food choices.*

	Mean	Median	SD	Range	Min	Max
FI Money	0.145	0.093	0.162	0.85	−0.11	0.74
FI Food	0.126	0.111	0.148	0.76	−0.09	0.67

FI: Framing Index. SD: Standard Deviation.

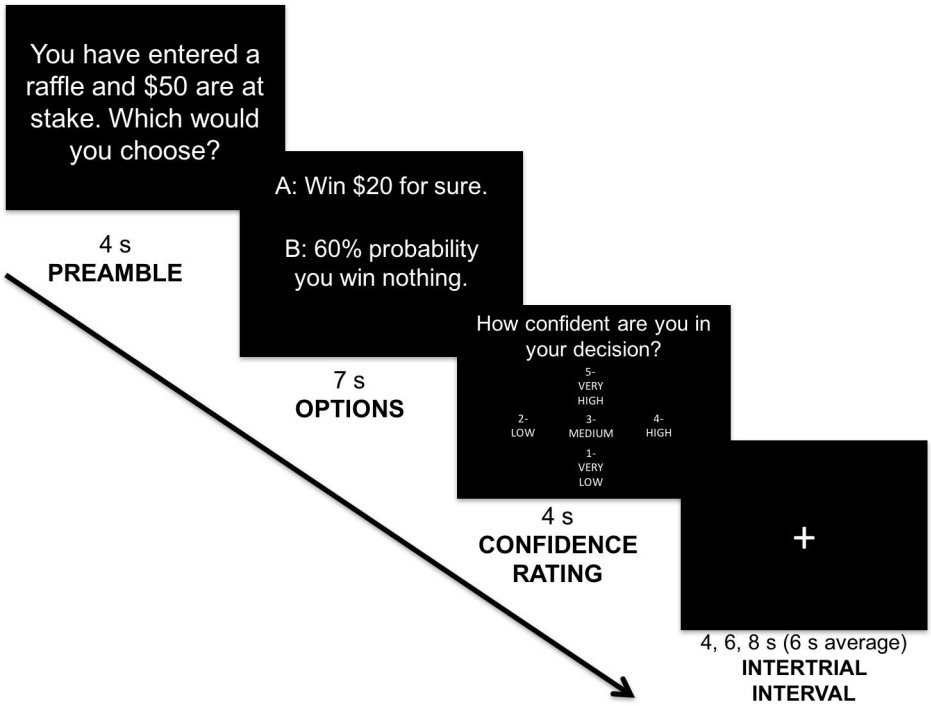

Figure 2.1 . Trials timeline.

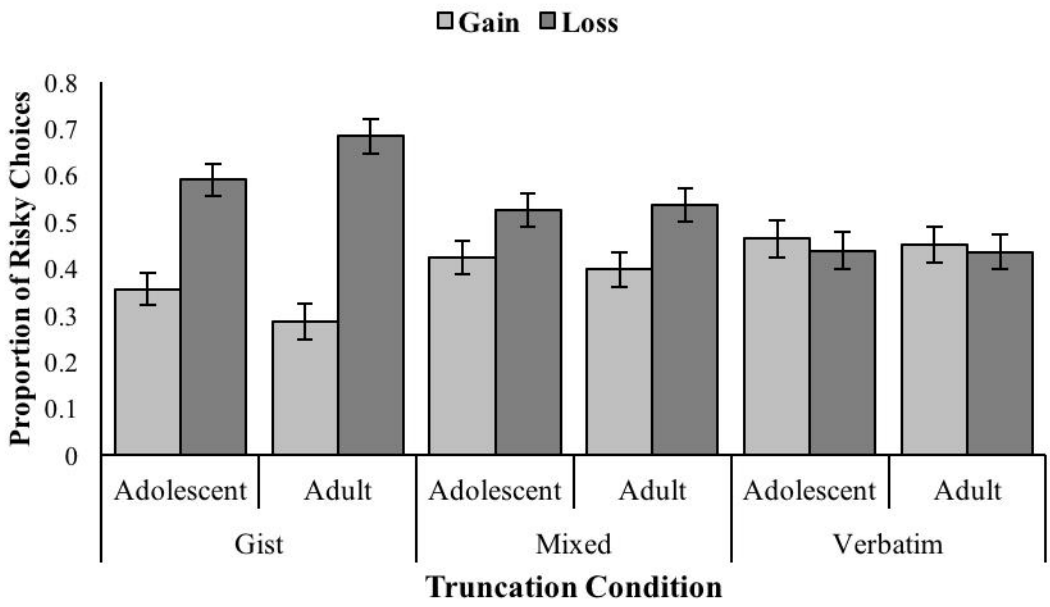

Figure 2.2 . A three-way interaction effect of decision frame, age group, and FTT truncation. Bars represent mean proportion of risky choices. Error bars represent ±1 *SE*.

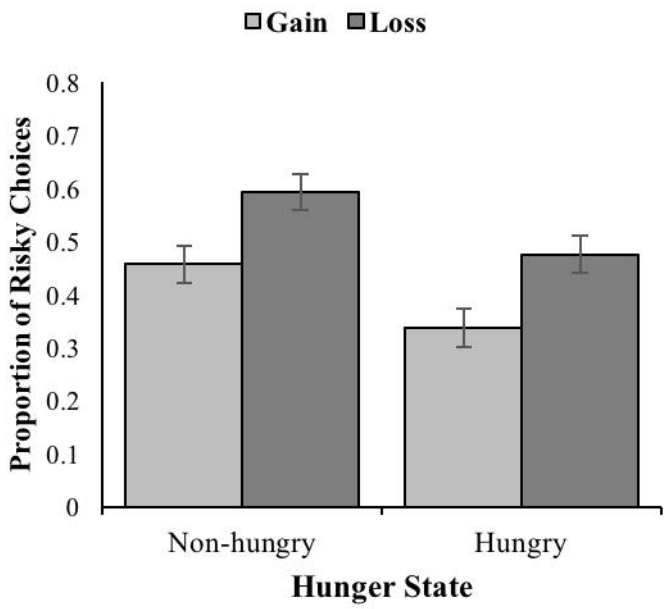

Figure 2.3 . Interaction between hunger group, and decision frame. Bars represent mean proportion of risky choices. The interaction is not significant, i.e., the same patterns of risk and framing behavior hold across the two hunger states and within each frame. Error bars represent ±1 *SE*.

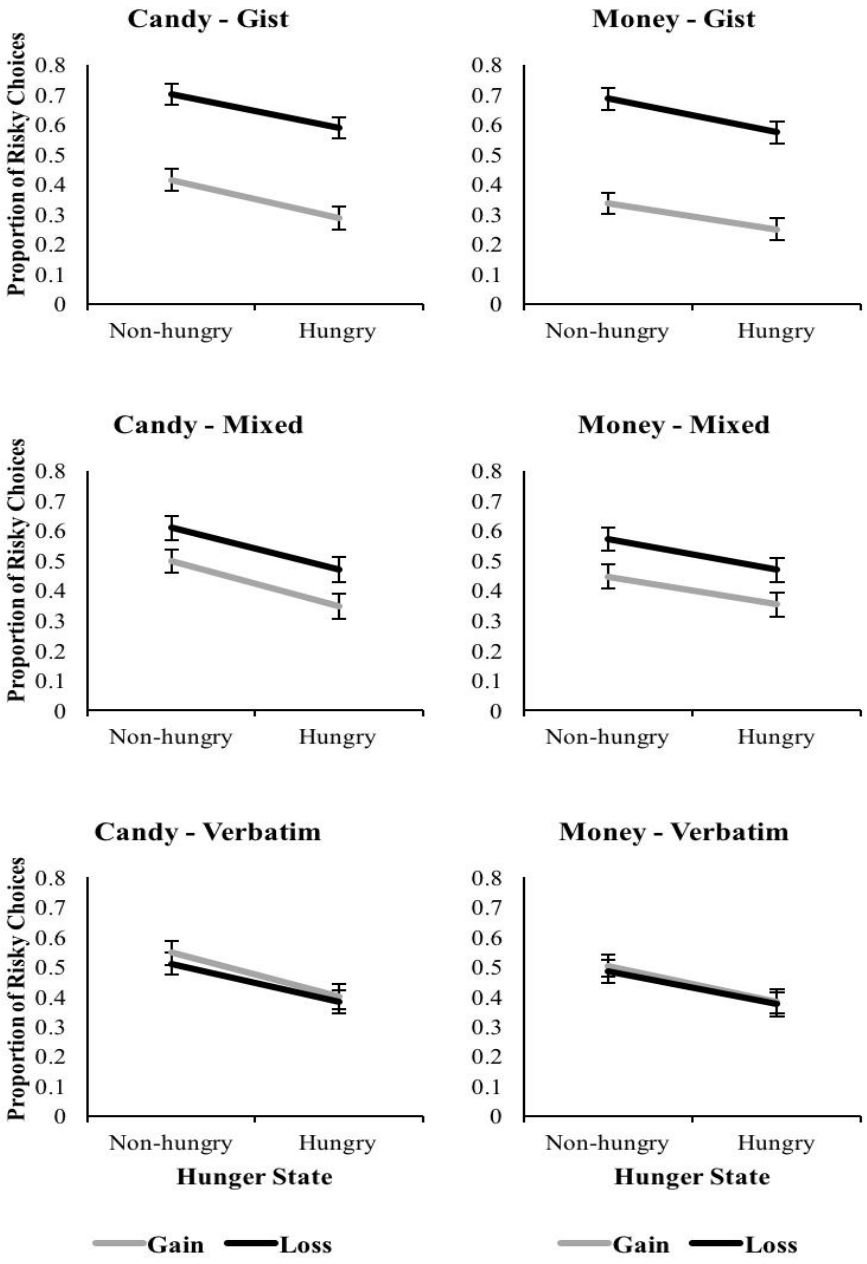

Figure 2.4 . The effect of hunger within each reward type, decision frame, and FTT truncation condition on mean proportion of risky choices. The effect is significant for candy in each truncation condition, and for money-gist-lost frame, and money-verbatim-gain frame, $p < .05$. For the remaining conditions $p < .1$. Error bars represent ±1 *SE*.

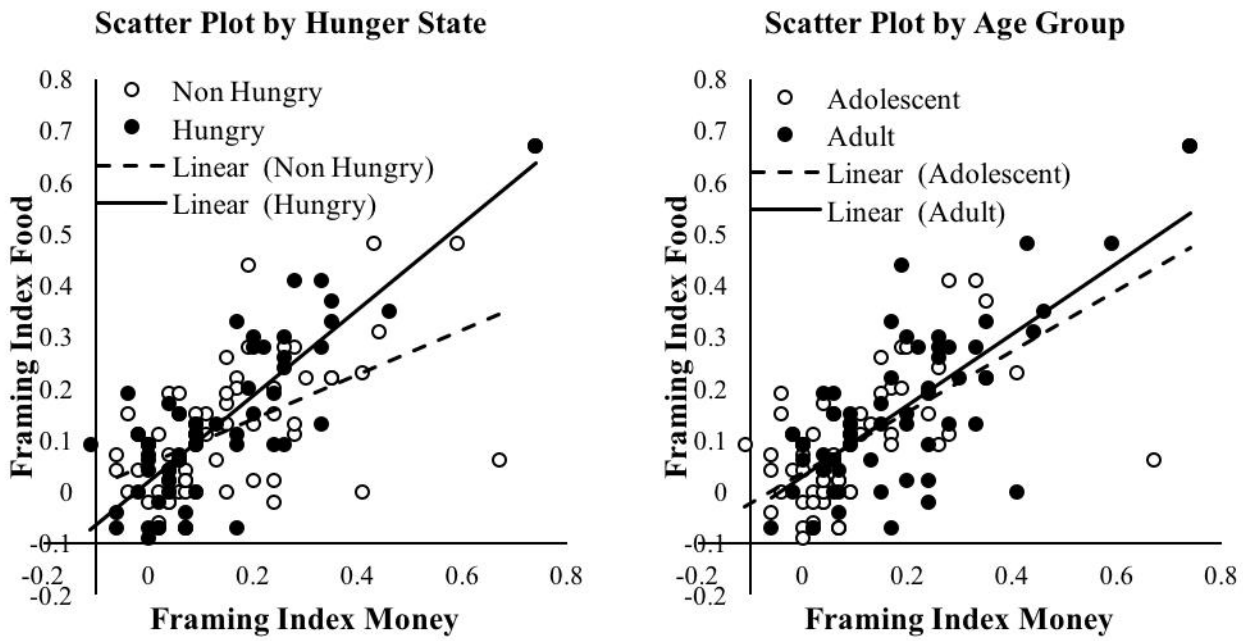

Figure 2.5 . A scatter plot with fitted linear trend lines between framing index for money and framing index for food choices for the entire population sample, divided by hunger state (left panel) and by age group (right panel).

Appendix

Significant effects from the repeated measures ANOVA

Table A1

	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial η^2
1. Tests of Between-Subjects Effects						
Intercept	5548.96	1	5548.96	366.29	<.001	0.76
Hunger	90.82	1	90.82	5.99	0.016	0.05
Error	1742.14	115	15.149			
2. Tests of Within-Subjects Effects						
Type	4.81	1	4.81	6.03	0.016	0.05
Type * Age * Hunger	3.32	1	3.32	4.16	0.044	0.04
FTT	4.50	2	2.25	7.15	0.001	0.06
Frame	120.94	1	120.94	113.83	<.001	0.50
Frame * Age	7.70	1	7.70	7.25	0.008	0.06
Magnitude	104.02	2	52.01	35.17	<.001	0.23
Probability	70.47	2	35.24	36.97	<.001	0.24
Repetition * Frame	1.16	1	1.16	5.17	0.025	0.04
FTT * Frame	122.20	2	61.10	125.20	<.001	0.52
FTT * Frame * Age	6.99	2	3.50	7.16	0.001	0.06
Repetition * FTT * Frame	6.05	2	3.03	17.85	<.001	0.13
Type * Magnitude	2.32	2	1.16	4.17	0.017	0.04
Type * Magnitude * Age * Hunger	3.08	2	1.54	5.54	0.004	0.05
Repetition * Type * Magnitude * Age * Hunger	0.98	2	0.49	3.79	0.024	0.03
FTT * Magnitude	1.22	4	0.30	2.50	0.042	0.02
FTT * Magnitude * Age * Hunger	1.43	4	0.36	2.93	0.02	0.03
Repetition * Type * FTT * Magnitude	0.99	4	0.25	2.41	0.049	0.02
Frame * Magnitude	1.61	2	0.81	4.18	0.017	0.04
FTT * Frame * Magnitude	2.48	4	0.62	5.10	<.001	0.04
FTT * Probability	5.92	4	1.48	10.05	<.001	0.08
FTT * Probability * Hunger	1.44	4	0.36	2.45	0.046	0.02
Frame * Probability	8.41	2	4.21	22.78	<.001	0.17
Frame * Probability * Age	2.49	2	1.25	6.76	0.001	0.06
Frame * Probability * Age * Hunger	1.15	2	0.57	3.11	0.047	0.03
FTT * Frame * Probability	3.65	4	0.91	5.54	<.001	0.05
FTT * Frame * Probability * Hunger	2.10	4	0.53	3.18	0.014	0.03

Type * Magnitude * Probability * Age	1.91	4	0.48	3.18	0.014	0.03
Type * FTT * Magnitude * Probability * Age	2.36	8	0.29	2.42	0.014	0.02
Repetition * FTT * Frame * Magnitude * Probability * Age * Hunger	1.83	8	0.23	2.22	0.024	0.02

CHAPTER 3

WHEN CHANGES IN PROBABILITY NEAR THE MIDPOINT PRODUCE LARGE CHANGES IN RISK PREFERENCES: CONTRASTING FUZZY-TRACE AND DUAL-SYSTEM AFFECTIVE MODELS

Introduction

In the current work we set out to study the influence that changes in probability near the middle of the range has on risk preferences and whether it is modulated by an incidental "hot" state – particularly the feeling of hunger. We test our results against the theoretical predictions of two, relatively similar, traditional dual-system models - Mukherjee (2010), and Loewenstein, O'Donoghue, and Bhatia (2015) [hereinafter, LOB] – and against that of *fuzzy-trace theory* (Reyna & Brainerd, 1991 ; see also Reyna, 2012), and find that the latter theory better explains our results.

Using a laboratory experiment we have manipulated hunger by randomly assigning subjects to a treatment (hungry) group – in which people refrained from eating for at least four hours prior to the experiment – and a control (non-hungry) group. Each participant responded to a series of decision problems in a risky-choice framing task. In every trial they were asked to choose between a riskless option and a binary gamble (with varying probabilities and payoff magnitudes) that were framed as either gains or losses. Furthermore, the task was designed such that gambles in each trial had zero as one of the two possible outcomes, and carried an expected payoff equal to that of the sure option. Consequently, any change to the level of risk resulted in a proportional change to the gamble's payoff to produce the appropriate EV that would match that of the alternative riskless option. For example, a 33% chance to win $60 could increase to 50% chance by decreasing the winning outcome to $40 in order to equate the EV to a riskless option

of $20. Thus, the attractiveness of the gamble in these kind of risky-choice framing tasks depends on a tradeoff between two contradicting forces – incurring more/less risk versus higher/lower payoffs (see Kühberger, Schulte-Mecklenbeck, & Perner, 1999).

A general consensus in the field of judgment and decision making posits that people distort probabilities in a non-linear fashion when facing choice problems under uncertainty. That is, they translate objective probabilities into subjective decision weights which guide their choices. An abundant empirical evidence has shown a tendency to overweight small probabilities and underweight large probabilities – known in the literature as the possibility effect and the certainty effect respectively (see Kahneman & Tversky, 1979) – and is usually represented by an inverse S-shaped probability weighting function (e.g., Abdellaoui, 2000; Gonzalez & Wu, 1999; Tversky & Fox, 1995; Tversky & Kahneman, 1992; Wu and Gonzalez, 1996) . This functional form entails a flattening of the slope along the midpoint of probabilities, which psychologically amounts to insensitivity to changes in probabilities when moving away from the edges (0 and 1).[34]

In order to compare our results with theoretically grounded hypotheses, we derived formal predictions from both Mukherjee's and LOB's dual-system-based models (System-1 ["cool" and rational] and System-2 ["hot" and affective in nature]), which are among the very few theories that can account for the effect of drive states (e.g., hunger) in the context of risky choice behavior, and from fuzzy-trace theory – an alternative dual-process model of memory, reasoning, Judgment, and decision making. Fuzzy-trace theory posits that informational inputs are encoded and processed along a continuum of mental representations with *gist* (i.e., bottom line meaning) being on one end and *verbatim* (exact numerical and verbal information) on the

[34] Other studies, however, found a convex weighting function, which implies an underweighting of the entire range of probabilities, and also entails high sensitivity along the mid-range (e.g., Krawczyk, 2015; Van De Kuilen & Wakker, 2011).

other. Within the framework of risky decision making, for example, information of the decision problem is simultaneously represented both as a simplest categorical gist (e.g., *some* versus *none*), an ordinal gist, which is a finer distinction (placed in the middle of the continuum; e.g., *less* versus *more*), and as a precise representation (verbatim). According to fuzzy-trace theory, there is a tendency to rely mainly on fuzzy (gist) representations when making choices – a reliance that increases with age and expertise, and often generates a different risk preferences (typically a more risk avoidance behavior) than that of a verbatim-based reasoning.

Mukherjee and LOB both assume that the interplay between two distinct cognitive systems, a deliberative ("cold") system and an affective ("hot") system, determines humans' decision making. Since the cold system is logical and deliberative, both models assume that it can be represented by a standard expected-value-maximizing behavior.[35] The two models are distinguished mostly by their treatment to the hot system. The affective system in Mukherjee's paper is assumed to be entirely insensitive to probabilities (i.e., every possible outcome is equally weighed) and is represented by prospect theory type value function (i.e., a reference dependent function that is monotonically increasing, concave in the gain frame, convex in the loss frame, and is characterized by the loss aversion property). LOB, instead, assume a linear value function, for both positive and negative outcomes, that reflects the property of loss aversion (the slope is steeper in the negative domain than in the positive one), and a relatively insensitive probability weighting function (with a functional form similar in nature to that described in the original Kahneman and Tversky's 1979 prospect theory paper).

Despite the few conceptual differences, predictions derived from both models are similar with regard to the effect of probabilities near the midpoint on risky choice behavior in a framing

[35] LOB are, in fact, using a general expected utility model to describe the cold system, but assume a linear functional form for small to moderate payoff magnitudes.

task, where risk levels and outcomes vary together to ascertain equal EV between the gamble and the sure outcome in every trial. It is straightforward to see that, under the guidance of the deliberative system, risk-neutral preferences are expected irrespective of the gamble's risk level (due to the EV structural form). This, however, is not the case for the affective system. Working through the models' equations, it is possible to show that under a hot state (e.g., hunger), the higher the (mid-range) chances to win/lose something (namely, to end up with the gamble's non-zero outcome), the less/more attractive the gamble becomes relative to the riskless option and a more/less risk-averse behavior is expected. Alternatively, fuzzy-trace theory predicts that – when relying on a more gist-based intuition – as the probability to win/lose *nothing* (the zero outcome) increases the gamble becomes less/more attractive and, thus, a more/less risk-averse behavior is expected.[36] Moreover, this prediction is opposite in direction to that of the two traditional dual-system models. (Table 3.1 lists the theoretical predictions of the above three theories, as well as of prospect theory, regarding the probability effect).

Our findings reveal that an increase in the winning/losing probabilities generates a more/less risk-taking behavior. Generally, this pattern holds true for both decision frames, yet the effect in the loss frame is less significant and more variable. These findings are incongruous with both Mukherjee's and LOB's predictions and are better supported by fuzzy-trace theory. Furthermore, this tendency of risk-taking behavior was largely obtained in a number of previous studies that were using a similar experimental design (e.g., Reyna & Ellis, 1994; Reyna et al., 2011), yet it is inconsistent with the results presented in the meta-analysis study of Kühberger et al. (1999).

[36] This prediction assumes a constant riskless option (e.g., $20 for sure regardless of the gamble's probability). In our experiment this is indeed the case in the gain frame but not in the loss frame. This affects the prediction accordingly, and we discuss this later in the paper.

Method

Participants and Design

A total of 132 right-handed subjects (83 women) from two different age groups (adolescent and adult) participated in the study. Adolescents were 69 high-school students (ages 14-18; *M* = 16.83, *SD* = 1.350) from central New-York. The adult group included 63 subjects, (ages 26-49; *M* = 34.21, *SD* = 6.577) from the same area. Hunger was manipulated by random assignment to treatment (hungry) and control (non-hungry) groups. Participants in the hungry group were instructed to abstain from any food consumption at least four hours prior to participating in the experiment. No special food restrictions (e.g., when or what to eat) were imposed on those in the non-hungry group.

The experiment included a risky-choice framing task with money (US dollars) and food reward (M&M's) in return for monetary compensation (described below), which took place in the laboratory at Cornell Magnetic Resonance Imaging Facility, at the Human Neuroscience Institute. Four subjects that could not be scanned (two were not in compliance with MRI safety procedure, one subject did not fit in the MRI scanner, and one subject was removed from the scanner due to persistent cough) and nine subjects with systematic missing data (due to human error by the experimenter) were excluded from all subsequent analyses (six adolescents and seven adults). Thus, we obtained analyzable choice data for 119 subjects (62% female; 72.3% Caucasian, 14.2% Asian, 4.2% African American; 8.4% of this group was Hispanic). Table 3.2 displays the age-hunger subgroups distribution for the framing task.

Materials and Procedure

Upon arriving to the laboratory participants self-evaluated and reported the intensity of their current feeling of hunger on a nine-point Likert scale, where 1 was labeled as "Not hungry

at all" and 9 was labeled as "As hungry as I ever felt". Then, they engaged in a risky choice framing session and fulfilled a series of 216 trials presented on a monitor by using a hand-held controller to communicate their responses. Each trial began with a short preamble displayed for 4 seconds (see Figure 3.1). The preamble was designed to set the stage for a subsequent framing decision problem and to clear away any ambiguity that might have been emerged from introducing different fuzzy-trace theory based truncated variations of the problem. Following the preamble, a decision problem was displayed for seven seconds. During this time frame subjects were required to choose between a riskless reward outcome (either money or food) and a binary gamble with zero as one of its outcomes, that carried an expected payoff equal to that of the sure option. Next, a five-point scale ranging from 1 (very low) to 5 (very high) was presented for 4 seconds prompting participants to rate the level of confidence in their decision. The trial ended with an inter-trial screen that included a fixation cross in the middle and was displayed for either 4, 6, or 8 seconds before the next trial has begun.

The framing task included a set of 108 decisions, consisting of the different levels of five different factors: reward type, decision frame, FTT truncation condition, reward magnitude, and probability. The set was presented twice (i.e., two repetitions). Within each repetition the decisions were randomly ordered.[37] US dollars and M&M's were the two types of rewards offered in each trial (either one or the other). Additionally, every decision problem was framed as either 'gain' or 'loss', such that for any given gain-framed decision there was a loss-framed counterpart generating the same possible net outcomes (in terms of final assets), where the preamble serves to adjust the appropriate endowment accordingly. The three (net) payoff levels, offered as the riskless option for each type of reward (dollars/M&M's), were small (1), medium

[37] We utilized the high choice consistency rate across the two repetitions (80%) to replace the few non-systematic missing observations with the choice made for the same exact decision problem in the opposite repetition.

(6), and large (20). The three probabilities employed for the gambles were 50%, 60%, and 67%. They represent the likelihood of the worse outcome (i.e., gain nothing in the gain frame; lose everything in the loss frame) whenever the gamble is chosen over the sure option. Each riskless payoff was crossed with three binary lotteries (corresponding to the three probabilities).[38]

Finally, based on fuzzy-trace theory's paradigm, the information of the gamble presented in each trial was manipulated according to three different truncation conditions – gist, mixed, and verbatim. In the mixed condition both the zero and nonzero complements of the gamble were shown in the traditional way (all the informational inputs were present). The nonzero complement was removed from the gamble in the gist condition, while the opposite was true for the verbatim condition, where the zero complement was omitted (Reyna & Brainerd, 1991; Reyna, Chick, Corbin, & Hsia, 2014). Note that this truncation method only removes redundant information while keeping the overall decision problem unaffected (Instructions made clear that truncated outcomes were known by subjects, verified by quizzes) (see also Chick, Reyna, & Corbin, 2016). Table 3.3 presents an example for fuzzy-trace theory manipulation (the three FTT truncations) on arbitrary decision problem (gain frame, $20, 67%) with the following preamble: "You have entered a raffle and $60 are at stake. Which would you choose?".

In return to their participation in the framing task, subjects received a payoff of $30. Additionally, to render this task incentive compatible, one of the decision problems was randomly selected at the end of the experiment and its outcome was given to the subject based on their choice made to this decision during the task. Thus, participants could have won an additional payoff ranging from 0 to 60 of either M&M's or US dollars.

[38] Note that the nonzero outcome of every gamble is governed by its probability and the magnitude of the sure outcome to ascertain equality of the expected values.

Results

Manipulation Check

In order to test whether our hunger manipulation protocol was indeed successful, a two-way ANOVA was conducted with scores from the self-reported hunger (SRH) scale serving as the dependent variable, and hunger group (non-hungry, hungry – based on random assignment) and age group (adolescent, adult) as factors.[39] We found that main effect of hunger group was the only one significant, F (1, 113) = 41.05, $p < .001$, $\eta^2 = .266$. Age group and the interaction between age and hunger were not significant. A pairwise test revealed that the SRH scores in the hungry group (M = 5.786, SE = .246) were significantly higher compared with the non-hungry group (M = 3.585, SE = .239); $p < 0.001$. As expected, food deprived subjects reported feeling hungrier relative to subjects in the control group (non-hungry group), which lends support to the success of our hunger manipulation.

The Probability Effect

A repeated measures ANOVA was conducted using 2 hunger group (hungry, non-hungry) × 2 age group (adolescent, adult) as between-subject factors, and 2 repetition × 2 reward type (US dollars, M&M's) × 2 decision frame (gain, loss) × 3 FTT truncation (gist, mixed, verbatim) × 3 reward magnitude (small(1), medium(6), large(20)) × 3 probability (50%, 60%, 67%) as within-subject factors.[40] Hunger was measured objectively based on our food deprivation protocol, in which subjects were randomly assigned to treatment (hungry) and control (non-hungry) groups.

[39] Two subjects who failed to report their level of hunger were excluded from this analysis.
[40] In cases where the assumption of sphericity was violated, we used the Greenhouse-Geisser correction.

We found a significant main effect of probability, F(1.364, 156.909) = 36.969, p < .001, η_p^2 = .243. That is, subjects made fewer risky choices the higher the probability of the worse outcome was (win nothing in the gain frame / lose something in the loss frame) with a statistical significant difference both between 50% and 60% probability (M_{Diff} = .095, *SE* = .014, *p* < .001), 50% and 67% probability (M_{Diff} = .123, *SE* = .019, *p* < .001), and between 60% and 67% probability (M_{Diff} = .027, *SE* = .01, *p* < .01). While this finding seems trivial (play safe with higher chances to obtain undesired outcome), it is important to keep in mind that the changes in probability do not operate in isolation, but always coincide with proportional changes of the gamble's possible payoffs to sustain the equality of the gamble's EV to the sure outcome.

An interaction between probability and decision frame was also found to be significant, F(1.931, 222.018) = 22.779, p < .001, η_p^2 = .165. As illustrated in Figure 3.2, our participants picked the gamble more frequently in the gain frame as the probability to win increases from 33% to 40% and from 40% to 50%. In the loss frame, a more risk avoidance behavior was observed in the higher-risk gambles, with 60% and 67% chances of losing, relative to those with only 50% chances to lose (the difference between 60% and 67% probability was not statistically significant).[41]

This two-way interaction was further qualified by two significant four-way interactions – hunger group, age group, probability, and decision frame, F(1.931, 222.018) = 3.105, p < .05, η_p^2 = .026, and hunger group, probability, FTT, and decision frame, F(3.81, 438.094) = 3.181, p < .05, η_p^2 = .027. Figures 3.3A and 3.3B illustrate the former interaction by breaking it out to the non-hungry and hungry states respectively, and Figures 3.4A, 3.4B, and 3.4C illustrate the latter for each FTT truncation condition – gist, mixed, and verbatim – respectively. Similar to the above findings from the two-way interaction, here too we see a strong and consistent tendency to

[41] Note that a framing effect is obtained at any probability level.

pick the risky option more frequently as the probability to win goes up (from 33% to 40% to 50%) in the gain frame. And, as before, we also see a more risk averse behavior in the loss frame for higher probabilities to lose (60% and 67%), yet this tendency is weaker than that obtained for the gain frame (i.e., it flattens out), and clearly less consistent – particularly for hungry adults (see Figure 3.3B) and in the gist condition (see Figure 3.4A).[42]

Discussion and conclusion

The nature of the framing task employed in our experiment, by which the probabilities and payoffs of the risky option in each trial varied to produce an EV that would match the outcome of the riskless option (in both the gain and the loss frame), hinders our ability to test the theory by eliciting a utility function or a probability weighting function from our dataset. However, we can certainly argue that the pattern of choice behavior outlined by our results is incommensurate with the type of theoretical predictions of both LOB's model and Mukherjee's model, that specifically correspond to the framing task we have been using.

According to these two formal dual-system models, the tendency to become insensitive to probabilities along the middle of the range should intensify the greater the involvement of the hot system is in the decision making process (e.g., when feeling hungry). Thus, under a "cold" state, people – being expected value maximizers – should be completely indifferent to changes in probabilities since the EV remains unchanged, whereas under a hot state the likelihood to choose the gamble in the gain/loss frame should decrease/increase as the winning/losing probability goes up.

[42] We also found a significant seven-way interaction with hunger group, age group, repetition, FTT, decision frame, magnitude, and probability. However, the overall qualitative patterns described earlier remain the same.

Nevertheless, our findings demonstrate that as the gamble becomes less risky in the gain frame (and so the smaller is the difference between the sure outcome and the gamble's winning payoff), the *more* frequently it is being chosen (e.g., a 50% probability to win $40 is chosen over a sure $20 more frequently than a 33% probability to win $60 does). In the loss frame, gambles with relatively high chances to lose (60% and 67%) are, generally, being chosen *less* frequently than those with only 50% chance to lose, yet this pattern is less significant and consistent compared to the gain frame. Recall that decision problems in the loss frame are contrived to match their counterpart gain-frame version. Thus, sure loss outcomes vary whenever the gamble's risk (and outcome) levels change, keeping the difference between the payoffs of the two options fixed (e.g., 50% chance of losing $40 versus a sure loss of $20 would change to 60% chance of losing $50 versus a sure loss of $30 – the difference between the amounts in each decision problem stays $20), which may explain the slight difference in choice behavior we observe between the two decision frames. However, this overall pattern, while weaker in the loss frame, does not agree with the behavior of an EV maximizer (i.e., the cold system), and more importantly, points to an opposite choice tendency than that predicted by the hot system. Furthermore, the pattern was quite immune to the different states of hunger (mainly in the gain frame), which further underlines the difference between our results and the theoretical predictions of the two dual-system models.

When comparing our results separately to each of the dual-system models (Mukherjee's and LOB) we obtain a slightly different interpretation of how sensitive people are to probabilities along the mid-range. Mukherjee's model derives its predictions by assuming that the affective system is characterized by a prospect-theory-based value function, and a complete insensitivity to probabilities. Hence, given the contradiction with our findings, people must exhibit some degree of sensitivity to probabilities, yet oversensitivity is not warranted (due to the curvature of

the value function). LOB, on the other hand, assume a linear value function (with a loss aversion property), and a relative (not necessarily complete though) insensitive probability weighting function for the affective system. Thus, our findings entail that either the value function cannot be linear or that people must exhibit oversensitivity to mid-level probabilities. Note that the payoffs used in our experiment were small to moderate in magnitude, so that the assumption of a linear value function is quite plausible, which lends some support to the conclusion that when controlling for the effect of uneven EV outcomes between choices, people have a tendency to become oversensitive to changes in mid-range probabilities.

Interestingly, fuzzy-trace theory can largely account for this pattern of behavior in both the gain and the loss frame – mainly when a gist based intuition is involved in the decision making process. In our gist truncation condition, for example, which is more likely to trigger a gist based reasoning, the some-none categorical distinction between a sure win/loss and a chance of winning/losing nothing is emphasized, while the exact numerical information of the gambles' probabilities is still presented "verbatim" in every trial. Thus, according to the theory, as the probability to win *nothing* in the gain frame increases – given a fixed EV – the gamble becomes *less* attractive. That is, as the winning probability goes up from 33% to 40% to 50% (i.e., the probability to win nothing decreases), the gamble becomes *more* attractive, which is precisely what we see in Figure 3.4A (and, in fact, in all the figures as well). The loss frame case in our experiment is slightly different since, unlike the gain frame, changes in the probability of losing also alter the gamble's EV and the riskless payoff. Particularly, an increase in the chances of losing something increase the amount of both the sure loss payoff and the gamble's losing payoff (keeping the difference between them constant) which, according to the theory, influences choices in opposite ways. The increasing amount of the riskless option (losing more) renders the gamble, which offers a chance to lose nothing, *more* attractive. However, at the same time, the

probability of losing nothing decreases, which makes the gamble *less* attractive. This creates a conflict that can explain the weaker and less consistent effect of probabilities on choices in the loss frame as illustrated, for example, in Figure 3.4A.

Perhaps it would be useful in future research to vary the risk and outcomes in such way that will enable us to estimate a value function or a probability weighting function to better understand the forces operating in the decision process when changes in mid-range probabilities occur – especially in the loss frame. We could then apply the theory to test real life risky decision problem such as choosing a financial portfolio (gain frame) or insurance policy (loss frame), where changes in the risk level are usually associated with counterbalanced changes in the magnitude of the payoff.

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Table 3.1. *Theoretical predictions for the probability effect.*

	Gains: 33%, 40%, 50% to win something (P_G) EV is constant (1, 6, or 20 dollars or M&M's) (Example: win $20 vs. 33% win $60; win $20 vs. 40% win $50; win $20 vs. 50% win $40)	**Losses: 50%, 60%, 67% to lose something (P_L)** endowments were varied so EV of gains = losses (Example: lose $20 vs. 50% lose $40; lose $30 vs. 60% lose $50; lose $40 vs. 67% lose $60)
Prospect Theory	Risk-taking behavior depends on the mutual structure of both the value function and the PWF	Risk-taking behavior depends on the mutual structure of both the value function and the PWF
Mukherjee and LOB (dual system models)	(The cold system is EV for Mukherjee and EU for LOB – EV for small to moderate outcomes) Hot System (e.g., hunger): preference for gamble **decreases** as P_G↑ (more **risk aversion**)	(The cold system is EV for Mukherjee and EU for LOB – EV for small to moderate outcomes) Hot System (e.g., hunger): preference for gamble **increases** as P_L↑ (more **risk seeking**)
Fuzzy-Trace Theory (mainly for the gist condition)	(Contrasts between sure and zero matter) As P_G↑, chance of winning nothing goes down (gamble is **more** attractive) ➔ preference for gamble **increases** (more **risk seeking**)	(Contrasts between sure and zero matter) As P_L↑, chance of losing nothing goes down (gamble is **less** attractive) BUT at the same time riskless payoff goes up (e.g., sure loss of $20, $30, $40, so gamble is **more** attractive) ➔ preference for gamble is **ambiguous**

Table 3.2. *Age-Hunger distribution for the risky-choice framing session.*

	Adolescents	Adults	Total
Non-hungry (control)	32	30	62
Hungry (treatment)	31	26	57
Total	63	56	119

Table 3.3. *Fuzzy-trace theory manipulation.*

Condition	Riskless option	Gamble
Gist	Win $20 for sure	2/3 probability you win nothing
Mixed	Win $20 for sure	1/3 probability you win $60 and
		2/3 probability you win nothing
Verbatim	Win $20 for sure	1/3 probability you win $60

Note: Presentation of the three truncation conditions is based on the same exact information given in the preamble ("You have entered a raffle and $60 are at stake. Which would you choose?").

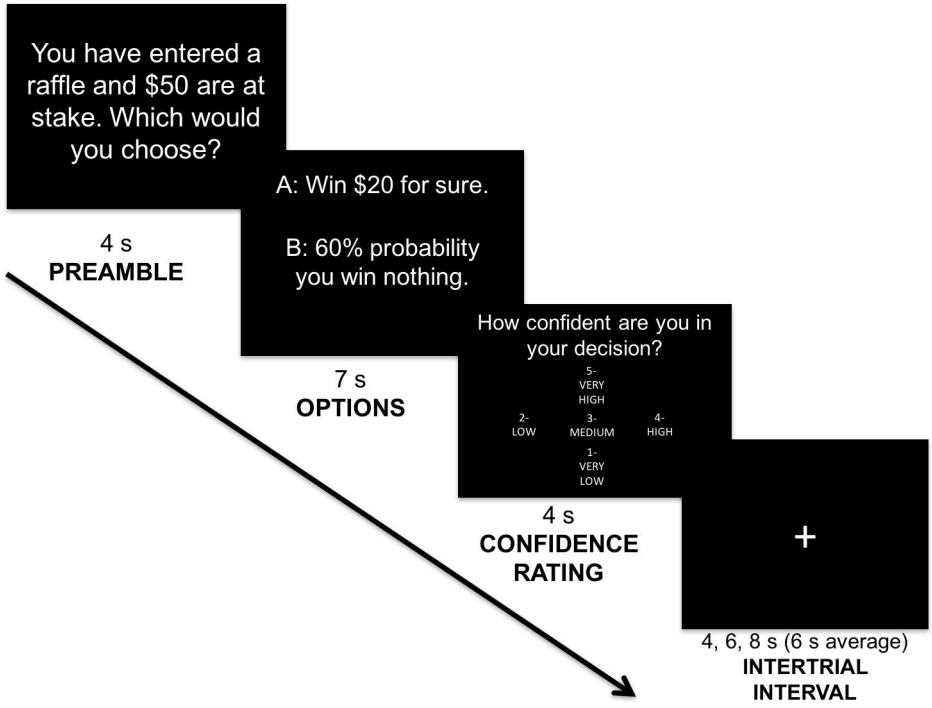


Figure 3.1 . Trials timeline.

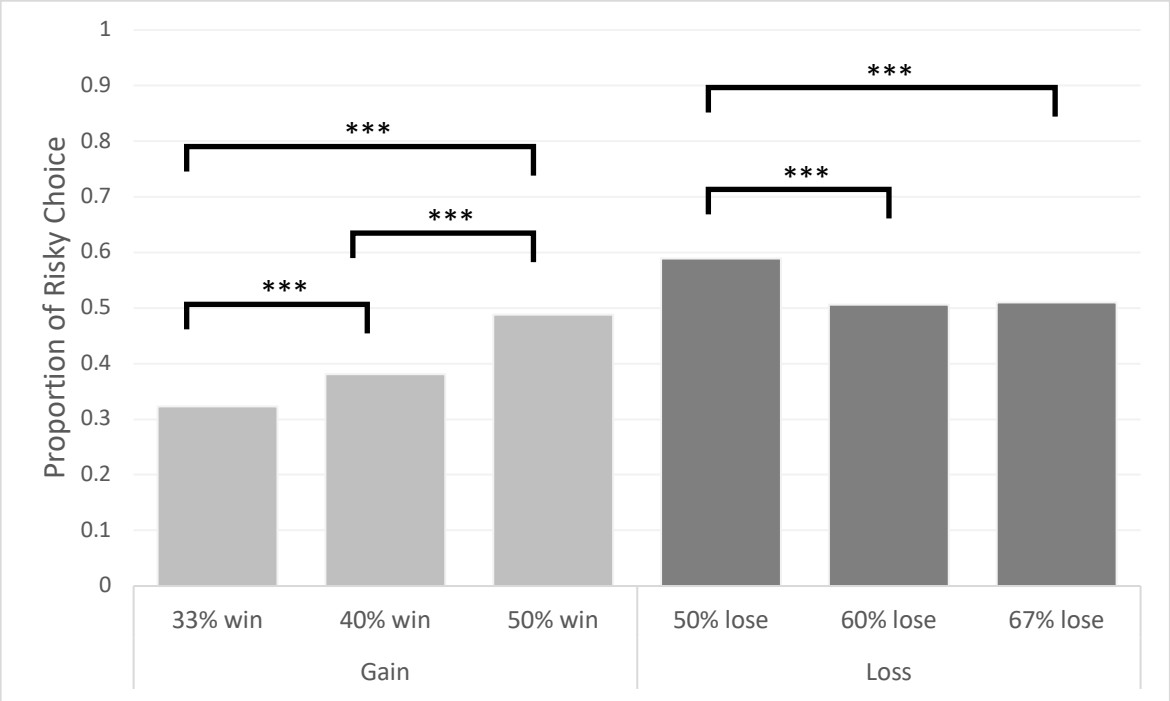
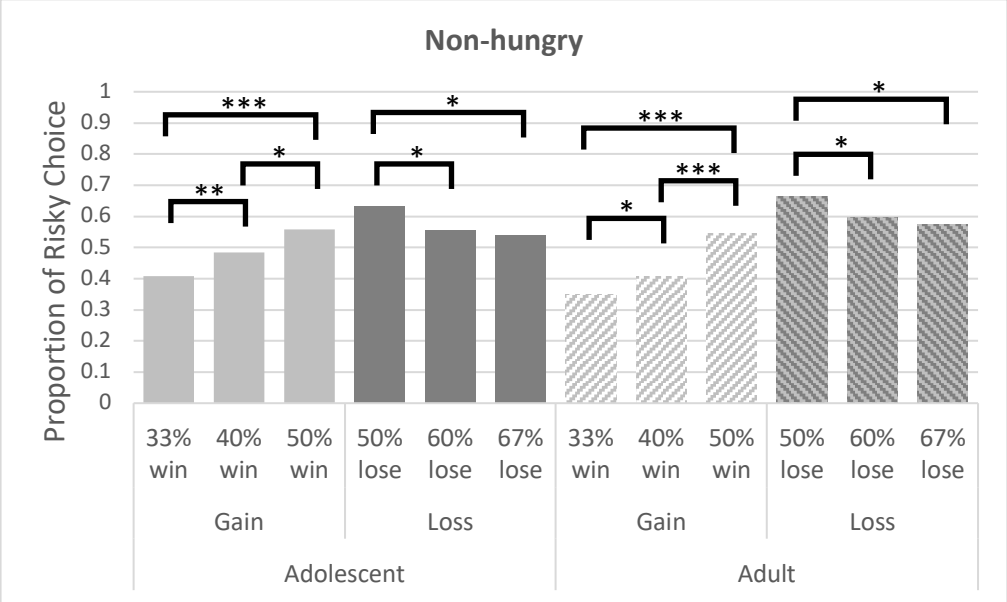


Figure 3.2. A two-way interaction effect of decision frame and probability. Bars represent mean proportion of risky choices.

A.



B.

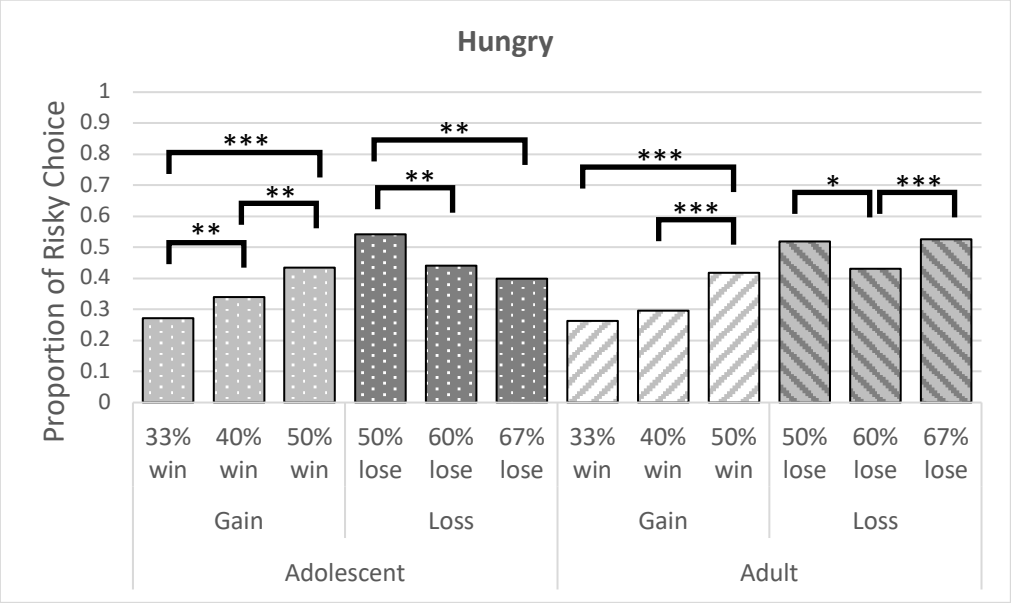
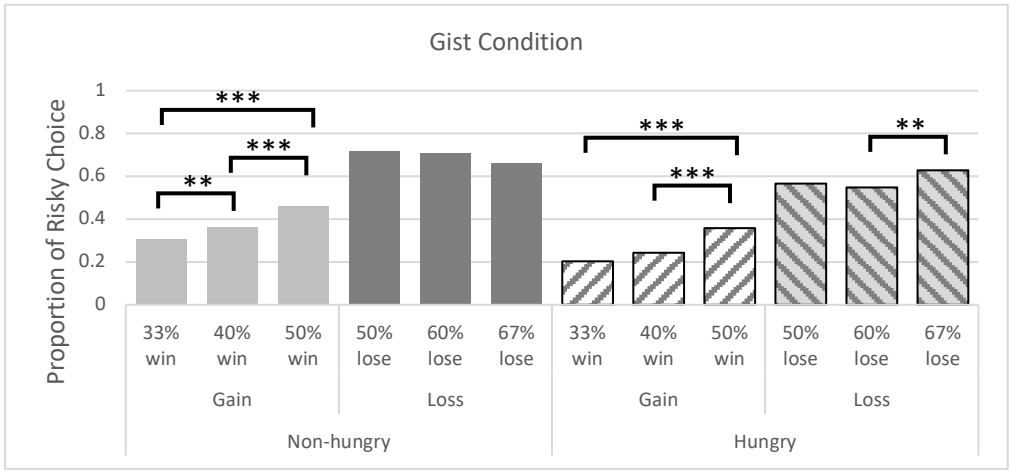
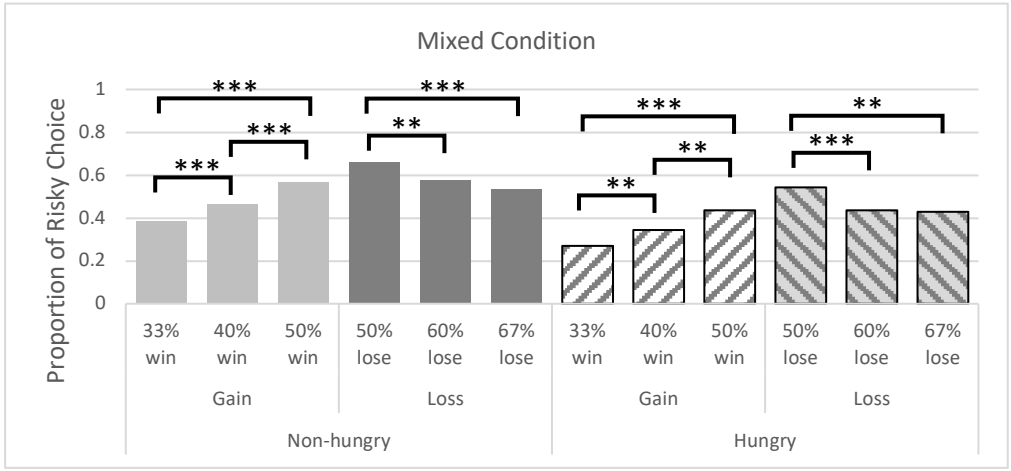


Figure 3.3. A four-way interaction effect of hunger group, age group, probability, and decision frame broken out by hunger state: (A) non-hungry subjects and (B) hungry subjects. Bars represent mean proportion of risky choices.

A



B.



C.

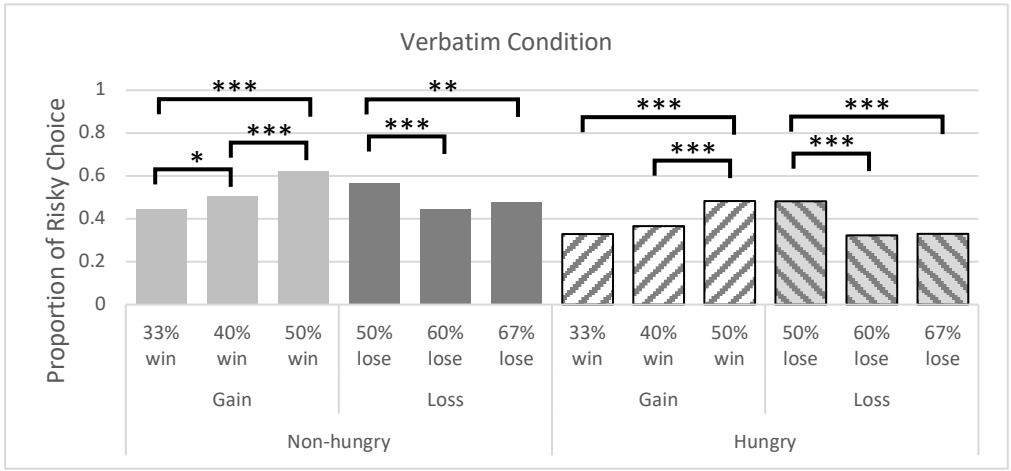


Figure 3.4. A four-way interaction effect of hunger group, age group, probability, and decision frame broken out by FTT truncation condition: (A) Gist, (B) Mixed, and (C) Verbatim. Bars represent mean proportion of risky choices.