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GAMBLING ON THE CIRCUMPLEX OF AFFECT: AN EMPIRICAL INVESTIGATION OF INCIDENTAL AND ANTICIPATED EMOTIONAL INFLUENCES ON RISKY CHOICE

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By

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GAMBLING ON THE CIRCUMPLEX OF AFFECT: AN EMPIRICAL INVESTIGATION OF INCIDENTAL AND ANTICIPATED EMOTIONAL INFLUENCES ON RISKY CHOICE

A DISSERTATION APPROVED FOR THE DEPARTMENT OF PSYCHOLOGY

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inspiring words on the research mine-field that is affective decision-making with some form of appreciation. I would like to thank him not only for the seed he planted during a symposium heard many moons ago, but also for establishing a bar for researchers in this area that likely will never be reached but is all too tantalizing to ignore.

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ABSTRACT

Affective decision-making has begun to change the face of the traditional decision science paradigm (Loewenstein, Weber, Hsee, & Welch, 2001), forcing researchers to consider direct influences of affect on both cognition and behavior, and no longer viewing affect as simple byproduct of each. In what follows, this more modern view of decision-making has been chronicled and summarized, focusing the reader on two broad types of affective influences: those attributable to incidental and expected (or anticipatory) affect. An attempt is made to combine these two types of affective influences into a more general theory of affective decision-making, one that incorporates aspects of the Pleasure-Arousal Hypothesis (Russell & Mehrabian, 1978) and the Circumplex of Affect (Russell & Barrett, 1999). An empirical investigation of this theory was tested using self-report measures of both incidental and expected affect and a certainty equivalency gambling task. Results suggested small direct influences of incidental and expected arousal and valence on gambling choices; yet, little support existed for an indirect effect of incidental affect on the gambling decision through mediating expected affect. Conclusions highlight the promise of a general affective decision-making theory that might explain current paradoxes in risk seeking behaviors, particularly those that occur during adolescence. Appeals were also made, however, for better measurement and methodology within this area of research so that empirically validated propositions can be generalized beyond the pen and well-controlled laboratories.

GAMBLING ON THE CIRCUMPLEX OF AFFECT: AN EMPIRICAL INVESTIGATION OF INCIDENTAL AND ANTICIPATED EMOTIONAL INFLUENCES ON RISKY CHOICE

CHAPTER I: Introduction and Literature Review

Normative Theories of Decision-Making

Traditional approaches to modeling decision-making have focused on two main variables: beliefs and preferences (Loewenstein & Furstenberg, 1991). Results from these normative decision-making studies have been equivocal. Not always do beliefs and preferences predict actual behavior. One of the suspected leading causes for lack of consistency in findings relates to the nature of impulsivity. Take for example, the continued problem of STDs and unwanted pregnancies among adolescents. Evidence suggests that despite increased efforts to educate adolescents on probabilities and the severity of negative sexual outcomes and despite greater reported knowledge and safe behavioral intentions among youth, rates of risky sexual behavior remain high (Boyer, Tschann, & Schafer, 1999; CDC, 2000). Susceptibility to the negative consequences associated with this risky behavior begs the question, "Why do so many young people engage in behaviors that potentially compromise their self-interest?" Impulsivity theorists argue that not unlike the allure of drug addiction, the fulfillment of sexual gratification can at times overwhelm any cognitive processing of normative decision criteria (Loewenstein, 1996; Loewenstein & Furstenberg, 1991; Loewenstein, Nagin, & Paternoster, 1997; Loewenstein, Weber, Hsee, & Welch, 2001). If true, the question then becomes, "What is it about gratification that negates or attenuates normative cognitive processing?" The current thesis attempts to investigate one potential culprit, affect.

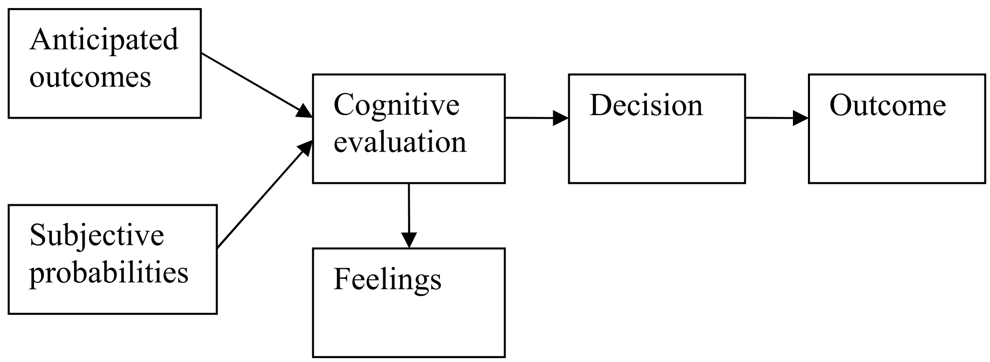
Affective Influences on Decision-Making

There are two broad types of affective influences present in the literature. Expected emotions are the distant a priori derived expectations of experienced affect that follow a decision or behavior, whereas immediate emotions are the emotions active during an actual decision process. Both types of affect have been shown to have a substantial influence on choice and behavior in laboratory experiments (Bell, 1985; Brandstätter, Kuhberger, & Schneider, 2002; Inman, Dyer, & Jia, 1997; Lerner & Keltner, 2001; Loomes & Sugden, 1982, 1986; Luce, 1998; Mellers, Schwartz, Ho, & Ritov, 1997; Mellers, Schwartz, & Ritov, 1999; Raghunathan & Pham, 1999; Schwarz & Clore, 1983). Extrapolating these two types of findings to real world choice and behavior, however, lacks theoretical development and suffers from virtually no empirical investigation. Loewenstein, Weber, Hsee, and Welch (2001) were perhaps the first to suggest that models incorporating both of these influences could overcome many of the pitfalls of traditional normative consequentialist decision theories. As Figure 1 depicts, the addition of emotions to anticipated outcomes (expected emotions are derived from the integration of anticipated emotions and their associated subjective probabilities of occurrence) and the inclusion of immediate emotions (feelings in Panel B) leads to a dual process influence on behavior.

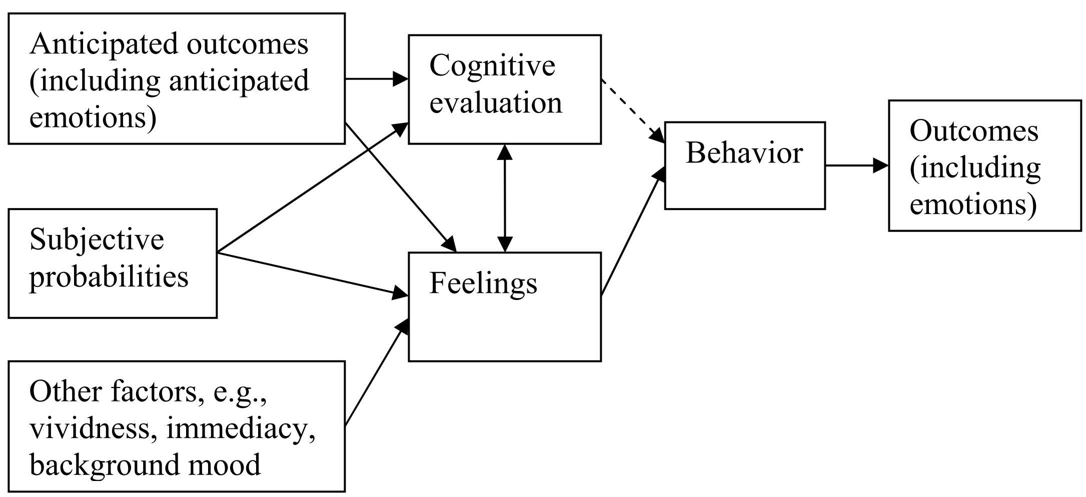
While this theoretical modification to traditional consequentialist decision theory is slowly permeating its way into recent decision science work, the idea of dual processes affecting behavior is not new. Contemporaries like Damasio (1994), Epstein

Figure 1. Panel A: The Traditional Consequentialist Model; Panel B: Newer Dual Process Model with Anticipated and Anticipatory Affect.[1]

Panel A



Panel B



[1] From "Risk as Feelings," by G. F. Loewenstein, E. U. Weber, C. K. Hsee, and N. Welch, 2006, *Psychological Bulletin, 127(2),* p. 268, 270. © 2006 by the American Psycholoigcal Association. Adapted with permission from author.

(1994), Le Doux (1996), and Zajonc (1980) have long promulgated the idea that two parallel processes, with unique evolutionary origins, operate behind our decision-making curtains. As Schultheiss (2001) explains, the feelings component in Figure 2 belongs to an evolutionarily older *experiential* system that is architecturally responsive to immediate stimuli that arouse one or more of the five bodily senses. Learning in this system is suspected to involve either incentive or instrumental conditioning, but the key contrasting component distinguishing experiential processing is that it encodes stimuli as they are without the need for abstract cognitive restructuring. This process of learning and subsequent decision-making need not involve consciousness either, and interestingly, has been suggested to develop much earlier in development than the *analytic* system (providing, perhaps, some link to findings suggesting underdeveloped abstract thinking in adolescence; see Boyer, 2006; Green, Johnson, & Kaplan, 1992; Johnson & Green, 1993; Speier et al., 1997). The analytic system (borrowing Slovic et al. (2004) terminology), on the other hand, seems to be evolutionarily more complex and, therefore, newer to the species. In fact, the birth of this system is suspected to correspond to the arrival of language acquisition. This system operates through complex verbal encoding of stimuli into new representations that can be retrieved long after the initial experience. The system is also capable of creating abstract concepts and representations that do not actually exist in the experiential world (e.g., moral beliefs, politics, etc.) and is responsible for complex memory processes that *chunk* large groups of stimuli into common categories, to enhance the informativeness and efficiency of subsequent retrieval. Its architectural knowledge structure allows for decision-making that considers both immediate and long-term consequences simultaneously, continuously updating beliefs and conceptions about the complexities of the environment from which it gathers information.

Loewenstein et al. (2001) argue that previous judgment and decision-making studies have all too often focused on the influence of expected emotion through the analytic system, and, yet, rarely, if ever, are real-world decisions devoid of any influences from expected and immediate emotions via the experiential system. A similar argument is made by Schultheiss (2001) when contrasting the effects of implicit and explicit motivational influences on behavior. Most real world experiences, he argues, are likely to trigger responses from both systems. Take our earlier sexual behavior example. One might expect that individuals who have, through incentive or instrumental processes, learned to associate sexual behavior with immediate pleasant feelings might be impulsively motivated to engage in unsafe sex. These same individuals may, however, also have verbally learned and accepted normative motives for abstaining from sex or engaging in protected sex. A competing influence model such as this may help explain the findings of Adler and Tschann (1993) and Miller (Miller, 1974; Miller & Pasta, 2000; 2002) who report substantial numbers of individuals experiencing conflicting implicit and explicit reactions toward unwanted pregnancies.

Theories of affective influence in the decision sciences are relatively new and, therefore, rapidly expanding and evolving. To date, most of the recent work in cognitive psychology has exclusively focused on the effects of incidental affect- a type of immediate affect that includes all background affect not specific to the decision task. While consistent terminology has yet to take hold, Forgas' (1995, 2003) Affect Infusion

Model (AIM) has provided an overarching perspective that highlights two major pathways of incidental influence. The text that follows will summarize his integrative approach and its more recent opponents before moving on to expected emotional influences.

Immediate Emotional Influences on Decision-Making

Incidental affect: Mood-congruence and the Affect Infusion Model (AIM). Perhaps the most widely discussed affective influence on decision-making is the *Affect as Information* (Schwarz & Clore, 1983; Clore et al., 1994) pathway, which characterizes affect as an informative agent that can be summoned (either implicitly or explicitly) for advice before a behavioral choice or judgment is selected. The proposed mechanism initially developed roots in classical conditioning with gradual adoption of the misattribution and self-attribution literature. Initial formulations proposed misattributions of source for incidental affect often resulting in biased judgments and behavioral decisions based on learned affective stimulus-response associations. For example, when deciding whether to purchase a pricy ice-cream cone, an incidentally experienced good mood might persuade one to consume the ice-cream no matter the excessive cost. Note, the direction of influence is always predicted as mood-congruent (i.e., positive moods lead to approach-like behavior, whereas negative mood leads to avoidance). As pointed out by Forgas (2000, 2001) and others (Schwarz, Strack, Kommer, & Wagner, 1987; Clore, Schwarz, & Conway, 1994), the effect described is most evident when the participant is unfamiliar with the task, lacks strong existing motivational influences, or lacks resource capacity for more complex analysis of stimuli. Other boundary condition searches (appearing as early as the seminal work of

Schwarz & Clore, 1983) have found that simply informing participants of the affect source was enough to prevent this heuristic cue from having much influence (Martin, Harlow, & Strack, 1992, Clore & Parrott, 1994; Berkowitz, Jaffee, Jo, & Troccoli, 2000). The ease of countering the affective information effects led researchers to coin the popular *"How-do-I-feel-about-it?"* heuristic label.

The second pathway discussed by Forgas exerts its influence through memory and, not surprisingly then, has been labeled affect-priming, where the priming influences also adhere to the affect-congruence principle. For example, before making judgments about a new acquaintance, an incidentally experienced good mood may prime positive memories of earlier acquaintances who share this new person's ethnic background, gender, personality, etc. These recollections then lead to an overall positive first impression of the acquaintance. Early work with priming effects of affect showed modest success in predicting such congruence but also quickly developed opposing boundary conditions (see review by Fiedler, 1991). The main boundary limitation appeared to involve the degree of constructive, elaborate processing necessary for problem-solving. If the decision task was novel and required development of a new choice strategy (especially a memory-based search for preferred actions or judgment), current affect exhibited coloring effects. However, if the task at hand was associated with previous experience, strong motivational influences, or well-defined schemata, the evidence for mood and behavior/judgment congruence via affect priming was far less convincing.

Affect-dependent processing and mood incongruence in the AIM. Newer explorations of affect-dependent processing have uncovered more complex influences underlying judgment and decision-making processes. Seminal suppositions revolved around valence characteristics of existing affect. Isen (1984, 1987) pioneered this development proposing an affect maintenance/mood repair mechanism that predicted behavioral and judgment responses that preferentially favored positive changes in valence. In other words, those in a negative mood might tend to favor decisions that can potentially bring positive benefits (even if those benefits were only remotely possible), in an effort to repair the current state of mood. On the other hand, those already in positive moods may shy away from risky ventures with sizeable potential losses in order to maintain a good mood. Forgas (1995) adapted this mechanism for inclusion in his AIM theory suggesting that affect can produce motivational strategies that counter the earlier noted mood-congruent principle. Subsequent work by Forgas and colleagues (Forgas & Ciarrochi, 2002; Ciarrochi & Forgas, 1999; Forgas, Johnson, & Ciarrochi, 1998; Forgas, Ciarrochi, & Moylan, 2000) argued that these types of motivational influences are more likely to surface when participants experience moods at greater intensity. For example, individuals induced to experience happy and sad moods showed a strong tendency to reverse early mood-congruent choices on descriptive labeling of persons, word-completion, and self-description tasks. Reversals to more mood-incongruent responses occurred toward the end of experimental sessions, when presumably the continual barrage of negative or positive thoughts and responses had raised induced affect to peak levels (Forgas & Ciarrochi, 2002). Similarly, individuals who scored highly on a trait anxiety (a negative mood) measure exhibited fewer negative mood-congruent discriminating judgments about out-group members (Ciarrochi & Forgas, 1999) than did low trait anxious individuals. This motivated reversal has become a key concept in the so called Mood Management hypothesis, which claims individuals will switch from substantive processing colored by affect to a more consciously-controlled processing strategy that attempts to manage the intensity of a particular mood. This hypothesis diverges from Isen's earlier mood repair/maintenance mechanism in that even happy moods will invoke self-regulatory mechanisms that search for negative information (e.g., negative self-descriptors or negatively-worded health risks) to counterbalance euphoric states.

Propelled by his work in *affect as information*, Schwarz and colleagues (Schwarz, 1990; Bless & Schwarz, 1999; Schwarz, 2000) identified one of the most robust and well-accepted affect-dependent processing effects on social reasoning tasks (Bless, 2000; Fiedler, 2001). They conceptualized this process as a cognitive tuning mechanism (Schwarz, 1990), whereby affect's valence signals an appropriate processing strategy. The tuning mechanism is informed (similar to the operation of the *"How do I feel about it?"* heuristic) by the alarms triggered from negative affect or the carefree bliss that often accompanies positive affect (a "happy-go-lucky" attitude). In alarming situations, the decision-maker attunes his processing strategy toward a more detail-oriented, data-driven approach- the "bottom-up" perceptual, processing strategy. This type of processing provides an opportunity for the individual to reassess his or her prior beliefs and schema which may have been partly responsible for the current (unhappy) circumstances. In more calming situations, the individual is cued to invoke a more heuristic, schema-driven processing approach- the "top-down" perceptual strategy. This approach reinforces the usefulness of prior established beliefs and schemata and encourages continued reliance on this information. Forgas (1995) acknowledges this distinction in his theory and claims that this *functional* processing mechanism can also serve to explain certain mood-incongruent affective effects. For example, in studies on stereotyping, Forgas and Fiedler (1996) found that positive affect individuals relied more on stereotypic information and gave faster (presumably more heuristic) judgments about reward allocations than did negative affect individuals. Importantly, however, this effect reversed (mood-congruence reemerged) when the judged groups evoked personal relevance for the individual. This moderating effect of relevance along with the earlier reviewed boundary conditions of mood-congruent influences led to the eventual formulation of the AIM, an overarching theory intended to capture and explain previously observed complexities and idiosyncrasies of affective decision-making influences.

Principle propositions of the AIM Theory. Although the theory was developed to predict effects of affect on decision-making, the AIM is equally descriptive about situations where affect is not influential. In short, the theory divides information processing into four main strategies: direct access, motivated, heuristic, and substantive processing. Direct access strategies are usually automatic implicit retrievals of preexisting responses for familiar situations. This type of processing does not allow for peripheral interference from other sources of information, including affect. Similarly, highly motivated processing strategies are not open for inclusion of outside sources of influence. The theory states that motivational pressures (like self-evaluation maintenance, ego enhancement, and achievement motivation) evoke a reliance on "selective and targeted information search strategies" (Forgas & East, 2003) tailored to efficiently and effectively attain goal satisfaction. It is important to note, however, that affect itself may provide a motivational incentive as described earlier in the mood management hypothesis. Affect maintenance or repair may motivate an individual to act in mood-congruent or incongruent ways.

The last two processing strategies do invite affective influences into behavioral decisions and judgments. The heuristic processing strategy provides an explicit route for affect inclusion through susceptibility to the *How-do-I-feel-about* heuristic. The theory purports that when situations are highly familiar but judgments or decisions lack strong personal relevance or motives for accuracy, mood-congruent influence may occur whereby responses are triggered by an immediate global assessment of feelings. When circumstances require more substantive processing of information and no preexisting preferential outcome motive persists, implicit affect infusion may occur through affect-priming mechanisms. In this processing context, ideas, memories, and evaluations pertaining to the situation are more easily summoned in a mood-congruent fashion. These thoughts then increase the probability of a mood-congruent behavior, choice, or judgment. Interestingly, the AIM actually predicts that as processing of information becomes more complex, due to difficulty of problem or presence of ambiguity, the effect of affect-priming infusion strengthens.

In addition to the four main types of processing that determine the degree of affect-infusion, the AIM also pinpoints several factors that promote the use of these various strategies. The most influential factors can be summarized as features of the target, judge, and situation. Target features include familiarity, complexity, and typicality. The theory hypothesizes that familiarity will often lead to a direct access strategy given that future exposure to similar circumstances should elicit more and more prescribed, rote responses. Complexity and typicality have an influence due to the extensive processing required. This feature is often indicative of unusual or ambiguous stimuli and events that lend themselves to the substantive processing strategy, opening the door for affective influences. Judge features include personal relevance, motivational goals, affective state, and cognitive capacity. Forgas (1995) claimed that as personal relevance increases, substantive processing will increase, provided motivational goals do not exist. As personal relevance decreases, direct access (if situation is familiar or typical) or heuristic processing takes over. As stated earlier, in the presence of strong motivational goals, motivated processing dominates decision-making. When cognitive capacity is reduced by affective preoccupation or other attentional demands, the theory argues for increased likelihood of heuristic processing due to lack of available resources for substantive or creative thinking. Finally, situational features include predominantly a need for accuracy, availability of criteria, and social desirability. These types of influences appear to help determine whether motivated and substantive processing or direct access and heuristic processing are summoned. As these variables increase in importance, the likelihood of the former strategies' use increases, while decreased importance more likely leads to the latter forms of processing.

Criticisms of the AIM. Although the AIM purports to provide a multiprocess integrative theory of affective influences on social judgments and behavior, most of its critics argue that in doing so, Forgas diminishes the importance of the informational value (or signal) provided by affect. Similarly, others argue that although the priming effects may be real, there is evidence suggesting that a third mediating variable (e.g., positive concepts or moral intuitions) explains the correlation between affect and memory/thought congruence (Clore & Tamir, 2002; Haidt, 2002). As Haidt (2002) commented, “[I]f somebody asks us to explain our judgment we search for reasons why our judgment is correct … [R]easoning works like a lawyer seeking evidence, not a like a judge seeking truth” (p. 54). These opponents of AIM claim that most judgments begin heuristically (often based on the informative value of affect) and that memory or thoughts are subsequently summoned to support the initial heuristic notion. Other problems pinpointed with the priming influence of affect include the asymmetric effectiveness of positive and negative retrieval cues (Isen 1984, 1985), the effects of stimuli or task-related affect on retrieval (Kahn & Isen, 1993; Isen & Geva, 1987; Isen, Johnson, Mertz, & Robinson, 1985; Isen & Patrick, 1983; Schiffenbauer, 1977), and the primary focus on only a single dimension of affect, valence (Keltner, Anderson, & Gonzaga, 2002; Lerner & Keltner, 2000; Schwarz, 2000). Another faction of opponents takes issue with the robustness of the processing influences of positive and negative affect (Fiedler, 2002; Manstead & van der Pligt, 2002). As Fiedler (2002) observes, “granting that the mediator assumption is correct, an interesting implication is that any comprehensive satisfactory theory of affect and cognition has to speak to both major sets of empirical findings, congruency effects and affective influences on cognitive style” (p. 51). In the body of work presented and discussed by Forgas, a comprehensive and satisfactory explanation for both effects is seriously lacking.

Perhaps the most devastating criticism of the AIM involves the above alluded lack of specificity in prediction. Seemingly, the model could overcome most of the major criticisms above if only the interaction of all AIM-defined variables was better clarified. This clarification would involve specification of circumstances where, for example, motivation may override affectively-infused substantive processing (Isen, 2002), thresholds for affect-incongruent effects are met, and positive and negative valence lead to top-down or bottom-up processing (Manstead & van der Pligt, 2002).

Incidental affect: Emotion-, dimension-, and appraisal-specific effects. Contrary to the AIM focus on valence of affect, other researchers interested in exploring the effects of incidental affect on behavior and judgment have taken broader approaches to its study. Some of these approaches have systematically varied multiple dimensions of affect and observed reliable changes in processing strategies and perceptions of risk. Mano (1990, 1992, 1994), for example, adopted the Russell (1980, 1991) circumplex[2] of affect, consisting of arousal and valence dimensions, to help explain processing differences in choice tasks. Lewinsohn and Mano (1993) argue that previous studies concluding positive relationships between top-down, heuristic processing and valence were compromised by ignoring any effects due to arousal. The real villain behind reduced processing, according to Mano and colleagues, is arousal. Mano (1990, 1992, 1994) suggests that incidental affective influences operate through two pathways: (1) a mood congruency pathway brought on by experienced valence; and (2) an attentional depletion pathway that leads to more heuristic processing as arousal increases. A more recent use of this two-dimensional view of affect has led theorists to believe arousal influences the level of processing, while valence affects the nature of processing (Shapiro, MacInnis, & Park, 2002). This formulation expects less devotion of attentional resources as arousal increases, and more schema-driven, as opposed to data-

[2] Describes a 2-dimensional space where polar coordinates define meaningful changes in the construct measured. Notice in Figure 6, for example, how discrete emotions are captured at equal intervals on the perimeter of the plane.

driven, processing as valence becomes more positive. Furthermore, these dimension effects appear to operate independently.

Others have adopted the same affect paradigm to explore differences in risk perception across various emotions. Eisenberg, Baron, and Seligman (1996) found that a combined measure of state and trait anxiety and a general measure of depression were positively correlated with risk aversion. Interestingly, though, the correlation between depression and aversion was almost completely mediated by the anxiety effect. Hence, two negatively-valenced affects, differing in their level of arousal (treated later in this document; see the Russell circumplex of affect, Figure 6), appear to have different relationships with risk perception. Those high on arousal (anxious), showed strong unique positive relationships with risk aversion, while effects of depression on aversion were nonexistent after controlling for the level of anxiety. Similar results appeared in a Raghunathan and Pham (1999) study looking at negative affective influences on gambling and job selection decisions. As in the Eisenberg et al. (1996) study, they found that manipulated anxiety predicted more low-risk/low-reward choices (i.e., risk aversion). In addition, they discovered that induced sadness was related to more high-risk/high-reward choices for these decisions. This work was recently replicated (Raghunathan, Pham, & Corfman, 2006), and the researchers found the effects to be present when either the source of the incidental affect was not salient, or when salient, the source was perceived to be related to the decision task. Proffered theoretical explanations of the findings centered on an *Affect-as-Information*-like mechanism; however, the affect providing the information was evoked by the outcomes of the risky choice. These explanations suggested that high anxiety and sadness create different perceptions of risk and reward. Anxious individuals may focus more attention toward the potential risk and, thus, select lower-risk options in an effort to decrease heightened arousal. Likewise, feelings of sadness may trigger a focus on the size of the reward, regardless of risk, in an effort to restore positive valence as quickly as possible. Interestingly, this supposition implies that incidental affect has an effect on preference for expected affect (the affect one expects to experience after the decision). As developed more completely in the sections that follow, this places expected affect in the role of a mediator, whereby incidental affective influences on choice are partially promulgated through influences on anticipated affect.

Still others argue that a two-dimensional view of affect does not sufficiently explain all incidental effects on processing or choice. Based on appraisal theorists predictions that emotions carry multiple cognitive components (e.g., see Smith & Ellsworth, 1985), Tiedens and Linton (2001) predicted that the degree of certainty associated with induced affect will determine certainty of judgments and use of heuristic versus systematic processing. Results showed that certainty of emotions not only correlated positively with confidence in judgments, but that higher certainty, and not positive valence, led to more reliance on less persuasive source cues (e.g., nonexpert versus expert opinion) and stereotypes (i.e., a reliance on more heuristic methods of processing). Lerner and Keltner (2000) proposed that this effect of certainty may also act independently of arousal. Their studies have shown that both experimentally-induced and naturally-occurring anger and fear, emotions of similar valence and arousal but different certainty and control (situational or individual), produced different assessments of risk perception and preferences (Lerner & Keltner, 2000; 2001). Both of these contrasted appraisals, certainty and control, were also shown to moderate the effect of emotion on risk perception. When risky situations were easily classified (majority of prescreening participants agreed) as either extremely certain/uncertain or controllable/uncontrollable, there were no significant differences in optimism between the fear and anger emotion conditions. Only when presented situations where certainty and control showed greater variability did the differential impact of fear and anger appear. Notably, the opposite pattern emerged between effects of happiness and anger, two emotions that share control and certainty appraisal tendencies but differ on valence. When risk situations were ambiguously labeled certain or controllable, no differences appeared between emotions. Yet, when situations were unambiguous (easily classified), happy individuals showed greater optimism than did angry participants.

Another approach to incidental affect has focused on the often-negative visceral impact of drives, pain, and addictions. Loewenstein (1996) was among the first to propose a theory of visceral influences to help explain why people's behavior often knowingly disregards self-interests. Loewenstein described these actions as "out of control" behaviors. His argument hinges on the presumption of a visceral influence component within a traditional decision-making utility function (although the exact functional form has yet to be specified or developed). The affect created can be brought on by any number of factors, e.g., sexual desire, pain, hunger, craving, even strong emotion or mood, and will have a direct effect on the desirableness of future outcomes. Once sexual desire, for example, is triggered (e.g., after viewing erotic photographs), the resulting emotions of elation or even the negative affect from sexual frustration can subsequently diminish the value of any outcome relative to that of sexual gratification. The full theory involves the seven propositions listed below:

1. As intensity of a visceral factor increases (e.g., getting more aroused or even feeling sexually deprived), the difference between the actual and desired utility increases;

2. Future experienced visceral intensity is underweighted in distant utility calculations;

3. As intensity of a visceral factor increases (e.g., getting more aroused or sexual deprivation) short time delays before consumption becomes more valuable;

4. Current visceral factors can have an effect on decisions about the future, even though these factors may not be active in the future (e.g., buying more groceries on empty stomach);

5. The influence of visceral factors on later behavior (as opposed to utility- see proposition 2) is underweighted.

6. Over time, people will forget how influential visceral factors were for previous behaviors.

7. The first six propositions describe both interpersonal and intrapersonal decisions and behaviors; for interpersonal situations, other people become analogous to the delayed self (e.g., proposition 1: actual altruism declines relative to desired altruism as a visceral influence intensifies).

As with the previous stances on incidental affect effects, this approach acknowledges cognitive components of affect. Together, the propositions above imply an attention-narrowing and motivational influence of visceral intensity. As intensity increases, attention narrows and motivation increases toward consumption of goods associated with the factor, immediacy of consumption, and a preference of self-indulgence over altruism. Therefore, performance on all tasks or decisions not associated with the visceral factor is diminished due the preoccupation with immediate self-gratification. While never tested directly, the above propositions potentially account for the growing number of impulsive behavior findings that have been previously unpredictable using volitional, consequentialist decision-making theories.

Integral affect: The Risk as Feelings Hypothesis. According to Loewenstein and Lerner (2003), immediate emotions can be partitioned into incidental and integral (or anticipatory using their terminology) affect. Integral affect represents the immediate emotions triggered by the task at hand. The AIM has little to say about the effects of task-related or, the otherwise termed, integral affect on decision-making. Garg, Inman, and Mittal (2005) tested the effects of integral affect while investigating a potential moderating influence of the appraisal-tendencies that distinguish anger and sadness (Lerner and Keltner, 2000). Results replicated an earlier integral affect finding (Luce, 1998) showing that negative affect produced from difficult decision tasks tends to increase the use of avoidance strategies (e.g., selection of status quo over a perceived risky option). Results also found support for incidental affect moderation of this effect, suggesting less avoidance among emotions characterized by less certainty (sadness). These findings indicate that both types of affect may act interdependently.

The earlier noted Loewenstein (1996) theory of visceral affective influences obviously also applies in the case of integral affect. If an experienced task involves features that trigger an increase in a visceral factor (e.g., sexual petting triggers sexual desire, smelling food triggers hunger, etc.), the propositions above suggest that the utility for consumption behavior related to the visceral factor will increase. This suggests a direct influence of affect on the cognitive valuation of the consumable good.

Summary of immediate affect effects on decision-making. Immediate emotions can act both directly and indirectly on the decision process. Directly, the intensity of emotion will determine the degree of influence. When high, emotions can consume the individual's decision-making process and lead to impulsive behaviors, while at low intensity, emotion serves more as a consultant through mechanisms like the *Affect-as-information* processes. Indirectly, emotions can influence the perceived likelihood of an outcome, the value of an outcome, cognitive evaluations, the nature of processing, and the depth of processing. Changes in likelihoods were noted earlier in the work of Lerner and Keltner (2001). Likewise, immediate emotion has been shown to exhibit the so called "hot/cold empathy gaps" (Loewenstein, 1996), whereby current feelings are projected onto future outcomes (Loewenstein, Prelec, & Shatto, 1996; Loewenstein et al., 2001). This type of projection tends to falter when predictions of the future are made while in a passionate or dispassionate state. When passionate, the expected reward (i.e., experienced affect) may seem much greater than when evaluated in a dispassionate state (Lowenstein & Schkade, 1999). Changes in processing were also noted earlier when discussing incidental affective influences. These effects suggest that components of affect like valence, arousal, and certainty can influence the cognitive evaluation of risk and value (Raghunathan & Pham, 1999; Vastfjall & Garling, 2002), the amount of data-driven versus abstract processing (Shapiro, MacInnis, & Park, 2002) and/or heuristic versus deep processing (Mano, 1990, 1992, 1994; Schwarz, 1990; Tiedens & Linton, 2001).

An interesting distinction is stressed between immediate affect and expected affect (see below). Although expected emotions represent cognitive evaluations of future behavior (e.g., the emotional utility of a behavior or choice), immediate affect reflects both the feeling state carried over into a decision task (incidental affect) and the feeling state experience from being placed in a decision task (integral affect). The idea of reliance on the current *feelings* as opposed to cognitive evaluations for decision-making is what led Loewenstein et al. (2001) to propose the *Risk as Feelings* hypothesis. As with the earlier work on intense emotions (e.g., drives, pain, etc.; Loewenstein, 1996), this hypothesis provides an explanation for the paradoxical divergence of behavior and self-interest highlighted in the opening paragraphs of this review. The culprit behind divergence can be found in the various determinants of immediate affect and expected emotions. Whereas expected affect represents, in theory, some formal integrative processing of probabilistic information and perceived hedonic value of outcomes, immediate affect may be relatively insensitive to changes in probabilities, especially as intensity of affect increases (Rottenstreich & Hsee, 2001). Immediate affect, unlike expected affect, may be more responsive to outcome delays (Loewenstein, 1987; Roth, Breivik, Jorgensen, & Hofmann, 1996) and perceived control (Seligman & Maier, 1967; Sanderson, Rapee, & Barlow, 1988). And finally, there may even be evolutionary determinants of immediate affective reactions (integral affect) to stimuli (e.g., instinctual fear of snakes) that completely bypass any use of cognitive evaluation (Loewenstein & Lerner, 2003). The defined distinction between these two, however, should not imply completely independent pathways of influence on decision-making. To the contrary, as Panel B of Figure 1 attempts to convey, influences of immediate affect need not preclude cognitive evaluation of future consequences, be they affective or otherwise. As this study attempts to address, estimation of expected affect is likely to depend greatly on an individual's profile of immediate affect.

Expected Affect and Decision-Making

Decisions involving known risk. Traditional prescriptive models of decision-making in finance and psychology have been dominated by the axioms of expected utility (EU) theory (von-Neumann & Morgenstern, 1947). Recent approaches to decision-making under risk, however, have begun to focus more attention on axioms that more descriptively model actual behavior (Fishburn 1988, 1989; Luce, 2000). Many of these descriptive models have abandoned the older EU approach in favor of more generalized theories of expected utility (GEU). The section that follows will describe one particular classification of GEU models, the risk-value models, and their potential usefulness in explaining effects of affect on choice behavior.

Risk-value GEU. EU theory assumes that perceived risk is defined by the shape of the utility function (Weber & Milliman, 1997). For example, risk aversion (seeking) from this perspective is observed when choices of certain amounts are favored (disfavored) over gambles with equal expected payoff. One class of GEU models, the risk-value (or risk-return) models, have reconceptualized perceived risk as an integral determinant of choice preference, rather than simply a descriptor. As the name implies, preference in the risk-value models depends on two components: one based on the perception of expected return and the other on a measure of perceived riskiness. From this perspective, the EU-specified roles reverse, and risk perception is thought to help define the utility function (e.g., preference partially depends on how much an individual values risk). One general form of the risk-value model described in Butler, Dyer, and Jia (*BDJ*; 2005; see also Jia, Dyer, & Butler, 2001) defines an evaluation of a gamble as

$$f(\bar{X}, X') = V(\bar{X}) + \phi(\bar{X})[R(X') + R(0)] \qquad [1]$$

where $V(\bar{X})$ is monotonically increasing value function of the expected outcome, $\phi(\bar{X})$ is a tradeoff coefficient (>0) that may be a function of the mean outcome, $X' = X - \bar{X}$, R(X') is the negative expectation of $u_0(X')$, and R(0) is the constant $-u_0(0)$, where $u_0(\cdot)$ represents a utility function describing preference for all zero-expectation lotteries. Risk and return are represented in this model by the terms $\phi(\bar{X})[R(X') + R(0)]$ and $V(\bar{X})$, respectively. Interestingly, this framework is general enough to capture many common forms of EU but can also be used to derive newer GEU models that better correspond to actual choice behavior and satisfy major assumptions underlying risk-value axiomatic theory (Butler, Dyer, & Jia, 2005; Weber & Bottom, 1989, 1990).

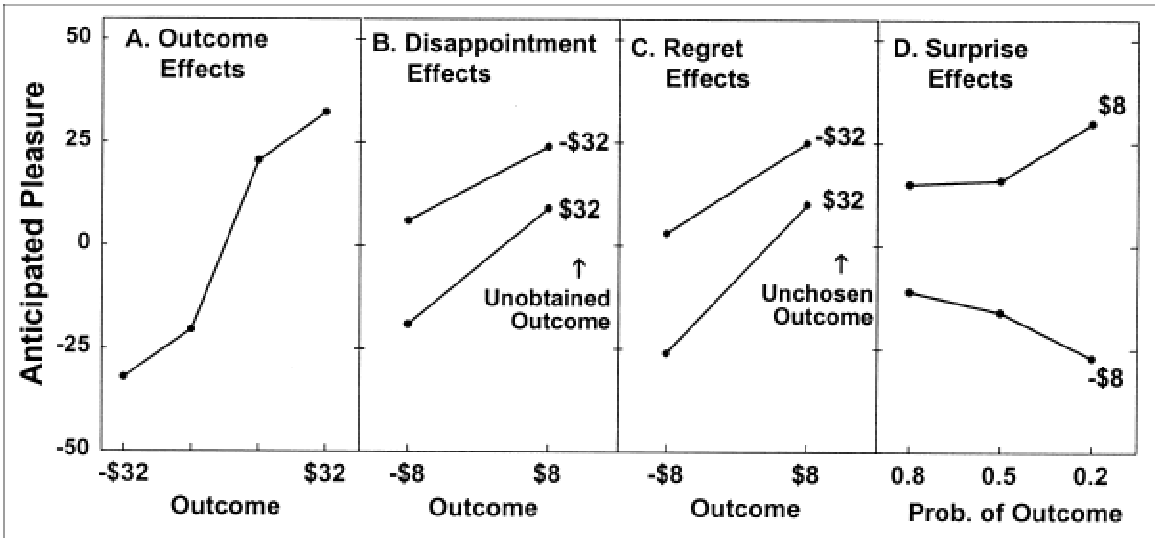
Decision Affect Theory and GEU. Mellers and colleagues (Mellers, Schwartz, Ho, & Ritov, 1997; Mellers, Schwartz, & Ritov, 1999) alongside Inman, Dyer, and Jia (1997) developed models of generalized expected utility of post-choice valuation (PCV), where PCV (Decision Affect in Mellers et al. models) represents the affect experienced after a choice is made (i.e., the satisfaction or subjective pleasure that follows a decision). The prediction equations developed generalized choice models that were created more than a decade earlier by Bell (1985) and Loomes and Sugden (1986). In most of these models (save Loomes & Sugden), two forms of affect share the stage, disappointment and regret. Both represent bipolar dimensions of affect which range from either disappointment to elation or regret to joy.

Effects of disappointment and regret on PCV are best described in equation form for experimental gambling choice tasks (e.g., which of the two gambles do you prefer). For example, imagine a choice between two 2-outcome gambles, denoted $\{X_i, p_i, Y_i\}$, where the better outcomes are represented by X_i, the worse outcomes by Y_i, and p_i represents the probability of winning X_i. In all but the Mellers et al. (1997;1999) models, disappointment effects are represented by a parameter that weights the influence of a function of the difference between the outcome won and the outcome expected from a particular choice, $df(Z_i - \overline{Z}_i)$. Typically, the influence of receiving X as opposed to Y, results in differential weighting of $f(Z_i - \overline{Z}_i)$. For this reason, most models allow two weights to be estimated, a d effect for when y occurs and an e effect for when X occurs. The d and e are commonly used to symbolically describe the influence of *d*isappointment over the worst possible outcome and *e*lation evoked from the best possible outcome. Regret effects are written in a similar manner except that the difference function now describes magnitude differences between the outcome obtained and the outcome expected from the gamble not chosen, $c_k f(Z_i - \overline{Z}_j)$. The k subscript on c denotes again that different weights may be applied for regret and rejoice (joyful) effects. Here regret is the low end of the affect dimension and is active when the outcome obtained is worse than that expected from gamble 2, $\overline{Z}_2$. The complement comparison describes the rejoice effect. For both disappointment and regret estimates, the lower end of each dimension tends to receive the higher weight (d and the regret c are larger than e and rejoice c, respectively).

Fitting of these models to post-choice affect elicited during gambling tasks has been very successful (Inman et al., 1997; Mellers et al., 1997, 1999) both at the group and individual level. Moreover, these models of PCV have predicted actual choice behavior as well as some GEU models which were fit to the actual choices (Inman et al., 1997), and markedly better than other simplified models of emotion-based choice (Mellers, 1997, 1999). Other notable characteristics of the model fits have been summarized by Mellers (2000; Mellers & McGraw, 2001). Figure 2 highlights fours types of results. Panel A displays the monotonic relationship evident between an imagined obtained outcome and subjective pleasure (or PCV). Panel B depicts an example of disappointment effects where the pleasure derived from the gamble depends on the unattained outcome. Similarly, Panel C describes subjective pleasure dependent on the outcome of an unselected gamble. Finally, the surprise effects in Panel D suggest that pleasure is also dependent on the probability of obtained outcomes. When the probability is low for an outcome, receipt of a rewarding outcome registers larger pleasure than when the same outcome is obtained with a higher probability. Conversely, the receipt of an unlikely, negative outcome registers lower subjective pleasure compared to the same negative outcome whose receipt is more likely (more expected). As described in detail below, it is the effects of Panels B and D that drive the hypotheses tested in this study.

A Generalized Disappointment Model (GDM). As mentioned above, the models of Mellers et al. (1997, 1999) and Inman et al. (1997) leveraged off earlier work on choice

Figure 2. Results of laboratory studies with gambles showing outcome, comparison, and surprise effects.[3]



models that included regret and/or disappointment effects (Bell, 1985; Loomes & Sugden, 1986). The generalization of these models did not end with PCV prediction. Brandstätter, Kuhberger, and Schneider (2002) and Jia, Dyer, and Butler (2001), for example, have each developed similar forms of a generalized disappointment model (GDM) that are intended to be fit to actual choices/preferences. For ease of exposition, I will focus on the Jia, Dyer, and Butler (2001) version (henceforth referred to as GDM) but will later discuss alternative formulations that equate these two approaches.

The GDM model can be represented in terms of equation [1] above, and so, therefore, it was fundamentally derived to fall under the classification of risk-value modeling. Assuming a linear value function, V(·), the model can be written in general form as follows:

$$f(\overline{X}, X') = \overline{X} + \phi(\overline{X})[d\mathrm{E}^{-}\left(\left|X - \overline{X}\right|^{\theta_2}\right) - e\mathrm{E}^{+}\left(\left|X - \overline{X}\right|^{\theta_1}\right)] \qquad [2]$$

[3] From "Anticipated Emotions as Guides to Choice," by B. A. Mellers and A. P. McGraw, 2001, *Current Directions in Psychological Science, 10(6),* p. 211. © 2001 by Blackwell Publishing. Reprinted with permission of the publisher.

where d is the disappointment weight, e is the elation weight, and θ_2 and θ_1 represent the shape of the utility functions for the positive (E^+)and negative (E^-) expectations of the standard risk measure. Several interesting characteristics of this equation deserve elaboration. First, notice the $\phi(\overline{X})$ coefficient which weights the risk portion of the model (i.e., $R(X') + R(0) = R(X') = dE^-\left(\left|X - \overline{X}\right|^{\theta_2}\right) - eE^+\left(\left|X - \overline{X}\right|^{\theta_1}\right)$). This coefficient determines the relative amount of importance an individual places on the perceived risk of a gamble/decision compared to the value or actual expected outcome of the gamble/decision. When $\phi(\overline{X})$ >1, risk is more important, and when $\phi(\overline{X}) < 1$, value is more of a determining factor in the overall evaluation of the gamble/decision. The second aspect to highlight concerns the d and e parameters. These are the same d and e effects discussed earlier, except now they are fitted to actual choice data. These are the effects that explain differences shown in Panel B of Figure 2. Lastly, the two θ 's can be shown to affect the surprise effects evident in Panel D of Figure 2. When combined with the d and e effects, these parameters can determine the degree of discrimination between probability values and the relative attractiveness of a gamble/decision's associated outcomes. This occurs due to the mixing of probabilities and outcomes for the expected outcome calculation in the standard risk measure. It is this mixing of probabilities and outcomes that provides a link to the Brandstätter et al. (2002) model which generalizes a version of Cumulative Prospect Theory (CPT; Tversky & Kahneman, 1992).

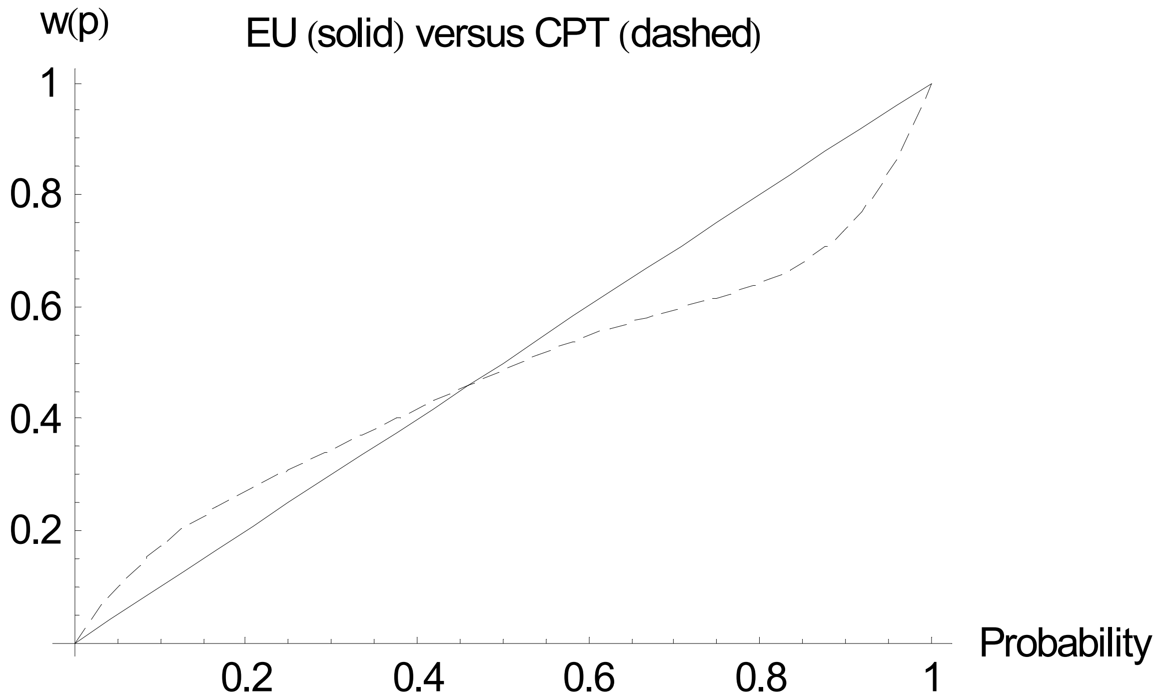
Tversky and Kahneman's (1992) CPT proposed the idea of diminishing sensitivity whereby changes in probabilities closer to the extremes (0 and 1) are weighted more heavily than changes near the middle of the distribution. For example, the absolute difference between a probability of .01 and .001 might seem larger than the same absolute difference occurring around the middle of the probability distribution, say between .4 and .389. Gonzalez and Wu (1999) called this difference in weighting, discriminability. They also added a second descriptor, attractiveness, which explained how this discriminability could have different meanings in terms of preference as one moves from one extreme end of the scale to the other. This second descriptor helped explain a common phenomenon in the data- an overweighting of small probabilities and an underweighting of large probabilities. Combined, these two features of probability weighting often produce graphs like that shown in Figure 3. The depiction reveals discrimination in the slope of the curve and attractiveness effects are evident in the comparison of the straight line, EU weighting, to the curve. This comparison reveals that the CPT weighting places more value on small probability outcomes than does EU, whereas the opposite is true for large probability outcomes. The intersection of the curve and line, where CPT attractiveness becomes worse than EU, is referred to as the crossover point.

Both Brandstätter et al. (2002) and Jia, Dyer, and Butler (JDB; 2001) have generalized weighting functions like that shown in Figure 3 to incorporate disappointment and elation effects. In the latter generalization, the previous GDM model [2] can be rewritten (as shown in JDB, 2001), for 2-outcome gambles, (X,p,Y), as:

$$\begin{aligned} f &= pX + (1-p)Y - \left[d(1-p)(pX + (1-p)Y - Y)^{\theta_2} - ep(X - px - (1-p)y)^{\theta_1}\right] \\ f &= Y + \pi(X,p,Y)(X-Y) \end{aligned} \quad [3]$$

where $\phi(X) = 1$, $\pi(X,p,Y) = p - d(1-p)p^{\theta_2}(X-Y)^{\theta_2 - 1} + ep(1-p)^{\theta_1}(X-Y)^{\theta_1 - 1}$, and f represents an early formulation of prospect theory with linear value functions on

Figure 3. The shape of the decision weight curve which overweights small probabilities and underweights large probabilities.



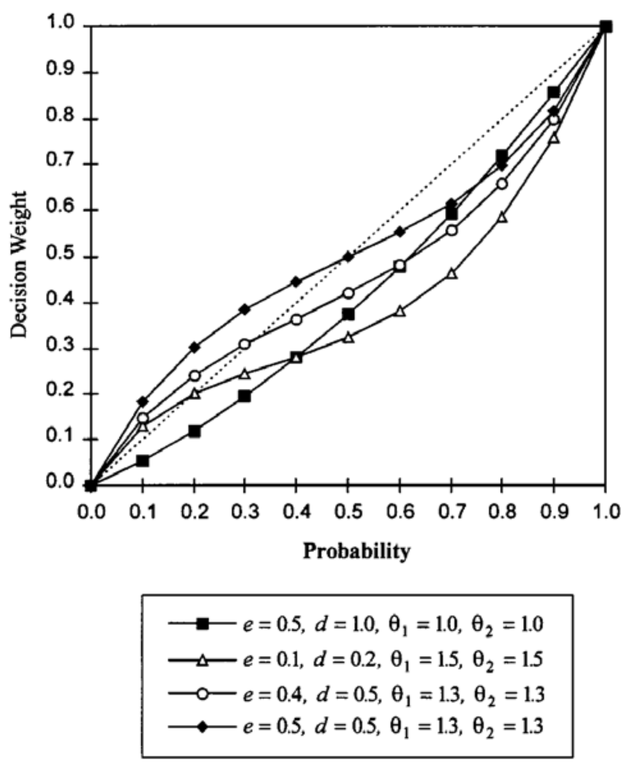
outcomes X andY. As mentioned earlier, the θ's and *d* and *e* effects allow the model to capture the Panel D surprise effects shown in Figure 2, which in CPT terms is another way of describing the over- and underweighting of extreme probabilities. For a common θ, $\theta_1 = \theta_2$, $\pi(X, p, Y)$ reduces to:

$$p - \left[dp^{\theta-1} - e(1-p)^{\theta-1}\right]p(1-p)(X-Y)^{\theta-1}. \qquad [4]$$

In this model, the effects of surprise are now represented by the magnitude difference of *d* and *e*. Moreover, when *d*=*e* and θ>1, the crossover point can be shown to be 0.5, and when *d*>e (as expected for most individuals), the crossover point is < 0.5. Figure 4 from JDB (2001) gives a visual display of possible decision weights fit using this reduced model. In these curves, the crossover point provides information about both the degree of surprise, and the amount of disappointment (Panels D & B from Figure 2).

The Brandstätter et al. (2002) weighting function, for the same two outcome gambles, can easily be linked to equation [3] by dropping the $(X - Y)^{\theta_i - 1}$ components and adding power value functions (as opposed to JDB's linear estimates) to prospects X and Y (as shown in JDB, 2001). Brandstätter et al. provide a direct test of fitting

Figure 4. Possible decision weights from a reduced model [3] where the crossover point represents both surprise and disappointment effects.[4]



disappointment and elation components in this fashion to the more modern versions of prospect theory (Tversky & Kahneman, 1992). In doing so, Brandstätter et al. commented on the communalities between this approach and that of Lopes (1987, 1995;

[4] From "Generalized Disappointment Models," by J. Jia, J. S. Butler, and J. C. Dyer, 2001, *Journal of Risk and Uncertainty, 22(1),* p. 74. © 2001 by Springer Science + Business Media (formerly Kluwer Academic Publishers). Reprinted with permission of the publisher.

Lopes & Oden, 1999) Security-Potential/Aspiration theory. Lopes' model is unique in that it is a *dual criterion* model allowing both a calculated utility and a psychological aspiration level to compete for choice decisions. The model predicts that when both criteria favor the same option, the choice is simple, whereas, when both disagree, conflict ensues, and one criterion overrules the other. The Security-Potential (SP) portion of the model describes utility calculations that weigh both security concerns (avoidance of the worst outcomes) and potential desires (achieving maximum payoffs in the gain domain and minimum losses in the loss domain). Ignoring the influence of Aspiration level for the time being, Lopes' SP portion of the model can be rewritten in the form of equation [3], for 2-outcome gambles, where

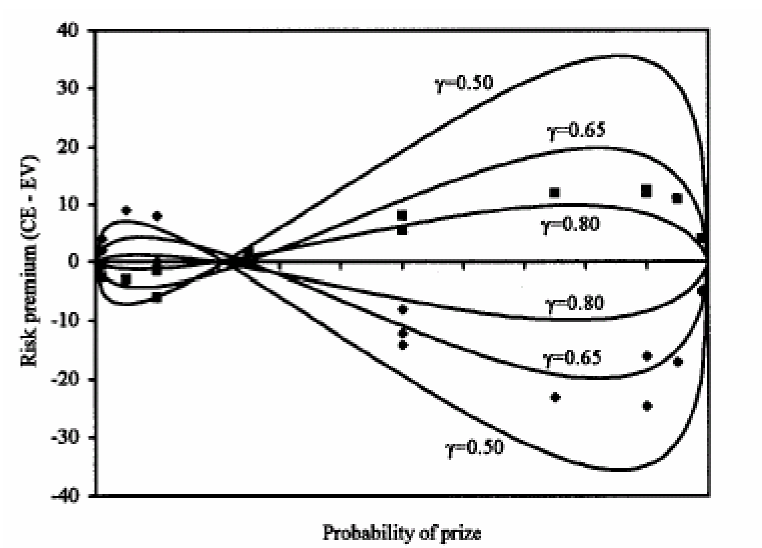
$$\begin{aligned}\pi(X,p,Y) &= \left[wp^{\theta_2} + (1-w)\left(1-(1-p)^{\theta_1}\right)\right] - \left[wp^{\theta_2-1} - (1-w)(1-p)^{\theta_1-1}\right]p(1-p) \\ &= p^* - \left[wp^{\theta_2-1} - (1-w)(1-p)^{\theta_1-1}\right]p(1-p).\end{aligned} \qquad [5]$$

The weights w and (1-w) in equation [5] represent constrained estimates of security and potential influences, respectively, and after recognizing p^* as a weighted estimate of p, also appear to analogously correspond to estimates of d and e from equation [3]. The similarities among these three separate theoretical and empirically derived models seems promising for further explorations of disappointment and elation effects.

GDM and the Allais Paradox, Reflection Effect, and Out-of-Sample Fit of GEU. As Figure 4 depicts, theoretically, the GDM and its cousins (e.g., Brandstätter et al., 2002; Lopes, 1987, 1995; Lopes & Oden, 1999; Mellers et al., 1997, 1999) are very appealing because of their modeling flexibility. This flexibility can describe a wide-array of choice behavior, not the least of which includes violations of expected utility theory like the Allais Paradox (see Lopes, 1994; JDB, 2001) and the reflection effect (see Kahneman & Tversky, 1979; JDB, 2001; BDJ, 2005). Furthermore, allowing both

θ_1 and θ_2, where $\theta_1 \neq \theta_2$, into estimation can help explain previous models' badness of fit, as shown in Figure 5 below from Neilson and Stowe (2002). Figure 5 displays loss risk premiums below the horizontal axis for low probabilities and above it for moderate to high probabilities. The opposite is true for gain risk premiums. As depicted, the modern Prospect Theory model (Cumulative PT; Tversky & Kahneman, 1992) and those akin to it (e.g., Prelec, 1998) have a hard time accounting for risk premiums at both low and high probabilities using only a single weighting parameter. As evidenced below, changes in this single parameter (γ) can only improve fit for one (e.g., low probabilities) by sacrificing fit for the other. This is not so for the models presented above, where differences in *d*, *e*, and θ_i allow for different trajectory shapes on each side of the horizontal axis.

Figure 5. Risk Premium Misfit Using Prospect Theory Weighting.[5]

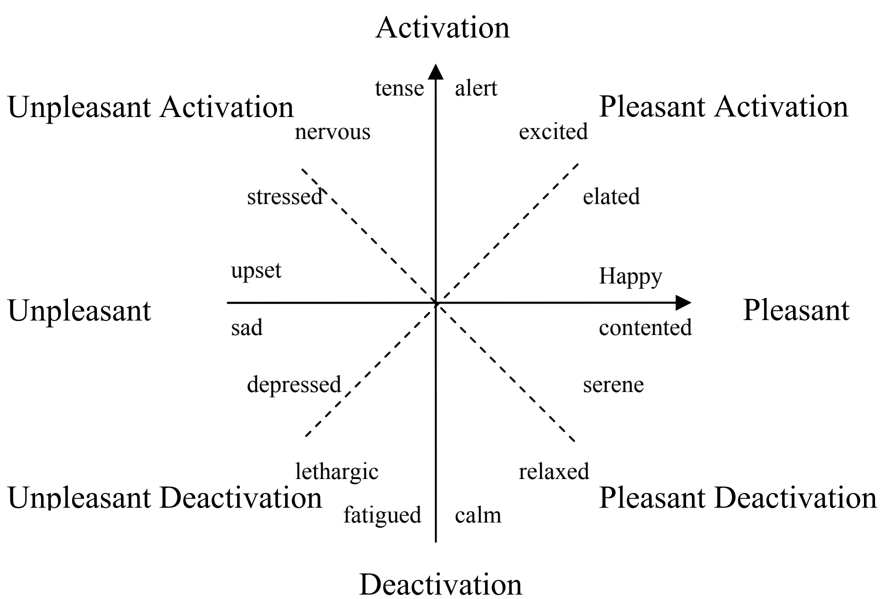


[5] From "A Further Examination of Cumulative Prospect Theory Parameterizations," by W. Neilson and J. Stowe, 2002, *Journal of Risk and Uncertainty, 22(1),* p. 74. © 2002 by Springer Science + Business Media (formerly Kluwer Academic Publishers). Reprinted with permission of the publisher.

Dimensionality of Affect and Its Relationship to Immediate and Expected Emotions

Whereas the earlier summarized studies investigated effects of incidental affect dimensions (e.g., valence and arousal) on future behavior, Vastfjall and colleagues (Vastfjall & Garling, 2002; Vastfjall, Garling, & Kleiner, 2004) have begun to investigate the preference for feeling particular dimensions of affect. Using a more direct approach than that of Mellers et al. (1997, 1999) and Inman et al. (1997), Vastfjall et al. (2002, 2004) have assessed whether self-reported preference for incidental, experienced (post- decision or behavior), and expected emotional reactions can be described by Russell and Barrett (1999) circumplex of affect (RBCA; depicted in Figure 6) using self-reported perceptions of valence and arousal dimensions.

Figure 6. The Affect Circumplex.[6]



[6] From "Independence and Bipolarity in the Structure of Current Affect" by L. F. Barrett and J. A. Russell, 1998, *Journal of Personality and Social Psychology, 74(4),* p. 970. © 1998 by American Psychological Association. Adapted with permission of the author.

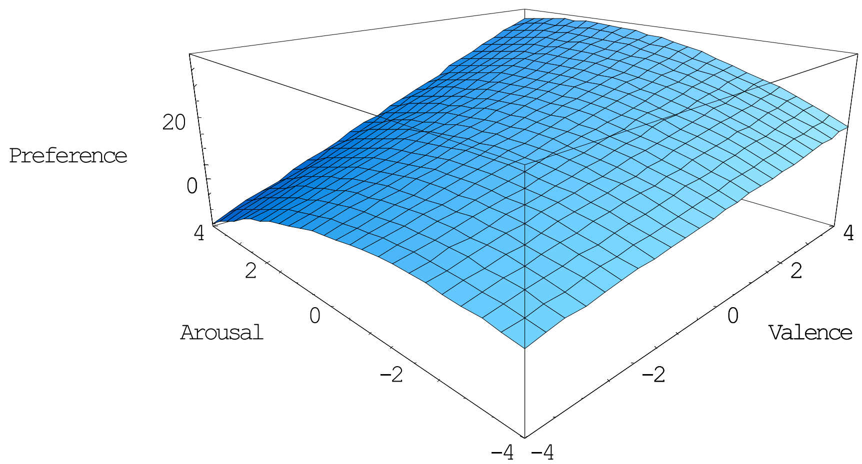
Adopting the Pleasure-Arousal Hypothesis from Russell and Mehrabian (1978), Vastfjall et al. (2002, 2004) predicted that preference for feeling a particular affect is dependent on three characteristics of the relationship between preference and the RBCA: (1) the marginal distribution of preference over arousal is linear with valence; (2) the marginal distribution of preference over valence is an inverted U-shaped curve along arousal; and (3) the maximum point of preference on the U-shaped distribution of preference by arousal increases with valence. This relationship can be captured in an equation that includes terms for a positive linear valence effect, a negative quadratic arousal effect, and a positive linear interaction between valence and arousal:

$$P = B_0 + w_v V + w_a A - w_{a2} A^2 + w_{va} (A^*V). \qquad [6]$$

Example predictions of preference from the Pleasure-Arousal Hypothesis across various degrees of arousal and valence are graphically displayed in Figure 7 below. The picture shows quite clearly the most defining characteristic of the Pleasure-Arousal Hypothesis as the interaction between valence and arousal. Notably, the model predicts that individuals experiencing low valence will prefer to feel less arousal, whereas for individuals experiencing high valence, preference will favor emotions that are associated with high arousal.

In their most recent work, Vastfjall et al. (2004) have shown that after controlling for expected/anticipated valence and arousal (or activation in Figure 6), current valence and arousal does not predict preference for the expected/anticipated emotional experience. The result was also true when predicting future experienced affect from previous valence and arousal. However, in both situations, while not noted by the authors, there were signs of a mediated effect, whereby current valence acted

Figure 7. Predictions from the Pleasure-Arousal Hypothesis.



indirectly on preference via its influence on anticipated valence. These findings suggest that preference for various affects may depend on current valence. For the purposes of this study, two major implications from the Vastfjall et al. (2002, 2004) findings need to be highlighted. First, the relationship between a two-dimensional view of affect and affect preference suggests that Decision Affect Theory might be improved upon by considering both expected/anticipated[7] valence and arousal, as opposed to just a single-dimension measure (as used in Mellers et al. ,1997, 1999, & Inman et al. ,1997). Second, the mediating influence of current valence on *preference* for anticipated affect, combined with the coloring effects of affect on gambling decisions like those observed in Eisenberg, Baron, and Seligman (1996) and Raghunathan and Pham (1999), suggested that when outcomes are uncertain, current mood might indirectly influence choice through its effect on *expectations* of affect. In GDM terms, this suggests

[7] *Anticipated* affect is sometimes used to distinguish the affect perceived to be associated with the imminent receipt of a particular outcome, whereas, *expected* affect represents the global integrated estimate of future affect informed by anticipated affect for and the associated likelihood of all possible outcomes.

coloring effects of affect on the disappointment and elation weighting curves shown in Figure 4, that if supported, could potentially explain findings of hot and cold empathy gaps (Loewenstein, 1996; Lowenstein & Schkade, 1999), impulsivity, and ultimately, divergence of behavioral intentions and actual behavior.

Statement of Purpose and Research Hypotheses

Summary of Literature and Its Relation to Proposed Investigations. As shown in Panel B of Figure 1, current decision-making findings suggest that emotions play both a direct and indirect role in determining behavior. Indirectly, they appear to influence both processing of information and weighting of information during the cognitive evaluation of a situation and selection of appropriate action. Directly, they may compete against cognitive evaluation through the impact of visceral influences (Loewenstein, 1996). The research study that follows focused on the former type of influence, investigating coloring effects related to the dimensions of affect.

Three major findings from previous research on affective decision-making guided hypothesis generation and study design. First, given the large body of evidence suggesting that various coloring and processing effects of emotion can be explained by opposing dimensions of affect, the current study chose to adopt the Russell and Barrett (1999) 2-dimensional affect structure to investigate valence and arousal influences on risky choices. Second, the work by Mellers et al. (1997, 1999) and Inman et al. (1997) suggesting experienced emotions (i.e., post-choice valuation) are influenced by both probabilities and outcomes, led to questions about specific effects of risk (e.g., probabilities) and reward (e.g., outcomes) on choice behavior and also expected emotions. Finally, borrowing from the work of Russell and Mehrabian (1978) and, more recently, Vastfjall and colleagues (Vastfjall & Garling, 2002; Vastfjall, Garling, & Kleiner, 2004) this proposal will attempt to unite the first and second major findings by exploring the influence of multiplicative effects of valence and arousal on expected emotions and choice (see Section 5). If the previous work on this third finding (Vastfjall, Garling, & Kleiner, 2004) suggesting immediate affect (e.g., current valence) indirectly influences preference for subsequent affect (expected emotion) is valid, the first (dimensional coloring effects) and second (effects of expected emotion on choice) predictive relationships might imply that the effects of immediate affect on choice are mediated by expected affect.

Hypotheses: Incidental Affective Effects on Expected Emotion. This study sought to explore the influences of 2-dimensional affect on anticipated emotions and choice preference on a standard gambling task. Hypotheses are as follows:

Hypothesis 1: Current valence and arousal will predict individual differences in certainty equivalency measures of choice preference across gambles.

Hypothesis 2: Current valence and arousal will predict individual differences in anticipated affect.

Hypothesis 3: Expected affect will mediate the influence of current affect on choice preference.

Hypothesis 4: The influence of incidental affect on expected affect will be mediated through perceptions of risk and expected payoff.

Assuming the Null hypotheses inherent above were false, appropriate tests for Hypotheses 1 through 4 required gambles that would elicit variation in both expected arousal and valence. Based on the earlier presented surprise effects (Panel D of Figure

2), an assumption was derived that changing levels of expected arousal, an affect at least partially indicated by surprise, would most closely align with changes in extreme outcome probabilities, while changes in expected valence would more closely align with changes in actual outcome values (amounts of money). So, attempting to incorporate the desired variation in expected affect, the current study manipulated both the probability distribution of outcomes and the expected values of several presented gambles. Hypotheses 1 and 2 are essentially replications of the Vastfjall et al. (2004) analyses, extended to gambling preference tasks. If Hypothesis 1 is upheld, one might expect the utility of gambles, differing in surprise by outcome combinations, to vary systematically across combinations of incidental valence and arousal. For example, an individual currently feeling both negative valence and high arousal (Unpleasant Activation in Figure 6) might place a lower utility on gambles with low probabilities for below average outcomes than would an individual who incidentally experiences high valence (pleasant deactivation or activation) or even low valence but low arousal (unpleasant deactivation). Such an effect might implicate an Unpleasant Activation signal that overemphasizes the possibility of more unpleasant activation (a larger GDM disappointment influence). Likewise, an individual experiencing high valence and low arousal (Pleasant Deactivation) might overemphasize the possibility of pleasant activation (a stronger elation effect) compared to individuals already experiencing high arousal and high valence. This type of finding might implicate maintenance of mood signals from high valence/high arousal combinations which then lead to risk-avoidant behavior, and a potentiation signal from high valence/low arousal emotions which focus attention on the possibility of unlikely rewards and lead to more risk-seeking behavior.

If Hypothesis 2 is also upheld, it is possible that the systematic differences in choice due to incidental valence may be related to the mediating effect of anticipated valence and arousal. Hypothesis 3 is designed to explore this unifying causal mechanism simultaneously. Finally, Hypothesis 4 investigates whether prediction of expected affect constructs from perceived risk and value, both measured through self-report, empirically substantiate the conceptual links identified between risk value GEU and Decision Affect Theory or PCV, and whether these perceived characteristics of gamble structure differ based on the incidental 2-dimensional affect space.

Chapter II: Methods

Participants

Ninety-nine undergraduate students from summer, lower-level psychology courses were recruited for participation. For participating, each student was rewarded with extra credit units as arranged by the faculty of psychology as part of the department's experimental system.

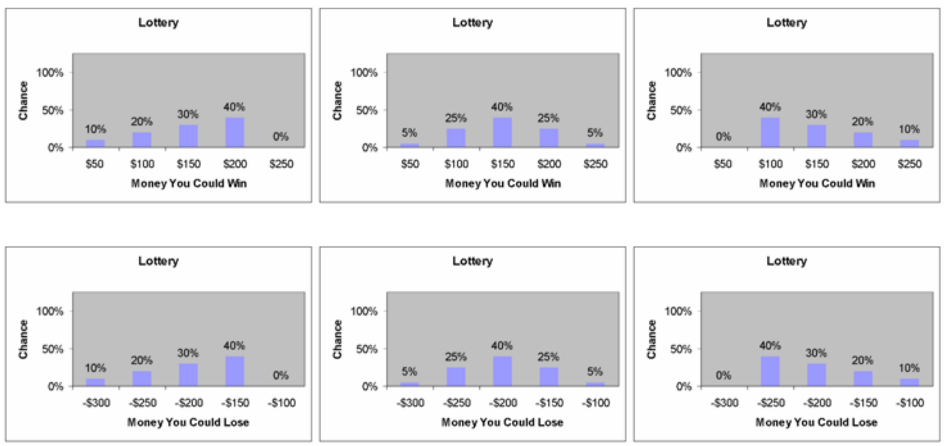
Stimuli

All hypotheses were tested using outcomes generated from a brief structured gambling task. The task involved twelve 5-outcome gambles that paired 3 probability distributions used in BDJ (2005; shown here in Figure 8 as s = /, \, and ^) with 4 payoff distributions (where $\overline{X}$ = \$150, \$200, -\$150, or -\$200). Notice that the probability distributions associate surprise with outcomes that are either below the mean (s = /), above the mean (s = \), or both (s = ^). These aspects will be key for testing differences in gamble preference among various valence and arousal combinations.

Procedure

The entire data collection procedure was conducted using Microsoft Access software for desktop PCs that were situated inside private cubicles. Participation began with informed consent to participate in a study advancing the development of a newly designed gambling task. After agreeing to participate, the procedure continued with demographic inquiries (age, gender, and ethnicity) and then current affect elicitation

Figure 8. Probability Distributions for Gambling Task.



s = / s = ^ s = \

using an abbreviated version of the valence and arousal scales developed by Mehrabian and Russell (1974). Upon completion of these scales, participants were briefly introduced to the gambling task with two example outcomes that used distributions not shown in Figure 8 (a uniform distribution and a U-shaped distribution). The computerized interview explained that these distributions represented hypothetical lotteries and that the goal of this task was to determine which of two options they preferred: pocketing a certain amount of money or playing a visible lottery, i.e., gambling. The computerized tradeoff procedure was set-up like most other tradeoff equivalency tasks, where certainty amounts ping-pong back-and forth across the range of payoffs until a stopping point is reached (where certainty amounts bounding a five dollar interval reflect opposing choices- i.e., gamble below and settle for cash above). Certainty equivalents are then determined by averaging the boundaries of the stopping interval. The procedure deviates from others (e.g., PEST procedure; see Luce, 2000), however, in that participants saw the same lottery over a series of consecutive choices, until a stopping interval was found, with the order of lottery presentation randomly determined. This unique aspect was incorporated in an effort to prevent participant fatigue which might have compromised the validity of subsequent choices. In addition, the method did not allow elicited certainty equivalents to violate stochastic dominance[8] (the computer explains the logical error, and the gamble is presented again). If CE estimation took more than 20 iterations, an error window appeared requesting the participant contact the research administrator. When summoned, the administrator re-explained the concept of the task and oversaw the next few choices, verifying verbally the participant's understanding.

After the certainty equivalency task was completed, participants were shown a series of questions about each of the 12 presented gambles, as well as questions about each individual lottery amount and probability (data to be used in a separate study). Participants were randomly assigned the order in which they viewed these two broad categories of questions. When viewing each gamble (which were, themselves, presented in random order), participants were asked to record the mean expected payoff and the perceived risk involved. Following these responses, participants once again

[8] Occurs when the probability of winning (losing) *at least* (most) x amount of dollars is higher for all possible x (gamble outcomes) for one of the choice options (gamble or sure-thing). In the choice task presented, the gamble stochastically dominates a sure-thing equaling the lowest (highest) gamble payoff (loss) and is stochastically dominated by a sure-thing equal to the highest (lowest) gamble payoff (loss).

viewed each gamble separately, in random order, and answered expected affect questions (how happy and surprised they felt by the outcome) concerning receipt of the best and worst lottery outcomes, under the hypothetical condition that the individual choose the lottery instead of a sure-thing amount that equaled the lottery mean (-200, -150, 150, or 200). Responses for the best outcome across all 12 lotteries were elicited first. The gambles were then randomly presented again, and affect questions were restated for the worst outcome. When viewing the lottery amounts alone (i.e., no lottery distribution visible), participants were asked to record the degree of happiness (using the Affect scale item Happy/Unhappy described below) they would feel were the amount either added (in the case of positive sure amounts) or deducted (for negative amounts) from their current status quo. Once all questions had been answered, participants viewed a debriefing summary of the research aims before leaving the laboratory.

Measures

Affect. An adapted short-form version of the Mehrabian and Russell (1974) 2-dimensional affect scales was administered to assess incidental mood over the past week. This adaptation retained the 6 items from each scale garnering the highest factor loadings during seminal development, except for the arousal scale's Jittery/Dull item which was replaced with the dichotomy Surprised/Unsurprised. Adapted instructions for the task were as follows:

> Each pair of words below describes a feeling dimension. Some of the pairs might seem unusual, but you may generally feel more one way than the other. So, for each pair, move the sliding scale toward the adjective that best describes

how you **IN GENERAL** (that is, most of the time) felt during the **PAST WEEK**. As the slider moves closer to an adjective, it should indicate stronger feelings of that type. The numbers below the scale are presented to help you judge the appropriate distance of each slider move. Please take your time so as to arrive at a real characteristic description of your feelings.

Instructions were immediately followed by two examples and then the valence and arousal items. One item from the valence scale, Happy/Unhappy, and the new item, Surprised/Unsurprised, were used to measure both valence and arousal, respectively, during the anticipated affect elicitation procedure. Two Happy/Unhappy and Surprised/Unsurprised responses were elicited for every gamble, one each for best and worst possible outcomes. These items were prefaced with the phrase:

> Imagine you chose to play the lottery shown instead of accepting a sure win/loss of [lottery mean]. Now for each pair of descriptors below, use the slider to describe how you would feel if the lottery performs BETTER/WORSE than the sure thing and you win/lose [best/worst lottery outcome].

For all affect items, instructions indicated that the extreme polar opposites (e.g., Happy and Unhappy) anchoring each rating scale were meant to represent the ultimate level of that feeling state (e.g., extreme happiness or extreme unhappiness).

Expected Payoff/Loss. To measure these perceptions, participants were asked to consider taking each gamble 10 times in succession. They were then asked to elicit the expected average outcome received per gamble. Wording was as follows:

> For the lottery above, answer the following question. Imagine you were to play this lottery 10 times in succession (in a row). In your opinion, how much

money, ON AVERAGE, do you expect to win/lose PER PLAY? [The value entered can fall between the lottery amounts shown.]

Perceived Risk. These judgments were elicited using a scale from 0 (not at all risky) to 100 (extremely risky). As in previous investigations of subjective risk perception (Holtgrave & Weber, 1993; Weber & Milliman, 1997), the term "risk" was left undefined. Responses were designed to convey the risk of each lottery play versus a sure-thing amount that equaled the lottery's mean. Phrasing was as follows:

> Imagine you play the lottery above. Use the scale below to express how risky this play would feel knowing you passed up a sure win/loss of [lottery mean].

Data Analysis

Descriptive statistics and data manipulation were conducted in the base package of SPSS version 14.0.2 (SPSS, Inc., Chicago, IL); all other analyses were accomplished within Mplus version 4.2 (Muthén & Muthén, 1998-2006). Before conducting any hypothesis testing, models were constructed to explore both the severity of unintended effects from varying testing conditions (variation due to different cubicles, computers, and application software) and the fit of the proposed 2-dimensional factor solution to the measures of incidental affect. In the hypothesis testing that followed, separate models for all gender by outcome-sign (payoffs or losses- hereafter referred to as positive and negative gambles) levels were assessed. Outcome-type (anticipated valence for best gamble outcome, certainty equivalency responses, etc.) was assessed both univariately and multivariately, depending on whether direct effects or mediation were of interest. For greater efficiency, the structural changes across gambles were considered simultaneously, resulting in a 2 by 3 within-subject factorial (expected value by probability distribution) embedded within each model. Hypothesis testing began with the often-cited progression of direct effect tests that lead up to multivariate outcome models that include terms for partial mediation (Judd & Kenny, 1981; Baron & Kenny, 1986). Ignoring the within-subject factorials, we can describe the direct tests found in Hypothesis 1 as linear multiple regression equations, where the incidental affect dimensions predict CE. These equations can be written as:

$$CE = \beta_0 + \beta_1 V_I + \beta_2 A_I + \beta_3 A_I^2 + \beta_4 AV_I + e, \qquad [7]$$

where V_I and A_I represent centered values of incidental valence and arousal, respectively. The tests found in Hypothesis 2 are identical to equation [7] except that the incidental affect dimensions are replaced with expected valence (V_E) and arousal (A_E). Finally, mediation models can be constructed that assess both types of regressions, simultaneously, and include separate regressions of expected valence and arousal on the incidental affect. Tests for mediation can be accomplished by comparing the significance of products of regression coefficients involved in indirect paths that lead from an incidental affect term to CE responses by way of a direct effect on expected valence and/or arousal (MacKinnon et al., 2002; MacKinnon, Lockwood, & Williams, 2004). Because the indirect effect may pass through higher order effects involving the mediators (quadratic arousal or interaction between arousal and valence), newly developed techniques for testing "moderated mediation" were adapted to handle this particular situation (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, in press). More detail on these testing procedures are provided under the Results section for Hypothesis 3.

The CE estimates generated represent a choice between a risky gamble (playing the lottery) and a degenerate gamble (the sure-thing CE estimate). More specifically, a CE represents an individual's breaking point, above which an individual will choose sure-things and below which they choose to risk their chances on the gamble. Plugging these estimates in as dependent variables of the models described in the previous paragraph allows for tests of Hypotheses 1 and 2. Since multiple gambles are presented to each participant, potentially, we could assess six different tests of these direct effect hypotheses (and for that matter, the mediation hypotheses, too), were each gamble-structure (expected value by probability distribution) considered independently. However, meaningful differences that can be explained by features of the manipulated gambles are likely to exist across these various CE estimates. Under the assumption that a monotonic-increasing function underlies the relation between a CE and gamble utility, differences in CEs across the presented gambles represent ordered changes in preference for sets of gambles. For example, comparison of $CE_{s=/,\, \bar{X}=150}$ and $CE_{s=\backslash,\, \bar{X}=200}$ provides information about which lottery an individual will favor when choosing between the (s=/, $\bar{X} = 150$) and the (s=\, $\bar{X} = 200$) gambles. The within-subject effects mentioned above will investigate these differences by predicting CE profile changes related to gamble structure (fixed effects for expected value and probability distribution factors). Moreover, models will consider differential prediction from each set of independent variables across gamble structure (i.e., assessing interactions between gamble structure and predictor performance).

Chapter III: Results

Descriptive Information

Forty-three males and 53 females participated. Ages ranged from 18 to 28 with an average of 19.3 (SD = 1.8). The majority (75 individuals) of the sample classified their primary ethnicity as "White, not Hispanic." Tallies of other ethnic categories as well as mean responses to all other study questions can be found in Tables 1-3. One individual's information was discarded from subsequent analyses due to outlier status on all 12 certainty equivalent (CE) responses.

Table 1. Sample Distribution of Race/Ethnicity.

	Freq.	Percent
Black	7	7.1
American Indiar	7	7.1
Asian	4	4.0
Hispanic	2	2.0
White	75	75.8
Other	4	4.0
Total	99	100.0

Table 2. Descriptive Information for Bipolar Affect Adjective Pairs.

	N	Min	Max	Mean	Std Dev
Happy	98	0	90	28.66	22.18
Pleased	98	0	90	35.64	22.40
Satisfy	98	0	83	34.20	20.93
Content	98	0	90	35.62	22.39
Hopeful	98	0	93	30.87	20.15
Relaxed	98	0	91	41.81	21.55
Stimulated	98	0	100	45.91	23.41
Excited	98	2	100	44.35	22.23
Frenzied	98	0	95	49.58	20.15
Surprised	98	10	100	52.77	19.69
Awake	98	0	100	52.52	26.48
Arouse	98	0	90	45.36	19.56

Table 3. Descriptive Information on Completion Time for Experimental Tasks.

	N	Min	Max	Mean	Std Dev
Time to complete Demographic Q in seconds	98	8	41	19.59	6.99
Time to complete Affect Q in seconds	98	37	236	112.81	41.88
Time to complete TradeOff Q in seconds	98	435	2463	991.22	356.86
Time to complete Amount Valence Q in seconds	97	33	148	64.01	18.06
Time to complete Probability Arousal Q in seconds	97	19	88	38.15	13.27
Time to complete Expected Payoff Q in seconds	98	75	833	211.38	113.51
Time to complete Riskiness Q in seconds	98	51	429	163.73	53.04
Time to complete Best Outcome Affect Q in seconds	98	76	341	201.84	54.84
Time to complete Worst Outcome Affect Q in seconds	98	49	840	163.05	87.61
Time to complete Entire Q in minutes	98	15	61.38	32.75	8.01

Assessing Cubicle/Computer Induced Non-Independence

As Table 4 indicates below, a total of 12 private interview cubicles were used in this study, each with separate desktop computers. In order to optimize data collection numbers, two different desktop models with varying processors (Pentium2 and 4), operating systems (Windows 98 and Windows XP), monitor sizes (15 and 17 inches), and software (Microsoft Access 2000 for Pentium 2 processors and Access 2003 for Pentium 4) were utilized. Despite the variations in computer specifications, very little evidence emerged for clustering effects. As shown in Table 5, estimated intraclass correlations for both the Affect scale indicators and the CE outcomes showed little cluster-level influence on variation in responses. Unfortunately, the small number of clusters (= 12) and small average cluster size (= 8.2) preclude any reliable statistical adjustment, using available Mplus latent variable modeling procedures, for such non-independence in observations (Muthén, L., 2006, Muthen, B., 2005). However, the combination of these factors (i.e., small intraclass correlations, number of clusters, and average cluster size), produce approximate design effects far below 2, a suggested benchmark for cluster-level control necessity in previous simulation work (Muthén &

Satorra, 1995; Muthén, L., 1999). For these reasons, the latent variable models that follow ignored cubicle/computer design effects.

Table 4. Number of Participants per Cubicle/Computer.

PC	Freq.	Percent
1	10	10.2
2	18	18.4
3	10	10.2
4	8	8.2
5	10	10.2
6	7	7.1
7	3	3.1
8	11	11.2
9	6	6.1
10	10	10.2
11	4	4.1
12	1	1.0

Table 5. *Intraclass Correlations and Approximate Design Effects for Affect and CE.*

	ICC	Approximate Design Effect
Affect		
Happy/Unhappy	0.001	1.007
Pleased/Annoyed	0.001	1.007
Satisfy/Unsatisfied	0.001	1.007
Contented/Depressed	0.001	1.007
Hopeful/Despairing	0.001	1.007
Peaceful/Bored	0.001	1.007
Simulated/Relaxed	0.019	1.136
Excited/Calm	0.024	1.172
Frenzied/Sluggish	0.002	1.014
Surprised/Unsurprised	0.064	1.459
Awake/Sleepy	0.001	1.007
Aroused/Unaroused	0.001	1.007
Certainty Equivalents		
Lottery [\,-150]	0.001	1.007
Lottery [^,-150]	0.001	1.007
Lottery [/,-150]	0.001	1.007
Lottery [\,-200]	0.001	1.007
Lottery [^,-200]	0.001	1.007
Lottery [/,-200]	0.001	1.007
Lottery [\,150]	0.002	1.014
Lottery [^,150]	0.054	1.387
Lottery [/,150]	0.001	1.007
Lottery [\,200]	0.001	1.007
Lottery [^,200]	0.006	1.043
Lottery [/,200]	0.022	1.158

Note. Approximate Design Effect = $1 + (\tilde{m} - 1)\rho$; $\tilde{m}$ = average cluster size, ρ = ICC.

Affect Measurement Model

Preliminary analyses began with inspection of the measurement of the adapted Mehrabian and Russell (1974) 2-dimensional affect scales. The model was originally specified as an orthogonal (valence and arousal uncorrelated), congeneric (requiring one factor loading per item; see Jöreskog, 1971) 2-dimensional structure, with six items per factor. Estimation was performed using maximum likelihood (ML) in Mplus version 4.2 (Muthén, 1998-2004; Muthén & Muthén, 1998-2006), fixing the latent variances equal to one.

The estimated Satorra-Bentler (SB) mean-adjusted chi-square statistic (Satorra & Bentler, 1994) suggested poor overall fit, $\chi^2(54) = 106.7$, $p < .01$. Inspection of the bivariate Pearson correlation matrix revealed significant relationships between Arousal's Awake/Sleepy item and all six Valence items. This was nearly true for Arousal's Aroused/Unaroused item as well, where only the bivariate relationship with the Pleased/Annoyed item lacked significance. In light of these observations, both Awake/Sleepy and Aroused/Unaroused items were allowed to load on Valence and Arousal in a subsequent model run. This new model appeared to fit adequately with a calculated SB $\chi^2(52) = 62.6$, $p < .15$, a root mean square error of approximation (RMSEA; see Browne & Cudeck, 1993; Steiger & Lind, 1980) = 0.046, and a weighted root mean square error (WRMR; see Yu, 2002) of 0.92. [A nonsignificant chi-square value, an RMSEA of 0.06 or less (see Hu & Bentler, 1999), and WRMR of 0.90 or less (see Yu, 2002) are all suggestive of good fit.] The resulting loading matrix from this new model is shown in Table 6. All models assessing the predictive relationship of valence and arousal latent constructs utilized this factor pattern structure.

Table 6. Estimates from Final 2-Dimension Incidental Affect Model.

Valence Factor Loadings			Arousal Factor Loadings		
	Estimates	S.E.		Estimates	S.E.
Happy	20.68	1.72	Stimul	15.74	2.27
Pleased	19.31	1.68	Excite	16.7	1.99
Satisfied	18.64	1.27	Frenzy	13.85	2.02
Content	19.48	1.57	Surprise	13.3	1.94
Hopeful	15.7	1.87	Awake	6.72	2.46
Relax	11.17	1.9	Arouse	8.14	2.43
Awake	14.55	2.27			
Arouse	3.6	1.96			

Variances		
VALENCE	1	----
AROUSAL	1	----

Residual Variances			Observed Variable	R-Square
Happy	59.32	12.17	Happy	0.88
Pleased	123.72	20.8	Pleased	0.75
Satisfied	86.05	15.5	Satisfied	0.8
Content	116.93	18.22	Content	0.76
Hopeful	155.27	25.66	Hopeful	0.61
Relax	334.91	49.22	Relax	0.27
Stimul	294.85	63.32	Stimul	0.46
Excite	210.24	43.93	Excite	0.57
Frenzy	210.14	37.03	Frenzy	0.48
Surprise	206.61	30.59	Surprise	0.46
Awake	414.52	49.45	Awake	0.38
Arouse	292.83	47.18	Arouse	0.21

Hypothesis Testing

Hypotheses 1 through 4, restated below, are tested using a repeated measures regression approach with fixed coefficients for all main effects and interactions involved in the manipulated gambling structure (expected value by probability distribution). The \ probability distribution and the 150 expected value levels were chosen as referent categories for all main effects and interactions (i.e., coded as 0 in all the relevant effect dummy variables). All models estimated unstructured error covariance matrices. These analyses were run as structural equation models. Models were run separately for both positive and negative gambles and males and females. Each main effect was allowed to interact with the incidental affect measures. Model reduction was accomplished through a backward elimination selection procedure with removal criterion set at p-values greater than 0.10 for Wald test statistics using robust (to non-normality) standard errors. Terms were eligible for elimination only if higher-order terms involving each variable were either nonexistent or already eliminated[9]. The affect measures were created using the latent variable score formulas of Anderson and Rubin (1956) as described in Jöreskog (2000). The factor scores used in all analyses below were created from the Lisrel student version 8.7 (Jöreskog & Sörbom, 2004). Notably, unlike other factor scoring techniques, this procedure results in scores that reproduce the latent factor covariance matrix. In this case, the procedure produced uncorrelated factor scores for Valence and Arousal that near perfectly reproduce the factor communalities.

Hypothesis 1. Current valence and arousal will predict individual differences in certainty equivalency (CE) measures of choice preference across gambles.

Before examining the gamble structure and affect model effects, Tables 7 and 8 show the mean estimates, ranges, and standard deviations by gender for each individual gamble. Notice that for negative gambles, the usual pattern of the means (the only

[9] Note. Tests involving the dummy variables for the categorical gambling structure main effects and interactions, i.e., expected value by probability distribution, were assessed individually and not in omnibus fashion; e.g., the omnibus test of probability distribution by valence was not assessed, but instead a test of the ^ distribution by valence and the / distribution by valence were assessed as separate interaction effects.

exception is the -150 mean for the female /,-150 gamble) reflect risk aversion, indicating CE estimates that are below the lotteries' expected values. For males, the positive gamble means are fairly risk neutral among \$150 gambles and risk averse among the \$200 gambles. Females, on the other hand, showed risk seeking for \ gambles, risk aversion for / gambles, and a reversal from risk seeking to aversion as ^ gambles' EV increases. Also notice that in both genders and within all EVs, the pattern of inequalities \ ≥ ^ ≥ / is fairly consistent, possibly lending credence to the notion of risk partly informing preference (the only difference between gambles that shared an EV is the probability distribution shape- an objective measure of risk). Yet, this general pattern, across both positive and negative gambles, would appear to contradict the well-known reflection effect (Kahneman & Tversky, 1979), where preference order (inferring higher CEs are associated with greater preference) for positive gamble structures with the same EV reverses when the gains are replaced with losses (the negative gambles- where lower CEs, i.e., those more negative, are suggestive of preferred choice). In this study, such a finding would be supported were the order of preferences in the positive gambles opposite the order observed in the negative gambles. This contradiction may be tied to the order of the losses on each negative gamble display, where losses decreased from left to right (e.g., -250, -200, -150, -100, -50) so as to increase saliency of changes from gains to losses (see Figure 8). (Note: at a fixed EV, flipping the monetary axis of the / negative gambles produces the same structure as the \ positive gambles, except gains are replaced with losses; the same is true of \ negative and / positive gambles). This, somewhat unique, presentation style may have prevented this preference reversal tendency.

Table 7. Male Descriptive Statistics for CEs and Affect Factor Scores.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] CE	43	-162.5	-87.5	-140.87	15.34
Lottery [^,-150] CE	43	-187.5	-52.5	-140.06	25.81
Lottery [/,-150] CE	43	-177.5	-102.5	-143.31	18.32
Lottery [\,-200] CE	43	-217.5	-102.5	-182.97	24.54
Lottery [^,-200] CE	43	-222.5	-102.5	-191.34	25.21
Lottery [/,-200] CE	43	-247.5	-152.5	-191.69	20.41
Lottery [\,150] CE	43	102.5	197.5	152.15	17.97
Lottery [^,150] CE	43	112.5	197.5	150.99	17.88
Lottery [/,150] CE	43	102.5	192.5	149.48	17.53
Lottery [\,200] CE	43	152.5	247.5	197.97	19.82
Lottery [^,200] CE	43	142.5	252.5	197.97	20.32
Lottery [/,200] CE	43	102.5	237.5	189.36	24.47
Valence Factor Scores	43	-2.81	1.79	-0.17	1.06
Arousal Factor Scores	43	-2.53	2.68	-0.08	1.04

Table 8. Female Descriptive Statistics for CEs and Affect Factor Scores.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] CE	55	-197.5	-52.5	-140.77	27.89
Lottery [^,-150] CE	55	-177.5	-52.5	-133.95	29.73
Lottery [/,-150] CE	55	-202.5	-102.5	-150.23	19.76
Lottery [\,-200] CE	55	-247.5	-102.5	-180.14	36.25
Lottery [^,-200] CE	55	-227.5	-102.5	-187.14	26.00
Lottery [/,-200] CE	55	-247.5	-152.5	-192.95	21.59
Lottery [\,150] CE	55	102.5	247.5	156.86	30.57
Lottery [^,150] CE	55	97.5	247.5	155.05	25.42
Lottery [/,150] CE	55	52.5	197.5	145.14	26.42
Lottery [\,200] CE	55	152.5	297.5	205.68	28.19
Lottery [^,200] CE	55	102.5	297.5	197.05	36.10
Lottery [/,200] CE	55	107.5	247.5	188.77	25.93
Valence Factor Scores	55	-1.97	1.47	0.13	0.94
Arousal Factor Scores	55	-2.09	2.11	0.06	0.97

Among males, for the positive gamble responses, the backward selection procedure described above resulted in a final model that included mean effects for the / distribution, the EV main effect, and the interaction between these two. There was no significant difference between the mean elicited responses from the \ and ^ distributions at either EV ($150 or $200). The model estimates, as shown in Table 9, suggest an increase in elicited CEs of approximately $46.25 as the EV of gambles changed from $150 to $200, replicating the usual downward concavity of CEs for positive gambles. The estimates for the / distribution suggest an average CE approximately $2.17 less than those for \ and ^ distributions at an EV of $150; this estimated difference at an EV of $200 declined further to approximately $8.71 (-2.17 + -6.54). The model also included the quadratic and linear arousal effects, but these effects did not interact with the various gamble structure conditions. Therefore, one can interpret the influence of arousal as fairly stable across each gambling condition. From the Table 9 estimates, one notices that the linear effect is nearly zero. Ignoring this linear effect, one is left with a very simple description of the arousal influence, whereby CEs tend to increase approximately $2 for every standardized unit squared increase in arousal (Note: arousal and valence in all models are standardized factor scores based on the entire sample; mean and standard deviation estimates of arousal and valence differ only slightly across males (mean valence = -0.08, s = 1.04; mean arousal = -0.17, s = 1.06) and females (mean valence = 0.13, s = 0.94; mean arousal = 0.061, s = 0.97)). Panel C of Figure 9 depicts the implications of this arousal effect by plotting the predicted monetary differences from average valence and arousal individuals at 1 and 2 standard deviation intervals on each dimension's axis. Negative and positive monetary differences represent more risk-seeking and more risk- averse responses, respectively, relative to individuals at the sample averages of arousal and valence. Because in the male model the only practical affect effect present is quadratic, all individuals above and below the valence axis (where arousal = 0) are predicted to be more risk seeking relative to individuals experiencing average levels of arousal. Importantly, this quadratic arousal effect was only marginally significant (at a conventional α=0.05 level) and did not account for a substantial amount of variation (only 2-4%) in the individual CE responses.

As for females, the final positive gamble model left both gamble structure main effects, but no interactions. The probability structure model estimates (Table 9) suggested an approximate $4.60 and $13.52 lower CEs in the ^ and / distributions, respectively, relative to the \ distribution. The estimates are comparable to those found for males, when considering the marginally significant / by $200 interaction in the male model and the marginally significant ^ main effect in the female model. The female estimate for the EV effect suggested $46.10 increase in CEs, very consistent with the $46.25 estimate produced in the male model. In addition to the gamble structural effects, the female model included an overall linear and quadratic arousal effect and linear valence effect. Unlike the males, the female arousal effects suggested lower CEs as arousal deviated from the mean. The overall valence effect was positive, implicating higher CEs as valence increased. However, there was also a significant interaction between the EV main effect and valence. This effect essentially canceled out the positive influence of valence found in the $150 gambles when assessing responses to the $200 gambles. Panels A and B of Figure 9 display the relative differences in CEs across the affect circumplex. The overall quadratic arousal and linear valence effects accounted for roughly 5-7% of the variance in the $150 gambles, while the influence of these effects alongside the EV by valence interaction explained roughly 2-4% of the variance in $200 gambles.

Table 9. Results from Model Selection Procedure for Positive Gamble Certainty Equivalents Regressed on Current Affect.

		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		149.43	2.37	0.00	163.38	3.96	0.00
Valence		0[a]			5.88	3.19	0.07
Arousal		-0.03	1.66	0.98	-0.13	2.33	0.95
	Arousal by Arousal	1.96	1.03	0.06	-4.55	1.28	0.00
^ Prob Dist.		0[a]			-4.60	2.30	0.05
	by Valence	0[a]			0[a]		
	by Arousal	0[a]			0[a]		
	Arousal by Arousal	0[a]			0[a]		
/ Prob Dist.		-2.17	2.64	0.41	-13.52	2.98	0.00
	by Valence	0[a]			0[a]		
	by Arousal	0[a]			0[a]		
	Arousal by Arousal	0[a]			0[a]		
$200 EV		46.25	2.17	0.00	46.10	2.20	0.00
	by Valence	0[a]			-6.32	2.05	0.00
	by Arousal	0[a]			0[a]		
	Arousal by Arousal	0[a]			0[a]		
	^ by $200	0[a]			0[a]		
	/ by $200	-6.54	3.88	0.09	0[a]		

Note. All valence by arousal interaction terms were nonsignificant and, therefore, constrained to equal 0 in the final models. To conserve space, this constraint does not appear in the table.

[a] Indicates nonsignificant effects constrained to 0 in the final model.

Figure 9. Expected Monetary Difference from Average Arousal and Valence [point (0,0)] Predicted Values in the Positive Gamble Models.

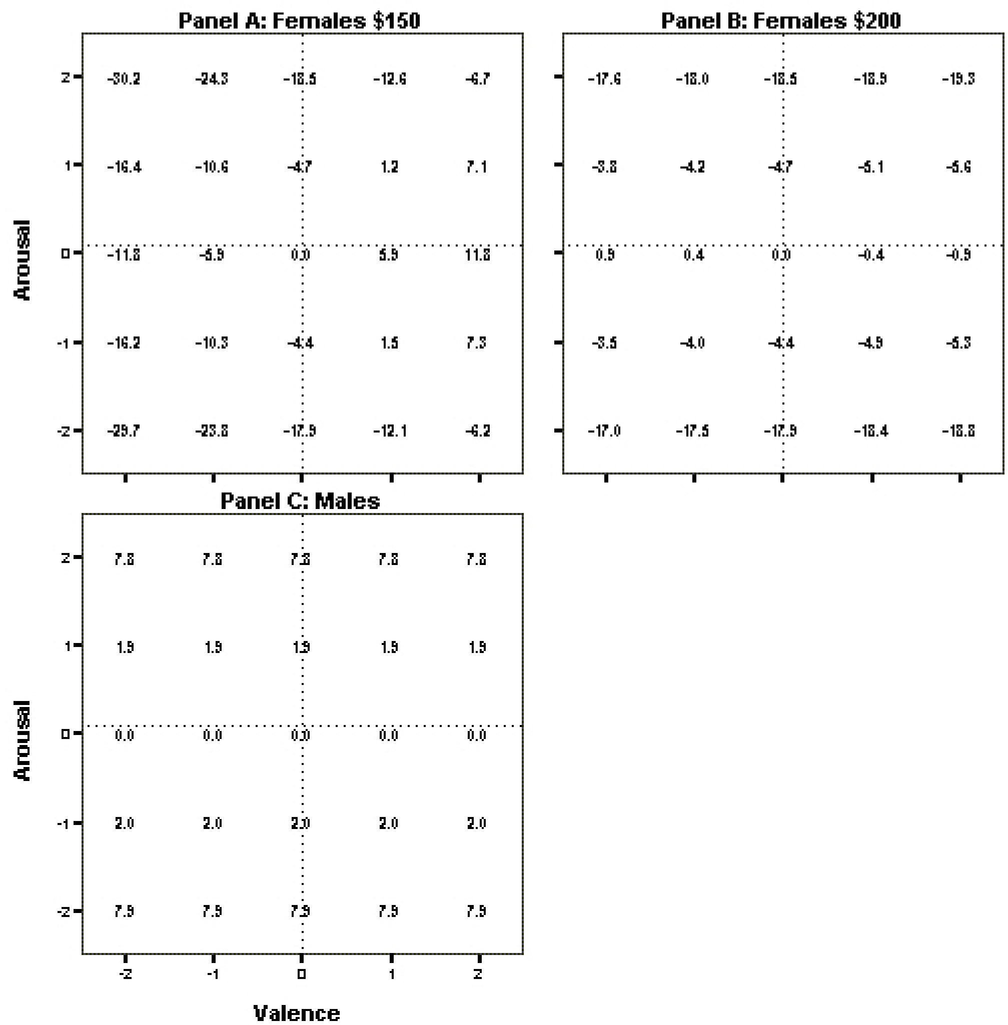


Table 10 contains the model results for the negative gamble models. All negative gamble structure main effects were significant among both genders. The sole significant interaction remaining involved ^ and $200 structures, but this effect only appeared in the female model. The probability structure main effect terms for males suggested lower CEs for both ^ and / distributions relative to the referent \ distributions (roughly a $5.00 difference for both comparisons). Interestingly, while the direction of the / distribution effect is similar across positive and negative gambles (i.e., lower CEs compared to referent), the implications are opposing. Lower CEs for positive gambles reflect more risk averse (or less risk seeking) behavior, while for negative gambles they indicate more risk seeking (less risk aversion).

As for the affect effects, it was the valence by arousal interaction terms that predicted CE estimates this time, and not the quadratic arousal term that was evident in the positive gambles. In the male model, this, marginally significant, overall valence by arousal interaction was the only affect effect present at the end of model reduction. The simple effects of valence and arousal that help define this interaction were both negative. The interaction term, itself, was also negative, suggesting lower slopes for each dimension as the other dimension increased. Panel D of Figure 10 displays the totality of the interaction predictions in terms of relative (to the mean affect vector) monetary differences. There, it is evident that below the valence axis (arousal low) the valence effect is positive, while above the axis (arousal high) the valence effect is negative. This interaction accounted for a very small amount of variation (roughly 1-2%) in the individual CE responses.

For females, the overall valence by arousal interaction term was included because of a significant 3-way interaction involving the ^ distribution and both affect dimensions. This 3-way interaction term was strongly negative, suggesting lower slope estimates for each dimension as the other dimension decreased for ^ gambles, counteracting the slightly positive overall valence by arousal interaction. The configuration of CEs across the affect circumplex was also affected by an interaction between the / distribution and valence, in essence, changing the valence simple effect term for / gambles. Panels A, B, and C of Figure 10 best display the predictive implications of these affect effects. Notice that for the \ distribution, the main influence appears to be a positive valence effect which happened to account for roughly 12 and 7% of the variation in the \$150 and \$200 CE responses, respectively. In the ^ distribution, below an arousal score of 1 (1 standard deviation above the mean), one notices an increasingly positive relationship between valence and CE estimates, while above an arousal score of 1, this relationship becomes negative. The 3-way interaction and the overall effects combined to account for roughly 5 and 7% of the variance in the ^$150 and ^$200 gambles, respectively. Finally, in the / distribution one will find comparable competing influences (in terms of magnitude) from valence and arousal: one positive (valence) and the other negative (arousal). This adjustment to the valence simple effect, combined with the overall effects, explained roughly 2 and 1% of the /$150 and /$200 gamble responses, respectively.

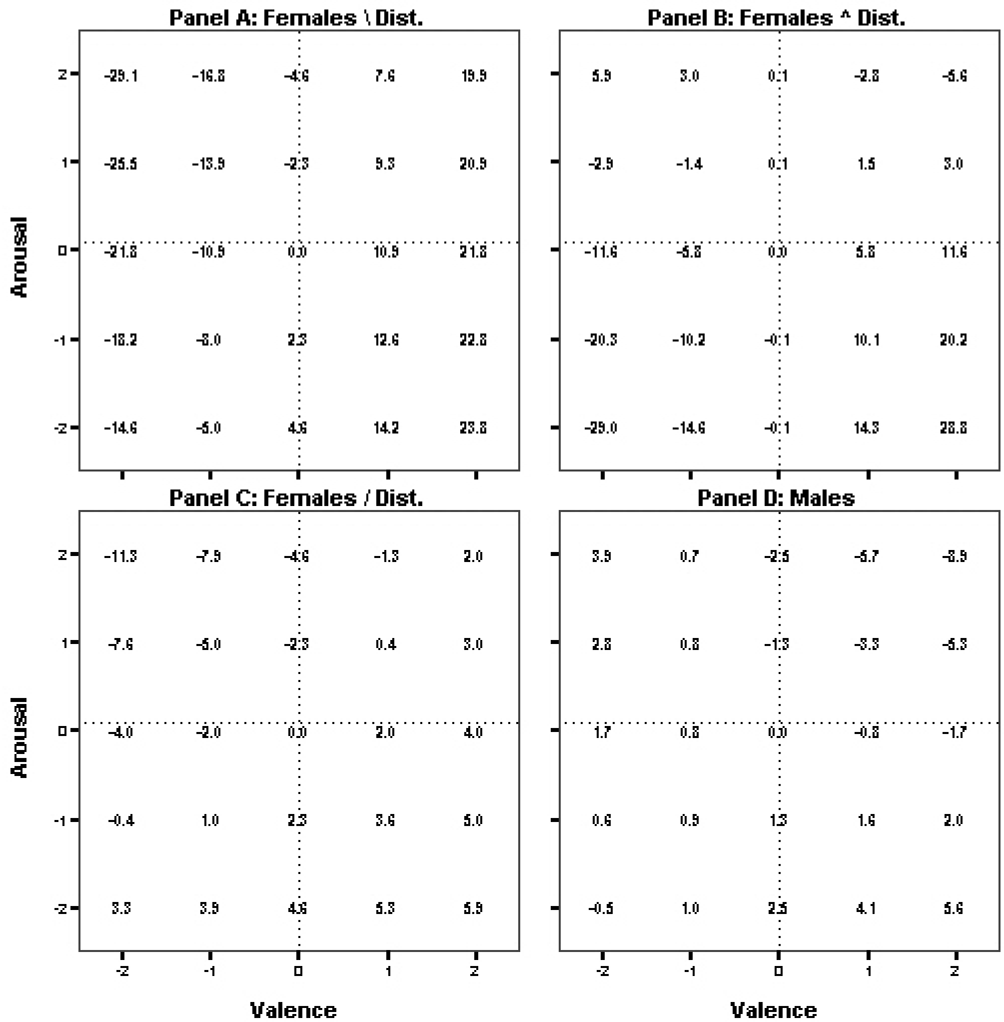
Table 10. Results from Model Selection Procedure for Negative Gamble Certainty Equivalents Regressed on Current Affect.

		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		-140.30	2.28	0.00	-141.60	3.29	0.00
Valence		-0.84	1.56	0.59	10.92	4.18	0.01
Arousal		-1.26	1.50	0.40	-2.30	2.05	0.26
	Valence by Arousal	-1.19	0.66	0.07	0.66	1.74	0.70
^ Prob Dist.		-5.16	2.11	0.01	7.27	3.22	0.02
	by Valence	0[a]			-5.13	2.74	0.06
	by Arousal	0[a]			2.36	1.98	0.23
	by Valence by Arousal	0[a]			-5.00	1.92	0.01
/ Prob Dist.		-5.98	2.41	0.01	-9.70	3.37	0.00
	by Valence	0[a]			-8.92	3.82	0.02
	by Arousal	0[a]			0[a]		
	by Valence by Arousal	0[a]			0[a]		
$200 EV		-47.59	1.78	0.00	-41.93	2.66	0.00
	by Valence	0[a]			0[a]		
	by Arousal	0[a]			0[a]		
	by Valence by Arousal	0[a]			0[a]		
	^ by $200	0[a]			-10.41	4.74	0.03
	/ by $200	0[a]			0[a]		

Note. All quadratic arousal terms were nonsignificant and, therefore, constrained to equal 0 in the final models. To conserve space, this constraint does not appear in the table.

[a] Indicates nonsignificant effects constrained to 0 in the final model.

Figure 10. Expected Monetary Difference from Average Arousal and Valence [point (0,0)] Predicted Values in the Negative Gamble Models.



Summary of Hypothesis 1 Results

The observed pattern of means suggested risk aversion in the negative domain, while in the positive domain, evidence for both risk aversion and risk seeking was found. Interestingly, in both male and female samples and negative and positive domains, the size of the CEs across the probability structures followed the pattern \ ≥ ^ ≥ /, a finding counter to the reflection effect. Importantly, however, only the main effect contrast between the \ and / distributions was both consistently negative and statistical significant, reaching the conventional α=0.05 level in all ±$200 gambles and in all but the three male -$150 gambles. Not surprisingly, the EV main effect contrast was highly significant in all gambles, with raw effects ranging from absolute values of approximately $42 to $48.

The incidental affect measures never accounted for more than 12% of variance in any of the individual CE responses. For males, only marginally significant affect effects remained after model reduction. For positive gambles, the overall quadratic arousal effect suggested somewhat riskier CE estimates for low and high arousal individuals, relative to mean arousal participants. For negative gambles, the overall valence by arousal interaction suggested a slight positive relationship between valence and CEs for those low on arousal, and an even smaller negative relationship between valence and CE for those high on arousal. In the female sample, again terms involving quadratic arousal influences for positive gambles and valence by arousal interactions for negative gambles make appearances in the final models, this time reaching levels of significance. In the positive domain, the quadratic arousal effect suggested, unlike for males, more risk *averse* behaviors for those low and high on arousal, relative to mean arousal. A positive valence main effect was also present among the $150 gambles. In the negative domain, the valence by arousal interaction was mostly evident in the ^ distributed gambles. Similar to males, in these ^ negative gambles, positive valence effects are found for individuals at or below mean levels of arousal and negative valence effects begin to appear for those extremely high on arousal. In the \ distribution, a strong positive valence effect overweighed all other effects, while in the / distribution, small and approximately equal, but opposite directional main effects for valence (positive relationship) and arousal (negative relationship) explained the female model predictions. In sum, the strongest affective effects found in the positive gambles appeared to influence all gambling structures (i.e., overall effects), but did not account for large proportions of variance. This was also true for males in the negative domain, but for females, affect effects mostly explained changes in CE responses across the probability structures (i.e., \, ^, and /). Finally, relative to arousal influences, valence took a backseat in all but the female $150 gambles in the positive domain. For the negative gambles, both valence and arousal appeared to play a role, albeit diminutive.

Hypothesis 2. Current valence and arousal will predict individual differences in anticipated affect.

To begin, descriptive information for each type of anticipated affect (happiness- the proxy for anticipated valence- and surprise- a proxy for arousal) for both the best and worst gamble outcomes were inspected. This information is provided in Tables 11-18 below. For comparative purposes, it may be helpful to revisit the components of each gamble associated with the best and worst outcomes. In terms of monetary outcomes, the \, ^, and / distributions list best outcomes as μ+$100, μ+$100, and μ+$50, respectively. Worst outcomes, in respective order, are μ-$50, μ-$100, and μ-$100. Notice that for a given expected value (μ), the best outcomes of \ and ^ are identical, while the worst outcomes for / and ^ and identical. These similarities in outcomes seem to be apparent in the mean estimates of happiness (e.g., the best happiness responses for

/ and ^ gambles are always very similar). Unfortunately, the design manipulation closely confounds these outcome values with the probabilities associated with best and worst outcomes. The probability of the best and worst outcome for \, ^, and / distributions are 0.10, 0.05, and 0.40 and 0.40, 0.05, and 0.10, respectively. Not surprisingly then, we see the same pattern noted for happiness appear in the surprise responses with similar mean estimates for best \ and ^ outcomes and worst / and ^ outcomes. The patterns observed in the means should appear in the estimates of the gamble structure effects. For example, there should be little need for the effect describing mean differences between the ^ gamble structure and the referent \ structure when assessing happiness and surprise for best outcomes.

Finally, before leaving these descriptive data for the incidental-affect predictive modeling, notice the range of the anticipated valence responses often suggest floor and ceiling effects. In fact, for happiness responses, distributions for all best outcomes exhibited strong ceiling effects, while those for worst outcomes displayed strong floor effects. For surprise responses, ceiling and floor effects were less evident, but the distributions were negatively skewed when probabilities of the extreme outcomes (both best and worst) were lower than 0.40 (the / distributions in the best domain and \ distributions in the worst domain seemed to be unaffected). To account for the distributional censoring in the happiness responses, the models analyzed Probit latent response variables that were associated with categorized outcomes. As with the previous modeling exercise, the error covariance matrix of the new categorical outcomes was unrestrictive. Within each analytic block of happiness outcomes, cutoffs to the original scale were identical (e.g., when analyzing positive best valence, cutpoints

Table 11. Male Descriptive Statistics for Anticipated Valence for Best Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Best Valence	43	19	100	77.30	21.83
Lottery [^,-150] Best Valence	43	23	100	80.74	19.45
Lottery [/,-150] Best Valence	43	26	100	68.88	21.06
Lottery [\,-200] Best Valence	43	25	100	75.33	23.28
Lottery [^,-200] Best Valence	43	20	100	76.09	21.51
Lottery [/,-200] Best Valence	43	27	100	70.02	21.83
Lottery [\,150] Best Valence	43	50	100	87.05	12.64
Lottery [^,150] Best Valence	43	56	100	88.02	13.27
Lottery [/,150] Best Valence	43	57	100	81.16	13.94
Lottery [\,200] Best Valence	43	17	100	85.93	17.27
Lottery [^,200] Best Valence	43	66	100	91.79	10.10
Lottery [/,200] Best Valence	43	57	100	80.30	15.22

Table 12. Male Descriptive Statistics for Anticipated Valence for Worst Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Worst Valence	43	0	45	22.74	14.78
Lottery [^,-150] Worst Valence	43	0	38	12.81	11.97
Lottery [/,-150] Worst Valence	43	0	50	13.88	13.02
Lottery [\,-200] Worst Valence	43	0	44	22.77	14.41
Lottery [^,-200] Worst Valence	43	0	48	12.95	12.78
Lottery [/,-200] Worst Valence	43	0	70	15.09	15.78
Lottery [\,150] Worst Valence	43	0	85	36.58	23.51
Lottery [^,150] Worst Valence	43	0	100	28.70	24.72
Lottery [/,150] Worst Valence	43	0	100	28.07	22.92
Lottery [\,200] Worst Valence	43	0	100	37.05	24.78
Lottery [^,200] Worst Valence	43	0	80	29.44	23.70
Lottery [/,200] Worst Valence	43	0	100	31.00	23.72

for the 6 outcomes were set at scores of 85 and 99), and estimates of the associated latent thresholds were equated across outcomes (e.g., the estimated latent threshold marking scores at or below 85 for the \,$150 best valence outcome was identical to the threshold marking scores at or below 85 for the remaining positive best valence

Table 13. Male Descriptive Statistics for Anticipated Arousal for Best Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Best Arousal	43	21	100	76.23	19.63
Lottery [^,-150] Best Arousal	43	25	100	78.02	19.23
Lottery [/,-150] Best Arousal	43	21	100	56.23	19.49
Lottery [\,-200] Best Arousal	43	30	100	76.42	18.07
Lottery [^,-200] Best Arousal	43	0	100	76.88	21.85
Lottery [/,-200] Best Arousal	43	14	100	53.98	20.49
Lottery [\,150] Best Arousal	43	47	100	79.05	15.73
Lottery [^,150] Best Arousal	43	40	100	81.47	17.57
Lottery [/,150] Best Arousal	43	0	100	59.47	21.77
Lottery [\,200] Best Arousal	43	16	100	80.95	18.14
Lottery [^,200] Best Arousal	43	50	100	87.88	13.57
Lottery [/,200] Best Arousal	43	29	100	59.74	18.68

Table 14. Male Descriptive Statistics for Anticipated Arousal for Worst Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Worst Arousal	43	0	76	43.67	17.30
Lottery [^,-150] Worst Arousal	43	0	100	66.09	31.48
Lottery [/,-150] Worst Arousal	43	0	100	61.74	28.72
Lottery [\,-200] Worst Arousal	43	0	94	44.70	21.86
Lottery [^,-200] Worst Arousal	43	0	100	64.09	30.16
Lottery [/,-200] Worst Arousal	43	0	100	63.93	29.64
Lottery [\,150] Worst Arousal	43	0	72	46.67	17.49
Lottery [^,150] Worst Arousal	43	0	100	63.81	30.20
Lottery [/,150] Worst Arousal	43	0	100	61.16	26.66
Lottery [\,200] Worst Arousal	43	0	71	46.12	17.19
Lottery [^,200] Worst Arousal	43	0	100	61.77	26.79
Lottery [/,200] Worst Arousal	43	0	100	59.49	26.00

outcomes). Fixing thresholds to be equal and allowing all but one latent response residual and mean to be free produced a more meaningful interpretation of mean differences in the latent response variables (preserving the integrity of a common

Table 15. Female Descriptive Statistics for Anticipated Valence for Best Gamble. *Outcome*

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Best Valence	55	0	100	77.15	23.30
Lottery [^,-150] Best Valence	55	0	100	74.75	25.59
Lottery [/,-150] Best Valence	55	13	100	70.13	23.73
Lottery [\,-200] Best Valence	55	21	100	76.05	22.24
Lottery [^,-200] Best Valence	55	15	100	72.65	25.31
Lottery [/,-200] Best Valence	55	4	100	73.55	22.62
Lottery [\,150] Best Valence	55	2	100	88.20	16.63
Lottery [^,150] Best Valence	55	56	100	90.96	11.82
Lottery [/,150] Best Valence	55	54	100	83.78	14.63
Lottery [\,200] Best Valence	55	15	100	90.65	14.71
Lottery [^,200] Best Valence	55	59	100	90.78	12.18
Lottery [/,200] Best Valence	55	22	100	80.76	18.24

Table 16. Female Descriptive Statistics for Anticipated Valence for Worst Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Worst Valence	55	0	74	23.82	17.10
Lottery [^,-150] Worst Valence	55	0	100	17.75	19.32
Lottery [/,-150] Worst Valence	55	0	73	17.42	14.97
Lottery [\,-200] Worst Valence	55	0	73	24.42	18.30
Lottery [^,-200] Worst Valence	55	0	84	13.04	15.67
Lottery [/,-200] Worst Valence	55	0	91	12.53	16.37
Lottery [\,150] Worst Valence	55	0	100	43.29	22.83
Lottery [^,150] Worst Valence	55	0	96	32.55	22.51
Lottery [/,150] Worst Valence	55	0	100	36.22	23.29
Lottery [\,200] Worst Valence	55	0	100	41.93	23.65
Lottery [^,200] Worst Valence	55	0	100	37.29	24.75
Lottery [/,200] Worst Valence	55	0	100	38.62	24.11

original scale; see Mehta, Neale, & Flay, 2004). Restricting the number of thresholds to two ensures that the estimated univariate and bivariate proportions equal their observed counterparts (Chi-square fit statistic = 0). Anticipated surprise outcomes were modeled

Table 17. Female Descriptive Statistics for Anticipated Arousal for Best Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Best Arousal	55	26	100	78.45	20.01
Lottery [^,-150] Best Arousal	55	0	100	74.13	22.72
Lottery [/,-150] Best Arousal	55	16	100	58.31	19.79
Lottery [\,-200] Best Arousal	55	32	100	76.22	16.58
Lottery [^,-200] Best Arousal	55	18	100	73.95	20.88
Lottery [/,-200] Best Arousal	55	5	91	57.58	20.26
Lottery [\,150] Best Arousal	55	20	100	81.91	16.69
Lottery [^,150] Best Arousal	55	25	100	83.82	17.42
Lottery [/,150] Best Arousal	55	21	100	63.93	17.95
Lottery [\,200] Best Arousal	55	30	100	84.75	15.66
Lottery [^,200] Best Arousal	55	7	100	80.93	21.45
Lottery [/,200] Best Arousal	55	4	100	61.22	21.34

Table 18. Female Descriptive Statistics for Anticipated Arousal for Worst Gamble Outcome.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Worst Arousal	55	0	100	40.35	20.83
Lottery [^,-150] Worst Arousal	55	0	100	64.05	31.94
Lottery [/,-150] Worst Arousal	55	0	100	65.24	27.60
Lottery [\,-200] Worst Arousal	55	0	92	38.09	18.94
Lottery [^,-200] Worst Arousal	55	0	100	64.05	32.38
Lottery [/,-200] Worst Arousal	55	0	100	62.00	29.54
Lottery [\,150] Worst Arousal	55	0	100	37.82	20.23
Lottery [^,150] Worst Arousal	55	0	100	59.27	29.56
Lottery [/,150] Worst Arousal	55	0	100	63.24	25.71
Lottery [\,200] Worst Arousal	55	0	100	40.55	20.59
Lottery [^,200] Worst Arousal	55	0	100	63.25	29.20
Lottery [/,200] Worst Arousal	55	0	100	63.18	25.90

as continuous variables, but as with the earlier CE models, the standard errors used for coefficient testing were robust to non-normality.

Anticipated Valence/Happiness for Best Gamble Outcomes

Model testing and reduction results for anticipated valence given best outcomes are listed in Table 19. Overall, there is little evidence to suggest strong associations between the incidental affect dimensions and the anticipated valence item, yet, in all but the Male positive gamble model, marginally significant effects were present. For males, the negative gamble model did find a marginally significant overall quadratic arousal effect. The effect suggested an increased probability for higher anticipated valence responses as incidental arousal deviated farther from its mean (the mean of the latent Normal response distribution approaches or exceeds the threshold for the highest ordered category), and, combined, these effects accounted for between 16% (for \150) and 37% (for /150) of the latent response variable variance. Panel A of Figure 11 describes the impact of these effects by plotting the predicted difference in the latent response at various points on the 2-dimensional circumplex of affect. These are relative differences, indicating latent response change as incidental affect moves outward from the origin (i.e., away from average incidental valence and arousal). As the plotted values increase, the probability for the lowest category (<= 85) declines, relative to those at the origin, while the probability of the highest category (right censored scores of 100) rises. (Note: the probability of the middle category, 85 < x < 100, will increase as the latent response mean rises to the mid-point of the thresholds, but then decrease once the latent mean exceeds this mid-point.) A marginally significant quadratic arousal effect was also found among positive / gambles for females. Again, the effect suggested an increased probability of higher reported anticipated valence as incidental arousal deviated farther from the mean, accounting for 7% of the \150 and 9% of the

\200 latent response variance (see Figure 11 for visual depiction). In the negative domain, females exhibited a marginally significant 3-way EV by valence by arousal interaction. The simple effects for valence and arousal in the EV $200 gambles were in opposite directions (positive for valence and negative for arousal). The interaction term was positive suggesting higher slope estimates for each dimension as the other dimension increases. A visual summary of these incidental affect effects is presented in Figure 12 below. Combined, the 3-way interaction and its associated lower order terms accounted for 9, 19, and 18% of the latent response variance for the respective \, ^, and / $200 gambles.

As anticipated in the introduction to this hypothesis, very few significant gamble structure effects were found. Aside from the necessary inclusion of the nonsignificant simple EV $200 effect in the Female model (left in the model because of the EV by valence by arousal interaction), the negative gamble structure effects were not strong enough to warrant model inclusion. In these ordered categorical models, only latent residual effects were needed to effectively model the observed probability response distributions. In the positive gambles, the change in expected value did not seem to matter much, while the change in the gamble's payoff distribution was statistically significant for both genders. Both males and females reported higher probabilities of low anticipated valence for the / distribution relative to the referent \ distribution. These effects accounted for a male -0.46 (/150) and -0.41 (/200) and a female -0.56 (/150) and -0.64 (/200) standard deviation shift in the latent response means. Males also reported higher probabilities of high anticipated valence in the ^ distribution relative to the \

distribution, an effect accounting for 0.25 (^150) and 0.28 (^200) standard deviation shifts in the latent response means.

Table 19. Model Effects for Best Outcome Anticipated Valence.

Valence: Best Outcome for Positive Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		0[a]			0[a]		
Arousal		0[b]			-0.13	0.13	0.31
	Arousal by Arousal	0[b]			0.09	0.11	0.42
^ Prob Dist.		0.28	0.13	0.03	0[b]		
/ Prob Dist.		-0.87	0.45	0.05	-0.65	0.20	0.00
	by Arousal	0[b]			-0.11	0.09	0.23
	Arousal by Arousal	0[b]			0.12	0.07	0.06
Thresholds							
<= 85		-0.27	0.22	0.21	-0.44	0.17	0.01
> 99		0.58	0.22	0.01	0.25	0.16	0.12

Valence: Best Outcome for Negative Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		0[b]			0[b]		
Valence		0[b]			0.17	0.13	0.21
Arousal		0.22	0.15	0.14	-0.10	0.13	0.46
	Valence by Arousal	0[b]			0.02	0.12	0.87
	Arousal by Arousal	0.25	0.14	0.08	0[b]		
$200 EV		0[b]			-0.07	0.11	0.50
	by Valence	0[b]			0.08	0.08	0.35
	by Arousal	0[b]			-0.15	0.09	0.09
	Valence by Arousal	0[b]			0.12	0.07	0.08
Thresholds							
<= 85		0.52	0.19	0.01	0.19	0.13	0.16
> 99		0.95	0.27	0.00	0.68	0.22	0.00

Note. Effects that were dropped from both male and female models are not shown.

[a] Intercept terms were constrained equal to 0 for identification purposes.

[b] Constrained equal to zero.

Figure 11. Expected Latent-Response-Scale Difference between Anticipated Valence and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Positive Best Outcome Gamble Models.

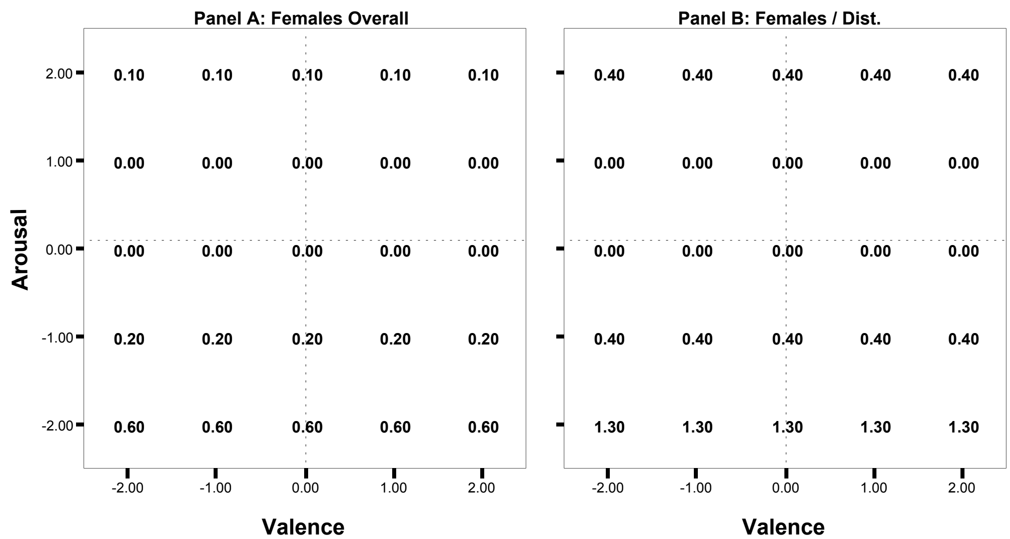
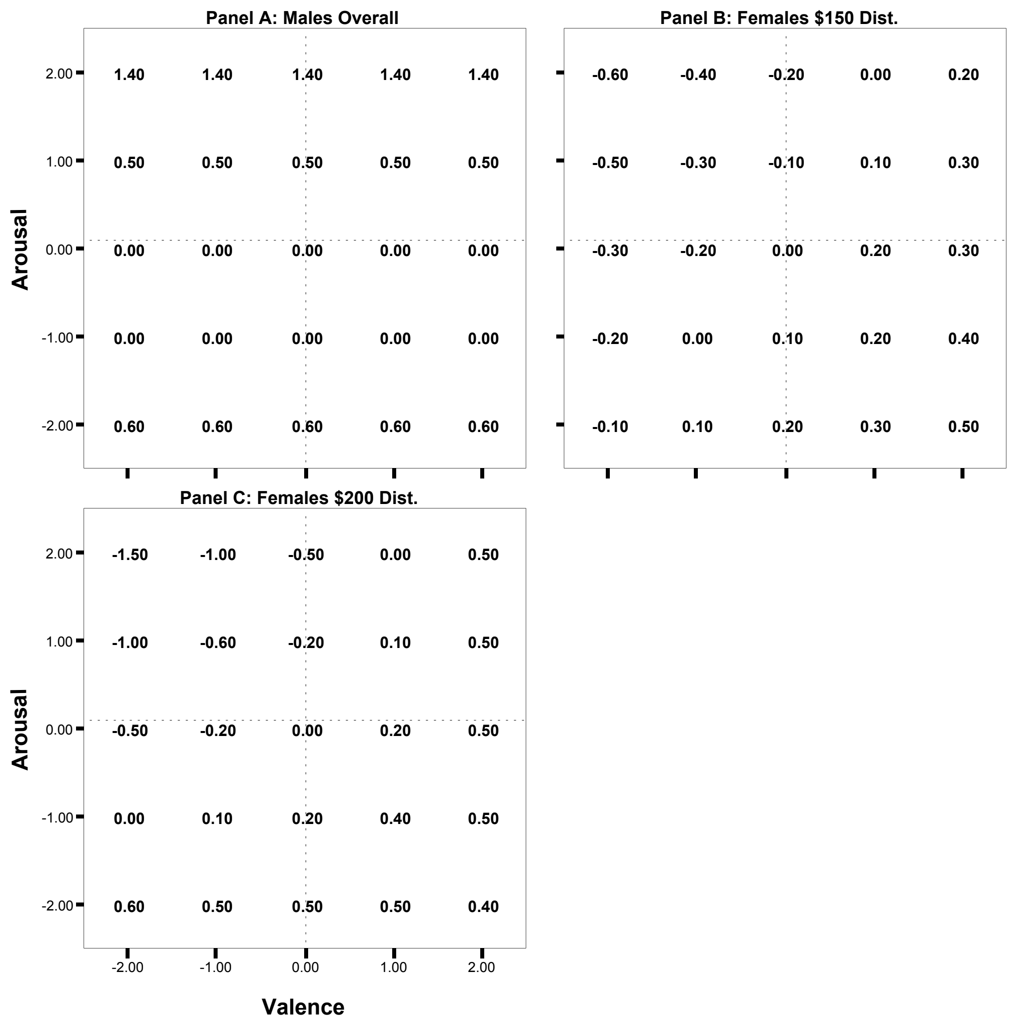


Figure 12. Expected Latent-Response-Scale Difference between Anticipated Valence and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Negative Best Outcome Gamble Models.



Anticipated Valence/Happiness for Worst Gamble Outcomes

Reports of valence for the worst outcome of each presented gamble did not show support for incidental affective influences. All affect predictors were dropped from the final models described in Table 20. The structural features of the gambles did play a role, however, verifying the visually noted patterns in the earlier descriptive tables (Tables 12 & 16). As with the positive gambles, the anticipated valence did not seem to depend as much on the change in EV as it did changes in the payoff/loss distributions. The EV factor was only significant in the negative Female gambles, where the probability for low valence responses increased as gambles changed from -$150 to -$200 expected losses. This effect accounted for a -0.26, -0.37, and -0.39 standard deviation shift in the latent response means for the \, ^, and / -$200 gambles, respectively. Lower probabilities for low valence responses were also evident when comparing the ^ and / distributions to the \ distribution. Within each gender by outcome-sign (positive versus negative) grouping, the size of the ^ and / effects were very similar across gambles, accounting for anywhere from a -0.43 (female ^150) to -3.08 (male ^150) standard deviation shift in the latent response mean.

Table 20. Model Effects for Worst Outcome Anticipated Valence.

Valence: Worst Outcome for Positive Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		0[a]			0[a]		
^ Prob Dist.		-0.73	0.18	0.00	-0.48	0.21	0.02
/ Prob Dist.		-0.48	0.17	0.01	-0.45	0.25	0.07
Thresholds							
= 0		-0.96	0.24	0.00	-1.62	0.26	0.00
> 25		-0.72	0.19	0.00	-0.89	0.19	0.00

Valence: Worst Outcome for Negative Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		0[a]			0[a]		
^ Prob Dist.		-0.48	0.13	0.00	-0.53	0.12	0.00
/ Prob Dist.		-0.48	0.12	0.00	-0.53	0.12	0.00
$200 EV		0[b]			-0.23	0.06	0.00
Thresholds							
= 0		-0.74	0.19	0.00	-0.95	0.20	0.00
> 25		-0.10	0.27	0.70	-0.24	0.14	0.08

Note. Effects that were dropped from both male and female models are not shown.

[a] Intercept terms were constrained equal to 0 for identification purposes.

[b] Constrained equal to 0.

Anticipated Arousal/Surprise for Best Gamble Outcomes

Incidental affect appeared to have a wide range of influences on anticipated arousal as shown in Table 21. Among males, incidental arousal was most important in both positive and negative gambles, with an overall quadratic effect suggesting higher anticipated surprise as incidental arousal deviated farther from the mean. This quadratic effect was tempered, however, in the ^ gambles. Negative gamble arousal effects for males were also accompanied by a positive overall incidental valence effect. Panels A-B from Figures 13 and 14 visually depict this mixture of incidental affect influences relative to the average of each dimension. For females, both types of higher-order affect effects, quadratic arousal and the valence by arousal interaction, remained in the final models. In the positive domain, an overall negative valence by arousal interaction and positive quadratic arousal effect reversed directions in the / distribution. For negative gambles, a small overall positive interaction and negative quadratic effect became a large negative interaction and positive quadratic effect for ^ gambles. Panels C and D of Figures 13 and 14 below summarize these effects. Despite the number of affect predictors kept in the final models, the amount of anticipated arousal variation explained was relatively small, accounting for 4-14% and 10-17% in male positive and negative outcomes, respectively, and 2-6% and 1-9% in females, respectively.

Much like the anticipated valence models above, these models required few gamble structure effects when estimating mean responses. Only the male responses to positive gambles required more than an intercept and the two probability distributions effects (^ and /). Even in the male positive gamble instance, the additional EV main effect (Cohen d = 0.23, 0.32, and 0.24 in the \, ^, and / distributions, respectively) and

EV by / interaction were relatively small; moreover, the interaction mostly canceled out the main effect for the / \$200 distribution (leaving a Cohen $d = 0.01$). As with the best outcome valence responses, the differences due to probability structure were most evident in the / effect. The / distribution accounted for an approximate 14 to 21 unit decrease in anticipated surprise when compared to the \ distribution, effects that were highly significant (Cohen d ranging from -0.70 to -1.11). The ^ comparison to \ distribution was only significant in the male positive gamble model, where an approximate 7 unit increase in anticipated surprise was predicted (Cohen $d = 0.39$ for ^150 and $d = 0.49$ for ^200). Other ^ effects were included because of their association with higher order interaction terms.

Table 21. Model Effects for Best Outcome Anticipated Arousal.

Anticipated Arousal: Best Outcome for Positive Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		75.72	2.52	0.00	81.47	2.50	0.00
Valence		0[a]			0.31	2.03	0.88
Arousal		4.28	2.03	0.04	-1.68	1.68	0.32
	Valence by Arousal	0[a]			-3.15	2.03	0.12
	Arousal by Arousal	2.72	1.23	0.03	3.23	1.44	0.02
^ Prob Dist.		6.75	1.58	0.00	0[a]		
	by Arousal	-1.11	1.40	0.43	0[a]		
	Arousal by Arousal	-2.11	0.78	0.01	0[a]		
/ Prob Dist.		-18.71	2.98	0.00	-14.80	2.53	0.00
	by Valence	0[a]			1.75	2.36	0.46
	by Arousal	0[a]			1.04	2.11	0.62
	Valence by Arousal	0[a]			5.60	2.26	0.01
	Arousal by Arousal	0[a]			-6.76	1.78	0.00
$200 EV		4.33	1.64	0.01	0[a]		
	^ by $200	0[a]			0[a]		
	/ by $200	-4.11	2.26	0.07	0[a]		

Anticipated Arousal: Best Outcome for Negative Gambles							
		Males			Females		
Main Effects	Interactions with Main Effects	Est	SD	P-Val	Est	SD	P-Val
Intercept		73.22	2.73	0.00	77.11	2.57	0.00
Valence		3.34	1.62	0.04	0.17	2.40	0.94
Arousal		5.99	1.81	0.00	-2.45	2.07	0.24
	Valence by Arousal	0[a]			1.48	2.54	0.56
	Arousal by Arousal	3.81	1.29	0.00	-0.80	1.86	0.67
^ Prob Dist.		2.87	2.16	0.18	-4.94	2.69	0.07
	by Valence	0[a]			-2.16	2.12	0.31
	by Arousal	0.51	2.05	0.80	-0.17	1.59	0.92
	Valence by Arousal	0[a]			-7.48	2.24	0.00
	Arousal by Arousal	-1.45	0.74	0.05	4.67	1.70	0.01
/ Prob Dist.		-21.04	2.84	0.00	-18.56	2.81	0.00

Note. Effects dropped from both male and female models not shown. [a] Constrained = 0.

Figure 13. Expected Difference between Anticipated Arousal and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Positive Best Outcome Gamble Models.

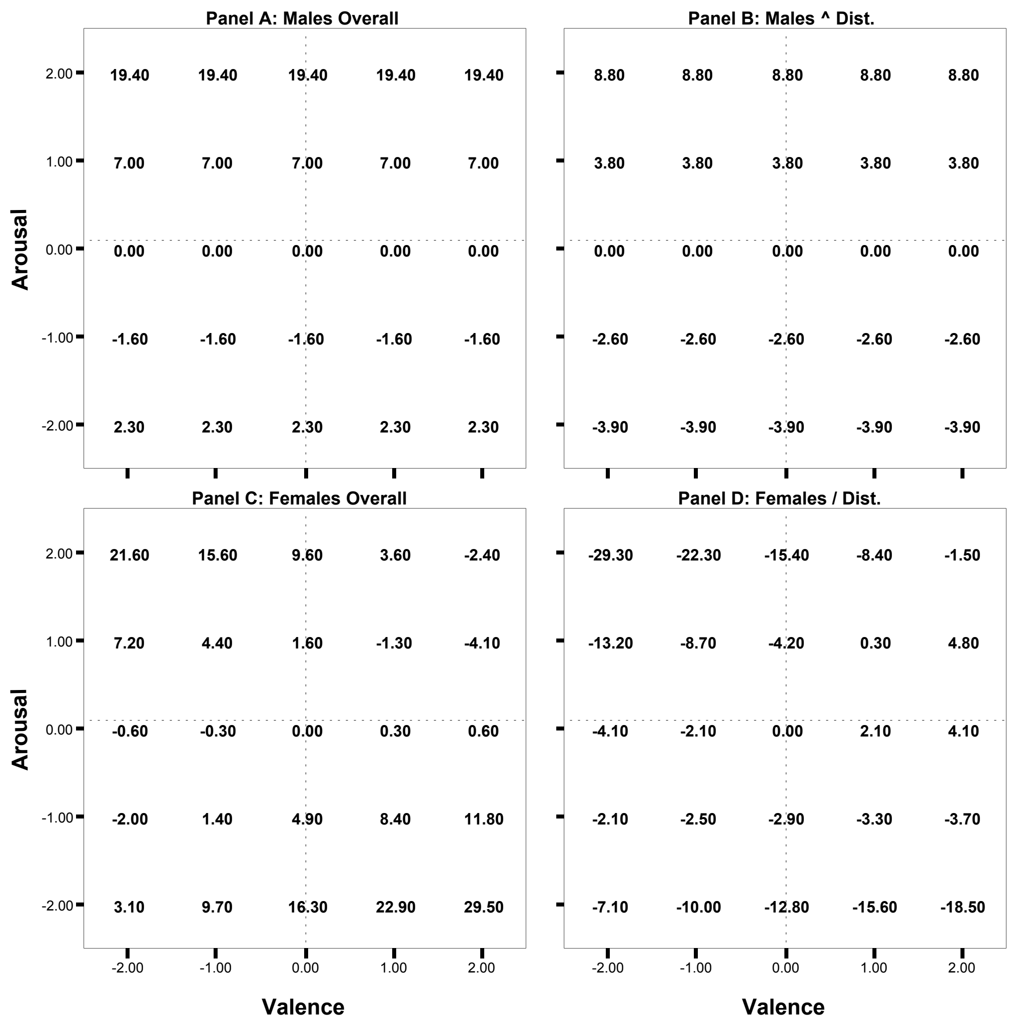
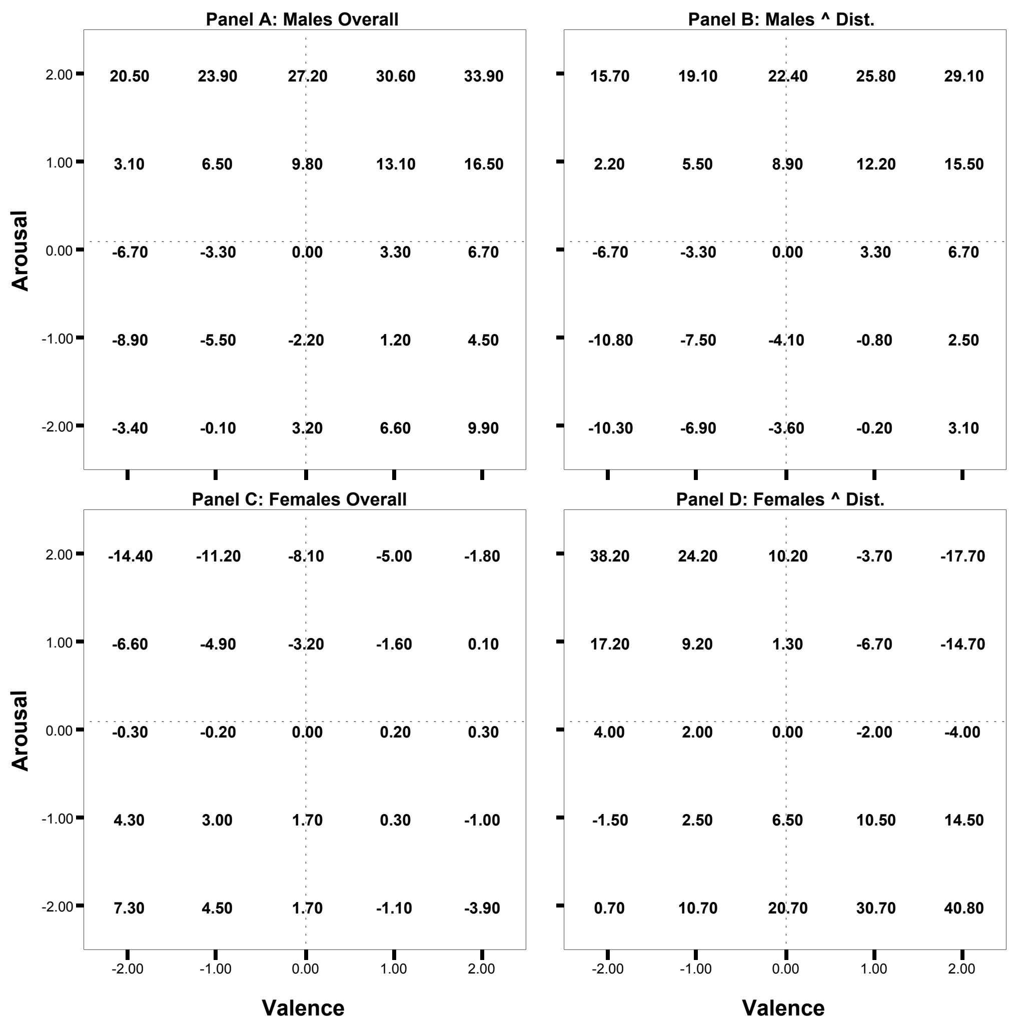


Figure 14. Expected Difference between Anticipated Arousal and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Negative Best Outcome Gamble Models.



Anticipated Arousal/Surprise for Worst Gamble Outcomes

Incidental affect effects on anticipated arousal for worst outcomes were similar to those observed for best outcome arousal (see Table 22). Male responses again showed stronger relationships with arousal than valence. In the positive domain, a marginally significant overall quadratic arousal effect suggested lower surprise as incidental arousal deviated farther from the mean. This effect was accompanied by a significant and positive overall main effect for valence. Combined, these incidental affect influences accounted for anywhere from 5 to 15% of the response variance. Panel A of Figure 15 displays the expected anticipated surprise in relation to average levels of incidental valence and arousal for these positive gambles. In the negative domain, another negative quadratic arousal effect survived model reduction, but took shape mostly in the ^ distribution. An overall positive valence effect was also present in this model. Unlike the positive domain, though, this effect heightened in the \ distribution. Combined these effects accounted for 5 to 12% of the variance in responses. Panels A-C of Figure 16 exhibit the anticipated affect predictions relative to mean incidental affect. On the female side of Table 22, both higher order incidental affect terms make an appearance. In the positive gambles, the quadratic arousal effect becomes noticeably positive in the ^ and / distributions. The valence by arousal interaction, however, becomes significantly negative in the \ distribution, while somewhat nonexistent elsewhere. Lastly, evidence for a fairly substantial simple effect due to arousal was essentially erased in the $200 gambles. Combined, these effects accounted for 4 to 11% of the total variance in worst outcome surprise responses. Panels B-G of Figure 15 provide a visual depiction of these effects. In the negative domain, the higher order effects had the same pattern with positive quadratic arousal influences in ^ and / gambles alongside a negative valence by arousal interaction in the / distribution. These effects accounted for 3 to 9% of the response variation. Panels D-E of Figure 16 depict these influences relative to the mean levels of incidental affect.

As with the best outcome arousal, worst outcome arousal was least affected by the change in EV and most affected by the probability changes. This time, however, ^ and / distributions both differed significantly from the \ distribution and in the same direction. In line with the earlier descriptive table comments (see Tables 14 and 18), the ^ and / responses were very similar to one another and on average were approximately 13 to 24 units higher on anticipated arousal (Cohen *d* ranged from 0.45 to 0.81). This same pattern was noted for the worst outcome valence responses.

Table 22. Model Effects for Worst Outcome Arousal.

Anticipated Arousal: Worst Outcome for Positive Gambles

Main Effects	Interactions with Main Effects	Males Est	Males SD	Males P-Val	Females Est	Females SD	Females P-Val
Intercept		46.49	2.90	0.00	39.68	2.80	0.00
Valence		3.71	1.55	0.02	0.46	1.72	0.79
Arousal		-2.22	2.70	0.41	4.80	2.40	0.05
	Valence by Arousal	0[a]			0.46	2.27	0.84
	Arousal by Arousal	-2.81	1.64	0.09	-2.41	2.38	0.31
^ Prob Dist.		15.76	3.61	0.00	16.09	6.05	0.01
	by Arousal	0[a]			-4.74	4.37	0.28
	Arousal by Arousal	0[a]			7.29	4.36	0.09
/ Prob Dist.		13.18	3.05	0.00	16.07	4.80	0.00
	by Valence	0[a]			2.40	1.76	0.17
	by Arousal	0[a]			-2.16	3.55	0.54
	Valence by Arousal	0[a]			-5.56	2.00	0.01
	Arousal by Arousal	0[a]			9.99	3.28	0.00
		0[a]					
$200 EV		0[a]			2.47	1.73	0.15
	by Arousal	0[a]			-4.85	2.01	0.02

Anticipated Arousal: Worst Outcome for Negative Gambles

Main Effects	Interactions with Main Effects	Males Est	Males SD	Males P-Val	Females Est	Females SD	Females P-Val
Intercept		46.49	2.90	0.00	39.36	2.43	0.00
Valence		3.40	1.71	0.05	-1.94	2.45	0.43
Arousal		-0.51	3.04	0.87	5.77	2.74	0.04
	Valence by Arousal	0[a]			-0.52	2.89	0.86
	Arousal by Arousal	-1.68	2.03	0.41	-0.37	1.90	0.85
^ Prob Dist.		24.47	4.07	0.00	20.60	5.27	0.00
	by Arousal	-0.84	2.42	0.73	-3.91	3.75	0.30
	Arousal by Arousal	-4.24	1.39	0.00	5.74	3.24	0.08
/ Prob Dist.		18.24	2.95	0.00	19.49	4.76	0.00
	by Valence	3.75	1.63	0.02	-0.10	2.34	0.97
	by Arousal	0[a]			1.05	3.14	0.74
	Valence by Arousal	0[a]			-4.55	1.76	0.01
	Arousal by Arousal	0[a]			7.46	2.99	0.01

Note. Effects that were dropped from both male and female models are not shown.

[a] Constrained equal to 0.

Figure 15. Expected Difference between Anticipated Arousal and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Positive Worst Outcome Gamble Models.

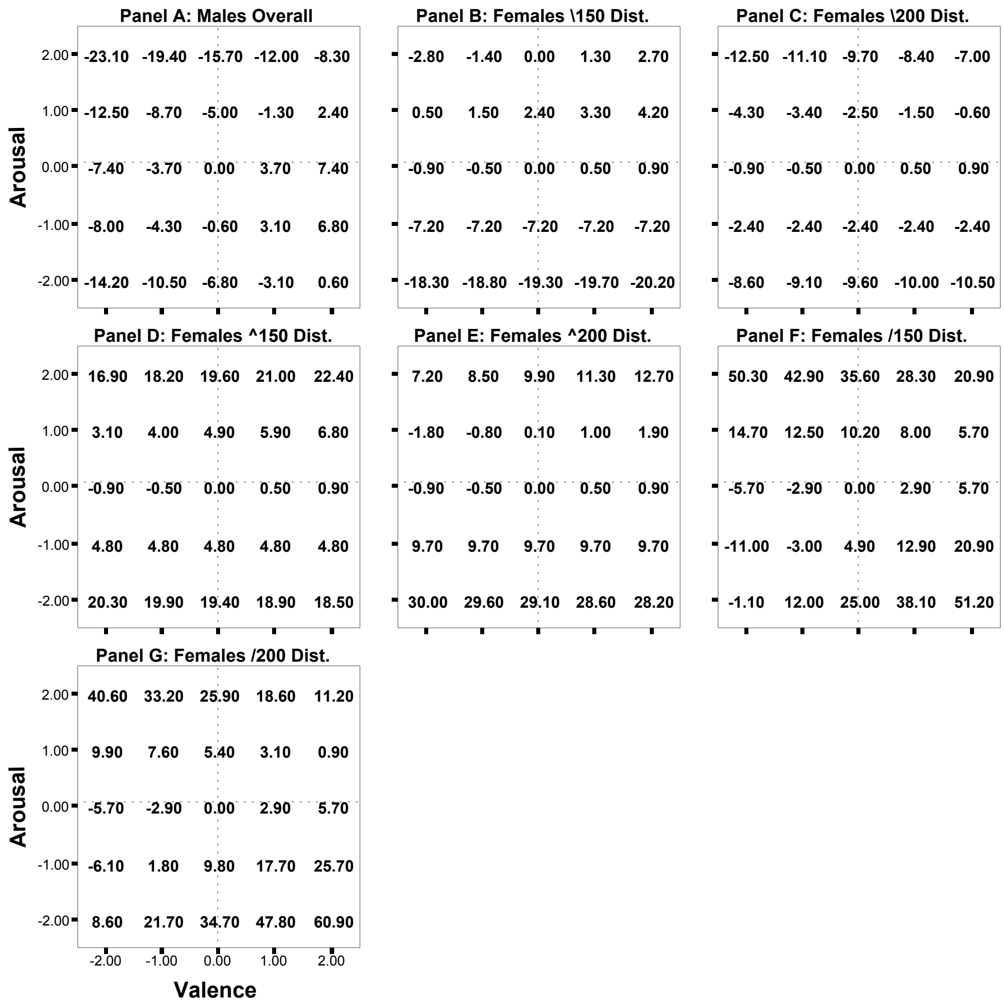
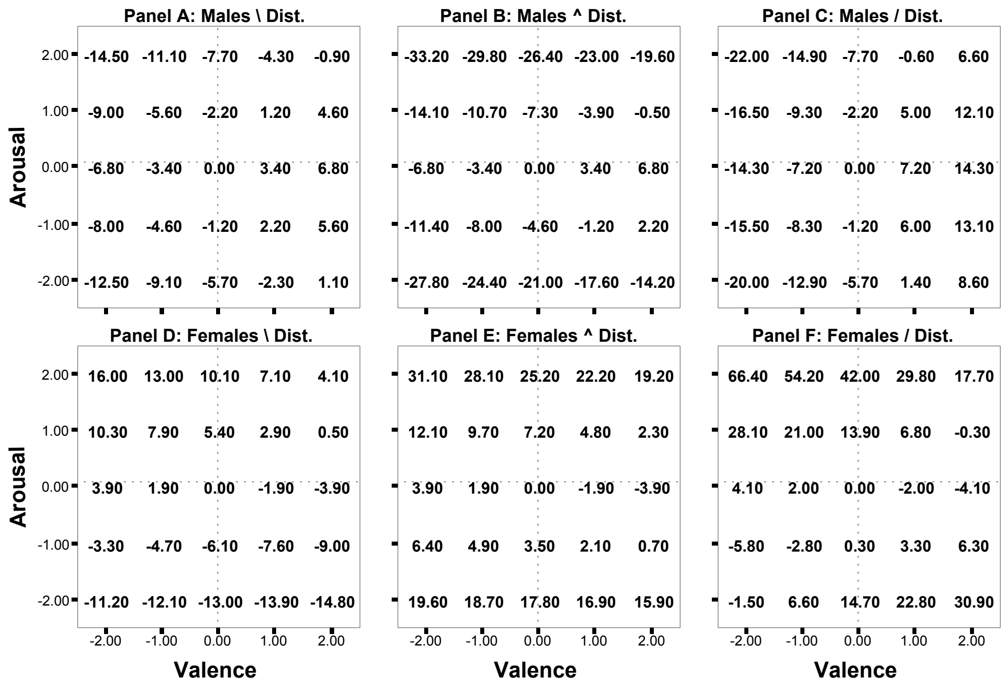


Figure 16. Expected Difference between Anticipated Arousal and Predicted Values for Average Incidental Arousal and Valence [point (0,0)] in the Negative Worst Outcome Gamble Models.



Summary of Hypothesis 2 Results

As noted in the descriptive introduction to this section, average responses of expected (anticipated) valence and arousal were similar in the best and worst outcome conditions. In the best condition, responses to the \ and ^ distributed gambles were closely related, while in the worst condition, the ^ and / distributed gambles elicited more similar feelings. No strong differences were visible in the means of the $150 and $200 expected value gambles independent of the probability distribution changes. These patterns played out in the modeling exercises that followed, with strong influences evident for the / gamble compared to the \ gambles in the positive domain, and strong reasonably similar differences between the referent \ gamble and both the ^ and / gambles in the negative domain. EV effects were rarely included as more than simple effects accompanying higher order interactions. Only female worst outcome valence and male best outcome arousal (for \ and ^ distributed gambles) appeared to be influenced strongly by this manipulation. Consideration of the patterns of expected affect across the gamble structures is covered in more depth under Hypothesis 3.

As for the regression of expected affect on incidental affect, much like the regression of CE on incidental affect, effects were small and diverse across gender. Males tended to have less complex final models. For expected valence, only one incidental affect effect surfaced, an overall quadratic arousal influence for negative best outcomes. The implication of the effect was greater expected valence among those extremely high or low on arousal. Quadratic arousal effects also dominated the males' expected arousal models. For best outcomes, an overall quadratic arousal suggested greater arousal for those high on arousal, an effect tempered somewhat in the ^ gambles. For worst outcomes, overall quadratic arousal effects suggested less expected arousal for those on the extreme ends of incidental arousal, but particularly for those high on incidental arousal. This effect was exacerbated in the negative gambles. There were also positive incidental valence main effects in the male models for negative best expected arousal and both positive and negative worst expected arousal. The quadratic arousal effects are intriguing, particularly for the expected arousal models. Combined, they suggest that those high on incidental arousal tend to anticipate greater arousal after receipt of best outcomes and lower arousal after receipt of worst outcomes.

Among females, quadratic arousal again played a key role for best outcome expected valence, but this time in the positive models. The effect suggested greater valence among those on the extreme end of incidental arousal, but particularly those low on incidental arousal and primarily for the / gambles. For negative best expected valence, an incidental valence by arousal interaction was observed for the EV $200 gambles. The overriding result of this interaction was lower expected valence for those low on both incidental arousal and valence (those in the upper left quadrant of Figure 12). As with males, no incidental affect effects were present in the worst expected valence models. In the best outcome expected arousal models, both quadratic arousal and the valence by arousal interactions took center stage. In the positive gambles, these overall higher order effects resulted in greater expected arousal for those either high in both incidental arousal and valence or low in both. This effect reversed, however, in the / gambles, with those high or low in both reporting lower expected arousal. In the negative gambles, the higher order effects took shape mostly in the ^ gambles, with strong positive valence effects for those low on incidental arousal and strong negative valence effects for those high on incidental arousal. These effects led to much higher expected arousal among those either high on both arousal and valence or low on both. Among the worst outcome expected arousal models, again higher order effects were the story. However, the implications of the effects were tremendously diversified across the 6 types of positive and negative gambles, producing different effects in nearly all gambles (see Figures 15 and 16 for visual depictions).

In sum, as with the CE regression exercise, the incidental affect effects for males were largely overall effects, whereas for females, they tended to be specific to particular types of gamble structures. For males, incidental arousal was the more predictive of the two affect dimensions, whereas for females, a complex interplay between incidental arousal and valence was more often the case. Finally, very few incidental affect effects were found in the expected valence models, compared to those of expected arousal; in fact, no effects were found for expected valence of worst outcomes. Yet, importantly, expected valence was categorized for the analysis in order to accommodate obvious signs of ceiling and floor effects. Expected arousal models, on the other hand, used all observed intervals to determine predictive models. The lack of measurement precision induced from the categorization process for expected valence may have much to do with the smaller number of observed incidental affect effects.

Hypothesis 3. Expected affect will mediate the influence of current affect on choice preference.

Before analysis, responses were inspected for obvious outliers, and several were found among the valence responses to the 12 monetary amounts presented. In all but one situation, responses to adjacent monetary values suggested either an accidental miscoding on the wrong end of the scale or misidentified losses or gains (e.g., scores of 0=Happy for a loss of $300 may have been intended to be 100=Unhappy or the word “loss” may have been overlooked and the listed amount assumed a gain). Because it was impossible to decipher the source of these errors, these outliers were simply recoded as missing. For one individual, all adjacent monetary responses actually corresponded, implicating the error was most likely an inadvertent use of the response scale. For this individual, the responses were recoded as 100 minus the original response.

Implicitly, Hypothesis 3 implicates a direct relationship between expected affect and the CE responses investigated under Hypothesis 1. Before considering the linkage between incidental affect effects on CE and expected affect, one may first wish to broadly explore the implicated direct relationship between the two dependent variables from Hypotheses 1 and 2. Theoretically, expected affect represents a function of, not only the extreme outcomes (best and worst) explored in the previous hypothesis, but also those in between. Unfortunately, due the existing demands of the study questionnaire, direct elicitation of expected affect was only deemed feasible for two outcomes per gamble. Therefore, the regression of CE estimates on these measures of expected affect undoubtedly represents an under-specified model, a limitation more thoroughly discussed in the summary section below. Aside from underspecification, in order to the make the models more tractable, a method for creating weighted estimates of overall expected valence and arousal was desired to avoid the perils of fitting an inordinate number of higher order effects. Without a weighting gold-standard to follow, the decision was made to use the available probability structure from each gamble (analogous to Expected Utility Theory calculations), so that, for example, overall expected valence for a /$150 gamble equaled: best expected valence times the probability for the best outcome plus the worst expected valence times the probability of the worst outcome. This resulted in single measures of expected valence and arousal for each gamble, which could easily be transformed into single measures of valence by arousal and arousal by arousal products (i.e., the interaction and quadratic terms under investigation). Note, the expected valence calculations used the full reported scale of best and worst outcome valence without adjustment for ceiling or floor effects. Below are the results of a model using these overall expected affect measures to predict the CE responses.

CE Regressed on Expected Affect Measures

Anticipating the next step in the mediation model (i.e. the inclusion of incidental affect), the expected affect composites were actually derived within the SEM models. Overall expected valence and arousal were constructed as “phantom variables” (Rindskopf, 1984), whose total variance emanated from the a priori determined functions (i.e., weighted by associated payoff/loss probabilities) of the observed best and worst outcome variables (the observed measures were formative indicators of these overall expected affect composites- see Diamantopoulos & Siguaw, 2006; MacCallum & Browne, 1993). Higher order terms were then constructed using the full-information maximum likelihood approach of Klein and Moosbrugger (2000; see also Muthén & Asparouhov, 2003). This somewhat unconventional approach properly channels the indirect effect of incidental affect on CE responses through both the mediated expected affect main and higher order effect terms.

Before constructing these higher order mediation models, it is sensible to first test the necessity of higher order expected affect terms. To do so, the model described in the previous paragraph was built for prediction of the four groups of CE responses investigated under Hypothesis 1 (male and female positive and negative gambles). Since both expected affect and CEs were elicited on every gamble, the model reduction began with a comparison of fit between gamble-specific (affect influences were allowed to vary across all gambles) versus common (affect influences were fixed to be the same for all gambles) prediction (this is analogous to the distinction between time-varying and time-invariant prediction commonly tested for in longitudinal modeling). Three indicators of model fit were utilized to determine the necessity of gamble-specific prediction: a robust Chi-square difference test (Satorra & Bentler, 1999), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). Lower values of the latter two indicate better fit. Results from these model comparisons are displayed in Table 23 below. Notice that all AIC and BIC statistics favor the common prediction model, and all but the Male positive CE Chi-square tests favor this model. For reasons of parsimony and the fit indicated, all models that follow specified a constant expected affect effect across all gambles.

Table 23. Model Fit Comparison for Gamble-Specific versus Common Expected Affect Prediction.

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	-1080.55	51			2263.09	2352.91
	Null	-1097.31	31	38.18	0.01	2256.62	2311.22
Female Pos	Alt	-1473.66	51			3049.33	3151.70
	Null	-1482.22	31	18.60	0.55	3026.45	3088.67
Male Neg	Alt	-1078.89	51			2259.78	2349.60
	Null	-1087.32	31	22.85	0.30	2236.63	2291.23
Female Neg	Alt	-1477.74	51			3057.49	3159.86
	Null	-1488.92	31	15.42	0.75	3039.83	3102.06

Note. Alt = Gamble-Specific; Null = Common.

Model reduction resumed by examining the significance of the common predictors in the same manner as performed under previous hypotheses (eliminating higher order terms before embedded lower order terms). The final models are presented in Table 24. Notice that only expected arousal survived the complete model reduction and that no effects met inclusion criteria for the female negative gamble outcomes. Of course, the lack of predictive power among expected valence terms may be related to ceiling and floor effects noted under Hypothesis 2. Despite the significance of the expected arousal terms in two of the models, no effect ever accounted for more than 2% of the variance in any of the CE responses.

Table 24. Final Models of CE Responses Regressed on Expected Affect.

		Males				Females			
Outcome	Effects	Est	SD	Est/Sd	P-Val	Est	SD	Est/Sd	P-Val
Positive	Arousal	-1.58	0.90	-1.77	0.08	0.36	0.16	2.25	0.02
	Arousal by Arousal	0.03	0.02	1.73	0.08	0[a]			
Negative	Arousal	-0.34	0.14	-2.45	0.01	0[a]			

[a] These terms were dropped (constrained to 0) from the final model.

Using the output above to guide the mediation models, focus shifted to tests of indirect effects emanating from incidental affect, down through mediating expected affect, eventually impacting the CE outcomes. The diagram in Figure 17 demonstrates the structure of these models, including the direct effects remaining from the male $150-positive-gamble models of Hypotheses 1-3 (similar effects exist in the model for the $200 gambles). Indirect effects involve the product of arrows that connect incidental affect to the CE responses via the paths that predict expected affect. Estimates for the mediation models are shown in Tables 25-27. Note, female negative gamble models were deemed unnecessary due to the exclusion of all direct expected affect effects on CE.

Table 25. Male Positive-Gamble Mediation Models.

Gambles	Outcome	Predictor	Est	SD	Est/Sd	P-Val
All		Valence_i	2.86	1.88	1.52	0.13
	Best	Arouse_i	6.43	1.93	3.33	0.00
\ & /	Arouse_e	Arouse_i by				
		Arouse_i	3.90	1.14	3.43	0.00
		Arouse_i	6.84	2.91	2.35	0.02
^	Best Arouse_e	Arouse_i by				
		Arouse_i	2.47	1.55	1.59	0.11
\ & ^		Valence_i	4.62	1.71	2.70	0.01
	Worst	Arouse_i	-1.71	2.70	-0.63	0.53
\ & /	Arouse_e	Arouse_i by				
		Arouse_i	-1.99	1.61	-1.24	0.22
/		Valence_i	6.31	2.54	2.49	0.01
	Worst	Arouse_i	-2.56	3.35	-0.76	0.44
^	Arouse_e	Arouse_i by				
		Arouse_i	-5.93	1.57	-3.77	0.00
		Valence_i	6.31	2.539	2.49	0.01
		Arouse_i	-1.71	2.70	-0.63	0.53
All	CE	Arouse_i by				
		Arouse_i	-1.99	1.61	-1.24	0.22
All	CE	Arouse_e	-0.33	0.16	-2.13	0.03

Table 26. Female Positive-Gamble Mediation Models.

Gambles	Outcome	Predictor	Est	SD	Est/Sd	P-Val
\ & ^	Best Arouse_e	Valence_i	0.90	1.85	0.49	0.63
		Arouse_i	-1.78	1.73	-1.03	0.30
		Valence_i by Arouse_i	-3.37	1.66	-2.03	0.04
		Arouse_i by Arouse_i	3.78	1.58	2.38	0.02
/	Best Arouse_e	Valence_i	1.89	2.35	0.80	0.42
		Arouse_i	-0.44	2.60	-0.17	0.87
		Valence_i by Arouse_i	1.78	2.59	0.69	0.49
		Arouse_i by Arouse_i	-2.59	2.04	-1.27	0.20
\ & ^	Worst Arouse_e	Valence_i	0.19	1.87	0.10	0.92
\$150		Arouse_i	4.94	2.47	2.00	0.05
\ & ^		Valence_i by Arouse_i	0.51	2.41	0.21	0.83
\		Arouse_i by Arouse_i	-2.69	2.42	-1.11	0.27
^$150	Worst Arouse_e	Arouse_i	-0.21	3.83	-0.06	0.96
^		Arouse_i by Arouse_i	4.30	3.33	1.29	0.20
/	Worst Arouse_e	Valence_i	1.96	1.97	0.99	0.32
/$150		Arouse_i	1.79	3.09	0.58	0.56
/		Valence_i by Arouse_i	-4.80	2.62	-1.83	0.07
/		Arouse_i by Arouse_i	6.95	2.29	3.03	0.00
\$200	Worst Arouse_e	Arouse_i	-0.10	2.65	-0.04	0.97
^$200		Arouse_i	-5.56	3.94	-1.41	0.16
/$200		Arouse_i	-2.97	3.50	-0.85	0.40
$150	CE	Valence_i	5.71	3.17	1.80	0.07
All		Arouse_i	0.01	2.20	0.00	1.00
		Arouse_i by Arouse_i	-4.15	1.37	-3.03	0.00
$200	CE	Valence_i	-0.41	3.92	-0.10	0.92
All	CE	Arouse_e	0.29	0.20	1.47	0.14

Table 27. Male Negative-Gamble Mediation Models.

Gambles	Outcome	Predictor	Est	SD	Est/Sd	P-Val
All		Valence_i	2.86	1.88	1.52	0.13
	Best	Arouse_i	6.43	1.93	3.33	0.00
\ & /	Arouse_e	Arouse_i by				
		Arouse_i	3.90	1.14	3.43	0.00
		Arouse_i	6.84	2.91	2.35	0.02
^	Best Arouse_e	Arouse_i by				
		Arouse_i	2.47	1.55	1.59	0.11
\ & ^		Valence_i	4.62	1.71	2.70	0.01
	Worst	Arouse_i	-1.71	2.70	-0.63	0.53
\ & /	Arouse_e	Arouse_i by				
		Arouse_i	-1.99	1.61	-1.24	0.22
/		Valence_i	6.31	2.54	2.49	0.01
	Worst	Arouse_i	-2.56	3.35	-0.76	0.44
^	Arouse_e	Arouse_i by				
		Arouse_i	-5.93	1.57	-3.77	0.00
		Valence_i	6.31	2.539	2.49	0.01
		Arouse_i	-1.71	2.70	-0.63	0.53
All	CE	Arouse_i by				
		Arouse_i	-1.99	1.61	-1.24	0.22
All	CE	Arouse_e	-0.33	0.16	-2.13	0.03

In the SEM models constructed to fit these terms for female positive and male negative outcomes, statistical significance of the multivariate indirect incidental affect effects can be estimated through model constraints on the sum of involved coefficient products (see MacKinnon et al., 2002; MacKinnon, Lockwood, & Williams, 2004). For the male positive outcome model, statistical significance of the indirect paths is complicated by the higher order effect relation between the mediator (expected arousal) and the CE outcomes. As shown below, the size of the indirect paths is conditional on the latent mediator residual, i.e., the unique portion of expected arousal that is not predicted by incidental valence or arousal. The system of equations below demonstrates this dependency for \ and / positive gambles:

$$A_{E,Best} = B_{0i_{EB}} + B_{1_{EB}} A_I + B_{2_{EB}} A_I^2 + e_{EB} \tag{8}$$

$$A_{E,Worst} = B_{0i_{EW}} + B_{1_{EW}} A_I + B_{2_{EW}} A_I^2 + B_{3_{EW}} V_I + e_{EW} \tag{9}$$

$$EA = 0.1 \cdot A_{E,Best} + 0.4 \cdot A_{E,Worst} \tag{10}$$

$$CE = B_{0i_{CE}} + B_{1_{CE}} A_I + B_{2_{CE}} A_I^2 + B_{3_{CE}} EA + B_{CE} EA^2 + e_{CE} \tag{11}$$

where incidental arousal and valence are A_I and V_I, expected arousal for best and worst outcomes are $A_{E,Best}$ and $A_{E,Worst}$, and the "phantom" expected affect variable is EA. Substitution of equations 8-10 into 11 provides a clearer picture of the total indirect effect of interest, revealing a complex function of incidental arousal and valence product coefficients and expected arousal residuals:

$$\begin{aligned} IndEff &= B_{3_{CE}} \left(0.1 \cdot \left(B_{1_{EB}} A_I + B_{2_{EB}} A_I^2\right) + 0.4 \cdot \left(B_{1_{EW}} A_I + B_{2_{EW}} A_I^2 + B_{3_{EW}} V_I\right)\right) \\ &+ B_{4_{CE}} \left(0.1 \cdot \left(B_{1_{EB}} A_I + B_{2_{EB}} A_I^2\right) + 0.4 \cdot \left(B_{1_{EW}} A_I + B_{2_{EW}} A_I^2 + B_{3_{EW}} V_I\right)\right)^2 \\ &+ 2B_{4_{CE}} \left(0.1 \cdot \left(B_{1_{EB}} A_I + B_{2_{EB}} A_I^2\right) + 0.4 \cdot \left(B_{1_{EW}} A_I + B_{2_{EW}} A_I^2 + B_{3_{EW}} V_I\right)\right) \\ &\cdot \left(B_{0i_{EB}} + B_{0i_{EW}} + e_{EB} + e_{EW}\right). \end{aligned} \tag{12}$$

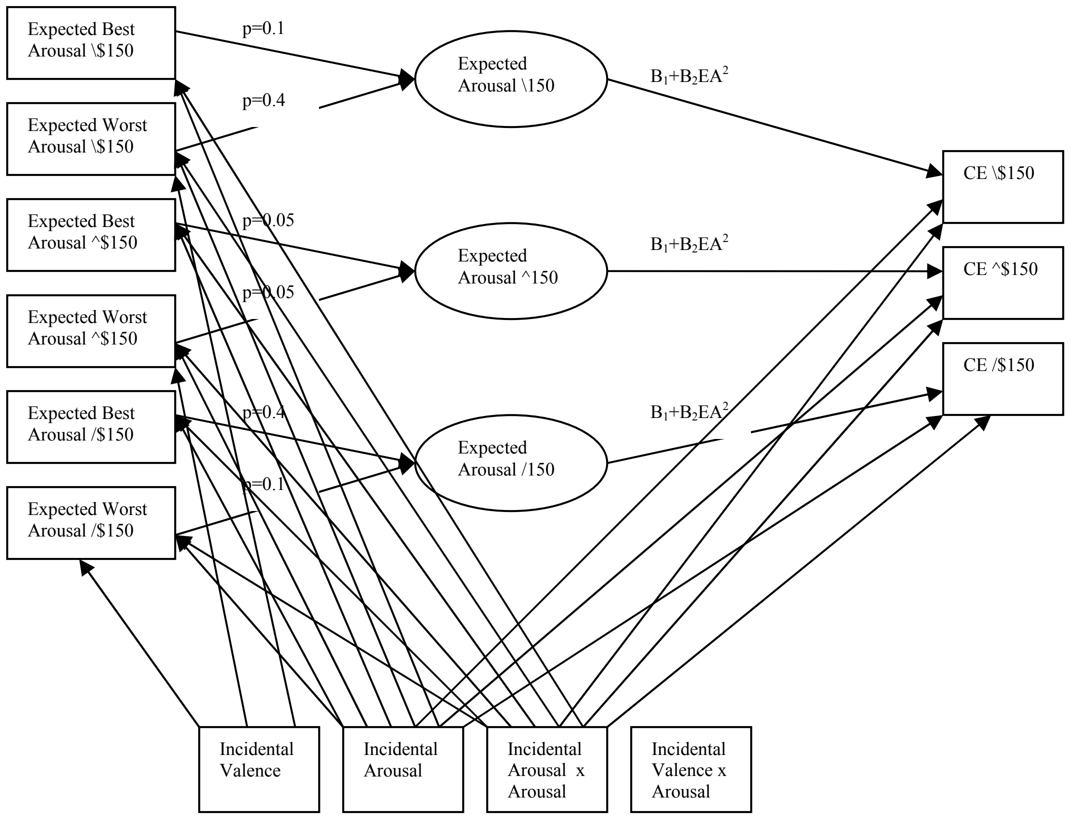
Because of the dependence on the expected arousal residuals, the usual product coefficient tests carry limited meaning. We can, however, assess the size and significance of various indirect effects at specified values of these two residuals adapting the newly proposed methods of Edwards and Lambert (2007) and Preacher, Rucker, and Hayes (in press). These tests are essentially extensions of the simple slope tests of Aiken and West (1991) applied to the conditional indirect effects. Both types of tests (usual and conditional) were run for the 3 models shown in Tables 25-27 using first-order derivative Delta estimation of standard errors (SE) for constraint estimates. These statistics alongside Normal distribution p-values (2-tailed) for the ratio of the indirect effect over the Delta SE are shown in Table 28. Notice estimated indirect effects for positive male outcomes are given for -1, 0, and 1 standard deviation units above the mean for the two residuals (labeled e_{Best} and e_{Worst}) shown in equation 12[10]. Not surprisingly, given the small direct effects displayed in the Tables 25-27, these results indicate no statistically significant mediation within any of the models.

[10] This tests requires a non-obvious adaptation to the Edwards and Lambert (2007) and Preacher et al. (in press) techniques. In addition to the constraints on the indirect effect in equation [12], constraints are required for new parameter estimates that equal the standard deviation of the e_{Best} and e_{Worst} residual terms. These estimates are used to calculate the indirect affect at 1 standard deviation above and below each residual mean.

Table 28. Tests of Significance for Total Indirect Effects within Mediating Models.

Outcome Set	Dist.	$150 Σ of Products (SE*)	P-Val	$200 Σ of Products (SE*)	P-Val		
Male Neg	\	-0.56(0.59)	0.34				
	^	-0.09(0.10)	0.35				
	/	-1.84(0.99)	0.06				
Female Pos	\	0.42(0.74)	0.57	-0.17(0.63)	0.78		
	^	0.12(0.16)	0.45	0.04(0.13)	0.73		
	/	0.46(0.66)	0.49	0.95(0.86)	0.27		
Outcome Set	Dist.	$150 Σ of Products (SE*)	P-Val	$200 Σ of Products (SE*)	P-Val	e_{Best}	e_{Worst}
Male Pos	\	2.27(13.53)	0.87	2.66(20.49)	0.90	-1	-1
		0(0)	1.00	2.53(15.49)	0.87	-1	0
		3.01(18.77)	0.87	3.05(18.44)	0.87	-1	1
		2.76(16.78)	0.87	2.54(15.20)	0.87	0	-1
		3.01(18.14)	0.87	3.12(18.80)	0.87	0	0
		3.54(21.20)	0.87	3.60(21.65)	0.87	0	1
		3.00(18.22)	0.87	1.83(18.03)	0.92	1	-1
		3.52(20.89)	0.87	3.56(21.52)	0.87	1	0
		3.77(23.08)	0.87	4.09(24.10)	0.87	1	1
	^	1.54(3.03)	0.61	1.84(3.50)	0.60	-1	-1
		2.02(4.04)	0.62	2.29(4.47)	0.61	-1	0
		2.56(5.16)	0.62	2.78(5.39)	0.61	-1	1
		1.94(3.76)	0.61	2.01(3.91)	0.61	0	-1
		2.48(4.83)	0.61	2.40(4.82)	0.62	0	0
		2.95(5.82)	0.61	3.12(5.99)	0.60	0	1
		2.17(4.28)	0.61	2.30(4.48)	0.61	1	-1
		2.74(5.42)	0.61	2.77(5.74)	0.63	1	0
		2.76(5.51)	0.62	3.13(6.35)	0.62	1	1
	/	18.51(27.04)	0.49	18.39(28.47)	0.52	-1	-1
		26.06(39.96)	0.51	27.13(41.44)	0.51	-1	0
		33.87(52.75)	0.52	34.43(54.06)	0.52	-1	1
		25.99(37.99)	0.49	25.06(37.75)	0.51	0	-1
		32.30(50.81)	0.52	31.76(50.37)	0.53	0	0
		41.49(64.95)	0.52	40.42(62.83)	0.52	0	1
		32.86(49.06)	0.50	30.91(46.52)	0.51	1	-1
		40.30(62.43)	0.52	38.96(59.34)	0.51	1	0
		48.64(75.05)	0.52	45.50(71.87)	0.53	1	1

Figure 17. Diagram of Mediating Model.



Note. Correlated residuals for observed (boxed) sets of Expected Arousal and CE outcomes not shown. The coefficients for the regression of expected worst and best arousal on incidental affect not labeled. The 'p = x' labels indicate the fixed formative (causal) effects (= probability of best or worst outcome) that define the Expected Arousal "phantom" composites (ovals). The '$B_1+B_2EA^2$' labels indicate the quadratic and linear terms in the regression of CE on Expected Arousal. Incidental influences on CE are not labeled.

Summary of Hypothesis 3 Results

Inspection of the direct effects of expected affect on CE responses revealed only small influences from expected arousal. Expected valence had no effect in any of the models, and none of the expected affect measures influenced the negative gamble, female CE responses. Evidence for indirect effects of incidental affect on CE, via mediating expected affect influences, were also nonexistent. Limitations abound, however, for these particular effects. For example, the lack of impact from expected valence may in part be due to the lack of measurement precision at one end of the scale, where previously (Hypothesis 2), strong ceiling and floor were noted. The single indictor measurement of both expected arousal and valence also likely contributed to a dampening of effects. This latter limitation could, theoretically, have been accounted for by constraining the ratio of “true score” to unique variance in each measure to an a priori estimate of reliability (such as the ratio estimated for the incidental “Happy” and “Surprise” items in Table 6). Unfortunately, attempts to model this more constant influence of measurement error failed to produce reliable estimates in the full higher order mediating models, nullifying any real practical benefit. Finally, due to constraints on the length of the participant questionnaire, only expected affect for extreme payoffs/losses were elicited. To the extent that outcomes in between these extremes add unique predictive variance to the models and to the extent that the expected outcome responses are aggregated in a manner inconsistent with associated gamble probabilities, the impact of expected affect on CE is underestimated. For these reasons, effects of expected affect on CE responses can safely be assumed conservative and far from definitive.

Hypothesis 4. The influence of incidental affect on expected affect will be mediated through perceptions of risk and expected payoff.

The final hypothesis under investigation concerned subjective estimates of the various gambles' expected values and "risk." Based on the premise that valence more directly relates to actual value of an expected outcome and arousal to the odds of an expected outcome, one might anticipate strong correspondence between subjective measures of risk and value and expected affect. In what follows, these possible relationships were explored, as well as the relationship of subjective value and risk to the CE outcomes. The size of these direct effects were hypothesized to explain some of the previously observed relations between incidental affect and both expected affect and CE responses.

Tables 29-32 provide descriptive information for the subjective value and risk responses in each of the four outcome groups found in Hypotheses 1 and 3. As with Hypothesis 3, analysis began with comparisons of fit between models that allowed for differential and common prediction. For the regression of expected valence on expected value, we see in Tables 33 and 34 moderate support for common predictive weighting across the sample of gambles (all AIC and BIC values favor the common model, except for male positive AIC; Similarly, only the male positive S-B Chi-squares are significant ($p<0.05$)). The common prediction estimates are also included in these Tables in the bottom left corner. Interestingly, the only significant relationships identified are for worst outcome gambles among males, and these effects only accounted for between <1 to 2% of the variance in the outcomes. The model fit statistics and estimates shown correspond to models treating expected valence as a

Table 29. Male Positive Gamble Responses to Subjective Expected Value and Risk.

	N	Min	Max	Mean	Std Dev
Lottery [\,150] Expected Value	43	100	250	140.70	26.24
Lottery [^,150] Expected Value	43	75	175	145.00	18.48
Lottery [/,150] Expected Value	43	100	200	153.60	20.94
Lottery [\,200] Expected Value	43	150	225	186.63	21.23
Lottery [^,200] Expected Value	43	100	250	188.60	26.58
Lottery [/,200] Expected Value	43	100	250	196.05	33.25
Lottery [\,150] Riskiness	43	0	80	48.70	21.07
Lottery [^,150] Riskiness	43	0	82	44.19	18.13
Lottery [/,150] Riskiness	43	0	96	48.14	22.16
Lottery [\,200] Riskiness	43	0	100	51.91	21.82
Lottery [^,200] Riskiness	43	0	81	51.14	18.88
Lottery [/,200] Riskiness	43	0	90	47.67	20.22

Table 30. Male Negative Gamble Responses to Subjective Expected Value and Risk.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Expected Value	43	-200	-100	-153.60	21.69
Lottery [^,-150] Expected Value	43	-175	-100	-146.51	17.30
Lottery [/,-150] Expected Value	43	-200	-100	-140.23	23.70
Lottery [\,-200] Expected Value	43	-250	-100	-200.00	30.55
Lottery [^,-200] Expected Value	43	-275	-100	-193.02	28.97
Lottery [/,-200] Expected Value	43	-230	-150	-188.37	23.75
Lottery [\,-150] Riskiness	43	16	81	51.21	17.83
Lottery [^,-150] Riskiness	43	0	90	47.84	18.50
Lottery [/,-150] Riskiness	43	26	86	51.53	18.11
Lottery [\,-200] Riskiness	43	11	86	51.47	20.55
Lottery [^,-200] Riskiness	43	17	96	52.12	16.06
Lottery [/,-200] Riskiness	43	0	90	47.09	21.53

continuous outcome. Results from models treating expected valence as categorical (to help account for ceiling and floor effects) were also run, but not reported, and conclusions were not substantively different.

Prediction of expected arousal from the subjective risk responses were similarly weak. In these models, support for the common predictors were not as strong, with significant improvement for the gamble-specific models indicated in the adjusted Chi-

Table 31. Female Positive Gamble Responses to Subjective Expected Value and Risk.

	N	Min	Max	Mean	Std Dev
Lottery [\,150] Expected Value	55	100	200	129.45	28.16
Lottery [^,150] Expected Value	55	50	200	146.91	23.28
Lottery [/,150] Expected Value	55	50	200	161.58	34.53
Lottery [\,200] Expected Value	55	150	300	183.00	32.75
Lottery [^,200] Expected Value	55	100	250	195.55	24.32
Lottery [/,200] Expected Value	55	100	250	213.73	36.38
Lottery [\,150] Riskiness	55	9	91	51.75	20.56
Lottery [^,150] Riskiness	55	0	91	47.62	19.28
Lottery [/,150] Riskiness	55	0	85	48.85	20.44
Lottery [\,200] Riskiness	55	10	84	52.85	18.93
Lottery [^,200] Riskiness	55	0	92	54.18	20.51
Lottery [/,200] Riskiness	55	2	92	48.87	20.42

Table 32. Female Negative Gamble Responses to Subjective Expected Value and Risk.

	N	Min	Max	Mean	Std Dev
Lottery [\,-150] Expected Value	55	-200	-50	-163.73	36.92
Lottery [^,-150] Expected Value	55	-180	-50	-145.82	26.87
Lottery [/,-150] Expected Value	55	-250	-100	-130.09	31.63
Lottery [\,-200] Expected Value	55	-250	-100	-209.73	36.56
Lottery [^,-200] Expected Value	55	-225	-100	-194.82	27.57
Lottery [/,-200] Expected Value	55	-300	-150	-180.36	32.17
Lottery [\,-150] Riskiness	55	10	100	57.98	19.71
Lottery [^,-150] Riskiness	55	0	90	50.80	19.32
Lottery [/,-150] Riskiness	55	18	100	54.44	18.26
Lottery [\,-200] Riskiness	55	19	94	54.45	20.32
Lottery [^,-200] Riskiness	55	10	90	50.71	18.04
Lottery [/,-200] Riskiness	55	3	90	53.33	19.54

square statistics for all positive outcomes and male negative best outcome responses. Yet, the AIC and BIC statistics slightly favored the common predictor model in 12 of 16 comparisons. Since neither model appears to dominant the other in fit, the results reported favor the parsimony of the common predictor estimates which are shown in the bottom left corner of Tables 35 and 36. None of these common effects reach levels of significance.

Table 33. Model Comparison of Gamble-Specific and Common Prediction of Expected Valence for Best Outcomes from Subjective Expected Value Responses.

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	-2098.47	33			4262.95	4321.07
	Null	-2104.56	28	17.02	0.00	4265.12	4314.44
Female Pos	Alt	-2772.86	33			5611.72	5677.96
	Null	-2776.63	28	10.98	0.05	5609.26	5665.46
Male Neg	Alt	-2172.98	33			4411.97	4470.09
	Null	-2174.17	28	3.64	0.60	4404.33	4453.64
Female Neg	Alt	-2900.40	33			5866.80	5933.05
	Null	-2902.82	28	1.85	0.87	5861.64	5917.85

Outcome	Common Est.	SE	p-val
Male Pos	0.02	0.02	0.36
Female Pos	0.00	0.02	0.93
Male Neg	0.05	0.03	0.12
Female Neg	-0.01	0.02	0.56

Note. Alt = Gamble-Specific; Null = Common.

Table 34. Model Comparison of Gamble-Specific and Common Prediction of Expected Valence for Worst Outcomes from Subjective Expected Value Responses.

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	-2174.23	33.00			4414.46	4472.58
	Null	-2179.65	28.00	14.81	0.01	4415.30	4464.62
Female Pos	Alt	-2822.57	33.00			5711.14	5777.38
	Null	-2823.94	28.00	4.15	0.53	5703.88	5760.08
Male Neg	Alt	-2090.99	33.00			4247.97	4306.09
	Null	-2093.78	28.00	5.01	0.41	4243.56	4292.88
Female Neg	Alt	-2775.33	33.00			5616.66	5682.90
	Null	-2776.74	28.00	1.22	0.94	5609.49	5665.69

Outcome	Common Est.	SE	p-val
Male Pos	0.06	0.02	0.01
Female Pos	0.03	0.02	0.15
Male Neg	0.05	0.02	0.02
Female Neg	0.01	0.01	0.67

Note. Alt = Gamble-Specific; Null = Common.

Table 35. Model Comparison of Gamble-Specific and Common Prediction of Expected Arousal for Best Outcomes from Subjective Risk Responses.

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	-2154.65	33.00			4375.30	4433.42
	Null	-2160.33	28.00	15.32	0.01	4376.66	4425.97
Female Pos	Alt	-2745.69	33.00			5557.37	5623.62
	Null	-2749.86	28.00	15.26	0.01	5555.72	5611.93
Male Neg	Alt	-2153.81	33.00			4373.63	4431.75
	Null	-2161.33	28.00	14.10	0.02	4378.65	4427.97
Female Neg	Alt	-2776.88	33.00			5619.77	5686.01
	Null	-2778.27	28.00	2.03	0.85	5612.55	5668.75

Outcome	Common Est.	SE	p-val
Male Pos	0.04	0.04	0.25
Female Pos	-0.04	0.04	0.41
Male Neg	-0.01	0.05	0.79
Female Neg	0.03	0.04	0.51

Note. Alt = Gamble-Specific; Null = Common.

Table 36. Model Comparison of Gamble-Specific and Common Prediction of Expected Arousal for Worst Outcomes from Subjective Risk Responses.

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	-2180.21	33.00			4426.41	4484.53
	Null	-2189.40	28.00	24.66	0.00	4434.80	4484.11
Female Pos	Alt	-2863.01	33.00			5792.03	5858.27
	Null	-2866.65	28.00	12.12	0.03	5789.31	5845.51
Male Neg	Alt	-2192.31	33.00			4450.62	4508.74
	Null	-2193.00	28.00	2.37	0.80	4442.00	4491.31
Female Neg	Alt	-2858.43	33.00			5782.86	5849.11
	Null	-2864.78	28.00	5.29	0.38	5785.55	5841.76

Outcome	Common Est.	SE	p-val
Male Pos	-0.06	0.04	0.10
Female Pos	-0.01	0.06	0.92
Male Neg	-0.02	0.06	0.73
Female Neg	-0.11	0.07	0.14

Note. Alt = Gamble-Specific; Null = Common.

The same caveats expressed in the summary to Hypothesis 3 carry over into these prediction exercises, particularly the lack of a gold-standard weighting system for combining the two types of expected affect (best and worst) and the missing expected affect for non-extreme payoffs/losses. Nevertheless, it is noteworthy that these perceived characteristics (expected value and risk) of the gamble structure do not seem to share much variance with expected reactions to potential gamble outcomes. Given the weak relationships demonstrated in Hypothesis 3 between expected affect and the CE responses, one might wonder how much better these subjective measures perform.

When comparing common and differential predictor models for the regression of CE on subjective EV and risk, again support for the necessity of gamble-specific prediction was lacking. In line with earlier supposed relations between these perceptions of gamble structure and expected affect, the common prediction model was estimated with subjective EV and risk main effects and higher order effects for an EV by risk interaction and a quadratic risk term. Model fit statistics for common and gamble-specific prediction and results are shown in Table 37 below. Adopting the reduction criteria from earlier exercises, EV and risk terms remained in only the female negative gamble model due to a small EV by risk interaction that was marginally significant. Combined, however, the inclusion of these three terms accounted for no more than 1% of the total variance in any of the CE responses.

Table 37. Model Comparison of Gamble-Specific and Common Prediction of CE.

Outcomes from Subjective Expected Value and Risk Responses

Outcome	Model	LL	#Free Parms	S-B Chisq	p-value	AIC	BIC
Male Pos	Alt	No Convrg	51			---	---
	Null	-7010.023	31	---	---	14082.05	14136.64
Female Pos	Alt	-9174.973	51			18451.95	18554.32
	Null	-9183.938	31	21.72	0.36	18429.88	18492.10
Male Neg	Alt	-6969.089	51			14040.18	14130.00
	Null	-6979.624	31	25.29	0.19	14021.25	14075.85
Female Neg	Alt	-9325.025	51			18752.05	18854.42
	Null	-9339.734	31	19.10	0.52	18741.47	18803.70

Outcome	Predictor	Common Est.	SE	p-val
Female Neg	EV	-0.165	0.096	0.09
	Risk	-0.026	0.064	0.68
	EV by Risk	-0.002	0.001	0.05

Note. Alt = Gamble-Specific; Null = Common; NoCnvrg = Model failed to converge.

Summary of Hypothesis 4 Results

Subjective reports of each gambles' expected value and perceived risk did not appear to account for meaningful amounts of variation in either expected affect outcomes or CE responses. Moreover, as demonstrated in the mediation models under Hypothesis 3, the size of the direct effects present in the Hypothesis 4 models (accounting for no more than 2% of any CE response variable) would not be sufficient to explain substantial mediation of subjective risk and expected value on the relationship between incidental affect and CE outcomes. The finding that these measures are not related is puzzling, however, and prompts some proverbial back-to-drawing-board discussion, both theoretical and methodological, in the sections that follow.

Chapter IV: Discussion

The current study explored the connection between three parallel but somewhat independent decision science research programs. The unifying theme among each rested on the shoulders of affect, hypothesizing emotional influences on the cognitive evaluation of gambles. The study marks one of the first attempts to empirically test a causal model of the intervening mechanistic components of evaluations that possibly underlie the recent body of evidence supporting background mood influences on risky choice (Eisenberg et al., 1996; Lerner & Keltner, 2000, 2001; Raghunathan & Pham, 1999; Raghunathan et al., 2006). More specifically, the study investigated the influences of incidental affect on two sets of evaluated gamble components previously theorized and empirically validated to predict choice outcomes: (1) perceived structural features of the gambles (riskiness and expected monetary value) and (2) global assessments of potential hedonic value (expectations of future affect- anticipated affect). Overall, little support was found for consistent mechanistic influences at any stage of the causal model, summarized by weak and often isolated (context-specific) influences of incidental affect and evaluation components (risk, expected value, and expected affect) on choice outcomes. These findings are highlighted below and followed by an examination of the limiting study factors possibly responsible for the poor predictive performance of the proposed model.

Incidental Affective Influences on Risky Choice

The first hypothesis tested the impact of immediate affect on elicited certainty equivalency measures (CE) of gamble preference. Using the Pleasure-Arousal Hypothesis (Russell & Mehrabian, 1978) to guide prediction, a 2-dimensional measure of incidental affect, tapping valence and arousal, never accounted for more than 12% of variance in any of the individual CE responses. The affective effects identified for males and for positive gamble responses (those with only gain outcomes) of females most often influenced all types of gamble structures presented (i.e., overall effects). Responses of females to the negative gambles (only loss outcomes), on the other hand, were diverse across the three types of probability structures presented (i.e., \, ^, and /). Finally, relative to arousal influences, valence seemed to be a less valuable predictor in all positive gambles, excepting the female $150 gambles. For the negative gambles, both valence and arousal contributed to prediction.

Incidental Affective Influences on Anticipated Affect

Again adopting the Pleasure-Arousal Hypothesis (Russell & Mehrabian, 1978), 2-dimensional incidental affect was allowed to predict 2-dimensional anticipated affect responses to receipt of the best and worst outcomes from every gamble. The anticipated affect responses were elicited as relative expectations conditional on hypothetical scenarios where each gamble was selected over a certain payoff or loss equal in amount to the played gamble's expected value. Much like the effects on CE, the incidental affect predictions of anticipated affect were largely overall effects for males and more often structure-dependent effects for females. Male models were typically defined by the inclusion of linear and quadratic arousal terms, while for females, complex interactive relationships involving both incidental arousal and valence were more commonly left in the final models. Finally, very few affect effects were found in the expected valence models, compared to those of expected arousal, a finding possibly related to strong ceiling and floor effects evident in the expected valence responses and methodologically adjusted for in the modeling exercise.

Expected Affect as a Mediator of the Relationship between Incidental Affect and CE

Treating composite estimates of expected valence and arousal as continuous predictors of CE responses, the model reduction procedure utilized left only expected arousal influences in the positive-gamble female model and both the positive and negative male models. No effects remained in the negative gamble female model estimation. The effects identified were all small in magnitude and did not appear to account for any of the direct incidental affect effects on CE. Conclusions from this particular investigation are complicated by the fact that only anticipated affect for extreme outcomes was elicited in the participant interviews. In the event that unique predictions from outcomes falling in between these extremes exist, these effects of expected affect on CE are underrepresented. There is also some concern about how to incorporate the distinct measures of anticipated affect (affect anticipated to be experienced from a defined outcome scenario) into a global measure of expected affect. The current study documented a technique for combining individual anticipated affect measures into main effect and higher order terms at the expected affect level by creating a composite weighted by the probability of associated extreme outcomes within the actual mediation model. Yet, in the event that participants subjectively value probabilities nonlinearly (as is often assumed in GEU models; see Figure 4), these composites may reflect substantial bias and error in measurement. Although not reported, other composite estimates were also explored as was a model allowing linear effects from each individual measure of anticipated valence and arousal to predict CE. Results from these exploratory models did not reveal substantially different conclusions (small direct influences and no mediation) from those presented. Yet, for the reasons identified here and those in the section *Summary of Hypothesis 3 Results*, the results and conclusions from the full mediation model and prediction of CE from expected affect are presented with caution.

Structural Features of Gambles Influence Expected Affect and CE

Both objective and subjective measures of structural features were assessed for predictive influence in this study. Objectively, Hypotheses 1 and 2 estimated main effects and interactions of the two manipulated structural features, probability distribution (objective risk) and expected value (objective value), on CE and anticipated affect responses. Not surprisingly, in contrast to the previously noted effects of incidental and anticipatory affect, these influences tended to be quite large. The largest objective structural effects were observed for changes in expected value (EV) in the CE outcome models, where consistently an absolute value difference of \$42 to \$48 was detected. Given the actual absolute value difference in expected values within positive and negative domains was \$50, these EV findings are suggestive of risk aversion for gambles of losses and gambles of gains. This global aversion is somewhat inconsistent with the know *reflection effect* of Kahneman and Tversky (1979), where risk-aversion for gains and risk-seeking for comparable losses frequently describes the utility curves. A possible explanation for this inconsistency involves the actual display of negative gambles. In most, if not all, gambling tasks of this sort (at least to this author's knowledge), negative gamble counterparts to positive gambles are usually displayed with outcomes ordered least to greatest in *absolute value*. In this study, order of outcomes was simply least to greatest, resulting in a reversal of absolute value order in negative and positive domains. If true, such an explanation would identify an important boundary condition on the reflection effect, but more evidence is needed before drawing any firm conclusions.

Systematic differences in CE responses were also found within sets of gambles with a common EV. These probability distribution effects lend support to the risk-value model contention that both value of the outcome and perceived risk play a role in determining preference. Generally speaking, the preference order within each EV was \ ≥ ^ ≥ / (see Figure 3 for symbolic notation) in both positive and negative gambles (again counter to the reflection effect). Effects contrasting the referent \ distribution to the ^

and / distributions revealed significant difference between \ and / only for all but the -$150 male gambles. Because of the limited number of probability distributions investigated, it is hard to draw any precise generalizations from this finding. The finding could suggest either a preference for distributions whose right tail extends farther and incorporates more desired outcomes with low probabilities and/or a distaste for distributions with left tails that include more less-desired outcomes at low probabilities. To the extent that the latter plays a part, the Security-Potential/Aspiration theory of Lopes and colleagues (1987, 1995; Lopes & Oden, 1999) may find favor, given its emphasis on the decision criterion for avoidance of the worst possible outcomes. In the generalized disappointment model (GDM) version of a risk-value GEU (and its relatives, e.g., Brandstätter et al., 2002; Lopes, 1987, 1995; Lopes & Oden, 1999; Mellers et al., 1997, 1999), this could also be further support for the overweighting of the disappointment coefficient (weighting outcomes below the mean) relative to the elation coefficient (weighting outcome above the mean).

Objective structural differences in the anticipated affect responses were also observed, but these were largely attributable to changes in probability distributions and not EV. Responses of anticipated valence and arousal were similar in the best and worst outcome conditions. For best outcomes, the \ and ^ distributed gambles produced similar responses, while in the worst outcome scenario, it was the anticipated affect for the ^ and / distributed gambles that clustered together. These effects were not surprising given the actual probability values and expected values associated with each of the presented best and worst outcomes. For best outcomes, the probability of receipt among the \, ^, and / distributions were 0.10, 0.05, and 0.40, respectively, and for negative outcomes these were 0.40, 0.05, and 0.10, respectively. These probability differences are closely confounded with the expected value differences of μ+$100, μ+$100, and μ+$50, respectively, for best outcomes and μ-$50, μ-$100, and μ-$100, for worst outcomes. Future investigations that do not confound these structural features are necessary for determining which components are more strongly related to each type of anticipated affect.

Oddly, the subjective measures of risk and expected value for each gamble did not seem to correspond well at all to the anticipated affect or CE outcomes. This seems strangely peculiar, particularly given the strong influences just reviewed from the objective measures. However, it is important to point out that the modeling approach taken only allowed for prediction of individual differences within each anticipated affect and CE gamble response outcome (i.e., intercept terms for each outcome were estimated to handle fixed structural changes across the EV by probability within-subject factorial[11]). In other words, this subjective prediction can be viewed as a method for determining how far individuals deviate from the objective measure effects (i.e., the means, or rather intercepts, of each outcome). Still, this seems to be the most surprising result of all. If perceived risk and EV do not map well onto the individual variation present in anticipated affect and CE judgments, one has to strongly question the mechanism that generates variability in the first place. One can certainly rely on the measurement error arguments to be discussed in the section that follows, but invariably, even were all these limitations active simultaneously, it is hard to imagine that no

[11] Yet, inspection of descriptive Tables 29-32 reveals that even had these variables been used to detect fixed changes across gambles, only the EV trend appears to match the observed differences found in CE responses among both genders and outcome-sign gambles. Importantly, the descriptive patterns of perceived riskiness do not seem to pick up the observed differences between CE \ and / preferences found in the objective tests, but again this went un-modeled and was not statistically assessed.

meaningful variation was extracted and that no relationship existed between meaningful variation across measures of CE and subjective structural features. To some extent this may call for a substantial editing to the theoretical model presented in Figure 1.

Limitations

Many caveats accompany the analyses and results provided above. The vast majority of these involve measurement concerns. For starters, unlike most of the economic studies in this area, where measurement of anticipated affect and preference revolve around actual choice responses, this particular study utilized both economic measures of choice (the CE estimates) and psychological measurement of anticipated affect. Following the completion of the data collection for this study, Connolly and Butler (2006) published work that used a similar measurement approach. They sought to test the correspondence between self-reported emotion on gambling tasks and the emotion-laden descriptors placed on many of the choice-derived parameters of GEU models like the GDM. Their results indicated little correspondence between the GEU defined measures of happiness, sadness, rejoicing, regret, elation, and disappointment and self-reported measures, at least as discrete, prototypical emotions. There was support for correspondence between predictions from the regret/rejoicing mechanism and an aggregate 2-dimensional measure of affect. The same was not true when this 2-dimensional measure was used to predict effects of disappointment/elation. Connolly and Butler also found the measures of self-reported affect to be internally reliable (substantially high test-retest correlations and high Cronbach alphas for dimensional scales), monotonically related to payoffs, and uniquely predictive of preference. Moreover, Decision Affect Theory (Mellers, Schwartz, Ho, & Ritov, 1997; Mellers, Schwartz, & Ritov, 1999) and post-choice valuation models (Inman, Dyer, & Jia, 1997) also used self-reported measures of affect to successful model choice outcomes. So, despite its infrequent use in economic gambling tasks, psychological measurement appears to have some interesting viability in choice modeling.

Measurement concerns do not end with self-reporting procedures, however. As detailed earlier, many investigators have attempted to measure and use dimensions of affect to predict risky decisions, yet, rarely has agreement been reached on what dimensions to study. Lerner and Keltner (2000, 2001), for example, argue that emotions of the same valence and arousal can often differ in their impact on decision-making because of their differences in other dimensions (*appraisals* in their work, like control and certainty). Interestingly, Mehrabian (1995) has recently extended the Pleasure-Arousal Hypothesis to include dimensional influences of dominance. Other researchers have opted to avoid the use of dimensional affect in favor of prototypical, discrete measures of emotions like depression and anxiety (e.g., Eisenberg et al., 1996; Raghunathan & Pham, 1999; Raghunathan et al., 2006). The current methodology used the Russell and Mehrabian (1974) measure of affect, which greatly limits any attempts to extract these types of prototypical emotions. Future work in this area could avoid this limitation with either multiple measures of affect or scales designed to tap both types of affect (e.g., Vastfjall, Friman, Garling, & Kleiner, 2002).

As alluded to repeatedly above, the self-reported measurement of anticipated affect was particularly difficult. Not only does this type of elicitation require a considerable amount of time on behalf of the participant, but once measured, determining how to combine the various pieces of this affect (best, worst, and all those in between) remains a challenge, theoretically and methodologically, for future research (especially for gambles with more than two outcomes). This particular study only assessed expected affect for extreme outcomes and did so with only single-item measures. Guided by the aspiration level theories in rank-dependent GEU, it was believed that this may be sufficient to assess the major impact of expected affect on CE responses. The results presented above imply that either this presumption was untrue, single-item indicators are not reliable enough, or that perhaps, in this particular context, the relationship between these measures is not as strong as predicted. As evident in Hypothesis 2 analysis, one major improvement in future measurement will concern the avoidance of floor and ceiling effects. Given the nature of the task, it seems reasonable that a scale can be developed to detect real differences along the anticipated affect dimensions across such large differences in expected outcomes (e.g., EV differences of $150 and $200). Perhaps better coaching methods, instructions, or response anchors can be used with these affect self-report measures so that respondents are more likely to use responses that do not lie on the extreme boundaries.

Measurement concerns envelope the choice outcomes as well. The current method of CE elicitation deviates from previous methods (e.g., PEST procedure; Luce, 2000) in that each gamble's CE was estimated within consecutive iterations (i.e., consecutive choices between the sure-thing amounts and gambles used the same gamble until a CE was established). Much like the limitations on measurement of anticipated affect, this can also be a methodological Catch-22. On the one hand, you would like to design an elicitation procedure that limits the burden on the respondent and in turn any effects of fatigue, while on the other hand, there is genuine concern with biased reporting of CEs once the internal iteration procedure has been learned. Moreover, simply using certainty amounts has also been shown to produce bias (Luce, 2000) when compared to comparable judgments of actual choice (all pair-wise preference comparisons of gambles). The degree to which these biases affected results in this study are hard to determine. Future research with alternative elicitation procedures are a necessary progression.

Finally, as with any gambling study, the results are not easily generalized beyond the domain of the task. Moreover, generalizing within other gambling scenarios may even be difficult due to the very limited number of investigated gamble structures. In some situations (e.g., the elicitation of best and worst anticipated affect), the selected gambles suffered from unnecessary confounding of structural features (see *Summary of Hypothesis 2 Results*). Also, the study did not attempt to assess mixed gambles, where both losses and gains are possible. As the previous literature attests, even small changes to the current gambling task are likely to produce dramatically different results. Again future research is needed to expand these manipulated features.

Future Research

Aside from the measurement improvements highlighted in the previous section, much work remains to be done in the theoretical development of these affective influence models. A second follow-up study by this investigator is underway to explore the coloring effects of integral affect on risky choice (in fact data for this study were collected concurrently with the data reported in this dissertation). This second study will present work on how positive and negative feedback on gamble performance impacts current emotions (integral affect), and in turn how well these emotions predict future gambling performance. Similar studies are starting to trickle into the literature. Heyman, Meller, Tishcenko, and Schwartz (2004) recently explored the influence of immediate feedback to that of previous performance using time series analysis and an extended Decision Affect Theory model. Results indicated that while background performance did have an impact, immediate feedback was disproportionately weighted more heavily for future decisions. The findings suggested that whereas trends of outcomes over time were important, it was a person's most immediate experience that had a greater impact on the path they chose next. This speaks directly to the power of visceral influences as reviewed by Loewenstein (1996). Extending this work into contexts outside of gambling tasks seems a promising and valuable contribution to the literature.

Finally, although not particularly effective in this study, the close relationships between the risk perception and attitude literature with the affective decision-making theories seems to call for more attempts at unification. In the Weber and Milliman (1997) work reviewed earlier and a Mellers, Schwartz, and Weber (1997) study strong support emerged for consistent, trait-like measurement of risk perceptions. In both studies, choices based on preference and on risk (choosing the option believed to be riskier) closely matched one another, but for a large group this was a positive relationship, and, yet, for another substantial group of people these choices were negatively related. These findings suggest that individual differences on choice tasks may be a reflection of individual differences in personal tastes for risk-taking. Importantly, risk needed to be subjectively measured in these studies for these effects to emerge. So, although risk attitudes (i.e., how risky is this gamble) may differ from task to task and situation to situation, preference for risk may be stable. Future research in this area may benefit greatly from a comparison of stable prototypical affect like depression and anxiety and these trait-like measures of risk-perception. If these types of measures cluster in any manner, evidence for mediating mechanisms like that proposed in Hypothesis 4 could provide mechanistic explanations for previously identified incidental affect effects. This may be especially true for studies using self-report measures that tap, not only state, but also traces of trait affect (a situation unapologetically welcomed in Lerner & Keltner, 2000, 2001). Assessing the viability of these relationships in a variety of contexts, to include both in laboratory gambling tasks and more real-world based decisions (e.g., sexual decision-making), may prove to be an exciting extension of both these research programs.

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