Effects of Probabilistic Arrangements of Incentives and Disincentives on Work Task Performance in an Analogue Setting

By

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Abstract

The current study seeks to synthesize concepts from organizational behavior management and behavioral economics through an exploratory, translational paradigm. The degree to which workplace contingencies are subject to variables common to the behavioral economic literature was assessed in three experiments. The first experiment was a hypothetical discounting task that extended the cross-commodity discounting literature by comparing monetary outcomes with access to mobile devices, a potential competing reward in organizational settings. The second experiment was a systematic replication of Experiment 1 in the context of the workplace. The third experiment examined the effects of probability on the efficacy of an incentive system in an analogue work environment. The applicability of behavioral economics, specifically discounting, for organizations are discussed.

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Since the early 1900s, psychologists have studied the workplace in an effort to provide assessment, improve employee performance, and revise personnel selection procedures. The field of Industrial and Organizational Psychology (IOP) has been a staple of workplaces ever since. Organizations have turned to psychology to understand why some employees perform better than others. Some employees will go above and beyond the call of duty, expend more effort, complain less, take initiative, and become champions for organizational improvement while others expend only enough effort to avoid being fired or disciplined. Myriad management fads have emerged over the course of time, each promising to resolve organizational problems and convert problem employees into model employees. Fads are rarely based on evidence and even the mainstay organizational practices typical of modern workplaces remain problematic (Daniels, 1994). For example, traditional wage-pay systems fail to produce desired workplace behaviors and characterize what Abernathy (2011) describes as "sins." Pay for time will yield employees who are consistently present, but not motivated employees. Another "sin" involves manager reliance on punishment for discretions and adoption of the credo "no news is good news" resulting in ignoring employees performing adequately. Managers often adopt a style they feel suits them and fail to base their methods on a precise science of human behavior, which Daniels (1994) suggests is akin to a surgeon ignoring medical science and established procedures by adopting a personal style.

Through this lens, the necessity of psychology in the workplace is clear. Many issues have plagued supervisors and employees and historically, the traditional methods of management do not address the causal variables behind them. Overall, the systems and processes in

workplaces often fail to yield the results organizations are seeking, prompting managers to ask how to best motivate their employees. Daniels (2011) suggests managers should not ask why some employees are more motivated than others, but why the workplace is less motivating than non-work contexts. He points out that many people will expend a great deal of effort and personal resources without complaint in pursuit of their hobbies, in effect behaving like perfect employees. The reasons for differences in motivation are rooted in the science of behavior.

Behavior Analysis in the Workplace

The application of psychological principles to the workplace is within the purview of two disciplines: IOP and Organizational Behavior Management (OBM). While the purpose of both disciplines is similar, some substantial differences exist. IOP has made several contributions to understanding organizational issues such as personnel selection, performance appraisal (Bucklin, Alvero, Dickinson, Austin, & Jackson, 2000), and job "fit" and satisfaction (Mawhinney, 2011). However, IOP lacks a cohesive theoretical base leading to the absence of conceptually systematic applications. The data-driven focus on the prediction and control of well-defined measures of individual performance and organization-level outcomes characteristic of OBM approaches are arguably better suited to address a variety of relevant subjects. OBM is a sub-discipline of applied behavior analysis, which is its unifying conceptual foundation. OBM is the application of the principles of behavior discovered and developed by E. L. Thorndike, J. B. Watson, and B. F. Skinner (Wilder, Austin, & Casella, 2009). OBM has three sub-disciplines: behavioral systems analysis, behavior-based safety, and performance management.

Behavioral systems analysis (BSA) is the integration of behavior analysis and systems theory and provides a method for identifying areas for improvement and maintaining high performance within organizations, processes, and at the individual level (Brethower, 2002;

Diener, McGee, & Miguel, 2009). BSA focuses on the practices of groups of individuals (e.g., within organizations) that are either maintained or fail to be maintained as a function of the collective contingencies experienced by its members (e.g., Glenn, 1988). Several models for evaluating and changing organizationally relevant behaviors of employees have been described including the Total Performance System (Brethower, 1982) and the adaptive systems model (Rummler & Brache, 1995). The goals of systems analyses include improving organizational outcomes through four steps including identification of outcomes, organizational practices, the contingencies between practices and outcomes, and factors that immediately affect practices (Redmon & Mason, 2001).

The prevalence of workplace injuries in industry and the newly emerging health risks of repetitive, sedentary lifestyles typical of modern business have created the necessity for behavior-based safety (BBS). BBS is a sub-discipline focused on changing work environments to reduce and prevent injury. Unlike other approaches to reducing injury that focus on industrial design and mechanical safety devices, BBS targets the human behavior related to workplace safety (Wilder et al., 2009). Safety interventions in OBM have been implemented in a variety of settings including construction, manufacturing, transportation, mining, and several other industries (Sulzer-Azaroff & Austin, 2000). BBS interventions may also target cultural variables within an organization to promote safety using principles from humanistic psychology, referred to as person-based safety or a Total Safety Culture (e.g., Geller, 2001). BBS interventions promote the use of employees as change agents where peers conduct safety observations and provide feedback when they observe risky situations or behaviors.

Performance management refers to the application of behavioral principles to employee behavior broadly—in contrast to the specialized focus of the above disciplines (Wilder et al.,

2009). As a sort of umbrella term, performance management encompasses a variety of procedures and methods. Similarly to practices with children and individuals with disabilities, performance management practitioners may conduct assessments of performance issues to determine the cause of the problem (e.g., Austin, 2000). An intervention that addresses performance problems due to a lack of skills is behavioral skills training (Sarokoff & Sturmey, 2004), which is a multicomponent training package typically consisting of instructions, modeling, rehearsal, and feedback. For issues resulting from motivational or effort deficits—employees are adequately trained but fail to perform as desired—other interventions may be employed. Such interventions include feedback (e.g., Prue & Fairbank, 1981), goal setting (e.g., Fellner & Sulzer-Azaroff, 1984), self-monitoring (e.g., Olson & Winchester, 2008), and incentive systems (e.g., Bucklin & Dickinson, 2001)

Within performance management, several research themes have emerged, including rule-governance, feedback, analogues to reinforcement, and the economics of reinforcement in the workplace via behavioral economics (Johnson, Mawhinney, & Redmon, 2001). The emphasis of the following sections will be on workplace reinforcement and economics.

Skinner (1987) outlines the three determinant of human behavior: natural selection, ontogenic selection by consequences, and socially mediated cultural contingencies. As phylogeny refers to the selection of variants at the level of species, so ontogeny refers to the selection of variants in behavior within the lifetime of an organism. Behaviors that are reinforced are maintained while others are extinguished or suppressed through punishment. Within cultures, behaviors and practices are selectively passed on to new generations, comprising the third mode of selection. These hold true for employee behavior as well. That is, employees come to work and produce organizational outcomes according to the contingencies

that establish and maintain the relevant behaviors. Work behaviors are selected because employees contact success, either automatically through completing a task, or through commendation or praise from others. Perhaps one of the most salient contingencies in the workplace is the contingency between work behaviors and pay. Unfortunately, a lack of a tight contingency between work and pay exists in traditional organizational systems (Abernathy, 2011). Employees typically receive pay on the basis of time spent in the work setting. Pay arrangements that directly tie pay to employee output are called *pay-for-performance* or *performance pay* in the literature. Making payment contingent on observable and clearly defined performance is effective in improving employee behavior across a variety of arrangements (Bucklin & Dickinson, 2001).

Several methods exist for making pay at least partially contingent on performance (e.g., Dixon, Hayes, & Stack, 2003). Profit sharing is the practice of linking employee bonuses to organizational profit. When the organization does well, the employees receive a share of increased profits as a bonus. Gainsharing is a similar practice, but employee bonuses are determined through cost-savings in organizational processes. When employees make improvement in organizational processes that reduce the operating costs of the organization, the savings are placed into an incentive pool and employees receive a share. Both of these practices align employee goals with organizational goals—increased profits and reduced costs—but the contingency between performance and pay is still indirect. Presumably the employee behaviors that led to improvements in outcomes would be maintained, but there is a delay between behavior and reward up to a year in annual bonus arrangements. Finally, employees may receive incentive pay directly linked to individual performance. Organizations may deliver incentive arrangements in piecemeal in which employees receive payment on the basis of the number of

work units completed. Other methods for linking empirical measures of performance to pay are available for employees whose work outcomes are not discrete and countable (e.g., profit-indexed performance pay; Abernathy, 2011).

Currently, the literature has provided several considerations for designing an effective incentive system. The subject of individual incentives is one of few in the literature that has received attention across the full spectrum of basic-to-applied research. Bucklin and Dickinson (2001) identified three themes in the individual incentive literature in their extensive review, including (a) the proportion of an employee's pay available through incentives compared to base pay; (b) the schedule of incentive delivery; and (c) arrangements of incentive amount as a function of performance level (e.g., accelerating, decelerating, or linear piece-rates). First, a line a research arose from a case study in incentives systems at a bank (Dierks & McNally, 1987). The bank case study led to research questions regarding what proportion of employee pay made available as incentives would promote the highest performance. This proportion can range from 100%—where employees earn pay as piece rate—to lower proportions in which incentives are available above some amount of base-pay (Bucklin & Dickinson, 2001). Abernathy (2001) analyzed data from several companies, concluding incentive systems offering bonuses amounting to less than 20% of base pay were less effective. However, other applied studies and reviews in incentive systems suggested smaller incentives were still effective (e.g., Komaki, Coombs, Redding, & Schepman, 2000). Laboratory and translational studies of incentive proportions also suggested performance was higher when participants were able to earn incentives compared to receiving a base or hourly payment (e.g., Frisch & Dickinson, 1990).

Ambiguous results were also produced when fixed versus variable schedules of incentive delivery were arranged. In both the laboratory and applied settings, researchers have compared

continuous schedules of reinforcement to fixed or variable ratio schedules (e.g., Pritchard, Hollenback, & DeLeo, 1980; Latham & Dossett, 1978). Dickinson and Poling (1996) concluded in their review of this literature that incentive pay again produced better performance than hourly pay alone. In addition, they did not obtain systematic differences in performance across studies with respect to fixed versus variable schedules of reinforcement.

Finally, researchers have evaluated the effects of varying the amount of the incentive depending on the number of work units produced. Oah and Dickinson (1991) compared a linear piece rate (in which the incentive amount was the same for each unit completed) to an accelerating piece rate (in which the incentive amount was increased for each unit completed). Their rationale for the accelerating piece rate is that as more units are completed, it becomes qualitatively more difficult to produce further gains in rate (i.e., as performance approaches the ceiling of what can be done in some amount of time). However, their results showed comparable levels of performance for both incentive schemes. Smoot and Duncan (1997) evaluated linear, accelerating and decelerating piece rates. In one experiment, participants performed the best under a linear piece rate while a second experiment showed better performance under the accelerating piece rate. Given the varied and inconsistent results across studies in these three thematic lines of research, Bucklin and Dickinson (2001) concluded the ratio contingency between performance and pay appears to be the most consistently effective variable in increasing work performance.

In practice, incentives are often arranged for instances of employee behavior other than as a direct exchange between work units and reward. Managers might want to reward employees in the moment just for being on-task or for performing particularly well in a given instance. This is the crux of the method referred to as "catch them being good." Although an empirical study

could not be located that describes the use of monetary reinforcement in this way, the literature provides examples of the use of social reinforcement For example, Eikenhout and Austin (2004) reported an intervention in a department store with the goal to improve customer service behaviors among employees. The intervention consisted of a package of goal-setting, graphic feedback, and reinforcement. Reinforcement was delivered both weekly and immediately with the immediate feedback being delivered by supervisors contingent upon being "caught in the act" of delivering good customer service. Supervisors were trained to deliver feedback and were encouraged to spend time on the sales floor at least three times daily to observe for instances of good customer service to reinforce. The package intervention was very effective, with effect sizes of 1.68 or higher for all targeted behaviors (Cohen's *d*). The effects of the immediate reinforcement alone cannot be determined from the results because a component analysis was not completed.

Effective managers immediately deliver reinforcers contingent upon a desired behavior, which means they spend time among employees so they can directly observe behavior (Daniels, 1994). The problem is that although managers and supervisors are responsible for checking in on employees, they also spend a great deal of time in their own offices during which time they are not directly monitoring staff (Roberts & Geller, 1995). In scenarios such as this, employees are under a variable or random schedule of reinforcement, or an approximation to these schedules. Hantula (2001) describes the importance of looking to the literature on schedules of reinforcement in designing incentive systems claiming, "[t]he question to be addressed is not *whether* schedules are operating in a given context, but *which* schedules are operating" (p.160, emphasis in original). The relevance of this perspective to organizations is that whether consequences are deliberately delivered according to a specific schedule of reinforcement or

delivered without regard to a pre-planned schedule, a schedule is in effect and can be quantified. Ferster and Skinner (1957) and Herrnstein (1970) describe the profound impact varying schedules of reinforcement can have on behavior. Understanding how schedules affect employee behavior allows organizations to leverage these effects rather than simply hope whatever schedule happens to be in effect is maintaining optimum levels of performance.

The study of the effects of schedules of reinforcement on organizational performance provides a connection to economic principles (Hantula, 2001). Behavioral interventions essentially constitute an economic system and the characteristics of that system will influence the effectiveness of the intervention (Hursh, 1980). Findings from the field of microeconomics can complement decades of behavior analytic research about the links between schedules, response rates, and choice. A synthesis of microeconomics and behavior analysis could help to provide a more complete account of behavior. The following section will provide an overview of two alternative views of economics (i.e., normative economic theory and behavioral economics), and highlight areas of behavioral economics relevant to the design of incentive systems in organizational settings including choice architecture and environmental arrangements that affect consumer behavior, concepts related to consumer demand for commodities, and factors that affect the valuation of consequences (i.e., discounting).

Behavioral Economics

Among its several definitions, economics is a field studying the financial considerations regarding an activity or commodity (Oxford English Dictionary). Economists have studied how humans behave and make choices under various conditions, including how people value commodities. Camerer and Loewenstein (2004) posit that economics is implicitly a science of behavior and as such, the goals of economics include the identification of factors that affect

consumer behavior and the ability to predict such behavior. Economic models of human decision making tend to be normative (i.e., what rational consumers *should* do) as opposed to being descriptive of what consumers *actually* do, leading to failures in predicting real economic behavior (Thaler, 1980). Thaler and Sunstein (2008) suggest standard economic theory assumes humans have a high degree of rationality, self-control, and the absence of biases that leads to behaving in ways that achieve outcomes that are objectively best. Ariely (2008) suggests humans consistently make errors in decision making—behaving predictably irrationally. For example, the difference between one apple today or two tomorrow, and one apple in a year or two apples in a year plus one day are the same. Empirical research in choice and decision making reveals that perception of those options differs. When both outcomes are delayed, people tend to show more self-control and choose the larger of the two outcomes. As time passes and the options become more proximal as in the former pair, more people tend to choose the less delayed option (Thaler, 1981). The changing of preference between these two pairs represents a violation of the principle of invariance, which states that when two outcomes differ in utility, the preference order between them should not vary depending on how they are presented (Kahneman & Tversky, 1984). To better explain patterns of human choice and decision making, behavioral economics has emerged as the empirical examination of realistic economic behavior that focuses on testable and generalizable theories and predictions (Camerer & Loewenstein, 2004).

Having the means to more completely understand human choice and decision behavior is likely to directly benefit the analysis of behavior in several contexts including organizations. Employee behavior occurs in a complex context in which several concurrent contingencies may be in place, and employees engage in choice behavior insofar as they allocate their behavior one way or another. Understanding how environmental variables affect such choices may impact an

organization's ability to shift said allocation from unproductive to productive, risky to safe, or inefficient to efficient. Some relevant findings from the behavioral economics literature are described below.

Formulation effects and choice architecture. Framing, priming, and anchoring are phenomena by which the formulation of options affects choice. Framing refers to the phenomenon in which the description of a scenario influences the perception of outcomes (Tversky & Kahneman, 1981). For example, gains are treated differently than losses, items an individual owns are more valuable than the same item before it is owned (the endowment effect), and pure losses are treated differently than costs—in which some loss is accompanied by the receipt of some benefit—despite objectively equivalent values. Priming refers to a phenomenon in which the information provided before a choice scenario influences preference. Lee, Frederick, and Ariely (2006) asked participants to choose between two beers, a commercial beer and the same beer with vinegar added. Without the information about the added ingredient, more participants preferred the doctored beer. When the experimenter told participants the difference between the two beers was the addition of vinegar, more participants preferred the regular beer. Bertini, Ofek, and Ariely (2009) obtained a similar effect with coffee. When the experimenter presented coffee in an analogue scenario along with condiments in attractive commercial containers, participants rated the coffee as more desirable and agreed to pay more than when the experimenter presented the same coffee alongside the same condiments in foam cups.

In another study, Ariely, Loewenstein, and Prelec (2003) describe how prior exposure to arbitrary numbers based on survey respondents' social security numbers influenced their answers to questions asking about the value of retail items. Respondents who received a high number

prior to evaluating the items gave higher values than respondents who received a lower number, an example of the anchoring phenomenon. In addition, Thaler and Sunstein (2008) describe a range of other environmental manipulations that alter choice behaviors, referred to as choice architecture. Briefly, choice architecture is the arrangement of the choice environment that increases the likelihood that an individual will choose one option over another. For example, such arrangements might include changing the default option, making the desired option less effortful, or structuring complex choices with which people have less experience.

Demand. In addition to the aforementioned phenomena in choice arrangements, Hursh (1980) argues scientists can obtain a more complete account of behavior by borrowing from economics. If an organization arranges consequences to change behavior, it is necessary to understand how valuable such a consequence is to employees, realistically. That is, managers need to understand the relation between effort and consumption of the arranged consequence. Behavioral economic research has facilitated this understanding by observing the consumption of varying reinforcers in closed economic systems and allocation of behavior between competing contingencies, or choice behavior (Hursh, Madden, Spiga, DeLeon, & Francisco, 2013). Analysis of consumption parallels the economic concept of demand in which price is determined by a schedule of reinforcement and consumption refers to the quantity of the reinforcer obtained by the organism. The law of demand states that as the price of a commodity increases, consumption will decrease (Hursh et al., 2013). By providing access to a given contingency for an extended period of time, experimenters can determine the amount of the reinforcer that participants will consume at that price. Studies that have evaluated consumption over a wide range of prices have demonstrated a curvilinear relation between price and consumption. The properties of demand curves provide useful information about the value of commodities under

varying conditions and a means for empirically comparing relative value across commodities. For example, as price increases, organisms will work harder to defend rates of consumption for some commodities over others. That is, demand is more inelastic for some commodities than others. Commodities for which an organism will work harder to defend baseline levels of consumption have a higher essential value (Hursh et al., 2013).

Other variables influence the value of commodities. When the commodity is available outside of the experimental context—as it is in some operant arrangements where the organism receives a free maintenance ration following the experimental session to maintain a constant level of deprivation—the organism is in an open economy. Hursh (1980) showed that in an open economy, response rates decreased as a function of price whereas in a closed economic system—one in which the organism earns its entire daily ration in the experimental context—response rates increased with price. The availability of other commodities that are fully or partially substitutable for the commodity under study can also influence demand. The effect of the availability of a commodity on demand for another commodity is used to classify the commodity as a substitute, complement, or independent. Demand for a commodity increases with consumption of a complementary commodity, decreases with consumption of substitutes, and does not change with consumption of independent commodities (Hursh et al., 2013).

The selection of effective reinforcers is a topic where demand is particularly relevant for organizations. Wilder, Rost, and McMahon (2007) showed that managers are not particularly proficient at predicting employee preference for reinforcers. Managers may turn to reinforcer surveys or formal preference assessments to identify reinforcers (e.g., Waldvogel & Dixon, 2008). The issue of realistic value still remains once preferred stimuli have been identified. That is, the effectiveness of a reward may be substantially higher when the price for obtaining it is

relatively low. As price increases, however, individuals may be less willing to work for the reward (e.g., Reed, Niileksela, & Kaplan, 2013). A demand-based analysis of the relation between price and consumption is uniquely suited to facilitating the identification of effective and resource-efficient reinforcers.

Discounting. Beyond demand, other features of consequence delivery impact the value and effectiveness of commodities and outcomes as either reinforcers or punishers. Collectively, these factors are evaluated under a framework referred to as discounting. The systematic reduction in the subjective value of a delayed outcome is referred to as temporal discounting, which has been suggested as a mechanism for impulsivity as discounting describes the undervaluing of delayed consequences and overvaluing of immediate consequences (e.g., Ainslie, 1975). In addition, an expanding literature base has proposed temporal discounting plays a role in a variety of clinical disorders including drug addiction, pathological gambling, obesity, and other health problems (e.g., Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012; Bickel, Miller, Yi, Kowal, Lindquist, & Pitcock, 2007).

Binary choice procedures are often used in the assessment of discounting. In the case of temporal discounting, the choices presented are an immediate outcome and a delayed one. The goal is to determine a measure of indifference between the two options. This indifference point, then, provides a measure of the value or effectiveness of a delayed outcome compared to an immediate one. Mazur (1987) used an adjusting-delay procedure in which he presented subjects (pigeons) with a small reinforcer immediately, or a larger reinforcer following a delay. If the pigeons selected the key that produced the smaller reinforcer, the delay to the larger reinforcer was reduced. Conversely, the delay increased if the pigeons selected the larger reinforcer. The goal of this adjusting procedure is to find the delay value at which subjects are indifferent

between the two options. The procedure repeats with the smaller reinforcer being made available at several fixed-delay values.

The more common method for assessing discounting with humans is an adjusting-amount procedure. Rachlin, Raineri, and Cross (1991) conducted a study in which participants were presented with a choice between two hypothetical monetary outcomes of equal magnitude, one immediate and one delayed, a condition in which they preferred the immediate of the two options. The amount of the immediate reward decreased across subsequent trials and an ascending sequence of amounts was implemented. The indifference point was the average of the two values at which participants switched preference from immediate to delayed (descending) and from delayed to immediate (ascending).

Other variations on the adjusting-amount procedure have also been reported. The adjustment of the amount of the immediate alternative can occur in ascending, descending, or random order (e.g., Robles & Vargas, 2007). So that participants are not required to respond to a large number of option pairs as is the case in the above procedures, researchers developed several abbreviated procedures. Du, Green, and Myerson (2002) titrated the amount of the immediate monetary reward based on the participant's previous choice. Their procedure began by presenting a larger, delayed option and a smaller immediate option that was 50% of the value of the large option. The amount of the immediate option increased by 50% if the delayed option was chosen or decreased by 50% if the immediate option was chosen. Subsequent adjustments to the smaller amount were equal to 50% of the previous adjustment. This procedure is referred to as a titrating-amount procedure subsequently to differentiate it from fixed-sequence, adjusting-amount procedures. These procedures arrive at an indifference point more rapidly than procedures using a fixed sequence as the participant's first choice eliminates all values either

above or below the midpoint. If a participant prefers an option worth half of the delayed value when it is available immediately, one may presume that he or she would also prefer any larger amount provided immediately as well. Finally, the Monetary Choice Questionnaire (Kirby & Marakovic, 1996; Kirby, Petry, & Bickel, 1999) provides an efficient means by which to obtain an estimate of discounting using only 27 questions. Each question poses a choice between a smaller, immediate option and a larger, delayed option. The nominal values of both options and the value of the delay vary across questions. The rate at which participants discount delayed rewards is then estimated through an analysis of their choices.

The above procedures with humans present participants with hypothetical alternatives. Whether participants' responses to hypothetical scenarios resemble responding under real conditions in which participants receive the chosen reward has been the subject of several studies. For example, Kirby and Marakovic (1996) used a lottery system to increase the likelihood that participants would respond as though the consequences were real, rather than hypothetical. That is, they told participants there was a chance one of the outcomes they selected would actually be delivered. Richards, Zhang, Mitchell, and de Wit (1999) also informed participants one of their selections would be delivered at the end of the experiment. The results of both studies closely resembled findings of studies using hypothetical tasks. In addition, human responding on hypothetical discounting tasks parallels responding by non-human animals exposed to selected consequences (e.g., Critchfield & Kollins, 2001).

Empirically determining the discounted value of a reward or an outcome at several delays generates a discounting curve that illustrates the effect of delay on subjective value. Commonly, a mathematical function is fitted to the indifference points obtained to generate a curve illustrating the functional relation between value and delay. The shape of the discounting curve

differs depending on the scientific perspective taken. From the traditional economic perspective, the subjective value of a commodity decreases as a function of the delay to its receipt, and this decrease occurs at a constant rate (e.g., Samuelson, 1937). The subjective value of a commodity over a range of temporal delays, then, would take the form of an exponential decay function given by

$$V_D = Ae^{-kD} \qquad \textit{Equation 1.}$$

where V_D is the subjective value of the delayed outcome, *A* is the objective amount, *k* is a constant that specifies the rate at which the value is discounted, and *D* is the delay to receipt (Mazur, 1997). Any model of discounting must also account for reversals in preference that occur in studies of discounting. Thaler (1981) describes this consistent pattern in human choice as dynamic inconsistency in which delays of equal magnitude affect choice differently. He gives an example of two pairs of choices involving apples available after a delay. One pair of options is between an apple in one year and two apples in one year plus one day. The second pair is a choice between one apple today and two apples tomorrow. Despite the difference in the delay to receiving the larger of the two options in both pairs being objectively equal (i.e., one day), people tend to respond differently to the two scenarios.

When the exponential model assumes that the discounting rate (*k*) is equal across both the smaller and larger rewards, it does not predict these reversals in preference and subjective value (e.g., Rachlin, 2000). However, Green and Myerson (1993) argue *k* varies inversely with amount and if an amount-dependent *k* is used, the exponential function can predict preference reversals. The literature has also proposed other models that both predict dynamic inconsistency and provide better fits to empirical data. One such model is a hyperbola as

$$V_D = \frac{A}{1+kD} \qquad \textit{Equation 2.}$$

with the parameters being the same as Equation 1 (Mazur, 1997). The hyperbolic equation describes empirical discounting data substantially better than an exponential decay function (Madden & Johnson, 2010). In addition to the objectively better fit, the hyperbolic equation also predicts the reversals of preference (i.e., dynamic inconsistency) described above. When the choice is temporally delayed as in the choice between one year and one year plus one day, preference tends to be greater for the higher magnitude reward, despite that option being slightly more delayed. However, at a certain point in time as the choice becomes temporally proximal, preference reverses and more selections of the smaller, but sooner reward occur (Green & Myerson, 2004). Others have proposed that the addition of a psychophysical scaling parameter to the hyperbolic equation provides improved fits of empirical data. The scaling parameter is either added to the denominator of the hyperbolic equation (e.g., Myerson & Green, 1995)

$$V_D = \frac{A}{(1+kD)^s} \qquad \textit{Equation 3.}$$

or just the delay (e.g., Rachlin, 2006)

$$V_D = \frac{A}{1+kD^s} \qquad \textit{Equation 4.}$$

The *s* parameter is proposed to represent the psychophysical scaling of amount and time (Equation 3) or just time (Equation 4) and has been shown to be relatively stable within participants (e.g., McKerchar, Green, & Myerson, 2010; Myerson & Green, 1995) whereas *k* varies with amount.

In an inductive science, experimenters obtain empirical measures of a phenomenon and then seek a model that adequately accounts for the data observed. To this end, measures of fit can inform the choice of one of the several available models of temporal discounting. However, model selection based on goodness-of-fit for each individual data set presents a problem for experimental comparisons of discounting across subjects and conditions. Researchers can

compare rates of discounting using the *k* parameter. However, the addition of another parameter means that *k* cannot be used to compare discounting across subjects or conditions unless *s* is held constant. The alternative is to use a one-parameter model, but in either case, these lead to sacrifices in the degree to which the models fit the empirical data. Two alternative methods have been proposed to overcome this experimental limitation. Myerson, Green, and Warusawitharana (2001) calculated the area under discounting curves using the formula

$$\sum(x_2 - x_1)\left(\frac{y_1 + y_2}{2}\right) \qquad \textit{Equation 5.}$$

which takes the area of the trapezoid formed by two adjacent points. Higher AUC values represent shallower discounting, or, less sensitivity to delay. Alternatively, Franck, Koffarnus, House, and Bickel (2015) propose an objective method for selecting the best model for each data set and yielding an index of discounting comparable across data sets regardless of which model is used. First, the experimenter selects a set of models to compare. Using an information criterion (e.g., Bayesian information criterion, BIC) the probabilities that each model fits the data best are compared and the most probable model is selected and fit to the data. Because different models may be selected for each data set, differences in the number of parameters prohibit comparisons based on *k* values. Instead, the effective delay 50% (ED50) is calculated as the delay value at which the subjective value of the delayed reward is 50% of the objective value (Yoon & Higgins, 2008). Using ED50, lower values indicate steeper discounting compared to larger values.

Similar mathematical models also describe the discounting of outcomes as a function of effort. Grossbard and Mazur (1986) used an adjusting-effort procedure with pigeons. Choosing one alternative resulted in 6 s of access to grain contingent upon the completion of a fixed-ratio schedule of reinforcement. The second alternative resulted in 2 s of access to grain contingent

upon a richer ratio schedule of reinforcement. If the pigeon displayed a preference for the less effortful option, the response requirement was subsequently increased. Conversely, if the pigeon displayed a preference for the more effortful alternative that resulted in more access to grain, then the response requirement for the less effortful alternative decreased. Although the authors did not plot hyperbolic discounting curves as a function of effort, when they plotted the ratio schedule for the larger reinforcer as a function of the ratio requirement for the smaller reinforcer, a linear relation was obtained, which is predicted through a derivation of the hyperbolic equation. A second study used an adjusting-amount procedure with Japanese students in which an effortful, but larger option was paired with a smaller, effortless option (Sugiwaka & Okouchi, 2004). The amount of the effortless option changed across trials in an ascending sequence to identify the point of indifference. The authors concluded the hyperbolic model well-described discounting of monetary rewards as a function of the effort required to obtain the larger reward. Reed and colleagues (Reed, DiGennaro Reed, Chok, & Brozyna, 2011; Reed, Kaplan, & Brewer, 2012) have also described a special case of effort discounting on the basis of search costs. A phenomenon called choice overload suggests having too much choice becomes aversive despite the typical preference for choice over conditions of limited choice. Participants preferred extensive options initially when presented with a choice between a single option, limited options, and extensive options. When the number of options was increased across trials, preference shifted to limited options.

Discounting may also apply when the outcomes are shared with someone other than the subject. Jones and Rachlin (2006) asked participants to imagine they had created a list of 100 people ordered from closest friend or relative to a distant acquaintance. Participants then completed a discounting task in which they chose between a smaller amount of money for only

them or a larger amount of money shared with a person on the list of varying social distance. A hyperbolic function fit the plot of maximum amounts of money forgone in exchange for obtaining the smaller amount of money for one's self suggesting the same function that describes delay also describes social discounting.

Probability discounting. The mode of discounting most relevant to the present investigation is probability. The following is a brief background on probability discounting, followed by a review of studies most relevant to organizational settings (i.e., probability discounting of monetary and non-monetary rewards by typical adults). A large portion of the literature has focused on discounting within the context of addiction and pathological gambling (e.g., Bickel et al., 2012). Because this literature supports differences in how gamblers and individuals using addictive substances discount outcomes compared to individuals without documented pathologies, studies focused on pathological discounting are excluded from this review. The literature search procedure and inclusionary criteria are provided in Appendix A.

Prospect theory, proposed by Kahneman and Tversky (1979), describes discrepancies between the rational, economic view of utility and consistent violations of rationality in empirical studies of utility. When faced with a risky prospect, the expected utility (i.e., rational evaluation of risk) of a commodity is given as the nominal value of the outcomes weighted by their probability. For example, the utility of \$100 with a probability of 0.50 is given by (0.50)\$100 + (0.50)\$0 = \$50. Utility plotted over a range of probabilities using expected utility would take the form

$$E_V = pA \qquad \textit{Equation 6.}$$

where p is the probability and A is the nominal amount of the outcome. However, the manner in which individuals weight the value of risky prospects does not correspond with models of

rational decision making (e.g., Kahneman & Tversky, 1984; Thaler, 1980). Rather, additional factors influence decision weights when faced with risky prospects. For example, people tend to overweight lower probabilities and underweight higher probabilities. The difference between a prospect with a 0% probability and 5% is greater than the difference between the same prospect at 50% or 55% (Kahneman & Tversky, 1984). Parallel to the finding that discounting delayed consequences is hyperbolic, research has supported hyperbola-like discounting of probabilistic outcomes (e.g., Rachlin et al., 1991).

The similarity in form between probability and temporal discounting led to hypotheses that delay and probability are examples of the same process, such as impulsivity (e.g., Green, Myerson, Oliveira, & Chang, 2014). For example, temporal discounting of outcomes may be a function of a reduced expectancy that the outcome will actually be obtained (e.g., Mahrer, 1956), which would suggest that temporal discounting is a case of probability discounting. Rachlin, Logue, Gibbon, and Frankel (1986) propose the inverse. Organisms with a history of repeated gambles may interpret uncertain outcomes as delayed outcomes. For example, if a gamble has a 20% probability of producing a reward, it will require five responses on average before the reward is obtained, which would delay the outcome more than a more certain gamble.

Rachlin et al. (1991) presented undergraduate participants with either a temporal or probability discounting task using an adjusting-amount procedure with both an ascending and descending sequence of amounts for the immediate or certain options. The authors tested seven delay and probability values with an ascending sequence of delays and descending sequence of probabilities. The hyperbolic functions described the obtained data well. For temporal discounting, Equation 2 was shown to provide an excellent fit ($r^2 = .995$) of the group data. An analogous hyperbolic function described probability discounting data given by

$$V_p = \frac{A}{(1+h\theta)} \qquad \textit{Equation 7.}$$

where θ is the odds against an outcome as $(1/p) - 1$. Equation 7 produced better fits of the data than an exponential decay function (Equation 1 with θ in place of k) extending the similar finding in temporal discounting research. In a second study, participants chose between a probabilistic amount of money and an equal amount of delayed money. The delays changed across trials to find a point of equivalence between delay and probability. Plotting the points of equivalence revealed a proportionality between h and k parameters in the discounting functions. Taken together, the formal similarity of the probability and temporal discounting functions and the proportionality of the parameters suggest probability and delay correspond in their effects on subjective value. Mathematical similarity does not provide direct evidence for or against the hypothesis that probability affects value as a function of the waiting time before the delivery of a reward, however. Although Equation 7 is commonly used in the behavioral discounting literature, a recent cross-disciplinary study concluded that other models may provide better descriptions of discounting, but the differences were small (Takahashi, Oono, & Radford, 2007).

Rachlin and Siegel (1994) provided a more direct analysis of whether temporal and probability discounting are related processes. The experimenters gave participants the choice to spin one of two spinners, each with a difference chance to produce a monetary reward. They programmed the probability by changing the number of white tiles around the outside of the spinner. One spinner produced $0.10 with a probability of 17/18 (17 white tiles, one black tile) while the other produced $0.25 with a varying probability that was adjusted across trials. Across groups, the inter-trial interval (ITI) differed, either imposing an ITI following each spin, or permitting several spins before the ITI. Preference shifts across groups differed. Given that all participants experienced the same values of probability, the authors concluded the differences

cannot be independent of temporal factors. Generally, risky options were less preferred when ITI length was higher. Again, the authors concluded the results do not fully support the function of time in risky decision-making, but argued a theory of probability discounting would need to include time as a factor to explain their findings.

Navarick (1987) manipulated delay, probability, and reward magnitude in a human operant chamber with two buttons operating on concurrent chains. Pressing a button resulted in the programmed schedule taking effect, presenting the reward (projected images) with a varying probability, delay, and/or duration. Varying only probability or amount, participants preferred the certain option or longer reward duration, respectively. Two groups chose between options differing on all three schedule parameters. Participants demonstrated a stronger preference for an option that was immediate and certain over one that was uncertain and delayed but longer in duration. However, participants also preferred an uncertain, larger option when it was immediate over one that was certain but delayed. The patterns obtained resembled a choice between gambling over placing money in a savings account. That is, the former is an uncertain but immediate outcome whereas the latter is certain but substantially delayed, adding face validity to discounting as a mechanism of impulsivity. Navarick also concluded the results are more parsimoniously interpreted with delay and probability being independent parameters in contrast to Rachlin et al. (1986).

The aforementioned studies provide some evidence that delay and probability interact in choice arrangements. However, the effect of manipulating reward amount differs in studies of temporal and probability discounting. In the former, individuals discount rewards of larger magnitudes less steeply and the outcomes retain more value as delay increases (e.g., Green, Myerson, & McFadden, 1997). Conversely, the literature shows a relatively robust magnitude

effect in the inverse direction with probability discounting. Green, Myerson, and Ostaszewski (1999) collected both temporal and probability discounting measures from 68 Polish undergraduate students to examine whether the same mathematical function describes both. In addition, they posited, if both forms of discounting share a process, experimental manipulations of the discounting tasks should affect subjective value similarly across modes of discounting. Participants completed an adjusting-amount discounting task for both temporal and probability discounting twice. During one administration, the value of the delayed or uncertain monetary outcome was $500 and during the other, it was $10,000. The results indicated the two-parameter, hyperbola-like model (Equation 3 above with θ substituted for *k* for probability discounting) accounted for over 99% of variance for both forms of discounting. Participants discounted the delayed receipt of $10,000 less steeply than $500, replicating the magnitude effect described above. However, participants discounted $10,000 more than $500 when the outcomes were probabilistic. In a second study, $200, $5,000, and $100,000 rewards were compared and the same findings were replicated with the hyperbola-like model accounting for more than 98% of the variance. Rachlin, Brown, and Cross (2000) obtained similar results with amounts ranging from $10 to $1,000,000. Despite procedural differences, the hyperbolic function well described subjective value. Comparing data obtained for larger amounts to smaller amounts, discounting was steeper for uncertain rewards. To date, several studies have replicated the effect of magnitude in probability discounting (Estle, Green, Myerson, & Holt, 2006; Estle, Green, Myerson, & Holt, 2007; Mitchell & Wilson, 2010; Myerson, Green, Hanson, Holt, & Estle, 2003; Ostaszewski & Bialaszek, 2010; Rachlin et al., 2000; Weatherly & Derenne, 2013; Yi, de la Piedad, & Bickel, 2006).

In their evaluation of the effect of amount on probability discounting, Myerson, Green, and Morris (2011) proposed the effect of amount primarily influences the exponent *s* rather than *h* in the probability discounting function. This is in contrast to findings in temporal discounting where *s* is constant over both delays and amounts while *k* varies (e.g., Estle et al., 2006). That is, *s* is representative of the psychophysical scaling of amount and delay and describes how a given individual perceives differences in these variables (e.g., Stevens, 1957). When Myerson et al. (2011) plotted parameter fits of the hyperboloid model against amount, they found only *s* significantly correlated with amount. This finding suggests *s* is not a scaling parameter for amount, but rather reflects the weighting of the odds against an outcome. Myerson et al. argue this interpretation is consistent with the decision weighting aspect of prospect theory (Kahneman & Tversky, 1979). That is, *s* may describe the weight an individual gives to a given probability in relation to the amount at stake.

Collectively, the differences between temporal and probability discounting suggest they do not share the same underlying mechanism. A large-scale study by Jarmolowicz, Bickel, Carter, Franck, and Mueller (2012) provided further evidence that while similar mathematical functions describe the two modes of discounting, they are likely to be separate processes. They recruited 904 participants using Amazon Mechanical Turk. The participants completed sets of Monetary Choice Questionnaires for both temporal and probability discounting. They found the rate parameters *k* and *h* were only weakly correlated. The correlation was also in the opposite direction one might expect. Shead and Hodgins (2009) provide an interpretation of probability discounting that parallels the impulsivity interpretation of temporal discounting. Compared to the expected value of a prospect (i.e., the rational value of a risky outcome described by Equation 6 above), subjective values that are higher than expected value represent risk-seeking

and subjective values less than expected value represent risk-aversion. A negative correlation between rates of discounting across delay and probability would be expected if both modes of discounting are manifestations of impulsivity (intolerance for delay and accepting risk). The positive correlation found reveals participants who were impatient also tended to be risk-averse. A principal component analysis yielded two factors rather than one further adding to the conclusion that temporal and probability discounting are not results of impulsivity (see also Green et al., 2014).

Despite this evidence for differing processes, researchers have found many variables that influence rates of temporal discounting also have an effect on rates of probability discounting. For example, several studies have shown the discounting of losses differs from that of gains. Shead and Hodgins (2006) presented participants with both a probability discounting of gains task as well as one for losses, both using a titrating-amount procedure. A correlational analysis revealed a negative, but not significant, correlation between probability discounting of gains and losses. The probability of replicating the negative correlation in 2000 resamples (p_{rep}; Killeen, 2005) was .97 making it a relatively robust finding. The authors concluded individuals who discount gains steeply tend to discount losses less steeply (risk-aversion) and *vice versa* (risk-seeking).

Mitchell and Wilson (2010) reported similar findings, but also manipulated the amount of probabilistic gain and loss. They divided participants into four groups, each completing four discounting tasks. One group completed a gain and loss task with both $10 and $100. Participants discounted probabilistic gains more steeply than losses and larger gains more steeply than smaller gains. No effect of amount was obtained for losses. Estle et al. (2006) examined the effect of amount on probability discounting using $200 and $40,000. The results showed a

strong effect of amount on uncertain gains, but not losses. Green et al. (2014) obtained discounting measures for uncertain losses over a wide range of amounts from $20 to $500,000 and found amount had no systematic effect on discounting. Because amount also had no effect on delayed losses, the authors concluded discounting of gains in either mode does not predict discounting of losses. At the individual level, there appeared to be three distinct patterns of discounting: delayed gains, uncertain gains, and amount-insensitive discounting of losses.

Two studies took a novel approach to the effects of gains versus losses in probability discounting. Ostaszewski and Bialaszek (2010) combined gains and losses in outcomes that participants either chose to accept or reject as a pair. For example, they told participants if they chose to take a certain gain, there was a chance they may also incur a loss or a certain loss may also result in a gain. In both conditions, the uncertain amount of gain or loss was either 900PLN (Polish Zloty currency) or 9,000PLN and the certain amount was adjusted in either an ascending or descending sequence. The authors used four probability values from 5% to 95% in a descending sequence. They defined subjective value as the amount of the certain option at the point where participants switched from accepting the offer to rejecting it. In this method, the subjective value represents the amount of certain gain that would compensate for the risk of loss or the amount of certain loss that participants would tolerate to have the chance for a gain. The two-parameter hyperboloid model (Equation 3) fit the group median indifference points well. AUC was also calculated and for the certain-loss, uncertain-gain condition, AUC was smaller for the larger amount (the larger amount was discounted more steeply) replicating the effect of amount in previous studies. In the certain-gain, uncertain-loss condition, AUC values for both amounts were nearly identical, replicating the amount-insensitivity for uncertain losses.

Weatherly and Derenne (2013) framed gains and losses as either winning a sweepstakes or failing to be repaid money that is owed. In the gains condition, participants received a scenario in which there was a chance they may win a prize in a sweepstakes, but they may choose to accept a smaller, guaranteed amount of money instead. In the loss condition, the scenario presented was one in which someone owed the participant money, but there was a chance they would not be able to repay it. Alternatively, participants could choose to accept a certain amount of money less than the amount owed. The experimenters tested two uncertain amounts—$1,000 and $100,000—in each condition. Across two experiments, participants were either asked to select a certain amount they would accept in lieu of the uncertain amount (multiple-choice) or give the minimum amount they would accept (fill-in-the-blank). Comparing gains to losses using the frame of won and owed money, the results revealed owed money was discounted less steeply than won money, further extending the findings on the effects of gain/loss framing.

The literature on probability discounting has also described several other variables that affect rates of probability discounting. For example, Dai, Grace, and Kemp (2009) obtained a reward contrast effect on subjective value in which being presented with a discounting task involving either a small or large amount affected the degree to which an intermediate-size reward was discounted. In a first experiment, two groups of participants completed four discounting tasks each. One group completed a discounting task with a probabilistic amount of $5,000 and then a second task in which the probabilistic amount was $500. The first standard amount for the other group was $50, with the second standard amount also being $500. Each group also completed temporal discounting tasks with the same amounts. The results for the initial standard amounts ($50 and $5,000) replicated the magnitude effect with $5,000 being discounted more

steeply than $50. The authors compared discounting across groups for the $500 reward. When $500 followed $5,000 as a standard amount, the former was discounted less steeply than when $500 followed $50. The direction of this effect is expected based on the direction of the magnitude effect in probability discounting. Notably, the effect of reward contrast was in the opposite direction for temporal discounting tasks, a difference also expected given the direction of the magnitude effect in temporal discounting. In a second experiment, Dai et al. replicated these findings using a within-subjects comparison in which participants completed discounting tasks with standard amounts being $50 and $5,000. Following each task, participants completed a probe to obtain an indifference point for only a probability of 70% and an intermediate standard amount.

The subjective value of delayed and probabilistic outcomes is commonly reported as the amount of an immediate or certain outcome that is subjectively equivalent and is derived from procedures in which participants make a series of choices between two options. However, Hsee, Zhang, Wang, and Zhang (2013) argue individuals do not always encounter delayed and probabilistic outcomes as a choice scenario. Rather, individuals must sometimes decide whether to accept a single outcome of a given value that may be delayed or uncertain. The authors compared discounting in situations of joint evaluation with two options available for comparison, and single evaluation, in which participants had only one option and reported how acceptable that option was. In one experiment, the experimenters told participants they had 120 min of free time during which they might choose to wait in line to receive a $50 gift certificate. The probability of obtaining the gift certificate was either 100%, 90%, or 80%. Participants assigned to one of the three single evaluation groups were presented with only one of the three probabilities and asked to decide how much time they would be willing to wait in line.

Participants in the joint evaluation group were presented with all three probability levels at the same time and asked to report how much time they would wait in line for each of the scenarios. The results revealed participants in single evaluation were less sensitive to the degree of uncertainty than those in joint evaluation. Specifically, participants in single evaluation reported they would wait about as long in the 80% scenario as those in joint evaluation reported they would wait in the 90% scenario. Both groups were equally sensitive to the difference between 90% and 100%. At the other end of the probability spectrum (impossibility), similar results were obtained. Participants in the single evaluation group were willing to wait about as long in the 10% and 20% scenarios while participants responded differently to joint options.

Hsee et al. (2013) also hypothesized when individuals have one option, discounting would be relatively insensitive to the magnitude of the outcome while magnitude would affect decisions in joint evaluation. In two experiments, participants were presented either with two scenarios jointly (joint evaluation), or one of those two options alone (single evaluation). One option was smaller and riskless while the other was large and risky. The results supported their hypothesis as single evaluation participants reported stronger preference for the riskless option while the joint evaluation participants preferred the larger, risky option. The authors concluded that when evaluated alone, the risk affects acceptability more than magnitude and the opposite is true for joint evaluations.

Another effect of option framing was reported by Jones and Oaksford (2011). They argue gains and losses of commodities in studies of discounting do not resemble the context in which individuals might typically encounter them. Specifically, commodities are gained or lost in a transaction where one exchanges something for the commodity. To determine whether the context of transaction influences subjective value under delay or uncertainty, they presented

participants with a discounting task in which they chose between two ways to pay for some commodity that was already received. The options included an amount that would be paid for certain and a probability that a larger amount would be paid. Participants completed the task with uncertain amounts of $200, $2,500, and $15,000 and five probabilities between 10% and 90%. In each scenario, the authors told participants they had already received the item they are paying for and that to assume they have enough money to pay for the item in either option. The authors reported subjective points of indifference between the options varied as a function of odds against paying the larger amount. A significant effect of amount was also obtained with the direction of the relation being the same as the standard magnitude effect in temporal discounting (i.e., larger costs were discounted less steeply than smaller costs). As described above, the magnitude effect for uncertain gains is typically in the opposite direction compared to delayed gains. However, amount did not affect losses in either modality. The magnitude effect found by Jones and Oaksford, however, cannot be confidently attributed to the transactional content of the instructions as the same effect was obtained in another experiment in which transactional content was removed as a control. The main difference between transactional and non-transactional conditions was that discounting in the latter was less steep. The authors argue transactional content influences probability discounting by adding an implicit benefit to the uncertain loss. That is, the loss is balanced against the gain of obtaining the commodity for which payment is being considered. Choosing the uncertain payment option adds to the benefit of obtaining the commodity through the possibility that the gain could be had with no cost. These results contrast with those described by Ostaszewski and Bialaszek (2010) but the experimental preparations differed.

The framing of options may also have an effect on how individuals discount gains. Yi and Bickel (2005) argued many studies in probability discounting present options as one-time decisions, meaning the value of the uncertain outcome is either nothing or the full amount of the reward. When presented with risky prospects as one-time gambles, probability discounting deviates from expected value, but the availability of repeated gambles has been shown to increase the degree to which subjective value resembles an expected value function (Yi & Bickel, 2005). Information about probability may also be presented in terms of relative frequencies (e.g., 25% is 1 of 4). The purpose of the study by Yi and Bickel, therefore, was to determine what effect expressing probability as a relative frequency in a one-shot choice would have on discounting compared to expressing the same information as a percentage. In addition, participants completed a discounting task in which they chose between a smaller certain amount of money and ten chances—expressed as a frequency—to obtain a larger amount of money (i.e., repeated gambles). The authors held expected value constant across conditions by altering the amounts in the repeated gambles condition. Participants responded differently to the three tasks (one-shot percentage, one-shot frequency, and repeated frequency). With probabilities stated as a relative frequency, discounting occurred less steeply than when expressed as a percentage. A significant difference was obtained between the one-shot frequency and one-shot percentage conditions. The mean *h* value for the repeated gambles condition fell between the other two conditions, but the difference failed to reach significance. The authors argued the difference obtained does not invalidate procedures that express probability as a percentage, but that individuals may interpret or process frequencies differently.

Another series of studies evaluated the combination of probability and delay in discounting. Blackburn and El-Deredy (2013) set out to examine how best to characterize the

discounting of outcomes that are both delayed and uncertain. Participants completed three tasks. One task was a standard temporal discounting task with the delayed amount being set at £100. Uncertainty was introduced as both uncertainty of the outcome occurring (e.g., a 50% chance of obtaining £200) and as uncertainty of the amount of the reward (i.e., a 100% chance of obtaining either £50, £100, or £150). The authors presented the standard amounts described above along with a smaller, immediate, and certain monetary reward, which they adjusted across trials to converge at an indifference point. Participants completed each of the three tasks with eight delays ranging from no delay to 10 yrs. The authors suggested the hyperbolic model could describe discounting of both delayed and uncertain rewards. However, the objective value used for *A* in Equation 2 must account for the presence of uncertainty in the options. They compared using the expected value of the delayed reward, which would be £100 for both conditions with uncertainty, and an empirically derived certain equivalent as the value of *A*. Participants indicated their certain equivalent of an uncertain £200 and a certain opportunity to obtain one of three reward amounts through indifference points when the outcomes were available with no delay. The results showed using the certain equivalents for *A* resulted in better fits of the indifference points compared to using expected value. The authors found the lowest rate of discounting under the uncertain reward amount condition using fits based on certain equivalents. A second study examined both the magnitude and outcome valence (gain vs. loss) using the same procedures. Participants discounted gains more steeply than losses, and smaller gains more steeply than larger gains, with losses being insensitive to reward amount.

Yi et al. (2006) took a different approach to characterizing the discounting of delayed and uncertain outcomes. They proposed if an outcome is both delayed and uncertain, the probability could be converted to an equivalent delay using the constant of proportionality ($h/k = 35.3$)

described by Rachlin et al. (1991). Discounting can then be modeled using the resulting equivalent or composite delay. Participants completed standard temporal and probability discounting tasks along with two combined tasks. In one, participants were given a scenario in which they were given a lottery ticket with a known probability of winning, but the determination for whether the ticket was a winner would not be made until after a delay. The immediate certain option was an amount of money paid by a lottery agent who would buy the ticket. In the other combined condition, the lottery ticket had a known probability of winning and the determination would be made immediately, but the winnings would be delayed. The authors found no significant differences between the two combined conditions. In both combined conditions, the hyperbolic model using composite delay values provided good fits.

Keren and Roelofsma (1995) suggested probability only affects how individuals discount delayed rewards at shorter delays. Across groups, they gave participants a choice between smaller reward now and a larger reward in four weeks, where both outcomes had a probability of 1.0, 0.9, or 0.5. Other groups of participants had similar options, but the delays were 26 and 30 weeks. The effect of uncertainty at short delays was a shift from the majority of participants selecting the immediate reward when it was certain to the majority of participants selecting the reward delayed by 4 weeks when the probability was 0.5. However, at longer delays, no substantial effect of uncertainty was obtained as the majority of participants already preferred the larger, more delayed option when the probability was 1.0.

As in studies on other forms of discounting, many studies in probability discounting focus on the discounting of hypothetical, monetary rewards. However, several studies provide evidence that discounting of hypothetical rewards bears resemblance to discounting when the outcomes are real. For example, Hinvest and Anderson (2010) presented participants with a

discounting task using hypothetical outcomes and an identical task using real outcomes. In both, participants made choices between two options with option A being 10 pence with a probability of 1.0, .75, .5, or .25 and option B being 20 pence with a lower probability than option A. The probability of option B changed across trials (i.e., amount was not adjusted). The procedure used visual representation of probabilities using graphical depictions of spinner wheels similar to those used in Rachlin et al. (1991) with a green segment indicating a win and a red segment indicating a loss. After participants made a choice, a spinner was imposed on the wheel with a random orientation to determine whether the chosen reward would be delivered. The authors found no significant difference between probability discounting of real or hypothetical rewards. However, there was an effect of sequence. Participants tended to show a stronger preference for the larger amount (i.e., make riskier choices) when presented with hypothetical rewards first. Comparing the indifference points from the condition presented first across participants showed no significant differences in discounting, suggesting discounting measures do not differ between real and hypothetical outcomes. Thus, the findings of studies on probability discounting using hypothetical rewards are likely to resemble choices made in the context of real, experienced outcomes.

Another factor related to the generalizability of probability discounting is whether people discount other commodities similarly to money. Several studies have examined probability discounting with non-monetary commodities. Estle et al. (2007) compared discounting of money to candy, soft drinks, and beer. Participants completed a series of discounting tasks following a titrating-amount procedure. They indicated indifference points for each reward type at five probabilities and two reward amounts (40 units and 100 units). For comparison, participants also completed identical temporal discounting tasks. An ANOVA revealed no significant differences

in the rate at which participants discounted each reward type as a function of probability. This finding was in contrast to those for temporal discounting in which participants discounted money less steeply than non-monetary rewards. In addition, participants discounted larger rewards more steeply and less steeply for probability and delay, respectively.

Holt, Newquist, Smits, and Tiry (2014) partially replicated these results, showing participants discounted smaller amounts of food and money at similar rates. With larger amounts, however, participants discounted food less steeply than money. The authors also extended the comparison between money and non-monetary rewards to include sexual outcomes (see also Lawyer, 2008). For all three reward types, line segments represented relative quantities with the full length of the line being the ideal reward outcome and shorter lines being proportional magnitudes of the ideal. Participants discounted sex substantially less steeply than both food and money at both magnitudes. Notably, the authors also found no significant correlations between discounting rates for the three reward types. This finding suggests discounting of one reward type would not be an accurate predictor for how an individual discounts other commodities.

Further, discounting occurs as a function of probability for other commodities as well. One study examined responding in the context of a video game in which a tradeoff existed between probability and magnitude (Young, Webb, Rung, & McCoy, 2014). Participants chose in real-time when to initiate an attack, the effect of which was determined by a progressively decreasing magnitude of effect but a concurrently increasing probability of effect, or *vice versa*. When the probability the action would be successful started at a low level and increased with waiting time, participants waited longer than the optimal amount of time, showing a preference for higher probability over effect magnitude. Attema, Brouwer, and l'Haridon (2013) showed

participants discounted years of health as a function of probability when they were offered two hypothetical drugs, one that would extend the participant's life by a small number of years for certain and another that had a probability of extending life by more years. Kaplan, Reed, and McKerchar (2014) applied a discounting paradigm to environmental issues by asking participants to indicate how concerned and how willing they would be to help when presented with scenarios involving environmental losses. The hyperbolic model described the decrease in both and willingness to help was discounted more steeply than concern as a function of probability, delay, and social distance.

Taken together, the literature in probability discounting shows a robust effect of probability in decision-making across a variety of formats and commodities. A recent branch of this research has aimed to address one limitation with the studies described so far. Specifically, probability discounting studies typically determine a quantity or value of some certain commodity that is subjectively equivalent to the same commodity under conditions of uncertainty. However, real life choices often involve some tradeoff between two different commodities such as the choice between using drugs and being able to earn or save money (e.g., Bickel et al., 2011). To more closely examine these choice scenarios termed cross-commodity discounting, studies have determined an equivalence between two commodities using similar procedures as single-commodity discounting studies.

Mitchell (2004) recruited smokers to complete a series of discounting tasks both under conditions of normal use and nicotine deprivation. Three discounting tasks involved choices between monetary options that differed in delay, probability, and effort using an adjusting-amount procedure. In addition, participants also completed three similar tasks using the same procedures, but the smaller and more immediate, certain, or less effortful option was a number of

cigarettes. The experimenter selected one choice from the money-money tasks and one from the cigarette-money tasks at random and the chosen option was delivered to increase the likelihood participants would respond as if all options were being presented for real. A hyperbolic function was fitted to the indifference points for all six tasks. The authors did not report measures of fit for the regression, but inspection of the figures suggests indifference points decreased in a curvilinear fashion as a function of delay, probability, and effort in both money-money tasks and cigarette-money tasks. Acute nicotine deprivation affected discounting for cigarette-money tasks, but not money-money tasks. Most relevantly, though, was the demonstration that the subjective value of one commodity (money) can be described in terms of another commodity (cigarettes). The general shape of the discounting curve generated by discounting across commodities appears to remain hyperbolic. Yoon, Higgins, Bradstreet, Badger, and Thomas (2009) used a cross-commodity delay discounting task based on the procedures described by Mitchell in their examination of an abstinence program and found that the hyperbolic model fit well with r^2 values over .8.

Bickel et al. (2011) noted a flaw with the two cross-commodity discounting studies above in that they did not examine discounting for both commodities and in all combinations. Thus, one cannot draw conclusions regarding whether the type of commodities available in a choice scenario affects discounting. That is, rates of discounting when only non-monetary rewards are available both immediately or after a delay may not resemble discounting when the delayed commodity is either monetary or non-monetary. Bickel et al. presented participants with four discounting tasks representing all possible combinations of two commodities, money and cocaine: two single-commodity tasks pairing immediate and delayed commodities of the same type, and two cross commodity tasks pairing immediate cocaine with delayed money and

immediate money with delayed cocaine. The authors used the titrating-amount procedure for all tasks. To determine the range of amounts for cocaine as the immediate option, participants indicated in grams how much cocaine they would find to be subjectively equivalent to receiving $1,000. The authors concluded the type of commodity presented at the delayed option affected the rate of discounting. When money was the delayed outcome, rates of discounting were less steep than when cocaine was the delayed commodity. In a study using similar methods, Jarmolowicz et al. (2014) assessed single- and cross-commodity discounting of money and sex. For men, they obtained results similar to Bickel et al. (2011) suggesting delayed cocaine and sex do not retain value to the same degree as money.

Together, findings in cross-commodity discounting suggest the subjective values of commodities or outcomes vary systematically as a function of delay and probability and that these results hold whether individuals have a choice between identical or different commodities. Cross-commodity discounting may have particular relevance to illuminating how individuals make choices between options when a trade-off exists between them. To date, studies in cross-commodity discounting have focused on commodities with implications for health (cigarettes/cocaine/sex now vs. delayed financial or physical health). However, such trade-offs exist in many other forms. Practitioners of performance management recognize immediate and certain consequences have much more reliable effects on behavior than those that are delayed or uncertain (e.g., Daniels, 1994). These outcomes compete with naturally occurring, concurrently available contingencies. Employees may allocate behavior to contingencies that require less effort and provide positive consequences that are immediate and certain to occur due to a devaluation of longer-term consequences that may not come to pass. Envision an employee who makes momentary decisions between allocating substantial discretionary effort towards a

company performance initiative or towards less productive behaviors (e.g., surfing the internet, checking social media updates, taking a coffee break, conversing with fellow employees). The subjective value of a monetary incentive may be reduced by the delay to, or probability of, its receipt to a degree where it no longer serves as a viable consequence in competition with other available reinforcers.

Understanding how delay and probability affect the effectiveness of incentive systems might have significant implications for organizations (Jarmolowicz, Reed, DiGennaro Reed, & Bickel, in press). If employees discount the value of incentives in orderly and predictable ways, an analysis of delay and probability might reveal why incentive systems fail. In addition, organizations might be able to identify employees during the hiring process who are shallow discounters (i.e., individuals who do not discount uncertain outcomes at a high rate) who will respond well to a company's incentives, or design incentive systems that maximize efficiency while maintaining effectiveness. That is, approaching incentive schedules from a behavioral economic framework could identify the leanest incentive arrangement that is likely to be effective. Before incorporating such considerations into practice, experimental investigation into discounting as a controlling factor in subjective valuation of incentives is warranted. The present investigation is a first step in an attempt to synthesize considerations in organizational behavior management and behavioral economics in the context of performance incentives.

The purpose of Experiment 1 is to extend the current findings in cross-commodity discounting to include a commodity relevant to organizational settings—the use of personal electronic devices—as one that might compete with less certain organizational outcomes. Because there are many contingencies operating in workplace settings that may influence decision making, Experiment 2 aims to replicate the findings of Experiment 1 while framing

outcomes as occurring in the context of a workplace. Such a framing may affect discounting by the addition of implicit negative reinforcement contingencies endemic to work such as avoidance of progressive discipline or loss of compensation. Finally, Experiment 3 examines the effect of manipulating the subjective value of performance bonuses through probability on the performance of a simulated work task in a human-operant laboratory model of a probabilistic incentive system.

Experiment 1: Hypothetical Cross-Commodity Discounting of Currency and Leisure Activity

Method

Participants, setting, and apparatus. Participants included 57 undergraduate students enrolled in introductory-level courses in applied behavioral science. Participants completed the discounting assessment on Dell® OptiPlex computers in a testing lab measuring 9 m by 6 m. Each computer was placed on a desk and was equipped with a wide-aspect, flat-panel monitor, standard keyboard, and mouse. A series of discounting measures were presented by a computer program written in Microsoft® Visual Basic.Net. The discounting measures were developed based on procedures reported by Johnson and Bickel (2002) and Du et al. (2002). For each trial, the program presented two options to participants consisting of two buttons with text displayed side-by-side. The left button displayed a smaller, certain reward and the right button displayed a larger, probabilistic reward. Participants indicated their preferred option by clicking on one of the buttons. Following a response, the buttons dimmed on the screen and became non-responsive for a period of 2 s before the next option was presented. Centered below the buttons was a third button that allowed participants to return to the beginning of a trial block if they made a mistake. A sample of the interface is provided in Appendix B.

A trial block included six trials consisting of options between a certain reward and an uncertain reward at a given probability. After the participant made six choices, the same options were presented again using a different probability for the uncertain reward. Participants responded to an attending question at the beginning of each trial block requiring them to type the probability value of the uncertain option. Participants could not continue until typing the correct response. For each trial, the uncertain reward value was the undiscounted value, which was generated by participants during a pre-assessment questionnaire. At the start of each trial block, the certain reward value was presented as 50% of the undiscounted value. Depending on the participants' choice, the certain reward value was either increased or decreased using a titrating-amount algorithm described by Du et al. (2002). If the participant chose the certain reward on the first trial, the certain reward value presented on the next trial was decreased by 50%. If the participant chose the uncertain reward, the certain reward value was increased by 50%. For each subsequent trial, the amount by which the certain reward value was adjusted was 50% of the previous adjustment amount. For each condition, participants completed seven trial blocks with each block presenting a different probability level for the uncertain reward including 5%, 10%, 25%, 50%, 75%, 90%, and 95%. Probabilities were tested in either an ascending or descending order, determined by random assignment.

Dependent measure. The primary dependent measure for the present study was the indifference point between the certain and probabilistic rewards presented during the task. An indifference point represents the value of the certain reward that is subjectively equivalent to the value of the uncertain reward. This value was recorded as the adjusted amount of the certain reward value presented during the sixth trial in a trial block (i.e., the adjustment algorithm was applied to the sixth value based on the participant's choice).

Procedures. The computer program presented a prompt for participants to review an information and informed consent statement provided in hard copy by the experimenter. Two buttons corresponding to agreement to consent and disagreement to consent were displayed below the prompt on the left and right, respectively. No participants refused consent. After consenting to participate, participants completed a three-question pre-assessment questionnaire on the computer (Appendix C). The questions were adapted from Bickel et al. (2011) and were used to obtain a point of equivalence between the two commodities. First, participants specified (by selecting or typing) a leisure activity they most commonly consume on a mobile device during a typical day. Second, participants used a slider to indicate how much time (as a proportion of 24 hrs) they spend engaging in the activity they chose. Finally, participants indicated an amount of money that would be subjectively equivalent to having access to their chosen leisure activity for the amount of time they indicated in a given day. Once participants responded to all three questions and the program validated their responses, the computer presented the main discounting task.

Participants completed four discounting tasks, each comparing hypothetical monetary rewards, access to leisure activities on a mobile device, or a combination of the two. For each condition, the uncertain reward was presented as the undiscounted value of either access to a mobile device (from question two of the pre-assessment questionnaire) or the undiscounted value of equivalent money (question three of the pre-assessment questionnaire) and remained constant across trials. For certain rewards, the initial amount was 50% of the undiscounted amount and was adjusted across trials as described previously. Two of the conditions were single-commodity discounting tasks (certain money vs uncertain money, certain leisure versus uncertain

leisure) and two were cross-commodity discounting tasks (certain money versus uncertain leisure, certain leisure versus uncertain money).

Certain money versus uncertain money (MM). Prior to beginning each condition, participants were presented with a written orientation describing the options to be presented. For the MM condition, the orientation instructions read as follows:

> In the following questions, you will choose between a certain amount of money and a larger, uncertain amount of money. If you choose the certain amount of money, you will receive it immediately. If you choose the uncertain amount of money, you will have a chance to receive that amount of money, but there is also a chance that you will receive nothing.

The certain reward format was "$[value] for certain." The uncertain reward was presented on the right button and read, "A [probability]% chance of obtaining $[value]."

Certain leisure versus uncertain leisure (LL). In the LL condition, the orientation instructions were:

> In the following questions, you will choose between being able to have access to your mobile device for a limited amount of time for certain, or a chance to have normal access to your mobile device. If you choose the certain, limited access, you will be able to use your mobile device for the specified amount of time. After the time expires, your mobile device will turn off for the rest of the day. If you choose the uncertain amount of access to your mobile device, you have the chance to have access to your mobile device for that amount of time, but there is also the chance that you will have no access for 24 hours.

The format of the certain option was "The certain opportunity to use your mobile device for [hours/minutes] in a given day" and the uncertain reward was presented as "A [probability]% chance to use your mobile device for [hours/minutes] in a given day."

Certain money versus uncertain leisure (ML). In this condition, the orientation instructions were:

> In the following questions, you will choose between receiving some amount of money for certain or some amount of access to your mobile device that is uncertain. If you choose to receive the certain amount of money, you will receive it immediately, but you will also lose access to your mobile device for 24 hours. You cannot have both the money and

> your mobile device. If you choose the uncertain amount of access to your mobile device, you have the chance to have access to your mobile device for that amount of time, but there is also the chance that you will have no access for 24 hours.

Participants chose between certain money ("$[value] for certain.") and uncertain access to leisure activity ("A [probability]% chance to use your mobile device for [hours/minutes] in a given day.").

Certain leisure versus uncertain money (LM). The orientation instructions read:

> In the following questions, you will choose between receiving access to your mobile device for certain for a limited amount of time, or some amount of money that is uncertain. If you choose the certain, limited access, you will be able to use your mobile device for the specified amount of time. After the time expires, your mobile device will turn off for the rest of the day. If you choose the uncertain amount of money, you will have a chance to receive that amount of money, but there is also a chance that you will receive nothing. Whether you receive the money or not, you will not have access to your mobile device for 24 hours. You cannot have both the money and your mobile device.

Participants chose between certain access to leisure activities ("The certain opportunity to use your mobile device for [hours/minutes] in a given day") and uncertain monetary rewards ("A [probability]% chance of obtaining $[value]").

Data Analysis

Because the MM condition represents a previously validated discounting paradigm, participants who did not discount monotonically during this condition, meeting the two criteria established by Johnson and Bickel (2008), were excluded from analysis. The two criteria were (1) the indifference point under the lowest probability was less than the indifference point for the highest probability by at least 10% of the undiscounted value, and (2) no indifference points exceeded an adjacent, higher probability indifference point by more than 20% of the undiscounted value. The rationale for this exclusionary criterion was that if participants did not discount in a validated discounting condition, it was unlikely that they would discount in other conditions. Two participants were excluded on the basis of these criteria.

For participants who demonstrated orderly discounting in the MM condition, four alternate models of discounting were compared to determine the model that provided the best and most parsimonious fit of the empirical data (Equations 1, 3, 4, and 7) in addition to a random noise control model (a horizontal line). Model fits were compared using a selection algorithm based on Akaike's Information Criterion, corrected for small sample size (AIC_c) values, which is a method for comparing models that takes into account the number of parameters in a given model and penalizes it to avoid overfitting (Burnham & Anderson, 2004). The algorithm is similar to that proposed by Franck et al. (2014), substituting AIC_c for BIC. Model selection was made on the basis of Akaike weights derived from AIC_c values using the formulas (Appendix D) described by Burnham and Anderson (2004). Participant data were excluded from further analyses if the control model was selected as the most probable model in the MM condition. One additional participant was excluded for a total of three.

Discounting metrics were obtained for all participants and conditions using three methods. First, values of *h* were obtained using least squares non-linear regression. Additionally, two additional measures of discounting were also calculated: area under the discounting curve (AUC, trapezoidal method [Equation 5]) and Effective Probability 50% (EP50) calculated as the probability value at which the subjective value of the probabilistic outcomes is 50% of the undiscounted value. Results of these analyses were then compared across conditions. An ANOVA was conducted to determine whether significant differences existed between data across conditions. Because each participant completed each of the four conditions, a matched-set nonparametric ANOVA (Friedman's) was used. In addition, nonparametric correlations (Spearman's rho) were obtained for discounting values to determine whether subjective value in one condition predicted values in other conditions.

Results and Discussion

AIC_c values are provided in Table 1-4. For the MM condition, the hyperbolic model was selected for the most data sets than other models individually. The exponential model was only selected for four data sets and the control model (random noise) was selected for one data set. For the LL condition, similar results were obtained with the exception of the random noise model being selected for six data sets suggesting six participants did not discount systematically as a function of probability during the LL condition.

In the cross commodity conditions, model selections in the LM condition resembled those from the single-commodity conditions with modal selections of the hyperbolic model. For the ML condition, the modal model was Equation 4 (a hyperboloid model). The random noise model was selected for nine data sets across both conditions.

In sum, models of discounting appear to adequately describe the empirical data from each of the four conditions suggesting probability affects preference similarly to past studies in discounting with the hyperbolic model being selected for the most data sets overall. However, because the hyperbolic model did not provide the most probable fit for a clear majority of data sets, subsequent analyses were conducted using parameters obtained from the hyperbolic model as well as the model selected for each participant based on the AIC_c model selection algorithm.

Figure 1 depicts hyperbolic model fits of aggregate group data for each condition with the hyperbolic model fit to group medians. Comparison of the fitted curves to expected values in each figure indicates participants more steeply discounted uncertain access to leisure activities than uncertain money. That is, participants were more risk-averse when access to leisure activities was the uncertain outcome. This finding is similar to the findings of Bickel et al. (2011) in which the non-monetary outcome also did not retain value to the same degree as

money. An estimate of skewness for value of *h* indicated the values were not normally distributed, so values were log transformed and mean ln(*h*) values are depicted in Figure 2. A comparison of these discounting parameters supports the above conclusion that the largest differences were between conditions in which money was the uncertain outcome and conditions in which leisure was the uncertain outcome. A Friedman's matched-pairs ANOVA showed significant differences between conditions for values of ln(*h*) (χ^2 (3) = 29.84, $p < .0001$). A post-hoc multiple comparison test showed three of six comparisons to be statistically significant at the .05 level or better.

To determine whether using the most probable model for each data set would yield different conclusions, discounting parameters were obtained using the model selected by the AIC_c algorithm. From these parameters, EP50 was derived using the formulas provided by Franck et al. (2014). For ease of comparison, EP50 was also derived for each participant using the value of *h* obtained from the hyperbolic model. The mean EP50 for both hyperbolic fits and individualized fits is depicted in Figure 3. EP50 derived from both models illustrates the same patterns of differences between conditions compared to the analysis of ln(*h*) values. That is the largest differences between conditions visually are between conditions where the uncertain outcome was money and those in which the uncertain outcome was leisure. Another Friedman's test revealed significant differences between conditions (χ^2 (3) = 31.82, $p < .0001$) and the post-hoc test reached significance for three comparisons ($p < .05$) using the hyperbolic EP50. Using EP50 derived from individualized fits also showed condition differences (χ^2 (3) = 22.77, $p < .0001$) with two post-hoc tests reaching significance.

Finally, AUC was calculated for each participant as a model-independent metric of discounting. Mean AUC value with standard error is plotted in Figure 4. Again, the direction of

differences in discounting across conditions were preserved in this analysis, but failed to reach significance (χ^2 (3) = 5.912, p = .1160).

At the group level, the method of discounting analysis did not appear to alter conclusions drawn with the exception that some statistically significant differences were not confirmed across all methods. The hyperbolic model provided an adequate fit of group data for three of four conditions (MM, LL, and LM). However, the model selection algorithm revealed the hyperbolic model did not provide the most probable model of discounting data for all individuals. Comparing model selections across conditions revealed the same model was selected across all four conditions for only seven out of 23 participants. For four participants, the common model was the hyperbolic model. For two participants, Equation 4 was the common model while Equation 3 was common to all four conditions for one participant.

The failure of one model to best describe data across conditions within subjects suggests either that participants discounted differently as a function of the commodities being compared, or some other feature of the procedure artificially changed the shape of discounting curves across conditions. Table 5 displays correlation coefficients between conditions. All conditions except LM and ML were significantly and positively correlated. This supports the findings of previous cross-commodity discounting studies (e.g., Bickel et al., 2011).

Because participants affected the nominal values of both commodities presented, discounting may have varied as a function of amount (i.e., a magnitude effect or rate-dependency). A correlation analysis of discounting rates and the nominal amount of each commodity supplied by participants in the pre-assessment questionnaire revealed some significant correlations between amount and h values. Plots and coefficients are depicted in Figure 5.

In sum, these results suggest access to leisure activities does not retain its value well when access is uncertain, especially when a monetary reward is provided as a certain alternative. Leisure was discounted most steeply in the ML condition. Conversely, money retained more of its value when uncertain when the alternative was access to leisure. These findings should be well received in organizational settings in which monetary bonuses are available to suppress off-task behaviors in the workplace. However, in the LM condition, which would best represent such a bonus contingency, participants did discount the value of uncertain money. At a 25% chance of obtaining a monetary reward, the average subjective value had dropped to nearly 20% of the nominal value. The present study presented the monetary option as an uncertain but response-independent outcome. Thus, it may be the case that the reduced value paired with a response effort commensurate with workplace performance standards could further jeopardize the efficacy of such an incentive. Implications for workplace settings would be better formed following an investigation more closely modeling contingencies in a work setting.

The implications and findings of the present study should be tempered, though, as several limitations exist. First, the individual indifference points plotted in Figure 1 illustrate the range of discounting rates across participants. The degree to which participants discounted probabilistic commodities was idiosyncratic. Second, the population sampled may not be representative of employees as undergraduate students were a population of convenience. It could be the case that the participants in the present study represent a skewed or biased sample. Replication of these findings with a larger sample and different populations would strengthen conclusions that the patterns observed describe discounting in a larger population. Third, the amounts of both the certain and uncertain options presented to participants was dependent on responses to the initial questions. If this initial point of equivalency was inaccurate (i.e., the

response to the question did not reflect an actual point of equivalency) the range of amounts presented may have been limited, affecting obtained indifference points. This procedure has been used in past literature but may still be a limitation. Fourth, analysis of group data may have been affected by the differing amounts of both commodities presented to participants as a result of basing the options on responses to the pre-assessment questions. Amount has been shown to influence discount rate, so comparison of discounting parameters across amounts may have influenced the findings. Rate dependency based on differences in the strength of consumption behavior for leisure activities may also have had an effect as indicated by the correlation analysis (Figure 5). Particularly for MM and ML, the correlations resemble the magnitude effect for probability discounting where higher amounts were discounted more steeply (higher *h* values) than smaller amounts. This effect of amount may explain some of the variability between participants. Further investigation of the effects of amount on discounting would be beneficial. Finally, implications for work settings should also be tempered due to the lack of representation of workplace environmental characteristics. For example, earning a bonus is unlikely to be the only contingency controlling decisions between on-task and off-task response allocation. Avoidance of punitive measures or other sources of motivation to complete work tasks may alter the nature of discounting. The generality of these findings to less hypothetical and straightforward arrangements may be limited.

Experiment 2: Hypothetical Workplace Discounting Task

The purpose of Experiment 2 was to address some limitations to external validity present in Experiment 1. A similar procedure was used in conjunction with the presentation of a workplace scenario to determine whether features of a workplace might alter the degree to which participants discount uncertain monetary rewards.

Method

Participants and setting. Forty-one undergraduate participants from introductory behavior analysis courses were recruited to participate in the study. The materials were identical to those used in Experiment 1. The same computer testing lab and computer program were used. The program was modified slightly to present two different conditions described below.

Dependent measure. Indifference points were calculated for each participant and condition using the same method as Experiment 1.

Procedures. Participants were given an information statement to read in hard copy prior to beginning the computer task. They indicated consent to participate by clicking a button on the screen. The program then presented a scenario and modified versions of the three pre-assessment questions from Experiment 1. At the top of the screen, the program presented a scenario reading: "Imagine that you are an employee completing a repetitive task for $8.00 per hour (e.g., food service, cashier, call center/telemarketing, etc.). To begin, please respond to the following questions as an employee under the conditions described above." Instead of asking about mobile device use during a typical *24-hr day* as in Experiment 1, participants indicated an activity involving a mobile device they choose most frequently when taking a break from work tasks, the proportion of an *8-hr work day* they spend using the mobile device, and the amount of money that would be equivalent to using their mobile device for that period of time during a work day. After completing the three pre-assessment questions, the program presented three conditions of the discounting task. The general procedures were identical to those in Experiment 1. Participants made selections between a smaller, certain option and a larger, probabilistic option presented at 5%, 10%, 25%, 50%, 75%, 90%, and 95% probabilities in either an ascending or descending order, determined by random assignment. The amount of the uncertain

reward was taken from the participants' responses to the pre-assessment questions and the initial value of the certain reward was 50% of the undiscounted value. The same titrating-amount procedure was used, either increasing or decreasing the certain reward value by 50% of the previous adjustment amount following each of six trials at each probability level. In addition to the methods described for Experiment 1, participants were required to respond correctly to two true/false questions before beginning each of the three conditions. The questions were posed as an attending response to ensure participants understood the options to follow.

Certain money versus uncertain money (MM). This condition was identical to the MM condition in Experiment 1. Participants chose between a smaller, certain amount of money and a larger, probabilistic amount of money at each of the seven probability values listed above. The orientation instructions accompanying trials in the MM condition were identical to those given in Experiment 1. The phrasing of the certain option was, "$[value] for certain" and the uncertain options read, "A [probability]% chance of obtaining $[value]."

Certain money versus access to leisure with an uncertain outcome (ML). The purpose of this condition was to evaluate how participants value money in comparison to the opportunity to engage in leisure activities in the context of workplace consequences. Participants chose between receiving some amount of money for certain—with the caveat that they would have to surrender their mobile devices for the duration of the 8-hr work day—and the opportunity to use their mobile devices and risk being caught being unproductive by a supervisor. To avoid framing this condition as a loss, the latter option was presented as the probability of using mobile devices normally during a workday without any negative consequences. The orientation instructions for this condition were as follows:

The certain options was phrased as, "$[value] for certain, in exchange for refraining from using your mobile device for the entire work day" and the uncertain option read, "A [probability]% chance to use your mobile device normally during the day without any negative workplace consequences."

Certain leisure versus uncertain incentive (LM). The purpose of this condition was similar to that of the previous condition, but used a different frame. In this condition, participants chose between opting out of the incentive program in exchange for limited access to their mobile devices for certain and the probabilistic chance to earn an incentive by refraining from using their mobile devices for the entire work day. To orient participants to the options, orientation instructions were as follows:

The certain option was "The certain opportunity to use your mobile device for [value] h/min in a given work day, but you are not eligible for the $[value] bonus. The uncertain option was presented as, "A [probability]% chance of obtaining $[value] in exchange for refraining from using your mobile device for the entire work day."

Data Analysis

Because the two added conditions represent a departure from how past discounting measures have been formatted, four models of discounting were fitted to the data to evaluate whether discounting produces an accurate account of participant preferences. Curves were fitted to the data including the traditional exponential discounting equation, hyperbolic equation, and two variations of the hyperboloid equation proposed by Rachlin (2006) and Myerson and Green (1995). In addition, a random noise comparison model was tested to identify instances of unsystematic preference as a function of probability. Participant data were excluded using the same criteria as Experiment 1. If participants did not discount monotonically during the MM

condition according to the criteria proposed by Johnson and Bickel (2008), or the random noise model was selected as the most probable model for the data, those data were excluded from further analysis. Four participants were excluded based on the former and one additional participant was excluded on the basis of model selection for a total of five. Model fits were compared using the AIC_c value-based model selection algorithm described in Experiment 1. Finally, analyses were conducted to determine whether probability discounting of monetary rewards predicted participant preference in the workplace context conditions. Values of *h*, EP50 and AUC were calculated and tested using a Friedman's ANOVA and Spearman correlations.

Results and Discussion

Results from the model fits are displayed in Tables 6-8. The model selection algorithm produced results similar to those in Experiment 1 for the MM condition. The hyperbolic model was the modal, most probable model followed by the two hyperboloid models. The exponential model was not most probable for any data sets. For the ML condition, the hyperbolic model was again the mode, followed by the two hyperboloid models. However, the exponential model was most probable for four participants and five participants did not discount systematically as a function of probability (random noise model). The hyperbolic equation was also selected most frequently for the LM condition. The control model and exponential models were selected for three participants each.

Indifference points and the hyperbolic model fitted to the group median are displayed in Figure 6. Inspection of the curves suggests uncertain money retained its value when the certain alternative was access to leisure. That is, participants were relatively risk-seeking in the LM condition as indicated by the shallow curve. As in Experiment 1, discounting parameters were obtained using both the hyperbolic model as well as the model indicated as most probable by the

selection algorithm. Values of ln(h) from hyperbolic fits are displayed in Figure 7. The direction of effects was similar to Experiment 1 with discounting occurring more steeply in ML compared to MM and discounting occurring less steeply in LM compared to MM. A comparison between ln(h) values across conditions was made using Friedman's matched-pairs ANOVA and supported significant differences (χ^2 (3) = 17.56, p = .0002). Pair-wise post hoc comparisons supported significant differences between ML and LM (p < .001) as well as between MM and LM (p < .01).

EP50 was also calculated using both the h values derived from the hyperbolic model as well as the parameters derived from the preferred model as determined by the AIC_c selection algorithm; both are depicted in Figure 8. EP50 values for the hyperbolic model showed significant differences (χ^2 (3) = 17.56, p = .0002) between LM and both other conditions (LM vs. ML: p < .001; LM vs. MM: p < .01). EP50 derived from individualized model fits showed a significant difference (χ^2 (3) = 9.929, p = .007) only between ML and LM (p < .01) after 13 participants were excluded from the analysis due to missing values. The same analysis based on AUC (Figure 9) values yielded the same direction of differences (χ^2 (3) = 8.667, p = .0131) and a significant difference between ML and LM (p < .01) was obtained. Unlike Experiment 1, no significant correlation was obtained between nominal amounts for either commodity and rates of discounting.

Similarly to Experiment 1, the discounting model or analysis method used did not change the overall conclusions at the group level. The directions of differences in discounting rates mirrors those in Experiment 1, suggesting the addition of a hypothetical workplace scenario did not drastically change how participants perceived the values of the commodities presented.

When leisure is made available as a certain alternative, the monetary rewards retained more value than when the certain alternative was a smaller monetary amount.

The LM condition is the most relevant to organizational incentive arrangements. That is, employees working under an incentive system where reinforcement is contingent upon performance may choose between allocating behavior to off-task behaviors that produce certain consequences and allocating behavior to on-task behaviors that produce uncertain consequences through the bonus program. The median indifference points and EP50 showed that under these conditions, the monetary bonus retained nearly 50% of its value when the probability was 25% compared to MM and ML where the uncertain commodity lost 50% of its value at 49% and 59%, respectively.

The present experiment is subject to the same limitations as Experiment 1 because the experimental preparation is the same. The literature shows hypothetical discounting tasks to be reasonably valid in comparison to more experiential tasks (e.g., Madden & Johnson, 2010). However, participants coming to the experiment with different extra-experimental histories of workplace consequences may interpret the workplace scenario differently. The self-reported usage of mobile devices and equivalent monetary amount also differed widely between participants. Unlike Experiment 1, no clear or consistent relation between nominal amounts and discounting was obtained.

The experimental preparation used in the present study also differs in some potentially important ways from an actual workplace. The commodities presented were hypothetical and although the literature has supported the validity of hypothetical discounting tasks, contacting the contingencies described may affect preference and subsequent choice. In addition, participants chose between two options outside of the context of effort. That is, bonuses would be contingent

upon completing one or more effortful responses. Although the hypothetical scenario asked participants to imagine they were performing a repetitive task, it would be informative to determine whether having participants experience a real repetitive task would affect choice.

The purpose of Experiment 3 is to examine the effects of probabilistic bonus contingencies on the performance of a repetitive analogue work task and to extend the findings of the previous experiments to an analogue work environment using experiential rather than hypothetical contingencies.

Experiment 3: Experiential Operant Discounting Task in an Analogue Workplace Setting

Method

Participants and setting. The participants in the present study were six undergraduate students recruited via in-class announcements and flyers posted at a large Midwestern university. No exclusionary criteria were applied for initial admittance into the participant pool. In exchange for participation, participants were paid a base rate of $2.50 per 1-hr session. Throughout each session, participants also had the opportunity to earn monetary incentives or avoid disincentives. Sessions took place once per day, two to three days per week, with each session lasting approximately 1 hr. Within the 1-hr sessions, participants were given the opportunity to complete a simulated work task in blocks of 5 min with a brief rest period between blocks.

All sessions were conducted in a small research room measuring 2.21 m by 2.03 m by 2.44 m, designed to mimic a common office space/cubical. The room was adjoined to an observation booth of the same dimensions by a panel of mirrored glass. The research room was equipped with a Dell® computer connected to a 50.8 cm diagonal monitor, standard keyboard, and computer mouse. The monitor and input devices were situated on a table (1.8 m x 0.74 m x

0.74 m) with an office chair. The research room also contained several leisure materials including magazines and a current school newspaper. In addition to the computer's use for completing the experimental task, participants had access to the other features of the computer, including internet access. Finally, participants were permitted to bring any materials, such as homework, a cell phone, or a tablet computer into the room during sessions.

Apparatus and materials. The experimental task was presented in its entirety by a computer program written in Microsoft® Visual Basic.Net. The task was a check-processing task in which participants were asked to type the dollar amount of each generated check image into an entry box. The program was designed as a standalone desktop application. The interface window (Appendix E) was 30 cm by 13 cm and occupied a portion of the computer screen such that participants could access the other features of the computer. The program displayed a generated check image consisting of randomly generated routing numbers, account numbers, dates, check numbers, amounts, and payee names. The names were generated by randomly drawing a first name and last name from a list of 150 each. A text-entry box was displayed 4.5 cm to the right of the check image below the instructions, "Enter the amount displayed on the check in the box below. Press ENTER or click the Submit button to submit the amount and move to the next check." Once the amount was typed, clicking a button labeled "Submit" or pressing the ENTER key on the keyboard submitted the amount and displayed the next check. The program could be minimized to the computer's task bar or closed. When closed, the program displayed a button in the bottom-left corner of the monitor reading "Return to Task." Clicking this button restored the task window. After a period of 5 min elapsed, the program ended.

Additional materials for the present study included the Behavioral Inhibition System/Behavioral Activation System Scales (BIS/BAS; Carver & White, 1994). The BIS/BAS is a validated scale that assesses sensitivity to punishment (BIS) and reward (BAS). The BIS scale is a single factor scale and the BAS scale loads onto three factors, resulting in three BAS subscales: reward responsiveness, drive, and fun seeking. Alpha reliability for the BIS is .74 and reliability for reward responsiveness, drive, and fun seeking are .73, .76, and .66, respectively. The scale is presented in Appendix F.

Dependent variables and response measurement. Two primary dependent variables were collected: number of checks processed correctly and time on-task. A correctly processed check was recorded when the value the participant typed and submitted was identical to the numerical amount displayed on the check. To keep the time required to process each check constant, all amounts had five digits (i.e., all amounts were between $100.00 and $999.99). Time on task was defined as the number of seconds during which a participant was processing checks. Specifically, a timer for on-task behavior ran until 5 s had passed since the participant submitted the last check value. A timer for off-task behavior then ran until the participants submitted the next check amount. The computer program collected data for both measures automatically. Additionally, the computer collected data on whether participants met the performance criterion for earning incentives, or avoiding disincentives. The performance criterion is described in more detail below. Participants also completed the hypothetical discounting task described in Experiment 2, from which hyperbolic model fits were used to obtain *h* values.

Experimental design and procedures. The experimental design was a multielement design embedded within either an ABAB or BABA reversal design, counter-balanced across

participants. The multielement design was used to compare performance across varying levels of probability. The reversal design was used to compare performance between probabilistic incentives (A) and disincentives (B). To reduce the number of blocks run for each participant, reversal probes were conducted in lieu of a full reversal for a subset of five probabilities (5%, 10%, 25%, 50%, and 95%). If differentiation obtained in previous conditions was not replicated, additional blocks were implemented until stability was obtained.

Upon arriving, participants were greeted and shown into the research room. After obtaining written consent, the experimenter described the task. The orientation script is provided in Appendix G.

Incentive condition. The purpose of the incentive condition was to evaluate the effects of probabilistic incentive arrangements on the rate of correct check processing and time-on-task. During all blocks of this condition, participants were informed they may choose to complete as many or as few checks as they would like. Participants were also free to engage in other activities available in the session room, either using provided materials or materials they brought with them. If they worked on the check-processing task, they had a chance to earn a $0.75 monetary bonus, which was determined both by a programmed probability and a minimum performance criterion.

The probability programmed for each 5-min block determined whether the minimum performance criterion would be applied and the bonus delivered. The determination for whether the 5-min block was evaluated was made using a 20-sided die. Prior to beginning the block, the experimenter informed the participant of the probability that his or her performance would be evaluated for the incentive as well as the results of the die toss that would result in an evaluation. For example, if the probability was 5%, then the block was evaluated if the die landed on the

number 1. If the probability was 10%, the block was evaluated if the die landed on either 1 or 2. If a block was flagged for evaluation and the average rate of correctly processed checks was equal to or greater than 16.0/min, the bonus was delivered. Because one participant (06) expressed difficulty with using the keyboard number pad, the criterion was set at 14 correctly processed checks per minute for all sessions for this participant only. In each 5-min block, the probability that performance would be evaluated for the bonus was either 5%, 10%, 25%, 50%, 75%, 90%, or 95% presented in a pseudorandom sequence such that all seven probabilities were presented before repeating.

Disincentive condition. In addition to evaluating varying incentive arrangements, the present study also determined whether the probability of gaining an incentive differed from the opportunity to avoid loss of an incentive. Each probability described above was replicated using identical procedures with the exception that participants were informed they would receive a performance incentive, but there was a chance their performance would be evaluated and if their performance was observed to fall below the minimum criterion of 16.0 (or 14)/min, they would lose the bonus.

Choice phase and debriefing. After completing the procedures, participants were provided the opportunity to choose the conditions for one final block. Choice was given between the incentive and disincentive arrangements as well as the probability of evaluation. The purpose of the choice block was to determine subjective preference for conditions and a measure of the social validity of incentive arrangements. After completing the choice block, participants were asked to complete the BIS/BAS. The purpose of this scale in the present study was to determine whether it corresponded to differences in performance across incentive and disincentive arrangements or preference for the same. Finally, participants completed the

hypothetical discounting task described in Experiment 2 such that patterns of responding in the present experiment could be compared to a measure of discounting.

Data Analysis

Differences in check processing rates between incentive and disincentive conditions were determined within subjects using visual inspection of the reversal design graphs. Differences in check processing and time-on-task between levels of probability were determined via visual inspection of the multielement data series. In addition, the processing rate for the last data point in each probability for each participant was plotted with probability to evaluate whether the dependent measures vary hyperbolically as a function of probability in a manner similar to discounting. Quantitative comparison across conditions was made by calculating the area under the curve (AUC) of the graphs and comparing AUC across conditions using a Wilcoxon signed-rank test. Although the discounting literature has not provided precedence for using measures of effort as an index of subjective value, such a curvilinear relation may be useful in workplace settings to determine optimal arrangements for incentive systems in which some probability is inherent. Discounting measures were also obtained using the hyperbolic model of probability discounting fitted to indifference points derived from the hypothetical discounting task administered at the end of the experiment for each participant. The predictive validity of the hypothetical discounting measures were estimated by visually assessing whether a correspondence existed with responding during the analogue task.

To estimate relative costs and benefits associated with the use of the varying bonus arrangements, aggregate data were plotted. Benefits were estimated by plotting a scatterplot of check processing rates for all participants by condition and probability. Costs were also estimated by calculating the proportion of total bonuses paid for each condition and probability.

The proportion was calculated as the number of bonuses paid (resulting from both the die roll and the check processing rate) divided by the total number of blocks presented for each probability in each condition.

Because probability was determined using a 20-sided die, the potential for deviation from programmed probability existed. The obtained probabilities for each participant are provided in Table 9. Functionally, 5% probability was experienced as 0% for all participants and 95% probability was functionally 100%. The remaining obtained probabilities were compared to programmed using Wilcoxon signed rank tests and no significant differences were obtained.

Finally, the fidelity with which the experimenter implemented the conditions was evaluated. The implementation procedure was determined to have five steps for each block including (1) stating the probability as a percentage, (2) stating the corresponding number range on the 20-sided die, (3) stating the bonus contingency in effect, (4) re-stating the number range at the end of the session before rolling the die, and (5) stating whether the participant earned the bonus. Fidelity was calculated for 30% of blocks for each condition and each participant by dividing the total number of steps implemented correctly by the total number of steps and converting to a percentage. Fidelity was high across participants with the minimum being 90%. Fidelity data for all participants are provided in Table 10.

Results and Discussion

Figure 10 depicts the multielement/reversal graphs for participants 01, 02, and 04. The graphs depict a subset of the probabilities (excluding 75% and 90%) to reduce the number of data paths. For participant 01, a clear differentiation in check processing rate was obtained between 5% and all other probabilities. During sessions in both incentive and disincentive conditions, she allocated her behavior exclusively to off-task activities during 5% probability.

Similar allocation towards off-task behavior was initially obtained for 10% probability blocks in the incentive condition, but this was not replicated in the reversal design. When given a choice of condition, participant 01 selected the disincentive condition with a 95% probability of performance evaluation with processing rate remaining high.

Participant 02 exclusively allocated her behavior to the work task in the initial disincentive condition. When the incentive condition was implemented, rates of check processing decreased to zero during both 5% and 10% probabilities. This apparent difference between incentive and disincentive was not replicated, though, as check processing rates during 5% blocks decreased to zero during the second disincentive condition and rates during both 5% and 10% probability blocks were low during the third disincentive condition. In addition, participant 02 engaged in off-task behaviors during 25% probability blocks during incentive and disincentive conditions occurring in one day of the experiment. Attempts to replicate the resulting low rates of check processing during the next session resulted in a return to the previous, high rate of processing. On the day the participant was off-task during 25% probability blocks, she noted she was reading an e-book on her cell phone. When given a choice, she selected the disincentive condition with a 5% probability. As in previous 5% probabilities, she did not process checks during the choice block.

Participant 04 showed a similar pattern of responding as participant 02. All responding was allocated to the work task during the initial disincentive condition. During the incentive condition, processing rates during 5% and 10% declined to zero, which was replicated in a subsequent reversal probe. During the second disincentive condition, processing rate remained low for 5% probability blocks while rates during 10% blocks nearly returned to the original higher level. She also selected the 5% disincentive condition during the choice block. Unlike in

previous phases, she allocated her behavior to the work task during the choice block but the rate fell slightly below the criterion.

Data for participants 03, 05, and 06 are depicted in Figure 11. None of these participants demonstrated differentiated patterns of responding across either incentive and disincentive conditions or levels of probability. Some variability in the absolute rate of check processing was obtained for participant 03 across probabilities, but these differences were not consistent. Rate data for both participants 05 and 06 were level and stable across most blocks. Participant 03 selected the 95% disincentive condition during the choice block. Participants 05 and 06 both selected the disincentive condition, and chose 5% and 50% probabilities, respectively.

To facilitate ease of comparison between participants, Figure 12 depicts the rate of check processing obtained from the last block of each probability for both incentive and disincentive conditions. This figure also permits comparison between incentive and disincentive conditions within participants. Visual inspection yields no clear differences in processing rates between conditions, with the exception of participant 04 due to a difference during 10% probability blocks. Area under each curve was calculated as a means for statistical comparison between conditions. Areas under the curve for incentive and disincentive conditions were not statistically significantly different according to a Wilcoxon signed rank test ($p > .9999$).

As described previously, one goal of the present study was to determine whether existing measures have predictive validity for how individuals will respond to probabilistic incentive arrangements. One such face valid measure is the *h* value in probability discounting. Figure 13 depicts discounting curves derived from indifference points from the hypothetical discounting task administered at the end of the experiment. Data for participants for whom probability affected allocation of behavior during the analogue work task are provided in the left column

with participants for whom data were undifferentiated on the right. Visual comparison does not yield any clear and consistent differences. Generally, the hyperbolic model fits well described the indifference points. However, for participants 05 and 06, the hyperbolic model substantially underestimated subjective value at lower probabilities for the LM condition and the MM condition also for 05. This pattern was different than other participants and might indicate a relative insensitivity to probability beyond a certain threshold. Such an insensitivity to differences in probability at the lower end of the continuum would seem to have some face validity for predicting participant insensitivity to probability during the work task (i.e., allocating responding to the task despite low chances of contacting the bonus contingency). However, participant 03 did not share this pattern of discounting. Thus, discounting in the hypothetical task did not appear to have predictive value for performance in the work task. Further research is needed to examine whether probability discounting is not predictive of the type of performance measured in the present study, or if some feature of the hypothetical discounting task influenced the degree to which the same phenomenon was captured.

Scores for the three BAS subscales and the BIS scale are provided in Table 11. Although a planned analysis included evaluating the predictive validity of the BIS/BAS scales for differences in performance across incentive and disincentive conditions, no consistent differences between processing rates were obtained in the present study making such an analysis impossible. It is currently unclear whether the absence of differentiation is due to an artifact of the experimental preparation. Five participants indicated a preference for the disincentive condition during the choice phase, which may suggest it was not an aversive condition as such a condition may be in an actual workplace. Of note is that in the present study, the disincentive condition at all probabilities had a greater certainty of receiving the bonus payment than the

incentive condition. That is, if participants completed the work task and met the performance criterion, they were certain to receive the bonus whereas in the incentive condition, meeting the criterion did not guarantee receipt of the bonus. It may have been aversive, then, to have completed the work requirement and receive no bonus, which was only possible in the incentive condition.

A number of limitations are worth noting. A few limitations are related to external validity. The experimental preparation was designed to synthesize a workplace environment, but still differed from actual workplaces in a number of ways. The work blocks were only 5 min in duration rather than several hours or longer. In addition, the experimenter gave the participants the option to do any amount of work and explicitly stated the probabilistic contingencies each time, both of which are unlikely to occur in an organizational context. However, the present study was designed to isolate the effects of probability on allocation of behavior and exhibiting experimental control required some compromises to external validity in early stages of this line of research. Future research might extend the present findings to contexts and methods that bear better similarity to real world work settings. Another limitation is the absence of a clear difference between the disincentive and incentive conditions. The framing or design of the conditions may not have captured differences that would have exerted control over differentiated responding. Further research might examine modified preparations in which a disincentive condition is functionally aversive. Finally, the present study did not yield an assessment measure that is predictive of response allocation under varying probabilities. Identifying such a measure through additional research could have implications for a number of organizational practices.

Within the boundaries of the limitations, the present study suggests uncertainty in incentive systems can affect productivity for some individuals. The results are generally positive

for organizational settings. Half of the participants maintained productive behavior throughout the experiment regardless of the probability of contacting the incentive or disincentive contingencies. For the other half, a probability of 25% or higher appeared to be sufficient to maintain responding, suggesting employees do not need to be monitored continuously for an incentive program to be effective.

Neither of the two face-valid measures predicted performance during the analogue work task. Identifying a measure with predictive validity may prove useful moving forward as probability did not affect all participants equally. Such a measure may improve several aspects of organizational practices. For example, during initial screening and hiring employees might be chosen from applicants who would likely perform well under the incentive system an organization already has in place based on responding to a hypothetical task. Or, an organization interested in designing an incentive system might assess employee sensitivity to and preference for varying incentive arrangements to inform the design. If assessment measures that accurately predict performance are unavailable, another direction to pursue is an abbreviated direct observation procedure similar to the present preparation, which could help generate a curve similar to those presented in Figure 14. By aggregating data across employees, organizations may be able to make empirical decisions about how much productivity can be expected under varying conditions. The other side of the cost-benefit ratio is depicted in Figure 15. By plotting the actual amount paid as incentives under each arrangement, organizations could see whether a ceiling effect occurs such that higher probabilities cost more, but do not yield further benefit. Combining the Figures 14 and 15, employees are likely to prefer a disincentive arrangement with a lower probability of contacting the contingency as this would maximize bonus pay even when employee output is less. Management, on the other hand, would likely select an incentive

arrangement with a 25% probability as this would maximize employee output while keeping bonus pay low. Other implications are discussed in the context of all three studies in more detail below.

General Discussion

The purpose of the first experiment was to extend previous findings in probability and cross-commodity discounting research to a commodity that is relevant for organizational settings. The results showed the discounting phenomenon applies to choices between money and access to leisure activities via mobile device use. The second experiment examined whether discounting would be affected by framing the choice within a work context. The slope of the discounting curves changed slightly, but discounting as a paradigm appeared to apply to this novel scenario. In the third experiment, participants were placed in a simulated work context and given a choice between working for an uncertain bonus and allocating behavior to some other off-task behavior. For three of six participants, lower probabilities of contacting the bonus contingency consistently resulted in allocation of behavior to off-task behaviors, including use of mobile devices during the session. Collectively, these findings suggest probability and discounting can play a role in performance incentive efficacy as they are implemented in organizations.

These studies make a number of contributions to the literature. First, the first two experiments extended findings in the extant discounting and cross commodity literature. Second, the findings pose questions about how best to conceptualize the phenomena observed in Experiment 3. That is, the goal of Experiment 3 was to apply discounting to choices available in a work setting. However, other economic or behavior analytic concepts could potentially provide a better explanation. Finally, the potential merit in combining the fields of

organizational behavior management and behavioral economics has also been shown. The latter field has a robust literature in human choice and decision-making, which are directly relevant for organizations. The present study contributes to the organizational behavior management literature by adding to the growing body of research suggesting the utility of quantitative and economic analyses of employee behavior. Economic analyses have the potential to greatly increase understanding of and methods for correcting socially important issues. Each of these is discussed in more detail below.

The findings of Experiment 1 closely resembled those reported by Bickel et al. (2011) and Jarmolowicz et al. (2014) from which the experimental preparation was derived. These findings extended findings to both a new commodity as well as to probability discounting. As the temporal location of cocaine and sexual activity affected the degree to which participants in the extant literature discounted their value, participants in the present study discounted the non-monetary outcome more steeply when it was uncertain. In addition, only one other study could be located that examined probability discounting across commodities (i.e., Mitchell, 2004). Thus, the present study contributed to filling a gap in the discounting literature. Cross-commodity discounting is likely to be an important area for future behavioral economic research. The traditional single-commodity discounting paradigm has contributed to the understanding of how several factors affect subjective value, but real-world decisions are also likely to involve choices between two different commodities that differ along temporal or probabilistic dimensions (e.g., substance abuse, risky sexual behavior, saving for retirement, preventative medicine).

A conceptual interpretation of the formal similarity between the LM conditions in the first two experiments and the incentive arrangement combined with the results of all three

experiments is the shift in allocation in Experiment 3 under lower probabilities could be explained by a reduction in the subjective value of the incentive (i.e., probability discounting). Under a 10% or 5% probability of contacting the bonus contingency, the bonus did not retain sufficient value to maintain responding on the work task, which is to say probability functionally reduced the magnitude of reinforcement. The absence of such a shift in allocation for three participants would then have to be explained. Potentially, other contingencies or reinforcement histories may have been operating for those participants. Anecdotally, all three participants reported during the post-experiment debriefing that they continued working because there was always a chance to earn the bonus. Participant 06 went on to explain that she "has [bad] luck," which may be indicative of a certain history of experience with probabilistic outcomes. Participant 02 reported during the day she was off-task during 25% blocks that she had started reading an interesting e-book (she was engaged with her cell phone during those blocks). The availability of a particular activity on her phone appeared to change the relative efficacy of the bonus and leisure activities as consequences such that a 25% chance to earn a bonus was no longer sufficient to maintain responding. This value-altering effect was not present during subsequent sessions and the pattern of allocation returned to previously observed levels. Again, these are subjective self-reports. Further research is needed to increase confidence in this interpretation of the data.

Alternative explanations may provide an equal or more useful account of the data in Experiment 3. Relative reinforcer efficacy is in the domain of demand analyses in behavioral economics. That is, demand describes consumption of a commodity as a function of its unit price. Conceptually, probability may increase the unit price of an outcome. If given multiple opportunities to earn a bonus under each probability, a participant may expect to earn one bonus

per 20 blocks on average if the probability is 5%. Because the block during which the bonus will actually be available is unknown, a participant would essentially have to work consistently enough to meet the performance criterion for each of those blocks. Within the present experimental preparation, the unit price would be processing at least 1,600 checks (16 checks/min, 5 min/block for 20 blocks). Compared to a probability of 50% in which the unit price is 160 checks (16 checks/block, 5 min/block for 2 blocks), the unit price for the bonus under 5% probability is high. Hursh, Raslear, Bauman, and Black (1989) proposed such a conceptual interpretation with probability included in an equation for unit price. Beyond response effort, probability may also make receipt of the bonus more temporally remote if multiple blocks must be completed prior to the bonus being delivered, potentially resulting in a temporal discounting effect. Last, the concept of competing contingencies of reinforcement has been thoroughly studied in the matching law literature (e.g., Baum, 1974). If the function of probability is to change the relative rate of reinforcement, the matching law may provide an accurate account of relative allocation. These interpretations might serve to direct future research.

Whichever paradigm provides the best account and predictive validity for allocation of behavior under uncertain incentives, one common component is a quantitative model: hyperbolic discounting, demand curves, and the generalized matching equation. Quantitative analyses are likely to have utility for managers tasked with evaluating and designing mechanisms of organizational behavior change. That is, the performance incentive literature has shown a robust effect of imposing a contingency between work and pay (see Bucklin & Dickinson, 2001). Organizations must also consider the efficiency of an intervention, especially in resource-poor settings such as human services, non-profits, or smaller businesses. A quantitative approach

goes beyond predicting a qualitative improvement in performance resulting from an intervention, providing a prediction for the degree of improvement. The calculation of costs and benefits or return on investment require empirical estimates of both boosts in employee output expected from an intervention and the cost of the intervention associated with that improvement. By comparing data such as those depicted in Figures 14 and 15, managers have an objective means to identify an incentive arrangement that would maximize employee performance while minimizing the associated cost. In the context of Experiment 3, the ideal incentive system would resemble the incentive conditions with a 25% probability as all participants allocated responding exclusively or nearly exclusively to the work task, but incentives were paid less than 50% of the opportunities. Higher probabilities were not associated with substantial increases in check processing rate so the cost to the organization would be higher without a commensurate increase in benefit. However, depending on a number of factors, 25% may still be higher than what can be achieved by supervisors. For a supervisor with a large number of employees, ensuring employees contact a bonus contingency at least 25% of the time may still be overwhelming. In such cases, automatic or electromechanical means of measuring performance without direct intervention by a supervisor might be used when possible.

Because of the more translational/basic aspect of the study, implications should tempered; however, some limitations and findings in the present study do suggest more proximal directions for future research. As an exploratory study adopting a translational approach to researching a novel application of behavioral economics to applied issues in organizational behavior management, some limitations were inherent to the approach as discussed previously. The degree to which these findings will generalize to applied contexts should be the focus of future research including systematic replication and extension to settings and populations more

closely resembling the practical context of an organization. Undergraduate students may not be representative of employees and may have less or different histories with probability, organizational contingencies, and other contextual variables present in the workplace. The experimenter did not have control over a range of consequences for participants that would likely be present in an organization. These could include a system of progressive discipline, social contingencies between peers, or other consequences. A full work day or even more temporally extended intervals of incentive administration may also affect employees differently than 5-min blocks. Precedence for longer session affecting the degree to which incentives affect behavior was shown by Oah and Lee (2011).

Second, changing the magnitude of the incentive may impact the probability level at which participants shifted allocation away from the work task. That is, increasing the magnitude of the incentive might serve to maintain responding on the work task at even lower probabilities. Replications of Experiment 3 with varying incentive amounts could reveal whether amount has a consistent impact on allocation and performance. This extension would provide further utility for organizations as increasing the amount of the bonus adds to costs, which could be justified if commensurate increases in performance also result.

Finally, the hypothetical task did not appear to capture the same phenomenon as the work task given the absence of a correspondence between performance and discounting. It is unclear at present whether changes to the hypothetical task might better represent the type of choice scenario presented in Experiment 3. The identification of an assessment method—either a discounting assessment or some other measure—to generate a quantitative model of performance would prove beneficial for organizations. The prediction of employee performance is a subject of study in Industrial and Organizational Psychology (IOP). The personnel selection literature in

IOP has suggested some methods for predicting employee performance such as situational judgment tests, structured interviews in which hypothetical scenarios are presented to assess what an employee would do in a given context (DiGennaro Reed, Hirst, & Howard, 2013). The alternative is to directly measure actual behavior, such as in work sampling. Such an approach could be used to measure how employees would respond to incentives by administering a modified procedure similar to the methods described here. However, sampling work behavior directly could prove to be a costly undertaking for some organizations. A hypothetical task, survey, or battery of some kind with a reasonably good predictive value for how employees would respond to incentive systems could provide a cost-effective means for designing or evaluating an incentive intervention. Two metrics were proposed—discounting rate and BIS/BAS scores—but, given the current absence of clear relations to the data, further research is needed.

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Table 1. Akaike weights (ω) by participant for each model for the MM condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	**0.8119**	0.0438	0.1110	0.0333	0.0000
2	**0.6332**	0.0957	0.2626	0.0085	0.0000
3	0.4140	0.1006	0.0210	**0.4644**	0.0000
4	0.0079	**0.7759**	0.2157	0.0004	0.0002
5	0.0013	**0.7796**	0.2189	0.0001	0.0000
6	0.0607	0.2217	0.0209	**0.6966**	0.0000
7	**0.5442**	0.1476	0.2002	0.0909	0.0171
8	0.0335	**0.5849**	0.3786	0.0027	0.0002
9	0.0054	**0.3919**	0.3067	0.0013	0.2947
10	0.0029	0.3238	**0.6719**	0.0007	0.0007
11	**0.8511**	0.0405	0.0943	0.0140	0.0000
12	**0.8267**	0.0808	0.0352	0.0572	0.0000
13	0.0002	0.0966	**0.9031**	0.0000	0.0000
14	0.0163	**0.4800**	0.4091	0.0024	0.0922
15	**0.6246**	0.1113	0.0250	0.2392	0.0000
16	**0.6060**	0.1862	0.0746	0.1306	0.0027
17	**0.8890**	0.0318	0.0538	0.0254	0.0000
18	**0.7145**	0.0563	0.2088	0.0203	0.0000
19	0.2599	**0.4328**	0.2858	0.0165	0.0049
20	**0.6759**	0.0207	0.0284	0.2721	0.0029
21	0.1935	**0.6392**	0.1330	0.0306	0.0037
22	0.0051	0.1949	**0.7983**	0.0007	0.0011
23	0.1469	**0.4502**	0.3454	0.0286	0.0288
24	**0.8983**	0.0541	0.0280	0.0197	0.0000
25	0.0003	0.3128	0.2831	0.0001	**0.4037**
26	0.0285	**0.6712**	0.2971	0.0026	0.0006
27	0.0443	0.1726	**0.7774**	0.0046	0.0012
28	**0.8429**	0.0365	0.0953	0.0253	0.0000
29	0.0069	0.1544	**0.8369**	0.0008	0.0009
30	**0.5678**	0.2709	0.0500	0.1090	0.0023
31	**0.9359**	0.0291	0.0294	0.0056	0.0000
32	0.0858	**0.5140**	0.0117	0.3885	0.0000
33	**0.7187**	0.0953	0.0921	0.0925	0.0014
34	0.0398	**0.3499**	0.2879	0.0257	0.2967
35	**0.6163**	0.0205	0.0198	0.3434	0.0001
36	**0.7878**	0.0514	0.0843	0.0759	0.0007
37	**0.7096**	0.0267	0.0214	0.2422	0.0001
38	0.0258	**0.8544**	0.1174	0.0022	0.0002

39	0.2068	**0.5594**	0.2058	0.0251	0.0029
40	**0.4539**	0.2938	0.2133	0.0374	0.0015
41	0.4035	0.0169	0.0211	**0.5585**	0.0001
42	0.1755	0.0339	0.0232	**0.7673**	0.0001
43	**0.8156**	0.0451	0.1245	0.0148	0.0000
44	0.0000	**0.7957**	0.2042	0.0000	0.0000
45	**0.5753**	0.0631	0.3578	0.0038	0.0000
47	**0.8338**	0.0436	0.0996	0.0230	0.0000
48	0.0006	0.1155	**0.8837**	0.0001	0.0002
50	**0.9415**	0.0289	0.0284	0.0012	0.0000
51	**0.6318**	0.2456	0.1189	0.0037	0.0000
52	0.0013	0.3248	**0.6739**	0.0001	0.0000
53	0.0201	**0.5015**	0.3790	0.0030	0.0963
54	0.0814	0.2147	**0.6953**	0.0072	0.0013
55	0.0001	0.3474	**0.6524**	0.0000	0.0001
56	0.3491	**0.4712**	0.1240	0.0543	0.0014
57	**0.7724**	0.0253	0.0238	0.1785	0.0001
Total	25	16	9	4	1

Table 2. Akaike weights (ω) by participant for each model for the ML condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	0.0030	0.1559	**0.8409**	0.0001	0.0000
2	0.0005	**0.5708**	0.4166	0.0001	0.0121
3	0.3157	**0.3577**	0.1785	0.0472	0.1010
4	**0.4646**	0.1358	0.1260	0.0430	0.2307
5	0.0001	**0.8769**	0.1229	0.0000	0.0002
6	0.0066	0.0998	0.0968	0.0022	**0.7946**
7	0.0828	0.3209	0.2549	0.0173	**0.3241**
8	0.0023	**0.8472**	0.1472	0.0004	0.0029
9	0.0517	0.3161	**0.5534**	0.0114	0.0674
10	0.0166	**0.9445**	0.0363	0.0025	0.0001
11	**0.7566**	0.0228	0.0233	0.1971	0.0002
12	0.0194	0.4599	**0.4957**	0.0025	0.0224
13	0.0013	**0.6873**	0.2952	0.0002	0.0160
14	0.0005	**0.6828**	0.3022	0.0001	0.0143
15	0.1773	0.1388	0.0200	**0.6638**	0.0000
16	0.0655	**0.6906**	0.2417	0.0022	0.0001
17	**0.6941**	-	-	0.3057	-
18	0.0006	0.3678	**0.6311**	0.0000	0.0005
19	0.3075	0.1034	0.0954	0.0868	**0.4069**
20	**0.7605**	0.0408	0.0860	0.1109	0.0018
21	**0.6285**	0.1828	0.1774	0.0114	0.0000
22	0.0033	0.3960	**0.5213**	0.0007	0.0788
23	0.2071	0.0435	0.0588	0.1837	**0.5069**
24	**0.7738**	0.0862	0.0610	0.0784	0.0007
25	0.0000	0.3205	**0.3525**	0.0000	0.3270
26	0.0000	0.1278	0.1330	0.0000	**0.7391**
27	0.0123	**0.7555**	0.2298	0.0010	0.0014
28	**0.6103**	0.0656	0.2971	0.0268	0.0001
29	0.0453	**0.7863**	0.1603	0.0052	0.0029
30	0.2168	0.0072	0.0267	**0.7493**	0.0000
31	0.2173	**0.4957**	0.2748	0.0119	0.0003
32	0.0013	**0.4258**	0.4112	0.0003	0.1614
33	0.0004	0.0393	0.0389	0.0001	**0.9213**
34	0.0167	0.0520	0.0517	0.0080	**0.8717**
35	0.1085	**0.6499**	0.2274	0.0078	0.0063
36	0.0005	**0.6878**	0.3106	0.0001	0.0010
37	**0.6641**	0.0474	0.1922	0.0950	0.0014
38	0.0190	**0.8434**	0.1367	0.0009	0.0000

39	0.0015	**0.8107**	0.1845	0.0002	0.0031
40	0.0289	**0.6700**	0.2835	0.0027	0.0149
41	0.0052	**0.5019**	0.3889	0.0012	0.1029
42	**0.8756**	0.0317	0.0274	0.0654	0.0000
43	0.0396	**0.4240**	0.4013	0.0087	0.1264
44	0.0036	**0.6214**	0.3657	0.0004	0.0089
45	0.0069	**0.6513**	0.3218	0.0009	0.0190
47	**0.7168**	0.0220	0.0371	0.2236	0.0004
48	0.2382	0.1375	**0.5948**	0.0272	0.0023
50	**0.9060**	0.0276	0.0285	0.0379	0.0000
51	**0.5697**	0.3254	0.0946	0.0103	0.0000
52	0.0000	**0.8466**	0.1531	0.0000	0.0003
53	**0.6927**	-	-	0.3066	-
54	0.0016	0.1845	**0.8067**	0.0003	0.0068
55	0.0000	0.4545	**0.5201**	0.0000	0.0254
56	0.0747	**0.7455**	0.1757	0.0032	0.0009
57	0.0084	**0.4963**	0.4559	0.0010	0.0384
Total	13	24	9	2	7

Table 3. Akaike weights (ω) by participant for each model for the LL condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
Participant	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	0.1988	0.1826	0.0181	**0.6003**	0.0001
2	0.0104	0.4063	**0.5484**	0.0020	0.0330
3	**0.5512**	0.0173	0.0167	0.4104	0.0044
4	0.0000	0.2611	**0.7388**	0.0000	0.0001
5	**0.7624**	0.1193	0.1140	0.0038	0.0005
6	**0.7509**	0.0248	0.0234	0.2006	0.0003
7	0.0161	0.3732	0.2175	0.0047	**0.3885**
8	0.1154	**0.7232**	0.1527	0.0084	0.0002
9	0.0095	**0.4280**	0.5387	0.0015	0.0223
10	0.1659	**0.6627**	0.1486	0.0227	0.0001
11	**0.9004**	0.0313	0.0451	0.0232	0.0000
12	**0.6255**	0.0204	0.0190	0.3348	0.0003
13	**0.5737**	0.2751	0.0854	0.0645	0.0014
14	0.0000	0.4850	**0.5150**	0.0000	0.0000
15	0.2984	**0.4452**	0.2092	0.0235	0.0237
16	**0.5290**	0.2875	0.1266	0.0569	0.0000
17	0.0767	0.4480	**0.4733**	0.0017	0.0003
18	0.3360	0.2110	**0.4186**	0.0270	0.0074
19	0.0930	**0.6605**	0.2442	0.0020	0.0003
20	**0.6928**	0.1478	0.0454	0.1106	0.0034
21	**0.7066**	0.0221	0.0241	0.2473	0.0000
22	0.0001	**0.6420**	0.3302	0.0000	0.0278
23	0.0206	0.0324	-	0.0196	**0.9191**
24	0.0006	0.0673	0.0663	0.0002	**0.8657**
25	0.0002	**0.6281**	0.3715	0.0000	0.0002
26	**0.4899**	0.1050	0.3171	0.0798	0.0082
27	0.1098	0.2882	**0.5833**	0.0141	0.0046
28	**0.3992**	0.1536	0.3797	0.0666	0.0008
29	0.0772	**0.8302**	0.0902	0.0024	0.0000
30	0.0215	**0.6488**	0.3080	0.0021	0.0195
31	**0.8399**	0.0636	0.0371	0.0593	0.0000
32	0.1256	**0.4680**	0.3663	0.0080	0.0321
33	0.0057	0.0776	0.0671	0.0028	**0.8468**
34	0.0001	0.4517	**0.5042**	0.0000	0.0439
35	0.1301	0.0041	0.0254	**0.8402**	0.0002
36	**0.7101**	0.0235	0.0370	0.2294	0.0000
37	0.3213	0.0769	**0.6003**	0.0015	0.0000
38	0.2551	**0.4082**	0.2068	0.0347	0.0953

39	0.0013	0.4358	**0.5624**	0.0003	0.0002
40	0.4758	0.0144	0.0160	**0.4878**	0.0060
41	0.2034	**0.3490**	0.2248	0.0589	0.1640
42	**0.7318**	0.0223	0.0231	0.2226	0.0002
43	0.3921	0.0128	0.0217	**0.5734**	0.0000
44	0.3637	**0.4933**	0.1140	0.0288	0.0002
45	0.2117	0.0268	0.0238	0.1706	**0.5671**
47	**0.5932**	0.2107	0.1674	0.0285	0.0002
48	0.1533	0.1401	**0.6836**	0.0200	0.0030
50	**0.8346**	0.0505	0.0337	0.0812	0.0000
51	**0.4883**	0.2627	0.0942	0.1449	0.0099
52	0.0014	**0.5230**	0.4756	0.0000	0.0000
53	0.0007	0.2794	**0.7189**	0.0001	0.0010
54	0.0018	0.1691	**0.8291**	0.0001	0.0000
55	0.2914	0.1476	**0.5230**	0.0318	0.0061
56	0.2950	0.0611	0.0620	0.2526	**0.3293**
57	**0.7017**	0.0718	0.0683	0.1417	0.0166
Total	18	14	13	4	6

Table 4. Akaike weights (ω) by participant for each model for the LM condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	**0.6929**	0.1204	0.1163	0.0648	0.0057
2	**0.8823**	0.0273	0.0346	0.0558	0.0000
3	0.3098	0.0966	0.0174	**0.5760**	0.0002
4	**0.8479**	0.0269	0.0273	0.0978	0.0001
5	**0.7135**	0.0224	0.0218	0.2411	0.0012
6	0.2926	0.0894	0.0177	**0.5892**	0.0110
7	0.0593	**0.5601**	0.3680	0.0085	0.0040
8	0.1830	0.1715	**0.6136**	0.0299	0.0021
9	0.0017	0.0387	**0.9595**	0.0001	0.0000
10	0.0205	0.0929	**0.8727**	0.0052	0.0086
11	**0.6703**	0.0210	0.0202	0.2879	0.0005
12	0.0000	**0.9995**	0.0000	0.0005	0.0000
13	0.0867	**0.5067**	0.0119	0.3946	0.0000
14	0.4693	0.0187	0.0357	**0.4763**	0.0000
15	**0.8171**	0.0391	0.0470	0.0942	0.0026
16	0.2203	0.1061	0.0218	**0.6518**	0.0000
17	**0.7085**	0.0217	0.0264	0.2418	0.0016
18	0.1610	0.1634	**0.5818**	0.0284	0.0654
19	**0.5215**	0.0179	0.0205	0.4400	0.0001
20	**0.7306**	0.0358	0.0221	0.2114	0.0000
21	**0.6470**	0.0944	0.1644	0.0854	0.0087
22	0.0159	0.1101	0.1428	0.0134	**0.7178**
23	**0.5912**	0.0307	0.0266	0.2965	0.0549
24	**0.4784**	0.0225	0.0230	0.4760	0.0000
25	**0.7576**	0.0712	0.1168	0.0543	0.0001
26	**0.8701**	0.0280	0.0329	0.0690	0.0000
27	**0.5810**	0.0509	0.0179	0.3489	0.0013
28	**0.8001**	0.0467	0.1215	0.0316	0.0001
29	0.4508	0.0194	0.0143	**0.4739**	0.0415
30	0.0170	**0.6443**	0.3136	0.0019	0.0232
31	0.3081	0.0990	0.0258	**0.5670**	0.0000
32	0.0012	**0.9809**	0.0005	0.0173	0.0000
33	**0.5103**	0.0687	0.0616	0.3525	0.0070
34	0.1545	**0.7243**	0.0035	0.1150	0.0027
35	0.2013	0.0415	0.0222	**0.7349**	0.0002
36	**0.8658**	0.0293	0.0562	0.0486	0.0000
37	**0.8878**	0.0289	0.0609	0.0224	0.0000
38	0.1714	**0.4011**	0.2115	0.0283	0.1876

39	0.0286	**0.6067**	0.3625	0.0021	0.0001
40	0.0168	**0.9051**	0.0023	0.0758	0.0000
41	**0.8213**	0.0252	0.0287	0.1247	0.0001
42	**0.4802**	0.1161	0.3815	0.0220	0.0003
43	0.0028	**0.9818**	0.0004	0.0149	0.0000
44	**0.7011**	0.0669	0.1028	0.1091	0.0201
45	0.4080	0.0967	0.0146	**0.4693**	0.0115
47	**0.5636**	0.0431	0.0170	0.3759	0.0003
48	0.0005	**0.7267**	0.2727	0.0000	0.0000
50	0.0003	**0.9944**	0.0002	0.0052	0.0000
51	0.2569	**0.6352**	0.0922	0.0157	0.0000
52	0.0918	**0.8622**	0.0438	0.0022	0.0000
53	**0.6442**	0.1033	0.1613	0.0829	0.0083
54	0.0001	0.3440	**0.6556**	0.0000	0.0003
55	0.1368	0.0563	0.0898	0.0323	**0.6848**
56	**0.5000**	0.0000	0.0000	**0.5000**	0.0000
57	0.1620	0.0958	0.0234	**0.7188**	0.0000
Total	25	14	5	9	2

Table 5. Spearman correlation coefficients and sifnificance levels for ln(*h*) values across conditions. Significant correlations are in bold.

	MM	ML	LL	LM
MM	-			
ML	.508 (.0001)	-		
LL	.469 (.0001)	.305 (.05)	-	
LM	.289 (.05)	-.180 (ns)	.517 (.0001)	-

Table 6. Akaike weights (ω) by participant for each model for the MM condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	0.0311	**0.8014**	0.1642	0.0030	0.0003
2	**0.8307**	0.0382	0.1033	0.0279	0.0000
3	**0.7184**	0.0386	0.0443	0.1978	0.0009
4	0.0149	**0.7281**	0.2535	0.0011	0.0024
5	0.0121	**0.9208**	0.0660	0.0010	0.0001
6	0.1517	**0.5970**	0.2367	0.0082	0.0063
7	0.0010	0.2450	**0.7434**	0.0002	0.0104
10	0.0366	**0.6393**	0.3223	0.0018	0.0000
11	0.0618	**0.8798**	0.0484	0.0100	0.0000
12	**0.5545**	0.0220	0.0573	0.3662	0.0000
13	0.0269	0.1907	**0.7656**	0.0038	0.0131
14	0.0382	**0.4920**	0.4633	0.0035	0.0029
15	0.1579	0.0812	**0.7477**	0.0128	0.0004
16	**0.7797**	0.0263	0.0396	0.1543	0.0001
17	**0.7422**	0.1045	0.0755	0.0774	0.0003
18	0.3495	0.0884	**0.5240**	0.0367	0.0015
19	0.1143	0.0999	**0.7836**	0.0022	0.0000
20	**0.7123**	0.0380	0.0834	0.1663	0.0000
21	**0.6752**	0.0336	0.0206	0.2704	0.0002
23	0.0025	**0.8523**	0.1452	0.0000	0.0000
24	0.1412	**0.7241**	0.1336	0.0011	0.0000
25	0.1775	0.0886	**0.7269**	0.0070	0.0001
26	**0.4303**	0.1215	0.4239	0.0239	0.0004
27	0.0551	0.0965	**0.8372**	0.0062	0.0049
28	0.0201	**0.7284**	0.2486	0.0021	0.0009
29	0.0123	**0.9696**	0.0180	0.0000	0.0000
30	0.1136	0.3026	**0.4188**	0.0376	0.1274
31	0.0198	**0.5453**	0.2804	0.0051	0.1494
33	0.0187	0.1302	**0.8449**	0.0053	0.0009
34	0.3811	0.1653	**0.4340**	0.0191	0.0006
35	**0.6120**	0.2603	0.1053	0.0223	0.0001
36	**0.9114**	0.0318	0.0306	0.0262	0.0000
37	**0.6573**	0.1980	0.1137	0.0261	0.0049
39	**0.8906**	0.0272	0.0337	0.0485	0.0000
40	**0.7793**	0.0576	0.0496	0.1131	0.0004
41	0.2623	0.1536	**0.5075**	0.0482	0.0285
Total	13	12	11	0	0

Table 7. Akaike weights (ω) by participant for each model for the ML condition. Highest likelihood values are bolded, indicating most probable model.

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	0.0910	0.3371	**0.4329**	0.0169	0.1222
2	0.0534	0.0000	0.0273	0.0192	**0.9001**
3	0.0003	0.3404	**0.6202**	0.0001	0.0391
4	**0.8126**	0.0541	0.0281	0.1051	0.0001
5	**0.6428**	0.0216	0.0195	0.3160	0.0000
6	0.2728	**0.5834**	0.1328	0.0104	0.0005
7	0.0001	0.1942	0.1543	0.0001	**0.6513**
10	**0.6743**	0.0240	0.0435	0.2582	0.0000
11	0.2587	0.0544	0.0848	**0.6022**	0.0000
12	**0.6822**	0.0288	0.0271	0.2573	0.0046
13	0.0753	0.0445	0.2088	0.0749	**0.5965**
14	0.0009	0.3585	**0.4207**	0.0003	0.2196
15	0.0002	0.4537	**0.4990**	0.0000	0.0471
16	**0.5921**	0.2103	0.1438	0.0343	0.0195
17	0.0062	**0.4887**	0.4790	0.0010	0.0251
18	**0.5544**	0.1782	0.1142	0.1367	0.0166
19	0.0148	0.2758	**0.6551**	0.0031	0.0512
20	0.0000	0.0048	**0.9951**	0.0000	0.0000
21	**0.7068**	0.0000	0.0000	0.2932	0.0000
23	0.0013	0.4948	**0.4998**	0.0002	0.0038
24	0.0000	**0.7063**	0.2930	0.0000	0.0007
25	0.1434	**0.4786**	0.3129	0.0589	0.0061
26	**0.6692**	0.0407	0.1112	0.1718	0.0072
27	0.1423	0.1596	**0.5857**	0.0269	0.0854
28	0.0753	0.0252	0.0264	**0.8731**	0.0000
29	**0.3851**	0.0414	0.0264	0.2954	0.2517
30	0.0588	**0.5276**	0.2467	0.0104	0.1565
31	0.2461	0.1122	0.0737	0.1084	**0.4597**
33	0.0008	0.0354	0.0351	0.0006	**0.9280**
34	0.0007	0.4474	**0.5519**	0.0000	0.0001
35	0.0625	**0.6113**	0.0103	0.3159	0.0000
36	**0.5446**	0.2259	0.2214	0.0080	0.0000
37	**0.7820**	0.0902	0.1254	0.0024	0.0000
39	0.0723	0.0694	0.0252	**0.8332**	0.0000
40	0.3403	0.0107	0.0190	**0.6294**	0.0006
41	0.0001	0.2806	**0.7184**	0.0000	0.0009
Total	11	6	10	4	5

Table 8. Akaike weights (ω) by participant for each model for the LM condition. Highest likelihood values are bolded, indicating most probable model. Asterisks denote data sets for which AIC_c could not be calculated due to a perfect fit for the random noise model (r^2 =1).

	Akaike weight				
	$1/(1+h\theta)$	$1/(1+h\theta^s)$	$1/(1+h\theta)^s$	$e^{-h\theta}$	$V=c$
Participant	Eq. 7 Hyperbolic	Eq. 4 Hyperboloid	Eq. 3 Hyperboloid	Eq. 1 Exponential	Random Noise
1	0.2745	0.0267	0.0000	0.2704	**0.4284**
2					*
3	**0.7788**	0.0412	0.0761	0.1033	0.0006
4	**0.6454**	0.0288	0.0220	0.3003	0.0035
5	0.3538	0.1606	0.0149	**0.4705**	0.0001
6	0.4126	0.0125	0.0166	**0.5515**	0.0068
7					*
10	**0.6481**	0.0472	0.0221	0.2826	0.0001
11	0.0131	**0.7339**	0.0074	0.2455	0.0000
12	0.3561	0.0741	0.0196	**0.5501**	0.0001
13	0.0000	0.0323	0.0325	0.0000	**0.9352**
14	0.0267	**0.9406**	0.0010	0.0315	0.0001
15	**0.7548**	0.0228	0.0387	0.1834	0.0004
16	**0.8276**	0.0254	0.0251	0.1219	0.0000
17	0.0363	**0.8828**	0.0024	0.0785	0.0000
18	0.0000	**1.0000**	0.0000	0.0000	0.0000
19	**0.4518**	0.1108	0.3120	0.0921	0.0332
20	0.1425	0.0207	0.0207	0.1328	**0.6834**
21					*
23	**0.7533**	0.0839	0.1190	0.0436	0.0002
24	0.0084	0.3153	**0.6742**	0.0014	0.0006
25	0.0022	**0.9902**	0.0002	0.0074	0.0000
26	**0.8402**	0.0275	0.0339	0.0984	0.0001
27	**0.7438**	0.0459	0.2037	0.0066	0.0000
28	**0.6816**	0.0216	0.0209	0.2757	0.0001
29	0.0000	**1.0000**	0.0000	0.0000	0.0000
30	**0.5612**	0.0200	0.0271	0.3877	0.0040
31	**0.5105**	0.0452	0.0687	0.3304	0.0452
33					*
34	**0.7038**	0.0422	0.0788	0.1701	0.0051
35	0.0977	**0.3980**	0.3443	0.0115	0.1486
36	0.0048	**0.8646**	0.0038	0.1268	0.0000
37	0.0000	**1.0000**	0.0000	0.0000	0.0000
39	0.0000	**1.0000**	0.0000	0.0000	0.0000
40	**0.7467**	0.0257	0.0249	0.2025	0.0002
41	**0.8390**	0.0268	0.0329	0.1012	0.0001
Total	15	10	1	3	7

Table 9. Obtained probabilities.

Programmed Probability	Participant 01	02	03	04	05	06	Total
5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
10%	18.2%	0.0%	0.0%	16.7%	0.0%	12.5%	8.9%
25%	50.0%	28.6%	25.0%	28.6%	50.0%	37.5%	35.0%
50%	44.0%	40.0%	50.0%	81.8%	50.0%	62.5%	55.6%
95%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 10. Mean fidelity and range by participant and condition.

Participant	Incentive	Disincentive
01	90% (80%-100%)	100%
02	91.1% (80%-100%)	96.4% (80%-100%)
03	92.5% (80%-100%)	100%
04	100%	92.7% (80%-100%)
05	100%	100%
06	97.1% (80%-100%)	100%

Table 11. BIS/BAS

	Participant					
Item	01	02	03	04	05	06
1	3	4	4	3	4	3
2	2	1	3	1	2	2
3	3	3	4	2	3	3
4	3	3	4	4	3	3
5	3	3	4	4	3	3
6	2	2	4	4	2	2
7	4	3	4	4	3	3
8	2	3	2	4	3	2
9	2	3	4	2	3	3
10	3	3	3	4	3	2
11	2	2	2	3	2	2
12	2	3	3	2	2	3
13	3	4	4	4	3	3
14	3	3	4	3	3	3
15	2	4	4	1	2	2
16	3	3	2	4	2	3
17	2	3	4	4	4	3
18	2	3	4	4	3	3
19	3	4	4	4	3	3
20	3	2	4	3	3	2
21	2	3	3	2	3	2
22	2	2	3	1	2	2
23	4	3	4	4	3	3
24	3	3	4	4	3	3
BAS Drive Score	11	8	6	12	9	9
BAS Fun Seeking Score	9	8	5	8	9	11
BAS Reward Responsiveness Score	9	10	5	6	10	10
BIS Score	15	11	15	7	15	15

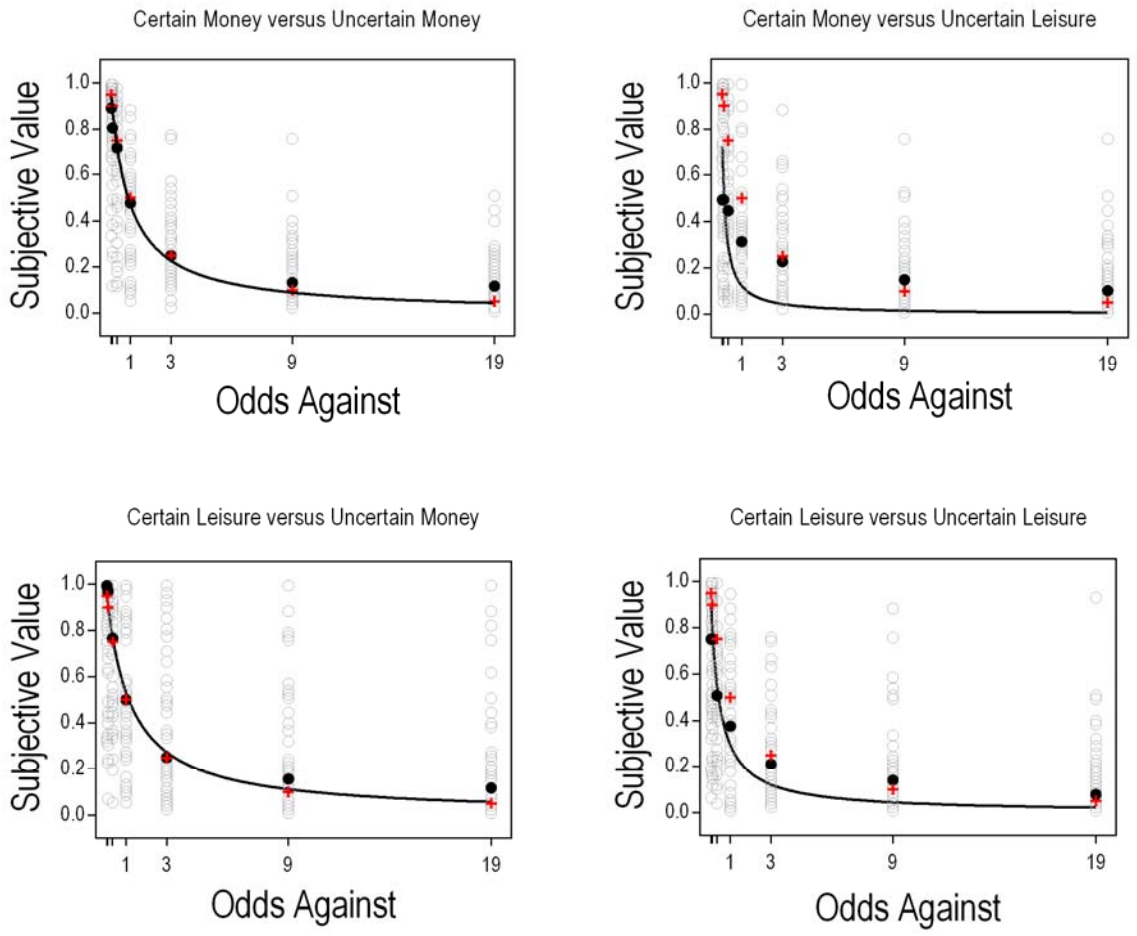


Figure 1. Open data points depict indifference points for each participant. Closed data points are group medians. Crosses depict the expected value function. The curve is the least-squares regression line for the simple hyperbolic function fitted to the group median indifference points.

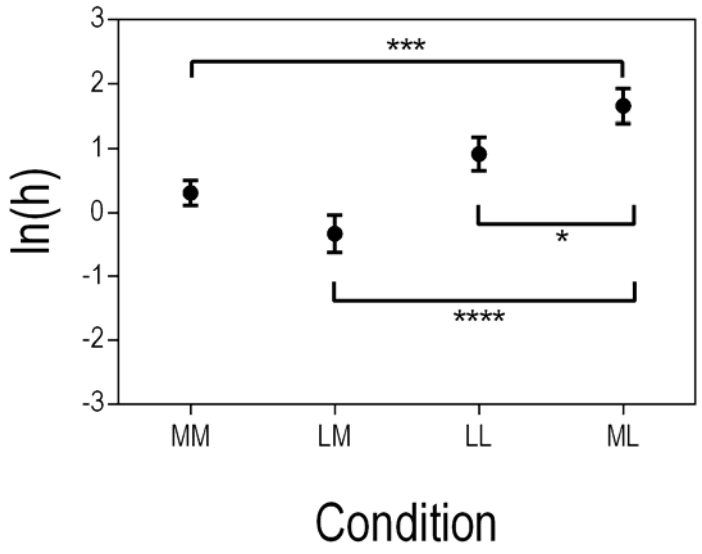


Figure 2. Mean and standard error for natural log-transformed values of *h* derived from the simple hyperbolic discounting function. The asterisks denote a statistically significant difference (* = p < .05; *** = p < .001; **** = p < .0001).

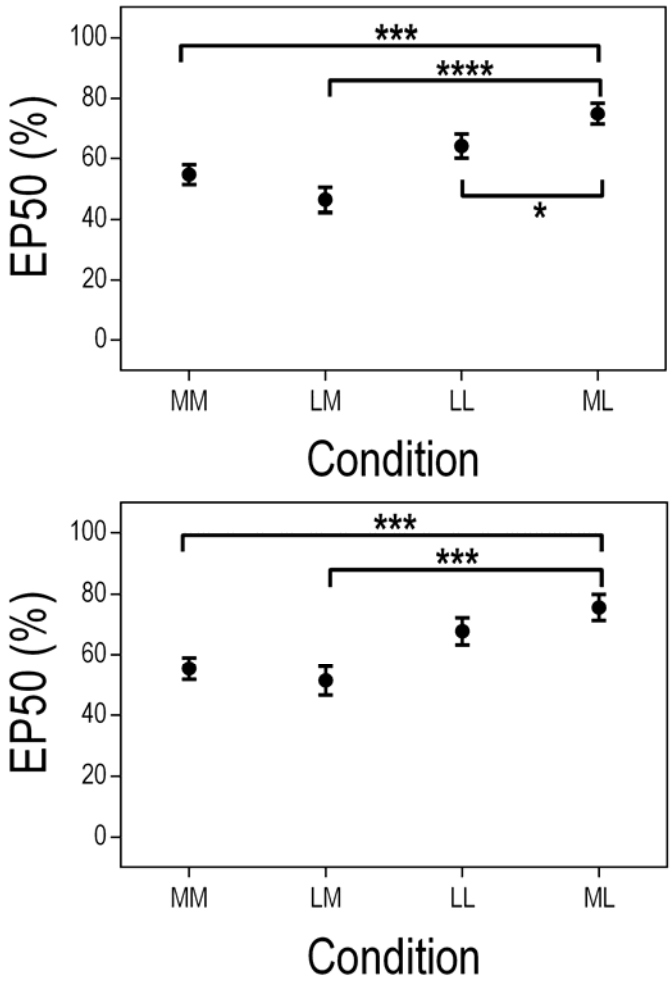


Figure 3. Mean and standard error for Effective Probability 50% (EP50) for hyperbolic fits (top panel) and individualized fits (bottom panel) based on the AIC algorithm. The asterisks denote a statistically significant difference (* = $p < .05$; *** = $p < .001$; **** = $p < .0001$).

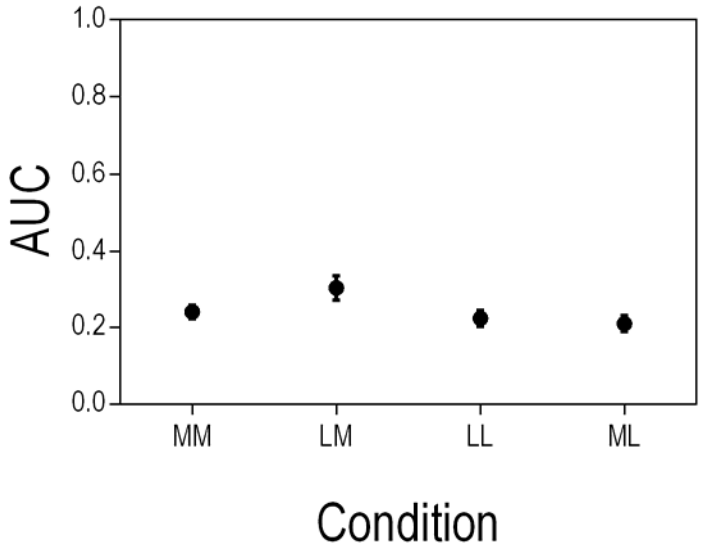


Figure 4. Mean and standard error for area under the curve (AUC).

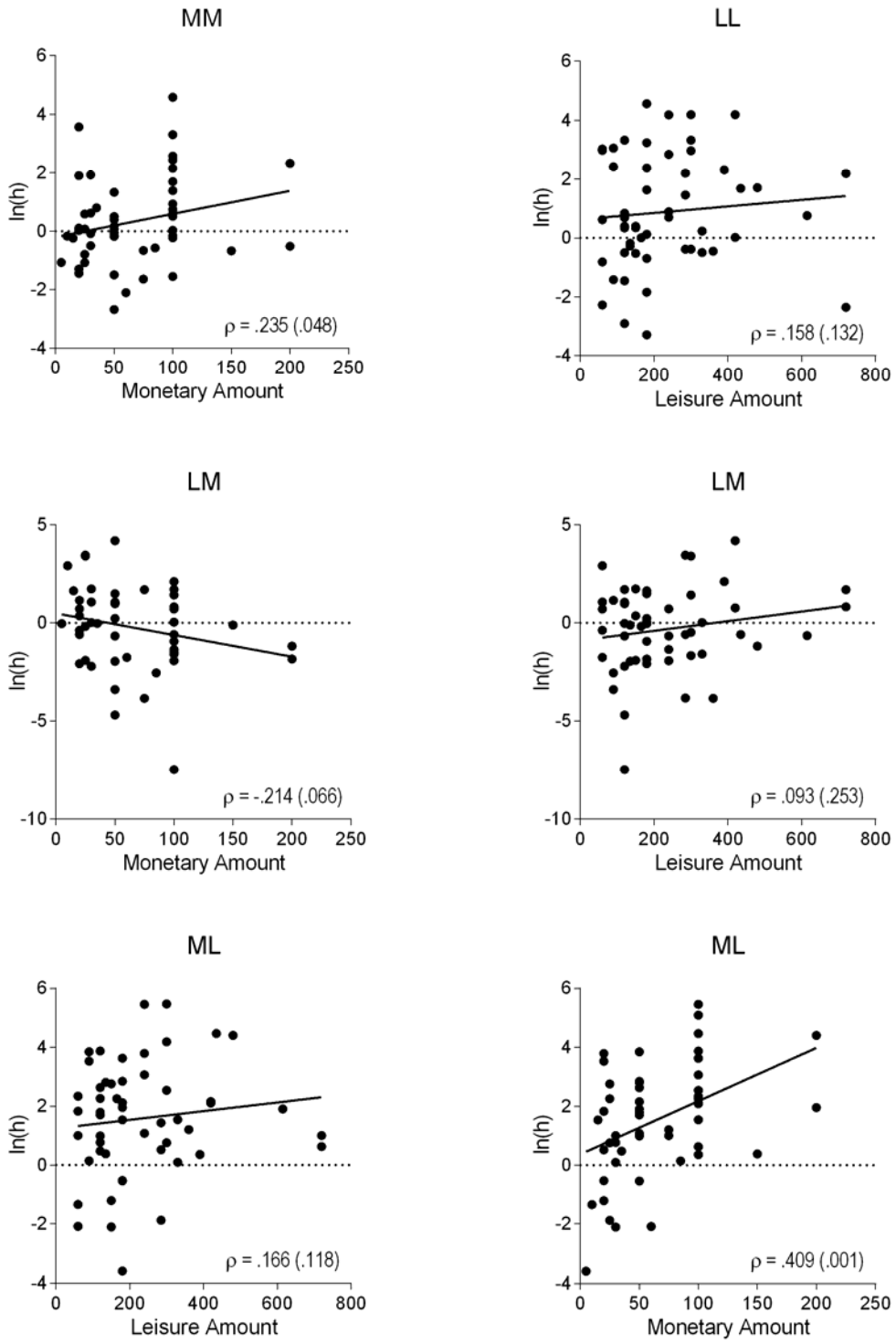


Figure 5. Scatterplots and best-fit linear regression lines for ln(*h*) values and nominal amounts of either money or leisure time. Spearman correlation coefficients (*p*-values) are also provided.

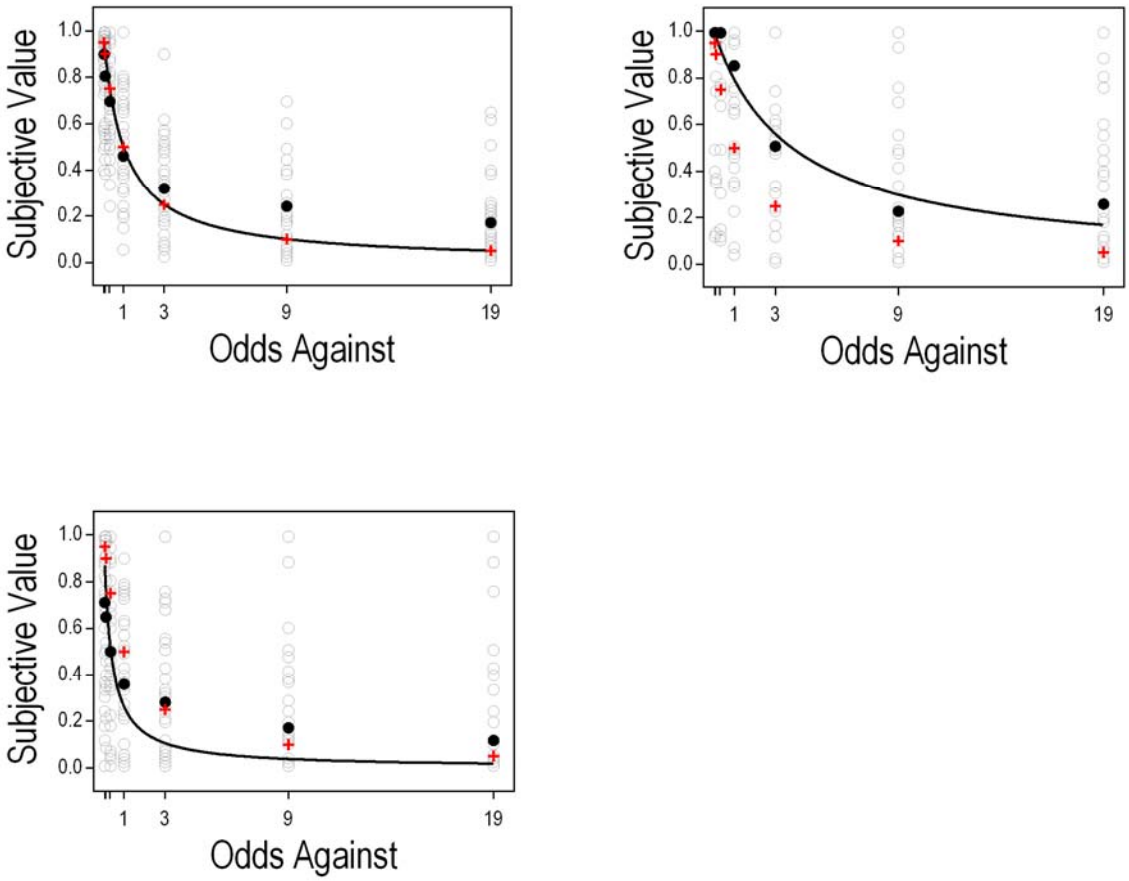


Figure 6. Open data points depict indifference points for each participant. Closed data points are group medians. Crosses depict the expected value function. The curve is the least-squares regression line for the simple hyperbolic function fitted to the group median indifference points.

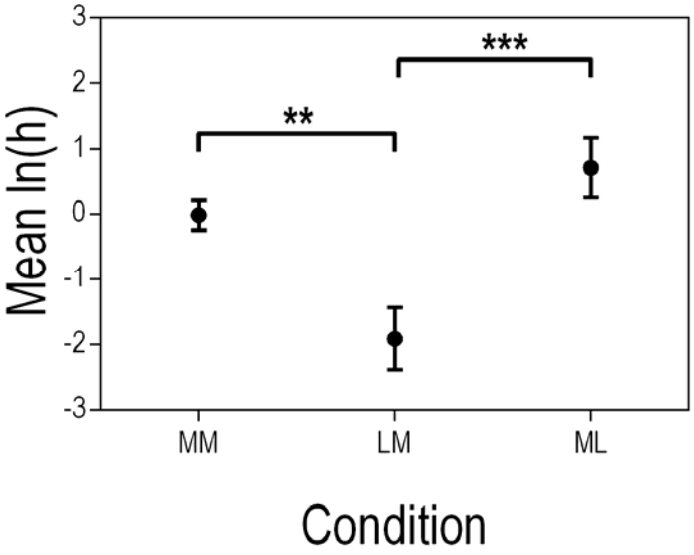


Figure 7. Mean and standard error for natural log-transformed values of *h* derived from the simple hyperbolic discounting function. Asterisks denote level of significance (**: $p < .01$; ***: $p < .001$).

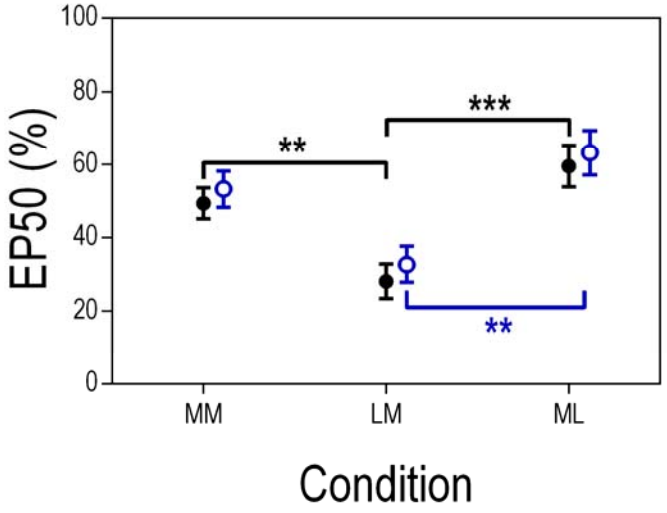


Figure 8. Mean and standard error for Effective Probability 50% (EP50) for hyperbolic fits (closed data points) and individualized fits (open data points) based on the AIC algorithm. Asterisks denote level of significance (**: $p < .01$; ***: $p < .001$).

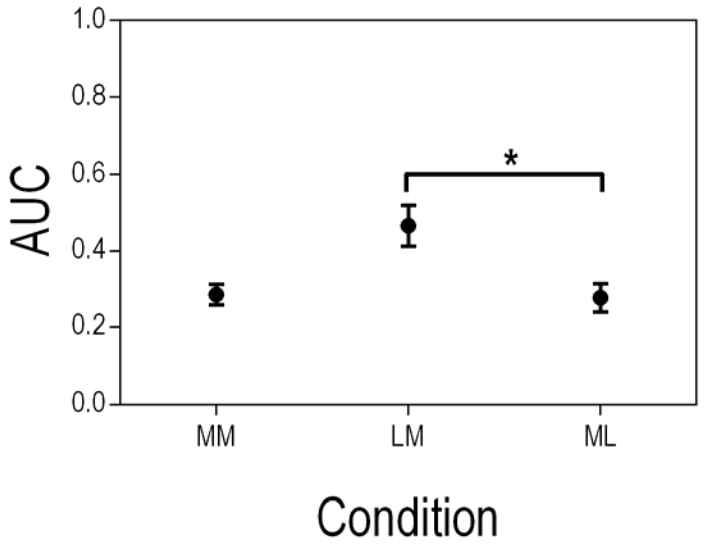


Figure 9. Mean and standard error for area under the curve (AUC). The asterisk denotes a statistically significant difference with $p < .05$.

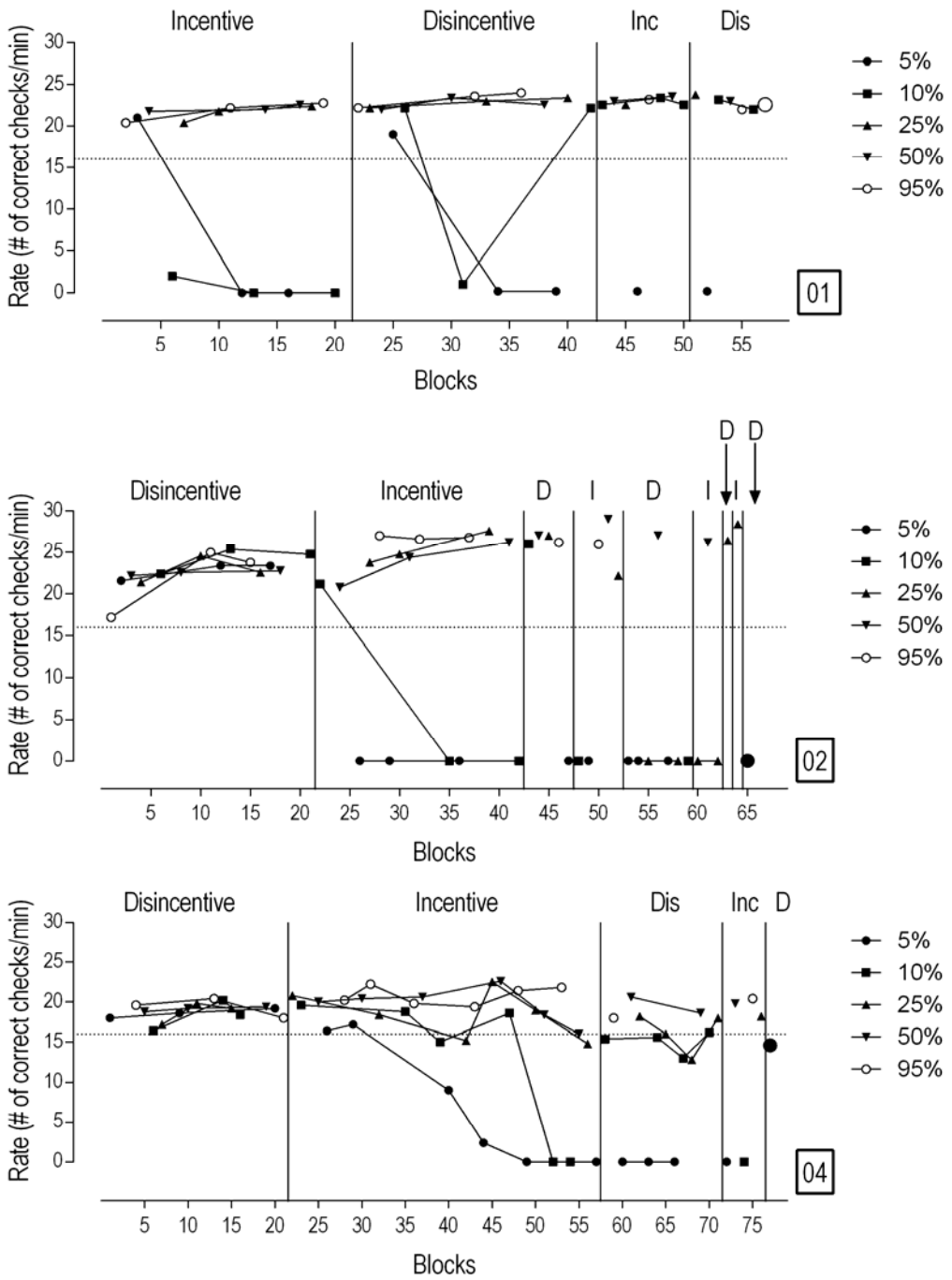


Figure 10. Time-series data for participants 01, 02, and 04. The last, larger data point denotes the conditions chosen and processing rate during the choice phase. The horizontal dotted line denotes the performance criterion for the bonus contingency.

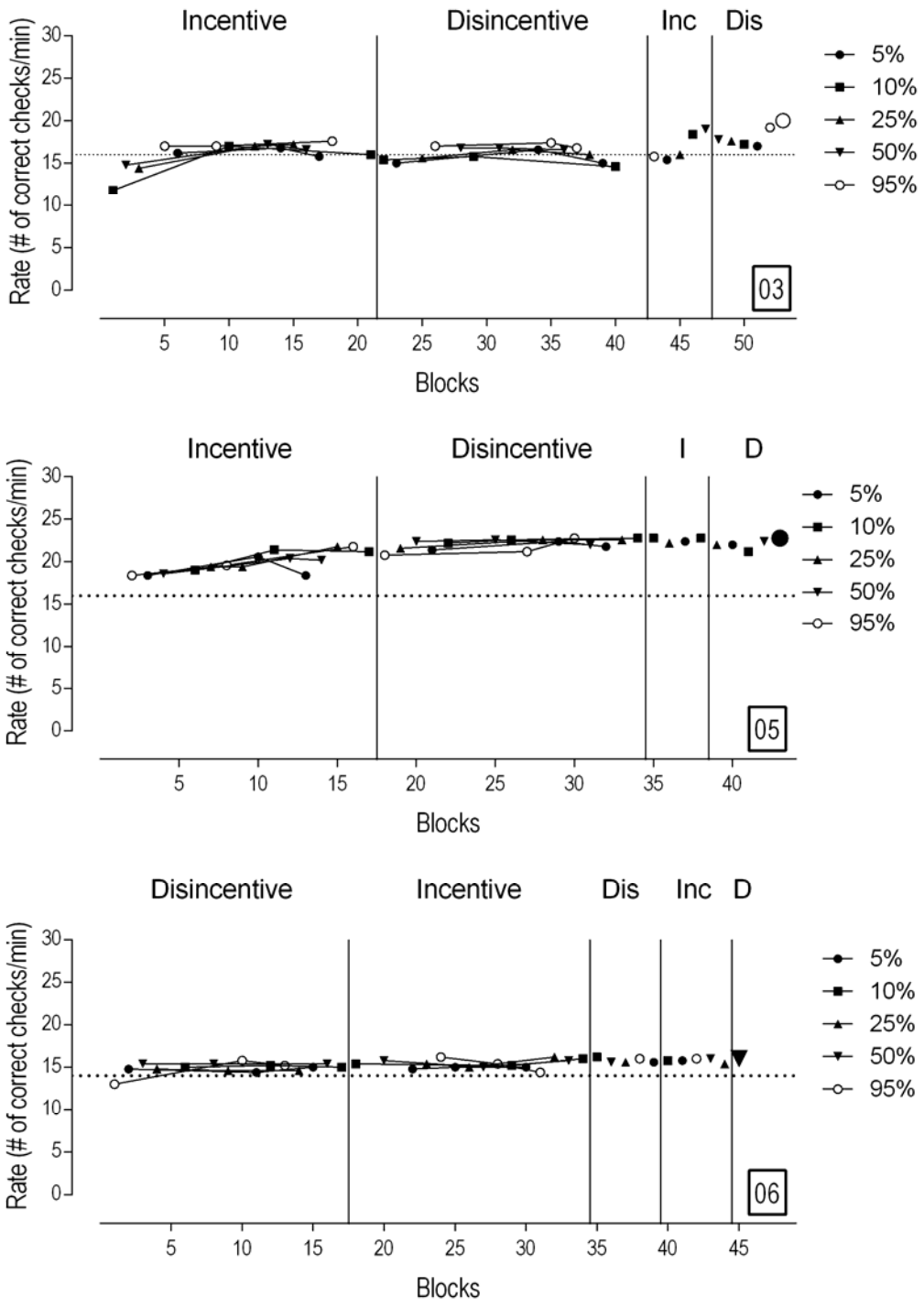


Figure 11. Time-series data for participants 03, 05, and 06. The last, larger data point denotes the conditions chosen and processing rate during the choice phase. The horizontal dotted line denotes the performance criterion for the bonus contingency.

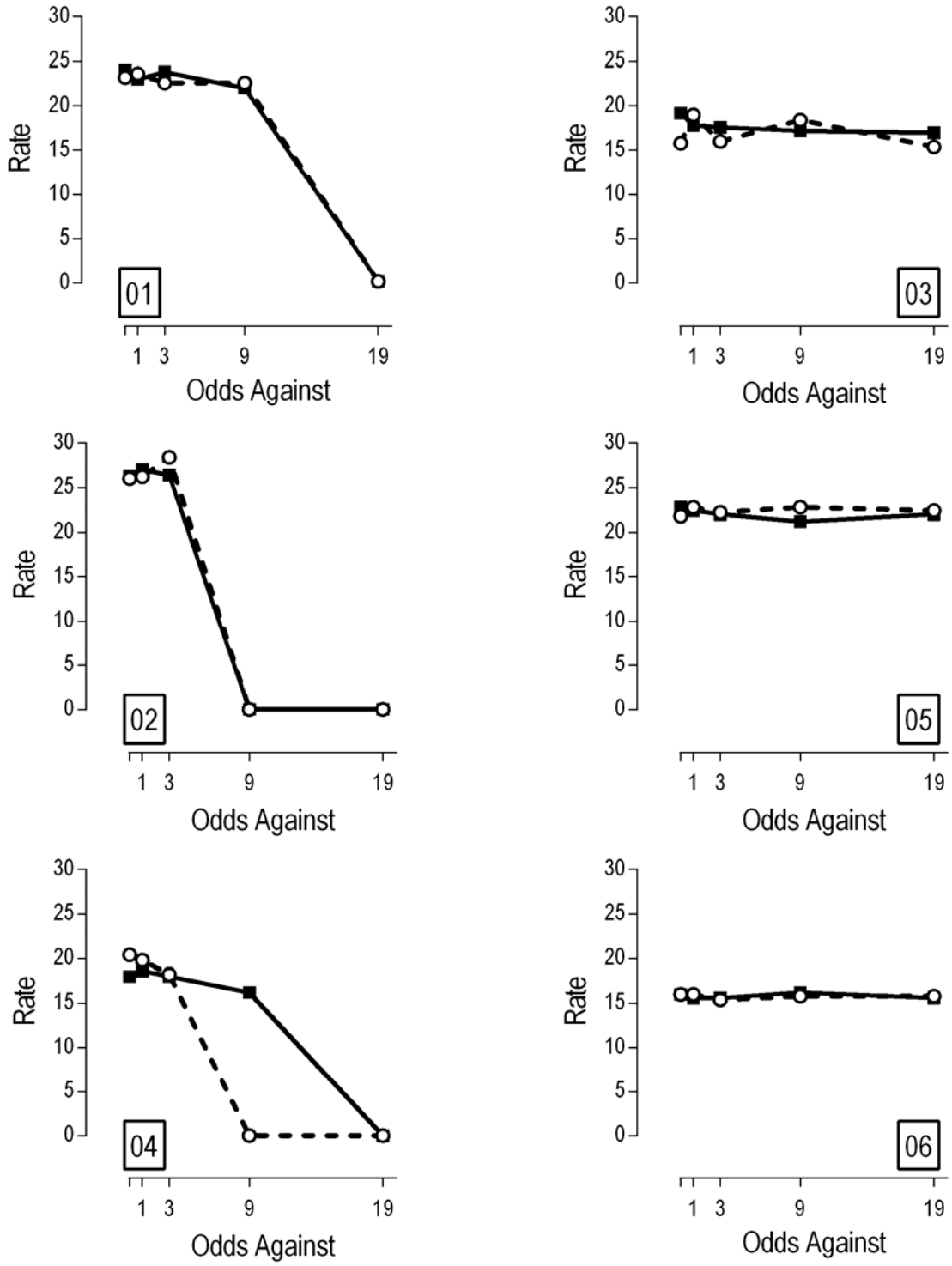


Figure 12. Check processing rate of last block for each probability. Open circles depict Incentive data while closed squares depict Disincentive data.

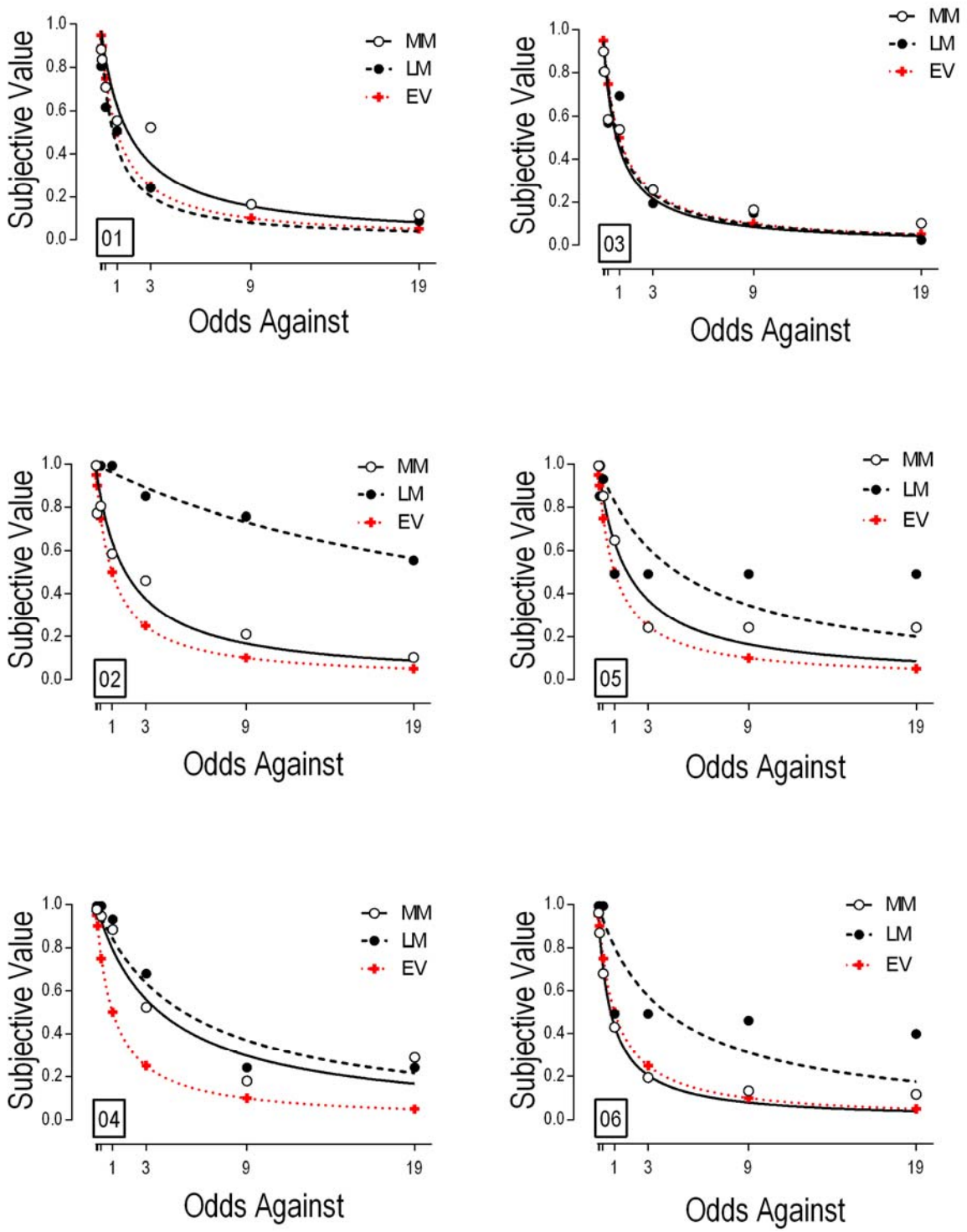


Figure 13. Discounting data and hyperbolic fits.

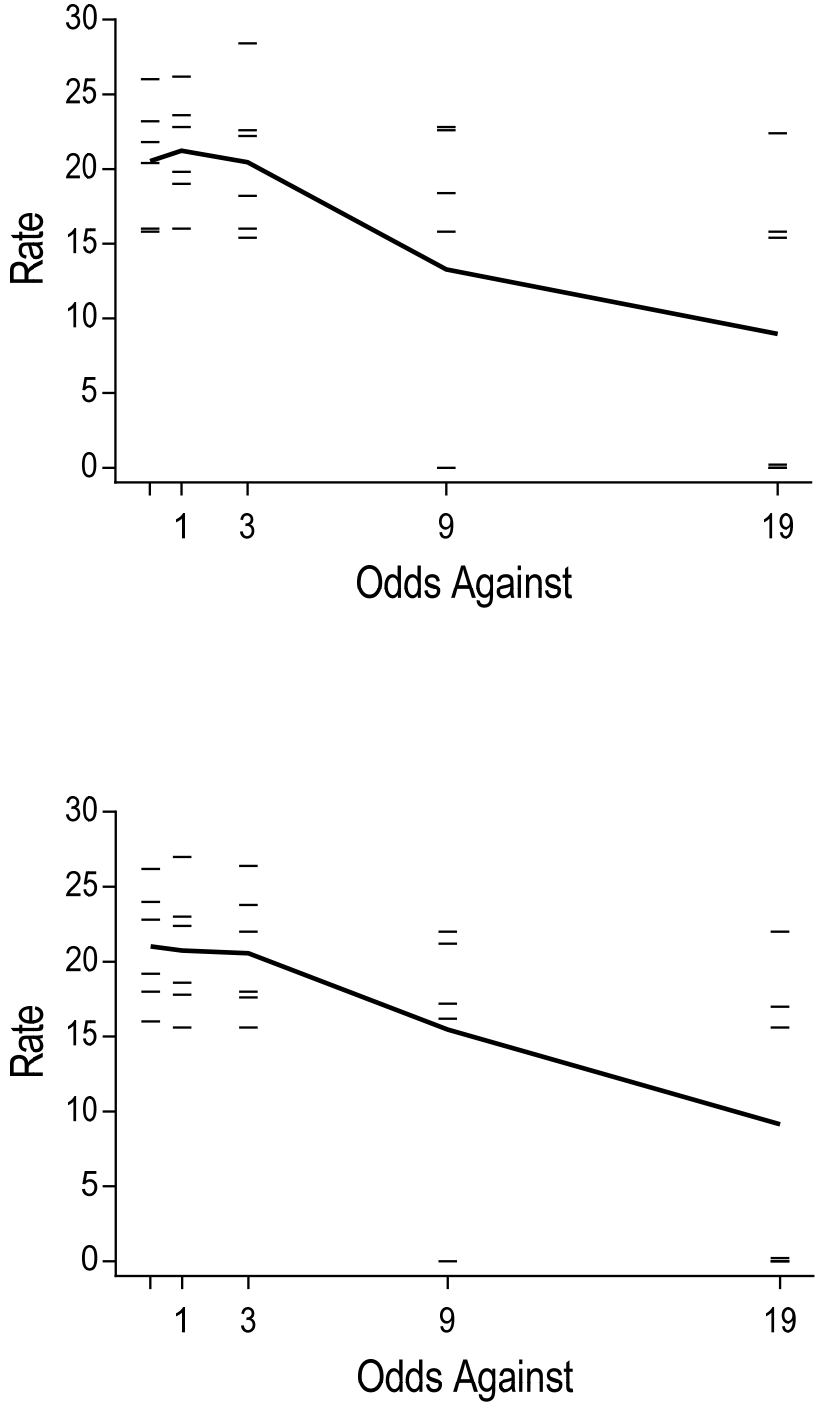


Figure 14. Scatterplot of last block rate by probability for incentive (top panel) and disincentive (bottom panel) with the data path connecting group means.

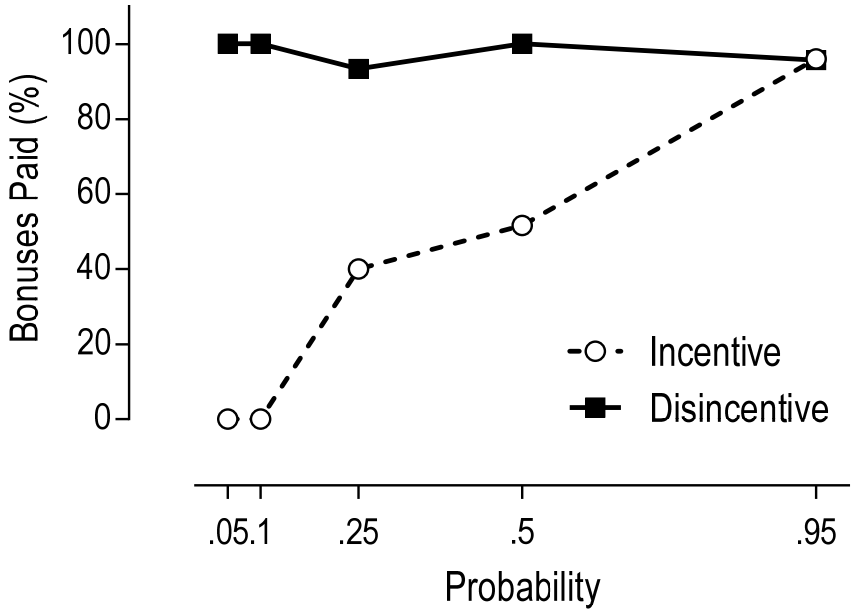
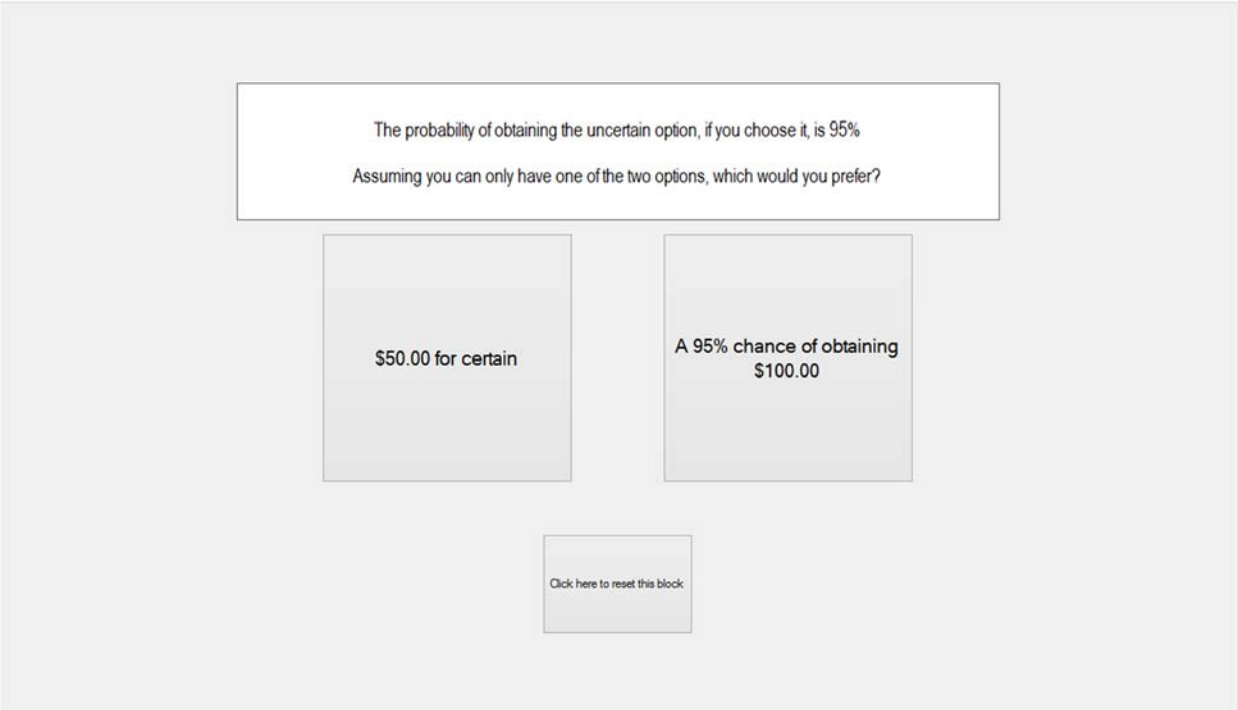


Figure 15. Percent of blocks resulting in a paid bonus across all participants by probability.

Appendix A

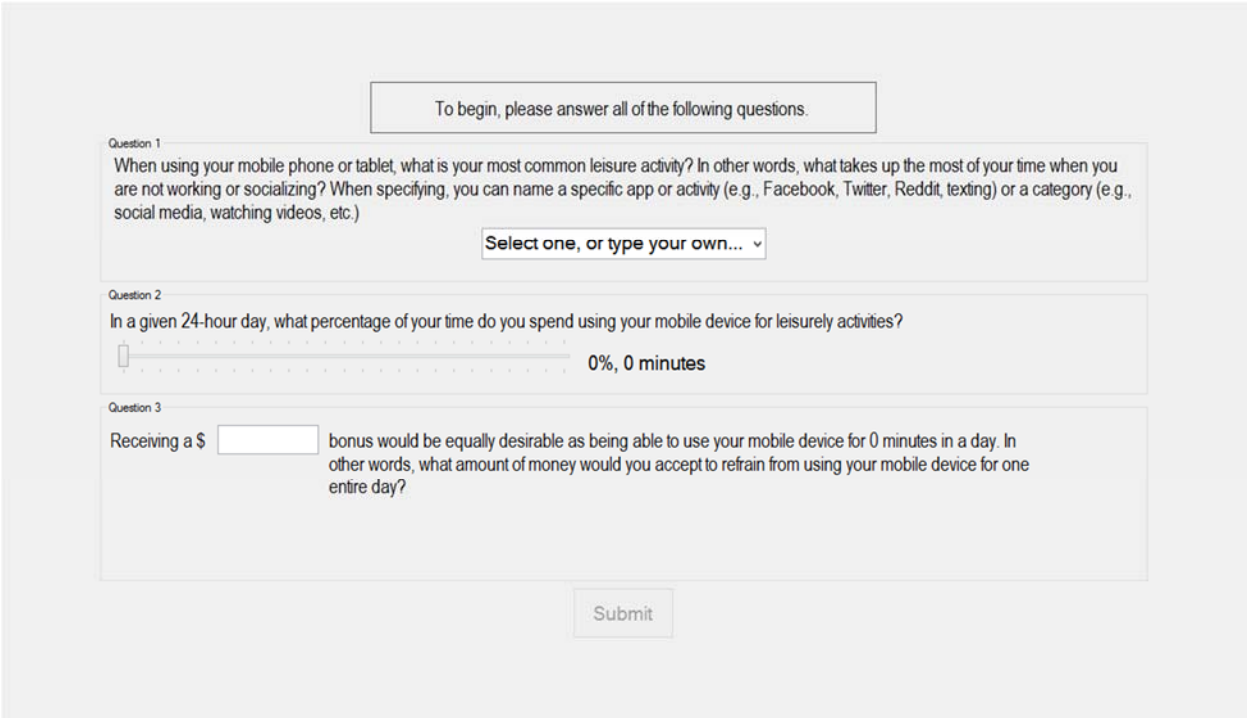
1. Database Search (*n* = 1,348)
    a. PsycINFO (keywords appear anywhere)
        i. (Probability OR Probabilistic) AND Discounting (*n* = 219)
        ii. (Risk OR Risky) AND Discounting (*n* = 319)
        iii. (Cross Commodity OR Cross-Commodity) AND Discounting (*n* = 1)
    b. PubMed (search all fields)
        i. (Probability OR Probabilistic) AND Discounting (*n* = 406)
        ii. (Risk OR Risky) AND Discounting (*n* = 398)
        iii. (Cross Commodity OR Cross-Commodity) AND Discounting (*n* = 3)
2. Removed Duplicate Records (*n* = 862)
3. Screening (*n* = 50)
    a. Published in English
    b. Peer-Reviewed
    c. Empirical
    d. Subject is probability and/or cross-commodity discounting (any mode)
    e. Non-clinical or pathological population (illicit/addictive substances, or gambling)
4. Applied Exclusionary Criteria (*n* = 34)
    a. Demographic comparative studies
    b. Psychometric property evaluations
    c. Methodological evaluations
    d. Correlational studies (e.g., predictor variables)

Appendix B



Main interface of the discounting task presented in Experiments 1 and 2.

Appendix C



Pre-assessment questionnaire administered prior to the discounting tasks (Experiments 1 and 2).

Appendix D

Burnham and Anderson (2004) state AIC_c is not easily interpretable alone because the value is dependent on the form of the data analyzed. They describe the calculations required to transform the values into weighted probabilities. First, AIC_c values are re-scaled relative to the minimum value obtained from the compared models.

$$\Delta_i = AIC_i - AIC_{min}$$

AIC_{min} is the minimum AIC value of all models compared. Δ_i represents the lost information resulting from using a given model compared to the best model. Models with a difference of 10 or greater than the minimum are not supported as a probable model for the data at hand.

From these values, a likelihood function is calculated with

$$\mathcal{L}(g_i \mid data) = \exp(-\Delta_i/2) \ .$$

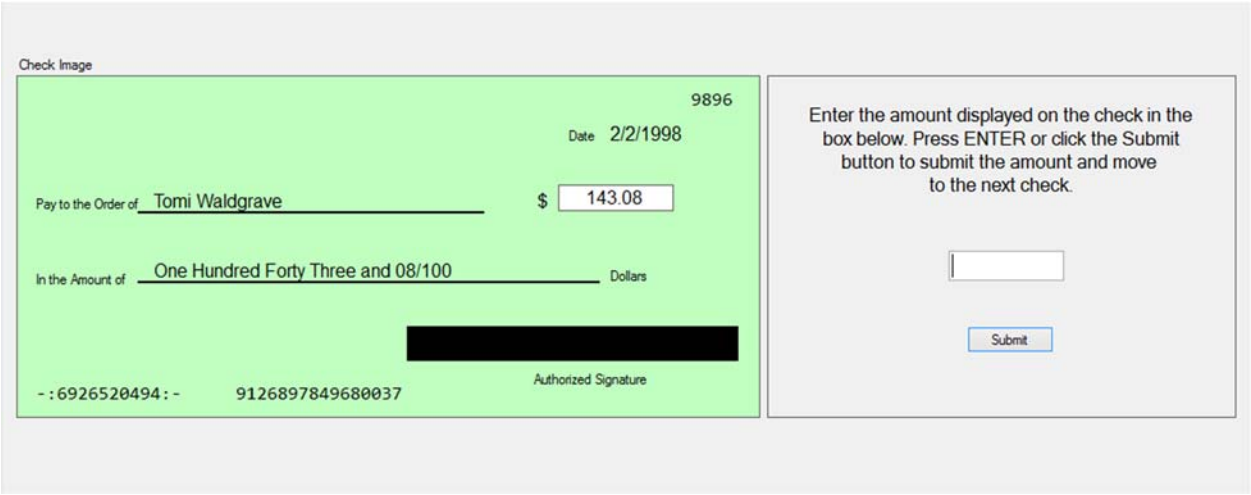
The ratio of the likelihood functions for two models is termed the evidence ratio and represents the relative likelihood of one model compared to the other.

Akaike weights normalize likelihood functions of the model set and represent the weight of evidence for a given model being the best model. Weights are calculated using

$$\omega_i = \frac{\exp(-\Delta_i/2)}{\sum_{r=1}^{R} \exp(-\Delta_r/2)}$$

The weights for all models compared sum to 1. The weight for each model can be interpreted as the probability that the given model is the best model given the data.

Appendix E


Check Image
9896
Date 2/2/1998
Pay to the Order of Tomi Waldgrave
$ 143.08
In the Amount of One Hundred Forty Three and 08/100
Dollars
Authorized Signature
-:6926520494:-
9126897849680037
Enter the amount displayed on the check in the box below. Press ENTER or click the Submit button to submit the amount and move to the next check.
Submit

Appendix F

BIS/BAS (Carver & White, 1994)

Instructions: Please respond to the following statements by indicating the degree to which you either Agree or Disagree. Select “1” to indicate Strong Disagreement; select 4 to indicate Strong Agreement.

	Disagree Strongly	Disagree	Agree	Agree Strongly
1. A person’s family is the most important thing in life.	1	2	3	4
2. Even if something bad is about to happen to me, I rarely experience fear or nervousness.	1	2	3	4
3. I go out of my way to get things I want.	1	2	3	4
4. When I'm doing well at something I love to keep at it.	1	2	3	4
5. I'm always willing to try something new if I think it will be fun.	1	2	3	4
6. How I dress is important to me.	1	2	3	4
7. When I get something I want, I feel excited and energized.	1	2	3	4
8. Criticism or scolding hurts me quite a bit.	1	2	3	4
9. When I want something I usually go all-out to get it.	1	2	3	4
10. I will often do things for no other reason than that they might be fun.	1	2	3	4
11. It's hard for me to find the time to do things such as get a haircut.	1	2	3	4
12. If I see a chance to get something I want I move on it right away.	1	2	3	4
13. I feel pretty worried or upset when I think or know somebody is angry at me.	1	2	3	4
14. When I see an opportunity for something I like I get excited right away.	1	2	3	4
15. I often act on the spur of the moment.	1	2	3	4
16. If I think something unpleasant is going to happen I usually get pretty "worked up."	1	2	3	4
17. I often wonder why people act the way they do.	1	2	3	4
18. When good things happen to me, it affects me strongly.	1	2	3	4
19. I feel worried when I think I have done poorly at something important.	1	2	3	4
20. I crave excitement and new sensations.	1	2	3	4
21. When I go after something I use a "no holds barred" approach.	1	2	3	4
22. I have very few fears compared to my friends.	1	2	3	4
23. It would excite me to win a contest.	1	2	3	4
24. I worry about making mistakes.	1	2	3	4

Appendix G

Orientation Script:

Welcome and thank you for keeping your appointment. The purpose of this study is to evaluate preference for the various bonus arrangements we are presenting. This will be your workspace for the duration of the experiment. You can feel free to bring anything with you into the room including your cellphone, laptop, or homework. You'll notice that there is a task that you may complete if you wish. To complete the task, type the amount of each check into the box on the right and press ENTER or click Submit. You can choose to process as many or as few checks as you'd like. Regardless of what you do, you will be paid $2.50 for your time. In a moment, I will leave the room for five minutes. Over the course of those five minutes, there is a chance that I will evaluate your performance.

Incentive Script:

If your performance is evaluated and your performance has met the criterion of 16 checks processed correctly per minute, you will also earn a $0.75 bonus. If your performance did not meet the criterion, you will not receive the bonus, but again, you will be paid $2.50 per hour either way. If your performance is not evaluated, you will not receive the bonus whether you completed the work task or not. For the next five minutes, the chance that your performance will be evaluated is XX% and the chance that you will not be evaluated is XX%. To determine whether your performance will be evaluated, I will roll a 20-sided die and if it lands on X-Y, then I will apply the criterion for the bonus. **Otherwise, you will not be eligible for the bonus.** As a reminder, you can do as much or as little work as you'd like. The purpose of this study is to evaluate preference for the various bonus arrangements we are presenting.

Disincentive Script:

You will receive a $0.75 bonus at the end of the session unless your performance is evaluated and you failed to meet the criterion of 16 checks processed correctly per minute. If your performance is not evaluated, you will receive the bonus regardless of how much work you did. For the next five minutes, the chance that your performance will be evaluated is XX% and the chance that you will not be evaluated is XX%. To determine whether your performance will be evaluated, I will roll a 20-sided die and if it lands on X-Y, then I will apply the criterion for the bonus. **Otherwise you will receive the bonus regardless of how much work you did.** As a reminder, you can do as much or as little work as you'd like.