# OBESITY AND HYPERBOLIC DISCOUNTING: AN EXPERIMENTAL ANALYSIS

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**Abstract:**

Behavioral economists maintain that addictions such as alcoholism, smoking and over-eating represent examples of present-bias in decision making that is fundamentally irrational. In this article, we develop a model of present bias and apparently hyperbolic discounting that is fully consistent with rational behavior. We construct an experiment to test our hypothesis and to determine whether discount rates differ for individuals who engage in behaviors that could endanger their health. Our results show that discount functions are quasi-hyperbolic in shape, and that obesity and drinking are positively related to the discount rate. Anti-obesity policy, therefore, would be best directed to informing individuals as to the long-term implications of short-term gratification, rather than taxing foods directly.

**keywords:** addiction, discounting, experiments, hyperbolic, obesity, time-inconsistency.

**JEL Codes:** C91, D12, D91, I18.

## 1. Introduction

Genetic arguments notwithstanding (Shell 2002), obese individuals appear to make systematically different food choices relative to others. Understanding why this is so is essential to developing a reasoned policy approach to obesity. Most of the recent research on obesity in the economics literature relies on the assumption that obese and non-obese individuals alike adhere to the *homo economicus* assumption, or that of the rational economic decision maker. Framed in terms of the household production model of Becker (1965) and Becker and Stigler (1977), food consumption decisions that appear to be excessive over time are nonetheless thought to be rational means of producing "health outcomes" by making both time allocation and goods consumption decisions (Cutler, Glaeser and Shaprio 2003; Chou, Grossman and Saffer, 2003; Philipson and Posner, 2003). Indeed, Cawley (1999) uses the rational addiction model of Becker and Murphy (1988) to show that what appears to be overconsumption of calories can be consistent with optimal economic behavior even in a dynamic model of behavior that would otherwise be considered to be pathological.[1]

An alternative view of individual behavior regarding choices that have long-term health implications has emerged in the behavioral economics literature (Thaler, 1981; Ainslie, 1992; Laibson, 1997; Shapiro, 2005). Specifically, if individual decisions are made with a "present bias" or a preference for immediate gratification, then the future costs of obesity are not likely to be appropriately balanced against the present benefits of consuming food, or avoiding the gym. Such behavior is thought to result if preferences are *time-inconsistent*. Models of rational addiction, on the other hand, assume individuals exhibit *time-consistent* preferences, which means that a decision between consuming at time $t + 2$ or time $t + 3$ from the perspective of time $t$ does not change when time $t + 2$ actually arrives. Conversely, time-inconsistent preferences arise if an individual exhibits what Loewenstein and Prelec (1992) refer to as the

[1] Rational addiction models have been used to explain many types of seemingly irrational behavior, from addiction to cigarettes (Becker, Grossman and Murphy, 1994), alcohol (Grossman, Chaloupka and Sirtalan, 1998; Waters and Sloan, 1995), cocaine (Chaloupka, 1991), caffeine (Olekalns and Bardsley, 1996), heroin (Bretteville-Jensen, 1999) and food (Cawley, 1999; Richards and Patterson, 2007). Addiction can be rational under a condition called "adjacent complementarity", which stipulates a consumer is more likely to use a product if s/he has used that particular product when last confronted with a choice among it and other available alternatives. Adjacent complementarity implies that the increment to utility a consumer experiences from consuming more of the addictive good rises in the amount consumed in the past, an intertemporal property that allows addicted consumers to formulate choices in present periods that account for the future cost of addiction in relation to the current benefit received.

"common difference effect," in which he prefers receiving \$100 today to \$101 tomorrow but prefers \$101 a year and a day from now to \$100 in exactly one year.[2] Time-inconsistency can arise if an individual's discount function is hyperbolic in nature, or if values at distant future dates are discounted at lower rates than near-term values (Ainslie, 1992; Ainslie and Haslam, 1992; Loewenstein and Prelec, 1992; Laibson, 1997).

Behavioral evidence suggests that individuals may have hyperbolic discount functions; for instance it is not uncommon for lab respondents to weight present values over those in the near future, while differentiating little between values at different points in the more distant future.[3] The aim of this study is to develop an explanation for why discount schedules may appear to be hyperbolic in nature, and to apply an experimental framework to determine whether subjects with seemingly time-inconsistent behaviors – drinking or smoking in addition to overeating – exhibit patterns of present-bias when evaluating future economic outcomes.

Many researchers argue that present bias may, in fact, be driven by some other underlying mechanism. Becker and Mulligan (1997) derive a theoretical model of intertemporal preference in which discount rates are endogenous in the sense that they depend on "...resources spent imagining the future..." (P. 734) or investments in better understanding the future implications of current behavior. By investing more, or achieving better health in the current context, an agent may better appreciate future rewards and, thereby, discount them less heavily. While Becker and Mulligan (1997) maintain that their model is not inconsistent with a constant underlying rate of time preference, Gafni (1995) and Bleichrodt and Gafni (1996) question the logical basis of constant discount rate models, arguing instead that discount rates are inherently variable. Among empirical studies, Rubinstein (2003) presents a series of experiments in which she shows that choices between pairs of outcomes can lead to a pattern of behavior that rejects both exponential and hyperbolic discounting. Harrison and Lau (2005), on the other hand, argue that the appearance of hyperbolic discounting is merely the result of experimental procedures that fail to account

[2] Gruber and Koszegi (2001) show that apparently addictive behavior can be explained by consumers' time-inconsistent preferences. Thaler (1981) also finds that the magnitude of the values offered at different time periods can cause similar preference reversals.

[3] See Frederick and Loewenstein (2002) for a review of the experimental literature on estimating discount rates, and documentation of the number and variety of studies which that have found evidence of hyperbolic discounting.

for a front-end delay, or pairs of awards that include an option that is near in time, but not instantaneous. Similarly, Andersen, et al. (2008) find that if risk aversion is appropriately considered, and a front-end delay is included in the payoffs, then there is little support for hyperbolic discount functions. When they include a fixed-cost associated with future rewards, Benhabib, Bisin and Schotter (2007) also reject hyperbolic discounting. Exploring more deeply into the causes of time inconsistency, Zauberman et al. (2008) argue that it is instead discrepancies between individuals' perceptions of duration relative to the actual duration that gives discount functions the appearance of being hyperbolic. In subjective time, they argue, discount functions are still exponential. Subadditivity, or the notion that discount rates are greater over shorter periods, added together, than over longer delays may also explain the appearance of hyperbolic discounting (Read, 2001). In this research, we account for a number of potential forms of present-bias in testing for the effect of health status on time preference in an experimental setting.

Our experiment, and subsequent data analysis, are designed to test the implications of a simple model of intertemporal decision making in which the appearance of hyperbolic discounting emerges as an expected response to uncertainty. Because health risks imply greater uncertainty over future outcomes, one implication of the model is that obese individuals (and smokers and drinkers) are likely to have higher discount rates, or discount functions that appear to be more hyperbolic, relative to non-obese individuals. Yaari (1965) demonstrates the equivalence between discount rates and an exogenous "hazard rate" in repeated gambles. Simply put, if an individual has a 95-percent probability of surviving to the subsequent period of a repeated lottery (a 5 percent hazard rate), intertemporal behavior arises that is equivalent to having a 5 percent rate of discount. Heterogeneity in hazard rates can thus explain variation in discount rates among individuals. Clearly, high mortality rates for obese individuals can lead to relatively high discount rates, which can skew consumption towards the present and deter long-term investments in health. The appearance of hyperbolic discounting in this framework emerge whenever path-dependence leads to a downward trend in the hazard rate in repeated play over time.

The paper begins with a brief review of the empirical research on discounting and health outcomes. In the second section, we develop a simple economic model of intertemporal decision making in which obese agents, and others who engage in risky health behaviors, are likely to have higher discount rates than others. A description of the time-value elicitation experiment is provided in the third section, while the empirical approach to estimating discount functions is explained in the fourth section. The results of the analysis and conclusions regarding the preferred form of the discount schedule are given in a fifth section. In the sixth section, we conclude and draw broader implications for public policy choices regarding obesity, drinking and smoking cessation programs.

## 2. Background on Present Bias and Health

A number of recent studies investigate the relationship between discount rates and present-bias and health status. We would expect that those in poor health, or those who engage in activities that are likely to shorten their expected life-spans, to have higher discount rates. Both due to the expectation of an early demise, or because impulsive behavior is a cause of their poor health (eg., overeating and obesity, smoking and lung disease, etc.), we expect a strong relationship between the rate of time preference and measures of health status over which the respondent has control. Using survey data from a sample of residents in Durban, South Africa, Chao et al., (2007) find an inverse-U shaped relationship between discount rates and health – those in very poor health or very good health have high discount rates relative to those in only average health. Kirby, et al., (2002) conduct a field experiment with members of the Tsimane' native tribe in the rain forest of Bolivia and find that discount rates are higher for older people, but lower for the less educated, and more wealthy. They did not find any significant relationship, however, between the rate of time preference and wealth, BMI or drug use. Read and Read (2004) similarly find no significant relationship between the rate of time preference and health status, but used very general measures for whether individuals considered themselves to be in either good or poor health. Tu, et al., (2004), however, find a positive relationship between BMI and the rate of discount, implying that more obese respondents are more likely to be impatient. In this study, we contribute to this literature in that we seek to examine whether risky health behaviors, particular over-eating, are related to subjects' rate of time preference. Unlike these studies, however, we allow for heterogeneity in discount rates and a specification that admits a number of forms of present-bias.

Present-bias has important implications policies designed to address not only obesity, but smoking, drinking, gambling, the failure to invest for retirement (Laibson, 1997), environmental degradation (Karp, 2005) or any one of a number of long-term decisions that seem to result in outcomes that favor present gratification over long-term utility. In the example at hand – obesity – if individuals behave according to some form of time-inconsistent model, then they are likely to make food choices today a strong present-bias, meaning that they tend toward instant gratification and do not fully consider the future costs on equal terms, as the rational addiction model would imply. This distinction between one of these models and addiction results in starkly different policy implications. If an individual is addicted in an economic sense, then addiction can be ameliorated by raising future healthcare costs that should reasonably be expected to accrue as a result of the addiction. If, however, the individual discounts future costs in non-exponential way, then the necessary increase in future costs to prevent addiction from taking place can be prohibitive. Incentives, in the latter case, would need to emphasize immediate rewards.

## 3. Economic Model of Present-Bias in Decision Making

Read (2001) shows, both theoretically and with experimental data, that the appearance of hyperbolic discounting can be attributed to the inherent subadditivity of the discounting process. Namely, discount functions, when composed of rates calculated over segments of time, will necessarily show higher rates of discount than when comparisons are made across the entire period. However, he does not show why this is the case. In this section, we argue that the appearance of hyperbolic discounting, or a declining rate of impatience (Read, 2001) is due to the fact that the conditional probability of "surviving" between period $t$ and period $t$+1 increases in $t$ along the equilibrium path. And, perhaps more important to the hypothesis of this paper, this property is more likely to hold for individuals with unhealthy living habits (overeating, drinking or smoking) than others. The reason is that relatively unhealthy individuals are less likely to survive from period 0 to period 1 than others, but face a similar probability of surviving to period 21 conditional on survival through the first 20 periods. Because obese individuals are less healthy than other individuals, this provides them with greater opportunities to improve their health status over time (e.g., by taking cholesterol medication). While including the likelihood of future death in an empirical model of intertemporal choice is not feasible, the implication of this model is that discount rates will depend not only on whether an individual is obese, but whether he or she engages in any activity that may influence the probability of death, such as smoking or drinking to excess. In short, we predict that discount rates for individuals who engage in risky behaviors are likely to have higher discount rates than others, but their discount functions are likely to appear to be hyperbolic in nature.

The model is related to that of Yaari (1965), who demonstrates the equivalence between discount factors and expected survival rates when individuals have uncertain lifespans. The idea is that if individuals evaluating a future value with stochastic returns do not anticipate being active players in all future states (i.e., death occurs in a subset of future states), the distribution of future returns is truncated. In Yaari (1965), individuals optimize over future survivorship states, and an (exogenous) death probability is isomorphic in this context to a constant discount rate. Here, we consider the quite natural application of trends in survival rates, which accordingly correspond to trends in the observed rate of discount. These trends can be driven by expected health outcomes for consumers, for instance the reduction in life expectancy due to unhealthy behaviors in the current period.

In this model, the appearance of hyperbolic discounting is independent of the curvature properties of the value function, unlike Andersen et al. (2008). The hazard rate is uncertain, but, unlike in Azfar (1999), the hazard rate is a result of a health accumulation process that is subject to random shocks. The individual "dies" whenever the accumulated health status falls below a critical level. While Read (2001) does not explain why subadditivity causes declining rates of impatience, our model does. Discount rates depend on trends in the probability of death over time which, in turn, depends on health behaviors. We find that hyperbolic discounting emerges quite naturally in the context of a simple repeated, stochastic game.

Consider an infinitely-lived agent who begins to play stochastic game(s) at time 0 with a finite initial stock of health, $h \in [h_L, h_U]$. The agent plays a series of games over time that involve both positive and negative payoff states (eg., eating decisions, drinking occasions, etc.). The cumulative outcome of these games has the capacity to exhaust the agents initial stock of health.

There are two possibilities to consider. Either: (1) the value of a future game is state-independent; or (2) the value of a future game is state-dependent. If the value of a future game is state-independent, then the expected present value of a series of future games played at various points in time is simply the discounted sum of the expected value of each game. On the other hand, if the value of a future game is state-dependent, then the series of realized outcomes between the current period and the beginning of the future game influences the value of the game. This case corresponds to the model we examine here in terms of "solvency constraints" that limit play at time $t$ to occur only after a series of health realizations that leaves the agent with a level of health that (at least weakly) exceeds some lower boundary, for instance if the agent is still living at time $t$. Suppose the agent is constrained to play games only if her health status remains above some exogenous lower bound, $h_t \geq h_L$.

Define a solvent player to be one that meets the solvency constraint $h_t \geq 0$, where the lower bound on allowable health ($h$) has been normalized to zero without loss of generality. Next, consider for simplicity the case in which the value of each temporal game is the same to all players regardless of their health level. Games have exogenous stakes that are the same for all agents (although the sequence of realized health outcomes for each agent will generally differ). In this case, the value of a contemporaneous game played by a solvent player at time $t$ is independent of the health level of the player at time $t$, a convenient (though not necessary) property for deriving the results that follow.[4] Assume agents receive the same temporal utility level from a given product at time $t$, but intertemporal utility levels will differ according to the health status of the agents. Let $\pi_t$ denote the expected value of the contemporaneous game played by solvent players at time $t$. Consider first the case of unconstrained probability space in which an agent remains solvent at all times and along all possible paths of realized outcomes. Define the expected present value of a series of games in this case by the recursive equation:

$$V_t = \pi_t + \beta_t V_{t+1}, \qquad \textbf{(1)}$$

where $\beta_t$ is the discount factor in period $t$ defined for a discount rate, $\delta_t$, and $V_t$ is the value function at time $t$. Iterating (1), the expected present value of the series of games over an expected lifetime horizon of $T$ periods can be expressed as:

$$V = \sum_{t=0}^{T} \pi_t \left( \prod_{t=0}^{T} \beta_t \right). \qquad \textbf{(2)}$$

The value stream (2) is characterized by hyperbolic discounting when $\beta_{t+\tau} > \beta_t$, for all $\tau > 0$, whereas $\beta_{t+\tau} = \beta_t$, for all $\tau > 0$ under constant discounting.

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[4] As we show below, this does not imply that the value of a series of games is independent of $h_t$; indeed, the value of all future games at times $t + \tau$, $\tau = 1, 2, \ldots$, will depend on the physical level of health of an agent at time $t$, and not just on whether the solvency constraint is binding at time $t$.

Now consider the more interesting case in which values are generated under a solvency constraint. Let $V_t^S(h_t)$ be the expected value of receiving the future random health stream when the agent has the cumulative health of $h_t$ and is still solvent at time $t$ (i.e., $h_t \geq h_L$). Then,

$$V_t^S(h_t) = \pi_t + e^{-\delta} E_{h_{t+1} \geq h_L | h_t} V_{t+1}^S(h_{t+1}), \tag{3}$$

where $E_{h_{t+1} \geq h | h_t}$ is the expectation on the values of $h_{t+1}$ in the range above $h_L$ and $\delta$ is a constant discount rate. Let:

$$P_{t+1}^S(h_t) = \mathrm{Prob}(h_{t+1} \geq h_L | h_t) = \mathrm{Prob}(\pi_{t+1} \geq h_L - e^r h_t), \tag{4}$$

be the probability that the agent is still solvent at time $t$ given $h_t$. Then we know:

$$E_{h_{t+1} \geq h_L | h_t} V_{t+1}^S(h_{t+1}) = P_{t+1}^S(h_t) E_{h_{t+1}|h_t}^S V_{t+1}^S(h_{t+1}), \tag{5}$$

where $E_{h_{t+1}|h_t}^S$ is the conditional expectation operator, conditional on $h_{t+1} \geq h_L$. Let $\rho_t(h_t)$ be defined as: $e^{-\rho_t(h_t)} = P_{t+1}^S(h_t)$, then $P_{t+1}^S(h_t) \leq 1$ implies that $\rho_t(h_t) \geq 0$. Let $\delta_t(h_t) = \delta + \rho_t(h_t)$, then (3) can be rewritten as:

$$V_t^S(h_t) = \pi_t + e^{-\delta_t(h_t)} E_{h_{t+1}|h_t}^S V_{t+1}^S(h_{t+1}). \tag{6}$$

Unlike (2) in the case of no solvency constraints, the recursive representation in (6) cannot be reduced to an "open-loop," or state-independent representation. For example, since both $e^{-\delta_t(h_t)}$ and $E_{h_{t+1}|h_t}^S V_{t+1}^S(h_{t+1})$ and are functions of $h_t$, they are correlated when $h_t$ is random. Thus, given $h_{t-1}$,

$$E^S_{h_t|h_{t-1}} V^S_t(h_t) \;=\; E^S_{h_t|h_{t-1}} \pi_t \;+\; E^S_{h_t|h_{t-1}} [e^{\,-\delta_t(h_t)} E^S_{h_{t+1}|h_t} V^S_{t+1}(h_{t+1})], \qquad \textbf{(7)}$$

and the two terms in the square brackets cannot be separated. This observation shows that when the future discount rate depends on future realizations of the health shocks, there does not exist an "open-loop" representation in the form of (2), even if δ is random.

The discount rate $\delta_t(h_t)$ in (6) is decreasing in $h_t$, and approaches the intrinsic rate δ when $h_t$ is so high that the solvency probability in (4) goes to one. Since the future discount rates are random, to show any time trend of the discount rates, we will compare the expected values of $e^{\,-\delta_t(h_t)}$ with the expectation taken on $h_t$ conditional on the agent being solvent at time *t*. That is, we will compare $E^S_{h_t|h_0} e^{\,-\delta_t(h_t)},\ t = 1, 2, \ldots,$ where $E^S_{h_t|h_0}$ is the expectation of $h_t$.

Now consider the case of constrained probability space in which the solvency of a particular player at time *t*+1 depends on the past realizations of all games played at times on the interval [0, *t*]. To highlight the role of constrained probability space in determining the possible origins of discounting, consider an agent who does not discount values that acrue at future solvency points. Hence, if we denote the value of a solvent player at time *t* as $V^S_t$, the (non-discounted) solvency value function is defined by:

$$V^S_t \;=\; \pi_t \;+\; V^S_{t+1}. \qquad \textbf{(8)}$$

Starting from time 0, the future probability space is constrained in the sense that each agent will remain solvent at time *t* only along certain paths of realized outcomes on [0, *t*]. For example, an agent that begins play with a fixed level of initial health ($h_0$) can sustain a string of consecutive losses in the stock of health of only a limited length, which implies that paths associated with sufficiently long strings of consecutive losses are truncated from the cumulative value distribution by the solvency constraint. Moreover, the particular truncation points on the cumulative value distribution depend on agent-specific characteristics, such as the initial health level. For a given agent, define $Pr(S_{t+1}|S_t)$ to be the conditional probability that the agent is solvent at time $t$+1 given that she is solvent at time $t$. This implies that the expected solvency value of a game played one period in the future relates to the expected value of the game as:

$$V^S_{t+1} \; = \; Pr(S_{t+1}|S_t)V_{t+1}. \tag{9}$$

Given that an agent is solvent at time $t$, the expected solvency value of a game played at time $t$+1 is the product of two terms, the conditional probability that the agent remains solvent after the realization of the period $t$ game and the value of the period $t$+1 game. If solvency constraints are non-binding at a particular point in time (i.e., if an agent remains solvent after all possible realizations of the game played at time t), then $V^S_{t+1} = V_{t+1}$. If solvency constraints never bind on any player, then the model reduces to a non-discounted stream of expected values. Substituting (9) into (8) and iterating values yields:

$$V^S_0 \; = \; \sum_{t=0}^{T} \pi_t \left( \prod_{t=0}^{T} \gamma_t \right), \tag{10}$$

where $\gamma_t = Pr(S_t|S_{t-1})$ is the conditional probability of remaining solvent at time $t$ given solvency at $t$-1. By definition, all active players that begin play at time zero are solvent, so that $\gamma_0$ = 1. Notice the symmetry between (10) and (2). The expressions are identical given that we interpret the conditional probability as the discount factor. This illustrates the potential origins of discounting as a conditioning phenomenon; a value earned today is worth more than an equal-magnitude value earned in the future only to the extent that a positive probability exists that play terminates before receiving the future value.

In terms of the central hypothesis of this paper, the model provides a set of implications that can easily be tested. If there exists some probability $\alpha < 1$ that an individuals' consumption behavior in a given period leads to a decrement in health status, then it is sensible to weight contemporaneous utility more highly than utility earned in future periods. However, when making considerations for consumption decisions farther in the future, the conditional probability of surviving to period 30 given that the individual survives to period 29 approaches unitary value. The lower the initial health status, moreover, the more dramatic this outcome becomes, as immediate gratification, which provides contemporaneous utility for certain, is valued more highly relative to consumption at nearby future dates, while the conditional probability of surviving 30 periods given survival through 29 periods is more similar for both healthy and obese individuals. Therefore, we expect to observe discount functions that appear to be hyperbolic, or show declining impatience, with discount rates that rise in the instance of unhealthy behaviors, such as drinking, smoking or overeating.

## 4. Experiment Design

In the current study, we test the implications of the theoretical model derived above for intertemporal decision making by conducting a time-value elicitation experiment in a sample of 82 students at Arizona State University. Although the original sample consisted of 96 students, 14 were rejected as they clearly did not understand the question to be answered, or otherwise submitted unuseable responses. Our experiment follows Benhabib, Bisin and Schotter (2007) in adopting the Becker-DeGroot-Marschak (Becker, DeGroot and Marschak 1964, BDM) method of reward-time value elicitation. The rules of the experiment were well explained to the subjects, both verbally and through written instructions, before the start of the experiment, and practice scenarios were used prior to handing out the reward-time value elicitation instrument. All subjects were presented with a series of questions designed to assess the extent of present-bias in choosing financial rewards at varying time periods.

Using a BDM mechanism is intended to ensure truthful value elicitation.[5] The mechanics of the BDM procedure were carefully explained to the students, including the fact that it is incentive compatible, or in their best interests to report their true indifference amounts. Subjects were provided the incentive to respond with their true values during each round of the experiment in the following way. We asked subjects to respond to indifference amounts for 50 different reward-time pairs (two rounds of 25 questions each) as described below. One of the pairs in each round was chosen at random to determine the payment. For example, assume the random reward-time pair represents a payment of $10 in four weeks. The agent's task is to respond with an amount that he or she is indifferent between receiving today and the $10 in four weeks. A random value was then drawn between $0 and $10. If the subject's indifference

[5] The incentive compatibility of the BDM mechanism has been questioned by Horowitz (2006), among others. We assume that the argument advanced there, that the agent's willingness-to-pay depends on the distribution of future values, is of minor consequence.

amount, say \$8, is more than the random draw, they will have to wait four weeks and receive the \$10 value. If the indifference amount is less than the random draw, then they are paid their bid immediately. With this mechanism, subjects can ensure that they are paid immediately by offering \$0 and that they are paid in four weeks by bidding \$10. Therefore, they have an incentive to bid their true indifference amount to avoid taking the money now if they state a value that is too low (high implicit rate of time preference) or in the future if they state a value that is too high (low implicit rate of time preference).

All indifference amounts, or "bids," were submitted using standard pen-and-paper response instruments. Each subject's response was then recorded, their payment calculated, and the data submitted to a database for further processing. Because discount rates are theoretically subject-independent, monetary rewards are sufficient to elicit discount rates. That is, there should not be different discount rates for different items to be received at various points in time. To test whether our data exhibit a significant "magnitude effect," we varied the amounts involved within each round (Thaler, 1981; Green, Myerson and McFadden, 1997). Namely, the amounts were \$1.00, \$5.00, \$10.00, \$50 and \$100.00 to be received at various points in the future. Separate questions were asked for each time period: (1) in one day, (2) one week, (3) four weeks, (4) six months, and (3) in one year. The same subjects were asked to bid on each reward-time pair in the same session. The questions in the first round were phrased as follows: "...what amount of money, \$x, if paid to you today would make you indifferent to being paid \$y (\$1.00, \$5.00, \$10.00, \$50.00, \$100.00) in (one day, one week, four weeks, six months, one year)?..."

In the second round, we test for a "framing" effect by reversing the questions such that the subjects were asked to state a future amount that would make them indifferent between that amount and a fixed amount today: "...what amount of money, \$x, would you require to make you indifferent between receiving \$y (\$1.00, \$5.00, \$10.00, \$50.0, \$100.00) today and \$x in (one day, one week, four weeks, six months, one year)?" The subjects, therefore, submit \$x bids in order to receive an amount \$y today. The amount of each \$x bid is capped for each question at some upper bound and the BDM mechanism is applied as in the first round. Namely, a random value is drawn between \$0.00 and the upper limit for \$x for the chosen payoff reward-time pair (which is communicated clearly to all subjects beforehand) and all indifference amounts less than the random value paid immediately, and more than the random value result in the fixed amount being paid after the relevant time period for that round. Asking isomorphic questions in a different way is important to test for the potential of framing effects that are common in other experimental time preference studies (Frederick, Loewenstein, and O'Donoghue 2002). As in the first round, we are confident that the subjects understood the task, their incentive to respond truthfully and the fact that they would be paid for doing so.

Rounds one and two are designed to capture basic reward-time pair data for the sample participants that will allow us to fit discount functions for each individual using an appropriate panel-data estimator. With these data, we are able to test whether their responses fit the exponential, quasi-hyperbolic or some other functional form and, moreover, test whether individuals with differing socioeconomic, health or behavior attributes are more or less likely to discount in a way that is described by the quasi-hyperbolic discount function.

## 5. Econometric Model of Hyperbolic Discounting

There are a number of specifications for a discount function, $D(y, t)$, that nest the hyperbolic and exponential discounting models. The most general of these also allow for the inclusion of a fixed-cost component, risk aversion, and demographic effects in either the discount rate, the curvature of the discount function, or both. With data on only the reward-time pairs and demographic attributes of each respondent, however, it is difficult to identify all of these effects in a single model.[6] Therefore, we sacrifice a measure of generality for parsimony and robustness in estimation and adopt the general model proposed by Prelec (2004), but allow for risk aversion (constant relative risk aversion, CRRA) as in Andersen, et al. (2008) and estimate using panel data methods. Because individual-level discount functions are likely to contain a large amount of both observed and unobserved heterogeneity, we estimate this model using a random parameters specification in which the discount rate depends on a set of demographic and behavioral variables, as well as a purely random effect. In this way, we test whether observed individual-level attributes have a significant positive or negative impact on discount rates. As such, our econometric model represents a test of the hypotheses developed in Becker and Mulligan (1997) in a rather direct way.

[6] Benhabib, Bisin and Schotter (2007) specify and estimate perhaps the most general empirical model, but find that their nesting parameter is estimated imprecisely in nearly all specifications with individual-level models. It is not clear from their data how their data are able to identify the separate fixed- and variable-cost effects that they report.

In its most general form, therefore, the econometric model is written as:

$$x_h^r = y_h^r D(y,t;\delta_h,r_h,\alpha,\beta) = y_h^r \tau(\exp(-\delta_h t^{\alpha}) - \beta/y_h^r)\varphi(z_h,\varepsilon_h), \quad \textbf{(11)}$$

where $x_h$ is the promised payment for the particular question for subject $h$, $y_h$ is the subject's indifference amount or their bid, $D$ is the discount function, $t$ is the number of days over which the subject is being asked to discount (defined as a proportion of a year), $z_h$ is a vector of subject attributes, $\delta_h$ is the discount rate, $r$ is the risk aversion parameter, $\tau$ is a variable-cost component that determines whether the discount function is quasi-hyperbolic ($\tau < 1$), $\beta$ is a fixed-cost component that Benhabib, Bisin and Schotter (2007) find to be the primary contributor to the present-bias evident in their data.[7] Among the random components, the discount rate is assumed to reflect both observed and unobserved heterogeneity such that $\delta_h \sim N(\boldsymbol{z_h'\delta_h},\sigma_\delta)$, while $v$ and $\varepsilon$ are unobservable random effects ($v_h \sim N(\mu_{v_h},\sigma_{v_h})$, $\varepsilon_h \sim N(\mu_{\varepsilon_h},\sigma_{\varepsilon_h})$) and $\beta$ is a fixed-cost component.[8] If $\alpha = 1$ the discount function is exponential and as $\alpha$ falls below 1.0, the function assumes more of a hyperbolic shape (Prelec 2004; Andersen, et al. 2008).

Present bias will arise with this specification, therefore, with lower values of $\alpha$, higher values of $\beta$ or $r$, or, of course, higher values of the underlying discount rate, $\delta$. In the most general model, we also allow the agent-specific error term, $\varphi$, to include a vector of demographic and socioeconomic attributes, and a log-normally distributed error term, $\varepsilon$. This panel estimator is unlike Benhabib, Bisin and Schotter (2007), who estimate separate models for each individual, so index all four parameters by $h$. In this study, we are interested in testing for systematic differences among individuals' time preference rates as a function of some observable behaviors or characteristics. Therefore, we assume all parameters are constant across individuals, except for the rate of time preference. In this way, we examine differences in time-preference rates over individuals, while accounting for observed and unobserved heterogeneity, as well as other possible sources of present-bias.

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[7] This factor is also akin to the "...additive constant..." of Becker and Mulligan (1997).

[8] Note that $r = 1$ implies risk neutrality and the degree of risk aversion rises as $r$ moves away from 1.0. This is a constant relative risk aversion specification (CRRA), which is a common assumption in this literature.

We estimate the various forms of (11) using simulated maximum likelihood (SML), which is necessary given the random-parameters assumption described above. With this specification, however, it was not possible to estimate the curvature parameter in the same SML routine as the other parameters. Consequently, we adopt a grid-search technique and find the value of $\alpha$ that maximizes the likelihood function conditional on the optimal estimates of the other parameters. This approach provides consistent estimates of the curvature parameter, but does not allow us to recover standard errors for $\alpha$ without resorting to bootstrapping techniques (Cameron and Trivedi 2005). For the SML routine, we use a Halton draw technique in order to speed convergence and find that no gains in performance were obtained for draw numbers greater than 75 (Train 2003).

## 6. Results and Discussion

In this section, we summarize the data gathered through our time-value elicitation exercise and interpret the results from comparing various forms of the econometric model in (11). We conduct a number of specification tests on several versions of this model in order to test alternative mechanisms that may lead to the appearance of present-bias.

Table 1 summarizes the experimental and demographic behavioral data gathered through the time-value elicitation exercise. Several features of the data are apparent from this summary. First, the responses appear to be plausible in both magnitude and dispersion among agents. Second, their pattern of variation with time and magnitude is consistent with other studies. Namely, as in Benhabib, Bisin and Schotter (2007), discount rates decrease in the amount of delay and slightly with the magnitude of the amount at stake. On the surface, therefore, the subjects in this study appear to exhibit a present-bias. However, because these discount rates are calculated without econometric estimation, these results are not yet conclusive. Third, the sample exhibits considerable variation in both demographics and behavior (ie., smoking, drinking and obesity) to uncover any relationships that may exist between risky lifestyles and discount rates.

[Table 1 in here]

In order to control for factors other than pure time-preference, however, it is necessary to estimate the discount function described above. To this end, Table 2 presents results from estimating hyperbolic and exponential discount functions, without allowing for risk aversion ($r$ = 1), quasi-hyperbolic discounting (or variable-cost of discounting, $\tau = 0$) or a fixed-cost of discounting ($\beta = 0$). The primary purpose of this model is to establish a benchmark discount rate and to estimate the curvature parameter in the discount function ($\alpha$). Using the grid-search procedure described above, the log-likelihood function is maximized at value of $\alpha$ of 0.704. Therefore, we compare the exponential and hyperbolic specifications, conditional on this estimate, using a likelihood ratio (LR) test with one degree of freedom (in the hyperbolic specification used here, the exponential is a special case where $\alpha = 1$). From the results in Table 2, we find a chi-square LR statistic of 271.62, so we reject the exponential specification in favor of the hyperbolic. Although estimates of $\delta$ cannot be interpreted literally as "discount rates" as in the exponential model, it is instructive to compare the estimates of the mean value of $\delta$ to get a sense of the extent of present-bias that may be present. In this case, the value of $\delta$ for the hyperbolic model is slightly higher (0.472 > 0.465) than for the exponential, suggesting that subjects' discount rates decline over time (a property of the hyperbolic function) and are generally higher than in the exponential model.

[Table 2 in here]

With the random parameters specification, we can also get a sense of which personal attributes correlate with high discount rates. Clearly, the results in Table 2 show that much of the variation in discount rates among individuals can be explained by observed heterogeneity, both in demographic and behavioral attributes. Moreover, the pattern of effects is similar between the hyperbolic and exponential models. Namely, discount rates tend to be higher for older males of races other than the four major classifications considered in our survey. Marital status, household size and income appear to be uncorrelated with time preference. This latter result, the irrelevance of income, appears to be at odds with the predictions of Becker and Mulligan (1997), who suggest that higher wealth is associated with lower rates of time preference. Income, however, is only indirectly related to wealth so our results are not entirely contradictory. Of greater interest given the objectives described in the introduction, however, are the relationships between smoking, drinking, obesity and time preference. In both models, discount rates tend to rise for heavier drinkers and those who are more obese. Both of these effects are consistent with our theoretical expectations – that individuals who engage in risky health behaviors have a greater probability of not surviving until the next period, so should discount the future more heavily. Perhaps surprisingly, however, smokers have lower discount rates than non-smokers. One explanation for this finding is that the estimates are conditional on drinking and obesity. If one is already an obese drinker, then it is possible that these individuals experience an "immortality syndrome" and believe they are among the few for whom smoking does not seem to be a health hazard.[9] Admittedly, however, this inference is only speculative and we offer this result as a puzzle for future research. In the remaining specifications, we test the robustness of these findings regarding the potential profile of present-bias.

In the next model, we relax the assumption of risk neutrality. Andersen, at al. (2008) find that controlling for risk aversion causes estimated discount rates to fall significantly, thus explaining some of the apparent present bias found in previous studies. Table 3 provides estimates of the two discount functions while allowing for risk aversion of a constant relative risk aversion (CRRA) form. Comparing the risk-averse specifications to their risk-neutral counterparts in Table 2, again using a LR test, shows that for each discount function (hyperbolic and exponential), the risk neutral specification is rejected in favor of the CRRA model. Clearly, risk aversion is a characteristic of our experimental data. Controlling for risk aversion, the rate of time preference falls in each case, but not as dramatically as in Andersen, et al. (2008). Among the other parameters, the pattern of covariates is very similar to the base-model case so risk aversion is apparently not an inherent trait of any of the demographic or behavioral segments described in our survey. It may, however, be the case that the present bias is of a form that is not captured by either our hyperbolic or CRRA forms.

[Table 3 in here]

Quasi-hyperbolic discounting involves discounting values in future periods at higher rates as if there were a "variable cost" of discounting – the discount associated with future rewards rises with the amount of the reward in a linear way. Table 4 shows the SML estimates of the hyperbolic and exponential discounting functions allowing for risk aversion and quasi-hyperbolic (variable cost) discounting. Comparing the combined hyperbolic / quasi-hyperbolic model and the exponential / quasi-hyperbolic models to the specifications in Table 3 shows a significant improvement in fit. Moreover, the estimates of $\tau$ (the variable cost component) are individually significant in both the hyperbolic and exponential models. Interestingly, when we add this potential explanation for present-bias, the estimated

[9] This result is not due our sample containing only a small number of smokers as 12.7% of participants smoke, nor due to excessive multicollinearity among the attribute variables as there are no significant correlates with the tendency to smoke.

discount rate rises in the hyperbolic model, but falls in the exponential. Some of the behavior that appeared to be consistent with discount rates falling over time, therefore, is more plausibly explained by a positive variable cost of discounting. Further, when we account for quasi-hyperbolic discounting the estimate of $r$ falls in each case. This finding suggests that imposing a zero variable cost of discounting creates a bias away from finding risk aversion, and attributing apparently hyperbolic discount functions to something else entirely.

[Table 4 in here]

Finally, we consider the most general form of the empirical model in (1), accounting for both a variable and fixed cost of discounting. Comparing the log-likelihood function value of each specification in Table 5 with those shown in Table 4 suggests that the most comprehensive model is preferred in the hyperbolic case, but not the exponential. In the hyperbolic model, a fixed cost of \$0.217 is small relative to the size of the values offered in the experiment, but is nonetheless statistically significant. While the variable cost estimate is the same as in the restricted model, note that the value of $\delta$ assumes its lowest value of all the specifications considered. This finding suggests that each of the other plausible explanations for present-bias is as at least partially valid and accounts for some of the effect others attribute to hyperbolic discounting.

[Table 5 in here]

More importantly, however, the pattern of covariates is robust to this specification. In particular, both obesity and drinking are positively related to the extent of present-bias. This is an important result. If obesity (and excessive drinking) is associated with higher discount rates, then not only are explanations based on rational addiction models incorrect, but efforts directed at modifying behavior that don't address an agent's need for immediate gratification are likely wasted. Policy prescriptions that follow from explanations based on the presumption of a rational addiction seek to raise the expected cost of future health problems in order to offset higher current benefits from satisfying an addiction. If individual's discount the future heavily, and even discount according to a hyperbolic pattern as suggested here, then higher costs expected in the future will be of little consequence. Further, the smoking results notwithstanding, it is likely that this pattern of behavior extends to financial decisions, retirement planning, career preparation and even child-raising. Extreme present-bias in each of these cases portends far deeper problems than excessive drinking and eating.

We also test for whether the results found here are due to a framing effect, or how the questions in the experiment were phrased. In Table 6, we report the results obtained by estimating the most general form of the discount function with data from the second set of questions, phrased from a future instead of a present-perspective. Again employing the grid-search technique to estimate the curvature parameter, we find a value of $\alpha = 0.153$, which represents a significantly greater departure from exponential discounting relative to the present-perspective case. Because this model provides a better fit to the data than the exponential model, based on a LR test, we find that framing questions in this way does indeed cause discount functions to appear to be "more hyperbolic." However, the remaining parameters, conditional on this estimate of $\alpha$, are broadly consistent with the present-perspective responses. Of direct relevance to our objectives, the sign and magnitude of the obesity effect (as well as the smoking and drinking effects) on discount rates is very similar to that found using the present-perspective questions. In the hyperbolic model, estimates of the mean of $\delta$ are nearly the same as the estimates reported in Table 5, so we have no reason to believe that framing has a significant effect on the structural parameters of potential interest to policymakers.

[Table 6 in here]

## 7. Conclusions and Implications

In this study, we use experimental data to test whether individuals' time preference decisions exhibit present-bias and, if they do, to examine whether the extent of bias is related to personal characteristics, including demographic attributes as well as patterns of behavior that are often regarded as pathological. We frame our empirical analysis in a general, nested specification in which we test for the importance of risk aversion, fixed or variable discounting costs, and hyperbolic discounting in generating the appearance of present bias. Resolving the empirical question of whether individual agents discount according to a hyperbolic discount schedule is important because many of the critical social issues we face today can be attributed to short-term decision making on the part of consumers.

We find that a hyperbolic specification that includes both fixed and variable costs of discounting and risk aversion provides the best fit to the data. Our discount function is sufficiently general to nest both the hyperbolic and exponential interpretations and, using nested specification testing methods, reject the exponential in favor of the hyperbolic model. This is true even after controlling for many other factors that may explain present bias. We also find a small magnitude effect, meaning that discount rates fall in the size of the reward, but no framing effects regarding how our time preference questions are phrased. Consequently, we conclude that the subjects in our experiment discount future costs and benefits according to a modified hyperbolic process.

Within the context of this hyperbolic model, we also allow discount rates to vary with a number of demographic and behavioral traits. Importantly, we find that the more individuals drink, and the higher their BMI, the higher their personal discount rates. This is consistent with a theoretical model of time preference in which less healthy people have a higher hazard rate during each period. Interestingly, however, we also find that smokers have generally lower discount rates, a result that is seemingly contrary to the drinking and obesity effects. Nonetheless, if it is indeed the case that obesity and discount rates are positively related, then public policy efforts to reduce obesity must target more general behaviors associated with impatience and immediate gratification and not the usual nutrition education or fitness messages that are currently being developed. Moreover, taxing foods that are deemed to be unhealthy is likely to be less effective than expected because raising the future costs of fattening foods has less of an impact to agents who care little about future costs.

There are many avenues to extend our research. Future research in this area should consider larger, more diverse samples that include subjects with a greater range of behaviors. Second, in terms of the time preference experiment, Andersen et al. (2008) argue that much of the evidence for hyperbolic discounting is due, in fact, to the existence of a front end delay. Phrasing the reward-time pairs such that no immediate reward is available would allow a test of their hypothesis in settings other than their Norwegian experiment. Finally, more theoretical research on why individuals may appear to follow hyperbolic discount functions would be helpful. Currently, most of the work in this area is empirical and the econometric models not grounded in theory. Devising theoretical models of hyperbolic discounting that can be tested directly is the next logical step for this research.

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**Table 1. Summary of Experimental Data and Respondent Attributes**

| Amount | Delay | N | Units | Mean | Std. Dev. |
|---|---|---|---|---|---|
| **$1.00** | 1 day | 82 | $ | $0.83 | $0.24 |
| **$5.00** | 1 day | 82 | $ | $3.91 | $1.17 |
| **$10.00** | 1 day | 82 | $ | $8.11 | $2.05 |
| **$50.00** | 1 day | 82 | $ | $40.64 | $10.45 |
| **$100.00** | 1 day | 82 | $ | $83.53 | $20.46 |
| **$1.00** | 7 days | 82 | $ | $0.80 | $0.23 |
| **$5.00** | 7 days | 82 | $ | $3.92 | $1.07 |
| **$10.00** | 7 days | 82 | $ | $7.93 | $2.09 |
| **$50.00** | 7 days | 82 | $ | $39.63 | $10.73 |
| **$100.00** | 7 days | 82 | $ | $81.01 | $19.90 |
| **$1.00** | 1 month | 82 | $ | $0.79 | $0.25 |
| **$5.00** | 1 month | 82 | $ | $3.79 | $1.27 |
| **$10.00** | 1 month | 82 | $ | $7.79 | $2.47 |
| **$50.00** | 1 month | 82 | $ | $36.89 | $12.13 |
| **$100.00** | 1 month | 82 | $ | $77.40 | $22.62 |
| **$1.00** | 6 months | 82 | $ | $0.72 | $0.31 |
| **$5.00** | 6 months | 82 | $ | $3.56 | $1.40 |
| **$10.00** | 6 months | 82 | $ | $7.16 | $2.64 |
| **$50.00** | 6 months | 82 | $ | $36.72 | $12.30 |
| **$100.00** | 6 months | 82 | $ | $75.10 | $24.24 |
| **$1.00** | 1 year | 82 | $ | $0.70 | $0.35 |
| **$5.00** | 1 year | 82 | $ | $3.35 | $1.59 |
| **$10.00** | 1 year | 82 | $ | $6.72 | $2.94 |
| **$50.00** | 1 year | 82 | $ | $33.58 | $14.85 |
| **$100.00** | 1 year | 82 | $ | $67.26 | $28.81 |
| **Age** | | 82 | Years | 23.51 | 6.50 |
| **% Male** | | 82 | % | 0.62 | 0.49 |
| **% White** | | 82 | % | 0.73 | 0.44 |
| **% Black** | | 82 | % | 0.02 | 0.15 |
| **% Hispanic** | | 82 | % | 0.09 | 0.28 |
| **% Asian** | | 82 | % | 0.09 | 0.28 |
| **% Married** | | 82 | % | 0.13 | 0.34 |
| **Household Size** | | 82 | # | 1.67 | 1.20 |

| | | | | |
|---|---|---|---|---|
| **Income** | 82 | $ / year | $31,737.80 | $32,048.90 |
| **% Smoke** | 82 | % | 0.13 | 0.34 |
| **Drink** | 82 | # / week | 4.96 | 10.89 |
| **BMI** | 82 | Index | 25.73 | 4.98 |

Notes: BMI is calculated as the ratio of weight (in kg.) divided by the square of height (in cm.). Empirical problems with BMI as a measure of obesity are well understood, but it remains the most accepted measure of overweight or obesity in the general population. Time-value pairs are drawn from the first set of questions; the second set of responses are qualitatively similar and are available from the authors upon request.

**Table 2. Hyperbolic vs Exponential Model Estimates**

| | Hyperbolic | | Exponential | |
|---|---|---|---|---|
| **Random Parameter Estimate** | | | | |
| **δ** | 0.472* | 2.959 | 0.465* | 2.577 |
| **Standard Deviation of Random Parameter** | | | | |
| $\boldsymbol{\sigma_\delta}$ | 0.727* | 34.275 | 0.738* | 32.434 |
| **Random Parameter Function** | | | | |
| **Age** | 0.006* | 2.017 | 0.006 | 1.634 |
| **Gender** | 0.194* | 4.554 | 0.194* | 4.063 |
| **White** | -0.498* | -6.525 | -0.484* | -5.711 |
| **Black** | -0.417* | -3.083 | -0.348* | -2.225 |
| **Hispanic** | -1.071* | -10.576 | -1.059* | -9.464 |
| **Asian** | -0.533* | -5.288 | -0.486* | -4.381 |
| **Marital Status** | -0.022 | -0.362 | -0.046 | -0.661 |
| **Household Size** | 0.011 | 0.658 | 0.013 | 0.672 |
| **Income** | 0.117 | 1.469 | 0.741 | 0.828 |
| **Smoke?** | -0.443* | -6.727 | -0.469* | -6.344 |
| **Drink Number** | 0.021* | 10.412 | 0.022* | 10.207 |
| **BMI** | 0.012* | 3.035 | 0.013* | 2.878 |
| **Standard Deviation of Model** | | | | |
| **σ** | 0.451* | 349.122 | 0.479* | 357.924 |
| **LLF** | -1,280.061 | | -1,415.873 | |

Notes: δ represents the annualized discount rate. LLF is the log-likelihood function. Estimation is by simulated maximum likelihood (Train, 2003). A single asterisk indicates significance at a 5% level.

**Table 3 Hyperbolic and Exponential Models: CRRA Form**

| | Hyperbolic | | Exponential | |
|---|---|---|---|---|
| **Fixed Parameter Estimate** | | | | |
| ***r*** | 0.953* | 294.634 | 0.956* | 279.121 |
| **Random Parameter Estimates** | | | | |
| **δ** | 0.418* | 2.622 | 0.395* | 2.202 |
| **Standard Deviation of Random Parameter** | | | | |
| $\boldsymbol{\sigma_\delta}$ | 0.742* | 34.089 | 0.760* | 34.300 |
| **Random Parameter Function** | | | | |
| **Age** | 0.006* | 2.084 | 0.006 | 1.679 |
| **Gender** | 0.196* | 4.647 | 0.194* | 4.101 |
| **White** | -0.516* | -6.809 | -0.508* | -6.289 |
| **Black** | -0.441* | -3.640 | -0.370* | -2.719 |
| **Hispanic** | -1.101* | -10.829 | -1.098* | -10.236 |
| **Asian** | -0.559* | -5.523 | -0.521* | -4.880 |
| **Marital Status** | -0.019 | -0.312 | -0.044 | -0.644 |
| **Household Size** | 0.011 | 0.654 | 0.013 | 0.684 |
| **Income** | 0.124 | 1.578 | 0.849 | 0.966 |
| **Smoke?** | -0.448* | -6.719 | -0.482* | -6.600 |
| **Drink Number** | 0.022* | 10.075 | 0.023* | 11.783 |
| **BMI** | 0.013* | 3.086 | 0.014* | 2.990 |
| **Standard Deviation of Model** | | | | |
| **σ** | 0.447* | 333.044 | 0.474* | 340.456 |
| **LLF** | -1,257.327 | | -1,380.392 | |

Notes: *r* represents the coefficient of relative risk aversion, δ represents the annualized discount rate. LLF is the log-likelihood function. Estimation is by simulated maximum likelihood (Train, 2003). A single asterisk indicates significance at a 5% level.

**Table 4. Hyperbolic and Exponential Models: CRRA and Quasi-Hyperbolic Forms**

| | Hyperbolic | | Exponential | |
|---|---|---|---|---|
| **Fixed Parameter Estimate** | | | | |
| **$\tau$** | 0.419* | 40.622 | 0.447* | 43.519 |
| ***r*** | 0.872* | 241.609 | 0.863* | 224.897 |
| **Random Parameter Estimates** | | | | |
| **$\delta$** | 0.507* | 3.553 | 0.350* | 2.239 |
| **Standard Deviation of Random Parameter** | | | | |
| **$\sigma_\delta$** | 0.648* | 45.927 | 0.684* | 35.130 |
| **Random Parameter Function** | | | | |
| **Age** | 0.014* | 5.089 | 0.006 | 1.901 |
| **Gender** | 0.451* | 12.134 | 0.224* | 5.550 |
| **White** | -0.484* | -7.377 | -0.569* | -7.727 |
| **Black** | -0.216 | -1.657 | -0.268 | -1.835 |
| **Hispanic** | -1.023* | -12.062 | -1.073* | -11.038 |
| **Asian** | -0.315* | -3.563 | -0.542* | -5.479 |
| **Marital Status** | -0.088 | -1.640 | 0.126* | 2.098 |
| **Household Size** | -0.028 | -1.873 | 0.009 | 0.557 |
| **Income** | 0.456* | 6.499 | -0.276 | -0.350 |
| **Smoke?** | -1.214* | -20.865 | -0.399* | -6.168 |
| **Drink Number** | 0.035* | 25.879 | 0.019* | 9.347 |
| **BMI** | 0.021* | 5.779 | 0.006* | 1.529 |
| **Standard Deviation of Model** | | | | |
| **$\sigma$** | 0.389* | 168.357 | 0.404* | 164.334 |
| **LLF** | -976.591 | | -1053.134 | |

Notes: $\tau$ represents variable cost to discounting, or the quasi-hyperbolic parameter, *r* represents the coefficient of relative risk aversion, $\delta$ represents the annualized discount rate. LLF is the log-likelihood function. Estimation is by simulated maximum likelihood (Train, 2003). A single asterisk indicates significance at a 5% level.

**Table 5. Hyperbolic and Exponential Models: CRRA, Fixed and Variable Cost of Discounting**

| | Hyperbolic | | Exponential | |
|---|---|---|---|---|
| **Fixed Parameter Estimate** | | | | |
| **$\tau$** | 0.419* | 40.092 | 0.447* | 43.304 |
| ***r*** | 0.872* | 243.907 | 0.863* | 227.873 |
| **$\beta$** | 0.217* | 11.907 | 0.099* | 4.710 |
| **Random Parameter Estimates** | | | | |
| **$\delta$** | 0.398* | 2.654 | 0.843* | 5.060 |
| **Standard Deviation of Random Parameter** | | | | |
| **$\sigma_\delta$** | 0.704* | 34.309 | 0.608* | 33.138 |
| **Random Parameter Function** | | | | |
| **Age** | -0.001 | -0.134 | 0.009* | 2.900 |
| **Gender** | 0.451* | 11.920 | 0.233* | 5.602 |
| **White** | -0.283* | -3.934 | -0.527* | -6.840 |
| **Black** | -0.131 | -0.979 | -0.032 | -0.222 |
| **Hispanic** | -0.914* | -9.636 | -0.809* | -7.972 |
| **Asian** | -0.361* | -3.884 | -0.306* | -3.141 |
| **Marital Status** | 0.082 | 1.387 | -0.083 | -1.382 |
| **Household Size** | 0.057* | 3.588 | -0.016 | -0.945 |
| **Income** | -0.247* | -3.431 | 0.543* | 7.038 |
| **Smoke?** | -0.380* | -6.399 | -1.187* | -17.108 |
| **Drink Number** | 0.021* | 9.888 | 0.028* | 13.464 |
| **BMI** | 0.015* | 4.218 | 0.035* | 9.171 |
| **Standard Deviation of Model** | | | | |
| **$\sigma$** | 0.389* | 167.915 | 0.404* | 163.818 |
| **LLF** | -965.991 | | -1,057.476 | |

Notes: $\beta$ represents a fixed cost of discounting, $\tau$ represents variable cost, or the quasi-hyperbolic parameter, $r$ represents the coefficient of relative risk aversion, $\delta$ represents the annualized discount rate. LLF is the log-likelihood function. Estimation is by simulated maximum likelihood (Train, 2003). A single asterisk indicates significance at a 5% level.

**Table 6. Hyperbolic and Exponential Models: CRRA, Fixed and Variable Cost of Discounting, Framing Effects**

| | Hyperbolic | | Exponential | |
|---|---|---|---|---|
| **Fixed Parameter Estimates** | | | | |
| **τ** | 0.464* | 13.645 | 0.446* | 43.612 |
| ***r*** | 0.877* | 223.081 | 0.863* | 223.901 |
| **β** | 0.195* | 30.785 | 0.139* | 7.191 |
| **Random Parameter Estimates** | | | | |
| **δ** | 0.388* | 2.585 | 0.435* | 2.674 |
| **Standard Deviation of Random Parameter** | | | | |
| $\boldsymbol{\sigma_\delta}$ | 0.681* | 38.462 | 0.696* | 44.159 |
| **Random Parameter Function** | | | | |
| **Age** | -0.03* | -13.243 | 0.005 | 1.662 |
| **Gender** | 0.131* | 3.983 | 0.472* | 11.515 |
| **White** | 0.537* | 10.226 | -0.537* | -7.152 |
| **Black** | -0.383* | -2.977 | -0.382* | -2.633 |
| **Hispanic** | -0.009 | -0.118 | -0.997* | -10.539 |
| **Asian** | 0.486* | 6.232 | -0.496* | -5.073 |
| **Marital Status** | -0.277* | -5.027 | 0.078 | 1.302 |
| **Household Size** | -0.092* | -5.022 | -0.047* | -2.701 |
| **Income** | 0.269* | 3.458 | 0.489* | 6.383 |
| **Smoke?** | -0.372* | -6.386 | -1.389* | -21.761 |
| **Drink Number** | 0.009* | 5.468 | 0.033* | 21.754 |
| **BMI** | 0.055* | 14.843 | 0.035* | 8.974 |
| **Standard Deviation of Model** | | | | |
| **σ** | 0.528* | 164.022 | -0.404* | -163.355 |
| **LLF** | -1,556.342 | | -1,602.261 | |

Notes: β represents a fixed cost of discounting, *τ* represents variable cost, or the quasi-hyperbolic parameter, *r* represents the coefficient of relative risk aversion, δ represents the annualized discount rate. LLF is the log-likelihood function. Estimation is by simulated maximum likelihood (Train, 2003). A single asterisk indicates significance at a 5% level.