Journal of Agricultural and Resource Economics 37(2):181–198

Obesity and Hyperbolic Discounting: An Experimental Analysis

Timothy J. Richards and Stephen F. Hamilton

Models of rational addiction suggest that obesity is consistent with time-consistent preferences. 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, conduct an experiment to test whether individual discount schedules are time-consistent and whether discount rates are higher for subjects who exhibit patterns of risky behavior. 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.

Key words: addiction, discounting, experiments, hyperbolic, obesity, time-inconsistency

Introduction

Genetic arguments notwithstanding (Shell, 2002), obese individuals appear to make systematically different food choices relative to others. Understanding why obese people make different choices 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 both obese and non-obese individuals are rational economic decision makers. Framed in terms of the household production models of Becker (1965) and Becker and Stigler (1977), food consumption decisions that appear to be excessive over time are nonetheless thought to be the result of rational time allocation and goods consumption decisions (Cutler, Glaeser, and Shapiro, 2003; Chou, Grossman, and Saffer, 2004; Philipson and Posner, 1999). Cawley (1999), for example, uses the rational addiction model 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 choices with 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 preference for immediate gratification, then the future costs of obesity are not likely to be appropriately balanced against the

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Review coordinated by Vincent Smith.

[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, Patterson, and Tegene, 2007). Addiction can be rational under a condition called "adjacent complementarity," which stipulates that 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.

present benefits of consuming food, or avoiding the gym. Such behavior occurs if preferences are time-inconsistent.

Models of rational addiction, on the other hand, assume individuals exhibit time-consistent preferences, that is, a decision at time t between consuming at time $t+2$ or $t+3$ 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 a "common difference effect," when the individual 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, that is, 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 respondents in a lab setting to weight present values over those in the near future, while differentiating little between values at different points in the more distant future.[3] We use an experimental framework to examine whether time preferences are indeed time consistent, and whether subjects who exhibit patterns of risky behavior are likely to discount the future more heavily than others.

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. Becker and Mulligan (1997) maintain that their model is not inconsistent with a constant underlying rate of time preference, but Gafni (1995) and Bleichrodt and Gafni (1996) question the logical basis of constant discount rate models, arguing instead that discount rates are inherently variable.

Evidence of hyperbolic discounting is mixed in empirical studies. Rubinstein (2003) presents a series of experiments in which he shows that choices among 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 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 (2010) also reject hyperbolic discounting.

There may be other explanations for the appearance of hyperbolic-like discount schedules. Zauberman et al. (2008) argue instead that discrepancies among individuals' perceptions of duration relative to actual duration give discount functions the appearance of being hyperbolic. In subjective time, they argue, discount functions are still exponential. Subadditivity, the idea that discount rates are greater over shorter periods, added together, than over longer delays, may also explain the appearance of hyperbolic discounting (Read and Read, 2004). In this research, we account for a number of potential forms of present-bias in testing for the effect of behavioral choices (excessive drinking, smoking, over-eating or obesity) on time preferences in an experimental setting.

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[2] Gruber and Köszegi (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, O'Donoghue, 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.

Background on Present Bias and Health

Several recent studies investigate the relationships among discount rates, present-bias and health status. We would expect that people in poor health, or who engage in activities that shorten their expected life-spans, to have higher discount rates. Both the expectation of an early demise and impulsive behavior may be causes of their poor health (e.g., overeating and obesity, smoking and lung disease, etc.). Hence, 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. They find that discount rates are higher for older people and lower for the less educated, and more wealthy, but they did not find any significant relationship between the rate of time preference and wealth, BMI, or drug use. Read and Read (2004) find no significant relationship between the rate of time preference and health status, but use 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 also seek to examine whether risky health behaviors, particular over-eating, are related to subjects' rate of time preference. Unlike previous 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 for policies designed to address not only obesity, but smoking, drinking, gambling, the failure to invest for retirement (Laibson, 1997), environmental degradation (Karp, 2005) or other long-term decisions that seem to favor present gratification over long-term utility. With respect to obesity, if individuals behave according to some form of time-inconsistent model, then they are likely to make food choices today that exhibit a strong present-bias, leaning toward instant gratification while not fully considering the future costs on equal terms, as the rational addiction model would imply. The two alternative addiction models yield starkly different policy implications. If an individual is rationally addicted, then addiction can be ameliorated by increasing future healthcare costs associated with the addiction. If, however, the individual discounts future costs non-exponentially, then the increases in future costs to prevent addiction can be prohibitive. Incentives, in the latter case, would need to emphasize immediate rewards for individuals who abandon their addiction.

Experiment Design

We investigate the nature of subjects' discount schedules—whether they are hyperbolic and whether discount rates vary among individuals engaging in risky behaviors—by conducting a time-value elicitation experiment in a sample of eighty-two students at Arizona State University, each of whom provided fifty time-value preference observations. The experiment follows Benhabib, Bisin, and Schotter (2010) in adopting the Becker, DeGroot, and Marschak (1964), or BDM, method of reward-time value elicitation. The rules of the experiment were explained to the subjects, both verbally and through written instructions, before the start of the experiment, practice scenarios prior to handing out the reward-time value elicitation instrument (see the details of the experimental method and the instrument in the appendix). All subjects were presented with a series of questions designed to assess the extent of present-bias in choosing financial rewards over varying time periods.

Using a BDM mechanism is intended to ensure truthful value elicitation.[4] The mechanics of the BDM procedure were carefully explained to the students, including the fact that it is incentive

[4] 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.

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. They were asked to respond to indifference amounts for fifty different reward-time pairs (two rounds of twenty-five questions). One pair 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 amount, say $8, is more than the random draw, they have to wait four weeks to receive the $10. If the indifference amount is less than the random draw, 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 should be 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). The amounts were $1.00, $5.00, $10.00, $50.00 and $100.00 to be received at various points in the future. Separate questions were asked for each time period in: (1) 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 so 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, $50.00, $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 was capped for each question at some upper bound and the BDM mechanism is applied as in the first round. Hence, a random value was 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 were paid immediately. An indifference amount more than the random value resulted in the fixed amount being paid after the relevant time period for that round. Asking isomorphic questions in a different way is used to test for the potential of framing effects that are common in other experimental time preference studies (Frederick, O'Donoghue, and Loewenstein, 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.[5]

Rounds one and two were designed to capture basic reward-time pair data for the sample participants that allow us to fit discount functions for each individual using an appropriate panel-data estimator. Using these data, we test whether subjects' 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 ways described by the quasi-hyperbolic discount function.

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[5] While our procedure allows us to control for framing and magnitude effects, we did not vary the order in which the present (future) amounts were presented to the subjects. Our results, therefore, may reflect an unknown amount of "ordering bias" if a magnitude effect does indeed exist.

Econometric Model of Hyperbolic Discounting

Several discount function specifications, $D(y,t)$, 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 or both the discount rate, and curvature of the discount function. 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 generality for parsimony and robustness in estimation and adopt a general model proposed by Prelec (2004), while allowing for constant relative risk aversion (CRRA) as in Andersen et al. (2008). We estimate the discount function 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. This allows for tests of whether observed individual-level attributes have a significant positive or negative impact on discount rates. As such, the econometric model can be used to test the hypotheses developed in Becker and Mulligan (1997).

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

$$x_h^r = y_h^r D(y, z^h, t; \delta_h, r_h, \alpha, \beta) = y_h^r \tau(\exp(-\delta_h t^{\alpha}) - \beta / y_h^r)\phi(\varepsilon_h), \tag{1}$$

where x_h is the promised payment for the particular question for subject h, y_h is the subject's indifference amount (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, δ_h is the discount rate, r is the risk aversion parameter, τ is a variable-cost component that determines whether the discount function is quasi-hyperbolic $(\tau < 1)$ and β is a fixed-cost component. Benhabib, Bisin, and Schotter (2010) find fixed-costs 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 $\delta_h \sim N(\mathbf{z}_h' \delta_h, \sigma_\delta)$, while v and ε are unobserved random effects ($v_h \sim N(\mu_{v_h}, \sigma_{v_h})$, $\varepsilon \sim N(\mu_{\varepsilon_h}, \sigma_{\varepsilon_h})$), and β is a fixed-cost component.[8] If $\alpha = 1$, the discount function is exponential and as α 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 α, higher values of β or r, or, of course, higher values of the underlying discount rate, δ. We also allow the agent-specific error term, φ, to include a log-normally distributed error term, ε. This panel estimator is unlike Benhabib, Bisin, and Schotter (2010), who estimate separate models for each individual, so index all four parameters by h.

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, and other possible sources of present-bias.

The primary attributes of interest are those associated with risky behaviors: smoking, drinking, and overeating, or its consequence, obesity. We measure drinking as the number of alcoholic beverages consumed per week. In general, adverse health effects are believed to be associated primarily with heavy drinking, as moderate drinking may have positive effects on heart disease or a number of other disorders (Ashley et al., 2000). Consequently, if excessive drinking reflects a more

[6] Benhabib, Bisin, and Schotter (2010) 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.

[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.

fundamental disregard for the future, we expect to find a positive relationship between the number of drinks per week and discount rates. Obesity is measured by the respondent's self-reported body mass index (BMI).[9] Despite well-reported weaknesses of BMI as a measure of obesity (Sturm), it remains a standard metric in the health economics literature. We expect to find a positive relationship between discount rates and obesity. Smoking is defined as the number of cigarettes smoked per day.[10]

The impact of smoking on discount rates could be either positive or negative. While smoking clearly poses a risk to future health, and should therefore be associated with higher discount rates, the fact that the adverse health effects do not appear until later in life may mean that they are not yet tangible to our sample of college-age students.[11] Differences in the long-term effects of smoking, drinking, and obesity are critical as Cutler and Glaeser (2005) find that beliefs regarding future health effects are important for smoking, but less so for obesity and excessive drinking. Individuals who believe smoking to be harmful to their future health are significantly less likely to smoke, but the same cannot be said of subjects who drink too much or are obese. In other words, if those who understand the health effects of smoking either do not start or are successful quitters, then smokers in the sample may not believe they are inflicting any harm on their future selves. Controlling for those smokers who are also heavy drinkers and obese, and likely to have high discount rates, the remaining smokers are likely to discount the future at a relatively lower rate. Further, Cutler and Glaeser (2005) use data from the Minnesota Twin Registry to show that genetic variation explains much more of heavy drinking and obesity than smoking. This suggests that if individuals have an inherent tendency toward obesity or drinking, they may believe, at least implicitly, that they are pre-destined to a relatively short lifetime and make decisions that reflect higher discount rates. Smokers, on the other hand, smoke from a behavioral preference and clearly do not believe that doing so will shorten their lifespan, and make decisions as if their discount rates are correspondingly lower.

We estimate the various forms of equation (1) 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 to identify the value of α 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 α 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 seventy-five (Train, 2003).

Results and Discussion

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 behavioral profile of our sample (undergraduate students) differs from that of the general population. Although we follow Lusk and Shogren (2007, p. 46) in our belief that "…using a student sample in a laboratory auction for a study designed to test a theory or behavioral phenomenon is likely to be of little concern…" given that the theory we test is a general one and " …should hold for everyone, *including students*" (authors' italics), some parameter estimates may be unique to

[9] BMI is defined as the ratio of weight (in kilograms) to height (in meters) squared.

[10] We also measured smoking as a binary (0 / 1) variable depending on whether the respondent reports any positive number of cigarettes smoked per day. This definition of smoking reflects the medical observation that the negative effects of smoking occur with even light and intermittent smoking (Schane, Ling, and Glantz, 2010), whereas the negative effects of drinking are likely to appear only if the individual is a heavy drinker (Sturm). The results with smoking defined as a binary variable are qualitatively similar to those found with a continuous-smoking definition.

[11] We thank the editor for pointing this out.

our sample. Because a student-sample is likely to be younger and from a more highly-educated social strata than the average individual in the population, our sample is likely consist of individuals who are less obese, less likely to smoke, and, perhaps, drink less than the general population. A comparison with a representative national survey confirms our expectations. In fact, 13% of our sample are smokers while the smoking rate among adults (> 18 years) in 2010 was 19.3 %. Further, defining a "regular drinker" as one who has five or more drinks per week, we find that 28% of our sample are regular drinkers, compared to 51% of the general population. With respect to BMI, 56.1% of our sample are either overweight (BMI > 25.0) or obese (BMI > 30.0), while 62% of the general population have a BMI > 25.0.

We calculate implied discount rates for each observation (subject / question). The implied discount rates are very large for short delays (one day or one week) but they appear to be plausible in both magnitude and dispersion among agents relative to other studies. Benhabib, Bisin, and Schotter (2010), for example, report that discount rates for short delays are very high and 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.

In table 2, we report results from a simple linear regression of implied discount rates on variables measuring various demographic and behavioral (i.e., smoking, drinking, and obesity) attributes. The parameter estimates show that discount rates are higher for older subjects and for males. Whites, blacks, Asians, and Hispanics tend to have lower discount rates than those in the “other” category. However, marital status, income and household size have no effect on discounting.

Obesity and drinking have the expected effect on discount rates, that is, those who tend to engage in risky behaviors discount the future at a higher rate. Smoking, however, does not have a significant effect, perhaps because of the competing effects described above or, alternatively, smokers may indeed make more risky decisions, the smokers in our sample may simply not be aware of the future implications of their behavior (Cutler and Glaeser, 2005). Or, it may be the case that negative health effects due to smoking have yet to manifest in our relatively-young sample. On average, these two effects counteract each other. It is also conceivable that these summary discount rates may conflate risk attitudes, quasi-hyperbolic discounting or fixed costs of discounting.

We control for these other factors that may cloud estimates of pure time-preference by estimating the discount function presented in (1). Table 3 presents estimates based on both 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 estimate the curvature parameter in the discount function (α). Using the grid-search procedure described above, the log-likelihood function is maximized at an α value 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 $\alpha = 1$). We find a chi-square LR statistic of 283.32, implying rejection of the exponential specification. Comparing estimates of the mean value of δ between the exponential and hyperbolic models provides some sense of the extent of present-bias that may exist in the data. The value of δ for the hyperbolic model is slightly higher 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 estimated exponential model.

The random parameters specification provides estimates of how individual attributes correlate with discount rates. Because discount rates vary directly with each element of the z^h vector, the estimates shown in table 3 are interpreted as marginal impacts on the rate at which subjects discount the future. In general, the results in table 3 show that much of the variation in discount rates among individuals can be explained by observed heterogeneity, both in demographic and behavioral attributes. Comparing specific parameter estimates among the various econometric models, we note that the pattern of effects is similar between the hyperbolic and exponential models and the summary evidence provided by the simple OLS regression. Using the hyperbolic estimates for interpretation

Table 1: Summary of Experimental Data and Respondent Attributes (N = 82)

Amount	Delay	Units	Mean	Std. Dev.
$1.00	1 day	$	$0.83	$0.24
$5.00	1 day	$	$3.91	$1.17
$10.00	1 day	$	$8.11	$2.05
$50.00	1 day	$	$40.64	$10.45
$100.00	1 day	$	$83.53	$20.46
$1.00	7 days	$	$0.80	$0.23
$5.00	7 days	$	$3.92	$1.07
$10.00	7 days	$	$7.93	$2.09
$50.00	7 days	$	$39.63	$10.73
$100.00	7 days	$	$81.01	$19.90
$1.00	1 month	$	$0.79	$0.25
$5.00	1 month	$	$3.79	$1.27
$10.00	1 month	$	$7.79	$2.47
$50.00	1 month	$	$36.89	$12.13
$100.00	1 month	$	$77.40	$22.62
$1.00	6 months	$	$0.72	$0.31
$5.00	6 months	$	$3.56	$1.40
$10.00	6 months	$	$7.16	$2.64
$50.00	6 months	$	$36.72	$12.30
$100.00	6 months	$	$75.10	$24.24
Age		Years	23.51	6.50
% Male		%	62.0	49.0
% White		%	73.0	44.0
% Black		%	2.1	15.0
% Hispanic		%	9.0	28.0
% Asian		%	9.0	28.0
% Married		%	13.0	34.0
Household Size		#	1.67	1.20
Income		$ / year	$31,737.80	$32,048.90
% Smoke		%	13.0	34.0
Number of Cigarettes		# pk / day	0.63	0.37
% Drink		%	28.0	44.9
Drink		# / week	4.96	10.89
BMI		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.

purposes, discount rates tend to be higher for older males of races other than the four major classifications considered in our survey. In terms of the marginal effects, discount rates increase 0.008 (0.8 of 1%) for every year of age and are fully 29.7% higher for men than women. Given that the mean discount rate is 0.727, racial effects are important, in addition to being statistically significant. Based on the estimates in table 3, relative to the excluded group whites have discount rates that are 0.651 lower, for blacks 0.474 lower, Hispanics 1.279 lower, and Asians 0.576 lower. Married individuals tend to have discount rates that are 0.192 higher than the mean, while household size and income are uncorrelated with time preference.[12] The irrelevance of income appears to be

[12] We also tested for non-linear income effects, but found that fit did not improve with either log or quadratic income effects. Neither parental education nor GPA were found to be significant in any of the specifications tested.

Table 2: OLS Model of Implied Discount Rates

Variable	Estimate	t-ratio
Constant	0.371	3.317
Age	0.005*	2.220
Gender	0.082*	2.885
White	−0.298*	−5.694
Black	−0.354*	−3.530
Hispanic	−0.612*	−9.160
Asian	−0.248*	−3.630
Marital Status	0.040	0.943
Household Size	−0.013	−0.934
Income	−0.006	−0.114
Smoke Number	−0.103	−1.885
Drink Number	0.006*	4.228
BMI	0.006*	2.197
LLF	-1783.785	
R^2	0.059	

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.

at odds with predictions made by Becker and Mulligan (1997), who suggest that higher wealth is associated with lower rates of time preference.

The relationships between smoking, drinking, obesity, and time preference are of more interest. In both models, discount rates tend to rise for heavier drinkers and those who are more obese. Both effects are consistent with prior expectations: Individuals who engage in risky health behaviors have a lower probability of surviving from one period to the next and should discount the future more heavily. Based on the results from the hyperbolic model in table 3, heavy drinkers have discount rates that rise 0.017 (1.7%) above the mean for each drink per week, but the estimate for BMI is not significant.

Smokers have lower discount rates than non-smokers (0.297 lower for every pack of cigarettes per day). Unlike the summary-regression results, the smoking effect is significant in the structural discounting model. Previous research provides no definitive priors with respect to the effect of smoking on discount rates, it is perhaps surprising that this negative effect is so strong (and consistent across all models discussed below). Promises of future tax increases appear to be particularly effective in reducing current smoking if smoking is indeed addictive and smokers are forward-looking. Hence, lower discount rates imply that higher taxes will have an even greater impact than previously thought. Moreover, monopolist-cigarette makers will raise prices further as there is little incentive to offer lower current prices in order to build larger cohort of addicted smokers (Becker, Grossman, and Murphy, 1994).

In the next model, we relax the assumption of risk neutrality. Andersen et al. (2008) find that controlling for risk aversion causes estimated discount rates to fall slightly, explaining some of the apparent present bias found in previous studies. Table 4 provides estimates of the two discount functions while allowing for constant relative risk aversion. Comparing risk-averse specifications to risk-neutral counterparts in table 3, a LR test shows that the risk neutral specification is rejected in favor of the CRRA model. Controlling for risk aversion, the rate of time preference falls in each case, but not as dramatically as in Andersen et al. (2008). Among 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 the hyperbolic or CRRA models.

Quasi-hyperbolic discounting involves discounting values in future periods at higher rates as if

Table 3: Hyperbolic vs. Exponential Model Estimates

	Hyperbolic		Exponential	
Random Parameter Estimate				
δ	0.73*	4.46	0.63*	3.47
Standard Deviation of Random Parameter				
σ_δ	0.74*	36.45	0.75*	32.74
Random Parameter Function				
Age	0.01*	2.45	−0.00	−0.57
Gender	0.30*	6.99	0.03	0.06
White	−0.65*	−8.43	−0.55*	−6.52
Black	−0.47*	−3.46	−0.29	−1.87
Hispanic	−1.28*	−12.87	−1.76*	−15.52
Asian	−0.57*	−5.54	−0.84*	−7.38
Marital Status	0.19*	3.10	0.16*	2.36
Household Size	0.01	0.56	0.06*	3.21
Income	−0.08	−0.95	0.16	1.89
Smoke Number	−0.30*	−3.57	−1.12*	−11.02
Drink Number	0.02*	9.02	0.04*	18.55
BMI	0.01	1.23	0.02*	3.48
Standard Deviation of Model				
σ	0.45*	352.36	0.48*	361.29
LLF	-1,279.94		-1,421.60	

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.

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 5 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 4 shows a significant improvement in fit. Moreover, the estimates of τ (the variable cost component) are individually significant in both the hyperbolic and exponential models. Interestingly, the estimated discount rate increases in the hyperbolic model, but decreases 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, the estimate of r falls in each case when we account for hyperbolic discounting. This finding suggests that imposing a zero variable cost of discounting creates a bias against finding risk aversion.

Finally, we consider the most general form of the empirical model in equation (1), accounting for both a variable and fixed cost of discounting. Comparing the log-likelihood function value of each specification in table 6 with the specifications shown in table 5 suggests that the most comprehensive model is preferred in both the hyperbolic and exponential cases. In the hyperbolic model, a fixed cost of \$0.235 is small relative to the size of the values offered in the experiment but nonetheless statistically significant. While the variable cost estimate is the same as in the restricted model, the value of δ is very similar in the hyperbolic case but significantly lower in the exponential. This finding suggests that the other plausible explanations for present-bias are as at least partially valid and account for some of the effect others attribute to hyperbolic discounting.

More importantly, parameter estimates are robust to this specification. In particular, both obesity and drinking are positively related to present-bias. This is an important result. If obesity—and excessive drinking—are associated with higher discount rates, then not only are explanations based on rational addiction models incorrect, but behavior modification efforts that do not address an

Table 4: Hyperbolic and Exponential Models: CRRA Form

	Hyperbolic		Exponential	
Fixed Parameter Estimate				
r	0.95*	295.74	0.96*	280.42
Random Parameter Estimates				
δ	0.68*	4.18	0.59*	3.23
Standard Deviation of Random Parameter				
σ_δ	0.75*	36.83	0.78*	34.55
Random Parameter Function				
Age	0.01*	2.45	−0.00	−0.79
Gender	0.31*	7.23	0.01	0.24
White	−0.67*	−8.69	−0.57*	−7.00
Black	−0.48*	−3.83	−1.18*	−8.69
Hispanic	−1.31*	−13.03	−1.82*	−16.59
Asian	−0.59*	−5.67	−0.88*	−7.98
Marital Status	0.20*	3.20	0.18*	2.59
Household Size	0.01	0.56	0.07*	3.28
Income	−0.08	−0.99	0.16	1.93
Smoke Number	−0.30*	−3.64	−1.15*	−11.41
Drink Number	0.02*	8.80	0.04*	21.19
BMI	0.01	1.23	0.02*	3.64
Standard Deviation of Model				
σ	0.45*	338.29	0.47*	342.28
LLF	-1,257.26		-1,386.13	

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.

agent's need for immediate gratification are likely to be ineffective. 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 individuals discount the future heavily and discount according to a hyperbolic pattern as suggested here, then higher expected future costs 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 more extensive problems than excessive drinking and eating.

We also test whether the results we report are due to framing effects.[13] Table 7 reports 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. Using a grid-search technique to estimate the curvature parameter, we find a value for α of 0.154, which represents a significantly greater departure from exponential discounting relative to the present-perspective case. This model provides a better fit to the data than the exponential model, based on a LR test, indicating that framing questions in this way causes discount functions to appear to be " more hyperbolic." However, the remaining parameters, conditional on this estimate of α, are broadly consistent with the present-perspective responses. For example, the signs and magnitudes of the obesity effect (as well as the smoking and drinking effects) on discount rates are very similar to those obtained using the present-perspective questions. In the hyperbolic model, estimates of the mean of δ are significantly higher

[13] While we test for framing in terms of the present- or future-perspective of the questions, we do not randomize dollar values within each session. This is a limitation of our experimental design, but was thought necessary to reduce the computational burden on experiment subjects.

Table 5: Hyperbolic and Exponential Models: CRRA and Quasi-Hyperbolic Forms

	Hyperbolic		Exponential	
Fixed Parameter Estimate				
τ	0.42*	40.70	0.45*	43.41
r	0.87*	246.91	0.86*	226.17
Random Parameter Estimates				
δ	0.69*	4.87	0.44*	2.80
Standard Deviation of Random Parameter				
σ_δ	0.68*	32.81	0.64*	33.76
Random Parameter Function				
Age	0.01*	3.05	0.01*	3.56
Gender	0.30*	7.95	0.22*	5.39
White	−0.59*	−8.51	−0.87*	−12.08
Black	−0.77*	−6.00	−0.43*	−2.54
Hispanic	−1.17*	−12.33	−1.54*	−15.89
Asian	−0.83*	−8.67	−1.13*	−10.83
Marital Status	0.14*	2.67	0.39*	6.83
Household Size	0.04*	2.38	0.01	0.48
Income	0.08	1.19	0.36*	4.82
Smoke Number	−1.18*	−14.21	−0.26*	−3.14
Drink Number	0.03*	14.15	0.03*	17.33
BMI	0.02*	4.39	−0.00*	−0.17
Standard Deviation of Model				
σ	0.39*	167.58	0.40*	163.84
LLF	-976.37		-1059.30	

Notes: τ represents variable cost to discounting, 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.

than the estimates reported in table 6, indicating that framing has no effect on our behavioral findings (smoking, drinking and obesity effects) but appears to have a significant effect on discount rate estimates.

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 and 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, and a slight framing effect regarding how our time

Table 6: Hyperbolic and Exponential Models: CRRA, Fixed and Variable Cost of Discounting

	Hyperbolic		Exponential	
Fixed Parameter Estimate				
τ	0.42*	40.39	0.45*	43.42
r	0.87*	242.17	0.86*	226.95
β	0.24*	12.05	0.22*	10.07
Random Parameter Estimates				
δ	0.70*	4.49	0.63*	3.69
Standard Deviation of Random Parameter				
σ_δ	0.77*	33.72	0.78*	33.95
Random Parameter Function				
Age	0.00	−1.17	0.01	1.53
Gender	0.52*	13.34	0.49*	11.42
White	−0.47*	−6.48	−0.48*	−6.24
Black	−0.42*	−3.14	−0.41*	2.82
Hispanic	−1.38*	−14.28	−1.40*	−14.27
Asian	−1.12*	−11.01	−1.13*	−10.70
Marital Status	−0.04	−0.80	−0.06	−0.97
Household Size	0.12*	7.72	0.12*	6.50
Income	−0.12	−1.72	−0.14	1.91
Smoke Number	−0.35*	−4.80	−0.37*	−4.65
Drink Number	0.03*	13.91	0.03*	15.24
BMI	0.02*	5.68	0.02*	5.00
Standard Deviation of Model				
σ	0.39*	168.67	0.40*	165.16
LLF	-972.34		-1,057.68	

Notes: β represents a fixed cost of discounting, τ represents variable cost to discounting, 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.

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 our expectations that less healthy people have a higher hazard rate each period. Interestingly, however, we also find that smokers have generally lower discount rates, a result that seemingly contradicts the drinking and obesity effects, but which may be consistent with the relatively youthful nature of our sample, and prior evaluations of how smokers perceive the health effects of their habit.

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, although taxes raise current prices and reduce current consumption, taxing foods deemed to be unhealthy is intended to raise consumers' expectations of future prices. "Rational addicts" in the sense of Becker and Murphy (1988) who discount the future lightly will significantly reduce current consumption if they expect future prices to be higher as a result of the tax. Consumers who discount heavily, or even in a manner consistent with quasi-hyperbolic discounting, will be less likely to change their consumption because the future costs mean less to them than to other, exponentially-discounting addicts.

Table 7: Hyperbolic and Exponential Models: CRRA, Fixed and Variable Cost of Discounting

	Hyperbolic		Exponential	
Fixed Parameter Estimates				
τ	0.21*	6.68	0.41*	38.61
r	0.78*	256.64	0.78*	172.74
β	0.18*	34.82	0.13*	12.89
Random Parameter Estimates				
δ	1.07*	7.96	0.50*	2.33
Standard Deviation of Random Parameter				
σ_δ	0.62*	33.82	0.94*	39.05
Random Parameter Function				
Age	−0.03*	−15.31	−0.04*	−12.57
Gender	−0.03	−1.12	0.10	1.72
White	0.46*	8.31	0.46*	4.38
Black	−1.01*	−7.91	−0.52*	−2.59
Hispanic	−0.13	−1.70	−0.23	−1.67
Asian	0.84*	10.90	0.67*	4.79
Marital Status	0.06	1.06	−0.07	−0.87
Household Size	−0.06*	−3.62	−0.03	−0.92
Income	−0.01*	−0.19	−0.15	−1.49
Smoke Number	−1.10*	−13.94	−0.42*	−3.73
Drink Number	0.01*	7.59	0.01*	4.03
BMI	0.03*	9.15	0.04*	8.17
Standard Deviation of Model				
σ	0.49*	141.89	0.58	213.23
LLF	-1,417.52		-1,822.60	

Notes: β represents a fixed cost of discounting, τ represents variable cost to discounting, 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.

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.

[Received June 2009; final revision received March 2012.]

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Appendix A: Experimental Procedures

In this appendix, we provide additional details on our experimental procedure (a more complete version is available upon request). Our sample consisted of eighty-two members of a 400-level management class at Arizona State University. All participants were familiar with the concept of "time value of money" so the conceptual explanation was kept to a minimum. All auction procedures are carried out using pen-and-paper responses and the data were entered into an Excel spreadsheet for preparation for further statistical analysis.

On the day of the auction, the experiment consisted of seven steps. Each of the seven steps are described below:

Step 1: In step 1, each participant was asked to sit and not discuss the experimental procedure with anyone else in the room. All subjects were then shown a Powerpoint presentation introducing and motivating the nature of the experiment, which was also narrated by the experimenter. Next, we briefly described the subject matter of the experiment and explained that we intended to measure each student's personal discount rate. They were told that their participation was completely voluntary and that they had the option to leave at any time.

Step 2: In step 2, participants were introduced to the time-value elicitation procedure. Using a second part of the Powerpoint presentation, we explained how the BDM mechanism works and provided an intuitive explanation of why it is incentive-compatible. All participants were told that one round per part of the experiment (Part I = Present Value, Part II = Future Value) would be chosen at random to be binding, and that they were to pick up their payment after the session was complete and they had signed their payment receipt.

Step 3: Once the BDM mechanism had been explained carefully, we went through a simple example involving the choice between $1.00 one year in the future and an amount today (similar to Part I). Once we were confident that all the participants understood how the experiment was to be conducted and answered any questions they had, we conducted a second practice session, offering $1.00 today and an amount of their choosing one year in the future (similar to Part II).

Step 4: After completing the practice round, the participants were then instructed that we would begin the experiment. Because all time-values are individual-specific, there is no need to define treatment and control groups as in a more conventional auction setting. Participants were instructed to complete Part I of the experiment and were reminded that it was similar to the first practice round. Once all subjects had completed Part I, we then instructed them to move on to Part II, and reminded them that it was similar to the second practice round.

Step 5: After all subjects had completed both Part I and Part II, they were asked to complete the demographic / behavioral survey and to return their completed instrument to the experimenter (see the instrument below).

Step 6: Once the surveys were all completed, each participant was instructed to leave the room and enter the adjoining room to receive their payment and to sign the payment receipt form. The rounds chosen to determine payment were $5.00 in one week for Part I and $10.00 in four weeks for Part II.

Step 7: The final step involves recording and analyzing the bid and survey data.

Appendix B: Interview Questions

A summary of the instruments used to elicit time-value preferences and demographic information is provided below (more detailed versions are available upon request).

Demographic Section

The first section of the survey consisted of a set of demographic questions designed to gather data on subject age, gender, race, major, income and, most importantly, self-reported metrics for weight, height, as well as smoking and drinking behaviors.

Time Value Elicitation Section

The second section consisted of the time-value elicitation questions. The first part of this section presented the questions from a present-value perspective, while the second did so from a future-value perspective. In the present-value part, we presented each subject with text that explained how "... we will ask a number of questions regarding how much you would take right now (in dollars) to be equally satisfied with (or indifferent between) this amount and some other amount to be paid in the future. We will vary the future amounts over five values ($1.00 to $100.00) and the length of time in which you would have to wait (one day to one year). To ensure that it is in your best interests to report your bids accurately, we will choose one combination of values and time periods and announce a random value between $0 and the future amount to be paid. If your bid is less than this random value, we will pay you that amount immediately, but if it is more than the random value, we will pay you your bid after the stated period of time... "

We then followed with five sets of five questions each in which we asked each subject to "Please enter your indifference amount in the blank following the $ sign in the questions below." Each question in each block then asks "What amount of money, $_____, if paid to you today would leave you equally satisfied with being paid $1.00 ($5.00, $10.00, $50.00 or $100.00) in one day (one week, four weeks, six months, one year)?

In the future-value part, we offered a similar set of instructions and followed with another five blocks of questions written as: "What amount of money would you require to leave you equally satisfied with receiving $1.00 ($5.00, $10.00, $50.00, $100.00) today and $_____ in one day (one week, four weeks, six months, one year)?