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Time preferences and consumer behavior

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Abstract We investigate the predictive power of survey-elicited time preferences. The discount factor elicited from choice experiments using real payments predicts various health, energy, and financial outcomes, including overall self-reported health, smoking, installing energy-efficient lighting, and credit card balance. Allowing for time-inconsistent preferences, both the long-run and present-bias discount factors (δ and β) are also significantly associated in the expected direction with several outcomes. We consider several hypotheses regarding the strength of the association between discount factors and outcomes, such as salience of the outcome or liquidity constraints.

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1 Introduction

Time preferences are generally considered to be a primitive of economic decision-making and so are predicted to affect behavior across many dimensions. Economic theories assume that less-patient individuals are less likely to spend money, time, or resources now to yield benefits in the future. Evidence from behavioral economics and psychology suggests that many individuals exhibit present bias, placing a disproportionate weight on immediate costs and benefits compared to more temporally distant outcomes. Present bias can yield time inconsistency and failure to stick to plans; the optimal decision at one point in time may no longer remain optimal as proximate time periods become increasingly salient. For instance, time-inconsistent consumers may plan to invest in energy-efficient technologies (e.g. hybrid cars, home energy improvements), but postpone the investment when the costs become immediate. This inconsistency is a potential explanation of the energy efficiency gap and provides a possible rationale for government intervention (Gillingham and Palmer 2014). Time inconsistency affects health policies, as present-biased consumers may underinvest in health, e.g. by eating too much, exercising too little, neglecting preventive health care, or failing to buy insurance. Policies designed to encourage retirement savings may need to accommodate the potential for time inconsistency (Carroll et al. 2009).

This paper investigates how elicited time preferences (defined across both time-consistent and time-inconsistent frames) predict consumer behavior across multiple domains. Since no secondary data exist that contain the wide range of information necessary for this analysis, we field our own survey and measure time preferences with an incentive-compatible choice experiment about intertemporal tradeoffs, paying out for one of the choices for randomly-selected respondents to mitigate any hypothetical bias. We use multiple price list (MPL) questions to compute the standard discount factor, both the present bias and long-run components of a quasi-hyperbolic (β, δ) specification (as in Laibson 1997), and the coefficient of relative risk aversion (CRRA). This allows for an empirical test for associations of both time-consistent impatience and time inconsistency with outcomes related to self-reported health, health behaviors, health insurance, use of energy-efficient technologies, and financial decisions, while holding risk preferences constant to avoid erroneously conflating time and risk preferences.

There is debate in the literature about how well discounting measures elicited from small-stakes financial tradeoffs actually reflect the rates of time preference used in real-world decisions. One concern is that the stakes are not high enough for individuals to respond accurately. Additionally, time preferences may vary across different domains (Chapman and Elstein 1995). For instance, questions about intertemporal health choices may predict health behavior better than they predict financial choices. To address these challenges, we consider alternative measures of time preferences, including questions specifically tailored to health decisions. These alternates allow us to assess how measurement error affects the estimates from regressions using elicited time preferences from the monetary domain.

Our data show that time preferences elicited using MPL questions over monetary payouts are associated with many outcomes related to health, energy use, and finances. In regressions controlling for demographic variables and risk preferences, the time-consistent discount factor, δ, is significantly correlated in the predicted direction with good or better overall and mental health, activity limitations, having health insurance, exercise, snacking, smoking, binge drinking, seatbelt use, refusal to report weight or height, installing energy-efficient compact fluorescent lighting, credit card balance, and having retirement savings. The present bias discount factor, β, is statistically associated in the expected direction with good or better overall health, excellent overall health, exercise, smoking, binge drinking, seatbelt use, driving a fuel-efficient car, adding weather stripping to one's home, and having non-retirement savings. The elicited discount factors from the monetary domain are only modestly associated with the alternative time preferences variables, suggesting that our estimated relationships between time preferences and consumer behaviors may be conservative.

Our study's contribution is four-fold. First, we examine how survey-elicited time preferences are related to a heterogeneous set of real-world outcomes, including those across the domains of health, energy, and financial decisions. To our knowledge, we are the first to estimate the link between time preferences and many of our outcomes: self-assessed physical and mental health, health-related limitations, health insurance, snacking, binge drinking, sunscreen and seatbelt use, automobile fuel economy, actual (as opposed to hypothetical) home energy-efficiency investments, thermostat temperature settings, overall home energy use, and having an energy audit. This is important because if the role of time preferences varies by frame, it is not clear to what degree the results for previously-studied outcomes (such as smoking and body mass index) generalize to other settings. We motivate our analyses with testable hypotheses about which types of behaviors are most likely to be influenced by time preferences.

Second, our study allows for quasi-hyperbolic discounting and disentangles whether the diverse group of observed relationships is driven by time-consistent preferences (δ), present bias (β), or both. We are unaware of prior research on the relationship between elicited time preference inconsistency and any of our outcomes, with the exception of smoking, BMI, and credit card debt. We hypothesize and test which outcomes are particularly likely to be correlated with present bias, as opposed to general time-consistent discounting.

Our third contribution relates to methodological advancements in the survey design. We improve on previous studies linking time preferences to consumer outcomes by surveying respondents that are representative of the U.S. population, using an incentivized measure of time preferences, studying many decision domains simultaneously, and using a greater sample size than studies relying on a student population. While some previous studies have incorporated some of these features, to our knowledge none have featured all these innovations at once.

Fourth, we assess how discount factors based on monetary outcomes compare to alternative time preference measures across different domains. These alternate measures include self-reported patience and willpower, as well as both elicited and self-reported measures specific to the health domain. These measures are only modestly associated with elicited money-based time preferences, implying that they provide new information related to intertemporal choices.

2 Background

Time preferences have been conceptualized in a variety of ways. Among the earliest modern theoretical frames is from Samuelson (1937), who assumed that individuals maximize the present value of a stream of current and future utility. Present value is calculated by discounting future payoffs by a constant amount in each time period. Future utilities are weighted less heavily compared to the current level of utility, but in a manner that does not produce preference reversals. Specifically, individuals are assumed to select consumption levels in each time period, x_t, to maximize

$$U(x_0, \ldots, x_T) = \sum_{t=0}^{T} \delta(t)u(x_t) \tag{1}$$

subject to an income/wealth constraint. An exponential weighting function $\delta(t) = \delta^t$ implies a constant discounting rate per time period; this is the basis for the most common understanding of a "discount rate" (from which the weighting factor $\delta(t)$ is derived) in economics.

Another framework, based upon Strotz (1955), suggests that individuals exhibit systematic biases in their decision-making. In particular, Ainslie (1991) and Laibson (1997) assume that individuals maximize a discounted utility stream that places disproportionately higher weight on the present payoffs relative to all future ones. This "quasi-hyperbolic" discounted utility function takes the form

$$U(x_0, \ldots, x_T) = u_0 + \beta \sum_{t=1}^{T} \delta^t u(x_t), \tag{2}$$

where the parameter β corresponds to a time-inconsistent preference for the current payoff (present bias when $\beta < 1$) and δ is the time-consistent (long-run) component of temporal preferences. The parameter β captures the degree to which an individual devalues all future payouts relative to the present period payout (u_0) over and above the down-weighting that is associated with the time-consistent discounting factor (δ^t). The consequence of assuming this "β, δ" discounted utility function is that the *rate* of discounting differs depending on the time period in the future that is being considered. Laibson (1997) argues that this characterization of the dynamic objective function is warranted if individuals are managing an interpersonal conflict between their current self (which he assumes the agent cares most about) and all future selves (which are less important to the current decision maker). We take no strong position about which description of dynamic preferences is more accurate; rather we model decisions in the energy, health, and financial spheres using both conceptual frames to explore the relationship between time preferences (dynamically consistent or not) and behavior.

We are, of course, not the first to be interested in empirical issues related to time preferences. A prior literature examines whether consumers' preferences are time-consistent (as opposed to our focus on whether the level of time inconsistency is associated with particular outcomes), with laboratory investigations going back to Thaler (1981). Other research examines whether specific aspects of consumer behavior suggest present bias. Individuals' choices about exercising (DellaVigna and Malmendier 2006), completing homework (Ariely and Wertenbroch 2002), participating in welfare programs (Fang and Silverman 2009), and eating (Ruhm 2012) all indicate time inconsistency and present bias. Buyers of cars seem to underweight future gasoline costs (Allcott and Wozny 2014). Gillingham and Palmer (2014) describe how several types of behavioral anomalies, including time-inconsistent preferences, could explain the "energy efficiency gap," in which there appears to be underinvestment in energy-saving technologies.

Other investigations estimate the associations between time preferences and various outcomes, but without distinguishing time-consistent from present-biased behavior. For instance, connections have been found between time preference and: BMI (Chabris et al. 2008; Weller et al. 2008; Sutter et al. 2013), exercise (Chabris et al. 2008; Bradford 2010), smoking (Bradford 2010; Scharff and Viscusi 2011; Sutter et al. 2013), drinking (Sutter et al. 2013), preventive health care utilization (Bradford 2010; Bradford et al. 2010), healthy behaviors among hypertensive patients (Axon et al. 2009), overall self-assessed health (Van der Pol 2011), and hypothetical energy-efficiency investments (Newell and Siikamäki 2015). Finally, present bias has been empirically linked to a limited set of outcomes: smoking (Burks et al. 2012), credit card borrowing (Meier and Sprenger 2010), credit score (Arya et al. 2013), BMI (Courtemanche et al. 2015), and "underwater" mortgages (Toubia et al. 2013).[1]

As mentioned, we examine a variety of behaviors that have not been previously explored in related research, testing whether each is associated with the long-run (δ) and/or the present bias (β) discount factors. Although we do not formally model all possible decisions, our predictions on how each outcome will be related to δ and β are motivated by hypotheses based on earlier investigations. First, since all of the outcomes involve intertemporal tradeoffs, they are expected to be correlated with the long-run discount factor δ. For instance, health behaviors like smoking or binge drinking yield immediate benefits but future health costs. Energy behaviors such as purchases of housing insulation or fuel-efficient vehicles require higher immediate payments for future savings.

Second, since prior research (e.g Augenblick 2015) shows that time inconsistency is more pronounced over consumption than cash flows, we hypothesize that outcomes directly related to consumption or experienced utility are more likely to be correlated with β than those that are purely about finances.[2] Therefore, we expect decisions with immediate and highly salient consequences, such as smoking, drinking, eating unhealthy foods, and exercising, to be highly prone to present bias and more likely to be correlated with β. In contrast, the short-term benefit of foregoing the purchase of more efficient light bulbs or of retirement savings is purely financial (less salient) and in any event often involves tradeoffs between strictly future periods (e.g., less net income in next month's paycheck compared to more monthly income in retirement years hence), so these outcomes are expected to be influenced by δ more than by β.

Third, with sufficient liquidity, individual time preferences need not be correlated with any intertemporal financial decision, since consumers can borrow to finance present consumption. Conversely, decisions over which consumers are likely to be liquidity-constrained, which include big-ticket purchases like cars, are anticipated to be more strongly correlated with time preferences than are decisions about inexpensive

[1] Von Gaudecker et al. (2011) perform a similar analysis but looking at risk, not time, preferences.
[2] A related prediction is found in the model of willpower in Bénabou and Tirole (2004).

purchases. Similarly, decisions that are highly liquidity-constrained (e.g., one cannot smooth the withdrawal pains from smoking cessation today) are also more likely to be influenced by present bias.

Fourth, we hypothesize that discount factors will be more correlated with aggregated measures of behaviors (e.g. overall health status or energy use) than their components (e.g. specific health behaviors or energy-related purchasing decisions). This hypothesis is motivated by Chabris et al.'s (2008) theoretical result that individual behaviors will only be weakly correlated with discount factors, since they are also a function of idiosyncratic effects. By contrast, for an aggregate index of behaviors, the average idiosyncratic effects converge to zero as the number of individual behaviors in the index increases.

3 Data and model

This analysis uses data from an online survey of 1325 respondents purchased from Qualtrics Panels (http://www.qualtrics.com/panel-management) based on a panel of 500,000 individuals provided by Clear Voice Research. Our respondents were chosen to be representative of the US adult population (18 and over), using quota sampling based on age, education, and gender. The average response rate of panelists to survey invitations was 20%. Appendix A documents the Qualtrics Panels recruitment methods. The entire text of our survey, which was conducted in July and August of 2013, is provided in Appendix B.

3.1 Elicited time and risk preferences

We utilized the double multiple price list method (Andersen et al. 2008) to simultaneously measure time and risk preferences. The procedure elicits time preferences allowing for non-linear utility, by separately eliciting risk preferences to control for utility curvature.

We measured impatience and present bias using three "blocks" of multiple price list (MPL) questions, as in Meier and Sprenger (2010). Each block contains several choices asking the respondent whether he/she would prefer a smaller earlier payment or a larger later payment. We observe respondents' choices between receiving money now versus in one month ("red block"), now versus in six months ("black block"), and in six months versus in seven months ("blue block"). In all cases, the larger payment (at the later date) was \$30, while the smaller (more proximate date) payment ranged from \$8 to \$29. Each respondent was asked 22 such questions; the values are listed in Table 1.[3]

Table 1 also lists the implied monthly discount factor for a consumer who is just indifferent between the larger and smaller payments (assuming linearity of utility), along with the percentage of respondents choosing the larger amount. For instance, in the first row of the red block, a consumer who is just indifferent between \$29 today and \$30 in one month has a one-month discount factor of 0.9667 (29 = 30 * 0.9667), and 15.3% of respondents chose \$30 in one month over \$29 today. For each block, the

[3] The time periods were the same as those used in Meier and Sprenger (2010). We adjusted the dollar values of the payments downward to reflect our budget (and rounded each to the nearest dollar integer).

Table 1 Hypothetical payoffs received in different time periods

Red block				Black block				Blue block			
Payoff today	Payoff in one month	Discount factor if indifferent	Percent choosing larger amount	Payoff today	Payoff in six months	Discount factor if indifferent	Percent choosing larger amount	Payoff in six months	Payoff in seven months	Discount factor if indifferent	Percent choosing larger amount
$29	$30	0.9667	15.3	$29	$30	0.9944	01.3	$29	$30	0.9667	31.5
$28	$30	0.9333	22.2	$28	$30	0.9886	03.8	$28	$30	0.9333	35.7
$26	$30	0.8667	39.2	$26	$30	0.9764	09.0	$26	$30	0.8667	47.9
$24	$30	0.8000	57.7	$24	$30	0.9634	21.0	$24	$30	0.8000	58.9
$21	$30	0.7000	73.4	$21	$30	0.9423	36.9	$21	$30	0.7000	71.6
$17	$30	0.5667	87.9	$17	$30	0.9097	62.8	$17	$30	0.5667	84.4
$13	$30	0.4333	90.1	$13	$30	0.8699	74.4	$13	$30	0.4333	86.6
				$8	$30	0.8023	81.4				

percentage choosing a delayed payout increases as the earlier payment decreases, as expected. Comparing the red block to the black block confirms that respondents are less willing to wait for a given (larger) payoff that occurs further in the future. Additionally, comparing the red to blue blocks provides evidence of present bias. Specifically, time-consistent consumers should answer each corresponding question in these two blocks the same way, since in each case there is the same rate of return from an additional one month delay in the payout. However, for the first three rows we see that substantially more people are willing to wait a month for the larger payout when both payout options are in the future. When the earlier payments are \$24 or less (in the fourth through seventh rows), the majority of respondents choose to wait but there is no difference in the percentage doing so between the red and blue blocks.

We presented respondents with an additional series of multiple price list choices over lotteries. In each case, the respondent chose between two lotteries, both having the same *probabilities* of winning larger or smaller amounts, but with the actual *amounts* varying. Table 2 summarizes the lotteries.[4] Moving down the table, the difference in the expected value of lottery B improves relative to that of lottery A. Since lottery B is always riskier, a higher fraction of choices for lottery A indicates greater risk aversion. As the expected value of B becomes relatively larger than that of A, the number of respondents that chose B (the riskier lottery) increases.

We estimate individuals' time and risk preference parameters by maximum likelihood estimation. We assume that an individual's utility for outcome x is of a constant relative risk aversion (CRRA) specification, with $u(x) = x^r$. Further, when faced with the MPL choice between the two risky lotteries A and B, we assume that individuals calculate the expected utility of each lottery, EU_A and EU_B, conditional on their risk aversion r. Individuals then choose lottery A or B based upon the difference between the two expected utilities, $EU_A - EU_B$. We assume that the probability that an individual chooses lottery A is $Pr(A) = \Phi(EU_A - EU_B)$, where Φ represents the standard cumulative normal distribution function. The conditional log-likelihood of an individual's observed responses y_i in the lottery task depends upon risk aversion r and is thus:

$$\ln L^R(r, y) = \sum_i((\ln(\Pr(A)|y_i = A) + \ln((1-\Pr(A))|y_i = B))$$

Similarly, for the intertemporal choice MPLs, we assume that individuals choose between the smaller sooner (SS) and the larger later (LL) outcome by calculating each option's discounted utility $DU(x_t) = \delta(t) * x^r$, with parameter r determined through an individual's choices in the lottery MPL. Individuals then decide between the two intertemporal options based upon the difference between the two discounted utilities, $DU_{SS} - DU_{LL}$. We assume that the probability that an individual chooses the smaller sooner option is given by $Pr(SS) = \Phi(DU_{SS} - DU_{LL})$.

We calculate two sets of discount factor parameters based on the MPL questions. In our first specification we assume time-consistent discounting and $\delta(t) = \delta^t$. The conditional log-likelihood of an individual's observed responses in the discounting

[4] The probabilities and dollar values are taken from Andersen et al. (2008).

Table 2 Estimate of risk aversion obtained using lottery questions

Lottery A				Lottery B				EV(A)	EV(B)	Difference	CRRA if just indifferent	Percent choosing A
Prob	\$	Prob	\$	Prob	\$	Prob	\$					
20%	\$ 20.00	80%	\$ 16.00	20%	\$ 38.50	80%	\$ 1.00	\$ 16.80	\$ 8.50	\$ 8.30	1.95	99.0
30%	\$ 20.00	70%	\$ 16.00	30%	\$ 38.50	70%	\$ 1.00	\$ 17.20	\$ 12.25	\$ 4.95	1.49	98.3
40%	\$ 20.00	60%	\$ 16.00	40%	\$ 38.50	60%	\$ 1.00	\$ 17.60	\$ 16.00	\$ 1.60	1.14	93.6
50%	\$ 20.00	50%	\$ 16.00	50%	\$ 38.50	50%	\$ 1.00	\$ 18.00	\$ 19.75	\$ (1.75)	0.85	80.0
60%	\$ 20.00	40%	\$ 16.00	60%	\$ 38.50	40%	\$ 1.00	\$ 18.40	\$ 23.50	\$ (5.10)	0.59	69.7
70%	\$ 20.00	30%	\$ 16.00	70%	\$ 38.50	30%	\$ 1.00	\$ 18.80	\$ 27.25	\$ (8.45)	0.32	54.2
80%	\$ 20.00	20%	\$ 16.00	80%	\$ 38.50	20%	\$ 1.00	\$ 19.20	\$ 31.00	\$ (11.80)	0.03	44.0
90%	\$ 20.00	10%	\$ 16.00	90%	\$ 38.50	10%	\$ 1.00	\$ 19.60	\$ 34.75	\$ (15.15)	−0.37	36.6

task depends upon the discounting parameter δ as well as risk aversion r. The log-likelihood for the time discounting task is thus:

$$\ln L^D(r,\delta,y) = \sum_i ((\ln(\Pr(SS)|y_i = SS) + \ln((1-\Pr(SS))|y_i = LL))$$

In our second specification, we allow for quasi-hyperbolic time-inconsistent discounting, with $\delta(t) = \beta\delta^t$, and estimate parameters β and δ, which we label as β_{qh} and δ_{qh}. We estimate the risk aversion parameter r and time-discounting parameter(s) of $\delta(t)$ (which we label as δ_{avg} in the univariate time-consistent specification and β_{qh} and δ_{qh} in the time-inconsistent discounting specification) that best explain an individual's choices.

Typically, a respondent chooses the smaller sooner option for a portion of the choices and switches to the larger later option for the remainder. Shifting between the smaller earlier and larger later options implies that the subject was indifferent at some point along the interval between the two rows, which defines a range of values for a time preference parameter. We utilize the point estimates for r, δ_{avg}, δ_{qh}, and β_{qh} as identified by maximum likelihood.[5] Intuitively, r is identified by the row in the risky choices that an individual switches from risky to safe choices, δ_{avg} and δ_{qh} are identified by the rows within the intertemporal question blocks that an individual switches from sooner to later options, and β_{qh} is identified by the consistency of the individual's choices between the intertemporal choice blocks. For the intertemporal questions, 90% of respondents exhibited zero or one switch (consistent with preference monotonicity) for the black block of questions, and 91% of respondents exhibited zero or one switch for the red and blue blocks. For the risk questions, 75% of respondents exhibited zero or one switch within the lottery series.[6]

To combat any hypothetical bias, we paid a random subset of between 5% and 20% of respondents (depending on the phase of the survey) based on their responses to the MPL questions. For each chosen respondent, one question was randomly selected as the payout question.[7] Payments were Amazon.com gift cards. To ensure trustworthiness

[5] Ferecatu and Önçüler (2016) provide an alternative methodology for estimating time and risk preferences, based on a hierarchical Bayesian methodology.

[6] An alternative and somewhat simpler way to calculate discount factors is employed by Meier and Sprenger (2010). They calculate a monthly discount factor for each of the three payout time pairs; call these $\delta_{0,1}$, $\delta_{0,6}$, and $\delta_{6,7}$. (That is, $\delta_{0,1}$ is the discount factor calculated using the respondent's answer to the MPL questions about payoffs now vs. one month from now.) The arithmetic mean of all three of these discount factors is δ_{avg}; this assumes time-consistent discounting. They allow for time-inconsistent discounting by noting that a respondent can have a different value for $\delta_{0,1}$ and $\delta_{6,7}$. If $\delta_{0,1}<\delta_{6,7}$, then consumers are present-biased. The present bias discount factor is $\beta_{qh}=\delta_{0,1}/\delta_{6,7}$ and the long-run discount factor $\delta_{qh}=\delta_{6,7}$. A caveat of using this method is that it drops observations for respondents failing to respond to one or more questions, as well as those with inconsistency in their responses, whereas our MLE method retains some of these individuals. Also, the present bias discount factors δ_{qh} and β_{qh} are calculated using just the red and blue blocks. Another methodology for calculating discount factors is to assume that a respondent was indifferent at any observed switching point; however, this method requires strong assumptions about whether to use the first or last switching point if a respondent leaves a question blank or exhibits multiple switches. Our results are robust to using these alternate calculation methods. An alternative strategy is to *require* that respondents only have at most one switching point by imposing that requirement in the survey, rather than asking about each pair separately; this is the method taken in, e.g., Tanaka et al. (2010).

[7] The payout questions include the time preference questions described here and the lottery questions asked to elicit risk preferences, described above.

of these payments, we emailed each winner immediately after the survey completion with one of the professors' contact information. The "today" payments were processed at 5 pm the day that the survey was completed, and the future payments were processed on the appropriate day (e.g. six months from the survey date). In either case, the payment was made via a gift card sent by email, and thus there was no difference in transaction costs across the present and future payments.

Two recent papers highlight potential problems with using MPLs to calculate individual time preferences. Andreoni and Sprenger (2012a, b) argue that discount rates from MPLs are upwardly-biased because of the frequent assumption of linearity in utility, and that risk and time preferences are intertwined, so calculating time preferences without risk preferences can lead to bias. They propose an alternative "convex time budget" (CTB) strategy for eliciting time (and risk) preferences, in which respondents are asked to make a continuous choice of saving versus consuming rather than a series of binary choices as in MPL.

Although the CTB method has advantages for analyses that focus on calculating the magnitude of discount factors, it is not practical for our application. The key drawback is that the procedure is far more time-consuming to administer since, unlike a series of binary choices, the choice set must be carefully explained and practice rounds used. The focus of our analysis is on how differences in discount factors between individuals (rather than their absolute level) are related to health, energy, and financial decisions. In this context, the experimental burden of the additional CTB questions would make the survey too lengthy to obtain an adequate sample. We do address other concerns raised by Andreoni and Sprenger by allowing for non-linear utility functions and by directly calculating and controlling for risk preferences. The ultimate purpose of our survey is not to provide point estimates of discount factors, but is instead to test for correlations between discount factors and outcomes. If all individual-level discount factors are biased downwards, this will not necessarily affect the direction or statistical significance of our estimated correlations between outcomes and the (potentially biased) discount factors. Despite the concerns about using MPLs to elicit time preferences, our results show that these methods do give values that are predictive of many real-world behaviors.

Table 3 presents summary statistics for our calculated time preference measures.[8] The empirical magnitudes of these calculated discount factors are not the main point of this study. Nevertheless, the magnitudes make sense and are in line with several previous papers that use MPLs for preference elicitation.[9] In Appendix C, we discuss in detail an account for these distinctions and how the MPL design in our paper may lead to this disparity. As discussed, an overall downward bias in the magnitudes of discount factors does not necessarily bias our main results about the relationship between discount factors and behavioral outcomes.

[8] For some subjects who exhibited multiple switching points (violating preference monotonicity), our MLE method returned implausibly large or small discounting parameters. We exclude subjects with fitted values of $\delta_{qh} < 0.45$, $\beta_{qh} < 0.25$, or $\beta_{qh} > 2.5$, which drops 8% of respondents.

[9] For examples, see Ioannou and Sadeh (2016), Meier and Sprenger (2010), and Frederick et al. (2002). The discount factors are low (discount rates are high) relative to studies that use alternative elicitation methods, such as convex time budgets (Andreoni and Sprenger 2012a) or Bayesian methods (Ferecatu and Önçüler 2016).

Table 3 Calculated discount factors

Parameter	Average [St. Error]	Percentile						
		5th	10th	25th	50th	75th	90th	95th
δ_{avg}	.889 [0.005]	0.450	0.664	0.887	0.943	0.974	0.998	1.015
δ_{qh}	0.893 [0.006]	0.450	0.682	0.892	0.953	0.982	1.004	1.024
β_{qh}	1.02 [0.011]	0.699	0.765	0.870	0.964	1.059	1.313	1.591

Table displays values of the specified parameter at given points in the distribution as well as the mean value and its standard error (in brackets). The sample size is 879

3.2 Dependent variables

We explore four categories of dependent variables: 1) health, 2) energy use, 3) finances, and 4) alternative measures of time preferences. The health questions were predominantly drawn from the US Center for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) 2011 questionnaire.[10] The first subset of these questions relates to self-assessed health. Respondents were asked if they would say that their health "in general" is excellent, very good, good, fair, or poor. We use this answer to create three binary outcomes: overall health good or better (versus poor or fair), very good or better (versus poor, fair, or good), and excellent (versus poor, fair, good, or very good). These categorizations implicitly combine those with poor and fair health because only 4% of respondents reported having poor health. Respondents were also asked the number of days in the past month that their physical and mental health were not good (two outcomes) and the number of days that health problems prevented them from doing their usual activities. We also include indicators for having any health insurance and for self-purchasing insurance conditional on not having employer-provided or public coverage.

The next subset of health questions pertain to behaviors. Respondents self-reported their height and weight, allowing us to compute body mass index (BMI). Since increases in BMI do not monotonically worsen health, we focus on a binary obesity indicator (BMI $\geq$ 30). To provide a preliminary assessment of behaviors directly affecting health and through which time preference may influence weight, we also asked respondents whether they had any non-work-related exercise in the past 30 days and how many snacks (sweet or salty) they consume on a typical day. In addition, we included current smoking status and number of cigarettes smoked per day among smokers, combined into a single variable for cigarettes smoked per day (0 for non-smokers).[11] Respondents were also asked about alcohol use. Since alcohol intake does

[10] That survey is available at: http://www.cdc.gov/brfss/.

[11] We considered separate models for smoking status and cigarettes per day among smokers, but the sample size in the regression containing only smokers was too small to obtain meaningful precision. We therefore are unable to disentangle whether effects of time preference on smoking occur along the extensive or intensive margins.

not monotonically worsen health, we focus on risky drinking as measured by the number of binge drinking occasions in the past month (4 or more drinks at one time for women and 5 or more for men). Finally, we included information on the use of sunscreen and seat belts, two behaviors that protect health. Table A1 in the Online Appendix reports summary statistics for these health-related variables.

The next set of outcomes relate to energy use, with questions predominantly drawn from the US Energy Information Administration's 2009 Residential Energy Consumption Survey.[12] First, we asked about the fuel economy of the respondent's primary vehicle, with the sample restricted to those owning any motor vehicles. Reporting options are <10 miles per gallon (mpg), 11–15 mpg, 16–20 mpg, 21–25 mpg, 26–30 mpg, 31–40 mpg, 41–50 mpg, and >50 mpg. We use answers to this question to construct three dependent variables: 16 mpg or greater (versus <10 and 11–15), 21 mpg or greater (versus <10, 11–15, and 16–20), and 26 mpg or greater (versus <10, 11–15, 16–20, and 21–25). This implicitly combines the two lowest categories since only 1.5% of the sample is in the lowest category, and also combines the four highest categories since only 10% of the sample is in any of the three highest categories.

The other energy use outcomes pertain to the home. Since renters are not fully incentivized to invest in energy-saving technologies (and may not even pay their own utility bills), we restrict the sample for the variables in this category to homeowners. The first four home energy dependent variables—dummies for having ever installed compact fluorescent lights (CFLs); frequently adding insulation; often caulking/weather stripping to seal windows, doors, and ducts; and having a programmable thermostat—relate specifically to investments in energy efficiency. The next two outcomes—a continuous measure of the temperature the respondents keep their home in the summer (with the sample restricted to those with thermostats) and a dummy variable for whether the respondent feels her household uses less energy than the average home in the neighborhood—relate to energy use more generally. Finally, we consider a dummy for having ever conducted a home energy audit. Summary statistics on the energy use outcomes, as well as those discussed next, are provided in Appendix Table A2.

We also include financial outcomes. We consider a small set of financial variables because the related literature is relatively well-developed compared to that on health and energy use (e.g. Meier and Sprenger 2010). The first is whether the respondent has any credit cards. We view the theoretical prediction for this outcome as ambiguous: impatience may increase the demand for credit, but also lead to a lower credit rating and therefore reduce access to it. Moreover, sophisticated time-inconsistent individuals may avoid credit cards to constrain their future behavior ("cutting up your credit cards"). Next is an estimate of total credit card debt, defined only for those with any credit cards. The last two outcomes are dichotomous and indicate whether the individual has any retirement or non-retirement savings.[13]

Finally, we consider five alternate time preference proxies to evaluate the robustness of MPL-elicited monetary time preferences. This also helps assess whether time

[12] That survey is available at: http://www.eia.gov/consumption/residential/. Additional questions were taken from the survey designed for Attari et al. (2010).

[13] Other health, energy, and financial variables were asked of respondents, although regression results are not reported here. The entire survey, including the questions not used in this study, is in Appendix B.

preferences differ across domains, in which case discount factors based on monetary tradeoffs may not be fully reflective of discount factors applied in health- or energy-related choices, and their estimated effects on these choices may therefore be conservative.[14] The first three, self-reported patience, willpower, and ability to resist junk food (willpower in a specific health-related domain) are answered on a scale of 1 to 10.[15] Our fourth measure is an elicited health-related discount factor, based on a series of hypothetical questions about drugs for migraine headache relief (Ganiats et al. 2000). Respondents are told to suppose that they suffer from debilitating migraines, and that two drugs are available to them. Both drugs are the same price but only one of them can be used. Drug A can be taken now, and Drug B will not be available until the future. Drug A will be effective for 12 months, but Drug B (once available) will be effective for 24 months. We then vary the delay for the availability of Drug B for periods ranging from 6 months to 7 years and compute each respondent's health-related monthly discount factor from the point at which he/she switches from Drug A to Drug B.[16]

The fifth outcome is a score based on responses to a Cognitive Reflection Test (CRT) developed by Frederick (2005). The CRT questions examine the ability to "reflect" on a response before committing to an answer provided by intuition.[17] Each of the three questions has one answer that springs quickly to mind based on intuition but is wrong. The questions are:

(1) A bat and a ball cost $1.10. The bat costs $1.00 more than the ball. How much does the ball cost? ____ cents
(2) If it takes 5 machines 5 min to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes
(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____ days

For instance, the answer that springs to mind for question 1 is 10 cents, although the correct answer is 5 cents.[18] Frederick (2005) posits that the CRT questions measure how able an individual is to use "system 2" to reflect on the answer provided by "system 1" (using the terminology coined by Stanovich and Wests (2000) and

[14] Chapman and Elstein (1995) find that individuals discount monetary and medical outcomes at different rates, whereas Ioannou and Sadeh (2016) find no difference in discount rates for money versus an environmental outcome: the number of bee-friendly flowers planted.

[15] The questions are: "How patient are you in general?", "How strong is your willpower/ability to control your impulses?", "How difficult is it for you to avoid eating a snack food you enjoy (e.g. chocolate chip cookies, ice cream, potato chips) if it is easily available, even if you are not hungry?"

[16] We calculated this health-related discount factor by assuming that a consumer was indifferent at the mid-point between the first observed switching row. For respondents that never switched, but for example always chose drug B, we assumed the respondent was indifferent at the most extreme delayed row. Eighty-two percent of subjects exhibited zero or one switch for these migraine questions. Note that this methodology implicitly assumes a linear utility function for health-related outcomes.

[17] CRT scores are also positively correlated with several standardized test scores, including the SAT and the ACT (Frederick 2005 Table 4).

[18] In question 2, the intuitive answer is 100 min, but the correct answer is 5 min. In question 3, the intuitive answer is 24 days, but the correct answer is 47 days.

popularized by Kahneman (2011)). Since correctly answering the CRT questions requires respondents to delay their response long enough for "system 2" reflection to take hold, correct responses to the CRT questions are likely related to time preference as well as cognitive ability. Summary statistics for these alternate time preference variables are reported in Appendix Table A3.

3.3 Control variables

Our models control for demographic characteristics that may be potential confounders of the relationships between time preferences and consumer behaviors including: age (in years), gender, income (in \$1000s), race, marital status, education, and number of children. Missing demographic variables are imputed based on regressions on the non-missing demographic variables.[19] Appendix Table A4 lists the control variables and provides summary statistics (before imputing missing variables).

3.4 Empirical model

The primary empirical objective is to test for statistically significant associations between time preferences and the dependent variables. We start by running two specifications for each outcome. The first models time preferences using the time-consistent discount factor δ_{avg}; the second uses the quasi-hyperbolic discount factors δ_{qh} and β_{qh}. These regressions take the form

$$y_i = \gamma_0 + \gamma_1 \delta_{avg,i} + \boldsymbol{\gamma}_2 \boldsymbol{X_i} + \varepsilon_i \tag{4}$$

and

$$y_i = \alpha_0 + \alpha_1 \delta_{qh,i} + \alpha_2 \beta_{qh,i} + \boldsymbol{\alpha}_3 \boldsymbol{X_i} + \epsilon_i \tag{5}$$

where i denotes individuals, X is a set of control variables, γ and α are parameters to be estimated, and ε and ϵ are error terms. The control variables are the CRRA score and dummies for age categories (25–34, 35–44, 45–54, 55–64, 65–74, and >74, with 18–24 being the omitted category); female; white non-Hispanic, black non-Hispanic, and Hispanic (other is the omitted category); high school graduate, some college, college graduate, and postgraduate degree (less than high school degree is the omitted category); currently married and never married (other is the omitted category); 1–2 children and 3 or more children (no children is the omitted category); and five income quintiles (lowest quintile is the omitted category).

[19] Age and income are the only control variables with a non-trivial number of missing values (3.3% and 5% of the sample, respectively). The results are robust (with occasionally slightly less significance) to simply dropping observations with any missing demographic variables or creating missing value dummy variables and including these observations. For the continuous variables that are modeled as a series of dummies (e.g. age and income), we impute by first running linear regressions for the continuous measure and then discretizing the predicted value by rounding to the nearest applicable unit (e.g. year of age, dollar of income).

Since a natural question is whether our elicited discount factors actually reflect time preferences as opposed to cognitive skill, we also consider two slight variations of this set of controls in unreported specifications (results available upon request). First, we exclude the education dummies, as these are the control variables that are likely most directly related to cognitive skill. Second, we include CRT score as an additional covariate since this variable is correlated with cognitive ability scores. The results using these alternate sets of explanatory variables are very similar to those from our main model.[20]

Our outcomes are a mix of continuous, binary, and count variables. We estimate probit models for the binary outcomes and negative binomial models for the count dependent variables. All reported estimates are average marginal effects.[21] In order to facilitate comparability of the estimated magnitudes of the effects of δ_{qh} and β_{qh}, we use standardized discount factor variables (with a mean of zero and a standard deviation of one) in all regressions. A one-unit increase in the discount factors therefore represents a rise of one standard deviation, and the average marginal effects can roughly be interpreted as the effects of one-standard-deviation increases.

4 Time preferences and outcomes

Tables 4, 5, 6 and 7 present average marginal effects for our main regressions examining the associations between time preferences and self-reported health, health behaviors, energy use, and financial outcomes.

4.1 Self-reported health status and health insurance

Self-reported health outcomes and health insurance coverage are focused upon in Table 4. All three discount factors are significantly positively correlated with the probability that respondents are in good or better (as opposed to fair or poor) health. While individuals with higher δ values are healthier than their counterparts who discount the future more heavily, the average marginal effect of a change in standardized present bias (β_{qh}) is about the same as that for standardized δ_{avg} or δ_{qh}: approximately a 2 percentage point increase (relative to the sample mean of 83%). Coefficients on the discount factors are still positive, though insignificant, in the very good or better health regressions. In the excellent health regressions, the only statistically significant discount factor is β_{qh}. The magnitude of a one standard deviation increase in β_{qh} is 2.2 percentage points, which is sizeable relative to the sample mean of 13%.

[20] We do not include CRT score as a control in the main specification because it likely depends at least partly on time preference. Adding it might therefore "control away" part of the causal effect of time preference. We acknowledge, though, that similar arguments could be made for some of the covariates we do include—namely education and income. It is therefore reassuring that including CRT score is of little consequence for the results.

[21] The results are generally similar using linear regressions, though the average marginal effects are often more precisely estimated by the non-linear models.

Table 4 Self-reported health status and health insurance

	Good or better health		Very good or better health		Excellent health		Days physical health not good	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
δ_{avg}	0.034*** (0.012)		0.021 (0.017)		0.011 (0.012)		−0.244 (0.295)	
δ_{qh}		0.023* (0.012)		0.012 (0.018)		−0.001 (0.012)		−0.131 (0.308)
β_{qh}		0.021* (0.013)		0.012 (0.017)		0.022** (0.010)		0.658** (0.331)
N	869	799	869	799	869	799	869	799
	Days mental health not good		Days activity is limited		Any health insurance		Bought own health insurance	
	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)	(8a)	(8b)
δ_{avg}	−0.797*** (0.282)		−0.793*** (0.270)		0.038*** (0.013)		0.059*** (0.022)	
δ_{qh}		−0.777*** (0.302)		−0.550** (0.266)		0.042*** (0.014)		0.061** (0.024)
β_{qh}		−0.252 (0.298)		−0.063 (0.311)		0.015 (0.015)		0.020 (0.031)
N	870	801	870	801	869	799	335	306

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include the following unreported controls: a constant, indicators for ten-year age categories, gender, race, indicators for five education categories, an indicator for married, indicators for three family size categories, indicators for five income categories, and CRRA. δ_{avg}, δ_{qh}, and β_{qh} are standardized to have a mean of 0 and standard deviation of 1. The sample in models (8a) and (8b) includes only persons who do not have health insurance through their or their spouse's employer or through the government

Turning to the other self-reported health variables, the results are more consistent with our predictions for mental health and activity limitations than for physical health. For number of days not in good physical health, both δ_{avg} and δ_{qh} have the expected negative association but are not statistically significant, whereas β_{qh} is significant but in the "wrong" direction. This coefficient suggests that a one-standard-deviation increase in β_{qh} is associated with an increase of about two-thirds of a day of not good physical health, relative to a sample standard deviation of 8.23 days. For days not in good mental health and days with activity-limiting health problems, the time-consistent discount factors are significant in the expected direction. The coefficient estimates for δ_{avg} are around −0.8 for both mental health and activity limitations, representing sizeable effects relative to the sample standard deviations of 7.9 for mental health and 6.8 for activity limitations. As a whole, the results for the self-reported health outcomes suggest that impatient individuals have worse health than their counterparts who discount the future less heavily. The evidence, however, is mixed as to whether present bias plays a role.

Patient individuals, measured by any of the three discount factors, are also more likely to have health insurance (though the effect is not statistically significant for β_{qh}). This holds for all consumers (models 7a and 7b), and among those without access to insurance through employers or government, who must purchase it themselves

Table 5 Health behaviors

	Obese		BMI missing		Days exercise last month		Snacks per day	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
δ_{avg}	0.021		−0.022***		0.960**		−0.182**	
	(0.018)		(0.007)		(0.405)		(0.072)	
δ_{qh}		0.026		−0.024***		0.754*		−0.155**
		(0.019)		(0.008)		(0.424)		(0.076)
β_{qh}		−0.002		0.004		0.770**		−0.005
		(0.017)		(0.008)		(0.375)		(0.066)
N	806	743	872	802	870	800	864	794
	Cigarettes per day		Times binge drinking last month		Always/nearly always use sunscreen		Always use seat belts	
	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)	(8a)	(8b)
δ_{avg}	−1.031**		−0.189**		−0.019		0.028**	
	(0.436)		(0.080)		(0.016)		(0.012)	
δ_{qh}		−1.195**		−0.153*		−0.019		0.028**
		(0.531)		(0.084)		(0.017)		(0.013)
β_{qh}		−2.399***		−0.163*		0.006		0.040**
		(0.702)		(0.096)		(0.016)		(0.016)
N	870	800	869	801	869	799	872	802

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include the following unreported controls: a constant, indicators for ten-year age categories, gender, race, indicators for five education categories, an indicator for married, indicators for three family size categories, indicators for five income categories, and CRRA. δ_{avg}, δ_{qh}, and β_{qh} are standardized to have a mean of 0 and standard deviation of 1

(columns 8a and 8b). Time preferences seem likely to be most important for this latter group since they directly buy health insurance rather than obtaining it from other sources. Consistent with this expectation, patience has a larger predictive effect for them: the average marginal effect of an increase in either standardized δ_{avg} or δ_{qh} is about a 6 percentage point increase in the likelihood of self-purchasing health insurance (sample rate 33%), versus a 4 point rise in the probability of having insurance from all sources (sample rate 74%).

4.2 Health behaviors

Table 5 examines the health behaviors exercise, snacking, smoking, drinking, and sunscreen and seatbelt use, as well as obesity. The time preference coefficients on obesity (models 1a and 1b) are surprising, as both δ_{avg} and δ_{qh} are associated with *higher* rates of obesity, though neither is statistically significant.[22] This is contrary to other studies finding a significant negative correlation between discount factor and BMI (e.g. Courtemanche et al. 2015). The next outcome in Table 5—a dummy for whether respondents' BMIs are missing—sheds some light on this puzzle. Both δ_{avg} and δ_{qh} are negatively and

[22] Results are similar for regressions where the dependent variable is BMI or severe obesity (BMI $\geq$ 35).

Table 6 Energy use

	MPG ≥ 16		MPG ≥ 21		MPG ≥ 26		Installed CFL		Added insulation	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
δ_{avg}	0.006 (0.013)		0.005 (0.020)		−0.010 (0.020)		0.046** (0.021)		−0.033 (0.024)	
δ_{qh}		0.000 (0.014)		−0.003 (0.021)		−0.014 (0.021)		0.046** (0.022)		−0.024 (0.026)
β_{qh}		0.007 (0.016)		0.021 (0.019)		0.035** (0.017)		−0.010 (0.021)		0.002 (0.023)
N	724	671	724	671	724	671	504	461	502	459
	Added weather stripping		Programmable thermostat		Summer temperature in home		Less energy than average		Energy audit	
	(6a)	(6b)	(7a)	(7b)	(8a)	(8b)	(9a)	(9b)	(10a)	(10b)
δ_{avg}	0.013 (0.025)		0.024 (0.026)		0.175 (0.242)		0.009 (0.025)		−0.014 (0.018)	
δ_{qh}		0.009 (0.027)		0.030 (0.028)		0.039 (0.248)		0.021 (0.027)		−0.002 (0.019)
β_{qh}		0.055** (0.023)		0.031 (0.023)		0.010 (0.169)		0.028 (0.023)		0.001 (0.016)
N	500	458	494	451	369	340	501	458	501	458

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include the following unreported controls: a constant, indicators for five-year age categories, gender, race, indicators for five education categories, an indicator for married, indicators for three family size categories, indicators for ten income categories, and CRRA. δ_{avg}, δ_{qh}, and β_{qh} are standardized to have a mean of 0 and standard deviation of 1. The sample in models (1a) through (3b) includes only vehicle owners, the sample in (4a) through (10b) includes only homeowners, and the sample in models (8a) and (8b) includes only those who have a thermostat

significantly associated with the failure to report at least one of the components of BMI: height or weight. This pattern would be explained if impatient individuals are more likely to be overweight, and if overweight people are more likely to be embarrassed about reporting their weight (or simply not know it).[23]

Time preferences seem to influence the behaviors that cause obesity in the predicted direction. The relationships between exercise and the discount factors are positive and significant. The average marginal effect of an increase in standardized δ_{avg} is just less than one day of exercise per month (the standard deviation for exercise is 9.96). Patient individuals consume significantly fewer snacks, with an average marginal δ_{avg} effect of about 0.18 less per day (standard deviation 2.37). These findings suggest that high discount rates reduce exercise and contribute to unhealthy eating. The point estimates further indicate that self-control problems may be relevant for these decisions, as present-biased individuals exercise less than their counterparts (though there is no significant relationship between present bias and snacking).

[23] There are 66 respondents for whom the information required to calculate BMI is unavailable. Of those, all of them fail to report their weight, compared to just 25 who fail to report height.

Table 7 Financial outcomes

	Any credit card		ln(credit card balance)		Any non-retirement savings		Any retirement savings	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
δ_{avg}	0.030**		−0.469**		0.035**		0.035**	
	(0.015)		(0.188)		(0.017)		(0.017)	
δ_{qh}		0.035**		−0.474**		0.026		0.040**
		(0.016)		(0.206)		(0.018)		(0.018)
β_{qh}		−0.005		−0.254		0.033*		0.010
		(0.015)		(0.202)		(0.017)		(0.015)
N	865	795	517	473	864	795	862	793

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include the following unreported controls: a constant, indicators for ten-year age categories, gender, race, indicators for five education categories, an indicator for married, indicators for three family size categories, indicators for five income categories, and CRRA. δ_{avg}, δ_{qh}, and β_{qh} are standardized to have a mean of 0 and standard deviation of 1. The sample in models (2a) and (2b) includes only those with a credit card

The three discount factors are negatively and significantly associated with both smoking and binge drinking: a one-standard-deviation increase in any of the discount factors predicts about a one to two cigarette reduction in daily smoking and a 0.15 to 0.19 occasions per month decrease in binge drinking (sample standard deviations of both outcomes are 2.2).[24] Particularly striking are the results in columns (5b) and (6b), which show that time-consistent discounting and present bias both play a role in explaining substance use. Our finding that impatient and present-biased individuals are more likely than others to smoke and drink excessively is consistent with our a priori hypotheses that more immediate and highly salient decisions are more likely to be affected by present bias and with prior research showing that δ is related to smoking and drinking (Sutter et al. 2013) and β to smoking (Chabris et al. 2008). Mixed results are obtained for the risk-reducing behaviors sunscreen and seat belt use. Patient individuals are more likely to use seatbelts, but there is no significant correlation with sunscreen use.[25]

[24] The results are robust to many other measures of smoking, including an indicator for being a regular smoker or for having smoked at least 100 cigarettes in one's life. Results are similar but less significant for some other drinking measures, including number of drinks per week. We focus on binge drinking because moderate alcohol consumption is not necessarily unhealthy.

[25] The negative (though insignificant) association between δ and sunscreen use might occur because more patient people are less likely to be out in the sun at all, and therefore less often use sunscreen. The positive coefficient for the seat belt regressions is consistent with our expectations and it is mirrored by a slightly larger coefficient on β_{qh}. An alternate hypothesis is that more patient people are less likely to wear a seat belt since they may drive more slowly or safely and not feel the need to wear one. The correlation we find could also be explained by aversion to being caught and fined, since this is a relatively easily detected violation.

4.3 Energy use

Table 6 presents regression results for the outcomes reflecting investments in energy-efficient technologies and energy consumption. There is little evidence of a relationship between discount factors and vehicle choice in columns (1a) through (2b), but when we look at the choice of the most fuel-efficient vehicles (at least 26 MPG), there is a significant positive correlation between β_{qh} and fuel economy. The coefficient estimate is 3.5 percentage points, a sizeable portion of the sample rate of 31%. Because cars are a big-ticket item, liquidity constraints mean that time preferences can be especially relevant to these decisions, consistent with our hypotheses.

The next four pairs of columns examine residential energy efficiency investments. Patient individuals are more likely to have installed energy-efficient lighting (columns 4a and 4b), and it is the time-consistent discount factor (δ) rather than present bias (β) that matters.[26] Adding insulation, weather stripping, and having a programmable thermostat are generally not significantly related to discount factors, with the exception being a positive coefficient on β_{qh} in the weather stripping regression (6b), but the positive point estimates in columns (6a) through (7b) are expected. More patient and less present-biased individuals cool their homes less in the summer and are more likely to self-report using less energy than average, but these relationships are not significant. There is no clear linkage between time preferences and having had an energy audit.[27]

4.4 Financial outcomes

Results for financial outcomes are reported in Table 7. Patient individuals as measured by δ are more likely to have a credit card—the average marginal effects of δ_{avg} and δ_{qh} are 3.0 and 3.5 percentage points, respectively—but, conditional on having one, to have a lower credit card outstanding balance. We observe a negative correlation between present bias β_{qh} and credit card balance, although the point estimate is insignificant. This is consistent with our hypothesis that purely financial decisions are more likely to be affected by δ than by β.[28] Patient individuals and those with lower present bias are more likely to have non-retirement or retirement savings, although the predicted positive relationship is not always significant: δ_{avg} is significant for both types of savings, with identical marginal effects of 3.5 percentage points; β_{qh} is significant in the non-retirement savings regression, whereas δ_{qh} is significant for retirement savings.

26 These findings are consistent with Allcott and Taubinsky (2015)—see their Table A2–1.

27 By contrast, Newell and Siikamäki (2015) find that elicited discount factors (not allowing for quasi-hyperbolic discounting) are significantly correlated with energy-efficiency investment decisions. Their study differs from ours in a number of ways that may influence the results. First, their elicited time preferences are calculated from a series of hypothetical money trade-off questions, rather than our MPL questions that can accommodate quasi-hyperbolic preferences and in which actual (non-hypothetical) payouts are made to a random subset of respondents. Second, their energy-efficiency outcome variable is based on responses to a hypothetical choice experiment over water heater purchases, rather than actual energy-efficiency purchases. Their robust, significant results combined with our less strong results may suggest that present bias can sever the link between planned energy-efficiency investments (as measured in their hypothetical water heater purchases) and actual investments.

28 However, Meier and Sprenger (2010) find a correlation between credit card balance and an indicator for present bias at either the 5% or 1% level depending on the specification. Their sample consists of primarily low- to moderate-income individuals whereas ours is representative of the overall population, which may explain the difference.

5 Robustness checks

Appendix Tables A5–A8 replicate the main regression results but use the sample that drops any respondent who exhibits a violation of preference monotonicity, as described earlier. The results are robust to this alternate specification, though the significance of the results is somewhat weaker due to the small sample size.[29]

Table 8 examines the robustness of our elicited monetary time preference measures by estimating their associations with the other variables potentially related to time preference. The first three outcomes are the self-reported indicators of patience, general willpower, and willpower over junk food, each ranked on a ten-point scale and modeled with negative binomial regressions. These can be thought of as measures of time preferences in their own right or, particularly for willpower, as indicators of present bias.

The self-reported patience and willpower measures are usually not significantly related to the elicited monetary discount factors. The exception is that general willpower is positively correlated with δ_{avg}. Willpower, or lack thereof, has been hypothesized to be a determinant of present bias (e.g. see Ruhm 2012), so one might expect a positive correlation with β. However, it is also reasonable to think of willpower as a more fundamental component of time discounting, potentially explaining the relationship with δ.

The fourth outcome is the monthly discount factor based on responses to the hypothetical migraine questions, denoted $\delta_{migraine}$. We run a linear regression with all discount factors standardized. One standard deviation increases in δ_{avg}, δ_{qh}, and β_{qh} are associated with increases in $\delta_{migraine}$ of around 0.06 to 0.08 standard deviations. δ_{avg} and β_{qh} are statistically significant, while δ_{qh} is not quite significant. These results can be interpreted in two ways. First, the significant associations provide evidence that the elicited discount factors represent actual time preferences, rather than just noise. Second, the relatively small magnitudes of these associations raise the possibility that individuals discount across domains in different ways (Chapman and Elstein 1995; Ioannou and Sadeh 2016), or that they do not perfectly understand the (fairly complicated) migraine medication questions, so that their responses indicate discount factors with error.

The results for the last dependent variable in Table 8 show that the monetary discount factors are significantly correlated with the CRT score, which likely reflects a combination of patience and cognitive ability. In these negative binomial regressions, the CRT score, which ranges from 0 to 3, is positively and significantly correlated with both measures of δ, with average marginal effects being around 0.1. The coefficient on the present bias parameter β_{qh} is smaller and insignificant, which is somewhat surprising since the CRT score has been viewed as a measure of the ability to resist intuitive but incorrect answers. An alternative possibility is that this score is associated with broader measures of cognitive skill which are either correlated with or a component of time-consistent discounting.

[29] In the main specifications in Tables 4 through 7, there are 41 statistically significant (at least the 10% level) coefficients, and in Appendix Tables A5 through A8 that number drops to 34, while the sample size for most of the regressions drops from about 800 to about 600 observations. Of the 41 coefficients that were statistically significant in our main results, the magnitudes actually increase for 25 of them after imposing the sample restriction, suggesting that the reduced statistical significance is merely the result of the smaller sample size.

Table 8 Alternate time preference measures

	Patience		Willpower		Willpower with junk food		$\delta_{migraine}$		CRT score	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
δ_{avg}	0.026		0.170*		0.031		0.077*		0.094***	
	(0.040)		(0.102)		(0.115)		(0.039)		(0.025)	
δ_{qh}		0.023		0.121		0.005		0.059		0.120***
		(0.043)		(0.109)		(0.122)		(0.042)		(0.027)
β_{qh}		0.002		−0.011		−0.055		0.081**		−0.000
		(0.035)		(0.094)		(0.111)		(0.034)		(0.035)
N	862	794	861	792	864	796	859	792	864	795

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include the following unreported controls: a constant, indicators for ten-year age categories, gender, race, indicators for five education categories, an indicator for married, indicators for three family size categories, indicators for five income categories, and CRRA. δ_{avg}, δ_{qh}, and β_{qh} are standardized to have a mean of 0 and standard deviation of 1

In sum, our elicited monetary time preference measures are only partly predictive of the other time preference proxies. This could indicate that the alternative indicators are not as informative about actual discounting behavior as the elicited time preferences, or that these other proxies capture information about "true" discount factors beyond those contained in the elicited small-stakes monetary measures. To the extent that the latter occurs, our estimated effects on consumer behaviors from Tables 4–7 may understate the true effects of time preference. In Appendix D, we implement Lubotsky and Wittenberg's (2006) method for leveraging the availability of multiple proxies to minimize attenuation bias; we find that, indeed, many of our estimated associations with consumer behaviors strengthen considerably when time preference is modeled as a composite index reflecting all the different candidate measures.

6 Conclusion

This paper provides evidence that many outcomes and behaviors related to health, energy, and finances are correlated with time preference parameters elicited from MPLs. The results are particularly strong for the health and financial outcomes. Significant effects are observed in our main specifications for several important dimensions of health and health behavior: good or better health, days in bad mental health, days where poor health significantly limited activities, health insurance, exercise, snacking, smoking, drinking, and seat belt use. In all, the only health outcome for which we do not observe any significant results is sunscreen use. Similarly, the evidence suggests that time preferences influence all our financial outcomes, which reflect the first-order financial considerations of savings and debt.

The evidence from the energy use regressions is generally weaker, although in almost all columns the sign is of the expected direction but not quite significant. This is likely due in part to the smaller sample size in these regressions, being restricted to either car owners or homeowners. Alternatively, the weaker results from the energy regressions could indicate that time preferences are less important to these decisions, suggesting that the energy efficiency gap is explained by something other than time preferences, for instance by lack of information.

Our results are generally but not universally supportive of the four hypotheses that motivated our analysis. First, discount factors were predicted to be correlated with all of the outcomes. Estimates for δ_{avg} or δ_{qh} generally had the expected sign, although they were not always statistically significant. Second, we predicted that highly salient decisions over utility or consumption are more likely to be correlated with β than are decisions only over money. This hypothesis is supported in Table 5 by the significant correlation between β and exercise, smoking, binge drinking, and seatbelt use. Third, we predicted that big-ticket items, for which consumers are more likely to face liquidity constraints, will be highly associated with time preferences; this was verified in the correlation with the fuel economy of one's car in Table 6, and in Table 4 in the relationship between time preferences and health insurance. Fourth, we predicted that time preferences are more highly correlated with aggregate measures, rather than individual intertemporal decisions, motivated by Chabris et al. (2008). We found mixed support for this hypothesis. In Table 4, several of the overall self-reported health measures (including "excellent health" and "days activity is limited") are significantly correlated with time preferences, but not any more so than individual decisions like smoking and drinking in Table 5. In Table 6, we find no evidence that time preferences affect the summary question about using less energy than average, though this could simply be because of the subjective nature of the question.

We also examine how well our elicited time preferences from the monetary domain predict alternative time preference measures. Self-reported willpower, an elicited discount factor related to migraine headaches, and CRT score all exhibit a modest association with monetary discount factors, but self-reported patience and willpower with junk food do not. The lack of strong associations suggests that monetary discount factors do not capture all aspects of time preferences, in which case their estimated effects on consumer behaviors are likely conservative.

One potential caveat of our analyses is that, since we study a large number of dependent variables, we might expect a few significant results to emerge by chance: around three per coefficient of interest at the 10% level, one or two at the 5% level, and possibly one at the 1% level. We elected not to employ specific methods to adjust the p-values for multiple hypothesis testing because even though such adjustments control the Type I error rate (probability of falsely rejecting any null hypotheses) they do so at the cost of substantially increasing the Type II error rate (probability of failing to reject false null hypotheses).[30] Moreover, for each coefficient of interest, we obtain far more significant results than could occur due to chance, so the overarching conclusion that time preferences influence consumer behavior is not merely the artifact of examining a large number of outcomes. Nonetheless, future research should revisit our questions using different data to evaluate whether any of the results for specific outcomes could be attributed to chance.

[30] For instance, a Bonferroni correction would mean multiplying the p-value for our most highly significant result by 30, which strikes us as excessively cautious for a relatively small-scale survey. The procedure from Holm (1979) is also very conservative.

This study also suggests many other areas for future research. First, would our results persist with larger samples or with preference elicitation strategies that provided respondents with larger risks or rewards? Second, do the observed responses of future bias represent true preferences or measurement error? If future bias exists, how do we explain it and what are the implications for these types of modeling efforts? Third, which of the outcomes examined in this investigation are most important and what other outcomes would be critical to analyze? More generally, are there strategies for deciding which dependent variables, among an almost infinite set of possibilities and domains, researchers should study? Fourth, do the phenomena observed in this analysis show systematic patterns among subgroups stratified by characteristics such as age, gender and socioeconomic status? Fifth, if present bias matters, what is the role of sophistication versus naiveté? Sixth, is there differential demand for commitment devices or elimination of choice sets across the domains of health, energy, and financial decisions? Finally, although our results suggest numerous potential avenues for policy, which interventions would actually lead to improvements in social welfare and how would these most effectively be implemented?

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