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Abstract

We investigate the predictive power of survey-elicited time preferences using a representative sample of US residents. In regressions controlling for demographics and risk preferences, we show that the discount factor elicited from choice experiments using multiple price lists and real payments predicts various health, energy, and financial outcomes, including overall self-reported health, smoking, drinking, car fuel efficiency, and credit card balance. We allow for time-inconsistent preferences and find that the long-run and present bias discount factors (δ and β) are each significantly associated in the expected direction with several of these outcomes. Finally, we explore alternate measures of time preference. Elicited discount factors are correlated with several such measures, including self-reported willpower. A multiple proxies approach using these alternate measures shows that our estimated associations between the time-consistent discount factor and health, energy, and financial outcomes may be conservative.

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I. Introduction

Time preferences are generally considered to be a primitive of economic decision-making and so 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. However, the specific manner in which patience (or future-orientation) affects intertemporal resource allocation is the subject of ongoing debate. The standard economic model assumes that agents make consistent intertemporal decisions – which implies a constant rate of discounting. Contrarily, growing evidence from behavioral economics and psychology suggests that many individuals exhibit present bias, whereby the weight placed on consumption now relative to tomorrow is greater than that placed on consumption one year from now relative to one year and a day from now.

Whether individuals have time-consistent preferences is not merely an academic question. Time inconsistency may induce inefficient decisions. Present bias, if real, provides a potential justification for government intervention, since individuals may make decisions in the present that they will regret in the future – a situation that government fiat may avoid (O'Donoghue and Rabin 2006). For instance, time-inconsistent consumers may be less willing to invest in energy-efficient technologies (e.g. hybrid cars, home energy improvements) if they do not account for future savings as much as the standard model assumes; this is a potential explanation of the energy efficiency gap and rationale for government intervention (Allcott and Greenstone 2012). Policies related to health behaviors are affected since time-inconsistent consumers may underinvest in health, e.g. by eating too much, exercising too little, or failing to buy insurance. Policies designed to encourage retirement savings may also 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. We contribute to the literature by considering a much broader range of outcomes than those studied previously. In so doing, we explore the degree to which consumer choices comport to the standard economic model or to the new behavioral economic models, and so illuminate how effective people can be at making decisions that maximize utility in the long run while also minimizing regret. The results provide direct evidence of the link between both time-consistent and time-inconsistent preferences and numerous outcomes related to health, energy, and financial behavior.

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 ($\beta\delta$) specification, 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 time preferences about monetary payoffs. To address these challenges, we also consider alternative measures of time preferences, including self-reported preferences and questions specifically tailored to health decisions. These alternate proxies allow us to investigate whether certain measures predict behavior better overall or in specific domains, and they enable us to assess how measurement error impacts our estimates from regressions using elicited time preferences.

Our data show that time preferences elicited using MPL questions over monetary payouts are significantly correlated in the expected direction with many outcomes related to health, energy use, and finances. In regressions controlling for demographic and risk preference variables, the time-consistent discount factor is significantly correlated with self-reported overall and mental health, activity limitations, refusal to report weight or height, snacking, smoking, binge drinking, seat belt use, having health insurance, installing energy-efficient lighting, the temperature setting on one's thermostat, retirement savings, and credit card balance. The present bias discount factor β is statistically associated in the predicted direction with self-reported overall and mental health, activity limitations, refusal to report weight or height, smoking, binge drinking, driving a fuel-efficient car, reporting a well-insulated home, the temperature setting on one's thermostat, and having non-retirement savings. Our elicited time preferences are also associated with some but not all of our alternative time preferences proxies. Interestingly, time preferences elicited from hypothetical questions related to health are generally less significant predictors of actual health outcomes than are time preferences for monetary outcomes elicited from MPL questions. Finally, we implement Lubotsky and Wittenberg’s (2006) method of using multiple proxies to correct for measurement error and provide evidence that our prior estimated effects of elicited time preferences on consumer behaviors may be conservative.

The results therefore suggest that both time-consistent and present-biased discounting influence many aspects of health, health behaviors, energy use, and financial decisions, with the relative extent to which each matters varying across different outcomes. The importance of present bias suggests additional potential implications for policy design, as mentioned above.

II. Background

Time preferences have been conceptualized in a variety of ways. Among the earliest modern theoretical frames is from Samuelson (1947). Samuelson 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 (if a person is willing to accept $1 to wait until tomorrow to consume something, then that person will be willing to accept $1 to delay that same consumption by a day in any future period). Thus individuals were assumed to select consumption levels in each time period, x_t, to maximize

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

subject to an income/wealth constraint. In Samuelson's model, which is still the canonical approach today, the exponential weighting function $\delta(t) = \delta^t$ implies constant discounting 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. In this paper we will label this time-consistent discount factor as δ_{avg}.

In the early 1990s, however, some researchers built an alternative framework based upon Strotz (1955) that suggested individuals may 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

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

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. In what follows, we label this pair of preference parameters as β_{qh} and δ_{qh}.

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 forthcoming). Gillingham and Palmer (2013) 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.

Still other investigations estimate the associations between elicited 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; 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), and overall self-assessed health (Van der Pol 2011). Finally, there is research indicating that present bias is related to a limited set of outcomes such as: smoking (Burks, et al. 2012), credit card borrowing (Meier and Sprenger 2010), BMI (Ikeda et al. 2010; Courtemanche et al. forthcoming), and “underwater” mortgages (Toubia et al. 2013).

Our study's contribution is threefold. First, we examine how survey-elicited time preferences are related to a large and 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 elicited time preferences and many of our outcomes: self-assessed physical and mental health, health-related limitations, snacking, binge drinking, sunscreen and seatbelt use, variables related to home and automobile energy use, among others. Second, our study allows for quasi-hyperbolic discounting and disentangles whether the diverse group of observed relationships are driven by time-consistent preferences (δ), present bias (β) or both. We are unaware of prior research on the relationship between elicited time inconsistency and any of our outcomes, with the exception of smoking, BMI, and credit card debt as noted above. Third, in our judgment we provide the most thorough attempt to assess how the predictive power of time preferences elicited over monetary outcomes compares to that of other time preference measures across different domains, and whether this implies meaningful attenuation bias in estimates based on elicited monetary measures.

III. Data and Model

An online survey of 1,325 respondents was conducted using Qualtrics software (www.qualtrics.com). Respondents were chosen to be representative of the US adult population (18 and over), using quota sampling based on age, education, and gender. The survey was conducted in July and August 2013.

Elicited Time Preferences

We measured impatience and present bias using three "blocks" of multiple price list (MPL) questions. 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 payment ranged from $8 to $29. Each respondent was asked 22 such questions; the values are listed in Table 1.[1] Typically respondents choose the smaller earlier option for a portion of the choices and switch 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.

Table 1 also lists the implied monthly discount factor for a consumer who is just indifferent between the larger and smaller payments, along with the percentage of respondents choosing the larger amount. For instance, in the first row of the red block, a consumer who is

[1] 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).

just indifferent between $29 today and $30 in one month has a one-month discount factor of 0.9667 (29 = 30 * 0.9667), and 24.22% of respondents chose $30 in one month over $29 today. For each block, the percentage choosing a delayed payout increases as the earlier payment decreases, as expected. Comparing the red block to the black block reveals the anticipated finding that respondents are less willing to wait for a given (larger) payoff that is farther in the future. Additionally, these responses provide 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 third through sixth 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 calculate two sets of discount factor parameters based on the MPL questions. Within each block of time preference choices, we assume that respondents were indifferent between the smaller earlier option and the larger later option at the mid-point between the values at which the respondent switched from earlier to later choices.[2] First, we impose time-consistent discounting using a single monthly discount factor and use non-linear least squares to determine the parameter δ_{avg} that best-fits a respondent's indifference points for the three blocks of time

[2] If a respondent never switched between earlier or later options, but for example always chose the larger later option, then we assume he/she was indifferent at the most extreme delayed row. If a respondent switched between smaller earlier and larger later options multiple times (violating preference monotonicity), we utilized the mid-point between the first switching row as our measure of indifference. 90% of respondents exhibited zero or one switch for the black block of questions, and 91% of respondents exhibited zero or one switch for the red and blue blocks. Our results are robust to either utilizing the last observed switch between smaller sooner and larger later choices, or to excluding subjects who exhibited multiple switches.

preference questions. Next, we best-fit a respondent's choices assuming a quasi-hyperbolic discounting specification with two parameters δ_{qh} and β_{qh}.[3]

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.[4] Payments were Amazon.com gift cards. To ensure trustworthiness of these payments, we emailed each winner immediately after the survey completion with one of the professors' contact information.

Table 2 presents summary statistics for our calculated time preference measures. The time-consistent monthly discount factor δ_{avg} averages around 0.85, which is low for a monthly discount factor but consistent with previous literature finding low discount factors when using MPLs (Meier and Sprenger 2010, Frederick, Loewenstein and O'Donoghue 2002). δ_{avg} exhibits significant variation; the 25th and 75th percentiles are 0.81 and 0.95 respectively.[5] The mean value of β_{qh} is 0.94, indicating that the average respondent is present biased. Once again there is considerable heterogeneity, with 10 percent of respondents having values below 0.68, 25 percent lower than 0.85, and 26% above 1.0 indicating future-bias. For a small number of respondents,

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[3] 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 $\beta_{qh} = \frac{\delta_{0,1}}{\delta_{6,7}}$ 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. Also, the present bias discount factors δ_{qh} and β_{qh} are calculated using just the red and blue blocks. In general, our results are robust to using this alternate calculation.

[4] The payout questions include the MPL questions described here and the lottery questions asked to elicit risk preferences, described below.

[5] Given the structure of the multiple price list questions, it is not possible to have a discount factor δ above 1, since no questions have a payoff in an earlier period that is greater than the payoff in a later one.

the results suggest implausibly extreme future bias, probably indicating reporting errors, an issue to which we return below. Because the mean value of β_{qh} is less than one, $\delta_{qh} > \delta_{avg}$, on average. Table 2 shows that this is also true throughout most of the distribution, although the differences are not huge.

Control Variables

A caveat to eliciting time preferences using solely MPL questions is that it relies on the assumption that utility is linear in income. Measuring time preferences without controlling for risk preferences can lead to misleading results (Andersen, et al. 2008, Andreoni, Kuhn and Sprenger 2013), although in our application the payoffs are sufficiently small that the assumption of linearity is likely to be innocuous. Nevertheless, to further reduce the possibility of incorrect inference, we adopt the strategy of using double multiple price lists (DMPL).[6] We included an additional series of questions about preferences over lotteries (see Andersen et al. (2008), p. 586). In each case, the respondent was asked to choose between two lotteries: both have the same *probabilities* of winning larger or smaller amounts, but the actual *amounts* vary. Table 3 summarizes the lotteries.[7] 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, the risk aversion coefficient that makes an individual indifferent between the two lotteries increases in the later rows. Specifically, the risk aversion coefficient is calculated based on the constant relative risk aversion (CRRA) specification:

$$U(M) = \frac{M^{1-r}}{1-r} \tag{3}$$

[6] In addition to DMPL, Andreoni et al. (2013) consider an alternative convex time budgets (CTB) strategy. We use DMPL, because the computational burden on the participants of the CTB questions would have been too great given the other questions that are asked in our survey.
[7] The probabilities and dollar values are taken from Andersen et al. (2008).

where the CRRA coefficient is *r* and consumption is *M*.[8] Table 3 shows that as the expected value of B becomes relatively larger than that of A, the number of respondents choosing B (the riskier lottery) increases. We calculate the CRRA by assuming a respondent was indifferent at the mid-point between the values at which he or she switched from certain to risky choices.[9] The average CRRA value is 0.422, implying that the typical sample member is risk averse. In our sample, we observe a negative correlation between CRRA and elicited time preferences (-0.084). However, excluding CRRA from the set of controls (results available upon request) has little effect on the regression estimates.

We also asked respondents a set of questions about demographic characteristics that included: age (in years), gender, income (in $1,000), race (non-Hispanic white vs. nonwhite or Hispanic), marital status (married vs. unmarried), education (less than high school, high school graduate, some college, college graduate, postgraduate) and number of children. Controlling for these variables allows us to account for many obvious potential confounders of the relationships between time preferences and consumer behaviors. Appendix Table 1 lists the control variables and provides their summary statistics.

Dependent Variables

We explore four categories of dependent variables: 1) health, 2) energy use, 3) finances, and 4) other measures of time preferences. The health questions were predominantly drawn from the US Center for Disease Control and Prevention's Behavioral Risk Factor Surveillance

[8] For instance, for a consumer who is just indifferent between lottery A and lottery B in the first row of Table 3, risk aversion is the r that solves the equation: $0.2\left(\frac{20^{1-r}}{1-r}\right)+0.8\left(\frac{20^{1-r}}{1-r}\right)=0.2\left(\frac{38.5^{1-r}}{1-r}\right)+0.8\left(\frac{1^{1-r}}{1-r}\right)$ so that $r=-0.95$. See Andersen et al. (2008), p. 590.

[9] Similar to the time preference methodology, we assumed indifference at the endpoint if a respondent never switched between certain and risky choices. If the respondent switched between certain and risky choices multiple times, we utilized the first observed switch. 75% of respondents exhibited zero or one switch for the lottery series.

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 two binary outcomes: overall health good or better (versus poor or fair) and very good or better (versus poor, fair, or good).[11] They 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 their health problems prevented them from doing their usual activities. We also included two indicators of the probability of having any health insurance and of 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≥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).[12] Respondents were also asked about alcohol use. Since alcohol intake does 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

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

[11] We also considered dependent variables measuring for overall health fair or better and excellent health. The results for fair or better were similar to those for good or better; those for excellent were similar to those for very good or better.

[12] 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.

men). Finally, we included information on the use of sunscreen and of seat belts, two behaviors that protect health. Appendix Table A2 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.[13] The first dependent variable indicates whether the respondent owns a high-fuel-economy vehicle (higher than 25 mpg), with the sample restricted to those owning any motor vehicles. The home energy outcomes include dummies for respondents having: ever installed compact fluorescent lights (CFLs) in their homes, a well-insulated home (in their opinion), a programmable thermostat, and ever conducted a home energy audit. Since renters are not fully incentivized to invest in energy-saving technologies, we restrict the sample for these variables to persons who have owned their current home for at least two years. The final outcome in this section is a continuous measure of the temperature the respondents keep their home in the summer (with the sample restricted to those with thermostats). Summary statistics on these outcomes, as well as those discussed next, are provided in Appendix Table A3.

We also include financial outcomes. We consider only a small set of financial variables because the literature on these and similar outcomes 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 demand for credit, but also lead to a lower credit rating and therefore reduce access to it. Moreover, sophisticated time-inconsistent individuals may refuse to have credit cards to constrain their future behavior (i.e. "cutting up your credit cards"). Next

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

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.

The final category of dependent variables, also used as covariates in some specifications, is included to evaluate the relationships between MPL-elicited monetary time preference measures and other measures. They also help address the concern that time preferences may differ across domains, in which case discount factors based on monetary tradeoffs may not be reflective of discount factors applied in health- or energy-related choices, and their estimated effects on these choices may therefore suffer from attenuation bias.[14] We consider five alternate time preference proxies. The first three are self-reported patience, willpower, and ability to resist junk food (willpower in a specific health-related domain), 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). In each question, the 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. We compute each respondent's health-related discount factor from the point at which he/she switches from Drug A to Drug B, identically to our methodology for discount factors over monetary outcomes.[16]

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[14] For instance, Augenblick et al. (2013) provide experimental evidence that consumers exhibit more present bias in choices over work effort tasks than in choices over money.

[15] The exact 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] 82% of subjects exhibited zero or one switch for these migraine questions.

Additionally, we consider another outcome in this category: a score based on responses to a "Cognitive Reflection Test" (CRT) developed by Frederick (2005). The CRT questions measure 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 minutes 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 West (2000) and popularized by Kahneman (2011)). Since answering the CRT questions correctly requires the patience to resist the immediately obvious answer, it is likely related to time preference as well as cognitive ability. Summary statistics for these alternate time preference variables are reported in Appendix Table A4.

We hypothesize that individuals with higher discount factors (more patience) will exhibit better health and healthier behaviors, engage in purchases or actions promoting energy

[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 minutes, but the correct answer is 5 minutes. In question 3, the intuitive answer is 2 days, but the correct answer is 47 days.

efficiency, and have more savings. This will generally be true for both the time-consistent (δ_{qh}) and quasi-hyperbolic (β_{qh}) components of preferences. However, we might expect the latter to be more important for outcomes that may reflect a failure to follow through with intended actions. For instance, *ex ante* we might expect impulse decisions such as snacking and binge drinking to be more heavily influenced by present bias than major purchases such as health insurance coverage.

Model

The primary empirical objective is to identify 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

$$y_i = \gamma_0 + \gamma_1 \delta_{avg,i} + \boldsymbol{\gamma_2 X_i} + \varepsilon_i \tag{4}$$

and

$$y_i = \alpha_0 + \alpha_1 \delta_{qh,i} + \alpha_2 \beta_{qh,i} + \boldsymbol{\alpha_3 X_i} + \epsilon_i \tag{5}$$

where *i* denotes individuals, $\boldsymbol{X_i}$ 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, age categories (18-20, 21-25, 26-30, …, 76-80, >80), gender, race (white non-Hispanic versus other), education categories (less than high school, high school graduate, some college, college graduate, and postgraduate degree), married, family size (0, 1 or 2 children, and 3 or more children); and indicators for ten income deciles. Missing demographic variables are imputed based on regressions on the non-missing demographic variables.[19]

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.[20] 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 an increase of one standard deviation, and the average marginal effects can roughly be interpreted as the effects of one-standard-deviation increases.

Throughout the analyses below, we restrict the sample by dropping the 57 respondents whose values of β_{qh} are above the 95th percentile, which is 1.25 in our sample. It is conceivable that some respondents exhibit future bias rather than present bias, which would indicate a β_{qh} greater than one. However, we believe that many of the very highest values of β_{qh} are erroneous and represent noise stemming from fitting two time preference parameters from a small number of questions.[21] After dropping these respondents, 21.7% of our sample is future-biased. This proportion is in the middle of the range from the literature.[22] Most of our results are maintained, though somewhat weakened, by including all values of β_{qh}. Interestingly, not dropping any

[19] 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.
[20] The results are generally similar using linear regressions, though the average marginal effects are often more precisely estimated by the non-linear models.
[21] For example, 100% of respondents for whom $\beta_{qh} > 1.5$ say they would take $21 in six months versus $30 in seven months but 88% of these same individuals state that they would accept $30 in one month versus $21 today. Although this is consistent with extremely strong future bias, we think it much more likely that this is due to reporting errors. If we do not drop any respondents, β_{qh} reaches as high as 5.423, which seems clearly unrealistic.
[22] Using MPLs similar to ours for time preference elicitation, Meier and Sprenger (2010) find 9 percent of their sample future-biased; for Ashraf et al. (2006) it is 19.8 percent. See also Sayman and Öncüler (2009). However, using a different methodology – a non-parametric time consistency check – Takeuchi (2011) finds that more respondents exhibit future bias than present bias.

outliers also eliminates any significant associations between β_{qh} and the alternate time preference proxies, which increases our confidence that these extremely high values of β_{qh} reflect noise rather than genuine future bias.

IV. Time Preferences and Outcomes

Tables 4-7 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. Here, and throughout the empirical analysis, relatively small sample sizes reduce the statistical power to reject false null hypotheses. Therefore, while we focus on statistically significant effects, we will also point out where the relationships are substantial and in the hypothesized direction but do not reach statistical significance.

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. Interestingly, while individuals with higher δs 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 twice as large as that for standardized δ_{avg} or δ_{qh}: a 5.5 percentage point increase versus 2 to 3 percentage points (relative to a sample rate of being in good or better health of 83%). However, the discount factors are insignificant in the very good or better health regressions, suggesting their influence on overall health occurs primarily in the left tail of the distribution.

None of the discounting variables significantly influence days not in good physical health, but all three are negatively and significantly associated with the number of days not in good mental health. Once again, the magnitude of the coefficient on β_{qh} is about twice as large as that on either δ_{avg} or δ_{qh}: the average marginal effect of standardized β_{qh} is 1.3 fewer days per month in not good mental health (compared to a standard deviation of 8 days), versus average marginal effects of both of the standardized δs of 0.6 to 0.8 days. However, the main conclusion, again, is that relatively patient individuals are in better health, with particularly large effects for persons who are less present-biased. And virtually the same pattern is found for days with activity limitations, where all three discount factors are negatively and significantly correlated with the dependent variable, and with predicted effects for standardized β_{qh} that are approximately about twice as large as for standardized δ_{avg} or δ_{qh}. The bottom line is that impatient individuals and present-biased individuals have worse overall health, lower mental health, and more activity limitations than their counterparts who discount the future less heavily.

The final two outcomes in Table 4 demonstrate that more patient individuals, measured by either δ_{avg} or δ_{qh}, are also more likely to have health insurance. This is true for all consumers (models 6a and 6b), and among the subset who do not have access to insurance through employers or government and so must purchase it themselves (columns 7a and 7b). This latter group is the one for whom time preferences seem likely to be most important (since they directly make decisions to buy health insurance rather than having it come from other sources) and, 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 standardized δ_{qh} is a 5 percentage point increase in the likelihood of purchasing one's own health insurance (sample rate 32%), versus a 4 point rise in the probability of having insurance from all sources (sample rate 73%). Conversely, neither health insurance outcome is correlated with β_{qh}, suggesting that such coverage is unrelated to present bias.

Health Behaviors

Table 5 examines the health behaviors exercise, smoking, drinking, and sunscreen and seatbelt use, as well as obesity, which is related to health behaviors. The relationships between exercise and the time-consistent discount factors are positive, though not quite significant at the 10% level. The average marginal effect of an increase in standardized δ is about half a day of exercise per month (the standard deviation for exercise is 9.96). Patient individuals consume significantly fewer snacks, with an average marginal effect of δ of about 0.2 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 snack more and exercise less than their counterparts. However, neither relationship is statistically significant and the estimated effect on snacking is only around half as large for β_{qh} as for δ_{qh}.

Models (3a) through (4b) examine smoking and drinking, measured by cigarettes per day and binge drinking occasions per month.[23] The three discount factors are negatively and significantly associated with both: a one-standard-deviation increase in any of the discount factors predicts about a one cigarette reduction in daily smoking and a 0.2 to 0.3 occasion per month decrease in binge drinking (sample standard deviations of both outcomes are 2.2). Particularly striking are the results in columns (3b) and (4b) 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 prior literature finding that δ is related to smoking and drinking (Sutter et al. 2013) and β to smoking (Chabris et al. 2008).

[23] 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 prefer to use binge drinking rather than a measure of average drinking because moderate alcohol consumption is not necessarily unhealthy.

Mixed results are obtained for the two risk-reducing behaviors – sunscreen and seat belt use – that are examined in models (5a) through (6b). Specifically, patient individuals are more likely to use seatbelts, as expected, but less often use sunscreen.[24] The negative correlation between δ and sunscreen use might occur because more patient people are less likely to be out in the sun at all (e.g. tanning), and therefore less likely to use sunscreen, although the question does explicitly ask about use while out in the sun. The positive coefficient for the seat belt regressions (the average marginal effect of δ is about three percentage points, compared to a sample rate of 79%) is consistent with our expectations and it is mirrored by a similarly sized but less precisely estimated coefficient on β.

Lastly, Table 5 examines unhealthy body weight. The results for time preference coefficients on obesity (models 7a and 7b) are surprising, as both δ_{avg} and δ_{qh} are associated with *higher* rates of obesity, though neither is statistically significant.[25] In other words, the point estimates suggest that patient individuals are *more* likely to have unhealthy weights, contrary to other studies finding a negative correlation between discount factor and BMI (e.g. Courtemanche, Heutel and McAlvanah forthcoming). The final 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 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 or obese and consequently more likely to be embarrassed about their weight (or simply not know it). Consistent with this possibility, 119 out of 121 respondents

[24] The sign of the coefficients on CRRA are similar: more risk-averse individuals are more likely to use seat belts but less likely to wear sunscreen, though the coefficients are not quite significant at the 10% level.
[25] Results are similar for regressions where the dependent variable is BMI or severe obesity.

for whom the information required to calculate BMI is unavailable do not report their weight in the survey.[26]

Energy Use

Table 6 presents regression results for the outcomes reflecting investments in energy-efficient technologies. Among vehicle owners, present-biased individuals are much less likely to have a car with high fuel economy (at least 25 miles per gallon): the average marginal effect of standardized β_{qh} is 7 percentage points, relative to a sample rate of 61%. Coefficients on the δs are positive but smaller and insignificant. Individuals with low discount factors are also more likely to have installed energy-efficient lighting but in this case it is the time-consistent discount factor (δ) rather than present bias (β) that matters.[27] In combination, these results suggest that car purchases often contain a substantial "impulse" component whereas those for light bulbs do not. They provide conflicting evidence on whether the energy efficiency gap (Allcott and Greenstone 2012) can be explained by present bias; taken at face value the findings suggest that it may for some energy-efficiency decisions (car fuel economy) but not for others (light bulbs).

The remainder of Table 6 examines residential energy use. Present-biased individuals are much less likely to live in a well-insulated residence – the average marginal effect of standardized β_{qh} is 7 percentage points, relative to a sample rate of 86% – but this outcome is uncorrelated with δ (models 3a and 3b). The next two pairs of models (4a-5b) demonstrate that the discount factor δ is positively correlated with having a programmable thermostat and with consuming less energy than average: the average marginal effects of the δs for these two outcomes are between 2 and 4 percentage points (sample rates are 45% for both), although the effects are not quite significant at the 10% level. Conversely, the correlations of these outcomes

[26] 54 of 121 also fail to report their height.
[27] These findings are consistent with Allcott and Taubinsky (2013) – see their Table A2-1.

with β_{qh} are less significant and even negative for less energy than average. None of the discount factors are correlated with the likelihood of having had an energy audit. However, more patient and less present-biased individuals keep their homes warmer (i.e. use less air conditioning) in the summer: a one standard deviation increase in δ predicts an increase of around 0.3 degrees and the estimated effect for a corresponding rise in β_{qh} is around 0.5 degrees.

The importance of δ_{qh} and β_{qh} for this last outcome supports an interpretation that individuals choose their home temperature partially through a longer-term decision-making process, where they presumably weigh the benefits of lower temperatures against the costs of more air conditioning expenses (and perhaps any environmental concerns that they have), but that some also suffer from self-control problems that cause them to use a more comfortable (lower) temperature setting that they would view as optimal from a time-consistent discounting framework.

Financial Outcomes

Results for financial outcomes are reported in Table 7. Patient individuals are more likely to have a credit card – the average marginal effect of δ_{avg} is 1.7 percentage points – and they also relatively often have non-retirement savings or retirement savings, although none of these coefficients are statistically significant. The strongest relationship here is between unpaid credit card balances and the time-consistent discount factor (either δ_{avg} or δ_{qh}), where patient individuals have significantly lower balances, as expected. Present bias (β_{qh}) is also positively and significantly correlated with the probability of having non-retirement savings – the average marginal effect is 4.5 percentage points – and somewhat less strongly and less significantly so with the likelihood of having retirement savings. This makes sense since the pre-commitment implied with many types of retirement savings (e.g. automatic deposits of funds from the paycheck and penalties for early withdrawal) would be expected to reduce the role of present bias. Conversely, unlike Meier and Sprenger (2010), we do not observe a significant correlation between present bias β_{qh} and credit card balance.

V. Other Time Preference Measures

We next turn to a consideration of the alternative time preference variables. This section has two objectives: to evaluate how closely our main elicited time preference measures for money are related to these alternative measures, and to analyze the extent of attenuation bias from measurement error in regressions using only the elicited monetary discount factor.

Associations Between Elicited Time Preferences and Alternative Measures

In Table 8, we examine the relationship between our elicited monetary time preference measures and 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 variables can be thought of as measures of time preferences in their own right or, particularly for the willpower variables, as measures of hyperbolic discounting.

Neither self-reported patience nor willpower over junk food is significantly related to the elicited monetary discount factors. General willpower, however, is positively correlated with both δ_{avg} from a specification that assumes time-consistent preferences, and with δ_{qh} and β_{qh} from a quasi-hyperbolic discounting specification. The average marginal effects of standardized δ_{avg}, δ_{qh}, and β_{qh} on a 10-point willpower score are all between 0.2 and 0.3, or about one-tenth of a standard deviation. Willpower, or lack thereof, has been hypothesized to be a determinant of present bias (e.g. see Ruhm, 2012), so that the significant effect on β_{qh} makes sense.

However, it is also reasonable to think of willpower as a more fundamental component of time discounting, potentially explaining the relationship with δ_{qh}.

The next 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, 0.07, and 0.04 standard deviations, respectively, with the first two of these being significant at the 10% level. These results can be interpreted in two ways. First, they provide evidence that the elicited discount factors represent actual time preferences, rather than just noise. Second, the relatively weak relationship raises the possibility that individuals discount in different ways across different domains (Chapman and Elstein 1995), or that respondents do not perfectly understand the (fairly complicated) migraine medication questions, so that these questions measure 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 the average marginal effects being around 0.1. The present bias parameter β_{qh} is positive but not significant. This last result is somewhat surprising, given that this the CRT score has been viewed as a measure of the ability to resist intuitive but incorrect answers. However, an alternative possibility is this score is associated with broader measures of cognitive skill which are either correlated with or a component of time-consistent discounting.

In sum, our elicited monetary time preference measures are only somewhat 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. Alternatively, these other proxies may capture information about one's "true" discount factor beyond that 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 suffer from attenuation bias, and incorporating the other time preference variables may help to mitigate this bias. We consider this possibility next.

Multiple Time Preference Proxies and Consumer Behaviors

We assess the extent of attenuation bias in our earlier estimates by implementing the approach of Lubotsky and Wittenberg (2006) (hereafter LW). They consider the case where several proxies are available for an unobserved variable, and show that attenuation bias can be minimized by running a regression including all of the proxies together and computing a weighted average of their coefficient estimates. This approach has some similarities to factor analysis, but is superior in our case because the weights are allowed to differ across outcomes, consistent with the notion of time preferences varying across domains.

We apply LW's method to our context as follows. Let δ_{yi}^{*} be the discount factor applied by individual *i* in the domain of outcome y. We do not observe the latent variable δ_{y}^{*}. Instead, we observe δ_{avg} – the elicited discount factor based on small-stakes financial questions and not allowed to vary for different outcomes – and the other proxies discussed above. As mentioned, we exclude CRT score from the set of proxies since it likely reflects cognitive ability as well as time preference, which violates the assumptions of the subsequent analysis.[28] For the health outcomes, the included proxies are δ_{avg}, the migraine discount factor $\delta_{migraine}$, and self-reported patience, willpower, and willpower over junk food. For the energy use and financial

[28] This ambiguity is also why we do not use CRT score as a control variable. Unreported regressions (available upon request) show that adding it to either the set of controls or proxies does not meaningfully affect the results.

outcomes, there is little rationale for including the health-specific discounting measures so we only utilize δ_{avg}, patience, and willpower.[29]

Our approach is modeled as

$$y_i = \gamma_0 + \gamma_1 \delta_{yi}^* + \boldsymbol{\gamma_2 X_i} + \varepsilon_i \tag{6}$$

$$x_{ji} = \rho_{0j} + \rho_{1j}\delta_{yi}^* + \rho_{2j}\boldsymbol{X_i} + u_{ji} \tag{7}$$

Where x_{ji} in equation (7) represents the proxy variables. Equations (6) and (7) cannot be estimated due to the unobservable covariate δ_y^*, but the parameter of interest γ_1 can be recovered from a linear combination of the coefficients from a regression of y on all the proxy variables together:

$$y_i = \theta_0 + \sum_{j=1}^{k} \theta_{1j} x_{ji} + \boldsymbol{\theta_2 X_i} + \mu_i. \tag{8}$$

where $k = 5$ for the health outcomes and 3 for the energy and financial outcomes. Assuming that δ_y^* is uncorrelated with ε and that $\forall\ j\ u_j$ is uncorrelated with δ_y^* and ε, LW show that γ_1 is estimated with the least amount of bias by

$$\widehat{\gamma_1} = \sum_{j=1}^{k} \frac{cov(y, x_j)}{cov(y, x_1)} \widehat{\theta_{1J}} \tag{9}$$

where x_1 is the proxy variable chosen as the base. We use as x_1 the proxy with the largest value of $cov(y, x_j)$, meaning that x_1's coefficient will have a weight of 1 and the weights for the other proxies' coefficients will be less than 1. LW show that when x_1 is chosen in this manner, δ_y^* will have the same scale as x_1. We standardize all our proxy variables before estimating (8), so regardless of which proxy emerges as x_1 – which could vary for different outcomes – the scale of

[29] In unreported regressions (available upon request), we verify that the health-related discounting proxies offer little predictive power for the energy use and financial outcomes beyond that of the more general time preference measures.

δ_y^* will be (approximately) that of a standardized variable, i.e. mean of 0 and standard deviation of 1. $\widehat{\gamma_1}$ from equation (9) can therefore be compared directly to $\widehat{\gamma_1}$ from equation (4).[30]

Before presenting our results, a few caveats should be discussed. First, it is unclear how LW's procedure should be applied to non-linear models, so we estimate linear models even for the binary and count outcomes.[31] Second, since it is also unclear how LW's method could be used in the case of two unobserved variables that are potentially both affected by the same proxies, we did not attempt to implement a multiple proxies procedure featuring a quasi-hyperbolic specification of β and δ. Finally, our multiple proxies procedure requires the strong assumption that all proxies are uncorrelated with the error term in (8). For these reasons, we consider the results from this section to be robustness checks of our main results as opposed to our preferred estimates.[32]

Table 9 reports the estimated effects of δ_y^* on the health, energy, and financial outcomes. For comparison purposes, we also present estimates using δ_{avg} as the only proxy for purposes of comparison; these estimates are nearly identical to those from Tables 4-7, differing only because we use linear models here to be consistent with the linear models used for the multiple proxies approach. Full regression results are in Appendix Tables A5-A8, including the coefficient

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[30] Intuitively, this procedure can be illustrated as follows. Suppose $\delta_{avg} = \delta_y^*$; i.e. the regression without the additional proxies – equation (4) – does not suffer from attenuation bias. The coefficient for δ_{avg} in (8) is the same as that from (4), the coefficients for the other proxies in (8) are 0, and γ_1 from (9) is the same as γ_1 from (4). Alternatively, suppose δ_{avg} is a fairly poor proxy for δ_y^* and equation (4) therefore suffers from considerable attenuation bias. To the extent that the additional proxies add explanatory power to regression (8), γ_1 from (9) will be larger than γ_1 from (4), meaning that (9) corrects for at least some of the attenuation bias.

[31] The average marginal effects from our previous probit and negative binomial regressions are very similar to those from linear regressions, so we do not expect that this limitation is consequential.

[32] Another possible issue is that LW's procedure allows for negative weights, and it is not clear how these should be interpreted. For instance, suppose one proxy is strongly related to the outcome in the expected direction, whereas another proxy is strongly related in the opposite direction. The "wrong-signed" coefficient could receive a negative weight, in which case it would count the same toward as $\widehat{\gamma_1}$ as if it were "right-signed." In practice, such strong wrong-signed correlations are rare in our data, and our conclusions are not meaningfully affected by replacing the negative weights with zeroes or positive weights of the same magnitudes (results available upon request).

estimates, standard errors, and covariance ratios (weights) for each proxy in regression (8), along with sample sizes.

The appendix tables show that the alternative proxies are occasionally statistically significant, but none of them are significant more frequently than the standard measure δ_{avg}. δ_{avg} and self-reported willpower are tied for the most significant associations in the expected direction (8 of the 26 outcomes for each), with the other three proxies performing worse.[33] A particularly interesting result is that the two health-specific time preference proxies – $\delta_{migraine}$ and willpower with junk food – are worse predictors of health-related outcomes than the analogous general proxies δ_{avg} and willpower. $\delta_{migraine}$ and willpower with junk food are only significantly associated in the expected direction for 2 and 3 of the 15 health outcomes, respectively, compared to 6 and 7 for δ_{avg} and general willpower. Willpower with junk food does seem to influence the weight-related outcomes exercise, snacking, and obesity, but general willpower predicts them just as well.

Turning to the estimated effects of δ_y^* in Table 9, we see that implementing the multiple proxies approach generally suggests that results using δ_{avg} may be conservative. In seven cases, δ_{avg} was insignificant or had a "wrong-signed" association in Tables 4-7 but becomes significant in the expected direction using the multiple proxies method. This occurs for the outcomes very good or better health, exercise, sunscreen use, obesity, well-insulated home, less energy than average, and any credit card. For ten other outcomes – good or better health, mental health, activity limitations, any health insurance, bought own health insurance, snacking, seat belt use, missing BMI, installed CFL, and summer temperature in the home – δ_{avg} was

[33] While 8 of 26 may not seem like a substantial number of statistically significant associations, note that including all the time preference proxies together in the same regressions results in considerable multicollinearity. For this reason, there are many more significant results for the linear combination of these coefficients than there are for any one coefficient individually.

significant in the expected direction in Tables 4-7 but the magnitude of its effect increases in Table 9. In six of these ten cases (good or better health, mental health, activity limitations, seat belts, installed CFL, and summer temperature), the increase in magnitude is greater than two of the original estimate's standard errors. For fuel-efficient car and programmable thermostat, neither δ_{avg} or δ_y^* are significant but the estimate for δ_y^* is notably larger and approaches significance at the 10% level. In the cases of smoking, binge drinking, and credit card balance, δ_{avg} was already significant and the magnitude for δ_y^* is nearly identical. For the final four outcomes – physical health, energy audit, and non-retirement and retirement savings – δ_{avg} and δ_y^* are both insignificant and their estimated effects are small.

In sum, for 19 of the 26 outcomes the multiple proxies approach strengthens the results. We therefore view the findings from Tables 4-7 as conservative. This appears to be especially true for energy use. Recall that Table 6 provided only weak evidence of an association between time-consistent discount factor and the seven energy outcomes, with δ_{avg} only being statistically significant twice. This number rises to four using the multiple proxies method, with significance almost being obtained in two other cases.

VI. 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 time-consistent discount factor δ_{avg} is statistically significantly associated, in the expected direction, with 14 of our 26 outcomes. Using the quasi-hyperbolic specification, δ_{qh} and present bias β_{qh} are significantly related to 13 and 9 outcomes, respectively, in the hypothesized direction. These are impressive results, given the relatively small sample and the modest financial payments provided to randomly chosen participants. We also explore alternate time preference measures, and show that in general they are no better at predicting outcomes than the standard, MPL-elicited measure. However, a multiple proxies approach to address measurement error in elicited monetary time preferences suggests that our estimated effects of δ_{avg} on these outcomes are likely conservative. Unfortunately, this method is not well suited to simultaneously examining the present-biased and time-consistent components of discounting, so we cannot say if our estimates of the coefficients on β_{qh} are similarly understated.

We believe that the findings are actually even more meaningful than they appear at first glance. Not all of the dependent variables are equally important, and some of the strongest and most interesting results are obtained for outcomes that we judge to be the most central. For example, we obtain the striking finding that patient individuals are in better health for all of our overall measures except days in poor physical health (i.e. for good or better health, very good or better health (in the multiple proxies regression only), days in bad mental health, and days where poor health significantly limited activities). Moreover, while both the time-consistent and present-biased components of discounting have a significant effect, the latter are larger.

The results are somewhat less consistent for health risks and behaviors, but our interpretation again is that the findings for some of the riskiest behaviors – e.g. binge drinking and smoking – tell a similar story: both δ_{qh} and β_{qh} matter but the latter is often more important. Most other results for health behaviors are in the hypothesized direction, and some that are anomalous (e.g. the use of sunscreen in the main specifications but not the multiple proxy regressions) we consider to be smaller health risks.

Though the estimates for energy use are somewhat mixed, once again some of the strongest and most interesting results are obtained for outcomes that we think are the most important. For instance, present-biased individuals are less likely to purchase high-fuel-economy vehicles, and passenger cars are the largest source of transportation-related carbon emissions.[34] Air-conditioning represents about one-fourth of total home electricity use (the largest single component),[35] and present-biased individuals (as well as persons with low discount factors more generally) report keeping their houses at higher temperatures during the summer, probably resulting in significant electricity savings. The results for many of the other energy outcomes (e.g. whether an energy audit has been conducted or there is a programmable thermostat in the home) seem likely to generate less energy savings than the factors just mentioned, although results for these variables are consistent with theoretical expectations more often than not.

Present-biased individuals are also less likely to have retirement or non-retirement savings, a first-order financial consideration, and persons who discount the future less heavily hold less credit card debt, as anticipated. Our limited data on financial outcomes prevents us from saying more in this regard, but these results seem informative and potentially important.

Finally, we examine how well alternative time preference measures perform at predicting behavior. Self-reported willpower is correlated with all MPL-elicited discount factors and also with about as many consumer behavior variables as the elicited monetary discount factor. There is no evidence that time preference parameters obtained from questions specifically about a health decision are better predictors of health outcomes than the standard time preference parameters pertaining to monetary outcomes.

This study suggests many areas for future research. First, would our results persist with larger samples or with preference elicitation strategies that provided respondents with larger risks

[34] See http://www.epa.gov/climatechange/ghgemissions/sources/transportation.html.
[35] See http://www.eia.gov/energyexplained/index.cfm?page=electricity_use.

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, research 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? And, 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?

References

Allcott, Hunt, and Michael Greenstone. "Is There an Energy Efficiency Gap?" *Journal of Economic Perspectives* 26, no. 1 (2012): 3-28.

Allcott, Hunt, and Dmitry Taubinsky. "The Lightbulb Paradox: Evidence from two Randomized Experiments." *NBER Working Paper*, 2013.

Allcott, Hunt, and Nathan Wozny. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics*, forthcoming.

Andersen, Steffen, Glenn Harrison, Morten Lau, and E. Elisabet Rutstrom. "Eliciting Risk and Time Preferences." *Econometrica* 76, no. 3 (May 2008): 583-618.

Andreoni, James, Michael Kuhn, and Charles Sprenger. "On Measuring Time Preferences." *NBER Working Paper #19392*, August 2013.

Ariely, Dan, and Klaus Wertenbroch. "Procrastination, Deadlines, and Performance: Self-Control by Precommitment." *Psychological Science* 13, no. 3 (May 2002): 219-224.

Ashraf, Nava, Dean Karlan, and Wesley Yin. "Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines." *Quarterly Journal of Economics* 121, no. 2 (2006): 635-672.

Attari, Shahzeen, Michael DeKay, Cliff Davidson, and Wändi Bruine de Bruin. "Public Perceptions of Energy Consumption and Savings." *Proceedings of the National Academy of Sciences* 107, no. 7 (September 2010): 16054–16059.

Augenblick, Ned, Muriel Niederle, and Charles Sprenger. "Working Over Time: Dynamic Inconsistency in Real Effort Tasks." *NBER Working Paper #18734*, January 2013.

Axon, R. Neal, W. David Bradford, and Brent M. Egan. "The Role of Individual Time Preferences in Health Behaviors among Hypertensive Adults." *Journal of the American Society of Hypertension* 3, no. 1 (January-February 2009): 35-41.

Bradford, W. David. "The Association Between Individual Time Preferences and Health Maintenance Habits." *Medical Decision Making* 30 (2010): 99-112.

Bradford, W.D., J. Zoller, and G. Silvestri. "Estimating the Effect of Individual Time Preferences on the Use of Disease Screening." *Southern Economic Journal* 76 (2010): 1005-1031.

Burks, Stephen, Jeffrey Carpenter, Lorenz Gotte, and Aldo Rusticini. "Which Measures of Time Preference Best Predict Outcomes? Evidence from a Large-Scale Field Experiment." *Journal of Economic Behavior and Organization* 84, no. 1 (September 2012): 308-320.

Carroll, Gabriel D., Jame J. Choi, David Laibson, Bridgit C. Madrian, and Andrew Metrick. "Optimal Defaults and Active Decisions." *Quarterly Journal of Economics* 124 (2009): 1639-1674.

Chabris, Christopher, David Laibson, Carrie Morris, Jonathon Schuldt, and Dmitri Taubinsky. "Individual laboratory-measured discount rates predict field behavior." *Journal of Risk and Uncertainty* 37 (2008): 237-269.

Chapman, G. B. and A. S. Elstein. "Valuing the Future: Temporal Discounting of Health and Money." *Medical Decision Making* 15 (1995): 373-386.

Courtemanche, Charles, Garth Heutel, and Patrick McAlvanah. "Impatience, Incentives and Obesity." *Economic Journal*, forthcoming.

Dellavigna, Stefano, and Ulrike Malmendier. "Paying Not to Go to the Gym." *American Economic Review* 96, no. 3 (June 2006): 694-719.

Fang, Hanming, and Dan Silverman. "Time-Inconsistency and Welfare Program Participation: Evidence from the NLSY." *International Economic Review* 50, no. 4 (November 2009): 1043-1077.

Frederick, Shane. "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives* 19, no. 4 (Fall 2005): 25-42.

Frederick, Shane, George Loewenstein, and Ted O'Donoghue. "Time Discounting and Time Preference: A Critical Review." *Journal of Economic Literature* 40, no. 2 (June 2002): 351-401.

Ganiats, Theodore G., Richard T. Carson, Robert M. Hamm, Scott B. Cantor, Walton Sumner, Stephen J. Spann, Michael D. Hagen, and Christopher Miller. "Population-based time preferences for future health outcomes." *Medical Decision Making* 20, no. 3 (2000): 263-270.

Gillingham, Kenneth, and Karen Palmer. "Bridging the Energy Efficiency Gap: Insights for Policy from Economic Theory and Empirical Analysis." *Resources For the Future Discussion Paper 13-02*, 2013.

Glimcher, Paul William, Joseph Kable and Kenway Louie. "Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible." *American Economic Review* 97, no. 2 (2007): 142-147.

Kahneman, Daniel. *Thinking, Fast and Slow.* Macmillan, 2011.

Lubotsky, Darren and Martin Wittenberg. "Interpretation of Regressions with Multiple Proxies." *Review of Economics and Statistics* 88, no. 3 (2006): 549-562.

Meier, Stephan, and Charles Spregner. "Present-Biased Preferences and Credit Card Borrowing." *American Economic Journal: Applied Economics* 2, no. 1 (January 2010): 193-210.

O'Donoghue, Ted, and Matthew Rabin. "Optimal Sin Taxes." *Journal of Public Economics* 90, no. 10-11 (November 2006): 1825-1849.

Ruhm, Christopher J. "Understanding Overeating and Obesity." *Journal of Health Economics* 31, no. 6 (December 2012): 781-796.

Sayman, Serdar, and Ayse Öncüler. "An investigation of time inconsistency." *Management Science* 55, no. 3 (2009): 470-482.

Sutter, M., M. Kocher, D. Rutzler, and S. Trautmann. "Impatience and uncertainty: Experimental decisions predict adolescents' field behavior." *American Economic Review* 103, no. 1 (February 2013): 510-531.

Stanovich, Keith, and Richard Wests. "Individual Differences in Reasoning: Implications for the Rationality Debate?" *Behavioral and Brain Sciences* 22, no. 5 (2000): 645-726.

Takeuchi, Kan. "Non-parametric test of time consistency: Present bias and future bias." *Games and Economic Behavior* 71, no. 2 (2011): 456-478.

Thaler, Richard. "Some Empirical Evidence on Dynamic Inconsistency." *Economics Letters* 8, no. 3 (1981): 201-207.

Toubia, Olivier, Eric Johnson, Theodoros Evgeniou, and Philippe Delquie. "Dynamic Experiments for Estimating Preferences: An Adaptive Method of Elciting Time and Risk Parameters." *Management Science* 59, no. 3 (March 2013): 613-640.

Van Der Pol, Marjon. "Health, Education, and Time Preference." *Health Economics* 20, no. 8 (August 2011): 917-929.

Weller, R., Cook, E., Avsar, K., Cox, J. "Obese Women Show Greater Delay Discounting than Healthy-Weight Women." *Appetite* 51 (2008): 563-569.

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	24.22	$29	$30	0.9944	10.43	$29	$30	0.9667	37.83
$28	$30	0.9333	31.38	$28	$30	0.9886	13.99	$28	$30	0.9333	42.80
$26	$30	0.8667	45.78	$26	$30	0.9764	18.68	$26	$30	0.8667	51.39
$24	$30	0.8000	60.37	$24	$30	0.9634	28.03	$24	$30	0.8000	61.81
$21	$30	0.7000	73.38	$21	$30	0.9423	40.31	$21	$30	0.7000	72.33
$17	$30	0.5667	85.69	$17	$30	0.9097	62.34	$17	$30	0.5667	83.99
$13	$30	0.4333	87.09	$13	$30	0.8699	71.88	$13	$30	0.4333	85.57
				$8	$30	0.8023	78.51				

Table 2: Calculated Discount Factors

Parameter	Average [St. Error]	Percentile 5th	10th	25th	50th	75th	90th	95th
δ_{avg}	0.846 [0.004]	0.447	0.578	0.808	0.905	0.945	0.967	0.979
δ_{qh}	0.864 [0.005]	0.458	0.508	0.834	0.924	0.964	0.990	0.997
β_{qh}	0.936 [0.007]	0.619	0.678	0.843	0.944	1.012	1.107	1.252

Note: 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 1,154.

Table 3: Estimate of Risk Aversion Obtained Using Lottery Questions

Lottery A				Lottery B								
Prob	$	Prob	$	Prob	$	Prob	$	EV(A)	EV(B)	Difference	CRRA if just indifferent	Percent Choosing A
20%	$ 20.00	80%	$ 16.00	20%	$ 38.50	80%	$ 1.00	$ 16.80	$ 8.50	$ 8.30	-0.95	86.96
30%	$ 20.00	70%	$ 16.00	30%	$ 38.50	70%	$ 1.00	$ 17.20	$ 12.25	$ 4.95	-0.49	84.46
40%	$ 20.00	60%	$ 16.00	40%	$ 38.50	60%	$ 1.00	$ 17.60	$ 16.00	$ 1.60	-0.15	82.62
50%	$ 20.00	50%	$ 16.00	50%	$ 38.50	50%	$ 1.00	$ 18.00	$ 19.75	$ (1.75)	0.14	73.11
60%	$ 20.00	40%	$ 16.00	60%	$ 38.50	40%	$ 1.00	$ 18.40	$ 23.50	$ (5.10)	0.41	64.67
70%	$ 20.00	30%	$ 16.00	70%	$ 38.50	30%	$ 1.00	$ 18.80	$ 27.25	$ (8.45)	0.68	54.73
80%	$ 20.00	20%	$ 16.00	80%	$ 38.50	20%	$ 1.00	$ 19.20	$ 31.00	$ (11.80)	0.97	46.63
90%	$ 20.00	10%	$ 16.00	90%	$ 38.50	10%	$ 1.00	$ 19.60	$ 34.75	$ (15.15)	1.37	41.55

Table 4: Self-Reported Health Status and Health Insurance

	Good or Better Health		Very Good or Better Health		Days Physical Health Not Good		Days Mental Health Not Good	
	(1a)	(1b)	(2a)	(4a)	(4a)	(3b)	(4a)	(4b)
δ_{avg}	0.024**		-0.008		0.239		-0.658**	
	(0.011)		(0.015)		(0.265)		(0.263)	
δ_{qh}		0.027**		-0.009		0.256		-0.753***
		(0.012)		(0.017)		(0.294)		(0.291)
β_{qh}		0.055***		0.015		-0.263		-1.331***
		(0.018)		(0.025)		(0.434)		(0.429)
N	1,085		1,085		1,085		1,086	
	Days Activity is Limited		Any Health Insurance		Bought Own Health Insurance			
	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)		
δ_{avg}	-0.658***		0.036***		0.048**			
	(0.246)		(0.012)		(0.020)			
δ_{qh}		-0.737***		0.041***		0.052**		
		(0.274)		(0.014)		(0.023)		
β_{qh}		-1.454***		0.009		0.013		
		(0.424)		(0.020)		(0.035)		
N	1,085		1,078		425			

Notes: 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 (7a) and (7b) includes only persons who do not have health insurance through their or their spouse's employer or through the government.

Table 5: Health Behaviors

	Days Exercise last Month		Snacks per Day		Cigarettes per Day		Times Binge Drinking last Month	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
δ_{avg}	0.409		-0.184***		-0.846***		-0.172**	
	(0.359)		(0.070)		(0.315)		(0.076)	
$\delta_{q\mathrm{h}}$		0.510		-0.197**		-1.032***		-0.199**
		(0.402)		(0.079)		(0.361)		(0.085)
$\beta_{q\mathrm{h}}$		0.631		-0.104		-1.569**		-0.335***
		(0.541)		(0.113)		(0.576)		(0.119)
N	1,087		1,077		1,083		1,083	
	Always/Nearly Always Use Sunscreen		Always Use Seat Belts		Obese		BMI Missing	
	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)	(8a)	(8b)
δ_{avg}	-0.031**		0.028**		0.017		-0.021***	
	(0.014)		(0.012)		(0.017)		(0.007)	
$\delta_{q\mathrm{h}}$		-0.033**		0.033**		0.020		-0.024***
		(0.016)		(0.013)		(0.019)		(0.008)
$\beta_{q\mathrm{h}}$		-0.031		0.028		-0.005		-0.006
		(0.023)		(0.020)		(0.025)		(0.014)
N	1,084		1,083		998		1,079	

Notes: 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}, $\delta_{q\mathrm{h}}$, and $\beta_{q\mathrm{h}}$ are standardized to have a mean of 0 and standard deviation of 1.

Table 6: Energy Use

	High mpg		Installed CFL		Well-Insulated		Programmable Thermostat	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
δ_{avg}	0.015		0.048**		-0.001		0.033	
	(0.018)		(0.021)		(0.018)		(0.024)	
$\delta_{q\mathrm{h}}$		0.016		0.059**		-0.012		0.037
		(0.020)		(0.024)		(0.022)		(0.028)
$\beta_{q\mathrm{h}}$		0.072**		0.004		0.070**		0.015
		(0.028)		(0.037)		(0.029)		(0.039)
N	881		526		494		510	

	Less Energy than Average		Energy Audit		Summer Temperature in Home	
	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)
δ_{avg}	0.029		-0.003		0.350*	
	(0.024)		(0.019)		(0.204)	
$\delta_{q\mathrm{h}}$		0.026		-0.001		0.348
		(0.028)		(0.021)		(0.227)
$\beta_{q\mathrm{h}}$		-0.037		-0.020		0.485*
		(0.040)		(0.033)		(0.283)
N	520		514		728	

Notes: 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}, $\delta_{q\mathrm{h}}$, and $\beta_{q\mathrm{h}}$ are standardized to have a mean of 0 and standard deviation of 1. The sample in models (2a) through (6b) includes only persons who have owned their home for more than two years, and the sample in models (7a) and (7b) includes only those homeowners who have a thermostat.

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}	0.017		-0.382**		0.003		0.017	
	(0.014)		(0.159)		(0.015)		(0.015)	
$\delta_{q\mathrm{h}}$		0.019		-0.463***		0.004		0.020
		(0.015)		(0.177)		(0.017)		(0.017)
$\beta_{q\mathrm{h}}$		0.011		-0.079		0.045*		0.033
		(0.022)		(0.273)		(0.024)		(0.023)
N	1,072		631		1,076		1,074	

Notes: 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}, $\delta_{q\mathrm{h}}$, and $\beta_{q\mathrm{h}}$ are standardized to have a mean of 0 and standard deviation of 1.

Table 8: Alternate Time Preference Measures

	Patience		Willpower		Willpower with Junk Food	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
δ_{avg}	0.016		0.201**		-0.018	
	(0.036)		(0.095)		(0.102)	
δ_{qh}		0.019		0.220**		-0.010
		(0.041)		(0.107)		(0.115)
β_{qh}		-0.055		0.282**		-0.065
		(0.051)		(0.135)		(0.158)
N	1,078		1,075		1,079	
	$\delta_{migraine}$		CRT Score			
	(4a)	(4b)	(5a)	(5b)		
δ_{avg}	0.059*		0.114***			
	(0.035)		(0.022)			
δ_{qh}		0.071*		0.125***		
		(0.039)		(0.025)		
β_{qh}		0.042		0.026		
		(0.051)		(0.045)		
N	1,075		1,076			

Notes: 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 are standardized to have a mean of 0 and standard deviation of 1.

Table 9: Multiple Proxies

	Good or Better Health	Very Good or Better Health	Days Physical Health Not Good	Days Mental Health Not Good	Days Activity Limited	Any Health Insurance	Bought Own Health Insurance	Days Exercise last Month	Snacks per Day
$\widehat{\delta_{y\iota}^{*}}$	0.072***	0.099***	-0.522	-1.767***	-1.161***	0.048**	0.067**	3.096***	-0.318***
mult. proxies	(0.019)	(0.019)	(0.639)	(0.436)	(0.330)	(0.019)	(0.028)	(0.372)	(0.114)
δ_{avg}	0.029**	-0.007	0.120	-0.840***	-0.541**	0.037**	0.043**	0.286	-0.203**
single proxy	(0.013)	(0.015)	(0.262)	(0.305)	(0.260)	(0.016)	(0.018)	(0.309)	(0.084)

	Cigarettes per Day	Binge Drinking last Month	Always/ Nearly Always Use Sunscreen	Always Use Seat Belts	Obese	BMI Missing	High mpg	Installed CFL	Well-Insulated
$\widehat{\delta_{y\iota}^{*}}$	-0.724**	-0.174	0.051***	0.077***	-0.071***	-0.029**	0.038	0.090***	0.052***
mult. proxies	(0.290)	(0.109)	(0.016)	(0.021)	(0.020)	(0.013)	(0.026)	(0.032)	(0.020)
δ_{avg}	-0.541**	-0.104	-0.031**	0.030**	0.017	-0.030**	0.015	0.053**	0.001
single proxy	(0.260)	(0.088)	(0.015)	(0.014)	(0.017)	(0.012)	(0.019)	(0.024)	(0.018)

	Programm-able Thermo-stat	Less Energy than Average	Energy Audit	Summer Tempera-ture in Home	Any Credit Card	ln(Credit Card Balance)	Any Non-Retire-ment Savings	Any Retire-ment Savings
$\widehat{\delta_{y\iota}^{*}}$	0.059	0.070**	0.0003	0.778***	0.032*	-0.371**	-0.004	0.010
mult. proxies	(0.036)	(0.034)	(0.020)	(0.281)	(0.019)	(0.164)	(0.017)	(0.014)
δ_{avg}	0.033	0.020	-0.0004	0.350*	0.016	-0.382**	0.003	0.017
single proxy	(0.024)	(0.025)	(0.019)	(0.204)	(0.015)	(0.159)	(0.015)	(0.014)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weights in the index are in brackets. 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. All discounting variables are standardized to have a mean of 0 and standard deviation of 1. The sample in the installed CFL through Energy Audit columns includes only persons who have owned their home for more than two years.

Appendix Table A1: Summary Statistics of Control Variables

Variable	Mean (Standard Error) [Number nonmissing]
CRRA	.4420 (.0212) [1310]
Age (years)	43.05 (.4437) [1268]
Income ($1,000)	57.85 (3.63) [1252]
Female	.5008 (.0139) [1302]
White	.757 (.0118) [1325]
Married	.4712 (.0137) [1320]
Less than High School	.1185 (.0089) [1317]
High School Graduate	.3204 (.0129) [1317]
Some College	.2065 (.0112) [1317]
College Graduate	.2627 (.0121) [1317]
Postgraduate	.0919 (.0080) [1317]
Number of Children	2.350 (.0411) [1310]

Appendix Table A2: Summary Statistics of Health Outcomes

Variable	Mean (Standard Error) [Number nonmissing]
Good or Better Health	.8284 (.0104) [1317]
Very Good or Better Health	.5110 (.0138) [1317]
Days of Last 30 Physical Health Not Good (0 if None)	4.467 (.2269) [1316]
Days of Last 30 Mental Health Not Good (0 if None)	5.016 (.2230) [1317]
Days of Last 30 Health-Related Functional Limitations (0 if None)	3.567 (.1980) [1316]
Any Health Insurance	.7289 (.0123) [1313]
Bought Own Health Insurance (Conditional on Not Having Employer Provided or Public Insurance)	.3219 (.0204) [525]
Obese (BMI≥30)	.3231 (.0135) [1204]
Days of Last 30 Exercised (0 if No Exercise)	10.68 (.2743) [1317]
Snacks (Salty or Sweet) in Typical Day (0 if No Snacks)	2.887 (.0657) [1306]
Cigarettes Smoked in Typical Day (0 for Non-Smokers)	4.035 (.0607) [1317]
Days of Last 30 Binge Drank (0 if No Binge Drinking)	1.053 (.0607) [1315]
Always/Nearly Always Uses Sunscreen when in Sun	.3260 (.0129) [1316]
Always/Nearly Always Uses Seat Belts in Car	.7932 (.0112) [1320]

Appendix Table A3: Summary Statistics of Energy and Financial Outcomes

Variable	Mean (Standard Error) [Number nonmissing]
High Miles per Gallon (>25) Car	.6136
(Car Owners Only)	(.015)
	[1056]
Ever Install CFL	.682
(Homeowners for 2+ Years Only)	(.0185)
	[632]
Home is Well-Insulated	.8619
(Homeowners for 2+ Years Only)	(.0138)
	[630]
Have a Programmable Thermostat	.4509
(Homeowners for 2+ Years Only)	(.0200)
	[621]
Consumes Less Energy than Average	.4483
(Homeowners for 2+ Years Only)	(.0198)
	[629]
Ever Had an Energy Audit	.2173
(Homeowners for 2+ Years Only)	(.0165)
	[626]
Summer Temperature in Home	73.78
(Homeowners for 2+ Years with a Thermostat Only)	(.1937)
	[456]
Have At Least One Credit Card	.5922
	(.0136)
	[1307]
Credit Card Balance	3396
(Those with Credit Cards Only)	(475.5)
	[754]
Any Non-Retirement Savings	.4440
	(.0138)
	[1304]
Any Retirement Savings	.3903
	(.0135)
	[1299]

Appendix Table A4: Summary Statistics of Alternate Time Preference Measures

Variable	Mean (Standard Error) [Number nonmissing]
Self-Assessed Patience (1 to 10; 10 is Most Patient)	5.995 (.0757) [1302]
Self-Assessed Willpower (1 to 10; 10 is Most Willpower)	6.386 (.0704) [1299]
Self-Assessed Willpower with Junk Food (1 to 10; 10 is Most Willpower)	5.238 (.0822) [1304]
$\delta_{migraine}$	.9361 (.0011) [1295]
CRT score	.5729 (.0252) [1304]

Table A5: Self-Reported Health and Health Insurance – Multiple Proxies

	Good or Better Health	Very Good or Better Health	Days Physical Health Not Good	Days Mental Health Not Good	Days Activity is Limited	Any Health Insurance	Bought Own Health Insurance
δ_{avg}	0.025*	-0.018	0.152	-0.772**	-0.423	0.037**	0.044**
	(0.013)	(0.015)	(0.270)	(0.311)	(0.262)	(0.016)	(0.018)
	[0.965]	[0.204]	[0.025]	[1]	[0.758]	[1]	[1]
$\delta_{migraine}$	0.001	0.029*	0.190	-0.237	0.080	-0.018	-0.031
	(0.012)	(0.016)	(0.287)	(0.270)	(0.239)	(0.013)	(0.022)
	[0.136]	[0.482]	[-0.880]	[0.121]	[-0.226]	[-0.534]	[-0.655]
Patience	-0.010	0.007	0.143	-0.598*	0.050	0.010	0.012
	(0.014)	(0.017)	(0.338)	(0.342)	(0.282)	(0.015)	(0.022)
	[0.262]	[0.475]	[-0.973]	[0.955]	[0.442]	[0.402]	[0.415]
Willpower	0.039***	0.053***	-0.204	-0.408	-0.859***	-0.009	-0.027
	(0.014)	(0.018)	(0.362)	(0.353)	(0.297)	(0.015)	(0.023)
	[1]	[1]	[0.834]	[0.961]	[1]	[0.421]	[0.340]
Willpower:	0.015	0.036**	-0.048	-0.011	0.277	0.008	0.016
Junk Food	(0.013)	(0.016)	(0.318)	(0.294)	(0.255)	(0.013)	(0.021)
	[0.712]	[0.905]	[1]	[0.331]	[0.049]	[0.284]	[0.431]
N	1,060	1,071	1,060	1,068	1,061	1,059	409

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weights in the index are in brackets. 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. All discounting variables are standardized to have a mean of 0 and standard deviation of 1. The sample in the last column includes only persons who do not have health insurance through their or their spouse's employer or through the government.

Table A6: Health Behaviors – Multiple Proxies

	Days Exercise last Month	Snacks per Day	Cigarettes per Day	Times Binge Drinking last Month	Always/ Nearly Always Use Sunscreen	Always Use Seat Belts	Obese	BMI Missing
δ_{avg}	0.202	-0.176**	-0.433	-0.107	-0.031**	0.024	0.018	-0.024**
	(0.306)	(0.087)	(0.267)	(0.091)	(0.015)	(0.014)	(0.017)	(0.012)
	[0.367]	[1]	[1]	[1]	[0.038]	[0.905]	[-0.170]	[1]
$\delta_{migraine}$	-0.964***	0.045	-0.257	0.035	0.044***	0.002	0.005	0.007
	(0.302)	(0.076)	(0.230)	(0.078)	(0.014)	(0.013)	(0.016)	(0.009)
	[-0.415]	[-0.579]	[0.107]	[-0.555]	[1]	[-0.287]	[-0.012]	[-0.236]
Patience	0.998***	0.068	0.473*	-0.008	-0.012	0.023	0.013	0.004
	(0.324)	(0.081)	(0.252)	(0.087)	(0.016)	(0.015)	(0.018)	(0.010)
	[0.823]	[0.378]	[0.045]	[0.339]	[0.095]	[0.994]	[0.043]	[0.380]
Willpower	1.198***	-0.114	-0.533*	-0.039	-0.003	0.033**	-0.038**	-0.015
	(0.327)	(0.092)	(0.277)	(0.096)	(0.016)	(0.015)	(0.018)	(0.011)
	[1]	[0.731]	[0.565]	[0.418]	[0.014]	[1]	[0.869]	[0.563]
Willpower:	0.795***	-0.118	0.081	0.088	0.012	-0.0002	-0.036**	0.004
Junk Food	(0.310)	(0.085)	(0.245)	(0.080)	(0.014)	(0.012)	(0.016)	(0.009)
	[0.758]	[0.493]	[0.199]	[-0.323]	[0.603]	[0.343]	[1]	[0.078]
N	1,069	1,060	1,058	1,069	1,062	1,070	979	1,062

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weights in the index are in brackets. 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. All discounting variables are standardized to have a mean of 0 and standard deviation of 1.

Table A7: Energy Use – Multiple Proxies

	High mpg	Installed CFL	Well-Insulated	Programmable Thermostat	Less Energy than Average	Energy Audit	Summer Temperature in Home
δ_{avg}	0.014	0.047*	-0.002	0.031	0.013	-0.0004	0.306
	(0.020)	(0.025)	(0.017)	(0.025)	(0.025)	(0.019)	(0.206)
	[1]	[0.763]	[0.027]	[0.936]	[0.751]	[1]	[1]
Patience	0.019	0.033	-0.008	0.042	0.038	0.022	0.335*
	(0.020)	(0.024)	(0.019)	(0.027)	(0.027)	(0.022)	(0.179)
	[0.912]	[0.909]	[0.771]	[0.977]	[1]	[-0.057]	[1]
Willpower	0.008	0.025	0.059***	-0.011	0.024	-0.017	0.169
	(0.020)	(0.025)	(0.020)	(0.027)	(0.028)	(0.022)	(0.184)
	[0.813]	[1]	[1]	[1]	[0.917]	[-0.113]	[0.811]
N	872	520	520	513	519	517	723

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weights in the index are in brackets. 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. All discounting variables are standardized to have a mean of 0 and standard deviation of 1. The sample in the middle five columns includes only persons who have owned their home for more than two years.

Table A8: Financial Outcomes – Multiple Proxies

	Any Credit Card	ln(Credit Card Balance)	Any Non-Retirement Savings	Any Retirement Savings
δ_{avg}	0.015	-0.361**	-0.001	0.013
	(0.015)	(0.162)	(0.015)	(0.014)
	[1]	[1]	[1]	[1]
Patience	0.025*	-0.051	-0.003	-0.016
	(0.015)	(0.171)	(0.016)	(0.015)
	[0.392]	[0.202]	[0.392]	[-0.020]
Willpower	-0.002	-0.005	-0.003	-0.016
	(0.016)	(0.175)	(0.017)	(0.016)
	[0.593]	[0.069]	[0.593]	[0.217]
N	1,067	621	1,066	1,054

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weights in the index are in brackets. 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. All discounting variables are standardized to have a mean of 0 and standard deviation of 1.