Time Preferences, Health Behaviors, and Energy Consumption

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Abstract

We conduct a survey eliciting time preferences from a representative sample of US residents, allowing for quasi-hyperbolic discounting. We also ask individuals about health behaviors and outcomes and energy consumption, hypothesizing that present-biased consumers will be less likely to invest in health and in energy-efficiency. Regression results with basic demographic controls suggest that present bias is associated with many outcomes in both of these dimensions, including overall self-assessed health, smoking, drinking, drug use, health insurance, automobile fuel economy, home insulation and weatherization, and use of thermostats. However, the time-consistent component of the quasi-hyperbolic specification is predictive of an even larger number of outcomes. These findings are robust to controlling for risk preferences. In all, our results suggest that both time-consistent and present-biased discounting influence health, health behaviors, and energy use.

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Growing evidence from economics and from psychology suggests that people make intertemporal trade-offs in a way that is not found in standard economic models. The standard assumption made in economic models is that consumers discount the future in a time-consistent manner; the relative weight that I place on consumption one year from now relative to now is equal to the weight that I place on consumption ten years from now relative to nine years from now. However, many laboratory and econometric studies suggest that consumers are time-inconsistent, and in particular exhibit present bias: the weight I place on consumption now relative to a year from now is greater than the weight I place on consumption nine years from now relative to ten years from now.

If consumers are time inconsistent and exhibit present bias, this may justify government intervention in a way that is not justified if decisions are based on time-consistent preferences (O'Donoghue and Rabin 2006). Environmental and energy policy is affected, since time-inconsistent consumers may be less willing to invest in energy-efficiency technologies (e.g. hybrid cars, home energy improvements) if they do not account for future savings as much as the standard model assumes. Health policies are affected by the fact that time-inconsistent consumers may underinvest in health (e.g. by eating too much, exercising too little, or failing to buy insurance) since the rewards from such investments occur in the future. Policies designed to encourage retirement savings need also to accommodate the potential for time inconsistency. In each of these examples, economists have suggested that an explanation for consumer behavior (e.g. underinvestment in energy efficiency, high obesity rates, lack of retirement savings) may be present bias.

The purpose of this paper is to provide direct evidence of the link between time-inconsistent preferences and numerous outcomes related to health behaviors and energy consumption. Since no secondary data exist that contain the wide range of information necessary for our analyses, we develop our own survey. We measure time preferences by asking questions about intertemporal tradeoffs, paying out one of the choices for randomly-selected respondents to mitigate hypothetical bias. We compute both the β (present bias) and δ (time consistent) components of a quasi-hyperbolic specification, allowing for an empirical test of the association between time inconsistency and outcomes including self-assessed health, preventive health care utilization, body mass index (BMI), dietary and exercise habits, smoking, drinking, drug use, health insurance status, car fuel efficiency, and use of energy-efficient technologies in the home. We also elicit risk preferences to examine whether controlling for risk preference has any effect on the relationship between time preference and these outcomes. Finally, we calculate an alternate measure of time preferences based on hypothetical questions about medical decisions rather than about money, and we compare how those alternate measures of time preferences compare to the standard measures calculated using questions about money.

A prior literature exists that merely asks whether or not consumers' time preferences are time-consistent, as opposed to whether the level of time inconsistency is associated with particular outcomes. Laboratory evidence goes back to Thaler (1981), and laboratory evidence combined with neurological evidence in McClure et. al. (2004) support the existence of present bias in preferences. Other studies examine consumer behavior in the market for evidence of present bias. Individuals' choices about exercising (Dellavigna and Malmendier 2006), doing homework (Ariely and Wertenbroch 2002), participating in welfare programs (Fang and Silverman 2009), and eating (Ruhm 2012) all show evidence of time inconsistency and present bias. Buyers of cars seem to underweight future gasoline costs (Allcott and Wozny 2012). 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 much less than optimal energy-saving investments.

Other papers elicit time preferences and estimate their associations with various outcomes, but without attempting to separate out a present bias in discounting from a time consistent discount factor. Such studies have found connections between time preference and BMI (Chabris et al. 2008, Weller et al. 2008, Sutter et al. 2013), exercise (Chabris et al. 2008), smoking (Sutter et. al. 2013), drinking (Sutter et. al. 2013), disease screening (Bradford et. al. 2010), behaviors to prevent hypertension (Axon et. al. 2009), healthy behaviors in general (Bradford 2010), and overall self-assessed health (Van der Pol 2011).[1]

Some studies do examine the influence of present bias on certain outcomes, but a much narrower range of outcomes than we consider. Prior work has demonstrated that elicited measures of present bias are related to smoking (Burks, et al. 2012), credit card borrowing (Meier and Spregner 2010), BMI (Ikeda et al. 2010; Courtemanche, Heutel, and McAvanah forthcoming), and a mortgage-holder being underwater on his or her mortgage (Toubia et al. 2013). However, Allcott and Taubinsky (2013) do not find evidence of a link between time-inconsistent preference parameters and use of energy-efficient lightbulbs.

We provide evidence to support our hypotheses relating time preferences to health and energy outcomes. In regressions controlling for demographic characteristics, the present bias discount factor β is significantly associated with many health-related outcomes, including overall self-assessed health, smoking, drinking, and drug use. It is also associated with several energy consumption behaviors, including automobile fuel economy, home insulation and

[1] Additionally, Newell and Siikamäki (2013) conduct a choice experiment to estimate the effect of information provision on demand for energy-efficient appliances. Individual discount rates are measured and used to calculate an individual-level present value of operation cost for each model. However, correlations between individual discount rates and demand for energy-efficiency are not presented, and time-inconsistent discounting is not measured.

weatherization, and use of thermostats. However, the time-consistent discount factor δ is associated with an even larger number of outcomes. Controlling for risk preferences does not meaningfully affect these estimates. Our results therefore suggest that both time-consistent and present-biased discounting influence health, health behaviors, and energy use, with the relative extent to which each matters varying across different outcomes.

I. Survey Design

An online survey was conducted using Qualtrics software. A panel of 1300 respondents was purchased from Qualtrics Panels. Respondents were chosen to be representative of the US adult population. Quota sampling based on age, education, and gender was employed. The survey was conducted online in July and August 2013.

We asked five sets of questions of the respondents. The first set consists of demographic questions. These include age, gender, income, race, and education.

The second set of questions is used to calculate individual discount factors and test for present bias. We asked each respondent whether he would prefer a smaller payment more quickly or a larger payment after a longer wait (these questions are called *multiple price list* (MPL) questions). There were three payout time pairs to choose among: now vs. one month from now, now vs. six months from now, and six months from now vs. seven months from now. For each of the three payout time pairs, the larger payment (after the longer wait) was $30, and the smaller payment ranged from $29 to $8. Each respondent was asked 22 such questions; the values are listed in Table 1. [2]

[2] The time periods of the questions 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).

The 22 questions are divided into three "blocks" based on the time frame used: the red, black, and blue blocks. Table 1 lists the implied monthly discount factor for a consumer who is just indifferent between the larger and smaller payments. It also indicates the percentage of respondents who chose the larger amount. For each block, the percentage choosing the larger amount increases as the smaller amount decreases, as we would expect. In comparing the responses for the red block and the black block, we see the expected result that respondents are less willing to wait for a larger payoff if it is farther in the future. Most importantly, in comparing the responses for the red block and the blue block, we see some evidence of present bias. Time-consistent consumers should answer each corresponding question in these two blocks the same. 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. This pattern only holds for the first three rows; when the sooner payments are $24 or less and the majority of respondents choose to wait, then there is no difference in the percentage who wait between the red and blue blocks.

Using these questions, we calculate several measures of discounting parameters. First, we can 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.)[3] Several individuals' responses to the MPL questions are missing or are such that we cannot calculate one or more of the discount factors; these individuals are dropped.[4] We take the average of all of these three discount factors and call it δ_{avg}. This assumes time-consistent discounting. However, we allow

[3] The discount factor is calculated based on the question where the respondent switched from preferring the later payout to preferring the earlier payout. This method is described in more detail in Meier and Sprenger (2010, 199-200).

[4] For example, some respondents switched from the earlier to the later payments more than one time within a single price list.

for time-inconsistent discounting by noting that a respondent can have a different value for $\delta_{0,1}$ and $\delta_{6,7}$. Under time-consistent discounting, these two values are equal to each other. If $\delta_{0,1} < \delta_{6,7}$, then consumers are present-biased. Imposing a quasi-hyperbolic structure to the subjects' discounting, the present bias discount factor $\beta_{qh} = \frac{\delta_{0,1}}{\delta_{6,7}}$ and the long-run discount factor $\delta_{qh} = \delta_{6,7}$. We call these measures of δ_{avg} and δ_{qh}, β_{qh} "method 1."

A caveat of method 1 of calculating these parameters is that it requires complete and consistent responses for each question within the MPL. Also, the present bias discount factor β_{qh} is calculated using just the red and blue blocks. An alternate method for calculating both δ_{avg} and δ_{qh}, β_{qh}, which we call "method 2," does not require completeness and uses all 22 MPL questions in each calculation. Method 2 is simple based on a nonlinear best-fit of either a time-consistent discounting specification or a quasi-hyperbolic discounting specification to all of the MPL responses. These measures are missing only for the consumers who exhibit no variation at all in their MPL responses (e.g. always choosing the larger payout).

To combat hypothetical bias, we paid a random subset of respondents based on their responses to these questions. Depending on the phase of the survey, between 5% and 20% of respondents were randomly selected to receive a payment. For each respondent chosen, one of the 22 MPL questions was randomly chosen to be the payout question. Payments were Amazon.com gift cards. To ensure trustworthiness of these payments, we emailed each winner immediately after the survey completion with information on the professor's contact information.

Table 2 presents summary statistics of these time preference measures. In general the number of observations is greater for the method 2 variables than for the method 1 variables. The time-consistent monthly discount factors δ_{avg} are about 0.85, which is quite low for a monthly discount factor but consistent with previous literature finding low discount factors when using MPLs (Meier and Spregner 2010) (Frederick, Loewenstein and O'Donoghue 2002). Under method 1, the average β_{qh} is no different than one, indicating time-consistent preferences. But the average of this variable under method 2 is 0.94, indicating present bias on average. We also present the statistics for a binary indicator "Present Bias Indicator," which is equal to one if method 1's $\beta_{qh} < 1$ (i.e. if $\delta_{0,1} < \delta_{6,7}$). This variable indicates that about one-third of respondents are present biased using this method. [5] The correlations between the corresponding measures across methods 1 and 2 are generally high; for δ_{avg} it is 0.94, for δ_{qh} it is 0.82, and for β_{qh} it is 0.86. For the remainder of the paper, we present results using just method 2, but most all of the results are robust to using the method 1 definitions instead.

There are caveats to this method for eliciting time preferences. In particular, using simply MPL questions relies on the assumption of linearity of utility. Andreoni et. al. (2013) consider two alternative measures to MPL: double multiple price lists (DMPL) and convex time budgets (CTB). We adopt the strategy of DMPL, because the computational burden on the participants of the CTB questions is too great given the other questions that are asked in our survey. To implement DMPL, we ask an additional series of questions about preferences over lotteries (see Andersen et al. (2008), p. 586). In each question, the respondent is asked to choose between two lotteries: both have the same probability of winning a larger amount or winning a smaller amount, but the amounts won vary. See Table 3 for a description of the lotteries.[6] Going down the table, the difference in the expected values between lottery A and lottery B is getting smaller. Lottery B is riskier, so the risk aversion coefficient that makes an individual indifferent between the two lotteries is getting larger down the rows. The risk aversion

[5] This is almost equal to the 36% found in Meier and Sprenger (2010). We find future bias ($\beta_{qh} > 1$) in 25% of the sample, compared with 9% in Meier and Sprenger (2010).

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

coefficient is calculated based on the following constant relative risk aversion (CRRA) specification:

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

The CRRA coefficient is *r*. This is assuming that consumption is *M*, or that background consumption is zero. Table 3 shows that as the expected value of B becomes relatively larger than that of A, the number of respondents choosing B increases. For each respondent, we choose the row at which he or she switches from Lottery A to Lottery B as being the indifference point, and the respondent's CRRA is assigned accordingly. Any respondent missing any response to a lottery question, or demonstrating inconsistent or multiple switching is dropped. The last row of table 2 shows the mean value of CRRA across the sample.

The third set of questions asks respondents about health-related economic decisions. These include questions about smoking (have you ever smoked, do you currently smoke, how many cigarettes per day do you currently smoke), wearing sunscreen, sexual behavior, and health insurance. These questions were predominantly drawn from the US Center for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) 2011 questionnaire.[7] The fourth and final set of questions asks respondents about energy use decisions. These include questions about transportation (what is your primary form of transportation, what is the fuel economy of your car) and home energy use (does your home have energy-efficient light bulbs, have you had an energy audit of your home conducted). These questions were predominantly drawn from questions asked in the US Energy Information Administration's 2009 Residential Energy Consumption Survey.[8]

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[7] That survey is available here: http://www.cdc.gov/brfss/.
[8] That survey is available here: http://www.eia.gov/consumption/residential/. Some additional questions were taken from the survey designed for Attari et. al. (2010).

The fifth and final set of questions includes self-reported measures of risk aversion, patience, and self-control, simple IQ/attention questions, and an alternative elicitation of time preferences that is based on choices over medicines rather than choices over money. These variables will be described below.

II. Results

II.a. Time Preferences and Outcomes

The primary empirical objective is to identify statistically significant associations between time preferences and these decisions or behaviors. Results are presented in Tables 4 through 8. Each table presents regression results where the dependent variable is one of several outcomes of interest. For each dependent variable, two regressions are reported. The first models time preferences using our time-consistent discount factor δ_{avg} (calculated using method 2), and the second uses our quasi-hyperbolic discount factors δ_{qh} and β_{qh} (also calculated using method 2). Although not reported, all regressions also control for a constant and the following demographic variables: age, gender, race (an indicator for "white" equal to one if respondent reported race is white and non-Hispanic status), education (an indicator equal to one if respondent attended college or greater), and income.

Table 4 presents regression results for several health-related outcomes. Respondents were asked if they would say that their health "in general" is excellent, very good, good, fair, or poor. The variable "health status" is that response on a scale from 1 to 5 where 5 is excellent and 1 is poor. The variable "good health" is a binary indicator equal to one if the response is excellent, very good, or good. Both health status measures are significantly positively correlated with δ in both specifications. This is as expected; more patient individuals are healthier. The coefficient on β_{qh} is positive as expected; present biased individuals are less healthy. But this is significant only for the binary indicator (column 4).

Respondents were asked the number of days per month that their mental health was not good, and the number of days per month that their health kept them from doing their usual activities. Both of these responses are negatively correlated with δ but uncorrelated with β. More patient individuals are less likely to have had a recent cholesterol check, and present-biased people are more likely to have had a recent complete physical examination. This is contrary to our hypothesis given that these examinations are health investments. However, there is conceivable a selection issue explaining this result: sicker people are more likely to require cholesterol checks or physicals all else equal.

The coefficient on δ in the BMI regressions is positive, suggesting that more patient individuals have a higher BMI. This is contrary to our hypothesis and contrary to many other studies that find a negative correlation between discount factor and BMI (Courtemanche, Heutel and McAlvanah forthcoming). The present bias discount factor β is uncorrelated with BMI. Two measures of unhealthy eating behavior, the number of times per day one eats sweet snacks and the number of times per day one eats salty snacks, are both negatively correlated with δ as expected. Neither is correlated with β.

The last outcome reported in Table 4 is a binary indicator for whether or not the respondent would like to weigh less than his or her current weight. This indicator is positively correlated with patience, which would be expected given the results from columns 13 and 14 that BMI is positively correlated with δ. On the whole the table provides evidence that a variety of health behaviors and outcomes are correlated with time preferences, though present bias usually does not add any more predictive power beyond a time-consistent discount factor.

Table 5 lists regressions for which the outcomes relate to tobacco, alcohol, and drug use. The first six columns relate to cigarette smoking. Less patient individuals are less likely to have ever tried smoking, to be a regular smoker, and to smoke fewer cigarettes per day. These outcomes are also correlated with present bias in the expected direction. We find a negative correlation between discount factor and trying to stop smoking. Present biased people consume more alcohol per session of drinking and binge drink more times per month than do non-present biased people. Time preferences are correlated with illegal drug use in the expected ways, though not always significantly. All of the results on this table confirm our hypothesis that more patient individuals are less likely to drink, smoke, and use drugs. Present bias but not the long-run discount factor is correlated with the quantity of alcohol consumption and the number of binge drinking occurrences per month, as well as marijuana use.

Table 6 lists more assorted health-related outcomes. More patient people are more likely to have health insurance and to have bought their own health insurance (among those respondents who do not have health insurance through their employer or the government). Patience is correlated with seat belt use and exercise in the expected way, but present bias is uncorrelated with these. More patient respondents (measured by the time-consistent discount factor) are more likely to have had sexual intercourse and to be in a monogamous relationship.

Table 7 lists regression results where outcomes are related to passenger vehicles. There is no significant relationship between an indicator for owning a large vehicle (an SUV, van, minivan, or pickup truck) and time preferences. Owning a high-mpg vehicle (higher than 25 mpg) is significantly correlated with present bias but not with the long-run discount factor. A binary indicator for owning a hybrid vehicle is correlated with both discount factors but in an unexpected direction. We suspect this is because the number of hybrid owners in the sample is so low (just 58 out of 1,058 vehicle owners). On the whole, Table 7 provides only weak evidence that the energy paradox in the transportation sector is related to present bias.

Table 8 examines consumption behaviors related to home energy use. The evidence from this table is rather mixed. More patient consumers are more likely to have installed compact fluorescent lights (CFLs) in their homes and to have a home that they claim is well-insulated (although the last correlation is not quite significant). But more patient consumers are less likely to have performed weather-stripping in their home (barely significantly) or to have conducted a home energy audit. In columns 9 and 10 the dependent variable is an indicator for whether or not the respondent had planned on conducting a home energy audit but not done so. Given that present bias predicts that individuals will make plans and not follow through, we predicted the negative correlation in this column (although again it is just as significant for the time-consistent discount factor). More patient individuals are more likely to own a thermostat, but less likely to use a programmable thermostat that to adjust the temperature of the house during the day or when sleeping. More patient people (measured with the time-consistent discounting specification) are *less* likely to say that they have plans to reduce their energy consumption.

Tables 4 through 8 demonstrate that many outcomes and behaviors related to health and energy consumption are correlated with time preferences parameters elicited from MPLs. Most of the outcomes are explained by the long-run or time-consistent discount factor δ, while a smaller but still substantial number are explained by present bias β. Our results therefore suggest that both time-consistent and present-biased discounting separately influence health, health behaviors, and energy use. Time-consistent discounting may on average matter more, but the relative extent to which each matters varies depending on the outcome.

II.b. Risk Preferences

Some literature has suggested that measuring time preferences without controlling for or simultaneously measuring risk preferences leads to misleading results (Andersen, et al. 2008) (Andreoni, Kuhn and Sprenger 2013). As described earlier, we measure risk preferences using a set of MPL questions over lotteries. Assuming a CRRA utility specification allows us to calculate each individual's risk coefficient. We calculate the CRRA using just the lottery MPL questions, and we calculate the time preference parameters using just the deferred payment MPL questions. By contrast, Andersen et al. (2008) suggests a simultaneous estimation of both sets of preference parameters using the responses to both sets of questions and a maximum likelihood specification. We leave that for future research.

In Table 9, we replicate some of the previous table's regressions while also controlling for the calculated risk coefficient. The odd-numbered columns replicate the regressions from earlier tables (without the risk coefficients), except that they only include the observations for which the risk coefficient calculations are non-missing. This reduction in sample size is why we did not include the CRRA variable in our main regressions. Then, the even-numbered columns add the risk coefficient. The results show that adding CRRA generally has little effect on the coefficient estimates for the discount factor parameters.

II.c. Discounting Rate from Health Question

The time preference measures are calculated based on individuals' responses to MPL questions about monetary payments (actually, Amazon.com gift card payments). Conceivably, consumers could exhibit different discounting behavior over money decisions than over other types of decisions, like health investments. Augenblick et al. (2013) provide experimental evidence that consumers exhibit more present bias in choices over work effort tasks than in choices over money.

To investigate this issue, we ask each respondent a series of hypothetical questions about drugs for migraine headache relief. In each question, the respondents are told to suppose that they suffer from debilitating migraines, and that two drugs are available to them. Both are the same price and cannot be used together. 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 vary the delay for the availability of Drug B from 6 months to 7 years. From these questions we can calculate a discount factor by fitting a time-consistent discounting specification to each response (i.e. analogous to our method 2 of calculating discount factors from the MPL questions).

Our alternate measure of discounting is labeled $\delta_{migraine}$. The main result from our calculation of this alternate measure is that it is uncorrelated with any of the measured outcome variables and with the discount factors calculated using the money-based MPL questions. The mean value of $\delta_{migraine}$ is 0.9361, compared to a mean of our preferred measure of a time-consistent δ of 0.8460. However, the correlation coefficient between the two measures is just 0.021. We do not present regression results that examine the conditional correlation of $\delta_{migraine}$ since all of the coefficients are insignificant.

II.d. Self-Reported Patience and Risk Tolerance

We ask each respondent a series of questions that give self-reported measures of patience and risk preferences. Each such question is answered on a scale of 1 to 10. Table 10 provides OLS regression results where the dependent variable is one of these 10-point responses, and we control for our measured time preferences (either imposing time-consistency or allowing for present bias).

Columns 1 and two present the results where the dependent variable is a self-reported willingness to take risks (a higher number corresponds to being more willing to take risks). The correlation between the discount factor δ and this measure is positive, but it is not quite significant. In columns 3 and 4 the dependent variable is self-reported patience; a higher number signifies more patient. As expected, the self-reported patience measure is positively correlated with the long-run discount factor from the MPL responses, although not quite significantly. There is no correlation between the present bias discount factor and self-reported patience.

The strongest results come from columns 5 and 6, where the dependent variable is a 10-point scale measure in response to the question "How strong is your willpower/ability to control your impulses?" A higher number means stronger willpower. We find a significant positive correlation between the long-run discount factor δ and this response. This is as expected. However, there is no significant correlation between the present bias discount factor β and the willpower measure. Our prior was that of all of the self-reported measures, this one would be the most likely to be positively correlated with β (since δ is sometimes thought of as "patience" while β is thought of as "willpower").

Lastly, we ask respondents how easy it is for them "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." There is no significant correlation between this response and any of the time preference measures.

In sum, the results from the self-reported risk and patience measures demonstrate that these measures are only weakly related to the elicited time preferences, and then only with the time-consistent discount factor δ and not with the present bias discount factor β.

II.e. Cognitive Reflection Test Questions

Finally, we move beyond health and environmental outcomes and ask respondents three questions taken from the "Cognitive Reflection Test" (CRT) of Frederick (2005). These three questions are each designed as a way to measure one type of cognitive ability: the ability to "reflect" on a response before committing to an answer provided by intuition. 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

The intuitive answer that springs to mind from question 1 is 10 cents, though the correct answer is 5 cents. Frederick (2005) posits that the CRT questions measure how able an individual is to reflect on an answer provided by her "system 1" using her "system 2", using the terminology coined by Stanovich and West (2000) (see also Kahneman (2011)). Frederick (2005) shows that more patient individuals, measured by MPL questions and self-reported patience questions, are more likely to answer CRT questions correctly. However, Frederick (2005) does not test for correlation between present bias and CRT responses.

We do so in regressions reported in Table 11. The dependent variable in each column is a binary indicator for whether or not the CRT question was answered correctly. Reinforcing the results from Frederick (2005), we find that more patient individuals are more likely to answer each question correctly. However, the present bias discount factor β is uncorrelated with the CRT questions. If the CRT questions are a measure of the reliance on "system 2" instead of "system 1", then these results do not provide evidence that quasi-hyperbolic discounting behavior is in any way related to the system 1/system 2 distinction.

III. Conclusion

We provide survey evidence demonstrating that elicited discounting parameters, including β from a quasi-hyperbolic discounting specification, are significantly associated with many outcomes related to health and energy consumption. This provides some evidence that present bias could be an explanation for many health outcomes, including the obesity epidemic, and for the "energy paradox." However, the time-consistent component of the quasi-hyperbolic specification, δ, is significantly associated with even more outcomes than present bias. Controlling for risk preference does not meaningfully affect any of our results. In sum, our results point to the importance of both time-consistent and time-inconsistent discounting in explaining variation in health, health behaviors, and energy use.

We contribute to the literature by providing empirical evidence on the relationships between present bias and a much larger array of outcomes than those previously studied. Prior work has demonstrated that present bias is related to smoking (Burks, et al. 2012), credit card borrowing (Meier and Spregner 2010), and BMI (Courtemanche, Heutel, and McAvanah forthcoming). In contrast, we consider dozens of outcomes across both health and environmental domains.

Several interesting questions are prompted from our findings. If the regressions results are taken at face value, it seems that some behaviors (smoking, drinking) are correlated with present bias in expected ways but some others (exercise, home weatherizing) are not. It is not apparent what the policy implications are if consumers are time-consistent over some domains or decisions and time-inconsistent over others. One of the most intuitive policy options for present-biased individuals, internality taxes (O'Donoghue and Rabin 2006), may not be optimal when present bias heterogeneously affects different behaviors. Future research could include both empirical refinements examining where and how present bias explains actions, and theoretical work designing optimal policy in the presence of present bias.

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Table 1

Red Block				Black Block				Blue Block			
Today	One Month	Discount factor if indifferent	Percent Choosing Larger Amount	Today	Six Months	Discount factor if indifferent	Percent Choosing Larger Amount	Six Months	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

δ_{avg} (method 1)	0.8680 (0.1228) [1029]
δ_{avg} (method 2)	0.8460 (0.1464) [1154]
δ_{qh} (method 1)	0.8406 (0.1888) [1175]
β_{qh} (method 1)	1.0101 (0.2457) [1094]
δ_{qh} (method 2)	0.8635 (0.1592) [1154]
β_{qh} (method 2)	0.9359 (0.2501) [1154]
Present Bias Indicator	0.3318 (0.4711) [1094]
CRRA	0.5756 (0.8383) [963]

Note: Table displays the mean, standard deviation (in parentheses) and number of observations (in square brackets) for each variable.

Table 3

Lottery A				Lottery B				EV(A)	EV(B)	Difference	CRRA if just indifferent	Percent Choosing A
p	$	p	$	p	$	p	$					
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

	(1) Health Status (1-5)	(2) Health Status (1-5)	(3) Health Status (binary)	(4) Health Status (binary)	(5) Days Mental Health not good	(6) Days Mental Health not good	(7) Days Health Affected Activity	(8) Days Health Affected Activity	(9) Recent Cholesterol Check	(10) Recent Cholesterol Check
δ	0.462*		0.283***		-6.902***		-4.890**		-0.189*	
	(0.244)		(0.0940)		(2.195)		(1.925)		(0.106)	
δ_{qh}		0.425*		0.282***		-6.517***		-4.205**		-0.205**
		(0.238)		(0.0916)		(2.174)		(1.932)		(0.103)
β_{qh}		0.103		0.116***		-1.867		-0.907		-0.133***
		(0.122)		(0.0447)		(1.228)		(1.206)		(0.0502)
N	1,039	1,039	1,039	1,039	1,038	1,038	1,037	1,037	1,037	1,037
R^2	0.078	0.078	0.047	0.049	0.044	0.043	0.025	0.023	0.149	0.152
	(11) Recent Physical	(12) Recent Physical	(13) BMI	(14) BMI	(15) Sweets per day	(16) Sweets per day	(17) Salty Snacks per day	(18) Salty Snacks per day	(19) Want to Weigh Less	(20) Want to Weigh Less
δ	0.0341		4.143**		-0.866***		-0.838***		0.259**	
	(0.111)		(1.830)		(0.292)		(0.307)		(0.104)	
δ_{qh}		0.00689		3.721**		-0.664**		-0.612*		0.266***
		(0.108)		(1.804)		(0.308)		(0.337)		(0.101)
β_{qh}		-0.0877*		-0.434		0.0424		-0.180		0.0788
		(0.0520)		(1.075)		(0.267)		(0.332)		(0.0490)
N	1,036	1,036	959	959	1,034	1,034	1,035	1,035	1,038	1,038
R^2	0.061	0.063	0.053	0.054	0.103	0.101	0.115	0.111	0.077	0.078

Table 5

	(1) Have Smoked 100 Cigarettes	(2) Have Smoked 100 Cigarettes	(3) Regular Smoker	(4) Regular Smoker	(5) Cigarettes Per Day	(6) Cigarettes Per Day	(7) Tried to Stop Smoking	(8) Tried to Stop Smoking	(9) Quantity of Alcohol Per Session	(10) Quantity of Alcohol Per Session	(11) Binge Drinking Per Month	(12) Binge Drinking Per Month
δ	-0.235**		-0.426***		-6.125***		-0.196**		0.0721		-0.662	
	(0.107)		(0.106)		(1.887)		(0.0894)		(0.499)		(0.553)	
δ_{qh}		-0.252**		-0.433***		-6.343***		-0.193**		0.0808		-0.592
		(0.104)		(0.104)		(1.852)		(0.0867)		(0.486)		(0.544)
β_{qh}		-0.164***		-0.133***		-1.669**		-0.0400		-0.701***		-0.729***
		(0.0502)		(0.0503)		(0.790)		(0.0419)		(0.248)		(0.280)
N	1,039	1,039	1,036	1,036	1,037	1,037	1,008	1,008	1,036	1,036	1,037	1,037
R^2	0.123	0.127	0.055	0.057	0.059	0.061	0.025	0.025	0.055	0.063	0.044	0.048
	(13) Tried to Stop Drinking	(14) Tried to Stop Drinking	(15) Prescription Drugs	(16) Prescription Drugs	(17) Steroids	(18) Steroids	(19) Marijuana	(20) Marijuana	(21) Cocaine	(22) Cocaine		
δ	-0.233***		-0.148*		-0.0830*		0.00943		-0.117			
	(0.0899)		(0.0762)		(0.0430)		(0.0986)		(0.0756)			
δ_{qh}		-0.228***		-0.145*		-0.0755*		-0.000632		-0.125*		
		(0.0875)		(0.0742)		(0.0419)		(0.0959)		(0.0743)		
β_{qh}		-0.0532		-0.0474		-0.0402**		-0.108**		-0.0700**		
		(0.0410)		(0.0381)		(0.0199)		(0.0482)		(0.0324)		
N	989	989	1,036	1,036	1,042	1,042	1,042	1,042	1,042	1,042		
R^2	0.037	0.037	0.024	0.024	0.030	0.031	0.024	0.027	0.017	0.019		

Table 6

	(1) Have Health Insurance	(2) Have Health Insurance	(3) Bought Own Health Insurance	(4) Bought Own Health Insurance	(5) Seat Belt	(6) Seat Belt
δ	0.330***		0.387***		0.270***	
	(0.109)		(0.126)		(0.0989)	
δ_{qh}		0.348***		0.410***		0.242**
		(0.107)		(0.120)		(0.103)
β_{qh}		0.0793*		0.144**		0.0351
		(0.0466)		(0.0571)		(0.0796)
N	1,035	1,035	405	405	1,040	1,040
R^2	0.085	0.087	0.061	0.066	0.024	0.022
	(7) Exercise Days Per Month	(8) Exercise Days Per Month	(9) Have Had Intercourse	(10) Have Had Intercourse	(11) In Monogamous Relationship	(12) In Monogamous Relationship
δ	5.923***		0.258***		0.286**	
	(2.099)		(0.0880)		(0.122)	
δ_{qh}		5.691***		0.265***		0.247**
		(2.043)		(0.0860)		(0.119)
β_{qh}		-0.0224		0.0568		-0.0422
		(1.235)		(0.0388)		(0.0593)
N	1,040	1,040	1,036	1,036	890	890
R^2	0.037	0.037	0.084	0.085	0.038	0.039

Table 7

	(1) Large Vehicle	(2) Large Vehicle	(3) High mpg	(4) High mpg	(5) Hybrid	(6) Hybrid
δ	0.0369		0.188		-0.176**	
	(0.127)		(0.130)		(0.0734)	
δ_{qh}		0.0705		0.184		-0.171**
		(0.129)		(0.135)		(0.0735)
β_{qh}		-0.0346		0.213**		-0.0942**
		(0.0917)		(0.106)		(0.0423)
Observations	840	840	841	841	840	840
R-squared	0.015	0.016	0.022	0.027	0.049	0.050

Table 8

	(1) Installed CFL	(2) Installed CFL	(3) Well Insulated	(4) Well Insulated	(5) Weather Stripping	(6) Weather Stripping	(7) Energy Audit	(8) Energy Audit	(9) Intended Energy Audit	(10) Intended Energy Audit
δ	0.354***		0.0871		-0.0773		-0.213**		-0.205**	
	(0.110)		(0.0882)		(0.113)		(0.0923)		(0.0831)	
δ_{qh}		0.323***		0.0778		-0.0824		-0.216**		-0.191**
		(0.109)		(0.0851)		(0.111)		(0.0900)		(0.0815)
β_{qh}		-0.0277		0.0689		-0.100*		-0.0855**		-0.114***
		(0.0615)		(0.0430)		(0.0530)		(0.0400)		(0.0420)
N	1,036	1,036	1,030	1,030	1,029	1,029	1,031	1,031	1,027	1,027
R^2	0.049	0.050	0.012	0.013	0.010	0.012	0.011	0.012	0.020	0.022

	(11) Replaced AC	(12) Replaced AC	(13) Thermostat	(14) Thermostat	(15) Cool When Sleeping	(16) Cool When Sleeping	(17) Cool During Day	(18) Cool During Day	(19) Plan to Reduce Energy	(20) Plan to Reduce Energy
δ	-0.216*		0.383***		-0.293		-0.379**		-0.245**	
	(0.119)		(0.104)		(0.179)		(0.163)		(0.112)	
δ_{qh}		-0.223*		0.344***		-0.336*		-0.424***		-0.255**
		(0.119)		(0.107)		(0.177)		(0.159)		(0.112)
β_{qh}		-0.103		0.0319		-0.310***		-0.332***		0.0177
		(0.0745)		(0.0778)		(0.107)		(0.103)		(0.0733)
N	902	902	1,024	1,024	381	381	381	381	1,031	1,031
R^2	0.016	0.017	0.039	0.036	0.015	0.028	0.019	0.033	0.020	0.022

Table 9

	(1) Health Status (binary)	(2) Health Status (binary)	(3) Recent Cholesterol Check	(4) Recent Cholesterol Check	(5) Sweets per day	(6) Sweets per day	(7) Have Smoked 100 Cigarettes	(8) Have Smoked 100 Cigarettes	(9) Regular Smoker	(10) Regular Smoker
δ_{qh}	0.228**	0.216**	-0.243*	-0.181	-0.574	-0.518	-0.210*	-0.231*	-0.414***	-0.413***
	(0.103)	(0.106)	(0.125)	(0.127)	(0.371)	(0.378)	(0.124)	(0.127)	(0.123)	(0.126)
β_{qh}	0.0593	0.0551	-0.134**	-0.110**	0.259	0.280	-0.150***	-0.158***	-0.105*	-0.104*
	(0.0482)	(0.0491)	(0.0549)	(0.0556)	(0.264)	(0.266)	(0.0543)	(0.0556)	(0.0538)	(0.0549)
CRRA		-0.00887		0.0495**		0.0446		-0.0171		0.00101
		(0.0190)		(0.0215)		(0.0652)		(0.0226)		(0.0215)
N	747	747	747	747	743	743	747	747	744	744
R^2	0.053	0.053	0.152	0.158	0.076	0.077	0.138	0.139	0.057	0.057
	(11) Have Health Insurance	(12) Have Health Insurance	(13) Bought Own Health Insurance	(14) Bought Own Health Insurance	(15) High mpg	(16) High mpg	(17) Installed CFL	(18) Installed CFL	(19) Intended Energy Audit	(20) Intended Energy Audit
δ_{qh}	0.370***	0.386***	0.451***	0.411***	0.187	0.161	0.342***	0.315**	-0.174*	-0.155
	(0.127)	(0.131)	(0.154)	(0.158)	(0.158)	(0.163)	(0.131)	(0.135)	(0.0942)	(0.0975)
β_{qh}	0.0501	0.0561	0.160***	0.144**	0.200*	0.189*	-0.00709	-0.0172	-0.0759*	-0.0691*
	(0.0540)	(0.0553)	(0.0527)	(0.0557)	(0.106)	(0.107)	(0.0757)	(0.0772)	(0.0409)	(0.0418)
CRRA		0.0126		-0.0415		-0.0197		-0.0216		0.0145
		(0.0202)		(0.0374)		(0.0263)		(0.0226)		(0.0137)
N	745	745	278	278	625	625	747	747	738	738
R^2	0.069	0.069	0.063	0.068	0.024	0.025	0.038	0.040	0.010	0.012

Table 10

	(1) Willing to Take Risks	(2) Willing to Take Risks	(3) Patient	(4) Patient	(5) Willpower	(6) Willpower	(7) Easy to Avoid Junk Food	(8) Easy to Avoid Junk Food
δ	0.944		1.089		2.006***		0.307	
	(0.710)		(0.698)		(0.672)		(0.715)	
δ_{qh}		0.737		0.933		1.677**		0.107
		(0.718)		(0.709)		(0.718)		(0.704)
β_{qh}		-0.245		-0.416		0.230		-0.588
		(0.452)		(0.468)		(0.624)		(0.380)
Observations	1,033	1,033	1,029	1,029	1,028	1,028	1,031	1,031
R-squared	0.034	0.034	0.028	0.031	0.043	0.040	0.011	0.014

Table 11

	(1) Bat and Ball Correct	(2) Bat and Ball Correct	(3) Widget Correct	(4) Widget Correct	(5) Lake Correct	(6) Lake Correct
δ	0.198***		0.289***		0.368***	
	(0.0462)		(0.0868)		(0.0737)	
δ_{qh}		0.178***		0.283***		0.333***
		(0.0452)		(0.0892)		(0.0725)
β_{qh}		5.63e-06		-0.0120		0.0200
		(0.0217)		(0.0677)		(0.0389)
Observations	1,023	1,023	959	959	992	992
R-squared	0.041	0.041	0.053	0.055	0.101	0.100