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Present bias and health

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Abstract

This study uses a dynamic discrete choice model to examine the degree of present bias and naivete about present bias in individuals' health care decisions. Clinical guidelines exist for several common chronic diseases. Although the empirical evidence for some guidelines is strong, many individuals with these diseases do not follow the guidelines. Using persons with diabetes as a case study, we find evidence of substantial present bias and naivete. Counterfactual simulations indicate the importance of present bias and naivete in explaining low adherence rates to health care guidelines.

Keywords

Hyperbolic discounting; Present bias; Naivete; Time preference; Diabetes; Adherence

1 Introduction

The default in economics has been to assume that individuals discount streams of utility over time exponentially, i.e., preferences are time-consistent. However, both some economic (e.g., Ikeda et al. 2010; Sloan et al. 2014; Fang and Wang 2015; Cavagnaro et al. 2016) and psychological research (e.g., Bickel et al. 1999) lend strong empirical support to the notion that individuals' preferences are time-inconsistent/present-biased in many domains, including in the health domain. In some health applications, the benefits of engaging in a particular activity accrue first, e.g., smoking, excess alcohol use, and opioid use, with the costs of these behaviors occurring downstream. By contrast, for adherence to guidelines for a chronic condition, costs are incurred first with benefits accruing later.

Hyperbolic discounting models have been designed to capture time inconsistency and have been applied in such contexts as saving, addiction, job search, and retirement decisions (e.g., O'Donoghue and Rabin 1999). With present bias, individuals exhibit a high discount rate in the short run but a relatively low discount rate in the long run. So they may plan to save, quit adverse health behaviors, or start searching for jobs next month, but when next month actually arrives, they tend to postpone immediate sacrifices for yet another month.

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Naivete about present bias may further explain individuals' time-inconsistent behaviors. The literature on time-inconsistent preferences distinguishes between *naive* and *sophisticated* decision-makers (O'Donoghue and Rabin 1999). Completely naive individuals believe that they will make time-consistent plans in the future even though they actually will not. Partially naive individuals believe that they will make time-inconsistent plans in the future but underestimate the extent of present bias in the future. Sophisticated individuals know the actual extent of their future present bias and correctly realize that they will keep postponing taking actions in the future (O'Donoghue and Rabin 1999). Intuitively, because naifs, complete or partial, overestimate their self-control and understate the extent of their present bias in the future, they have a greater tendency to repeatedly postpone unpleasant compliance activities. Or they may eventually complete these activities but with lesser quality than originally intended, which is another form of time inconsistency (Akin 2012). However, sophisticates foresee their future time inconsistency and suspect their future completion behavior. This increases their perceived costs of procrastination and encourages sophisticates to follow treatment recommendations now, to implement self-control devices, and/or to favor that society implement laws that facilitate self-control, e.g., raise cigarette excise taxes to curb smoking (Kan 2007). Exponential discounters and arguably sophisticated naifs are rational in that they take future behavior into account in making current decisions. Complete and partial naifs are irrational, the former more so than the latter. Particularly since irrational decision making often provides a rationale for public policy interventions, it is important to gauge naivete as well as present bias. For example, if people are present-biased and naive about their present bias, there is a case for societal concern about the internalities as well as the negative externalities stemming from individuals' decisions.

The decision to adhere to guidelines for diabetes care provides an interesting case study for the existence and the degree of present bias and naivete in individuals' health-related decisions. It is not only because present bias and naivete about present bias may explain why persons with diabetes frequently fail to follow treatment guidelines, but also because diabetes is a health condition with important policy implications.

Diabetes mellitus imposes a substantial burden and is a major threat to health in the U.S., and its prevalence is increasing (Cowie et al. 2006). The American Diabetes Association estimated that the cost of diabetes was $245 billion in 2012, including $176 billion in direct medical costs and $69 billion in reduced productivity due to increased work-related absenteeism, reduced labor force participation, and lost productive capacity due to premature mortality (American Diabetes Association. 2013). In addition, diabetes is the leading cause of blindness and non-traumatic lower-limb amputations among adults in the U.S. (U.S. Centers for Disease Control and Prevention 2011). In 2000, diabetes was the sixth leading cause of death in the U.S. (Mokdad et al. 2004). However, if anything, this ranking is too low since diabetes leads to cardiovascular and cerebrovascular complications, which, when they apply, are likely to be listed as the causes of death. The number of persons with diabetes is expected to increase by 165% from 11 million in 2000 (prevalence 4%) to 29 million in 2050 (prevalence 7.2%) (Boyle et al. 2001).

There is strong evidence from randomized controlled trials and studies based on observational data that patients who adhere to evidence-based treatment recommendations for diabetes care experience better health outcomes (e.g., Chen et al. 2015). A high degree of adherence leads to better glycemic control, fewer complications (e.g., blindness, leg amputations), and lower risks for all-cause hospitalization and all-cause mortality (Ho et al. 2006; Yashkin et al. 2016). However, a substantial proportion of persons who are diagnosed with diabetes do not adhere to guidelines for diabetes care, despite the potentially large benefits. Ho et al. (2006) report that about 20% of persons with diabetes are not adherent to guidelines for use of prescribed medications. And nonadherence rates for elements of lifestyle within the guidelines, including diet, exercise, glucose monitoring and regular eye examinations, are not higher (Ali et al. 2013). Nonadherence rates are high for other chronic conditions as well, such as for use of preventive medications following acute myocardial infarction. However, a comprehensive meta-analysis found that among 17 common disease conditions, diabetes ranked 16th in terms of mean adherence rates (DiMatteo 2004).

Present bias occurs in this context when the benefits of care for diabetes — avoidance of cardiovascular, cerebrovascular, ophthalmic, and lower extremity complications — often occur in the distant future. Although adherence offers substantial long-term benefits, the costs of adhering, e.g., obtaining screening on a regular basis, following dietary and exercise regimens, visiting health professionals, and use of medications are borne immediately.

Early empirical studies which were mainly designed to highlight the potential of the hyperbolic discounting framework based their analyses on assumed values of key parameters (Gruber and Köszegi 2001). More recently, most studies of discounting behavior have used a stated preference approach in which hypothetical situations are posed to respondents and discounting parameters are inferred from the responses. An advantage of this approach is that questions can be designed to deal with specific tradeoffs. A disadvantage is that the questions deal with hypothetical decisions, not actual decisions. By contrast, the revealed preference approach derives parameters based on actual decisions, but suffers from a potential lack of external validity of findings since these findings are based on a very specific decision-making problem.

The most closely related revealed preference study to ours, both methodologically and in terms of data used, is Fang and Wang's (2015) analysis of present bias and naivete about present bias in the context of decisions women make to undergo mammography.[1] Fang and Wang (2015) specify a dynamic model in which mammography potentially lowers the probability of death and the probability of bad health conditional on survival to investigate the role of time-inconsistent preferences in the choice to undergo mammography. Like our study, they reject the null hypotheses of exponential discounting and of sophistication given present bias. However, they find less present bias than we do.

Their decision problem is similar to ours in that early detection of breast cancer by mammography can lead to more timely therapy. The decision problem is different in that

[1]Fang and Wang (2015) develop methodologies for both finite and infinite time horizons. Here, like the empirical analysis in that paper, we assume a finite horizon with a maximum age of 100.

mammography is administered periodically (often annually or biennially) whereas adherence to diabetes guidelines involves many tasks, some undertaken daily. Furthermore, the latency period from the time an individual adheres to guidelines to the appearance of complications may be much longer for diabetes. Salience of being diagnosed with cancer is likely to be much greater than for diabetes. For these and other reasons, including the sequence of costs and benefits, findings for one condition about present bias and naivete may not generalize to all health behaviors. Like our study, Fang and Wang (2015) use longitudinal data from the Health and Retirement Study (HRS), but unlike Fang and Wang, the present study is also based on data from Medicare claims merged with HRS interview data. Our analysis sample consists of men and women already diagnosed with diabetes, unlike Fang and Wang in which no sample persons were diagnosed with breast cancer at the time the decision to undergo mammography was made. Fang and Wang provide a full description of the dynamic discrete choice model and the identification and estimation method. We provide a summary of the approach below with a focus on the intuition.

We find that present bias indeed exists among persons diagnosed with diabetes, and such persons are also completely naive about their present bias. Our statistical tests reject the null hypotheses of no present bias or of no naivete. Results from counterfactual simulations indicate that present bias and naivete both play important roles in the low adherence rates to diabetes guidelines. We find that without present bias and naivete, adherence rates would increase by 16.4%, and this change in adherence rate translates into substantial reductions in lifetime medical spending.

Section 2 sets up and briefly discusses a dynamic model for an individual diagnosed with diabetes making the discrete decision of whether to follow the guidelines or not under potentially time-inconsistent preferences and naivete. Section 3 discusses the data used in our study and provides descriptive statistics of our analysis sample. Section 4 provides details about the empirical estimation strategy. Section 5 reports the main estimation results. Section 6 offers some discussion and concluding remarks.

2 A dynamic discrete choice model for a potentially naive hyperbolic discounter

Consider a decision-maker whose instantaneous preferences are defined over several state variables (x, ε) where $x \in \mathcal{X}$ are observed by the researcher and ε is a vector of random preference shocks, and two choices $i \in \mathcal{I} = \{0, 1\}$.[2] In each period, the decision-maker chooses to follow the guidelines, $i = 1$ or not, $i = 0$. Her decision depends on her health, income, and demographic variables, which are in x.

The decision-maker's instantaneous utility from taking action i, $u_i^*(x, \varepsilon)$ for each $i \in \mathcal{I} \backslash \{0\}$ is additively separable and takes on the following form[3]:

[2]For a formal discussion and technical details of the identification and estimation method, see Fang and Wang (2015).

[3]We know from the standard theories of discrete choice that we have to normalize the utility for the reference alternative to 0, so without loss of generality we set $u_0^*(x, \varepsilon) = 0$ for all $x \in \mathcal{X}$.

$$u_i^*(x, \varepsilon) = u_i(x) + \varepsilon_i, \quad (1)$$

where $u_i(x)$ is the deterministic component of the utility from choosing i at x, and ε has a distribution G.

The decision-maker's time horizon extends from t, the current period, to T, the terminal period. Her intertemporal preferences are additively time separable and can be represented by a simple and commonly used formulation of potentially time-inconsistent preferences: (β, δ)-preferences (O'Donoghue and Rabin 1999):

$$U_t(u_t, u_{t+1}, \ldots) \equiv u_t + \beta \sum_{k=t+1}^{T} \delta^{k-t} u_k,$$

where $\beta \in (0, 1]$ and $\delta \in (0, 1]$.

Following O'Donoghue and Rabin (1999), δ is the *standard* discount factor, which captures long-run, time-consistent time preference, and β is the *present-bias* factor, which captures short-term impatience. The standard model in which the decision-maker's preferences are time-consistent is nested as a special case of (β, δ)-preferences when $\beta = 1$. When $\beta \in (0, 1)$, (β, δ)-preferences capture "quasi-hyperbolic" time discounting, and the decision-maker's preferences are present biased.

A *partially naive* decision-maker in each period t underestimates the present bias of her future selves, believing that her future selves' present bias is $\tilde{\beta} \in (\beta, 1)$. A *completely naive* decision-maker believes that her future selves are time-consistent, i.e. $\tilde{\beta} = 1$. A *sophisticated* decision-maker in every period t correctly knows her future selves' present bias β and accurately anticipates her behavior when making her future selves' period t decisions, i.e., $\tilde{\beta} = \beta$.

For the potentially time-inconsistent decision-maker, $V_t(x_t, \varepsilon_t)$ is the decision-maker's period-t expected continuation utility conditional on the state variables x_t and the shock vector ε_t if she discounts the future using δ, and $V_t(x_t, \varepsilon_t)$ reflects her intertemporal preferences without taking her present bias into account:

$$V_t(x_t, \varepsilon_t) = u^*(x_t, \varepsilon_t) + \delta \mathrm{E}\left[V_{t+1}(x_{t+1}, \varepsilon_{t+1}) \mid x_t, \varepsilon_t\right], \quad (2)$$

where the expectation E is taken over the future state x_{t+1} and ε_{t+1}.

Next, we define the *long-run* value function at time t, also perceived from a prior perspective, as:

$$V_t(x_t) \equiv \mathrm{E}_{\varepsilon_{\mathbf{t}}} V_t(x_t, \varepsilon_{\mathbf{t}}), \quad (3)$$

where $V_t(x_t, \varepsilon_t)$ is defined in (2).

In addition, we assume Conditional Independence for state transitions, thus x and ε move independently. Further, the shocks have a Type I Extreme Value Distribution (see, e.g., Rust 1994).[4]

Incorporating present bias, the current choice-specific value function, $W_{i,t}(x_t)$, is:

$$W_{i,t}(x_t) = u_{i,t}(x_t) + \beta\delta \sum_{x_{t+1} \in \mathcal{X}} V_{t+1}(x_{t+1})\pi(x_{t+1} | x_t, i), \quad (4)$$

where π represents the conditional transition probability matrix for x.

We distinguish between present-biased decision-makers who are naive from those who are sophisticated. First, we define the choice-specific value function of the next-period self *perceived* by the current self, $Z_{i,t+1}(x_{t+1})$, as:

$$Z_{i,t+1}(x_{t+1}) = u_{i,t+1}(x_{t+1}) + \tilde{\beta}\delta \sum_{x_{t+2} \in \mathcal{X}} V_{t+2}(x_{t+2})\pi(x_{t+2} | x_{t+1}, i). \quad (5)$$

Further,

$$V_{i,t+1}(x_{t+1}) = u_{i,t+1}(x_{t+1}) + \delta \sum_{x_{t+2} \in \mathcal{X}} V_{t+2}(x_{t+2})\pi(x_{t+2} | x_{t+1}, i), \quad (6)$$

then according to the definition of $V(\cdot)$ by (3), $V_{t+1}(x_{t+1})$is the expected value of $[V_{i,t+1} + (x_{t+1})\ \varepsilon_{i,t+1}]$ where i is the chosen alternative $\sigma(x_{t+1}, \varepsilon_{t+1})$. This yields the following relationship:

$$V_{t+1}(x_{t+1}) = \mathrm{E}_{\varepsilon_{t+1}}\left[V_{\sigma(x_{t+1}, \varepsilon_{t+1}), t+1}(x_{t+1}) + \varepsilon_{\sigma(x_{t+1}, \varepsilon_{t+1}), t+1}\right]. \quad (7)$$

The difference between $W_{i,t}(x_t)$, $Z_{i,t+1}(x_{t+1})$, and $V_{i,t+1}(x_{t+1})$ is important. In $W_{i,t}(x_t)$ the payoff t-periods removed from the current period is discounted by $\beta\delta^t$, while in $Z_{i,t+1}(x_{t+1})$ the payoff t-periods removed from now is discounted by $\tilde{\beta}\delta^t$. In addition, $W_{i,t}(x_t)$ represents

[4]Conditional Independence Assumption:

$$\pi(x_{t+1}, \varepsilon_{t+1} | x_t, \varepsilon_t, d_t) = q(\varepsilon_{t+1} | x_{t+1})\pi(x_{t+1} | x_t, d_t)$$
$$q(\varepsilon_{t+1} | x_{t+1}) = q(\varepsilon).$$

Extreme Value Distribution Assumption: ε_t is i.i.d Type I extreme value distributed.

how the current-period self evaluates the deterministic component of the payoff from choosing alternative i, while $Z_{i,t+1}(x_{t+1})$ is how the current-period self perceives how her next-period self would evaluate the deterministic component of the payoff from choosing alternative i. Therefore, $W_{i,t}(x_t)$ represents the current self's optimal choice, $Z_{i,t+1}(x_{t+1})$ reflects the *perception* of the current self regarding choices of her future selves, while $V_{i,t+1}(x_{t+1})$ is simply an auxiliary value function that uses the long-run discount factor δ to evaluate the payoffs from the choices that the current self perceives will be made by her future selves. W differs from Z in situations in which the decision-maker misperceives the choice she will make in the future.

If a person is not present biased, $W=Z=V$. If the decision-maker is present biased and completely naive, i.e., if $\tilde{\beta}=1$, from (5) and (6), $V_{i,t+1}(x_{t+1})=Z_{i,t+1}(x_{t+1})$ for all x, but W differs. This is so because when $\tilde{\beta}=1$, the current self perceives her future selves to be time-consistent. If a decision-maker is present biased and sophisticated, i.e., if $\tilde{\beta}=\beta$, then (4) and (5) imply that $W_{i,t}(x_t)=Z_{i,t}(x_t)$, but V differs; i.e., if the decision-maker is sophisticated, then the current self's own choice rule is identical to her perceived future self's choice rule.

The identification of $\langle \beta, \tilde{\beta}, \delta \rangle$ is based on Magnac and Thesmar (2002) who show that if there is a state variable satisfying the Exclusion Restriction assumption, i.e., a state variable that does not directly affect *contemporaneous* utility $u_i(\cdot)$ for all $i \in \mathscr{I}$, but affects choices indirectly through the transition of state variables, then it is possible to identify the discount factors.[5]

We assume that the decision-maker's instantaneous utility depends only on her health and income, but her health transitions are not only determined by her health and income but also her mother's longevity, her age, gender, marital status, educational attainment, and race/ethnicity. Variables from mother's longevity through race/ethnicity serve as the exclusion restrictions. Magnac and Thesmar (2002) identify a single long-term discount factor δ. If $\delta=0$, i.e., if individuals are completely myopic, the choice probabilities would not depend on the values of this state variable. To the extent that choice probabilities differ by different values of this excluded state variable, information about δ is revealed. Their intuition was extended to the hyperbolic discounting case, as formally discussed in Fang and Wang (2015). We maximize a pseudo-likelihood function to estimate the discount factors $\langle \beta, \tilde{\beta}, \delta \rangle$. Additional details on the identification and estimation of the model are described in the Appendix.

3 Data

Data for this study come from the HRS, a nationally representative biennial panel study of individuals born 1931 through 1941 and their spouses who could be of any age as of 1992, the baseline year. Older and younger cohorts have been added to the HRS subsequently. Our measure of adherence comes from Medicare claims data merged at the level of the individual respondent with HRS interview data. With claims data, we measure whether the respondents

[5]Formally, the Exclusion Restriction assumption says that there exist state variables $x_1 \in \mathscr{X}$ and $x_2 \in \mathscr{X}$ with $x_1 \neq x_2$, such that (1) for *all* $i \in \mathscr{I}$, $u_i(x_1)=u_i(x_2)$; and (2) for *some* $i \in \mathscr{I}$, $\pi(x'|x_1, i) \neq \pi(x'|x_2, i)$.

had a urine test, whether they had a hemoglobin A1C test (a test which gives a “snapshot” of mean blood glucose levels for the past two or three months), a lipid test, a blood pressure check, and a visit to an optometrist or ophthalmologist within the past year. We set a binary variable for adherence to one if the claims indicated that the person adhered to at least three of the five items, and zero otherwise.[6]

Data on individuals’ general health and demographic characteristics and household income also come from the HRS. Respondents were asked to self-report their health using the question: “What do you think is your current health status? 1. excellent; 2. very good; 3. good; 4. fair; 5. poor?” A binary indicator “bad health” (BadHealth) is set to one if the respondent said her health was “fair” or “poor”, and is zero otherwise. The individuals’ cognition level is measured by a binary variable “low cognition” (LowCog) which is set to one if the total cognition summary score[7] is below 12, about one-third of the maximum score, 35, and is set to zero otherwise.[8] There is no generally-accepted threshold score for “cognitively impaired”. We select the value 12 as a threshold because it represents about the lower third of the range of scores.

Other respondent attributes are the respondent’s age (Age), race (non-Hispanic white or not) (White), male gender (Male), the logarithm of household income (LogIncome), whether the person was married at the interview date (Married), whether the person had more than a high school education (> HighSchool), whether the person had any kind of health insurance coverage other than Medicare (HIoth), whether the respondent’s mother was still alive or had died at an age of 70+ at the interview date (Mother Died < 70) and whether the mother had more than a high school education (Mom > HighSchool). The variable measuring mothers’ longevity is a proxy for the respondent’s private information concerning her own expected longevity attributable to familial factors.

We limit our sample to respondents aged 65 to 80 at the interview date who had been told by a physician that they have diabetes. We use Medicare claims data to measure adherence, and the sample size becomes substantially smaller above age 80. In addition, with increasing age, competing health care risks lead individuals to focus on care for other chronic diseases. We exclude observations with missing information on the dependent and the explanatory variables. The analysis sample consists of data from even-numbered years starting with 1994 and ending with 2010. We first create two-period short panels, and then pool all eight short panels to generate one large two-period panel (N = 34,946).

Table 1 reports summary statistics for the analysis sample. About half (51.8%) of respondents are adherent. Mean age is 72.1. Under half (41.8%) of respondents are male. About two-thirds (66.2%) are married at the interview date, and most (62.4%) have more than a high school education. Non-Hispanic whites constitute almost nine-tenths of the

[6]To check the robustness of our findings, we set Adherence to one if at least two or four of the five questions were answered affirmatively. The results are qualitatively similar.

[7]The total cognition summary score is generated in the RAND version of HRS. The total word recall summary variables sum the immediate and delayed word recall scores. The mental status summary sums the scores for serial 7’s, backwards counting from 20, and object, date, and President/Vice-President naming tasks. The total cognition score sums the total word recall and mental status summary scores, resulting in a range of 0–35. This score has been used in the literature as a good measure of cognitive ability.

[8]In robustness checks not shown, we set LowCog to one when the score is below 10 or 15, and the results are qualitatively similar.

sample (87.1%). Most respondents (74.9%) have mothers who died at ages 70+ or were still alive at the interview date, and 25.8% of mothers have more than a high school education. Nearly a third (32.0%) of respondents have low cognition. Almost a third (30.2%) have self-rated bad health. Mean household income is $35,656. And the two-year mortality rate is 5.86%.

4 Empirical specification

Individuals in the sample are diagnosed with diabetes and are possibly time-inconsistent and naive about their present bias. Each individual decides whether to follow the guidelines by comparing the expected sum of instantaneous and discounted future utilities from each choice. Following the literature (e.g., Arcidiacono et al. 2007), we assume that the difference in instantaneous utilities between adhering ($u_1(x)$) and not adhering to the guidelines ($u_0(x)$) depends linearly on whether the individual is in bad health and on the logarithm of her household income,[9] which measures her consumption of the composite good, i.e.,

$$u_1(x) - u_0(x) = \alpha_0 + \alpha_1 \text{ BadHealth } + \alpha_2 \text{LogIncome}. \quad (8)$$

The individual is uncertain about her future. Specifically, she is uncertain about her survival probabilities and if alive, the transition probabilities for her future health and income. These probabilities depend on whether she follows the guidelines, her current health and household income, and all the other state variables listed above. The other state variables are excluded from (8), i.e., are irrelevant to the individual's instantaneous utility. However, these variables affect the individual's mortality and the transitions of BadHealth and LogIncome, variables that affect the individual's instantaneous utility. Thus, they qualify as excluded variables, which are required for identification of the utility and time preference parameters.

In the next section, we first present results from logit regressions for determinants of guideline adherence and for effects of guideline adherence on two-year outcomes. We then present estimates of the structural utility and time preference parameters.

5 Results

5.1 Probability of following diabetes care guidelines

Table 2 reports the marginal effects and the associated standard errors from logit regressions for determinants of guideline adherence. Most coefficients based on the full analysis sample (col. 1) are statistically significant at the 5% level or better. Persons who are more likely to be adherent tend to be in bad health — a measure of symptom salience, older, female, married, good (not low) cognition, have a mother with more than a high school education, a mother who died before age 70, have health insurance other than Medicare, and are more affluent. Results in the remaining columns are based on subsamples of the analysis sample:

[9]In the structural but not in the reduced form analysis presented below, we discretize LogIncome to estimate state transitions and utility and time preference; we set the person's instantaneous utility when dead to zero.

educational attainment, high versus low; married, no versus yes; and BadHealth, no versus yes.

5.2 State transition probabilities

Adherence lowers the probability of dying within two years and increases the probability of having higher household income, all else equal (Table 3). Adherence, however, does not affect the transition to bad health conditional on survival. Stratifying the analysis sample by high versus low educational attainment, marital status, and bad versus good health generally shows no statistical differences on marginal effects of adherence on survival, income, and health two years later. All 95% confidence intervals overlap with one exception, the effect of adherence when in bad versus in good health on mortality in the next two years. In this case, adherence has a greater effect in reducing the probability of death if the person is in bad health at the interview immediately prior to the two-year follow-up interview.

5.3 Utility and time preferences

Table 4 presents estimates and associated standard errors for utility and time preference parameters, i.e., estimates of α_s in (8) and estimates of δ, β, and $\tilde{\beta}$. All these parameter estimates are statistically significant at better than the 1% level. Parameter estimates of δ, β, and $\tilde{\beta}$ are 0.88, 0.38, and 1.00, respectively; we reject the null hypothesis that $\delta = 0$ or $\beta = \tilde{\beta}$, but we cannot reject the null hypothesis that $\tilde{\beta} = 1$.

These results indicate that elderly persons diagnosed with diabetes are forward-looking ($\delta >$ 0), they exhibit present bias ($\beta < 1$), and they are completely naive about their present bias ($\tilde{\beta} = 1$) when deciding whether or not to adhere to the guidelines. This finding is consistent with the fact that only slightly more than half of persons in our analysis sample adhered to the guidelines, despite the relatively low threshold we employ for adherence.

Estimates for utility parameters (α_s) reveal that persons with diabetes pay an instantaneous cost when they decide to follow the guidelines ($\alpha_0 < 0$), which is consistent with the tradeoff between short-term costs and long-run benefits that persons with this condition face; their instantaneous utility decreases if they are in bad health ($\alpha_1 < 0$) and increases with their household income ($\alpha_2 > 1$).

5.4 Comparisons of our results to those from previous studies

Bradford et al. (2017) use survey-elicited responses to time preference questions for health, smoking, installing energy-efficient lighting, and credit card balances. They find empirical evidence for hyperbolic discounting in several domains in the same study. Nevertheless, there is no reason to expect that our results necessarily coincide with this or other previous studies for several reasons.

First, the contexts in which preferences are measured differ. There is some evidence that discount rates in financial, environmental, and health domains differ (see e.g., Chapman 1996, Ioannou and Sadeh 2016). Intertemporal tradeoffs for gains and losses may also differ. Second, the elicitation method, stated versus revealed preference, may affect the results. In this paper, we use observed people's behavior to infer their preferences, a revealed preference approach. Some other papers, such as Bleichrodt et al. (2016), directly ask their survey respondents or experiment participants to state their preferences for one option over the other, a stated preference approach. Differences in elicitation methods could also lead to differences in sample size, with studies using revealed preferences having much larger samples than those using stated preferences. Third, econometric methodologies differ among studies. Fourth, populations on which preference parameters are measured differ. For example, obese persons are more likely to be diagnosed with diabetes, and obese persons have different preferences from those who have normal weight (Kan 2007).

Nevertheless, a comparison of our results with those of previous studies is useful for evaluating our findings. Are our findings outliers or are they broadly consistent with previous findings in health and other contexts?

Fang and Wang (2015) obtain estimates of β in the range of 0.51 to 0.79 for the decision to undergo mammography, which is higher than our corresponding estimate but also indicative of substantial present bias. The null hypotheses of exponential discounting ($\beta = 1$) and sophistication with present bias ($\tilde{\beta} = \beta$) are both rejected at $p < 0.01$ as in our study. Their estimates are based on a female-only sample, while our estimates are based on a sample that is two-fifths male. Also, the benefit of undergoing mammography is likely to be more immediate — reassurance that the woman does not have breast cancer or immediate steps to treat it if she does — than is the benefit from adhering to diabetes guidelines since diabetes complications may take years to develop if they ever do.

In a study of drinking and driving behavior, Sloan et al. (2014) use a series of questions about willingness to undergo an endoscopy to elicit short- and long-term rates of discount in a quasi-hyperbolic discounting framework. They find evidence of hyperbolic discounting. The authors elicit time preferences using the decision to undergo endoscopy to allow one to measure discounting outside the context of drinking and driving, the subject of their study. Relative to non-drinker drivers, the difference between short- and long-term discount rates is much higher for drinker drivers than for persons who consumed alcohol but did not drink and drive. Although the study provides empirical support for present bias, the study elicited time preferences using a stated preference rather than the revealed preference approach we use. Sloan et al. (2014) only measure present bias, not naivete.

Courtemanche et al. (2015), using data from the 1979 National Longitudinal Survey of Youth, estimate that β and δ are 0.80 and 0.75, respectively on average. They find higher rates of discount are associated with a higher probability of being overweight or obese. They report that the own-price elasticity for food is higher for more impatient individuals. Other studies, relying on stated preferences in the form of various types of laboratory experiments with health outcomes as rewards, report significant present bias (Van der Pol and Cairns 2011). Hinvest and Anderson (2010) present evidence that whether subjects are presented with real versus hypothetical rewards affects discount rates obtained. Our estimate of the value of the long-run discount factor, δ, is 0.88. In their mammography study, Fang and Wang (2015) estimate δ in the range of 0.68 and 0.95.

For real effort tasks with tradeoffs not involving health, Augenblick et al. (2015) report estimates of β in the range 0.877 to 0.900. By contrast, estimated β was 1.0 or nearly so when the tradeoffs involved money, a result consistent with other analysis of money tradeoffs (e.g., Andreoni and Sprenger 2012; Andreoni et al. 2015). One potential explanation for the discrepancy in findings between health and other studies is that money is fungible. Access to credit decouples money from consumption, and monetary rewards might pose difficulties for interpreting intertemporal choices and might be inadequate for gauging present bias (Andreoni and Sprenger 2012).

The second type of evidence for time inconsistency in non-health contexts comes from calibrating real-world behaviors with dynamic structural models using survey data. In their dynamic structural analysis of sales force response to a bonus-based compensation plan, Chung et al. (2013) report evidence consistent with present bias.

Both earlier experimental and field evidence suggest naivete about present bias. Using data from three U.S. health clubs on members' contract choice and day-to-day attendance decisions, DellaVigna and Malmendier (2006) find people erroneously overestimate their future attendance and delay cancellation of membership with the expectation that they will be more patient in the near future. Naivete has also been found in other contexts such as investment in 401(k) plans (Madrian and Shea 2001), task completion (Ariely and Wertenbroch 2002) and smoking (US Department of Health and Human Services. 1994). In laboratory experiments, Andreoni and Sprenger (2012) obtain values of δ between 0.74 and 0.80, using a convex time budget procedure to jointly estimate β and δ. In spite of the above evidence, there is no complete consensus that hyperbolic discounting provides a better explanation of intertemporal decision making.

5.5 Counterfactual simulations

Table 5 provides evidence on the model's goodness of fit as seen by comparing the observed and predicted adherence rates for our analysis sample. Observed and predicted adherence rates match closely (first and second rows).

Table 5 also shows guideline adherence rates predicted by our model (row 2) and implied by two counterfactual simulations. In Simulation 1, we set $\tilde{\beta}$ equal to the estimated β (row 3), and in Simulation 2 we set both $\tilde{\beta}$ and β to 1 (row 4). Simulation 1 demonstrates the importance of naivete on adherence, while Simulation 2 shows the importance of both present bias and naivete.

In Simulation 1, when individuals with diabetes mellitus are present-biased but fully sophisticated, the predicted adherence rate increases very slightly — by 0.2 percentage points (from 51.7% in the baseline prediction to 51.9% in the counterfactual simulation with full sophistication). In Simulation 2, when persons diagnosed with diabetes are standard exponential discounters, the adherence rate increases by 8.5 percentage points, representing a 16.4% (8.5/51.7) increase in the adherence rate relative to the baseline prediction, which indicates that time inconsistency resulting from present bias and (complete) naivete about present bias contributes to the low rate of adherence to diabetes care guidelines. The reason that the change in the predicted adherence rates is much smaller in the first simulation than in the second one could be that the first simulation fixes the values of δ and β and only changes the value of $\tilde{\beta}$ to equal β. Given that $\tilde{\beta}$ in a sense works through β and the level of present bias is already high, it is understandable that changing $\tilde{\beta}$ itself does not make a substantial difference in adherence. The second simulation, however, changes both present bias and naivete about present bias. People go from being completely naive about their high level of present bias to being completely time-consistent in this simulation. Such a large change in time preference, as indicated by our identification strategy, would certainly cause a much larger change in adherence. Referring to the results for adherence on two-year outcomes in Table 2, the effect of becoming an exponential discounter on adherence in Simulation 2 is roughly equivalent to the difference in mortality between the genders and having versus not having supplementary health insurance in addition to Medicare. The effect from Simulation 1 is about the same as changing age by a year.

Results from counterfactual simulations indicate that present bias and naivete both play important roles in the low adherence rates in this context. Specifically, the 16.4% increase in adherence rates in Simulation 2 would translate into substantial reductions in lifetime medical spending, based on the following simple back-of-the-envelope calculation: On average, the lifetime medical cost of caring for persons with diabetes was $85,500 in 2012 (Zhuo et al. 2013). Over half (53%) of such cost was for treating complications of diabetes. If being adherent could reduce one-third of such cost ($14,901) and considering the number of persons in the U.S. aged 65+ with a diabetes diagnosis, 9.9 million in 2015,[10] the saving in medical cost would be $1.48 billion. This estimate does not include increases in the relative future price of treatment, which is realistic, given the increases in prices of personal health care services relative to the prices of other goods and services, the non-pecuniary cost of pain and suffering, the value of lost lives due to premature death, or the cost of treating complications of a sizeable number of persons with diabetes who have not been diagnosed with this condition.[11]

6 Discussion and conclusion

This study uses a dynamic discrete choice model to evaluate the degree of present bias and naivete about present bias in people's decision-making process, and we use decisions of persons diagnosed with diabetes mellitus to follow evidence-based guidelines as a case study. We find evidence of sizable present bias and naivete, which provides an explanation for why so many persons diagnosed with diabetes fail to adhere to evidence-based care guidelines. The simulations further indicate that time-inconsistent preferences indeed play an important role in explaining the low adherence rate observed in people with diabetes.

Understanding the degree of present bias and naivete in personal decisions has important policy implications. For persons making decisions about whether to adhere to guidelines for diabetes care, it matters whether they are present-biased or not. If they are present-biased, it matters whether they are sophisticated or naive about their present bias. Empirical evidence

[10] https://www.cdc.gov/diabetes/pdfs/data/statistics/national-diabetes-statistics-report.pdf, accessed 10/01/17.

[11] There might be some future non-related costs. For example, increased life expectancy resulting from increased adherence could lead to an increase in the number of other diseases (e.g. Alzheimer's disease). The increase in adherence rates therefore might not necessarily be cost-saving when considering from a societal perspective.

on these aspects of decision making are important for the design of effective policies for increasing adherence rates for persons with diabetes. For example, information campaigns stressing the long-term benefits of adhering to guidelines would be unlikely to succeed if intended recipients of such information are present-biased.

A review of 74 trials involving training in self-management for diabetes care finds promising results in studies using up to a six-month follow-up period but finds mixed results when a longer follow-up period is used (Norris et al. 2001). An implication is that periodic re-training or reminders are needed, given individuals' short-term focus, assuming our results are not fully explained by biased beliefs. The mixed long-term results from studies of self-management using a longer-term follow-up period suggests present bias. Cash transfers conditional on recipients achieving specific adherence goals might be promising in that persons would only continue to receive money if they continued to adhere.

Whether individuals with a particular health condition are hyperbolic or exponential discounters yields starkly different public policy strategies. For example, Gruber and Köszegi (2001) show that welfare consequences of taxes on cigarettes and fatty foods depend critically on whether consumers are hyperbolic discounters: hyperbolic discounters are made better off by taxing addictive goods, but without accounting for the negative externalities of smoking, exponential discounters are made worse off by higher taxes. In the case of diabetes, the externalities are not health-related as they are for secondary smoke, but rather are entirely financial. Diabetes is especially common among the elderly who in the U.S. are covered by Medicare (Sloan et al. 2008). Particularly since Medicare does not employ experience-rated premiums, the extra cost of diabetes complications is shared by taxpayers and Medicare beneficiaries in the premiums they pay. Increasing beneficiary cost sharing at the point of service would reduce ex ante moral hazard in the form of nonadherence, but giving beneficiaries "more skin in the game" may face opposition on distributional grounds, i.e., creating additional cost sharing burdens on low-income persons with diabetes.

Since persons diagnosed with diabetes tend to be naive hyperbolic discounters, the thrust of efforts to improve adherence should be on reducing the cost of adhering since future benefits are substantially discounted and on implementing self-control devices. Adherence cost might be decreased by use of telemedicine, which may reduce the frequency of recommended visits by transmitting information on biomarker values electronically to health professionals and allowing for direct monitoring of specific activities such as exercise. Furthermore, various electronic devices might be used as self-control devices, e.g., for reminding patients of upcoming visits or telemedicine encounters at home or informing patients of adverse test results when communication in person may be more effective than a written report sent by electronic mail. Health insurance plans might eliminate cost sharing provisions for screening and preventive care visits. With exponential discounting, the affirmative case for decreased patient cost sharing is based on reducing financial externalities from higher treatment costs downstream that might be averted by having more screening/prevention upfront. With naive hyperbolic discounters, however, screening/prevention is suboptimal even to the individual, which justifies subsidies of care upfront on this basis as well. Disease management programs could monitor whether and when prescriptions are filled. All these measures could lower the instantaneous costs of and thus increase the rate of adhering to the guidelines for persons with diabetes. Since health insurance premiums are paid upfront, premium discounts based on adherence in the previous policy year might encourage greater adherence. More generally, public efforts in this context must recognize the need for immediate gratification.

We acknowledge several study limitations. First, although hyperbolic discounting models are the most popular alternative to exponential discounting, models with other functional forms of temporal discounting also allow for the propensity of individuals to discount future rewards more heavily than current rewards, and they may fit the data better (Cavagnaro et al. 2016). There is also some evidence for a “sign effect”, i.e., gains are discounted more than losses (e.g., Ikeda et al. 2010) and for a pattern of declining discount rates as the period over which benefits accrue is extended (e.g., Abdellaoui et al. 2010). Given the popularity of the hyperbolic discounting model, we have focused on it in this study. There is substantial empirical support for hyperbolic discounting, but there is also some evidence supporting constant discounting (see e.g., Attema et al. 2018).

Second, this study has focused on time preference. Individuals in general and those with diabetes in particular are likely to differ in risk preference as well. Ferecatu and Önçüler (2016) report a negative correlation between time and risk preferences. Individuals could also have the same time preferences but different risk preferences across different domains (Ioannou and Sadeh 2016). Estimating time and risk preferences together from observed decisions about diabetes care would be very complicated and thus is beyond the scope of the present study.

Finally, present bias is just one of several potential behavioral biases. For example, in addition to present bias, Baicker et al. (2015) also highlight symptom salience and false beliefs, among the many possibilities. In the context of diabetes, salience of symptoms of elevated glucose levels in the absence of diabetes complications, such as those involving vision or the lower extremities, is likely to be low, thus leading individuals with diabetes to underweight the importance of adhering. Symptom salience is further undermined by the fact that many complications, though more frequent among persons with diabetes, are also common, albeit less common, among persons without this diagnosis, e.g., stroke (Sloan et al. 2008). False beliefs as to the effectiveness of health practices may lead individuals to under- or overvalue specific practices, leading to under- or overuse. For persons with diabetes, substantial gaps in knowledge and skills needed for effective self-management of diabetes have been documented (Norris et al. 2001). In addition, biases in subjective beliefs about the effectiveness of adhering to guidelines and lack of self-control (Sloan et al. 2009) could also influence individuals’ decision-making process.

Even though the remedies may differ conceptually, e.g., educational interventions for symptom salience and false beliefs, and nudges such as appointment reminders for present bias, different reasons for nonadherence could be observationally equivalent. To disentangle the various sources of failure to adhere, several approaches are needed. For example, it would be useful to measure the accuracy of subjective beliefs about the health effects of adhering directly. To our knowledge, this type of study has not been undertaken to date.

Given that present bias may work to augment a person's uncertainty about the effectiveness of adherence in postponing diabetic complications, in practice it may be advisable to offer a package of interventions to improve adherence.

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Appendix

This appendix follows Section 2 and provides more details on the identification and estimation of the dynamic discrete choice model. Specifically, given the Extreme Value Distribution assumption, the probability of action i being chosen given x, $P_{i,t}(x_t)$, is:

$$P_{i,t}(x_t) = \Pr\left[W_{i,t}(x_t) + \varepsilon_{i,t} \geq W_{j,t}(x) + \varepsilon_{j,t}, \forall j \neq i\right] = \frac{\exp\left[W_{i,t}(x_t)\right]}{\sum_{j=0}^{1} \exp\left[W_{j,t}(x_t)\right]}. \quad (9)$$

While W, defined in (4), is not observable, actual choice probabilities $P_{i,t}(x_t)$ are observable in the data and can be used to infer W.

With the choice-specific value function of the next-period self perceived by the current self $Z_{i,t+1}(x_{t+1})$, defined in (5), the current self's perception of her future self's choice, σ, can be defined as

$$\sigma\left(x_{t+1}, \varepsilon_{i,t+1}\right) = arg \max_{i \in \mathcal{I}} \left[u_{i,t+1}\left(x_{t+1}\right) + \varepsilon_{i,t+1} + \tilde{\beta}\delta \sum_{x_{t+2} \in \mathcal{X}} V_{t+2}\left(x_{t+2}\right)\pi\left(x_{t+2} \mid x_{t+1}, i\right)\right]$$
$$= arg \max_{i \in \mathcal{I}} \left[Z_{i,t+1}\left(x_{t+1}\right) + \varepsilon_{i,t+1}\right].$$

Then the probability perceived by the current period self of choosing alternative i by the next period's self when the next period's state, again assuming an Extreme Value Distribution, is x_{t+1}, $\tilde{P}_{i,t+1}\left(x_{t+1}\right)$, is:

$$\tilde{P}_{i,t+1}\left(x_{t+1}\right) = \Pr\left[\sigma\left(x_{t+1}, \varepsilon_{t+1}\right) = i\right] \quad (10)$$
$$= \Pr\left[Z_{i,t+1}\left(x_{t+1}\right) + \varepsilon_{i,t+1} \geq Z_{j,t+1}\left(x_{t+1}\right) + \varepsilon_{j,t+1}, \forall j \neq i\right]$$
$$= \frac{\exp\left[Z_{i,t+1}\left(x_{t+1}\right)\right]}{\sum_{j=0}^{1} \exp\left[Z_{j,t+1}\left(x_{t+1}\right)\right]}.$$

The distinction between $\tilde{P}$ and P is that the sophisticated present-biased decision-maker knows the extent of her actual future present bias; by contrast, the naive person underestimates the extent of her present bias. That is, she thinks her β is larger than it actually will be. For sophisticated persons, $\tilde{P} = P$; for naive ones, $\tilde{P} \neq P$.

With non-stationarity and a finite horizon, at $t = T$, when the continuation value is zero, there is no distinction among W, Z, V, and u:

$$W_{i,T} = Z_{i,T} = V_{i,T} = u_{i,T},$$

which, according to the Extreme Value Distribution assumption, leads to:

$$V_T = \ln \sum_{i \in \mathcal{I}} \exp\left[Z_{i,T}\right] = \ln \sum_{i \in \mathcal{I}} \exp\left[u_{i,T}\right]. \quad (11)$$

Combining (11) and (5) yields $Z_{i,T-1}$. Given the link between $Z_{i,T-1}$ and V_{T-1}, using backward induction, V_{t+1} can be determined, which in turn relates to $W_{i,t}$ (4), and then to $P_{i,t}(x_t)$ (9). By this reasoning, we link instantaneous utility u to P, which is observable in the data. Once this relationship between u and P is established empirically from the choice probabilities ($P_{i,t}(x_t)$) and transition probabilities ($\pi(x_{t+1}|x_t, i)$) for all $x \in \mathcal{X}$ and for $i = (0, 1)$, we can estimate the utility parameters for a given $\langle \beta, \tilde{\beta}, \delta \rangle$.

The relationship between $Z_{i,t}$ and V_t can be described in three steps. First, combining (5) and (6) yields

$$V_{i,t+1}(x_{t+1}) = Z_{i,t+1}(x_{t+1}) + (1 - \tilde{\beta})\delta \sum_{x_{t+2} \in \mathcal{X}} V_{t+2}(x_{t+2})\pi(x_{t+2}|x_{t+1}, i). \quad (12)$$

Given (12), (7) can be rewritten as:

$$V_{t+1}(x_{t+1}) = \mathrm{E}_{\varepsilon_{t+1}}\left[V_{\sigma(x_{t+1}, \varepsilon_{t+1}), t+1}(x_{t+1}) + \varepsilon_{\sigma(x_{t+1}, s_{t+1}), t+1]}\right] \tag{13}$$

$$= \mathrm{E}_{\varepsilon_{t+1}}\left[\begin{array}{c} Z_{\sigma(x_{t+1}, \varepsilon_{t+1}), t+1}(x_{t+1}) + \varepsilon_{\sigma(x_{t+1}, \varepsilon_{t+1}), t+1} \\ +(1-\tilde{\beta})\delta \sum_{x_{t+2} \in \mathscr{X}} V_{t+2}(x_{t+2})\pi(x_{t+2} \mid x_{t+1}, \sigma(x_{t+1}, \varepsilon_{t+1})) \end{array}\right]$$

$$= \mathrm{E}_{\varepsilon_{t+1}} \max_{i \in \mathscr{J}}\left[Z_{i,t+1}(x_{t+1}) + \varepsilon_{i,t+1}\right] + (1-\tilde{\beta}$$

$$)\delta \mathrm{E}_{\varepsilon_{t+1}} \sum_{x_{t+2} \in \mathscr{X}} V_{t+2}(x_{t+2})\pi(x_{t+2} \mid x_{t+1}, \sigma(x_{t+1}, \varepsilon_{t+1}))$$

$$= \mathrm{E}_{\varepsilon_{t+1}} \max_{i \in \mathscr{J}}\left[Z_{i,t+1}(x_{t+1}) + \varepsilon_{i,t+1}\right]$$

$$+(1-\tilde{\beta})\delta \sum_{i \in \mathscr{J}} \tilde{P}_{i,t+1}(x_{t+1}) \sum_{x_{t+2} \in \mathscr{X}} V_{t+2}(x_{t+2})\pi(x_{t+2} \mid x_{t+1}, i).$$

Given the Extreme Value Distribution assumption,

$$\mathrm{E}_{\varepsilon_{t+1}} \max_{i \in \mathscr{J}}\left\{Z_{i,t+1}(x_{t+1}) + \varepsilon_{i,t+1}\right\} = \ln\left\{\sum_{i \in \mathscr{J}} \exp\left[Z_{i,t+1}(x_{t+1})\right]\right\}. \tag{14}$$

Combined with (14) and (10), (13) can be rewritten as

$$V_{t+1}(x_{t+1}) = \ln\left\{\sum_{i \in \mathscr{J}} \exp\left[Z_{i,t+1}(x_{t+1})\right]\right\} + (1-\tilde{\beta} \tag{15}$$

$$)\delta \sum_{i \in \mathscr{J}} \frac{\exp\left[Z_{i,t+1}(x_{t+1})\right]}{\sum_{j=0}^{1} \exp\left[Z_{j,t+1}(x_{t+2})\right]} \sum_{x_{t+2} \in \mathscr{X}} V_{(t+2)}(x_{t+2})\pi(x_{t+2} \mid x_{t+1}, i),$$

which relates $Z_{i,t}$ to V_t, a relationship that makes backward induction possible.

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Table 1

Summary statistics

Variable	**Mean Std.**	**Dev.**
Adherence	0.518	0.500
Bad Health	0.302	0.459
Income	31,545	55,230
Age	72.148	4.464
White	0.871	0.336
Male	0.418	0.493
Married	0.662	0.472
Low Cognition	0.320	0.467
>High School	0.624	0.484
Mom >High School	0.258	0.438
Mother Died <70	0.749	0.434
Other Health Insurance	0.608	0.488

Table 2

Determinants of adherence to guidelines: Marginal effects

		Educational Attainment		Married		Bad Health	
	All	Low	High	No	Yes	No	Yes
Bad Health	0.017 ** (0.006)	0.022 ** (0.007)	0.000 (0.011)	0.031 ** (0.010)	0.009 (0.008)		
Age	0.003 ** (0.001)	0.001 (0.001)	0.007 ** (0.001)	0.001 (0.001)	0.004 ** (0.001)	0.004 ** (0.001)	0.001 (0.001)
White	0.005 (0.008)	0.013 (0.010)	−0.012 (0.016)	0.017 (0.012)	−0.003 (0.012)	0.017 (0.011)	−0.006 (0.013)
Male	−0.068 ** (0.006)	−0.077 ** (0.007)	−0.052 ** (0.009)	−0.090 ** (0.011)	−0.061 ** (0.007)	−0.057 ** (0.007)	−0.091 ** (0.010)
Married	0.025 ** (0.007)	0.015 (0.008)	0.045 ** (0.011)			0.024 ** (0.008)	0.030 ** (0.012)
Low Cognition	−0.027 ** (0.006)	−0.020 ** (0.007)	−0.047 ** (0.012)	−0.023 * (0.011)	−0.029 ** (0.008)	−0.027 ** (0.008)	−0.031 ** (0.011)
>High School	−0.016 (0.006)			0.004 (0.011)	−0.023 ** (0.007)	−0.015 * (0.007)	−0.013 (0.012)
Mom >High School	0.052 ** (0.006)			0.021 (0.012)	0.063 ** (0.008)	0.054 ** (0.007)	0.045 ** (0.013)
Mother Died <70	0.013 * (0.006)	0.015 * (0.008)	0.007 (0.010)	0.008 (0.010)	0.014 (0.008)	0.019 * (0.008)	0.000 (0.011)
Other Health Insurance	0.080 ** (0.006)	0.084 ** (0.007)	0.080 ** (0.009)	0.080 ** (0.010)	0.081 ** (0.007)	0.090 ** (0.007)	0.065 ** (0.011)
Log Income	0.010 ** (0.004)	0.007 (0.006)	0.015 * (0.006)	0.016 * (0.007)	0.009 (0.005)	0.018 (0.005)	−0.006 (0.008)
Pseudo R^2	0.013	0.011	0.014	0.012	0.013	0.015	0.011
N	34,946	21,816	13,130	11,802	23,144	24,385	10,561

Notes: Standard errors of marginal effects are in parentheses.

*** p<0.01,

** p<0.05,

* p<0.1. Low educational attainment is education ≤ high school. High educational attainment is educational attainment >high school

Table 3

Effects of adherence in period t on health outcomes and income in period t+1

		Educational Attainment		Married		Bad Health	
Dependent Variable	**All**	**Low**	**High**	**No**	**Yes**	**No**	**Yes**
Mortality	−0.020** (0.002)	−0.023** (0.003)	−0.014** (0.004)	−0.025** (0.005)	−0.016** (0.003)	−0.009** (0.001)	−0.044** (0.006)
Bad Health	0.001 (0.004)	0.004 (0.006)	−0.003 (0.006)	0.018* (0.008)	−0.007 (0.005)	0.001 (0.005)	0.005 (0.009)
Log Income	0.0015* (0.006)	0.013 (0.007)	0.018 (0.011)	0.019 (0.011)	0.013 (0.007)	0.013 (0.007)	0.021 (0.011)

Notes: Standard errors of marginal effects are in parentheses. Low educational attainment is education ≤ high school. High educational attainment is educational attainment >high school

*** p<0.01,

** p<0.05,

* p<0.1. Results for Log Income are coefficients with associated errors in parentheses. All covariates shown in Table 2 are included in the analysis but not shown

Table 4

Estimated discount factors and preference parameters

Parameters	Estimated coefficients	Standard errors
δ (Exponential Discount Factor)	0.88	0.27
β (Hyperbolic Discount Factor/Present Bias)	0.38	0.11
β (Naivete)	1.00	0.31
α (Intercept of Instantaneous Utility Function)	−1.33	0.29
α_1 (Coefficient for Bad Health in Instantaneous Utility Function)	−0.37	0.035
α_2 (Coefficient for Income in Instantaneous Utility Function)	1.13	0.056

Notes: All parameter estimates are statistically significant $p < 0.01$

Table 5

Observed and predicted adherence rates

Observed adherence rate	**0.518**
Model predicted adherence rate	0.517
Adherence rate predicted in Simulation 1	0.519
Adherence rate predicted in Simulation 2	0.602