Present-Biased Preferences and Credit Card Borrowing

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ABSTRACT

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Some individuals borrow extensively on their credit cards. This paper tests whether present-biased time preferences correlate with credit card borrowing. In a field study, we elicit individual time preferences with incentivized choice experiments, and match resulting time preference measures to individual credit reports and annual tax returns. The results indicate that present-biased individuals are more likely to have credit card debt, and have significantly higher amounts of credit card debt, controlling for disposable income, other socio-demographics, and credit constraints.

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1 Introduction

Credit card debt is widespread. U.S. households with at least one credit card report carrying, on average, $3,027 in revolving debt (based on the 2004 Survey of Consumer Finances). There is, however, significant heterogeneity in credit card borrowing. Only 45 percent of card holders report that they, at least sometimes, carry balances on their credit cards. Among these individuals, average credit card debt is $5,799. These figures illustrate two important stylized facts of credit card debt: first, the level of card borrowing is substantial (and likely much higher than these self-reported figures suggest, as discussed below); and, second, some individuals charge their credit cards significantly while others accumulate no debt at all.

This paper tests whether heterogeneity in individual time preferences correlates with credit card borrowing. In a large field study, we measure individual time preferences using incentivized choice experiments and link resulting impatience measures to administrative data on borrowing. In particular, we investigate whether individuals who exhibit present-biased preferences, that is those who show a particular desire for immediate consumption, have higher credit card balances.

A number of theoretical papers suggest that present bias drives credit card borrowing (e.g., Laibson, 1997; Fehr, 2002; Heidhues and Koszegi, 2008). Present bias is argued to increase individuals' desire for instantaneous gratification and, as a result, increase borrowing.[1] However, there has been very little direct evidence to support the behavioral economics view that present-biased individuals borrow more.

Previous research on present bias and credit card debt used one of two approaches,

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[1]Present-biased preferences can be seen as the result of the interplay of two separate decision making systems: the affective system, which values immediate gratification and sharply discounts all future periods; and the deliberative system, which makes long-run plans and displays higher discount factors. This notion is captured in various models (for example, O'Donoghue and Rabin, 1999; Gul and Pesendorfer, 2001; Bertaut and Haliassos, 2002; Bernheim and Rangel, 2004; Loewenstein and O'Donoghue, 2004; Fudenberg and Levine, 2006) and finds support in neuroeconomics studies (Mc-Clure et al., 2004, 2007).

examining either aggregate or self-reported debt measures. Both of these approaches have limitations for examining the relationship between individual present bias and credit card debt. Studies using the first approach analyze aggregate credit and savings outcomes and show that models of consumer behavior with present-biased preferences predict aggregate consumption behavior better than standard exponential models (Laibson et al., 2008; Skiba and Tobacman, 2007; Shui and Ausubel, 2005).[2] These studies are important as they indicate that, in the aggregate, present-biased preferences are able to explain anomalies such as consumers simultaneously holding credit card debt and low-yield assets. The link between borrowing and present bias is, however, indirect. Additionally, examination of aggregates does not allow for evaluation of individual behavior.

A second approach measures individual time preferences directly with choice experiments, and correlates these measures to *self-reported* credit balances or spending problems. Harrison et al. (2002) find that individual long-run discount factors do not correlate with borrowing behavior, though their study remains silent on the association between present bias and credit card borrowing.[3] Using measurement techniques similar to our own, Dohmen et al. (2006) show that present-biased individuals report having more problems restricting their spending.[4] Though these studies provide important indications that exponential discount factors alone do not correlate with borrowing or that present bias is associated with spending problems, the accuracy of the self-reported measures from these studies is particularly difficult to assess. People generally either underreport their debt levels or lie altogether (for details, see Gross

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[2]Another set of studies show behavioral patterns in field data consistent with present-biased preferences (e.g., Ariely and Wertenbroch, 2002; Gine et al., 2008; Morton and Oster, 2005).

[3]By design all experimental payments in Harrison et al. (2002) were received with minimum delay of one month, eliminating potential identification of present bias.

[4]Ashraf et al. (2006) also directly elicit present bias parameters using hypothetical choices and correlate present bias to take-up of a savings commitment device. They do not, however, analyze the relationship between present bias and debt.

and Souleles, 2002; Karlan and Zinman, 2008; Zinman, 2009). It is therefore critical to analyze objective data on credit card borrowing.

The present study overcomes the limitations of both previous approaches by combining directly elicited time preference measures with administrative data on borrowing. This approach provides direct evidence on the link between present bias and credit card borrowing using objective, administrative data that eliminates the confounding factor of truthfulness in self-reported debt levels. For a sample of around 600 low-to-moderate income individuals, we measure time preferences using incentivized choice experiments. The choice experiments allow us to measure individual discount factors, and to identify individuals who exhibit dynamically inconsistent time preferences (e.g., present bias). Resulting parameter estimates are linked to individual credit reports and tax returns. Credit reports give objective information on card borrowing and credit constraints; and tax returns provide objective information on individual incomes.

Our results show that experimentally measured present bias correlates highly with credit card borrowing. Individuals who exhibit present-biased preferences have substantially higher revolving credit balances. In our sample, present-biased individuals are around 15 percentage points more likely than dynamically consistent individuals to have any credit card debt. Conditional on borrowing, present-biased individuals borrow around 25 percent more than dynamically consistent individuals. The association between present bias and credit card borrowing holds when controlling for income, credit constraints (both credit access and credit limits), and socio-demographic characteristics. These results are therefore the first direct support for behavioral economics models claiming that credit card debt is related to present-biased preferences.

The paper proceeds as follows: Section 2 discusses the design of the field study, our methodology for eliciting time preferences, and the data. Section 3 presents results and Section 4 concludes.

2 Data

2.1 Field Study Design

The field study was conducted with 606 individuals at two Volunteer Income Tax Assistance (VITA) sites in Boston, Massachusetts.[5] During the 2006 tax season, the study was conducted in the Dorchester neighborhood (N=139) and, during the 2007 tax season, in the Roxbury neighborhood (N=467). The two years differ mainly in the way in which time preferences were elicited (discussed in detail below).

We obtained consent from all participants to access their credit reports and to retrieve income information from their tax returns. Additionally, we surveyed participants to obtain certain socio-demographic characteristics (most likely measured with more error than information from tax data), and elicited their time preferences using incentivized choice experiments. Of the 606 participants, we obtain a usable measure of time preferences for 541 individuals (see Section 2.3.2 for details). These individuals represent our primary study sample.

Panel A of Table 1 shows the socio-demographic characteristics of all participants in column (1) and for those in our primary sample in column (2). The average participant has low disposable income of around \$18,000, is African-American, female, around 36 years old, with some college experience, and has less than one dependent.[6]

As the summary statistics indicate, study participants were largely low-to-moderate income (LMI) / subprime borrowers. This non-standard subject pool is of particular interest, as LMI and subprime households' less secure position puts them at great

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[5]There are currently 22 VITA sites in and around Boston, MA. Coordinated by a city-wide coalition of government and business leaders, VITA sites provide free tax preparation assistance to low-to-moderate income households. Taxes are prepared by volunteers throughout each tax season.

[6]For a number of observations we lack certain socio-demographic information (gender, race, and college experience). Each of these variables is binary. For the analysis below we set missing values to the value of the majority and add indicator variables for missing gender, race and college experience in each regression. Excluding observations with missing variables does not affect the results (see Section 3.2).

financial risk (see, Bertrand et al., 2004). There are also very few experimental studies focusing solely on the behavior of LMI families in developed countries (an exception is Eckel et al., 2005). When interpreting the magnitudes of the presented results, participants' low incomes should be taken into account. As in many experimental and survey studies, individuals select to come to the VITA sites and participate in our study. As we show in Meier and Sprenger (2008), study participants are more financially literate and more patient than individuals at the VITA site who elect not to participate. Though the direction of any potential bias is difficult to assess, one should keep the selection of the sample in mind when generalizing the results of this study.

[Table 1 about here]

2.2 Credit Bureau Data

Information on individual credit behavior was obtained from one of three major credit bureaus in the United States. The credit reports list detailed information on each individual's credit behavior, like outstanding balances and available credit limits (for details on credit reporting, see Avery et al., 2003). Unlike self-reported data, credit reports give a very detailed, objective picture of individual borrowing behavior.[7]

We measure credit card borrowing as outstanding balances on revolving accounts.[8]

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[7]Credit reports do not include non-traditional loan products (e.g. payday loans). For a subset of our sample in 2006 (N = 131), we use self-reported information on loans obtained from pawn brokers, check cashers, payday lenders, friends, family, or on any outstanding balances on bills due to medical providers, landlords, and utilities providers. Non-traditional debt of this type is relatively small, averaging $372 (s.d. $827) per person. Adding nontraditional debt to aggregate debt does not influence the results. As people often under-report their debt levels in surveys, we do not incorporate self-reported debt in our regression analysis.

[8]Though balances listed on credit reports are point-in-time measures, we argue that our borrowing measures closely reflect revolving balances and not convenience charges. In general, only around five to ten percent of total balances are convenience charges (Johnson, 2004). Additionally, we implemented a companion survey with questions on credit card bill payment habits as worded in the Survey of Consumer Finances (N = 174). Individuals who report normally paying the full amount on their credit card at the end of the month (21 percent of the sample), have significantly lower balances on revolving accounts ($1,093 versus $3,086; $p < 0.05$ in a t-test).

Panel B of Table 1 illustrates the two stylized facts of credit card borrowing previously noted: high borrowing and substantial debt heterogeneity. The average credit card balance is $1,059 (s.d. $2,414), with 40 percent of participants carrying credit balances.

Credit reports provide crucial information on credit card holdership and revolving credit limits. In our sample, the average revolving credit limit is $4,764 (s.d. $11,850) with 53 percent of study participants having no credit cards. Credit reports do not provide information on credit card interest rates. However, we use Fair Issac Corporation (FICO) credit scores as a proxy for interest rates, as most financial institutions use risk-based pricing strategies (see Furletti, 2003). The average FICO score in our sample is 610 (median: 596) indicating that subjects likely face subprime interest rates given the common subprime cutoff of 620.

2.3 Measuring Time Preferences

2.3.1 Methodology

Individual time preferences are measured using incentivized choice experiments (for similar approaches see Coller and Williams, 1999; Harrison et al., 2002; McClure et al., 2004; Tanaka et al., 2007, and for a survey on measuring time preferences see Frederick et al. (2002)). We analyze decisions from two multiple price lists in which individuals are asked to make a series of choices between a smaller reward (X) in period t and a larger reward ($Y > X) in period τ. We keep Y constant and vary X in two time frames: in time frame 1, t is the present ($t = 0$) and τ is in one month ($\tau = 1$) and in time frame 2, t is six months from the study date ($t = 6$) and τ is seven months from the study date ($\tau = 7$).[9] The delay length, d, is one month in both time frames.

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[9]Individuals were additionally asked to make choices between the present ($t = 0$) and in six months ($\tau = 6$) in a third time frame. As it may be cognitively more difficult to give dynamically consistent answers in this choice environment, responses from the third time frame are added to the analysis only as a robustness test. Results are qualitatively unchanged (see Section 3.2).

The design of the choice experiments in 2006 and 2007 differed in two dimensions (for instructions used and summary statistics for the two years, see the Web Appendix). First, the values of $X and $Y were varied between 2006 and 2007 to check the robustness of the results to such variation. In 2006, $Y = \$80$ and $X was varied from $75 to $30. In 2007, $Y = \$50$ and $X was varied from $49 to $14. Second, the presentation of the choice sets was varied between 2006 and 2007. While in 2006 the order of the price lists was the same for each individual, in 2007 the order was randomized. In the results section, we analyze the data from the two years jointly, controlling for the year of study. The results are very similar between the two years (see Web Appendix).

In order to provide an incentive for the truthful revelation of preferences, 10 percent of individuals were randomly paid one of their choices. This was done with a raffle ticket, given to subjects at the end of their tax filing indicating which choice, if any, would be effective. To ensure the credibility of the payments, we immediately filled out money orders for the winning amounts in the presence of the participants, put them in labeled, pre-stamped envelopes, and sealed the envelopes. The payment was guaranteed by the Federal Reserve Bank of Boston, and individuals were informed that they could return to VITA site coordinators to report any problems receiving payment. Money orders were sent by mail to the winner's home address on the same day as the experiment (if $t = 0$), or in one, six, or seven months, depending on the winner's choice. All payments were sent by mail to equate the transaction costs of sooner and later payments. The payment procedure therefore mimicked a front-end-delay design (Harrison et al., 2005). The details of the payment procedure were the same in both years, and participants were fully informed about the payment method.[10]

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[10]If individuals expect to move in the next seven months, they might question the likelihood that their mail would be forwarded to their new address in a timely manner. As movers might therefore prefer payments in the present for logistical reasons and not for reasons related to their underlying time preference, we ask individuals *"Do you expect to move in the next 7 months?"*. Whether individuals expect to move does not correlate with elicited time preferences and does not affect our results.

Using monetary rewards and multiple price lists as a preference elicitation mechanism allows us to identify differences in patience and present bias between individuals. This methodology yields measures that are highly correlated with time preference measures derived from other methodologies (e.g., Reuben et al., 2008; Chabris et al., 2008). Time preference measures obtained from price lists have also been shown to be stable at the individual level over time (see Meier and Sprenger, 2009). It is important to note that this research requires a reliable measure of the heterogeneity in time preferences *between* individuals, but not necessarily precise point estimates of the levels of parameters. Therefore, relatively less space in the following sections is dedicated to discussing parameter levels and relatively more attention is given to the correlation between preferences and borrowing behavior.

2.3.2 Time Preference Measures

In the two different time frames, individuals make choices between a smaller reward at time t and a larger amount one month later. Using information from both price lists allows us (1) to measure discount factors and (2) to identify present and future bias.

(1) *Individual discount factor (IDF)*: We estimate monthly *IDF*s by observing the point in a given price list, X^*, at which individuals switch from opting for the smaller, sooner payment to opting for the larger, later payment. That is, a discount factor is taken from the last point at which an individual prefers the sooner, smaller payment assuming that $X^* \approx IDF^d \times Y$, where d represents the delay length.[11] As the delay length, d, is one month for the time frames analyzed here, $IDF \approx (X^*/Y)^{1/1}$. For

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[11]This formulation is equivalent to positing a linear utility function over the experimental outcomes and normalizing extra-experimental consumption (e.g., background consumption) to zero. This procedure simplifies the analysis considerably and is consistent with expected utility theory, which implies that consumers are approximately risk neutral over small stakes outcomes (Rabin, 2000). However, parameters estimated from price lists may also capture differences across individuals in the degree utility function curvature (Andersen et al., 2008). As a robustness test, we control for a survey measure of individual risk attitudes. Controlling for risk attitudes does not affect the results of this paper (see Section 3.2).

example, if an individual prefers \$75 today over \$80 in one month, but prefers \$80 in one month over \$70 today, then we take \$75 as the switching point and calculate the monthly discount factor as $(75/80)^{1/1} = 0.94$.[12] Making these calculations for the two multiple price lists yields two discount measures, $IDF_{t,\tau}$: $IDF_{0,1}$, $IDF_{6,7}$. We use the average of these calculated monthly discount factors as the IDF in the main analysis.

(2) *Present Bias and Future Bias*: Using two time frames allows us to identify dynamic inconsistency. Dynamically inconsistent individuals exhibit a bias towards either present or future payments. An individual is present-biased if he is less patient (lower IDF) when the smaller, sooner payment is received in the present ($t = 0$). We classify an individual as present-biased if $IDF_{0,1} < IDF_{6,7}$ and as future-biased if $IDF_{0,1} > IDF_{6,7}$. For our primary analysis, we use indicator variables *Present Bias (=1)* and *Future Bias (=1)* following these classifications.

In robustness tests we use several additional measures for present bias. First, we use the ratio $IDF_{6,7}/IDF_{0,1}$ as a measure of the intensity of present (future) bias. Second, we calculate a quasi-hyperbolic discounting function (Strotz, 1956; Phelps and Pollak, 1968; Laibson, 1997; O'Donoghue and Rabin, 1999) and use the resulting present bias parameter, β. Third, we include additional information from a third time frame where $t = 0$ and $\tau = 6$, and construct composite measures of dynamic inconsistency (see Section 3.2).

In order to have useable measures of IDF and dynamic inconsistency, an individual must exhibit a unique switching point in each price list. In both years around 11% of participants do not exhibit unique switching points. In the main analysis, we focus on a primary sample of the 541 individuals who do show unique switching points in all price lists. When we include individuals with multiple switching points in a robustness

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[12]It should also be noted that the price list methodology does not elicit point estimates of the IDF but rather ranges of where the IDF lie. Our analysis accounts for this interval nature of the data both when identifying present (future) bias and when exploring the relationship between IDF, credit constraints and socio-demographics (see Table 2).

test by using their first switching point, the results are maintained (see Section 3.2).

For participants in the primary sample (Column (2) of Table 1), we measure a monthly discount factor, *IDF*, of 0.83 as shown in Panel C of Table 1. This discount factor is low, but consistent with previous research, which tends to find low discount factors in experimental studies (see Frederick et al., 2002). Decisions on payday loans or used cars often imply much lower discount factors for subprime borrowers than measured by our experiment (e.g., Skiba and Tobacman, 2007; Adams et al., 2008). 36 percent of study participants are classified as present-biased and 9 percent are classified as future-biased. Dohmen et al. (2006) find a similar proportion of present-biased individuals in their sample (28%), but more future-biased individuals (38%). Our levels of dynamic inconsistency are somewhat more comparable to Ashraf et al. (2006) who classify 27.5 (19.8) percent of their sample as present (future)-biased.

2.3.3 Measurement Validation

The method described above for measuring time preferences with incentivized choice experiments has many advantages (Frederick et al., 2002), but also several challenges. Experimental responses are argued to be impacted by extra-experimental borrowing and lending opportunities (Coller and Williams, 1999; Harrison et al., 2002, 2005; Cubitt and Read, 2007), and also potentially associated with credit and liquidity constraints, and credit experience. In the present study, these issues take on particular importance as we not only experimentally measure time preferences, but also correlate them with actual borrowing behavior.

The impact of extra-experimental borrowing and lending opportunities can be seen as an arbitrage argument. If an individual can borrow at a lower interest rate than the experimentally offered rate, then the individual should wait for later experimental payments, borrow outside the experiment, and repay with experimental earnings; thereby

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arbitraging the experiment with a "borrow low-save high" strategy. If an individual can lend (save) at a higher rate than the experimentally offered rate, a second arbitrage strategy is open and the individual should take the sooner experimental payment and invest it at the available higher rate.

We argue that prevailing interest rates for LMI individuals leave open only one of these strategies. The *lowest* annual interest rate offered in the experiment in either year is around 27 percent (calculated as $(50/49)^{12} - 1$) and the next lowest annual interest rate is around 110 percent. Study subjects are unlikely to have investment opportunites in excess of this rate. This feature of our experimental design largely eliminates the second arbitrage opportunity, leaving open primarily the strategy of borrowing low outside the experiment and saving high inside the experiment. Such a strategy would lead to a high degree of observed patience, and dynamic inconsistency only when individuals' extra-experimental opportunities are time dependent. The data are not consistent with a large number of individuals employing such a strategy: a high degree of impatience is observed and a substantial number of subjects are dynamically inconsistent.

Related to the issue of outside 'investment' opportunities is the potential impact of high-interest debt on experimental responses. Individuals with high-interest debt (e.g., payday or auto title loans not reported to credit bureaus) may pay down their expensive debts with earlier experimental payments, appearing relatively impatient. If such individuals also expect (rightly or wrongly) to not have such high-interest debt in the future, they may also appear present-biased. Such a strategy of paying down high interest debt with experimental earnings would be employed by individuals who are unable to borrow on better terms than the high experimentally offered rates. Credit constrained individuals are one critical group for whom this may be true. It is therefore important to test the impact of credit constraints on experimental responses.

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The credit report data enable us to determine precisely how much an individual is able to borrow on revolving accounts. Therefore, we have an exact measure of credit constraints. Additionally, we are able to develop other measures of liquidity positions and credit experience from tax and credit report data. Individual tax data allows us to measure the size of federal tax refunds (or liability), and whether or not tax refunds are direct deposited. This provides a picture of future liquidity (or constraint) and the timing of that future liquidity.[13] Credit reports allow us to measure the number of loan accounts in an individual's credit history and whether or not they have sufficient credit history to be FICO scored by the the credit bureau.

Table 2 presents regressions using measured time preferences as the dependent variables. Columns (1) and (2) present OLS models where the dependent variable is the average discount factor measure (IDF). Columns (3) and (4) present interval regressions (Stewart, 1983) where the dependent variable is the interval measure of an $IDF_{t,\tau}$. Columns (5) and (6) present OLS regressions where *Present Bias (=1)* is the dependent variable. In each specification, we control for basic demographic characteristics of age, gender and race. Columns (2), (4) and (6) additionally control for credit constraints (measured as the amount of available credit); for future liquidity (measured as future tax refund quantity and whether or not it will be direct deposited); and for credit experience proxies (measured as whether credit history is sufficient to to receive a FICO credit score and the number of credit history loan accounts). In columns (2), (4) and (6) we also control for potentially endogenous demographics: income, number of dependents, and education. In the interval regression, whether the price list involves the present, *Has Present* (=1), is also controlled for and standard errors are clustered on the individual level.

[Table 2 about here.]

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[13]Direct deposited refunds are supposed to be received in 7-10 business days while mailed refunds take substantially longer.

Table 2 shows that our time preference measures are generally uncorrelated with credit constraints, future liquidity, or credit experience. This indicates that differential credit access, liquidity and experience are unlikely to be drivers of experimental responses, and so cannot explain the observed heterogeneity of present bias or its correlation with borrowing behavior.[14]

Table 2 also presents results relevant for the general discussion of time preferences and socio-demographic characteristics (see, e.g., Harrison et al., 2002). Age is found to be negatively correlated with discount factors and whether individuals exhibit present bias. Men, though they have significantly lower discount factors than women, are equally likely to be present biased. Individuals with higher income have higher measured discount factors but are no more likely to be present-biased than others, while individuals of higher education have somewhat higher measured discount factors and are significantly more likely to be present biased. The observed correlation between education and present bias seems counterintuitive and requires attention in future research. Interestingly, the results of the interval regressions in columns (2) and (3) support the claim that individuals, on average, discount non-exponentially. Measured discount factors decrease when the present is involved, a pattern consistent with present-biased preferences (Frederick et al., 2002).

3   Results

The relationship between individual present bias and credit card borrowing is explored by estimating models of the following form:

$$Borrowing_i = \alpha + \gamma_1 IDF_i + \gamma_2 Present\ Bias_i + \gamma_3 Future\ Bias_i + \gamma_4 Y_i + \gamma_5 X_i + \epsilon_i \quad (1)$$

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[14]IDF and $Present\ Bias$ (= 1) are also found to be uncorrelated with credit constraints in regressions where credit card holdership and available credit limits are the dependent variables (results available on request).

$Borrowing_i$ is individual i's balance on revolving credit accounts on the study date. For the 2006 sample, we additionally examine balances on revolving accounts one year after the choice experiments. As *Borrowing* is censored at 0, we estimate tobit regressions. All results hold when estimating OLS regressions (see Web Appendix).

IDF_i, $Present\ Bias_i$, and $Future\ Bias_i$ are measures of individual i's time preferences. Y_i is a dummy for the year of study. The vector X_i reflects individual control variables, which include age, gender, race, and education, income and number of dependents claimed for tax purposes. In certain specifications, we control for credit card holdership, available credit limits and FICO scores. Though presented in regression, we acknowledge that our evidence does not establish a causal link between present-biased preferences and borrowing behavior. Evidence in this paper should rather be interpreted as correlation between measured preferences and outstanding credit card balances.

3.1   Present Bias and Credit Card Borrowing

Table 3 presents results from tobit regressions in which the dependent variable is total outstanding credit card balances. Column (1) presents results without control variables. To this basic specification, in column (2) we add exogenous control variables: age, gender and race. Column (3) adds further socio-demographics which may be correlated with time preferences: income, number of dependents and college experience. Across specifications, present-biased individuals are found to have substantially higher credit card balances. Controlling for demographics, the estimated relationship between present bias and card borrowing is economically important, given participants' low incomes, and statistically significant at the 99 percent level. Similar to Harrison et al. (2002), the results show that *IDF*s are not significantly correlated with credit card debt

levels.[15]

Marginal effects computed from the tobit model in column (3) indicate that present biased individuals are both more likely to borrow, and borrow more than dynamically consistent individuals. Present bias is associated with a 16 percentage point increase in the probability of borrowing, and, conditional on borrowing, around $540 more debt. Examining the average balance on revolving accounts for the reference group (see bottom of Table 3), indicates that this $540 translates into approximately 27 percent higher card balances for present-biased individuals.[16]

[Table 3 about here.]

Time preferences and credit card debt in this study are both point-in-time measures. Recent shocks could potentially influence both card borrowing and measured preferences. A negative shock could increase credit card debt, and, if individuals were sufficiently liquidity constrained, could also impact measured preferences (see Meier and Sprenger, 2009, for evidence that measured time preferences are stable over time and uncorrelated with changes in income or employment status). For this reason, we obtained the consent of the sample in 2006 to analyze their credit report again in 2007.[17] Column (4) presents this follow-up analyis. Tobit models are estimated with the dependent variable of credit card borrowing observed one year after the original time preference experiment. The results indicate that present bias remains substantially and significantly correlated with card borrowing even one year after time preferences are measured. Present-biased individuals are again found to be more likely to borrow and borrow more than dynamically consistent individuals. This follow-up analysis

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[15]The effect of *IDF* is also modest in magnitude, as a change in a standard deviation of *IDF* changes the probability to have any debt by only 2.5 percentage points.

[16]The results hold when analyzing only individuals with positive amounts of debt and when using the natural logarithm of the outstanding balance (see Web Appendix).

[17]For one individual in the 2006 sample, the outstanding balance increased from close to $4,000 in 2006 to over $35,000 in 2007. This individual's 2007 revolving debt level was twice as high as the next highest debt level. The follow-up analysis in column (4) excludes this outlier.

suggests that recent short-lived shocks are not driving the correlation between present bias and credit card debt.

Credit access and credit limits play an interesting role in the discussion of present bias and borrowing.[18] Not only may individuals choose their credit limits and number of credit cards, but also firms may grant high or low credit limits or deny credit entirely. Column (5) controls for the results of these interactions by adding as explanatory variables whether or not individuals have a credit card and their remaining available credit limit across all accounts (in natural logarithm). Controlling for these credit constraints, present bias is again associated with more credit card borrowing. Present biased individuals are roughly 20 percentage points more likely to borrow, and, conditional on borrowing, have around $430 more debt than dynamically consistent individuals.[19]

In general, the demand for credit card borrowing is responsive to interest rate changes (Gross and Souleles, 2002). Controlling for the price of credit in our analysis is, therefore, a key concern. Credit reports do not provide direct interest rate information. However, individual credit scores can be used as an interest rate proxy given the prevalence of risk-based pricing in credit markets (Furletti, 2003). Column (6) in Table 3 accounts for possible differences in interest rates across subjects by controlling for FICO scores.[20] Controlling for FICO scores as a proxy for interest rates, present bias is again associated with both a higher probability of borrowing and conditionally more debt.

In sum, the results indicate that individuals who exhibit present bias are between 15 and 20 percentage points more likely to borrow on their credit cards. Conditional upon

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[18]Borrowers aware of their present bias may want to restrict their borrowing opportunities and so may choose a lower credit limit or not to have a credit card at all. For a discussion of "sophisticated" borrowing, see Heidhues and Koszegi (2008).

[19]Results from analysis of a payment behavior question similar to the Survey of Consumer Finances indicate that present-biased individuals are also less likely to self-report that they normally pay their credit card in full at the end of the month. Results may be obtained from the authors on request.

[20]Individuals with insufficient credit history to be scored are bottom-coded as 0. We also include an indicator variable for whether or not an individual is scored.

borrowing, present-biased individuals have around \$400 - \$580 (around 25 percent) more debt than dynamically consistent individuals. The relationship between present bias and credit card debt is maintained when controlling for demographics, credit constraints (both credit access and limits), and a proxy for interest rates. One year after the original time preference experiment, present bias remains significantly correlated with card borrowing.

3.2 Robustness Tests

This section tests the robustness of the obtained results: first to changes in calculating time preferences; and second to controlling for risk attitudes and relaxing the sample restriction criteria.

Columns (1) through (3) in Table 4 present results with alternative specifications of present bias. In column (1), we calculate the ratio $IDF_{6,7}/IDF_{0,1}$. This ratio takes on the value 1 for dynamically consistent individuals, is above 1 for present-biased individuals and below 1 for future-biased individuals. This measure captures both the direction and the intensity of dynamic inconsistency. We again find that more present biased individuals have higher debt levels. In column (2), we fit experimental choices with a quasi-hyperbolic discounting, β, δ, model.[21] The results again indicate that present-biased individuals, i.e., those with lower β, have significantly higher revolving balances. In column (3), we add the information from a third time frame in which $t = 0$ and $\tau = 6$. This third time frame gives an additional indication of individual dynamic inconsistency. The composite measure $\overline{Present\ Bias}$ takes on the value of 1 if $IDF_{0,1} < IDF_{6,7}\ and\ IDF_{0,1} < IDF_{0,6}$.[22] The results are robust to adding the choices from this third time frame to the analysis.

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[21]The calculations are $\delta = IDF_{6,7};\ \beta = IDF_{0,1}/IDF_{6,7}$.

[22]The composite measure $\overline{Future\ Bias}$ is similarly generated and is given the value 1 when $IDF_{0,1} > IDF_{6,7}$ and $IDF_{0,1} > IDF_{0,6}$.

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[Table 4 about here.]

Columns (4) through (6) in Table 4 show the robustness of the results to including individual risk attitudes and to changes in sample restrictions. Individual risk attitudes are taken from a survey question on general risk attitudes previously validated in a large, representative sample (Dohmen et al., 2005).[23] Column (4) indicates that the results are maintained with the inclusion of this measure, providing suggestive evidence that individual risk preferences do not impact the association between card borrowing and present bias. Column (5) includes individuals who exhibit multiple switching points and therefore make it difficult to calculate a discount factor. For these individuals we take their first switching point to calculate their *IDF*s. The results are unchanged. Column (6) excludes all individuals for whom any demographic control variables are missing, and again the results do not change substantially.

4   Conclusions

This paper directly investigates the relationship between individual present bias and credit card borrowing. Unlike previous studies analyzing either aggregate or self-reported borrowing, we present evidence from a unique field study combining incentivized choice experiments and objective administrative data on credit card borrowing.

We find that present-biased individuals are more likely to borrow and, conditionally, borrow more than dynamically consistent individuals. The relationship between present bias and credit card debt is maintained when controlling for demographics, credit constraints (both access and limits), and a proxy for interest rates. One year after the original time preference experiment, present bias remains significantly corre-

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[23]Participants answer the following question: *"How willing are you to take risks in general? (on a scale from "unwilling" to "fully prepared")* on a scale from 0 to 7 in 2006 and from 0 to 10 in 2007. We rescale the answer to be on an 11-point scale in both years.

lated with card borrowing. The results are unaffected by changes to the calculation of present bias or sample selection criteria.

The finding that directly measured present bias correlates with card borrowing gives critical support to behavioral economics models of present-biased preferences in consumer choice. This paper opens a number of avenues for future research. First, the results presented here are correlative. Future research should focus on the more difficult problem of exploring the theoretically-proposed *causal* link between present bias and borrowing. Second, our efforts focus exclusively on credit card borrowing and not other forms of debt (e.g., installment loans, mortgages, etc.). Credit card debt is identified as being psychologically different from other forms of debt (e.g. Prelec and Simester, 2001), and so future work should determine whether our results extend to other borrowing behavior. Third, our analysis is largely silent on the discussion of sophistication and naivete in present bias. A number of policy implications with regards to card borrowing depend critically on borrower sophistication (see, for example Camerer et al., 2003). Research should investigate which present-biased consumers are and are not cognizant of their own present bias.

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Table 1: Summary Statistics

	(1) All Participants	(2) Primary Sample	(3) Present-Biased	(4) Not Present-Biased
Panel A: Socio-demographic variables				
Age	35.8	35.9	33.8	37.1
	(13.8)[606]	(13.4)[541]	(12.9)[194]	(13.5)[347]
Gender (Male=1)	0.36	0.35	0.41	0.32
	(0.48)[569]	(0.48)[510]	(0.49)[185]	(0.47)[325]
Race (African-American=1)	0.80	0.80	0.81	0.79
	(0.40)[548]	(0.40)[491]	(0.39)[178]	(0.41)[313]
College Experience (=1)	0.51	0.52	0.62	0.45
	(0.50)[522]	(0.50)[465]	(0.49)[173]	(0.50)[292]
Disposable Income	18084	18516	17361	19162
	(13695)[606]	(13692)[541]	(14151)[194]	(13407)[347]
# of Dependents	0.51	0.52	0.41	0.58
	(0.84)[606]	(0.84)[541]	(0.72)[194]	(0.89)[347]
Panel B: Credit information				
Debt (=1)	0.41	0.41	0.45	0.39
	(0.49)[606]	(0.49)[541]	(0.50)[194]	(0.49)[347]
Revolving Balance	1162	1059	1565	776
	(2838)[606]	(2414)[541]	(3216)[194]	(1761)[347]
Having a Revolving Account (=1)	0.53	0.53	0.54	0.52
	(0.50)[606]	(0.50)[541]	(0.50)[194]	(0.50)[347]
Revolving Credit Limit	4741	4764	5129	4560
	(11705)[606]	(11850)[541]	(12440)[194]	(11520)[347]
FICO Score	611	610	608	610
	(84)[437]	(84)[390]	(80)[133]	(86)[257]
Panel C: Time preferences				
IDF	0.84	0.83	0.85	0.81
	(0.19)[606]	(0.19)[541]	(0.11)[194]	(0.23)[347]
Present Bias (=1)	0.36	0.36	1	0
	(0.48)[606]	(0.48)[541]	(0)[194]	(0)[347]
Future Bias (=1)	0.11	0.09	0	0.14
	(0.31)[606]	(0.28)[541]	(0)[194]	(0.35)[347]

Notes: Summary statistics for different sample restrictions. The table shows means, standard deviations in parentheses, and number of observations in brackets. Column (1) shows summary statistics for all individuals. Column (2) only looks at individuals who exhibit a unique switching point in the choice experiments. Columns (3) and (4) splits individuals with unique switching points into those who exhibit present-biased preferences and those who do not.

Table 2: Time Preferences

	(1)	(2)	(3)	(4)	(5)	(6)
	IDF		*Interval of $IDF_{t,\tau}$*		*Present Bias (=1)*	
Dependent Variable:						
Age	-0.002***	-0.002**	-0.002***	-0.002**	-0.005***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Gender (Male=1)	-0.057***	-0.057***	-0.070***	-0.070***	0.092**	0.076
	(0.018)	(0.019)	(0.022)	(0.023)	(0.045)	(0.049)
Race (African-American=1)	-0.010	-0.013	-0.011	-0.015	0.031	0.028
	(0.020)	(0.019)	(0.024)	(0.023)	(0.049)	(0.049)
Ln(Disposable Income)		0.023***		0.030**		-0.023
		(0.009)		(0.012)		(0.020)
# of Dependents		-0.008		-0.009		0.009
		(0.014)		(0.017)		(0.035)
College Experience (=1)		0.042**		0.050**		0.181***
		(0.018)		(0.022)		(0.048)
Ln(Credit Amount Available)		0.004*		0.005*		-0.000
		(0.003)		(0.003)		(0.007)
Tax Refund(Liability) Amount		0.000		0.000		-0.000*
		(0.000)		(0.000)		(0.000)
Direct Deposit of Refund (=1)		0.023		0.028		-0.026
		(0.016)		(0.020)		(0.043)
Insufficient Credit to Be Scored (=1)		0.040*		0.048*		0.080
		(0.021)		(0.025)		(0.054)
# of Loan Accounts		-0.001		-0.002		0.003
		(0.001)		(0.002)		(0.003)
Has Present (=1)			-0.079***	-0.079***		
			(0.009)	(0.009)		
Constant	0.975***	0.697***	0.993***	0.647***	0.441***	0.539***
	(0.029)	(0.085)	(0.035)	(0.108)	(0.077)	(0.202)
R^2/Log-Likelihood	0.07	0.12	-2928.99	-2904.62	0.03	0.07
# of Observations	541	541	1082	1082	541	541
# of Individuals	541	541	541	541	541	541

Notes: Columns (1) and (2): OLS regressions. Dependent variable: *IDF*. Columns (3) and (4): Interval regressions (Stewart, 1983). Dependent variable: Interval of $IDF_{t,\tau}$ measured from one of two price lists: $IDF_{0,1}$, and $IDF_{6,7}$. Columns (5) and (6): OLS regressions. Dependent variable: Present Bias (=1). Robust standard errors clustered on individual level in parentheses. Coefficients of dummies for year of study, missing gender, missing race, missing education omitted from table.
Level of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 3: Present-Biased Preferences and Credit Card Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
IDF	1591.4	1653.3	413.2	2998.2	247.2	520.3
	(1167.4)	(1181.2)	(1183.5)	(3978.8)	(844.4)	(1095.3)
	[0.13; 477.9]	[0.14; 494.7]	[0.04; 121.2]	[0.26; 1019.1]	[0.02; 53.2]	[0.05; 141.6]
Present Bias (=1)	1304.4**	1611.0***	1779.4***	2885.3**	1874.0***	2013.6***
	(508.3)	(516.4)	(518.8)	(1255.8)	(402.9)	(492.2)
	[0.11; 402.2]	[0.14; 498.7]	[0.16; 542.9]	[0.25; 1047.1]	[0.20; 430.1]	[0.20; 576.5]
Future Bias (=1)	-270.5	-48.0	-487.9	-389.4	-315.5	-689.8
	(811.7)	(786.6)	(776.5)	(1341.0)	(666.9)	(732.1)
	[-0.02; -80.0]	[-0.004; -14.3]	[-0.04; -139.0]	[-0.03; -130.1]	[-0.03; -66.1]	[-0.06; -179.4]
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	No	Yes	Yes	Yes	Yes	Yes
Other Socio-Demographics	No	No	Yes	Yes	Yes	Yes
Credit Card Information	No	No	No	No	Yes	Yes
FICO Score Information	No	No	No	No	No	Yes
For Reference Group (Present Bias (=0) *and* Future Bias (=0)):						
Mean of DV:	786.8	786.8	786.8	1027.7	786.8	786.8
Mean of DV (if uncensored):	2028.1	2028.1	2028.1	2055.4	2028.1	2028.1
LL	-2351.4	-2340.5	-2321.2	-663.34	-2121.7	-2259.8
N	541	541	541	122	541	541

Note: Dependent variable: Outstanding balance on revolving accounts. In column (4), the dependent variable is the outstanding balance on revolving accounts one year after the experiment for the 2006 sample. Coefficient of tobit regressions. Robust standard errors in parentheses. Marginal effects in brackets [probability to be censored at 0; expected value of the dependent variable conditional on being uncensored]. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit Card Information*: dummy for having a revolving account and ln(Credit Limit). *FICO Score Information*: FICO score and a dummy for missing score.
Level of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{IDF_{6,7}}{IDF_{0,1}}$	1264.1**					
	(607.6)					
β		-2516.6**				
		(1019.4)				
δ		888.5				
		(1190.4)				
$\overline{IDF}$			113.8			
			(1533.5)			
$\overline{Present\ Bias}$ (=1)			1588.6***			
			(581.3)			
$\overline{Future\ Bias}$ (=1)			273.9			
			(1156.3)			
IDF				-533.6	1804.6	528.5
				(1281.1)	(1360.7)	(1426.3)
Present Bias (=1)				1895.0***	1681.9***	1418.1**
				(558.3)	(561.9)	(596.4)
Future Bias (=1)				-308.4	-54.0	-1086.1
				(818.8)	(801.1)	(844.7)
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Other Socio-Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Risk Attitudes	No	No	No	Yes	No	No
Including Multiple Switchers	No	No	No	No	Yes	No
Non-Missing Control Variables	No	No	No	No	No	Yes
LL	-2327.78	-2325.60	-2324.70	-2033.28	-2659.19	-1797.90
N	541	541	541	463	606	420

Note: Dependent variable: Outstanding balance on revolving accounts. Coefficient of tobit regressions. Robust standard errors in parentheses. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Risk Attitudes*: based on question *"How willing are you to take risks in general? (on a scale from 0 "unwilling" to 7 (in 2006) or 10 (in 2007) "fully prepared")*. The answers are rescaled to be on an 11-point scale for both years.
Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

A Web Appendix (Not for publication)

This Web Appendix provides some additional material (tables and instructions) for the paper **"Present-Biased Preferences and Credit Card Borrowing"** by [IN-CLUDE AUTHOR NAMES].

A.1 Appendix Tables

The Appendix includes the following additional tables:

- Separate summary statistics for the two years in which the study was undertaken in Table A1.

- OLS regressions for the paper's main table in Table A2.

- The association between present-biased preferences and credit card borrowing conditional on borrowing in Table A3.

- The association between present-biased preferences and credit card borrowing *in natural logarithm* conditional on borrowing in Table A4.

- The association between present-biased preferences and credit card borrowing separately for 2006 and 2007 in Table A5

Table A1: Summary Statistics for 2006 and 2007 Sample

	(1) 2006	(2) 2007
Panel A: Socio-demographic variables		
Age	32.2	37.0
	(11.5)[123]	(13.8)[418]
Gender (Male=1)	0.34	0.36
	(0.48)[123]	(0.48)[387]
Race (African-American=1)	0.81	0.79
	(0.39)[107]	(0.40)[384]
College Experience (=1)	0.57	0.50
	(0.50)[95]	(0.50)[370]
Disposable Income	18712	18459
	(12711)[123]	(13983)[418]
# of Dependents	0.54	0.51
	(0.82)[123]	(0.84)[418]
Panel B: Credit behavior		
Debt (=1)	0.46	0.39
	(0.50)[123]	(0.49)[418]
Revolving Balance	1016	1071
	(2280)[123]	(2455)[418]
Having a Revolving Account (=1)	0.57	0.51
	(0.50)[123]	(0.50)[418]
Revolving Credit Limit	5462	4559
	(14036)[123]	(11136)[418]
FICO Score	618	607
	(83)[93]	(84)[297]
Panel C: Time preferences		
IDF	0.89	0.81
	(0.13)[123]	(0.20)[418]
Present Bias (=1)	0.34	0.36
	(0.48)[123]	(0.48)[418]
Future Bias (=1)	0.17	0.06
	(0.38)[123]	(0.25)[418]

Notes: Summary statistics for participants who exhibited unique switching points in the choice experiments in 2006 and 2007 separately.

Table A2: Present-Biased Preferences and Credit Card Borrowing (OLS Regressions)

	(1)	(2)	(3)	(4)	(5)	(6)
IDF	194.4	275.0	-148.8	1055.3	-333.5	-252.4
	(423.6)	(454.1)	(456.7)	(2021.5)	(359.8)	(440.2)
Present Bias (=1)	771.0***	902.3***	950.4***	1819.9**	885.3***	1010.9***
	(252.2)	(260.0)	(262.7)	(784.9)	(196.9)	(250.7)
Future Bias (=1)	-72.9	60.2	-107.1	-185.4	-119.4	-179.1
	(343.1)	(345.7)	(341.3)	(647.1)	(294.7)	(325.8)
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	No	Yes	Yes	Yes	Yes	Yes
Other Socio-Demographics	No	No	Yes	Yes	Yes	Yes
Credit Card Information	No	No	No	No	Yes	No
FICO Score Information	No	No	No	No	No	Yes
Mean of DV for Reference Group (Present Bias (=0) *and* Future Bias (=0)):						
	786.8	786.8	786.8	1053.6	786.8	786.8
R^2	0.025	0.063	0.097	0.163	0.446	0.193
N	541	541	541	122	541	541

Note: Dependent variable: Outstanding balance on revolving accounts. In column (4), the dependent variable is the outstanding balance on revolving accounts one year after the experiment for the 2006 sample. Coefficient of OLS regressions. Robust standard errors in parentheses. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit Card Information*: dummy for having a revolving account and ln(Credit Limit). *FICO Score Information*: FICO score and a dummy for missing score. *Level of significance*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table A3: Present-Biased Preferences and Credit Card Borrowing (Conditional on Borrowing)

	(1)	(2)	(3)	(4)	(5)
IDF	-827.7	-360.4	-412.6	-191.7	-615.3
	(937.2)	(958.6)	(963.3)	(884.0)	(1024.9)
Present Bias (=1)	1496.8***	1716.1***	1649.0***	1712.6***	1688.8***
	(483.6)	(498.7)	(506.0)	(433.3)	(511.6)
Future Bias (=1)	-39.7	88.3	-180.0	-144.4	-195.1
	(791.5)	(683.7)	(676.7)	(660.3)	(681.5)
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	No	Yes	Yes	Yes	Yes
Other Socio-Demographics	No	No	Yes	Yes	Yes
Credit Card Information	No	No	No	Yes	No
FICO Score Information	No	No	No	No	Yes
Mean of DV for Reference Group (Present Bias (=0) *and* Future Bias (=0)):					
	2028.1	2028.1	2028.1	2028.1	2028.1
R^2	0.058	0.126	0.1547	0.366	0.168
N	221	221	221	221	221

Note: Dependent variable: Outstanding balance on revolving accounts. Coefficient of OLS regressions. Robust standard errors in parentheses. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit Card Information*: dummy for having a revolving account and ln(Credit Limit). *FICO Score Information*: FICO score and a dummy for missing score.
Level of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table A4: Present-Biased Preferences and Ln(Credit Card Borrowing) (Conditional on Borrowing)

	(1)	(2)	(3)	(4)	(5)
IDF	-0.5	-0.3	-0.4	-0.2	-0.2
	(0.5)	(0.6)	(0.5)	(0.5)	(0.6)
Present Bias (=1)	0.4*	0.5**	0.5**	0.5***	0.5**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Future Bias(=1)	-0.2	-0.2	-0.3	-0.3	-0.3
	(0.4)	(0.3)	(0.4)	(0.4)	(0.4)
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	No	Yes	Yes	Yes	Yes
Other Socio-Demographics	No	No	Yes	Yes	Yes
Credit Card Information	No	No	No	Yes	No
FICO Score Information	No	No	No	No	Yes
R^2	0.028	0.091	0.127	0.300	0.136
N	221	221	221	221	221

Note: Dependent variable: Ln(Outstanding balance on revolving accounts). Coefficient of OLS regressions. Robust standard errors in parentheses. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit Card Information*: dummy for having a revolving account and ln(Credit Limit). *FICO Score Information*: FICO score and a dummy for missing score. *Level of significance*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

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Table A5: Present-Biased Preferences and Credit Card Borrowing

	(1)	(2)	(3)	(4)	(5)
Panel A: 2006 Sample					
IDF	605.3	760.1	119.9	-1349.6	-283.4
	(2937.5)	(2994.4)	(2976.8)	(2024.3)	(2930.8)
Present Bias (=1)	1638.0	1649.1*	2371.6**	2074.6**	2527.5***
	(997.4)	(983.7)	(1044.5)	(831.8)	(923.5)
Future Bias (=1)	-1128.5	-974.2	-1103.1	-1186.3	-1154.4
	(1029.7)	(1063.9)	(1125.3)	(870.1)	(986.4)
N	123	123	123	123	123
Panel B: 2007 Sample					
IDF	1836.7	1880.5	681.6	590.5	897.1
	(1304.3)	(1315.3)	(1319.7)	(930.3)	(1216.3)
Present Bias (=1)	1146.4*	1521.7**	1618.0***	1823.2***	1952.0***
	(601.3)	(614.0)	(619.3)	(490.3)	(592.3)
Future Bias(=1)	386.9	614.1	182.0	89.9	54.9
	(1141.5)	(1109.2)	(1079.0)	(867.3)	(1009.4)
N	418	418	418	418	418
Constant & Year of Study	Yes	Yes	Yes	Yes	Yes
Exogenous Control Variables	No	Yes	Yes	Yes	Yes
Other Socio-Demographics	No	No	Yes	Yes	Yes
Credit Card Information	No	No	No	Yes	No
FICO Score Information	No	No	No	No	Yes

Note: Dependent variable: Outstanding balance on revolving accounts. Coefficient of tobit regressions. Robust standard errors in parentheses. *Exogenous Control Variables*: age, gender, race, and dummies for missing values. *Other Socio-Demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit Card Information*: dummy for having a revolving account and ln(Credit Limit). *FICO Score Information*: FICO score and a dummy for missing score.
Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

A.2 Instructions of Study 1 (2006)

Please indicate for each of the following 19 decisions, whether you would prefer the smaller payment in the near future or the bigger payment later. The number of your raffle ticket (none or 1 to 19), will indicate which decision you will be paid, if at all.

[Block 1; $t = 0$, $\tau = 1$]: Option A (**TODAY**) or Option B (**IN A MONTH**)
Decision (1): \$ 75 guaranteed **today** - \$ 80 guaranteed **in a month**
Decision (2): \$ 70 guaranteed **today** - \$ 80 guaranteed **in a month**
Decision (3): \$ 65 guaranteed **today** - \$ 80 guaranteed **in a month**
Decision (4): \$ 60 guaranteed **today** - \$ 80 guaranteed **in a month**
Decision (5): \$ 50 guaranteed **today** - \$ 80 guaranteed **in a month**
Decision (6): \$ 40 guaranteed **today** - \$ 80 guaranteed **in a month**

[Block 2; $t = 0$, $\tau = 6$]: Option A (**TODAY**) or Option B (**IN 6 MONTHS**)
Decision (7): \$ 75 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (8): \$ 70 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (9): \$ 65 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (10): \$ 60 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (11): \$ 50 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (12): \$ 40 guaranteed **today** - \$ 80 guaranteed **in 6 months**
Decision (13): \$ 30 guaranteed **today** - \$ 80 guaranteed **in 6 months**

[Block 3; $t = 6$, $\tau = 7$]: Option A (**IN 6 MONTHS**) or Option B (**IN 7 MONTHS**)
Decision (14): \$ 75 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**
Decision (15): \$ 70 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**
Decision (16): \$ 65 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**
Decision (17): \$ 60 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**
Decision (18): \$ 50 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**
Decision (19): \$ 40 guaranteed **in 6 months** - \$ 80 guaranteed **in 7 months**

A.3 Instructions of Study 2 (2007)

As a tax filer at this Volunteer Income Tax Assistance site you are automatically entered in a raffle in which you could win up to \$50. Just follow the directions below:

How It Works: In the boxes below you are asked to choose between smaller payments closer to today and larger payments further in the future. For each row, choose one payment: either the smaller, sooner payment or the later, larger payment. When you return this completed form, you will receive a raffle ticket. If you are a winner, the raffle ticket will have a number on it from 1 to 22. These numbers correspond to the numbered choices below. You will be paid your chosen payment. The choices you make could mean a difference in payment of more than \$35, so CHOOSE CAREFULLY!!!
RED BLOCK (Numbers 1 through 7): Decide between payment **today** and payment in **one month**
BLACK BLOCK (Numbers 8 through 15): Decide between payment **today** and payment in **six months**
BLUE BLOCK (Numbers 16 through 22): Decide between payment in **six months** and payment in **seven months**

Rules and Eligibility: For each possible number below, state whether you would like the earlier, smaller payment or the later, larger payment. Only completed raffle forms are eligible for the raffle. All prizes will be sent to you by normal mail and will be paid by money order. One out of ten raffle tickets will be a winner. You can obtain your raffle ticket as soon as your tax filing is complete. You may not participate in the raffle if you are associated with the EITC campaign (volunteer, business associate, etc.) or an employee (or relative of an employee) of the Federal Reserve Bank of Boston or the Federal Reserve System.

[Red Block; $t = 0$, $\tau = 1$]

TODAY VS. ONE MONTH FROM TODAY WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 1 AND 7? Decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **one month**? Please answer for each possible number (1) through (7) by filling in one box for each possible number.

Example: If you prefer $49 today in Question 1 mark as follows: ✓ $49 today or $50 in one month

If you prefer $50 in one month in Question 1, mark as follows: $49 today or ✓ $50 in one month

If you get number (1): Would you like to receive $49 **today** or $50 in **one month**

If you get number (2): Would you like to receive $47 **today** or $50 in **one month**

If you get number (3): Would you like to receive $44 **today** or $50 in **one month**

If you get number (4): Would you like to receive $40 **today** or $50 in **one month**

If you get number (5): Would you like to receive $35 **today** or $50 in **one month**

If you get number (6): Would you like to receive $29 **today** or $50 in **one month**

If you get number (7): Would you like to receive $22 **today** or $50 in **one month**

[Black Block; $t = 0$, $\tau = 6$]

TODAY VS. SIX MONTHS FROM TODAY WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 8 AND 15? Now, decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **six months**? Please answer each possible number (8) through (15) by filling in one box for each possible number.

If you get number (8): Would you like to receive $49 **today** or $50 in **six months**

If you get number (9): Would you like to receive $47 **today** or $50 in **six months**

If you get number (10): Would you like to receive $44 **today** or $50 in **six months**

If you get number (11): Would you like to receive $40 **today** or $50 in **six months**

If you get number (12): Would you like to receive $35 **today** or $50 in **six months**

If you get number (13): Would you like to receive $29 **today** or $50 in **six months**

If you get number (14): Would you like to receive $22 **today** or $50 in **six months**

If you get number (15): Would you like to receive $14 **today** or $50 in **six months**

[Blue Block; $t = 6$, $\tau = 7$]

SIX MONTHS FROM TODAY VS. SEVEN MONTHS FROM TODAY WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 16 AND 22? Decide for **each** possible number if you would like the smaller payment for sure in **six months** or the larger payment for sure in **seven months**? Please answer for each possible number (16) through (22) by filling in one box for each possible number.

If you get number (16): Would you like to receive $49 in **six months** or $50 in **seven months**

If you get number (17): Would you like to receive $47 in **six months** or $50 in **seven months**

If you get number (18): Would you like to receive $44 in **six months** or $50 in **seven months**

If you get number (19): Would you like to receive $40 in **six months** or $50 in **seven months**

If you get number (20): Would you like to receive $35 in **six months** or $50 in **seven months**

If you get number (21): Would you like to receive $29 in **six months** or $50 in **seven months**

If you get number (22): Would you like to receive $22 in **six months** or $50 in **seven months**