

Charging Myopically Ahead: Evidence on Present-Biased Preferences and Credit Card Borrowing

Stephan Meier^y Charles Sprenger^z

July, 2008

Abstract

Some individuals borrow extensively on their credit cards. This paper tests whether present-biased preferences, that is a disproportionate preference for immediate consumption, can explain differences in credit card borrowing. In a field study, we elicit individual time preferences through incentivized choice experiments, and match resulting time preference measures to individual credit reports and annual tax returns.

The results show that individuals with present-biased time preferences have significantly higher amounts of credit card debt, even after controlling for disposable income, credit constraints and other socio-demographic characteristics. Present-biased individuals appear to be naive, charging their cards too much given their long-run preferences.

JEL classification: D12, D14, D91, C93

Keywords: time preferences, dynamic inconsistency, credit card borrowing, field experiment

This paper is a substantial revision of the previous paper entitled: "Impatience and Credit Behavior: Evidence from a Field Experiment". We are grateful to Christine Benesch, Mary Burke, Jeff Carpenter, Jonathan Crook, Chris Foote, Andreas Fuster, Kris Gerardi, Lorenz Goette, Fabia Gumbau-Brisa, Glenn Harrison, David Huffman, Elif Incekara, Cathleen Johnson, Jane Katz, David Laibson, Borja Larrain, Felix Oberholzer-Gee, Jan Potters, Tanya Rosenblat, Julio Rotemberg, Jeremy Tobacman, Tyler Williams, and participants at seminars and conferences held by the Federal Reserve Bank of Boston, the European University Institute, the University of Arizona, the University of Lausanne, the Dutch Nationalbank, Columbia University, and the University of Texas at Dallas for helpful comments. Special thanks to Marques Benton (Department of Public and Community Affairs, Federal Reserve Bank of Boston) who made the study possible.

^yColumbia Business School, Columbia University, Uris Hall, 3022 Broadway, New York, NY 10027; sm3087@columbia.edu.

^zDepartment of Economics, University of California at San Diego, 9500 Gilman Drive, La Jolla, CA 92093; csprenge@ucsd.edu.

1 Introduction

People charge their credit cards extensively. U.S. households who have at least one credit card carried, on average, \$3,027 in revolving debt in 2004 (based on the Survey

to support the behavioral economics view that present-biased individuals have higher credit card borrowing. Previous research on the topic has used one of two approaches, examining either aggregate or self-reported debt measures. Both of these approaches have limitations for answering the question at hand. 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, Repetto, and Tobacman, 2008; Skiba and Tobacman, 2007; Shui and Ausubel, 2005). These studies are important as they indicate that, in the aggregate, present-biased preferences are able to explain why people simultaneously hold credit card debt and liquid assets. The link between borrowing and present bias is, however, indirect and examination of aggregates does not allow for evaluation of individual heterogeneity.

A second approach measures individual time preferences directly (often experimentally), and correlates these measures to *self-reported* individual credit balances or self-reported spending problems. In one such study, Harrison, Lau, and Williams (2002) find that individual long-run discount factors cannot explain borrowing behavior. As this study was not designed to explore the effects of present bias, it remains silent on the association between present bias and credit card borrowing. Dohmen, Falk,

borrowing and correlate these objective credit outcomes with directly measured present bias parameters from incentivized choice experiments. 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 individual truthfulness in reporting debt levels. Such efforts directly linking experimental results to real world outcomes are methodologically important as they expand our understanding of how preferences influence actual behavior in real life settings (see also Ashraf, Karlan, and Yin, 2006; Karlan, 2005).

The field study presented in this paper was conducted with around 600 individuals in collaboration with the City of Boston over two years. We find that heterogeneity in individual present bias, measured using incentivized choice experiments, is highly correlated with credit card borrowing. Individuals who are present-biased borrow significantly more on their credit cards. Though individuals may not be *charging blindly*, our findings suggest that some are at least *charging myopically* into financial trouble. The result is not driven by credit constraints or differences in socio-demographic characteristics and is robust to the possibility that sophisticated present-biased individuals may restrict their own borrowing activity by either choosing a low credit limit or choosing not to have a credit card at all. Due to the design of the study and the credit information obtained, we are able to verify that the results are robust to controlling for income (taken from individuals tax returns), information on credit constraints and a number of other socio-demographic characteristics (e.g. education).

The finding that present-biased individuals borrow more than others illustrates their naivete. Sophisticated consumers, aware of their own tendency to be present-biased in future periods, would be expected to take actions to restrict their own future borrowing activities. Naive present-biased consumers do not expect, *a priori*, that they will charge their credit cards as much as they actually do. As such, present-

biased preferences lead to dynamically inconsistent borrowing behavior. This dynamic inconsistency and the apparent naivete of present-biased consumers have implications for policy makers, firms and academics.

count for present bias as an important axis along which behavior may deviate from standard predictions.

The paper proceeds as follows: Section 2 presents conceptual considerations regarding present-biased preferences and credit card borrowing. In doing so, it distinguishes between individuals who are naive or sophisticated about the present bias. Section 3

Laibson, 1997; O'Donoghue and Rabin, 1999):

$$U_i = u(c_t) + \beta u(c_{t+1}) + \beta^2 u(c_{t+2}) + \dots + \beta^{T-t} u(c_{t+T}) \quad (1)$$

where c_t is consumption in period t , β is an individual's present bias parameter and δ is the individual's long-run discount factor. When $\beta = 1$, individuals are not present-biased and the quasi-hyperbolic model reduces to standard exponential discounting.

Maximizing the above lifetime utility function subject to a budget constraint yields important borrowing dynamics and testable implications for our empirical efforts. Present-biased individuals borrow more in the present than individuals for whom $\beta = 1$. Furthermore, present-biased individuals borrow more in each period than they would have previously intended. Additionally, sophisticated individuals, cognizant of their own present bias, may be willing to take specific actions to restrict borrowing. We show in a simple three period model of present bias with logarithmic utility how such dynamics are generated.

2.1 Charging Myopically

To illustrate how borrowing can be affected by present bias, we first examine the problem of a naive present-biased individual. Naive individuals believe they will not be present-biased in all future periods while sophisticated individuals recognize the likelihood that they will again be present-biased in the future. Consider a three period model of a naive present-biased individual with the opportunity to borrow at interest rate r and no uncertainty over income, y_t . At time $t = 1$ the individual maximizes the following logarithmic utility function:

$$U(c_1; c_2; c_3) =$$

subject to the three period budget constraint:

$$c_1 + \frac{c_2}{(1+r)} + \frac{c_3}{(1+r)^2} = y_1 + \frac{y_2}{(1+r)} + \frac{y_3}{(1+r)^2} \quad (3)$$

The optimization in $t = 1$ of a myopic individual yields the following planned consumption ratios:

$$\frac{c_1}{c_2} = \frac{1}{(1+r)} \quad (4)$$

$$\frac{c_2}{c_3} = \frac{1}{(1+r)} \quad (5)$$

These consumption ratios, combined with the budget constraint, determine the planned consumption of a present-biased individual in each of the three periods. This yields the following level of consumption, c_1 :

$$c_1 = \frac{y_1}{(1+r)^2} + \frac{y_2}{(1+r)^2(1+r)} + \frac{y_3}{(1+r)^2(1+r)^2} \quad (6)$$

Consumption (and borrowing) in $t = 1$ is decreasing in β . As an individual becomes more present-biased, he or she consumes more and, given fixed income, borrowing in $t = 1$ increases. The key prediction to be tested empirically is that present-biased individuals ($\beta < 1$) borrow more than individuals who are not present-biased ($\beta = 1$).

The solution of the above problem represents only the planned values of consumption as of $t = 1$. Though under the assumption of naivete the planned and actual values of consumption will coincide in period $t = 1$, these values will systematically deviate in later periods.

As of $t = 1$, the individual believes the relationship between his second and third

period consumption is governed by equation (5). However, when $t = 2$ arrives, he is again present-biased and the equation that actually governs this relationship is:

$$\frac{c_2}{c_3} = \frac{1}{(1 + r)} \quad (7)$$

With $\beta < 1$ a naive individual will consume more in $t = 2$ and less in

their own borrowing in such ways would reduce the expected relationship between card borrowing and present bias as these present-biased individuals would borrow less by construction.

Another factor entering into the relationship between present bias and borrowing is the effect of credit card firms when faced with present-biased consumers. As noted by Ausubel (1991) and DellaVigna and Malmendier (2004), naive present-biased individuals should be less sensitive to interest rate changes than individuals who are not present-biased. Furthermore, as naive present-biased individuals borrow and consume more than others, they may have less available funds to repay, increasing the risk of default. In the presence of such present-biased naive consumers, credit card firms may charge higher rates of interest to compensate for the increased risk or extract the surplus associated with such consumers' lower price sensitivity. In general, individuals are sensitive to increases in their card interest rates to at least some degree (Gross and Souleles, 2002). If present-biased individuals are charged higher rates of interest, this should lower their borrowing and empirically work against finding a difference in card debt levels between present-biased individuals and those who discount

3 Field Study: Credit Bureau Data and Choice Experiments

3.1 Design of Field Study

The field study was conducted with 606 individuals at two Volunteer Income Tax Assistance (VITA) sites in Boston, Massachusetts.² 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 studies in the two years mainly differ in the way in which we elicited time preferences (discussed in detail below).

The setting of the field study allowed us to obtain consent from all participants to access their credit report, to retrieve income information from their tax return, to ask participants further questions about certain socio-demographic variables, and to elicit time preferences using incentivized choice experiments. Of the 606 participants, we obtain a usable measure of time preferences for 541 (see below for details). These individuals represent our primary study sample.

Panel A of Table 1 shows the socio-demographic characteristics of the participants. 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. The participants do not differ in observable characteristics in the two years the study was conducted { with the exception of age. Participants are younger in 2007 compared to 2006 (not shown here). In the main analysis, missing socio-demographic variables were imputed by taking the value of the majority for the dummy variables gender, race, and college experience. The exclusion of observations

²There 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 tax season, from late-January to mid-April each year.

here on.

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). To ensure that our measures represent actual borrowing, we implemented a companion survey with questions on payment habits following 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, have significantly lower balances on revolving accounts (\$1,084 versus \$2,998; $p < 0.05$ in a t -test). Furthermore, the conclusion of our results hold when using these self-reported payment habits as the dependent variable or when analyzing credit card balances one year after we elicited individual time preferences.

Panel B of Table 1 illustrates for our participants the two general stylized facts about credit card borrowing: the high level and the large degree of heterogeneity. The average revolving credit card balance is \$1,059 (s.d. \$2,414) yielding an average revolving debt-to-income ratio of around 9 percent (for individuals with positive income). Relative to the general population, our sample has notably high levels of credit card debt. The average U.S. resident has a self-reported credit card debt to income ratio of only 4.3 percent (authors' calculation based on Bucks, Kennickell, and Moore, 2006). The large standard deviation of credit card balances illustrates the degree of heterogeneity in borrowing. Of all participants, only about half of the participants (44 percent) have any outstanding balances on credit cards. Conditional on having any credit card debt, participants have \$2,592 in credit card balances.

Credit reports also provide crucial information on who has a revolving credit account (i.e., credit card) and on individuals' revolving credit limits. In our sample, the average revolving credit limit is \$4,764 (s.d. \$11,850). Fifty-five percent of the par-

participants cannot currently borrow on revolving accounts listed on their credit report, either because they have no current access to credit or because they have hit the credit limit on their credit cards. As will be shown in the following sections, credit constraints cannot explain either the elicited time preference parameters or, importantly, the association between present bias and borrowing behavior. 53 percent of study participants don't have any revolving account, which might

and $\$Y$ in the different decisions 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 $\$30$ (see the instructions in Appendix A.2). In 2007, $\$Y = \50 and $\$X$ was varied from $\$49$ to $\$14$ (see the instructions in Appendix A.3). Second, the presentation of the choice sets was varied between 2006 and 2007. While in 2006 the order of the three price lists was the same for each individual, in 2007, the order was randomized. Additionally, while in 2006, the 139 participants were individually and extensively guided through the details of the price lists, the 467 participants in 2007 received a substantially shorter price list introduction. Most likely, the randomization of the price list order and the shorter introduction increased the noise in measuring time preferences in 2007 compared to 2006. In the results section, we mainly analyze the data from the two years jointly, controlling for the year of study. In the appendix, we report the results separately for the two years. As expected, the standard errors in 2007 are often larger than in 2006, but the results are qualitatively similar.

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, which subjects took at the end of their tax filing and which indicated which choice would be effective (if at all). To ensure credibility of the payments, we filled out money orders for the winning amounts on the spot 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 always return to the heads of the VITA sites where the experiments were run to report any problems receiving the payments.⁴ Money orders were sent by mail to the winner's home address on the same day as the experiment (if $t = 0$), or in

⁴In fact, one participant returned to his VITA site, a community health center, almost seven months after the experiment to ask about his payments. He was, however, three days too early and received the payment on time.

one, six, or seven months, depending on the winner's choice. The payment procedure therefore mimicked a front-end-delay design (Harrison, Lau, Rutstrom, and Williams, 2005). The details of the payment procedure of the choice experiments were kept the same in the two years and participants were fully informed about the method of payment.⁵

and Williams, 1999; Harrison, Lau, Rutstrom, and Williams, 2005, for details).⁶

(2) *Present Bias and Future Bias*: The three time frames allow us to identify individuals who are dynamically inconsistent; that is, they show a bias towards either present or future payouts, becoming more or less patient across price lists. By comparing individual choices in Time Frame 1 ($t = 0, \tau = 1$) with Time Frame 2 ($t = 0, \tau = 6$) and Time Frame 1 ($t = 0, \tau = 1$) with Time Frame 3 ($t = 6, \tau = 1$) we obtain two measures for whether individuals are dynamically inconsistent. Based on

lower discount factors for subprime borrowers than measured by our experiment (e.g., Skiba and Tobacman, 2007; Adams, Einav, and Levin, 2008). For our measure of dynamic inconsistency: 25 percent exhibit increasing discount factors (*Present Bias* ($=1$)) and only 2 percent have decreasing discount factors (*Future Bias* ($=1$)). The *IDF*

switching points in price lists implicitly assumes that utility is linear over the payments in question. 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 of curvature of the utility function (Andersen, Harrison, Lau, and Rutstrom, 2008).⁸ We therefore test whether differences in risk aversion affect our results using a question on general risk attitudes previously validated with a large, representative sample (Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner, 2005). The question reads as follows: *How willing are you to take risks in general? (on a scale from "unwilling" to "fully prepared")*. As the scale of the answer differed from 0 to 7 in 2006 to 0 to 10 in 2007, we rescale the answer to be on an 11-point scale in both years. While risk aversion is correlated with measured time preferences, controlling for it does not affect the results of this paper (see Section 4.3).

Fourth, credit availability (and constraints) might drive the behavior in the choice experiments, as individuals who are credit constrained might prefer earlier, lower payments. The data does not provide support for this possibility. The credit report data permit us to know precisely how much participants are still able to borrow on revolving accounts such as credit cards. If one correlates immediate credit availability, that is the amount individuals can still borrow (in natural logarithm), to present bias, the correlation is small in size, and is not statistically significant. Also, individuals who are credit constrained by this measure do not exhibit different degrees of present bias than individuals who can still borrow on their revolving accounts. Credit constraints are also uncorrelated with measured discount factors, \overline{TDF} . Importantly, the results

of this paper are unchanged when controlling for both disposable income (as a proxy for credit constraints) and an objective measure of credit availability from individual credit reports (see Section 4.3).

In general, our time preference measures are also uncorrelated with proxies for credit experience (whether an individual has sufficient credit experience to have a FICO score, the total number of loan accounts an individual has ever had and the number of revolving credit card accounts an individual has ever had). The fact that all of these indicators of credit constraints and experience are unrelated to measured time preferences supports the claim that differential credit experience also cannot explain heterogeneity of present bias and its correlation with borrowing behavior.

4 Results

We present results exploring the relationship between individual present bias and credit card borrowing in three steps.

In the first step, we examine present bias as it relates to borrowing for all individuals including those without credit cards. For a subsample we additionally examine credit card debt one year after the experiment to ensure that the results are maintained.

As noted above, sophisticated present-biased individuals may choose not to have a credit card in order to restrict their own future behavior. This should weaken the relationship between card borrowing and present bias presented in the first stage. In a second step, we examine card borrowing and present bias only for individuals with credit cards as measured by positive revolving credit limits. We additionally control for the value of individual credit limits as sophisticated individuals may restrict future behavior on both the intensive and extensive margin. We also control for firm pricing effects with individual FICO scores as a proxy for individual interest rates.

In a third stage we show that the results are robust to using different measures of present bias (e.g. a quasi-hyperbolic model) and to adding additional control variables. When interpreting all of these results, particularly the size of the estimated coefficients, one must take into account the low income of the study participants.

To obtain our results, we estimate models of the following form:

$$Borrowing_i = \alpha + \beta_1 \overline{IDF}_i + \beta_2 Present\ Bias_i + \beta_3 Future\ Bias_i + \beta_4 Y_i + \beta_5 X_i + \epsilon_i \quad (8)$$

$Borrowing_i$ is individual i 's balance on revolving accounts. \overline{IDF}_i , $Present\ Bias_i$, and $Future\ Bias_i$ are measures for individual i 's time preferences (as discussed above).

4.1 Present Bias and Credit Card Borrowing

A first indication of the relationship between time preferences and borrowing is the raw correlation between individuals' discount factors and credit card borrowing and a simple comparison of the balances on credit cards for individuals with and without present-biased preferences. The correlation between \overline{DF} and credit card borrowing is 0.03 and it is far from statistically significant. Similar to the results by Harrison, Lau, and Williams (2002) discount factors alone do not seem to be related to credit card borrowing. On the other hand, individuals exhibiting present-biased preferences have significantly higher balances than individuals with time-consistent preferences. Individuals with time-consistent preferences have, on average, \$855 in outstanding revolving balances, while individuals who exhibit present-biased time preferences (that is, who have increasing discount factors) have, on average, \$1,667 in outstanding balances. The difference is statistically significant at the 1 percent level in a t -test. Individuals who exhibit decreasing discount factors (i.e. are future biased) do not differ from individuals with time-consistent preferences. This result supports the prediction that present-biased individuals borrow more on their credit cards.

The results of this primary analysis are supported in multivariate regression models { controlling for the year of study and socio-demographic variables. Such t.15-402d9m4utrn66(or

dependent variable is the outstanding credit card balance with and without individual control variables. The results show that $\overline{TD\bar{F}}$ s are not significantly associated with debt levels. As predicted by the behavioral model outlined above, individuals who exhibit present-biased preferences have substantially higher outstanding balances on revolving accounts. Controlling for socio-demographic characteristics, the effect is statistically significant at the 95 percent level and substantial in size. Computing marginal effects for the tobit model in Column (2) shows that the probability of having revolving debt increases by 14 percentage points for individuals who exhibit present bias and that the amount of debt increases by about \$496 conditional on having debt. Columns (3) and (4) show that the results are similar when estimating equation (8) in an OLS framework. As will be shown below, the results are robust to the inclusion of credit limit, controlling for individual risk attitudes, changes in the definition of dynamic

erroneously attribute the correlation between measured present bias and borrowing to our hypothesized explanation while it is actually due to this shock.

To check whether such short-lived shocks can explain the association between present bias and borrowing, we obtained the consent of the sample in 2006 to check their report again one year later. Table 3 estimates the same tobit models as before but with credit card borrowing one year after we elicited time preferences. The results show that our measure of present bias can explain credit card borrowing one year later ($p = 0.06$). This is a very strong test of the association between experimentally measured time preferences and credit card borrowing and gives confidence that the choice experiments provide a reliable measure of the heterogeneity in individual present bias; measures which are then able to explain part of the heterogeneity in credit card borrowing.

[Table 3 about here.]

In sum, the results show that experimentally measured individual discount factors are not associated with credit card borrowing from individual credit reports. However, individuals who exhibit present-biased preferences have substantially higher levels of outstanding balances. Even one year after the choice experiments took place, the measure of present-biased preferences predicts higher credit card borrowing. This result supports the notion that individuals with present-biased time preferences have higher credit card borrowing.

4.2 Borrowing Conditional on Having a Credit Card

The analysis so far includes *all* individuals, whether they have a credit card or not. That is, our analysis treats all individuals including sophisticates that may have restricted their own borrowing activity by choosing not to have a credit card. As some

present-biased individuals will not borrow due to such a commitment strategy, the analysis presents a conservative test of the association between present bias and credit card borrowing. In the following section, we restrict the sample to individuals who have at least one credit card as measured by a positive revolving credit limit.

Table 4 presents the results for individuals with at least one credit card and controls for the credit limit on all credit cards (in natural logarithm). Consistent with the prediction in the conceptual considerations above, the association between present bias and credit card borrowing becomes stronger and more precisely estimated. Computing marginal effects for the tobit model in Column (2) shows that the probability of having revolving debt increases by 23 percentage points for individuals who exhibit present-biased preferences and that the amount of debt increases by about \$1,090 conditional on having debt. The inclusion of individuals' credit limit shows that credit limits are correlated with borrowing (Gross and Souleles, 2002), and also that with the inclusion of credit limit as a control variable the relationship between present bias and card borrowing is maintained.

[Table 4 about here.]

Table 5 extends the analysis by incorporating FICO credit scores. Credit scores reflect individuals' creditworthiness and, as such, are used by lenders to determine the interest rate on debt. We use FICO scores as a proxy for individuals' credit card interest rates. The results based on scored individuals show that, controlling for individual FICO scores, the association between present bias and credit card balances is maintained. Given individual credit limits, FICO scores are negatively associated with credit card borrowing. This could be due either to creditworthy consumers borrowing less or the fact that higher utilization of credit lines decreases one's credit score.

[Table 5 about here.]

In sum, we show that the result that present-biased individuals have higher credit card borrowing is robust to restricting the sample to individuals with positive credit limits and to controlling for FICO scores. In general, the results move in the directions suggested in our conceptual development. Eliminating potentially sophisticated individuals who restrict their own borrowing strengthens the relationship between borrowing and present bias. The relationship between card borrowing and present bias is also maintained when controlling for a proxy for credit card interest rates.

[Table 6 about here.]

Table 7 shows the robustness of the results to including individual risk attitudes and whether individuals expect to move in the next seven months as control variables

more, the results have important implications for policy makers, firms and economic theory:

The results show that present-biased individuals have higher debt levels on credit card accounts. The instantaneous access to credit offered by credit cards and the instant gratification associated with card purchases leads present-biased individuals to borrow more. The dynamic inconsistency inherent to present-biased preferences indicates that some of this borrowing is suboptimal and too high given individuals' own long-run plan. If borrowing is too high, given individuals' own objectives, then policy makers have an opportunity to design policy to reduce borrowing back to initially planned levels. In order to decide on ways to target this issue, the level of sophistication becomes, however, very relevant. This paper does *not* directly address the question of whether individuals know about their dynamic inconsistency; it only controls for the possibility. As a number of policy implications (as discussed, for example, in Camerer, Issacharo , Loewenstein, O'Donoghue, and Rabin, 2003) depend on the sophistication of present-biased consumers, future research should investigate who, among the population of present-biased consumers, actually anticipates their own future present bias.

In the presence of naive present-biased consumers, credit card firms could charge higher interest rates in response to lower price sensitivity. We provide direct evidence that indeed present-biased individuals borrow more on credit cards and might therefore be less sensitive to interest rate changes. This evidence provides empirical support for the notion that credit card firms might be able to charge prices above marginal costs (DellaVigna and Malmendier, 2004). For both naive and sophisticated present-biased individuals, higher interest rates may be attractive. The former do not expect to borrow extensively and the latter may view high prices as a commitment device against future borrowing. Such effects of present bias in borrowing might be one reason for the claimed stickiness of credit card rates (e.g Ausubel, 1991). Gabaix and Laibson (2006)

show that in the presence of naive, present-biased consumers, competition might also not eliminate such pricing strategies. A natural extension of the empirical research presented in this paper is to investigate whether present-biased individuals are indeed less sensitive to interest rate changes.

Direct evidence on the link between present bias and borrowing behavior has implications for consumer behavior theory. The results in this paper show not only that some individuals have non-standard, present-biased time preferences, but also that individual differences in these preferences have real behavioral effects. Because so much consumer behavior involves intertemporal choice, it is critical that research account for present bias as an important axis along which behavior may deviate from standard predictions.

References

- Johnson, K. (2004): "Convenience or Necessity? Understanding the Recent Rise in Credit Card Debt," *Finance and Economics Discussion Series 2004-47*. Washington: Board of Governors of the Federal Reserve System.
- Karlan, D. (2005): "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions," *American Economic Review*, 95(5), 1688{1699.
- Karlan, D., and J. Zinman (2008): "Lying about Borrowing," *Journal of the European Economic Association*, p. Forthcoming.
- Laibson, D. (1997): "Golden Eggs and Hyperbolic Discounting," *Quarterly Journal of Economics*, 112(2), 443{477.
- Laibson, D., A. Repetto, and J. Tobacman (2008): "Estimating Discount Functions with Consumption Choices over the Lifecycle," *American Economic Review*, p. Forthcoming.
- Lin, T.-F., and P. Schmidt (1984): "A test of the tobit specification against an alternative suggested by Cragg," *The Review of Economics and Statistics*, 66(1), 174{177.
- Loewenstein, G., and T. O'Donoghue (2004): "Animal spirit: Affective and deliberative processes in economic behavior," *Working Paper*.
- McClure, S., D. Laibson, G. Loewenstein, and J. Cohen (2004): "Separate neural systems value immediate and delayed monetary rewards," *Science*, 306, 503{507.
- (2007): "Time discounting for primary rewards," *Journal of Neuroscience*, 27(21), 5796{5804.
- Meier, S., and C. Sprenger (2008): "Discounting Financial Literacy: Time Preferences and Participation in Financial Education Programs," *Working Paper*.
- Mischel, W., Y. Shoda, and M. L. Rodriguez (1989): "Delay of gratification in children," *Science*, 244(4907), 933{938.
- O'Donoghue, T., and M. Rabin (1999): "Doing It Now or Later," *American Economic Review*, 89(1), 103{124.

Stewart, M. B. (1983): "On Least Squares Estimation when the Dependent Variable is Grouped,"

Table 1: Summary Statistics

Variable	N	Mean	s.d.
Panel A: Socio-demographic variables			
Age	541	35.9	13.4
Gender (Male=1)	510	0.35	0.48
Race (African-American=1)	491	0.80	0.40
College Experience (=1)	465	0.52	0.50
Disposable Income	541	18,517	13,693
# of Dependents	541	0.52	0.84
Panel B: Credit behavior			
Debt (=1)	541	0.41	0.49

Table 2: Credit Card Borrowing

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
\overline{CDF}	1746.343 (1604.307)	113.774 (1573.015)	61.299 (566.145)	-404.310 (607.434)
Present Bias (=1)	1246.680** (516.997)	1588.578*** (507.844)	804.212** (313.103)	948.195*** (320.095)
Future Bias (=1)	596.836 (1531.442)	273.872 (1457.899)	-138.749 (321.674)	-157.773 (393.715)
Ln(Disposable Income)		1271.837*** (247.481)		345.707*** (77.727)
# of Dependents		174.469 (264.586)		201.769 (155.878)
College Experience (=1)		324.945 (503.671)		121.994 (224.453)
Age		32.880* (17.389)		18.186** (7.868)
Gender (Male=1)		-1136.614** (496.319)		-332.440 (217.561)

Table 3: Credit Card Borrowing One Year After Choice Experiment

	(1)	(2)
\overline{IDF}	5613.736 (7568.913)	2229.050 (7099.805)
Present Bias (=1)	3069.762* (1649.718)	3013.868* (1595.827)
Future Bias (=1)	1875.382 (5313.317)	5529.135 (5188.061)
Control Variables	No	Yes
LL	-701.50	-694.10
N	123	123

Note: Dependent variable: Outstanding balance on revolving accounts one year after choice experiment. Coefficients of tobit regressions. Standard errors in parentheses. The sample consists of participants in 2006. Control variables include $\ln(\text{disposable income})$, number of dependents, age, gender, race, college experience, a constant term and dummies for imputed gender, race, and education.

Level of significance: * $p < 0.1$

Table 4: Credit Card Borrowing Conditional on Having a Revolving Account

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
\overline{TDF}	-332.459 (1565.758)	-747.800 (1282.354)	-667.538 (974.128)	-1006.841 (868.840)
Present Bias (=1)	1651.144*** (509.402)	2033.051*** (422.587)	1459.439*** (519.154)	1695.379*** (427.035)
Future Bias (=1)	-725.862 (1356.060)	-69.220 (1083.501)	-672.173 (442.400)	-296.529 (526.651)
ln(Credit Limit)		1290.379*** (114.640)		958.043*** (101.723)
Dummy for Year of Study	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes

Table 5: Credit Card Borrowing Controlling for FICO Score

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
\overline{TDF}	-147.858 (1586.510)	-234.196 (1316.621)	-482.399 (1003.892)	-631.262 (926.804)
Present Bias (=1)	1842.106*** (526.882)	2101.634*** (432.810)	1590.361*** (554.633)	1713.938*** (469.279)
Future Bias (=1)	-833.397 (1351.937)	-260.960 (1076.460)	-745.611* (449.220)	-434.535 (435.489)
ln(Credit Limit)		1448.964*** (137.079)		1083.259*** (116.751)
FICO Score		-6.755*** (2.579)		-5.095** (2.137)
Dummy for Year of Study	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes
LL/R ²	-2057.74	-1993.89	0.054	0.377
N	269	269	269	269

Note: Dependent variable: Outstanding balance on revolving accounts. (Robust) standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, a constant term and dummies for imputed gender, race, and education.

Level of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness: Additional Control Variables and Sample Restrictions

	(1)	(2)	(3)
	Tobit	Tobit	Tobit
Revolving Accounts > 0	No	No	Yes
Control Variables	No	Yes	Yes
Year Dummy	Yes	Yes	Yes
Panel A: Including Risk Attitudes and Moving Expectations			
\overline{IDF}	30.345	-1522.860	-1766.761
	(1731.514)	(1709.727)	(1425.559)
Present Bias (=1)	1408.246**	1528.351***	1888.896***
	(552.048)	(540.338)	(462.844)
Future Bias (=1)	1190.198	820.344	231.045
	(1670.256)	(1603.341)	(1201.680)
Risk Attitudes (standardized)	15.375	45.019	-24.757
	(86.005)	(84.024)	(71.787)
Expects to Move (=1)	-113.262	297.523	119.897
	(547.450)	(531.623)	(454.002)
N	430	430	227
Panel B: Including Multiple Switchers			
\overline{IDF}	2622.555	910.325	-708.948
	(1824.712)	(1750.144)	(1483.897)
Present Bias (=1)	783.041	1228.418**	1819.752***
	(561.529)	(541.663)	(468.693)
Future Bias (=1)	-1034.985	-921.985	-258.373
	(1521.030)	(1420.553)	(1191.072)
Multiple Switching (=1)	1287.599	2211.191***	2148.583***
	(786.205)	(752.525)	(642.706)
N	606	606	321
Panel C: Non-Missing Control Variables			
\overline{IDF}	1425.190	200.191	-926.844
	(1878.143)	(1846.504)	(1480.047)
Present Bias (=1)	1430.333**	1645.808***	2171.736***
	(591.894)	(583.257)	(481.227)
Future Bias (=1)	218.105	124.843	-890.161
	(1807.846)	(1732.871)	(1328.671)
N	420	420	223

Note: Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and, in Panel A and Panel B, dummies for imputed gender, race, and education. Additionally, in column (3) ln(Credit Limit) is controlled for. Risk attitudes are from the 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 Appendix

A.1 Appendix Tables

Table A1: Credit Card Borrowing for 2006 Sample

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
Control Variables	No	Yes	No	Yes
Panel A: Whole Sample				
\overline{IDF}	836.140 (4249.830)	-1174.086 (3991.119)	304.060 (1500.409)	-127.061 (1677.172)
Present Bias (=1)	2438.927*** (931.501)	2637.923*** (897.304)	1480.868* (767.402)	1494.005** (741.706)
Future Bias (=1)	1391.250 (2974.774)	4743.372 (2916.859)	830.569 (1100.642)	2047.394** (1012.728)
N	123	123	123	123
Panel B: Sample with Credit Cards				
\overline{IDF}	429.007 (3994.033)	-2437.233 (3482.816)	514.358 (2372.762)	-2296.121 (2355.031)
Present Bias (=1)	2730.657*** (900.371)	2665.444*** (766.693)	2296.968** (1145.550)	2211.976** (955.411)
Future Bias (=1)	2329.624 (3059.513)	1859.998 (2680.167)	1795.005*** (273.637)	1604.243 (1045.547)
N	70	70	70	70

Note: Dependent variable: outstanding balance on revolving accounts. Standard errors in parentheses. Control variables include $\ln(\text{disposable income})$, number of dependents, age, gender, race, college experience, and dummies for imputed gender, race, and education. Additionally, in Panel B $\ln(\text{credit limit})$ is controlled for.

Level of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Credit Card Borrowing for 2007 Sample

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
Control Variables	No	Yes	No	Yes
Panel A: Whole Sample				
\overline{IDF}	2362.155 (1801.389)	693.055 (1769.580)	211.046 (608.232)	-265.399 (659.033)
Present Bias (=1)	822.200 (622.702)	1182.621* (614.026)	621.620* (343.905)	805.948** (359.544)
Future Bias (=1)	385.237 (1779.566)	-588.247 (1701.735)	-377.225 (275.809)	-594.992* (307.223)
N	418	418	418	418
Panel B: Sample with Credit Cards				
\overline{IDF}	-17.806 (1763.928)	-83.293 (1425.573)	-570.525 (1075.277)	-543.522 (994.508)
Present Bias (=1)	1278.504** (618.394)	1705.958*** (509.996)	1219.413** (595.030)	1475.307*** (504.607)
Future Bias (=1)	-1314.686 (1537.235)	-569.352 (1225.328)	-1075.472*** (361.650)	-602.008 (568.613)
N	215	215	215	215

Note: Dependent variable: outstanding balance on revolving accounts. Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed gender, race, and education. Additionally, in Panel B ln(credit limit) is controlled for.

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 rate 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; $t = 6, \tau = 1$]: 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.3295(n)28(um)28(b)-28(er)-295(of)-296(y)28(ou)-28(er)-292007)

A28(e68(in)-3r0)-3r4(um)28(b)1(a34(=)-278(6,))TJ/F11 9.9626 Tf 21.586 0 Td [()TJ/r7a176 Tf6o95034thisa176 TV)346

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

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 circling 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; $t = 0, \beta = 6$]

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 circling 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; $t = 6, \beta = 1$]

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 circling 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**

A.4 Calculating discount parameters using choice experiments

The three time frames in which discount factors are elicited allow to calculate β s and δ s from a system equations. From the two time frames, $t = 0, \beta = 1$ and $t = 0, \beta = 6$, we get two equations and two unknowns: $X_{0,1} = \beta^1(Y)$ and $X_{0,6} = \beta^6(Y)$. From the choices in time frame 1 and time frame 2, we can calculate β_1 and β_6 .

The two time frames, $t = 0, \dots = 1$ and $t = 6, \dots = 7$, provide another system of equations: $X_{0,1} = \dots^1(Y)$ and $X_{6,7} = \dots^1(Y)$. From this system of equation, one can calculate \dots_2 and \dots_2 .

For the robustness test, we take the average of \dots_1 and \dots_2 and of \dots_1 and \dots_2

$$c_3 = \frac{6^2 y}{(1 + 2)(1 +)} \quad (14)$$

We determine the plan value of this consumption path as:

$$U_B = \ln(c_1) + \ln(c_2) + \ln(c_3) \quad (15)$$

A sophisticated present-biased individual may be willing to commit future selves to not borrowing. We propose the following commitment device: we allow the individual to borrow in the first period, keeping $t = 1$ consumption the same as previous. He is forced to repay in $t = 2$ and is restricted from further borrowing. He consumes only his income, y , in $t = 3$.¹⁰ The proposed consumption path with this commitment device is:

$$c_1 = c_1 = \frac{3y}{(1 + 2)} \quad (16)$$

$$c_2 = y - (c_1 - y) = 2y - \frac{3y}{(1 + 2)} \quad (17)$$

$$c_3 = y \quad (18)$$

The plan value from this consumption path is:

$$U_{NB} = \ln(c_1) + \ln(2y - c_1) + \ln(y) \quad (19)$$

We compare the plan values. A sophisticated consumer would be willing to commit to this device if:

$$U_{NB} > U_B$$

$$\ln(c_1) + \ln(2y - c_1) + \ln(y) > \ln(c_1) + \ln(c_2) + \ln(c_3)$$

$$\ln(2y - c_1) + \ln(y) - \ln(c_2) - \ln(c_3) > 0$$

It can be shown that the roots of this function are $\beta = 0.5$ and $\beta = 1$. For $\beta \in (0.5; 1)$ sophisticated present-biased individuals would strictly prefer to commit the $t = 2$ self to no borrowing. There exist values of β for which a sophisticated present-biased consumer would be willing to commit to restricting future borrowing activities. Furthermore, such a consumer would be willing to pay for such a commitment device.