Impatience and Credit Behavior: Using Choice Experiments to Explain Borrowing and Defaulting

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PRELIMINARY! COMMENTS VERY WELCOME!

Abstract

This paper tests whether heterogeneity of time preferences can explain individual credit behavior. In a field study targeting individuals from low-to-moderate income households, we elicit individual time preferences through incentivized choice experiments, and then match resulting time preference measures to individual credit reports and annual tax returns.

The paper finds that, controlling for disposable income and other individual characteristics, individuals with present biased time preferences have higher debt levels on revolving accounts such as credit cards. While borrowing is related to present bias, we find that default is, to a large degree, determined by overall impatience as measured by individual discount factors. (102 words)

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1 Introduction

Large differences in personal financial outcomes exist across individuals. Credit utilization and debt default show significant heterogeneity across the United States population (e.g. Bucks et al., 2006). Why is it that some individuals carry sizeable credit card debt while others remain debt free? Why is it that some individuals default on their credit obligations while others do not?

This paper uses a large field study to test whether heterogeneity of individual time preferences explains differences in credit outcomes. Credit behavior, borrowing and repaying debts, involves choices over time and so is expected to be influenced by an individual's time preference. Furthermore, certain types of borrowing, such as credit card borrowing, may be influenced by an individual's propensity to delay instant gratification. The propensity to delay instant gratification should be seen as a separate concept from overall impatience, though both are elements of time preference. The propensity to delay instant gratification is the disproportionate preference for immediate rewards, or the degree of present bias, *given* an individual's impatience. Credit cards generate instant access to credit and so individual heterogeneity in present bias may be related to card borrowing behavior.[1]

In the behavioral economics literature, present biased time preferences are claimed to explain credit card borrowing (e.g., Fehr, 2002; Laibson, 1997). There has been, however, very little direct empirical evidence to support this contention (discussed in detail below). Previous research has examined either aggregate or self-reported debt measures, which both have limitations for answering the question at hand. And, no study exists to our knowledge which links direct measures of time preferences to credit defaulting decisions.

This paper tests in two similar field studies of a combined 620 individuals whether heterogeneity of individual time preferences can explain differences in credit behavior, both credit card borrowing and default. This is the first study to elicit time preferences using incentivized choice experiments and to match measured time preference parameters to objective credit bureau information.[2] Our choice experiments are designed to measure both overall impatience, or individual discount factors[3], and present bias. We are able to examine the relationship between individual time preferences – individual discount factors and present bias – and objective financial outcomes – borrowing and defaulting – controlling for income levels, individual risk preferences, credit constraints, and a variety of other socio-economic factors with data obtained from individual tax filings and administered surveys.

Our results show that credit behavior is substantially related to individual time preferences. Both heterogeneity in individual discount factors and heterogeneity in individual present bias explain credit behavior. As predicted by behavioral models, we find that present biased individuals carry more debt on revolving credit accounts (primarily credit cards). Importantly, however, we find that default is, to a large degree, determined by individual discount factors. As defaulting does not involve instant gratification to the same extent as

[1]Payments on credit cards are experienced by individuals as particularly 'painless' and induce a greater willingness-to-pay than other payment methods, like cash (e.g., Prelec and Loewenstein, 1998).

[2]In the United States, credit reports contain extensive quantitative information provided by lenders on a person's credit behavior (Avery et al., 2003).

[3]In the paper, we will use individual discount factor (*IDF*) instead of individual discount rate (*IDR*); *IDF*=1/(1+*IDR*).

credit card borrowing, it is also not expected to be affected by present bias to the same extent. As a consequence of our default result, we find that credit scores are closely related to individual discount factors. Individuals who discount the future more are less creditworthy.

The finding that present biased individuals borrow more suggests that such individuals borrow more in the present than they actually would prefer to borrow given their long-term objectives. The paper supports therefore the conjecture by academics and policy makers that present bias is related to credit behavior and has as such critical implications about the need for regulatory measures (see, for example, Camerer et al., 2003).

The result have implications for pricing and contract design in the credit card market. According to the conjecture by Ausubel (1991) and the model by DellaVigna and Malmendier (2004), the presence of present-biased, naive individuals will affect pricing and might lead to opportunities for firms to charge prices higher than marginal costs. The paper provides direct evidence that indeed present biased individuals borrow more on credit cards than they planned and might therefore be less sensitive to interest rates. We will discuss some of the implication of the results presented here for behavioral industrial organization.

The paper proceeds as follows: section 2 presents conceptual considerations regarding time preference and credit behavior and surveys existing empirical efforts to understand the relationship between time preferences and credit outcomes. Section 3 discusses the two field studies, our methodology for eliciting time preferences, and the data. Section 4 presents the results and section 5 concludes.

2 Previous Conceptual and Empirical Research

2.1 Conceptual Issues

When deciding about borrowing levels and whether or not to default, individuals weigh sooner benefits and later costs. Heterogeneity in individual time preferences should, therefore, at least partially explain variation in credit behavior. Research in both psychology and economics has shown that there is indeed large individuals heterogeneity in the level of overall impatience and that these differences are quite stable over time (see Eigsti et al., 2006; Mischel et al., 1989).

Not only do individuals differ in their discount factors, they also differ in their degree of present bias (for evidence on heterogeneity in present bias, see Coller et al., 2005). A number of studies show that some individuals exhibit dynamically inconsistent time preferences. That is, individuals do not discount exponentially – as standard economics assumes – but rather they discount more steeply between "now" and a future period than between two subsequent periods in the future (for a survey of the literature in economics and psychology, see Frederick et al., 2002). An elegant way to capture such present bias is to assume a quasi-hyperbolic discounting function (Strotz, 1956; Phelps and Pollak, 1968; Laibson, 1997; O'Donoghue and Rabin, 1999) which yields the following stream of utility from present and future consumption.

$$U_i = u(c_t) + \beta(\delta(u(c_{t+1}) + \delta^2 u(c_{t+2}) + \ldots + \delta^T u(c_{t+T})) \tag{1}$$

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.

Present biased time preferences may be the result of the interplay between 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 (for neurological evidence, see McClure et al., 2004). This notion is captured in various two-system or dual-self models (for example, Gul and Pesendorfer, 2001; Bertaut and Haliassos, 2002; Bernheim and Rangel, 2004; Loewenstein and O'Donoghue, 2004; Fudenberg and Levine, 2006).

Importantly, present biased preferences are the result of individuals being tempted by instant gratification. Present bias, or $\beta < 1$, will therefore play a primary role in determining some financial outcomes and not others. Present bias will be important if c_t in period t is psychologically experienced as instantaneous. If a financial decision taken in period t does not involve instant gratification, the present bias parameter β should not be of primary importance. Loewenstein and O'Donoghue (2004) present a model which more explicitly takes into account that the affective system must be activated in order to generate present bias responses.

The evidence from psychological, neurological and economic research on present bias and overall impatience has critical implications for the financial decisions of borrowing and default. Deciding how much to borrow, particularly on credit cards, is closely linked to the instant gratification of card purchases. In this sense, we expect present bias to be related to credit card debt. We suggest that the default decision, rarely taken when facing a tempting purchase and having small immediate effects on individual budgets, is expected to be less related to present bias. Default, however, should be determined by an individual's appreciation of the long-run costs of financial exclusion; and so should be related to an individual's long-run discount factor. Below we discuss these decisions in more detail.

(1) Decision to borrow: Present biased individuals will borrow more than individuals who are not present biased simply because they value the instant gratification of present consumption more than their more self-controlled counterparts (see Laibson, 1997; Laibson et al., 2003; Shui and Ausubel, 2005). This is particularly true for so-called "naifs" who expect that in the future they will not be present biased. "Sophisticates," present biased individuals cognizant of the fact that they will be present biased in the future, may somehow commit future selves to a fixed consumption plan either by investing in illiquid assets (Laibson et al., 2005), or by changing present consumption as a way to ensure a desired level of consumption in the future. It should be noted that whether "sophisticates" borrow more than individuals who are not present biased depends critically on the availability of commitment devices and the actual degree of present bias.[4] Absent commitment devices, present biased individuals are likely to borrow more than individuals who are not present biased.

The increased borrowing of present biased individuals may be particularly notable for credit card debt. Credit cards provide instant access to credit and so provide present biased individuals the opportunity to easily and instantaneously move consumption from the future,

[4] If, for an extreme example, an individual is so present biased that the expected consumption in the next period, $t + 1$, is the entire lifetime budget, an individual gains nothing in periods $t + 2$ to T by consuming less in period t.

where its value is relatively low, to the present, where its value is disproportionately high. Furthermore, the mechanics of credit cards are widely cited to psychologically disconnect the instant purchase benefits obtained and the long-run credit-financing costs (see, e.g. Prelec and Loewenstein, 1998; Prelec and Simester, 2001; Fehr, 2002; Bar-Gill, 2004).

(2) Decision to default: Default is not a decision involving instant gratification. A consumer facing a past-due bill is in a fundamentally different situation than a consumer contemplating an enticing purchase. Paying or not paying the bill has implications primarily in the future. Individuals choose between a reduction of available funds in the upcoming weeks when the payment clears and the long-run costs of default such as financial exclusion. This decision seems to be one involving only future choices and so we would not expect present bias to play a primary role in determining default.

Not surprisingly, the evaluation of the long-run costs of default is an important determinant of repayment. If these costs are low in present value, then default is cheap. If these costs are high in present value, then default is expensive. The appreciation of these costs should be related to an individual's long-run discount factor. Consistent with this hypothesis, Meier and Sprenger (2007) show that individuals with higher discount factors are much more likely than individuals with lower discount factors to believe that credit scores are important for their lives. That is, individuals with a high discount factor are likely to have a higher appreciation of the long run costs of poor credit. Present bias has no affect on individual appreciation of the importance of credit scores. The decision to default is a more traditional intertemporal decision with benefits in the near future and costs in the further future. As such, individual discount factors should be of primary importance in this decision.

2.2 Empirical Research

Previous empirical research on time preferences and credit behavior has mainly taken one of two paths. First, field studies analyzing aggregate credit and consumption outcomes present indirect evidence that a quasi-hyperbolic model predicts behavior better than an exponential model. Laibson et al. (2005) estimate individual discount rates from aggregate credit card borrowing and conclude that a constant discount rate, as posited by exponential models, cannot account for the borrowing patterns seen in the data. Skiba and Tobacman (2007) also estimate individuals discount factors indirectly using data on borrowing and defaults from a payday lender. They show that a model with partially naive quasi-hyperbolic discounting is most consistent with consumers' behavior. Shui and Ausubel (2005) analyze a large-scale experiment in the credit card market and show that a model with quasi-hyperbolic time preferences is better able to predict why consumers react strongly to introductory offers with short-term, low-to-no interest "teaser rates." Based on their actual borrowing behavior, Shui and Ausubel calculate that individuals would ultimately pay less interest if they had chosen a contract with a higher initial interest rate but of a longer duration, as opposed to the short-term low teaser rate followed by a much higher subsequent interest rate.[5]

As the first path produces an indirect link between time preferences and credit behavior,

[5]Other studies that test the validity of present biased preferences analyze aggregate outcomes in food intake (Shapiro, 2005), in fitness center attendance (DellaVigna and Malmendier, 2006), in welfare program take-up (Fang and Silverman, 2006), in television watching (Benesch et al., 2006), and in smoking behavior (Gruber and Koeszegi, 2001).

a second approach measures individual time preferences directly (often experimentally), and correlates these to *self-reported* individual credit balances or self-reported spending problems. Measuring individual discount factors in a field experiment in Denmark, Harrison et al. (2002) present results on whether people who report having a balance on a line of credit or credit card exhibit lower individual discount factors. Their study does not find a correlation between individual discount factors and self-reported credit card balances; however, this experiment was not designed to measure individuals' present bias, as none of their choice experiment options involve present payoffs. Dohmen et al. (2006) show that their measure of time preferences and, in particular, their measure of dynamic inconsistency can explain whether individuals report having financial self-control problems. Specifically, they find that individuals who exhibit dynamic inconsistency report having more self-control problems in spending, a result that they interpret as indicating that dynamic inconsistency leads, ceteris paribus, to more borrowing than is optimal.[6] As the accuracy of self-reported measures of credit problems is particularly difficult to assess because people generally underreport their debt levels by a factor of three (for example, see Gross and Souleles, 2002), in this study we analyze objective data from credit reports on individual borrowing and default behavior.

Our approach in this paper therefore combines the two previous paths of research on heterogeneous time preferences and borrowing, and extends it with an analysis of time preference and repayment behavior. Using incentive-compatible choice experiments, we are able to directly calculate individual discount factors and present bias. Most importantly, we then match time preference information to objective credit outcomes provided by a credit reporting agency. Using time preference and credit report data in conjunction with socio-demographic variables, we are able to directly explore the relationship between time preferences and credit outcomes, controlling for socio-demographic effects. Methodologically, this is most similar to the approach used by Karlan (2005), who uses behavior in trust experiments to measure prosocial preferences in order to explain repayment behavior in a Peruvian microcredit program. The next section presents the design of our field study and discusses our methodology.

3 Field Study: Credit Bureau Data and Choice Experiments

Our combined field studies were conducted with 623 individuals at two Volunteer Income Tax Assistance (VITA) sites in Boston, Massachusetts.[7] During the 2006 tax season, the study was conducted in the Dorchester neighborhood (N=148) and during the 2007 tax season in the Roxbury neighborhood (N=475). The studies in the two years mainly differ in the way in which we elicited time preferences (discussed in detail below).

The studies were targeted towards low-to-moderate income (LMI) individuals without mortgages. In the terminology of Harrison and List (2004) this study is an "artefactual field experiment" linked to administrative data. As in many experimental studies, our sample is

[6] Other studies show that proxies for individual time preferences are correlated, for example, with uptake of a saving commitment device (Ashraf et al., 2006), job search behavior (DellaVigna and Paserman, 2005), and occupational choices (Munasinghe and Sicherman, 2006).

[7] 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 tax season, from late-January to mid-April each year.

a selection of individuals (see Levitt and List, 2007; Meier and Sprenger, 2007). However, this non-standard subject pool is of particular interest for the research question at hand, as there are very few experimental studies focusing solely on the behavior of LMI families in developed countries (an exception is Eckel et al., 2005) and LMI families' less secure position puts them at great financial risk to health and income shocks (see, Bertrand et al., 2004).

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).

As indicated by the varying number of observations for different variables, not all information was available for each individual. For the main analysis, missing variables were imputed. Individuals with no income information either did not file taxes at a VITA site in Greater Boston or did not have to file taxes due to their income level. For these individuals we impute their income as zero (the adjusted gross income and total refund of a non tax-filer) and control for any bias contributed by these observations in our analysis. Other missing variables were also imputed as taking the value of the majority for dummy variables or the average for continuous variables. The exclusion of observations with missing variables does not change the results (see section 4.4). These socio-demographic characteristics are controlled for in our analysis to address possible confounding correlations between socio-demographic status and both time preferences and credit behavior.

[Table 1 about here]

3.1 Credit Bureau Data

Information on individual credit behavior comes from TransUnion & Co., one of three major credit bureaus in the United States. TransUnion lists detailed information on credit behavior on each individual's credit history. In particular, credit reports reveal outstanding balances, how much of the available credit limit is utilized (and therefore whether people are credit constrained), and whether accounts are in debt collection (for more details on credit reporting, see Avery et al., 2003). All in all, unlike self-reported data, credit reports give a very detailed, objective picture of individual credit behavior.

This paper analyzes three crucial outcomes from individuals' credit reports (summarized in Panel B of Table 1):

Debt Levels: The paper focuses on outstanding balances on revolving and open accounts (which are mainly credit cards).[8] Of all participants, 46 percent have outstanding balances on revolving accounts. The average revolving debt is $1,261 (s.d. $2,981) yielding an average revolving debt-to-income ratio of around 10 percent (for individuals with positive income).

[8]Though balances listed on credit reports are point-in-time measures, there is evidence that our debt measures closely reflect revolving balances and not convenience charges. In a companion survey, carholders report their credit card payment habits (N = 174). Individuals who report normally paying the full amount on their credit card at the end of the months, have significantly lower balances on revolving accounts ($1,093 versus $3,086; $p < 0.01$ in a t-test).

Relative to the general population, our sample has notably high debt levels. According to the Survey of Consumer Finances, the average U.S. resident has a self-reported credit card debt to income ratio of 4.3 percent (authors' calculation based on Bucks et al., 2006).[9]

Defaulting Amounts: Credit reports contain information about defaulted debt in collection and closed accounts. Of all participants, 50 percent have a positive dollar amount in collection or in closed accounts. The average individual-level balance across all accounts that have gone into collection or were closed with balances is $2,062 (s.d. $6,986).

FICO scores: An individual's payment history, is combined in the Fair Issac Corporation (FICO) credit score. The FICO score calculates individual credit risk and assigns it a value ranging from 300 to 850 (where a higher number means a lower risk). Not every participant has a FICO score, due either to insufficiently long or nonexistent credit history. In our sample, 30 percent of the participants were unscored. For scored individuals, the mean FICO score was 611 (s.d 84), which is below the U.S. average of 678[10].

In addition to information about credit behavior, credit reports allow us to see whether an individual is credit constrained with respect to his or her revolving accounts. In our sample, the average revolving credit limit is $4,767 (s.d. $11,619). Fifty-four percent of the 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. The average individual in the sample has access to $3,660 (s.d $11,293) in immediate funds from revolving accounts. As will be shown in the following sections, credit constraints cannot explain either the elicited discount factors or, importantly, the association between time preferences and credit behavior.

3.2 Measuring Time Preferences

In this paper we measure individual time preferences with incentivized choice experiments (for similar approaches, see Harrison et al., 2002; McClure et al., 2004; Dohmen et al., 2006; Tanaka et al., 2007, and for a survey on measuring time preferences, see Frederick et al. (2002)). Individuals were given three multiple price lists and asked to make various choices between a smaller reward ($\$X$) in period t and a larger reward ($\$Y > \$X$) in period $t+\tau > t$. In order to measure individual discount factors (Harrison et al., 2005), we keep ($\$Y$) constant and vary ($\$X$) in three time frames: in two time frames t is the present ($t = 0$) and τ is either one ($\tau = 1$) or six months ($\tau = 6$). In the third time frame, t is in six months ($t = 6$) and τ is one month ($\tau = 1$).

The studies in 2006 and 2007 differed in two dimensions. First, the values of $\$X$ 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

[9]LMI populations frequently resort to non-traditional loan products. 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 real debt level in surveys, we do not present regression analysis using these self-reported debt levels.

[10]From www.experian.com, 8/4/2006.

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 148 participants were individually and extensively guided through the details of the price lists, the 475 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.

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. 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.[11] Money orders were sent by mail to the winners home addresses on the same day as the experiment (if $t = 0$), or in one, six, or seven months, depending on the winner's choice. The payment procedure therefore mimicked a front-end-delay design (Harrison et al., 2005).[12]

The multiple price list setup enables us to measure individuals' time preferences. Using information from all three price lists allows us to (1) measure discount factors and (2) see whether some individuals show a disproportionate preference for present or future rewards; that is, whether some individuals are dynamically inconsistent.

(1) *Individual discount factor (IDF)*: We estimate *IDF* for three different time frames by looking at the point, X^*, at which individuals switch from opting for the smaller, sooner payment to the larger, later payment in a given price list. That is, a discount factor is taken from the last point at which an individual prefers the sooner, smaller payment. For example, if an individual prefers \$75 today over \$80 in one month, but prefers \$80 in one month over \$70 today, we take \$75 as the switching point and the corresponding monthly discount factor of 0.94. Therefore, individual discount factors are calculated as: $IDF^{\tau} = X^*/Y$. We use the average of the calculated monthly discount factors, $\overline{IDF}$, in the main analysis. Importantly, the research question at hand needs a reliable measure of the heterogeneity in *IDF*s across individuals and not necessarily precise point estimates of the level of the *IDF*. The price lists, however, do not elicit point estimates of the *IDF* but rather ranges of where the *IDF*

[11] In 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.

[12] 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.

lie (see Coller and Williams, 1999; Harrison et al., 2005, for details). Especially for individuals accepting the smaller, earlier payment in all choices, the interval will be relatively large, as they might have accepted even lower amounts than offered in the price list. To address this issue, we also estimate interval regressions (Stewart, 1983) using the range of possible *IDF*s, and the results are maintained. The results are also robust to a measure of individual impatience which does not rely on any functional form, but just counts the number of patient (\$$Y$) choices (see section 4.4).

(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 the range of possible *IDF*s found in Time Frame 1 for a given individual, we find the range of choices in time Time Frames 2 and 3 that the individual would make if they discounted exponentially.[13] If the range of actual choices is higher than the implied range of choices for an exponential discounter, the individual exhibits an increasing discount factor. That is, in a quasi-hyperbolic model, $\beta < 1$ and the individual is present biased. Similarly if the range of actual choices is lower than the implied range of choices for an exponential discounter, the individual exhibits a decreasing discount factor. In a quasi-hyperbolic model, $\beta > 1$ and the individuals is future biased. A small number of individuals exhibit such decreasing discount factors. We classify an individual as having "*Increasing DF (=1)*" or "*Decreasing DF (=1)*" if they exhibit dynamic inconsistency in both measures. As a robustness test, we also report the results for the two measures of dynamic inconsistency separately and measure parameters of β and δ from a quasi-hyperbolic discounting function.

The applied method to measure time preferences with incentivized choice experiments as described above has many advantages over other approaches (Frederick et al., 2002), but the method also has challenges which have to be addressed.

First, in order to measure an *IDF* and whether individuals are dynamically inconsistent, an individual must exhibit a unique switching point in each price list. In both years around 11% do not exhibit a unique switching point in one or more price lists. In the main analysis we focus on the 556 individuals who show a unique switching point in all price lists. When we include individuals with multiple switching points in a robustness test (Section 4.4) by taking their first switching point, the results mainly hold.

As also seen in Panel C of Table 1, for individuals with unique switching points, we measure an average *IDF* of 0.86. This discount factor may seem low, but it is in line 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 imply, however, often much lower discount factors for LMI households than measured by our experiment (e.g., Skiba and Tobacman, 2007; Adams et al., 2007). Twenty-five percent exhibit increasing discount factors ("*Increasing DF (=1)*" and only 2 percent have decreasing discount factors ("*Decreasing DF (=1)*"). The *IDF*s are lower in 2007, but in both years, the same proportion of individuals exhibit dynamically inconsistent preferences.

[13] We therefore take into account that the choice experiments measure only ranges and not point estimates of *IDF*s.

Second, individuals' decisions in the price lists might be affected by either their outside lending or borrowing opportunities (see Harrison et al., 2005). On the one hand, an individual that can lend at an interest rate higher than the implied interest rate offered in the multiple price list should arbitrage the experiment by taking earlier payments. The lowest implied interest rate offered in the choice experiment for $\tau = 1$ is either 27 percent (2007 study) or 116 percent (2006 study) percent per year, which is difficult to beat in the real world. Some of the interest rates for $\tau = 6$ are substantially lower, for which it is easier to find investment opportunities outside the experiment. If outside investment opportunities play a role, individuals should appear more impatient for $\tau = 6$ than $\tau = 1$. But, individuals exhibit higher (not lower) *IDF*s when $\tau = 6$ compared to when $\tau = 1$ ($p < 0.01$). Outside investment opportunities therefore seem not to drive the experimental results. On the other hand, a person that can borrow at a rate lower than the experimentally offered rate should arbitrage the experiment by waiting for later payments. The individual may appear patient while actually arbitraging the experiment by borrowing externally at a lower rate and paying the loan back at a later date with earnings from the experiment. As the implied interest rates in the experiment are large (especially in the case of $\tau = 1$), this is a relatively easy thing to do.[14] However, not many individuals uniformly choose the later, larger payments to take advantage of the apparent arbitrage opportunity. As the implied *IDF*s are rather small and significantly less than one ($p < 0.01$), outside borrowing opportunities seem also not to drive the experimental results.

Third, the measurement of *IDF*s by taking individuals' switching points in price lists assumes that utility is linear over the payments in question. While some argue that this is a reasonable assumption (Rabin, 2000), others have shown that price lists such as the ones used in this paper might also measure the degree of curvature of the utility function (Anderson et al., 2005). Anderson et al. (2005) measure substantially higher discount factors when controlling for risk preferences. We therefore test whether differences in risk aversion affect our results using a question on general risk attitudes previously experimentally validated with a large, representative sample (Dohmen et al., 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. The inclusion of risk attitudes in our analysis does not affect the association between time preferences and credit behavior (see section 4.4).

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 *IDF*s, the correlation is small in size, and is not statistically significant ($\rho = 0.06; p > 0.2$). Also, individuals who are credit constrained by this measure do not exhibit different *IDF*s than individuals who can still borrow on their revolving accounts. Credit constraints are not correlated with either long run discount factors

[14] Many individuals with credit cards had not reached their limit and could still borrow for a probably lower interest rate. Also, in a companion survey we asked *"How many people do you know that would loan you $100 if you asked?"*. More than 80 percent of the people who answered the question ($N = 552$) have at least one friend who would do so.

or present bias. Most 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 4.4). In general, our time preference measures are 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 time preference parameters and their correlation with credit behavior.

4 Results

This section presents the results on the relationship between time preferences and credit behavior. First, the effect of time preferences on revolving debt levels is analyzed and, second, the effect of time preferences on defaulting and FICO scores. Next, we present potential reaction of credit card firms and robustness tests.

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

$$Outcome_i = \alpha + \gamma_1 \overline{IDF}_i + \gamma_2 IncreasingDF_i + \gamma_3 DecreasingDF_i + \gamma_4 Y_i + \gamma_5 X_i + \epsilon_i \quad (2)$$

$Outcome_i$ is one of the three measures of individual i's credit outcome. $\overline{IDF}_i$, $IncreasingDF_i$, and $DecreasingDF_i$ are measures for individual i's time preferences (as discussed above). Y_i is the a dummy for the year of study. The vector X_i reflects individual control variables, such as age, gender, race, and education. We also control for an individual's financial situation by entering disposable income and the number of dependents filed on annual tax returns in the regression. The paper will report results with and without controlling for X_i.

As two of the three outcome variables (*Debt level* and *Defaulting amount*) are censored at 0, we estimate tobit regressions for these outcomes. The tobit estimator, however, makes the crucial assumption that the same set of independent variables determine whether an observation is censored (for example, whether an individual does not have any debt) and the value of a noncensored observation (for example, how much debt an individual has accumulated)(Cragg, 1971; Lin and Schmidt, 1984). To get a notion of whether this is a valid assumption, we also report OLS regressions of all the models and discuss potential discrepancies between the two specifications. There are, however, very few differences.

4.1 Impatience and Debt Level

A first indication of the relationship between time preferences and debt levels is a simple comparison of the balances on revolving accounts for individuals with and without present biased preferences. Individuals exhibiting present biased preferences have significantly higher balances. Individuals with time-consistent preferences have, on average, \$981 in outstanding revolving balances, while individuals who exhibit present biased time preferences (that is, who have increasing discount factors) have, on average, \$1,691 in outstanding balances. The difference is statistically significant at the 1 percent level in a t-test. Individuals who exhibit decreasing discount factors do not differ from individuals with time-consistent preferences. Individuals who are more patient in general than the median (that is, who have $\overline{IDF}$ greater than the median in the respective year of study) have lower debt levels ($1,033 versus $1,287), but the difference is not statistically significant ($p > 0.25$).

[Table 2 about here]

The results of this primary analysis are supported in multivariate regression models – controlling for the year of study and socio-demographic variables. Columns (1) and (2) in Table 2 present results from tobit regressions in which the dependent variable is the outstanding balance on revolving and open accounts (mainly credit cards) - with and without individual control variables. The results show that higher $\overline{IDF}$s are negatively associated with debt levels when controlling for socio-demographic variables (the full regression results are shown in table A3 in the appendix), but the effect is not statistically significant. This result is similar to Harrison et al. (2002), who also do not find a correlation between long-run discount factors and whether people carry debt.

As predicted by a behavioral model outlined above, individuals who exhibit increasing discount factors have substantially higher outstanding balances on revolving accounts. Controlling for socio-demographic characteristics, the effect is statistically significant at the 5 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 11 percentage points for individuals who exhibit increasing discount factors and that the amount of debt increases by about $380 conditional on having debt. Columns (3) and (4) show that the results are similar when estimating equation (2) in an OLS framework. Table A1 in the appendix shows that the effects are similar in the two years in which we conducted the study but that the effect is larger and more precisely estimated in year 2006. As will be shown in section 4.4, the results are robust to the inclusion of credit limit, controlling for individual risk attitudes, changes in the definition of dynamic inconsistency and changes in the composition of the sample.

In sum, the results show that experimentally measured individual discount factors are not associated with revolving debt levels on individual credit reports. However, individuals who exhibit increasing discount factors have substantially higher levels of outstanding balances on revolving accounts. This result supports the notion that individuals with present biased time preferences have higher credit card borrowing.

The next section examines how time preferences affect repayment behavior, as reflected in defaults.

4.2 Impatience and Defaulting

Analyzing the association between time preference and defaulting by examining the descriptive statistics indicates that $\overline{IDF}$ and present bias have different effects on defaulting than they do on debt levels. Individuals who exhibit increasing discount factors are not significantly different from individuals with time-consistent preferences either in the average amount in collection and closed accounts or in their FICO scores. However, individuals who exhibit

$\overline{IDF}$s below the median in the year the study was conducted have higher amounts in collection and closed accounts (\$2,686 versus \$1,758; $p < 0.14$) and have significantly lower FICO scores (600 versus 621; $p < 0.01$). In sum, defaulting, and consequently FICO scores, seem to be more associated with long-run discount factors than with present biased preferences.

[Table 3 about here]

Table 3 supports the results from the primary analysis with multivariate regression results. In Columns (1)–(4) the dependent variable is the dollar amount in collection and closed accounts. The results show that whether individuals exhibit increasing or decreasing discount factors is not significantly associated with default amounts. However, $\overline{IDF}$ is negatively correlated with amounts in default. Individuals with higher discount factors have lower balances in default – controlling for socio-demographic variables. The effect is statistically significant and substantial in size. Computing marginal effects of the model in Column (2) shows that changing the $\overline{IDF}$ from 0 to 1 increases the probability of default by 40 percent. For the level of default, the same change increases the default amount by \$3,500. The results are similar when estimating the effects using OLS (Columns (3) and (4)): $\overline{IDF}$ is negatively correlated with the dollar amount in default. Table A2 in the appendix shows again that the effects are qualitatively similar in the two years in which we conducted the study but larger and more precisely estimated in year 2006.

In Columns (5) and (6) in Table 3 the dependent variable is the FICO score. The results show the consequence of defaulting: lower credit scores. In line with the results for the amount in default, individuals with lower $\overline{IDF}$ have lower credit scores – controlling for socio-demographic variables. Dynamically inconsistent time preferences are not associated with credit scores. As will be seen in section 4.4, the association of measures of $\overline{IDF}$ and defaulting and credit scores is robust to controlling for credit limit, individual attitudes towards risk, changes in the definition of dynamic inconsistency, and changes in the composition of the sample.

Our analysis to this point with respect to discount factors has taken $\overline{IDF}$ to be a point estimate. Our choice experimental design, however, generates interval ranges of *IDF*s. Table 4 follows Harrison et al. (2002) and estimates interval regressions (Stewart, 1983) with the interval of the *IDF* as the dependent variable. The interval of *IDF* is calculated by considering for each individual and each time frame the range of possible *IDF*s from IDF_{low} to IDF_{high}. This results in three interval observations for each individual. The regressions therefore correct the standard errors by clustering them on the individual level. The differences in t and τ of the underlying price lists are controlled for by using dummy variables equal to one when $\tau = 6$ and $t = 0$. The coefficients on those two variables indicate that individuals, on average, do exhibit dynamically inconsistent time preferences. Individuals have higher discount factors when the time period τ gets longer and when t is the present. The coefficients for *Default Amount* and *FICO* show that the results on time preferences, default behavior and FICO scores are robust to using intervals of *IDF* instead of point estimates.

[Table 4 about here]

In sum, the results show important relationships between time preferences and credit behavior. As expected, present bias is found to be strongly correlated with borrowing behavior on revolving accounts. Additionally *IDF*s are found to be significantly related to whether individuals default on their debt and, as a consequence, to their credit score. Individuals who heavily discount the future are less likely to repay their debts. As defaulting decisions are less related to instant gratification than borrowing decisions, present biased preferences are shown to be less important in repayment situations than they are for borrowing. All the results are robust to the inclusion of demographic and income controls. The next section presents some further robustness tests.

4.3 Potential Reaction of Credit Card Firms

The results show that present-biased individuals are more likely to borrow, but not more likely to default. For a credit card company to target those individuals specifically would be profitable as they borrow more without a higher risk of defaulting. This section analyzes whether credit card firms target present-biased individuals directly by approving more credit cards and/or extending higher credit limits. In principal, present biased individuals can also be charged higher interest rates (DellaVigna and Malmendier, 2004). Controlling for interest rates would in this case make the effect of presence bias even more pronounced. As there are no information on interest rates in our data set, we control for FICO score to see whether risked-based pricing can explain the result that present biased individuals borrow more.

[Table 5 about here]

Table 5 presents an analysis of whether some of those endogenous factors can explain the association between present bias and borrowing. The sample of the analysis in table 5 is restricted to individuals who are scored in order to control for FICO score in all specifications. Column (1) investigates in a tobit model whether individuals with a present bias have more credit cards. Present biased individuals could have more credit cards because credit firms are more likely to approve cards for those consumers. Or present biased individuals might be sophisticated and commit themselves to borrow less by not accepting credit cards. The results show that neither present bias nor *IDF* are associated with the number of revolving accounts an individual holds. Not surprisingly, both income and credit scores correlate with the number of accounts, most likely reflecting that credit card firms use both variables in their decision to approve revolving unsecured line of credit.

Column (2) in table 5 analyzes whether present biased individuals have higher limits on their revolving accounts - conditional on having a revolving account. The results of the tobit model show that there is no statistically significant correlation between the credit limit and present bias or *IDF*. Credit limits are higher for individuals with better credit scores and for individuals with more credit cards.

Finally, column (3) presents a tobit regression with the balance on revolving accounts controlling for such potentially endogenous factors, like FICO score, credit limit and the number of revolving accounts. The relationship between present bias and borrowing still holds. As this regression controls for the FICO score as a proxy for the risked-based price of borrowing, the result that present biased individuals borrow more seems not to be due to differences in interest rates.

The result in table 5 shows that present biased individuals do not differ in the number of revolving accounts or the cumulated credit limit on those accounts. Controlling for those endogenous factors does not affect the association between present bias and borrowing. In the following section, we present a number of further robustness tests.

4.4 Robustness Tests

In this section, we test the robustness of the obtained results to changes in calculating time preferences, to controlling for credit constraints and risk attitudes, and to relaxing the sample restriction criteria.

Table 6 shows how robust the results are to alternative measures of impatience. Panel A shows that the results are robust to changing the calculation of long-run discount factors. Instead of assuming an exponential structure, the *fraction of patient choices* simply calculates the fraction of choices in which an individual chooses the later but larger payment $Y – out of either 19 choices in 2006 or 22 in 2007. Panel B and C calculate a measure for *IDF* and dynamic inconsistency based on either Time Frame 1 ($t = 0$, $\tau = 1$) and Time Frame 2 ($t = 0$, $\tau = 6$) or Time Frame 1 ($t = 0$, $\tau = 1$) and Time Frame 3 ($t = 6$, $\tau = 1$). While qualitatively very similar, the two panels show that dynamic inconsistency measured by shifting Time Frame 1 six months into the future (similar to, for example Ashraf et al., 2006) predicts debt levels better. In Panel D, we fit the choices with a quasi-hyperbolic discounting, $\beta - \delta$, model (for example, Strotz, 1956; Laibson, 1997) and calculate individual βs and δs (see appendix A.4 for details). This robustness test reinforces the obtained results that present biased individuals, that is, those with lower βs, have higher debt levels, while individuals with lower long-run discount factors, that is, lower δs, are more likely to default.

[Table 6 about here]

Table 7 shows the robustness of the results to including credit constraints and individual risk attitudes as control variables and to changes in the sample restrictions. Panel A and Panel B show that the results are robust to including proxies for whether individuals are credit constrained. Panel A includes a variable for individuals' credit limits and Panel B includes a dummy for whether individuals can still borrow some money on their revolving accounts. Both indicators were calculated from information taken from individual credit reports. Not surprisingly, the results show that credit constraints are correlated with both borrowing and credit scores. However, controlling for credit constraints does not change the results that individuals who exhibit present bias are more likely to borrow and that individuals who exhibit low discount factors are more likely to default. Importantly the obtained results are also robust to controlling for individual attitudes toward risk (Panel C). This provides important suggestive evidence that when controlling for the confounding relationship between time preference and risk aversion, the obtained results are maintained.

[Table 7 about here]

Finally, Panels D and E explore whether sample restrictions affect the results. In Panel D, we include 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 stay qualitatively the same but the standard errors naturally increase. In Panel E, we exclude all the individuals for whom we have missing control variables (and for whom we imputed these variables in the main analysis). The results do not change.

One potential worry about the association between our measures of time preferences and credit outcomes is that both might be influenced simultaneously by recent negative or positive income shocks. For example, if such a negative shock is unobservable to the experimenter, not reflected in taxable income, and makes an individuals appear to be more impatience while being already reflected on the credit outcome, the association between discount factors and defaulting might be due to this shock. To check whether such short-lived shocks can explain the association between impatience and credit outcome, we got the consent of the sample in 2006 to check their report again one year later. Table 8 present then very similar estimations than in the previous section but with credit outcomes one year after we elicited time preferences: Column (1) has the amount on revolving accounts as the dependent variable, column (2) analyzes the amount in collection and closed accounts, and column (3) looks at FICO scores. The results strongly support the view that the association between measures of impatience and credit outcomes is not due to short-lived shocks. The experimentally measured proxy for present bias predicts higher borrowing also one year after the choice experiments. Also, the long-run discount factors predict defaulting and as a result credit scores one year after we elicited time preference in a choice experiment.[15] Overall, the results in table 8 support the view that the choice experiments provide a reliable measure of heterogeneity in people's time preferences which are then able to explain part of the heterogeneity in credit outcomes.

[Table 8 about here]

5 Conclusions

This paper investigates the association between time preferences and credit behavior. As self-reported measures of debt and credit problems are problematic, the paper presents a unique field study, combining incentivized choice experiments with administrative data from credit bureaus.

The results show that dynamically inconsistent individuals who exhibit present biased preferences have higher debt levels on revolving credit accounts (mainly credit cards). 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' long-run discount factors. To our knowledge, this is the first paper to present direct evidence that present biased individuals have higher levels of borrowing – using objective credit data.

The results additionally show that present bias is not related to defaulting. Defaulting on credit does not involve instant gratification but rather an evaluation of benefits in the near future and costs in the further future. In such a decision, present bias is not expected be of

[15] Not surprisingly, the number of individuals who are scored increased in this one year.

primary importance. The decision to default, however, is expected to be strongly associated with individuals' long-run discount factors. The more an individual discounts the future, the higher is his or her amount in default and the lower is his or her credit score. Importantly, all obtained results are robust to controlling for income from individuals' tax forms, demographic variables, and to controlling for credit constraints reported on individuals' credit reports and individual risk attitudes.

The results in this paper are important from a theoretical standpoint as it shows not only that some individuals have non-standard, dynamically inconsistent time preferences, but also that individual differences in these time preferences have real behavioral effects. This evidence provide empirical support 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 are attractive. For the former because they do not expect to borrow as much as they will do eventually and for the latter as a commitment device not to borrow too much. The effect of presence bias on borrowing might be one reason for the claimed relative 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 less sensitive to changes in interest rate changes.

The results can also inform policy makers that certain individuals borrow a suboptimal amount on credit cards (given their long-run discount factors). In order to decide on ways to target this issue, the level of sophistication becomes, however, very relevant. This paper does not address the question of whether individuals know about their dynamic inconsistency. As a number of policy implications (as discussed, for example, in Camerer et al., 2003) depend on the sophistication of present biased consumers, future research should investigate what fraction of present biased consumers anticipates their own future present bias.

Additionally, we do not address the question of where heterogeneity in individual time preferences originates. Impatient tendencies are quite stable over time, and the early childhood heterogeneity in impatience is found to predict behavior in adolescence and adulthood. However, it is still unclear whether parts of an individual's time preferences are determined endogenously (Becker and Mulligan, 1997). Though we do show that credit experiences and the number of accounts held over one's lifetime are unrelated to time preferences, it is possible that single adverse incidents, such as credit problems and bankruptcy, and educational efforts could have influential effects on individual preferences. Future research should focus on understanding the endogeneity of both individual discount factors and present bias.

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Table 1: Summary Statistics

Variable	N	Mean	s.d.
Panel A: Socio-demographic variables			
Age	615	35.8	13.7
Gender (Male=1)	585	0.36	0.48
Race (African-American=1)	557	0.80	0.40
College Experience (=1)	531	0.51	0.50
Disposable Income	606	18,085	13,696
# of Dependents	606	0.51	0.84
Panel B: Credit behavior			
Debt (=1)	623	0.46	0.50
Revolving Balance	623	1,261	2,981
Default (=1)	623	0.50	0.50
Defaults	623	2,062	6,986
No FICO Score (=1)	623	0.28	0.45
Fico Score	449	611	84
Credit Constrained (=1)	623	0.54	.50
Amount Able to Borrow	623	3,660	10,293
Revolving Credit Limit	623	4,767	11,619
Panel C: Time preferences			
Inconsistent (=1)	623	0.11	0.31
$\overline{IDF}$	556	0.86	0.15
Increasing DF (=1)	556	0.25	0.43
Decreasing DF (=1)	556	0.02	0.14

Table 2: Impatience and Debt Level

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
$\overline{IDF}$	830.837	-375.628	-523.218	-979.115
	(1526.793)	(1506.473)	(767.275)	(774.107)
Increasing DF (=1)	923.613*	1154.947**	734.453***	873.657***
	(502.558)	(496.070)	(259.463)	(259.725)
Decreasing DF (=1)	377.023	173.193	-28.329	-52.155
	(1524.262)	(1463.301)	(797.260)	(781.002)
Dummy for Year of Study	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes
LL/R^2	-2678.74	-2655.83	0.015	0.083
N	556	556	556	556

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 income, age, gender, race, and education. To see the effects of the control variables, the full estimation of column (2) is presented in Table A3 in the appendix.
Level of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 3: Impatience and Defaulting

	(1)	(2)	(3)	(4)	(5)	(6)
	Tobit	Tobit	OLS	OLS	OLS	OLS
Dependent Variable	Defaults	Defaults	Defaults	Defaults	FICO	FICO
$\overline{IDF}$	-10452.16***	-11382.84***	-6681.759***	-6837.469***	78.085***	69.765**
	(3631.671)	(3758.279)	(2147.268)	(2229.493)	(28.766)	(28.803)
Increasing DF (=1)	-674.500	-450.996	13.795	-9.532	-7.605	-10.730
	(1263.964)	(1286.116)	(726.124)	(748.029)	(9.873)	(9.787)
Decreasing DF (=1)	1877.330	1730.007	235.483	94.935	-4.408	-6.185
	(3667.525)	(3670.038)	(2231.182)	(2249.350)	(26.856)	(26.117)
Dummy for Year of Study	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes	No	Yes
LL / R^2	-3199.71	-3191.79	0.019	0.033	0.023	0.114
N	556	556	556	556	400	400

Note: Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education. To see the effects of the control variables, the full estimations of columns (2) and (6) are presented in Table A3 in the appendix.

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

Table 4: Interval Regressions of Impatience and Defaulting

	(1)	(2)	(3)	(4)
Amount in Default/1000	-0.004**	-0.004**		
	(0.002)	(0.002)		
FICO/10			0.003**	0.003**
			(0.001)	(0.001)
$\tau = 6$ (=1)	0.027***	0.027***	0.027***	0.027***
	(0.001)	(0.001)	(0.002)	(0.002)
$t = 0$ (=1)	-0.077***	-0.078***	-0.067***	-0.067***
	(0.009)	(0.009)	(0.010)	(0.010)
Dummy for Year of Study	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes
# of observations	1668	1668	1200	1200
# of individuals	556	556	400	400

Note: Dependent Variable: interval of *IDF*. Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education. *Level of significance*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 5: Endogenous Factors Influencing Credit Behavior

Dependent Variable	(1) No of Rev. Accounts	(2) Credit Limit	(3) Balance on Rev. Accounts
$\overline{IDF}$	-3.926	323.000	141.028
	(2.400)	(3909.041)	(1264.191)
Increasing DF (=1)	0.587	1875.376	1675.395***
	(0.808)	(1301.267)	(413.060)
Decreasing DF (=1)	1.227	-1463.951	-505.456
	(2.136)	(3293.747)	(1088.320)
FICO score	0.013***	75.123***	-2.288
	(0.004)	(6.752)	(2.419)
Ln(Disposable Income)	0.808***	61.136	52.983
	(0.302)	(519.613)	(155.188)
Ln(Revolving Credit Limit)			744.882***
			(82.310)
No of Revolving Accounts		1463.485***	57.462*
		(83.518)	(30.179)
Dummy for Year of Study	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Revolving Accounts > 0	No	Yes	Yes
Log Likelihood	-1250.41	-2982.87	-2285.25
N	400	370	370

Note: Tobit regressions. Standard errors in parentheses. Control variables include number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education. Sample is restricted to individuals who are scored.
Level of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 6: Robustness Tests: Alternative Impatience Measures

	(1) Tobit	(2) Tobit	(3) OLS
Dependent Variable	Rev. Debt	Defaults	FICO
Control Variables	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes
N	556	556	400
Panel A: Using Fraction of Patient Choices			
Fraction of Patient Choices	-281.200	-4073.303**	29.945**
	(654.605)	(1663.131)	(12.576)
Increasing DF (=1)	1144.826**	-861.037	-8.096
	(491.519)	(1278.533)	(9.705)
Decreasing DF (=1)	151.623	1309.716	-3.359
	(1462.705)	(3688.801)	(26.128)
Panel B: Dynamic Inconsistency: First and Second Time Frame			
$\overline{IDF}_{1-2}$	-956.750	-8611.066**	71.633**
	(1605.881)	(4075.381)	(30.713)
Increasing DF_{1-2} (=1)	689.885	-1139.658	-11.321
	(448.498)	(1148.105)	(8.676)
Decreasing DF_{1-2} (=1)	-841.898	1294.820	-23.703
	(864.929)	(2060.735)	(15.993)
Panel C: Dynamic Inconsistency: First and Third Time Frame			
$\overline{IDF}_{1-3}$	-131.596	-8901.320***	53.638**
	(1151.087)	(2848.164)	(22.058)
Increasing DF_{1-3} (=1)	1195.959***	-2058.501*	-6.787
	(456.372)	(1177.547)	(9.006)
Decreasing DF_{1-3} (=1)	-920.245	-1449.369	4.952
	(794.999)	(1917.887)	(14.388)
Panel D: Dynamic Inconsistency: Quasi-Hyperbolic Model ($\beta - \delta$)			
$\overline{\beta}$	-2330.552**	-320.266	19.953
	(1173.251)	(2886.440)	(21.403)
$\overline{\delta}$	2359.962	-1.58e+04***	69.774*
	(1967.102)	(4728.317)	(36.576)

Note: Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education.
Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Table 7: Robustness Tests: Constraints, Risk and Sample

	(1) Tobit	(2) Tobit	(3) OLS
Dependent Variable	Rev. Debt	Defaults	FICO
Control Variables	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes
Panel A: Including Credit Limit			
$\overline{IDF}$	-718.595	-1.14e+04***	62.500**
	(1306.116)	(3766.566)	(26.096)
Increasing DF (=1)	1214.115***	-426.023	-11.629
	(430.951)	(1288.799)	(8.864)
Decreasing DF (=1)	-463.436	1814.511	-10.852
	(1242.389)	(3680.761)	(23.657)
Ln(Revolving Credit Limit)	856.408***	-100.240	9.076***
	(59.561)	(141.306)	(0.982)
N	556	556	400
Panel B: Including Dummy for Credit Constraints (=1)			
$\overline{IDF}$	-854.875	-1.14e+04***	62.156**
	(1431.900)	(3759.149)	(26.249)
Increasing DF (=1)	1229.850***	-507.248	-9.678
	(472.895)	(1281.478)	(8.916)
Decreasing DF (=1)	-388.090		-12.990
	(1389.686)		(23.801)
Credit Constraint (=1)	-4412.488***	275.409	-70.463***
	(453.083)	(1137.092)	(7.875)
N	556	556	400
Panel C: Including Proxy for Risk Attitudes			
$\overline{IDF}$	-1695.509	-1.60e+04***	82.712***
	(1672.255)	(4377.593)	(31.882)
Increasing DF (=1)	1545.648***	-623.438	-11.171
	(529.662)	(1444.004)	(10.420)
Decreasing DF (=1)	1024.863		-4.082
	(1578.037)		(29.563)
Risk Attitudes (Standardized)	26.538	275.979	-0.084
	(83.487)	(220.791)	(1.665)
N	475	475	345
Panel D: Including Multiple Switchers			
$\overline{IDF}$	1191.841	-1.28e+04***	77.321***
	(1615.541)	(3476.617)	(27.397)
Increasing DF (=1)	860.961*	-544.766	-9.926
	(519.667)	(1169.292)	(9.098)
Decreasing DF (=1)	-747.174	1872.882	-13.431
	(1402.527)	(2877.612)	(22.823)
N	623	623	449
Panel E: Non-Missing Control Variables			
$\overline{IDF}$	-1129.553	-1.33e+04***	76.933**
	(1887.460)	(4893.591)	(33.690)
Increasing DF (=1)	1266.293**	46.477	-15.309
	(603.212)	(1615.028)	(11.061)
Decreasing DF (=1)	-221.441	1089.295	24.393
	(1819.118)	(4642.436)	(29.737)
N	420	420	300

Note: Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education. *Level of significance*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Table 8: Impatience and Credit Outcomes One Year Later

	(1) Tobit	(2) Tobit	(3) OLS
Dependent Variable	Rev. Debt	Defaults	FICO
$\overline{IDF}$	4649.094	-3.97e+04***	292.895***
	(6451.281)	(9554.899)	(85.915)
More Patient (=1)	3340.015**	338.405	17.741
	(1474.931)	(2347.594)	(21.333)
Less Patient (=1)	5521.971		0.195
	(4985.063)		(89.982)
Dummy for Year of Study	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
LL / R^2	-744.18	-785.56	0.240
N	131	131	102

Note: Standard errors in parentheses. The sample consists of participants in 2006. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, a constant term and dummies for imputed income, age, gender, race, and education.
Level of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

A Appendix

A.1 Appendix Tables

Table A1: Impatience and Debt for 2006 and 2007 separately

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS
Control Variables	No	Yes	No	Yes
Panel A: 2006 Sample				
$\overline{IDF}$	2264.456	669.319	554.091	167.706
	(4095.392)	(3874.725)	(2076.427)	(2101.457)
Increasing DF (=1)	2241.555**	2472.210***	1331.975***	1422.970***
	(927.555)	(895.872)	(503.418)	(504.295)
Decreasing DF (=1)	1224.962	4189.532	749.575	2061.628
	(3075.015)	(3010.675)	(1661.984)	(1703.840)
N	131	131	131	131
Panel B: 2007 Sample				
$\overline{IDF}$	1099.016	-183.474	-508.381	-962.697
	(1698.148)	(1681.514)	(848.943)	(862.956)
Increasing DF (=1)	509.901	708.228	583.423*	744.009**
	(599.968)	(595.889)	(305.185)	(307.832)
Decreasing DF (=1)	149.663	-573.047	-216.226	-449.067
	(1749.823)	(1685.728)	(910.578)	(899.942)
N	425	425	425	425

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 income, age, gender, race, and education.

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

Table A2: Impatience and Defaulting for 2006 and 2007 separately

	(1) Tobit	(2) Tobit	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Dependent Variable	Defaults	Defaults	Defaults	Defaults	FICO	FICO
Control Variables	No	Yes	No	Yes	No	Yes
Panel A: 2006 Sample						
$\overline{IDF}$	-3.15e+04***	-3.55e+04***	-1.82e+04***	-2.10e+04***	243.983***	224.165**
	(9467.497)	(9158.281)	(6142.406)	(6235.067)	(83.492)	(85.235)
Increasing DF (=1)	-700.180	-449.229	600.916	991.373	20.888	23.292
	(2398.870)	(2296.094)	(1489.192)	(1496.254)	(20.643)	(21.132)
Decreasing DF (=1)	-6.01e+04	-5.05e+04	-2451.319	959.834	20.587	45.811
	(0.000)	(0.000)	(4916.419)	(5055.330)	(81.225)	(84.272)
N	131	131	131	131	98	98
Panel B: 2007 Sample						
$\overline{IDF}$	-7298.255*	-7464.598*	-4983.521**	-4617.307*	62.348**	53.352*
	(4021.296)	(4168.149)	(2336.079)	(2434.630)	(31.100)	(31.146)
Increasing DF (=1)	-1094.205	-929.653	-397.024	-522.124	-12.158	-16.841
	(1485.962)	(1516.394)	(839.794)	(868.475)	(11.370)	(11.267)
Decreasing DF (=1)	3979.991	4337.742	717.652	908.815	-7.882	-13.965
	(4039.067)	(4035.840)	(2505.684)	(2538.976)	(28.539)	(27.792)
N	425	425	425	425	302	302

Note: Standard errors in parentheses. Control variables include ln(disposable income), number of dependents, age, gender, race, college experience, and dummies for imputed income, age, gender, race, and education.
Level of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A3: Full Regressions for Table 2 and Table 3

Table (T) and Column (C) Dependent Variable	T 2, C 2 Rev. Debt Tobit	T 3, C 2 Default Tobit	T 3, C 6 FICO OLS
$\overline{IDF}$	-375.628	-11382.84***	69.765**
	(1506.473)	(3758.279)	(28.803)
Increasing DF (=1)	1154.947**	-450.996	-10.730
	(496.070)	(1286.116)	(9.787)
Decreasing DF (=1)	173.193	1730.007	-6.185
	(1463.301)	(3670.038)	(26.117)
Year of Study (2007=1)	-36.669	-2021.887	-16.693*
	(522.473)	(1327.441)	(10.059)
Ln(Disposable Income)	891.462***	793.855	6.945*
	(205.100)	(526.338)	(3.640)
Income Imputed	9026.342***	7511.413	103.221**
	(2321.639)	(5982.326)	(43.870)
# of Dependents	254.452	660.585	-3.778
	(258.351)	(670.856)	(5.049)
College Experience (=1)	648.832	1397.765	27.611***
	(484.846)	(1222.294)	(9.516)
Education Imputed	557.632	2078.302	-8.874
	(701.922)	(1759.207)	(13.732)
Age	46.354***	76.629*	1.084***
	(16.957)	(43.388)	(0.335)
Gender (Male=1)	-893.161*	1257.894	-16.565*
	(478.664)	(1204.081)	(9.550)
Gender Imputed	47.359	-2818.082	48.982***
	(936.382)	(2453.705)	(18.341)
Race (African-American=1)	389.107	-1952.082	9.673
	(520.473)	(1308.764)	(10.119)
Race Imputed	-549.065	1174.951	-0.058
	(827.413)	(1969.284)	(15.472)
Constant	62085.268	4.05e+06	33929.731*
	(1.05e+06)	(2.66e+06)	(20190.027)
LL / R^2	-2655.83	-3191.79	0.114
N	556	556	400

Note: Standard errors in parentheses. For details, see Table 2 and Table 3.
Level of significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

A.2 Instructions of Study 1

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; $t = 6$, $\tau = 1$]: 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.3 Instructions of Study 2

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; $t = 6$, $\tau = 1$]
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 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**

A.4 Calculating $\beta - \delta$ parameters using choice experiments

The three time frames in which discount factors are elicited allow to calculate βs and δs from a system equations. From the two time frames, $t = 0$, $\tau = 1$ and $t = 0$, $\tau = 6$, we get two equations and two unknowns: $X^*_{0,1} = \beta\delta^1(Y)$ and $X^*_{0,6} = \beta\delta^6(Y)$. From the choices in time frame 1 and time frame 2, we can calculate β_1 and δ_1.

The two time frames, $t = 0$, $\tau = 1$ and $t = 6$, $\tau = 7$, provide another system of equations: $X^*_{0,1} = \beta\delta^1(Y)$ and $X^*_{6,7} = \delta^1(Y)$. From this system of equation, one can calculate β_2 and δ_2.

For the robustness test, we take the average of β_1 and β_2 and of δ_1 and δ_1 to create the measures of $\overline{\beta}$ and $\overline{\delta}$.