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Discounting and Defaulting:
Evidence from Time Preference Experiments and Administrative Credit Data*

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Abstract

Prior empirical analyses of credit default demonstrate the importance of policy-driven differences in costs and benefits. However, little is known about individual determinants of default within a given institutional setting.

Theoretically the defaulting decision is intertemporal in nature: present benefits of default are weighed against *discounted* delayed costs. We empirically test the relationship between discounting and defaulting by matching experimentally elicited time preference measures to credit reports and tax data. Within a common institutional setting and controlling for socio-demographics, debt levels, buffers against income shocks, and credit constraints, the results show substantial correlation between discounting and defaulting. (100 words)

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I Introduction

Defaulting on credit contracts is very costly for lenders and for society. Especially in the subprime market, default rates can be quite substantial. In the sample of subprime borrowers presented in this paper, about half are in default on a consumer loan contract. Similarly, Adams, Einav, and Levin (2009) show that around half of the loans originated by a subprime car loan company end up in default. Not surprisingly, financial economists, financial institutions and policy makers are very interested in understanding the determinants of credit default.

Economic theory generally views defaulting as a strategic decision, explicitly taking into account the costs and benefits of reneging on existing loan obligations (e.g., Fay, Hurst, and White, 2002).[1] The empirical literature then analyzes the link between bankruptcy and institutional variations affecting costs and benefits (see White, 1987; Fay, Hurst, and White, 2002; Domowitz and Sartain, 1999; Agarwal, Liu, and Mielnicki, 2003); or the effect of cost differences over time on defaulting (see Gross and Souleles, 2002; Foote, Gerardi, and Willen, 2008). Generally, these studies find that individuals are less likely to default if the costs of default are high or the benefits low.

Outside of institutional variation in costs and benefits, the determinants of default are somewhat more difficult to pin down. Prior studies provide little information on the determinants of defaulting *within* the same institutional setting. Credit companies try to predict default rates based on consumption patterns[2] or, at times, demographic characteristics[3]. The extent to which such predictions are incorrect determines both the efficiency of credit allocation and realized default rates.

[1]In contrast, other models see defaulting more as the consequence of bad luck (e.g., Sullivan, Warren, and Westbrook, 1989, 2000).

[2]For example, borrowers who buy felt pads are found to be less likely to default and borrowers who buy cheap automotive oil are found to be more likely to default (see Duhigg, 2009). Such analysis falls under the tag line 'behavioral scoring.'

[3]As in the case of illegal mortgage redlining. Cohen-Cole (2009) presents evidence that redlining is also prevalent in the credit card industry.

Largely ignored in prior empirical work by financial economists and industry analysts is the relationship between intertemporal preferences and credit default. The defaulting decision should be seen as intertemporal in nature. The costs of defaulting (some blend of future financial exclusion, social stigma and lost services) materialize primarily in the future, while the benefits of defaulting (not having to pay one's debt) are realized much sooner. As such, in recent general equilibrium models (e.g., Livshits, MacGee, and Tertilt, 2007a,b; Chatterjee, Corbae, Nakajima, and Rios-Rull, 2007; Chatterjee, Corbae, and Rios-Rull, 2008) individual time preferences are a key determinant of default. All else equal, less patient individuals assign lower value to future costs and should therefore default more.

This paper takes seriously the view that patience should correlate with credit default. We present evidence from a unique field study on the relationship between discounting and defaulting in a sample of around 500 low-to-moderate income (LMI) individuals for whom default rates on consumer credit contracts are notably high (around 50 percent). In recent years, economic research has made great progress in measuring preferences in general and time preferences in particular (see, for example, Frederick, Loewenstein, and O'Donoghue, 2002; Harrison, Lau, and Williams, 2002; Burks, Carpenter, Goette, and Rustichini, 2009; Benjamin, Choi, and Strickland, 2007).[4] We use established incentive-compatible experimental methods and match the resulting time preference parameters to tax return data and objective measures of defaulting obtained from individual credit reports.

Our results show that time preferences are significantly correlated with defaulting. Less patient individuals are more likely to default on their consumer credit contracts. Not only are less patient individuals more likely to default, they also have significantly

[4]Experimentally measured time preferences have also been shown to be remarkably stable over time. Meier and Sprenger (2009b) provide evidence on temporal stability from a longitudinal field experiment and Eigsti, Zayas, Mischel, Shoda, Ayduk, Dadlani, Davidson, Aber, and Casey (2006) show that the extent of impatience in small children predict their school behavior years later.

higher balances in default and significantly lower FICO credit scores. These results are maintained when controlling for socio-demographic characteristics such as income, age, education, race, gender and number of dependents claimed on an individual's tax filing.

We additionally show that less patient individuals default more controlling for the possibility that recent negative life events (i.e., shocks) simultaneously influence both defaulting outcomes and measured time preference parameters. Less patient individuals remain more likely to default taking into account potential buffers against shocks such as credit limits, other liabilities, health insurance status, and savings.

The results presented in this paper are the first to show the correlation between time preferences and defaulting. This gives critical support to the intertemporal view of credit default. The contribution of the paper is not, however, limited to providing empirical support for the intertemporal modeling of default. First, we make the important *experimental* step of showing that experimentally elicited time preferences are closely related to real-world financial decisions.[5] Second, the paper also shows that discounting correlates with defaulting *within* the same institutional setting, establishing a potential determinant of default independent of institutional variations in costs and benefits. As such, the results help to inform the risk models employed by lending institutions in order to select creditworthy (i.e., patient) borrowers. Similarly, the results inform public policy efforts focused on default reduction.

The remainder of the paper is organized as follows: Section II presents the design of the field study, the data on defaulting, and the measurement of time preferences. Section III presents the results analyzing the association between time preferences and defaulting; and Section IV explicitly controlling for the possibility that adverse life

[5] A number of papers used hypothetical surveys responses to explain investors' behavior (see, e.g., Dorn and Sengmueller, 2009; Dorn and Huberman, 2009) or household financial decisions (see, e.g., Stango and Zinman, 2008).

events affect the effect of impatience on defaulting. Section V concludes.

II Data

A Design of the Field Study

Empirical studies of default using individual-level data are rare. Defaulting data are difficult to obtain and defaulting is a relatively low-frequency event in the general population, hampering individual-level analysis (for a discussion about data availability and challenges, see Gross and Souleles, 2002). To mitigate these issues, we designed a field study combining various data sources focused on a sample of individuals for whom defaulting is relatively frequent.

The field study was conducted in 2006 and 2007 at two Volunteer Income Tax Assistance (VITA) sites in Boston, Massachusetts.[6] During the 2006 tax season, the study was conducted in the Dorchester neighborhood and during the 2007 tax season in the Roxbury neighborhood. At these two VITA sites, individuals were additionally offered free credit reports while they waited for tax filing assistance. Free credit reports were given to 541 study participants. In the terminology of Harrison and List (2004) this study is an "artefactual field experiment" linked to administrative data.

Implementing our field study in a tax filing environment where individuals are provided free credit reports allows us to create a data set combining:

1. *Tax information*: participants' complete tax filings are available to us.

2. *Credit reports*: participants consent to the use of their credit report information for research. In 2006, individuals additionally allowed access to their credit report

[6]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.

one year after the field study was conducted.

3. *Time preferences*: individuals participated in choice experiments designed to measure heterogeneity of time preferences.

4. *Survey questions*: participants also filled out a short auxiliary survey collecting further socio-demographic and behavioral information.

The field study concentrates on individuals *without* mortgages and *with* revolving or installment accounts in their credit history. Individuals with no revolving or installment accounts in their entire credit history have no repayment decisions to make and so are eliminated from the analysis. Of the 541 participants, 495 had at least one revolving or installment account in their credit history.[7] Of these 495 participants, we obtain a usable measure of time preferences for 446 (see below for details). These individuals represent our primary sample.

[Table 1 about here]

Panel A of Table 1 shows the socio-demographic characteristics of the primary sample. The average participant has low disposable income of around $20,000, is African-American, female, around 36 years old, with some college experience, and has less than one dependent reported on their tax filing. Unlike age, income and dependent counts, which are reported on individual tax returns, data for gender, race and college experience are obtained through the auxiliary survey noted above. As such, a non-negligible portion (around 10 to 15 percent) of observations in these categories are missing. In the main analysis, missing socio-demographic variables were set to the value of the majority for the indicator variables gender, race, and college experience and the imputation is controlled for with separate indicator variables. The exclusion

[7] Including the 95 individuals who don't have an account in their history to default on, does not change the results qualitatively.

of observations with missing variables does not qualitatively change the results (see Section III.B).

The study was targeted towards low-to-moderate income (LMI) / subprime borrowers without mortgages. As such, it is a selected sample and care should be taken in extrapolating broadly from the results presented below (see Meier and Sprenger, 2008, for a discussion of the selection process). This selected sample, however, is critical to the present study of default. As noted above, defaulting in the general population is a low-frequency event, which could preclude strong inference in small samples. In our sample, however, default is considerably more common which allows us to correlate individual time preferences to defaulting even in a sample of limited size. In addition, the growth of the subprime credit market in recent years, makes an analysis of such individuals particularly relevant (see Campbell, 2006).

B Data on Defaulting from Credit Reports

Information on individual defaulting behavior comes from credit reports from one of the three major credit bureaus in the United States. Credit reports list detailed information on each individual's credit behavior such as account histories, outstanding balances, how much available credit an individual has (and therefore whether they are credit constrained), and whether accounts have been closed with balances (for more details on credit reporting, see Avery, Bostic, Calem, and Canner, 2003). Unlike self-reported data, credit reports give a very detailed, objective picture of individuals' borrowing and defaulting behavior.

We measure default on consumer revolving and installment credit contracts as the value of accounts that are closed but have remaining balances. Such accounts are generally closed by credit grantors as a result of non-payment for more than 120 days (Avery, Bostic, Calem, and Canner, 2003).[8] Accounts closed with balances generally receive no payment, though payment plans may be organized on closed accounts. Dawsey and Ausubel (2004) refer to such non-servicing of debt as "informal bankruptcy". Three measures of defaulting are generated from individual credit report data:

1. *Default (= 1)*: an indicator variable for whether an individual has any closed account balances.
2. *Amount in Default*: the dollar value of closed account balances.
3. *FICO Score*: because defaulting will adversely affect individual credit scores, we additionally use FICO scores as a summary measure of defaulting behavior.

Panel B of Table 1 illustrates the defaulting characteristics of the sample. Forty-nine percent of study participants have some balances in closed accounts. The average value of closed account balances is $2,319. As mentioned above, the frequency and level of defaulting in our sample is notably high. The large standard deviations of these default measures indicate that there is also substantial heterogeneity in defaulting. The average FICO credit score in the sample is 610.[9] The median score is 597 confirming that most study participants would be considered sub-prime borrowers by the commonly used cutoff of 620 in the years of the study (see, e.g., Foote, Gerardi, Goette, and Willen, 2008).

Panel B of Table 1 additionally reports individual credit limits and non-deferred balances on accounts that remain open[10]. Individuals have credit limits of $5,778 and non-deferred open account balances of $4,833. As borrowing opportunities and current

[8] Regulatory guidance to creditors noted in Avery, Bostic, Calem, and Canner (2003) states that closed-end installment credit should be charged-off after 120 days of non-payment while open-ended revolving credit should be charged off after 180 days of non-payment.

[9] 65 individuals are unscored because there is insufficient information on file at the credit bureau to generate a FICO score.

[10] We subtract from total balances the portion which represents student loan debt in deferral as such deferred balances are not an immediate obligation of the individual.

liability position may impact an individual's ability to survive income shocks, these measures are used in the analysis of adverse life events in Section IV.

C Measuring Time Preferences

Methodology

The objectively reported credit default data are correlated to time preference measures obtained using incentive-compatible experimental methods. Time preference parameters have been elicited using similar experimental procedures in a variety of previous studies (see Harrison, Lau, and Williams, 2002; McClure, Laibson, Loewenstein, and Cohen, 2004; Dohmen, Falk, Huffman, and Sunde, 2006, and for a survey on measuring time preferences, see Frederick, Loewenstein, and O'Donoghue (2002)). Linking experimentally elicited time preference parameters to real-world outcomes, however, is a relatively novel use of such parameter measures (see Ashraf, Karlan, and Yin, 2006; Meier and Sprenger, 2009a).

In our study, individuals arriving at the VITA site were given three choice sets and asked to make various choices between a smaller reward ($\$X$) in period t and a larger reward ($\$Y > \$X$) in period $t + \tau > t$.[11] In total, individuals were given 22 choices over three different 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 ($\tau = 1$). In 2006, $\$Y = \$80$ and $\$X$ was varied from \$75 to \$30 (see the instructions in Appendix B). In 2007, $\$Y = \$50$ and $\$X$ was varied from \$49 to \$14 (see the instructions in Appendix C).[12] It has been shown that using

[11] The experimental literature refers to such choice sets as 'multiple price lists'.

[12] The field experiment in the two years also differed in the presentation style: The order of the three choice sets was the same for each individual in 2006, while the order was randomized in 2007. Additionally, while in 2006, the 113 participants were individually and extensively guided through the details of the choice sets, the 382 participants in 2007 received a substantially shorter choice set introduction. Most likely, the randomization of the choice set order and the shorter introduction increased the noise in measuring time preferences in 2007 compared to 2006. In the results section, we

monetary rewards to elicit time preferences yields reliable measures of time preferences that are very stable for a given individual over time (Meier and Sprenger, 2009b) and correlate highly with measures obtained using other methodologies (Reuben, Sapienza, and Zingales, 2008; Chabris, Laibson, Morris, Schuldt, and Taubinsky, 2008).

Experimental approaches generally encourage the truthful revelation of individual preferences by placing monetary stakes on the choices individuals make. In order to make experimental responses incentive compatible, 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.[13]

Individuals were informed that winning money orders would be sent by mail to the winner's home address on the same day as the experiment (if $t = 0$), or in one, six, or seven months, depending on the winner's previous experimental choice. Money orders were sent by mail to equate transaction costs across present and future payments. Such a payment procedure is similar to an experimental front-end-delay design (see Harrison, Lau, Rutstrom, and Williams, 2005).[14]

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.

[13]We believe that participants are familiar with the the Federal Reserve Bank of Boston. As part of the bank's public outreach, it is a key member of the city-wide coalition organizing the VITA sites. The bank is mentioned and the bank logo is featured both on VITA site material and the coalition website (see http://www.bostontaxhelp.org).

[14]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

Measure of Individual Discount Factors

The choice experiments enable us to measure an *individual discount factor (IDF).* We calculate an *IDF* for the 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 choice set. That is, a discount factor is taken from the last point at which an individual prefers the smaller, sooner 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:

$$IDF = (\tfrac{X^*}{Y})^{1/\tau}$$

Making these calculations yields three discount measures, $IDF_{t,\tau}$: $IDF_{0,1}$, $IDF_{0,6}$, $IDF_{6,1}$.[15] We use the average of the calculated monthly discount factors, $\overline{IDF}$, in the main analysis, but also show the effect of the three measures separately. In order to measure an *IDF*, an individual must exhibit a unique switching point in each choice set. In the main analysis we focus on the 446 individuals who have a unique switching point in all choice sets. When we include individuals with multiple switching points in a robustness test by taking their first switching point, the results hold (see Section III.B).

The choice sets employed do not elicit point estimates of the *IDF* but rather ranges of where the *IDF* lie (see Coller and Williams, 1999; Harrison, Lau, Rutstrom, and Williams, 2005, for details). In the above example, the individual's actual switching point lies somewhere between $70 and $75. As such, the monthly IDF lies in the interval $(0.875, 0.94)$. We calculate the interval within which our three discount measures

time preference, we ask individuals *"Do you expect to move in the next 7 months?"*. However, whether individuals expect to move does not correlate with elicited time preferences and does not affect our results.

[15]This formulation is equivalent to positing a linear utility function over the experimental outcomes and normalizing extra-experimental consumption (e.g., background consumption) to zero. In Section III.B we examine the robustness of our results to the assumption of linear preferences.

($IDF_{0,1}$, $IDF_{0,6}$, $IDF_{6,1}$) lie. When presenting results, we ensure that our findings are maintained in interval regressions (Stewart, 1983) using the range of possible *IDF*s (see Section III).

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*. That we measure heterogeneity of individuals' time preferences relies on at least three assumptions (for an extensive discussion of the assumptions made, see Frederick, Loewenstein, and O'Donoghue, 2002; Harrison, Lau, Rutstrom, and Williams, 2005; Meier and Sprenger, 2009a). We discuss and test the importance of these assumptions for our analysis:

First, the measurement of time preference parameters by observing individuals' switching points in choice sets 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).[16] However, parameters estimated from choice sets may also capture differences across individuals in the degree of curvature of the utility function (Andersen, Harrison, Lau, and Rutstrom, 2008). We therefore test whether differences in risk aversion affect the 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")*. A companion survey with this generalized risk question was implemented in both years. 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. Controlling for these risk attitudes does not affect our results (see Section III.B).

[16] It is, of course, debatable whether such payments represent small stakes for our sample.

Second, the switching points in the choice sets might potentially be influenced by outside borrowing and lending opportunities. The implied interest rates of the choice sets employed are generally extremely high such that individuals should prefer later payments in nearly all situations (see Meier and Sprenger, 2009a). That participants do not uniformly choose later payments suggests that outside opportunities are not critically impacting experimental results. Also, Meier and Sprenger (2009a) show that objectively measured credit limits are uncorrelated with time preference experimental responses indicating that credit constraints are unlikely to be driving experimental results. Furthermore, controlling for individual credit limits does not affect the results of this paper (see Section IV).

Third, if short term negative shocks affect individuals' choices, we might not measure differences in preferences, but rather differences in shocks. Such shocks may also negatively affect an individual's ability to service their debts. In Section IV we test whether adverse life events affect the association between time preferences and defaulting behavior.

III Results

The relationship between discounting and defaulting is presented in several steps. First, we present the association between time preferences and defaulting. We show the raw correlations between individual discount factors and defaulting and evaluate this correlation in multivariate regressions controlling for socio-demographic characteristics. In robustness tests, we show that these results are maintained when accounting for the interval nature of the measured discount factors and when controlling for risk attitudes and different sample selections. In a final step we explore the possibility that adverse events or shocks could influence the relationship between measured preferences and defaulting.

A Time Preferences and Defaulting Behavior

The intertemporal view of credit default states that because the benefits of default are realized in the present and the costs of default are realized in the future, individuals who value the future less should default more, all else equal. In support of this view, individuals in default have an average $\overline{IDF}$ of 0.85 while individuals not in default have an average $\overline{IDF}$ of 0.88. This difference is significant at the 95 percent level in a t-test. $\overline{IDF}$ also correlates with the amount in default ($\rho = -0.14$, $p < 0.01$) and with the FICO score ($\rho = 0.15$, $p < 0.01$). Less patient individuals are those who have defaulted on their consumer credit contracts and have both higher amounts in default and lower credit scores.

To explore whether the correlation between time preferences and defaulting behavior is maintained when controlling for socio-demographic characteristics, we present regressions of the following form:

$$Defaulting_i = \beta_0 + \beta_1 \overline{IDF}_i + \gamma X_i + \epsilon_i \tag{1}$$

$Defaulting_i$ is one of three defaulting outcomes: 1) *Default (= 1)*, an indicator variable for having any defaulted balances; 2) *Amount in Default*, the value of defaulted balances; or 3) *FICO Score*. $\overline{IDF}_i$ is the discount factor measure used. X_i is a vector of additional control variables which includes log income, the number of dependents claimed on an individual's tax return, an indicator for college experience, age, age squared, gender, race and the year of study. Importantly, income and education, two proxies for cognitive ability, control for the possibility that time preferences and defaulting are both affected by cognitive ability.

In Table 2, we present regression results estimating Equation 1. Columns 1 and 2 present probit regressions with an indicator for having defaulted balances ($Default$ $(= 1)$) as the dependent variable. Individuals with lower discount factors are significantly more likely to have any defaulted balances. Controlling for socio-demographic characteristics, we estimate a marginal effect of -0.37. A one standard deviation decrease in measured discount factor is associated with a roughly 5 percentage point (10 percent) increase in the probability that an individual will have any balances in default. Notably, income has no statistically significant effect on the probability of default, indicating that the ability to pay may not be a key determinant of defaulting. Other demographic characteristics are similarly insignificant with the exception of race for our sample.

[Table 2 about here.]

In Columns 3 and 4 of Table 2, we present regressions with the amount of defaulted balances ($Amount\ in\ Default$) as the dependent variable. To account for the fact that defaulting value levels are censored at zero, tobit regressions are estimated. Less patient individuals default more in value. The estimated marginal effect of -4,627, conditional on having defaulted balances, shows that a one standard deviation decrease in measured discount factor is associated with a roughly $682 (around 14.4 percent) increase in defaulted balances.

Less patient individuals are more likely to default and have higher amounts of defaulted balances. We would expect these higher defaults to translate into lower credit scores. In Columns 5 and 6 of Table 2, we estimate ordinary least squares regressions with *FICO Score* as the dependent variable. As expected, lower measured discount factors are associated with significantly lower FICO scores.

Controlling for socio-demographic characteristics, the results show that more impatient people are more likely to default, have higher defaulted balances and correspondingly have lower FICO scores.[17]

B Robustness Tests

The result that less patient individuals default more is robust to additional tests taking into account the interval nature of the time preference measure; controlling for differences in risk attitudes; allowing for individuals without unique switching points in the choice experiments; and examining only individuals for whom we have complete socio-demographic information.

In Table 3 we ensure that the results are maintained when accounting for the fact that our experimental procedure generates a discounting interval and not a point estimate. The implemented interval regression technique (Stewart, 1983) allows for interval-coded dependent variables. In Table 3, the dependent variable is the interval of the elicited discount factor in a single choice set and defaulting behavior is used as an independent variable. Because we elicit discounting in three choice sets, there are three observations per individual. The standard errors are adjusted by clustering on the individual level. Controlling for demographic characteristics and design elements of the choice experiments, we find that defaulting behavior remains strongly correlated with measured discount factors.[18] Having defaulted balances, having higher value balances in default and having a lower FICO score are all associated with lower individual discount factors.

[Table 3 about here.]

[17] In the appendix (Tables A1 and A2) we present the results for the two years of study separately. The results are qualitatively similar, though we estimate the relationships between discount factors and defaulting behavior less precisely in 2007.

[18] The design element controlled for are whether the choice set involves the present, *Has Present* ($t = 0$), and if the choice set involves a six month delay, *Six Month Delay* ($\tau = 6$). See Table A3 in the appendix for the full estimation results.

As noted in Section II.C, individual risk preferences could impact our time preference measures. Additionally, risk aversion might affect the decision to default if creditors respond only probabilistically to non-payment.[19] Panel A of Table 4 presents regressions following the specifications of Table 2 with the addition of a measure for individual risk attitudes (for wording of the question see Section II.C). Controlling for risk attitudes, less patient individuals remain more likely to default, have higher default values and have lower FICO scores.

In order to calculate $\overline{IDF}$ from an individual's experimental choices, they must have a unique switching point in each choice set (see Section II.C). Panel B of Table 4 presents regressions following the specifications of Table 2, admitting individuals without unique choice set switching points. For these individuals, $\overline{IDF}_i$ is calculated using their first switching point in each choice set. The results are unchanged.

In the main analysis, missing values for the demographic characteristics of gender, race and education are set to the value of the sample majority. In Panel C of Table 4, we examine only individuals for whom complete socio-demographic information is available. The number of observations is reduced and, though precision is lost in the relationship between discounting and *Default (= 1)*, the relationship between discounting and default value and FICO score are qualitatively unchanged.

[Table 4 about here.]

In sum, we find strong and significant support for the intertemporal view of credit default. Less patient individuals are more likely to default, have higher defaulted balances and have lower FICO scores. These results are maintained when we account for the interval nature of our individual discount factor measure; and are generally

[19] The probability of a creditor collecting (and the probability of a debtor actually having to pay) is reflected in the price of debt on the collection market. White (1998) models the bankruptcy filing decision in a game theoretic environment, indicating that consumer default is partially determined by some expectation of enforcement.

robust to the inclusion of risk attitudes and changes to our sample restrictions.

IV Alternative Explanation: Adverse Life Events

The results to here are broadly supportive of the intertemporal view of credit default. The most important alternative interpretation of our results is that some exogenous third factor, unaccounted for in the data, determines both experimental outcomes and credit default. For example, as claimed by Sullivan, Warren, and Westbrook (1989, 2000), adverse life events or shocks could lead individuals to default and could also impact experimentally measured time preference parameters. Individuals suffering an income shock may be liquidity constrained, needing sooner experimental payments to meet existing financial obligations and so appear impatient in our choice experiments.[20]

In general, previous results have shown that time preferences measured using monetary rewards are unlikely to be affected by adverse life events as they correlate highly with impatience measured using primary rewards like chocolate (Reuben, Sapienza, and Zingales, 2008) and are generally uncorrelated with credit constraints (Meier and Sprenger, 2009a). For the same subject pool and elicitation methodology, Meier and Sprenger (2009b) also show that time preferences are extremely stable over time and are not affected by major life events such as unemployment spells or major increases and decreases in income.

Nevertheless, the rich data set allows us to directly address this alternative explanation in several ways. First, we attempt to account for the possibility that people who default are credit constrained by controlling for individual credit limits and the burden of other debt obligations. We also include in these regressions proxies for the buffers that individuals employ to survive shocks. Second, we exploit the fact that some of our

[20]Such an effect could also be obtained if a negative wealth shock makes present payments more attractive overall.

choice experiments reference only future time periods. In these future periods, current period shocks are expected to have less effect on experimental responses. If shocks are driving current experimental responses and defaulting, but not future experimental responses, we would expect very different correlations between our three different discount factor measures and defaulting. Third, we examine defaulting outcomes for a subsample of individuals one year after the choice experiments were implemented. If short-term shocks drive both experimental responses and defaulting outcomes we would not expect the initial result to be maintained one year later.

A Credit Constraints and Buffers Against Shocks

Households likely differ in the degree to which they are exposed to shocks. When shocks arise some households may be buffered from default by having higher available credit limits, lower total liability levels or insurance. In Table 5 we assess whether the absence of buffering mechanisms, and hence the exposure to shocks, affects the obtained results. Table 5 shows the results of tobit regressions with *Amount in Default* as the dependent variable (the results for the dummy *Default (=1)* and for *FICO Score* can be found in Table A4).[21]

Column 1 controls for individual credit limits and balances on open credit accounts taken from individual credit reports. The results show that the association between *IDF* and defaulting is not affected by adding proxies for being credit constrained.

[21] Short term financial shocks could impact individual credit behavior. If so, such shocks would be expected to affect delinquency before translating into outright default, and we could use individual delinquency, i.e. late payments, as a proxy for the direct financial shocks affecting an individual (see Foote, Gerardi, and Willen, 2008). When we include an indicator variable for having delinquent payments (*Delinquent (= 1)*) as an explanatory variable to proxy for financial shocks, the results hold (results can be obtain upon request). Having delinquent balances is, however, strongly correlated with both the amount in default and with $\overline{IDF}$. This may indicate that delinquent balances are not an ideal proxy for income shocks as such shocks should be orthogonal to preferences. Another interpretation is that delinquency is a choice representing the first step to outright default and so is governed by the same preference parameter as default itself.

Column 2 controls for whether the individual has any health insurance, which reduces the exposure to health shocks dramatically.[22] The inclusion of this variable does not affect the results. Also, the inclusion of a dummy for whether individuals have a bank account as a lower bound of potential savings does not affect the results.[23] In Column 4 of Table 5, we include all buffering controls together and the relationship between the amount in default and time preferences is maintained. The inclusion of these additional control variables also does not greatly affect the association between $\overline{IDF}$ and *Default (=1)* or *FICO Score* (see Table A4 in the Appendix).

[Table 5 about here.]

B Different Measures of IDF

As a second test of whether shocks drive our empirical results, we use the fact that participants are asked to respond in three different choice settings. Two of these settings involve the present, while one involves only future payments. The measurement of $IDF_{6,1}$ should be less affected by current period income shocks as it involves only future choices six months from the experiment date. If shocks are affecting experimental responses and defaulting outcomes, we would expect not only that the measured discount factors $IDF_{0,1}$ and $IDF_{0,6}$ would differ greatly from $IDF_{6,1}$ but also that the obtained results would depend heavily on whether the discount factor used in the regression involves the present or not.[24]

[22] The information about health insurance and savings is taken from a survey. Missing variable are set to the value of the majority and controlled for in the regressions.

[23] One can also include self-reported savings amount as a control variable and the association between time preferences and defaulting is also robust.

[24] Measured discount factors from the three choice sets correlate extremely highly. The correlation between $IDF_{0,1}$ and $IDF_{6,1}$ is 0.66 while the correlation between $IDF_{0,6}$ and $IDF_{6,1}$ is 0.63. Both of these correlations are highly significant ($p < 0.01, p < 0.01$ respectively). While individuals exhibit dynamic inconsistency as in other studies (e.g., Ashraf, Karlan, and Yin, 2006), a measure for whether individuals are dynamic inconsistent does not correlated with defaulting.

In Table 6 we regress default balances on each of the three discounting measures in turn. The dependent variable is *Amount in Default* (the results for *Default (=1)* and *FICO Score* can be found in Appendix Table A5). Though the point estimates differ somewhat, the strong negative correlation between defaulting and patience is maintained across all three regressions.

[Table 6 about here.]

C Time Preferences and Defaulting One Year Later

In addition to experimentally measuring time preferences for a time frame when current period shocks are not expected to have an effect, we also received permission from study participants in 2006 to obtain their credit score a second time one year later. If shocks are short term, and defaulting is not an optimal intertemporal choice, we might expect individuals who had been driven temporarily to default by shocks to return to good standing in one year's time. The correlation then between measured discount factors and subsequent defaulting behavior should be largely eliminated.

In Table 7, we present regressions identical to Table 2 for the 2006 sub-sample one year after the original choice experiments. We find that experimentally measured discount factors remain significantly correlated with defaulting outcomes even one year after the original experiments. Controlling for socio-demographic characteristics, less patient individuals remain more likely to default, have higher balances in default and have lower FICO scores.

[Table 7 about here.]

In sum, the results show that adverse life events or shocks are very unlikely to affect the correlation between defaulting behavior and time preferences. When controlling both for shocks and the presence of buffers against such shocks, the correlation between defaulting and time preferences is maintained. This correlation is also maintained when we examine time preference measures upon which shocks are not expected to have an effect and when we examine defaulting outcomes one year after the original choice experiments.

V Conclusion

If defaulting is an intertemporal decision in which consumers weigh the present benefits of not having to repay their debts against the future costs of potentially being excluded from financial markets or stigmatized (as assumed in recent economic models), individual time preferences should be a key determinant of defaulting.

This paper takes this intertemporal interpretation seriously and links experimentally measured differences in time preferences to objectively measured differences in defaulting behavior. We find that time preferences elicited using incentive compatible experimental methods correlate highly with defaulting measures obtained from individual credit reports. Less patient individuals are more likely to default, have higher balances in default and have lower FICO credit scores. These results are maintained when controlling for socio-demographic characteristics; and when accounting for the interval nature of the measured time preference parameters and the potential impact of adverse life events.

The results presented in this paper are the first to document the correlation between discounting and defaulting. As such, our results give critical support to existing intertemporal models of the default decision. The contribution of the paper, however, is not simply a justification of certain modeling techniques. First, our results are important from an experimental perspective, as experimentally-elicited preference measures are rarely linked to real-world behavior. Our findings show that such preference measures can be used to empirically explore the relationship between preferences and behavior. Second, the findings provide key insights to credit-granting institutions when designing contract terms. For example, penalties for default that occur with delay, such as reporting to credit bureaus or default penalties that are later collected by a third-party agency, may be less successful at deterring default than immediate penalties, such as seizing security deposits. Future research should investigate how the temporal dimension of credit contracts affects default probabilities. Third, our findings inform the efforts of policy makers designing default reduction strategies. If discounting and default are closely related then such strategies should examine the timing of the costs and benefits of default and not focus only on the costs and benefits themselves.

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Table 1: Summary Statistics: The table shows summary statistics for the primary sample. The columns show the number of observations, the mean of the variables and the standard deviations, respectively. Panel A presents socio-demographic characteristics taken from individual tax returns and an auxiliary survey. Panel B presents information on defaulting and credit behavior from individual credit histories. Panel C presents information from the choice experiments eliciting time preferences: the proportion that exhibits unique experimental switching points and the measured individual discount factor ($\overline{IDF}$) for those who do.

Variable	N	Mean	s.d.
Panel A: Socio-demographic variables			
Age	446	36.3	13.0
Disposable Income	446	20,114	13,827
# of Dependents	446	0.56	0.85
Gender (Male=1)	419	0.33	0.47
Race (African-American=1)	404	0.80	0.40
College Experience (=1)	384	0.58	0.49
Panel B: Defaulting behavior			
Default (=1)	446	0.49	0.50
Amount in Default	446	2,319	7,691
FICO Score	381	610	83
Non-Deferred Outstanding Balance	446	4,833	11,844
Revolving Credit Limit	446	5,778	12,826
Panel C: Time preferences			
Unique Switching Point (=1)	495	0.90	0.30
$\overline{IDF}$	446	0.86	0.15

Table 2: Time Preferences and Defaulting: This table shows results of regressions of the following form: $Defaulting_i = \beta_0 + \beta_1 \overline{IDF}_i + \gamma X_i + \epsilon_i$. Columns (1) and (2) show results of probit regressions where the dependent variable is an indicator variable which equals 1 if an individual has any amount in default and 0 otherwise. Columns (3) and (4) show results of tobit regressions using the amount in default as the dependent variable. Columns (5) and (6) show results of OLS regressions using individuals credit score (FICO) as a dependent variable. All regressions control for an individual discount factor ($\overline{IDF}$) and the year of study. Columns (2), (4) and (6) control for additional socio-demographic control variables, X_i. In those regressions, coefficients of indicators variables for missing variables on gender, race, and education are included but omitted from the table. Robust standard errors are presented in parentheses. *Level of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Probit	Tobit	Tobit	OLS	OLS
Dependent variable:	Default (=1)		Amount in Default		FICO Score	
$\overline{IDF}$	-0.858**	-0.922**	-13977.999***	-15031.214***	83.282***	75.030***
	(0.411)	(0.440)	(4284.462)	(4449.810)	(29.226)	(28.888)
Ln(Disposable Income)		0.025		315.777		7.548
		(0.053)		(607.830)		(4.749)
# of Dependents		0.097		-181.183		-4.256
		(0.079)		(805.024)		(5.417)
College Experience (=1)		0.058		1029.428		22.572**
		(0.139)		(1446.889)		(9.668)
Age		0.001		516.961*		1.700
		(0.027)		(285.428)		(1.766)
Age Squared		0.000		-5.513		-0.008
		(0.000)		(3.375)		(0.021)
Gender (Male=1)		0.145		1054.110		-15.838*
		(0.142)		(1469.639)		(9.507)
Race (African-American=1)		-0.443***		-3905.874**		12.326
		(0.157)		(1567.732)		(11.012)
Year of Study (2007=1)	-0.083	-0.118	-1516.121	-1925.744	-2.975	-11.560
	(0.144)	(0.153)	(1537.992)	(1574.902)	(9.817)	(10.120)
Constant	0.787**	0.757	10048.328**	90.024	541.198***	416.293***
	(0.391)	(0.727)	(4050.087)	(7823.391)	(27.091)	(52.443)
LL/R^2	-306.870	-300.084	-2507.198	-2499.045	0.023	0.111
# of Observations	446	446	446	446	381	381

Table 3: Time Preferences and Defaulting (Interval Regressions): This table presents interval regressions based on Stewart (1983) using the upper (IDF_{Ui}) and the lower (IDF_{Li}) bound of *IDF*s for each of the three choice sets as the dependent variable. As explanatory variables, the table uses an indicator for whether the individual has any amount in default (Columns (1) and (2)), the amount in default divided by 1000 (Columns (3) and (4)), and the FICO score divided by 10 (Columns (5) and (6)). All regressions control for the year of study and design elements of the choice sets by including indicator variables which equal 1 if the choice set involves the present, *Has Present* ($t = 0$), and if the choice set involves a six month delay, *Six Month Delay* ($\tau = 6$)). Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and indicators for missing values of gender, race, and education. Standard errors clustered on the individual level in parentheses. *Level of significance*: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Default (=1)	-0.037**	-0.037**				
	(0.018)	(0.017)				
Amount in Default/1000			-0.004***	-0.004***		
			(0.001)	(0.001)		
FICO score /10					0.003***	0.003***
					(0.001)	(0.001)
Six Month Delay (τ=6)	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Has Present (t=0)	-0.072***	-0.072***	-0.072***	-0.072***	-0.068***	-0.067***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Constant	0.856***	0.608***	0.849***	0.576***	0.628***	0.415***
	(0.015)	(0.109)	(0.014)	(0.108)	(0.076)	(0.126)
Control Variables	No	Yes	No	Yes	No	Yes
Year Control	Yes	Yes	Yes	Yes	Yes	Yes
LL	-3817.249	-3766.856	-3810.420	-3760.174	-3255.327	-3217.489
N	1338	1338	1338	1338	1143	1143
# of Individuals	446	446	446	446	381	381

Table 4: Robustness: Additional Control Variables and Sample Restrictions: This table presents robustness tests of the regressions in Table 2. Column (1) presents results of probit regressions using a dummy which equals 1 if individuals have any amount in default and 0 otherwise. Column (2) presents results of tobit regressions using amount in default as the dependent variable. Column (3) presents results of OLS regressions using FICO score as the dependent variable. Panel A adds a variable on risk attitudes to the set of control variables. 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. Panel B admits individuals without unique choice set switching points (Multiple Switching (=1)). For these individuals, $\overline{IDF}_i$ is calculated using their first switching point in each choice set. Panel C restricts the sample to individuals for whom complete socio-demographic information is available. All regressions control for the year of study. Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and dummies for missing variables on gender, race, and education. Robust standard errors are presented in parentheses. *Level of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) Probit	(2) Tobit	(3) OLS
Dependent Variable:	Default (=1)	Amount in Default	FICO Score
Control Variables	Yes	Yes	Yes
Year Control	Yes	Yes	Yes
Panel A: Including Risk Attitudes			
$\overline{IDF}$	-1.335***	-19579.199***	89.378***
	(0.482)	(5166.531)	(31.219)
Risk Attitudes (standardized)	0.024	202.727	-0.646
	(0.024)	(264.824)	(1.768)
N	387	387	329
Panel B: Including Multiple Switchers			
$\overline{IDF}$	-1.041**	-15311.102***	80.648***
	(0.431)	(4177.470)	(28.239)
Multiple Switching (=1)	-0.113	-1324.313	5.897
	(0.197)	(2076.118)	(12.512)
N	495	495	426
Panel C: Non-Missing Control Variables			
$\overline{IDF}$	-0.755	-15222.939***	78.416**
	(0.496)	(5576.535)	(33.143)
N	346	346	291

Table 5: The Effect of Credit Constraints and Buffers Against Adverse Life Events: This table shows results of tobit regressions using default balances, *Amount in Default*, as the dependent variable. In addition to individual discount factor ($\overline{IDF}$), year controls and other control variables, the regressions control for potential buffers against adverse life events. Column (1) controls for revolving credit limit and the amount of non-deferred outstanding debt (both in natural logarithm). Column (2) controls for whether individuals report having health insurance. Column (3) controls for whether individuals have at least one bank account. And column (4) controls for all variables simultaneously. Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and dummies for missing variables on gender, race, education, no insurance, and no bank account. Robust standard errors are in parentheses. *Level of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
$\overline{IDF}$	-15084.249**	-15007.389**	-14764.197**	-14831.036**
	(6981.405)	(6902.604)	(6914.410)	(6996.037)
ln(Credit Limit)	-417.117*			-409.779*
	(217.596)			(220.639)
ln(Non-deferred outstanding balance)	135.248			141.817
	(215.320)			(216.004)
No Health Insurance (=1)		-2831.513		-2949.234
		(2712.143)		(2752.122)
No Bank Account (=1)			1298.640	762.569
			(1477.021)	(1504.643)
Constant	-1186.134	71.746	-1362.696	-2073.974
	(7106.483)	(6998.249)	(7254.169)	(7348.439)
Control Variables	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
LL	-2496.736	-2498.509	-2498.626	-2495.9574
N	446	446	446	446

Table 6: Different Choice Sets and Defaulting: This table shows results of tobit regressions using default balances, $Amount\ in\ Default$, as the dependent variable. As a measure of individual discounting, the table controls for each of the three $IDF_{t,\tau}$ from the three different choice sets separately. All regressions control for the year of study. Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and indicators for missing values of gender, race, and education. Robust standard errors are presented in parentheses. *Level of significance*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

	(1)	(2)	(3)
$IDF_{t=0,\tau=1}$	-7382.782**		
	(3054.556)		
$IDF_{t=0,\tau=6}$		-19429.615**	
		(9097.119)	
$IDF_{t=6,\tau=1}$			-12205.197***
			(3130.108)
Constant	-6644.641	5611.684	-985.274
	(7402.629)	(10379.931)	(7556.227)
Year Control	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
LL	-2501.807	-2502.435	-2497.105
N	446	446	446

Table 7: Time Preferences and Defaulting One Year Later: This table shows result of regressions of the following form: $Defaulting_{i,t+1} = \beta_0 + \beta_1 \overline{IDF}_i + \gamma X_i + \ _i$. The dependent variables correspond to the information from individual credit histories one year after the choice experiments took place. Column (1) shows results of probit regressions where the dependent variable is an indicator variable which equals 1 if an individual has any amount in default and 0 otherwise. Column (2) shows results of tobit regressions using the amount in default as the dependent variable. Column (3) shows results of OLS regressions using FICO credit score as the dependent variable. Coefficients of indicators for missing values of gender, race, and education are included but omitted from the table. Robust standard errors are in parentheses. *Level of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

	(1) Probit	(2) Tobit	(3) OLS
Dependent Variable:	Default (=1)	Amount in Default	FICO Score
$\overline{IDF}$	-5.161***	-45832.782***	282.525***
	(1.603)	(12511.099)	(77.252)
Ln(Disposable Income)	-0.508**	256.215	6.314
	(0.234)	(1879.783)	(11.373)
# of Dependents	-0.421**	-5846.211***	-6.220
	(0.201)	(2068.549)	(12.090)
College Experience (=1)	0.412	-3017.140	21.416
	(0.348)	(3523.004)	(20.937)
Age	0.210**	1641.351*	2.242
	(0.093)	(833.278)	(4.810)
Age Squared	-0.002*	-19.942*	-0.006
	(0.001)	(10.633)	(0.062)
Gender (Male=1)	-0.520	-9899.437***	-31.746*
	(0.354)	(3322.404)	(18.460)
Race (African-American=1)	0.199	5323.639	-59.493**
	(0.373)	(3851.883)	(25.274)
Constant	5.388**	9844.881	285.222**
	(2.290)	(18824.489)	(111.297)
LL/R^2	-59.670	-542.403	0.274
N	105	105	95

A Appendix

A Appendix Tables

Table A1: Time Preferences and Defaulting in 2006: This table shows result of regressions of the following form: $Defaulting_i = \beta_0 + \beta_1 \overline{IDF}_i + \gamma X_i + \ _i$ for the 2006 sub-sample. Columns (1) and (2) show results of probit regressions where the dependent variable is an indicator variable which equals 1 if an individual has any amount in default and 0 otherwise. Columns (3) and (4) show results of tobit regressions using the amount in default as the dependent variable. Columns (5) and (6) show results of OLS regressions using FICO credit score as the dependent variable. All regressions control for an individual's discount factor ($\overline{IDF}$) and the year of study. Columns (2), (4) and (6) controls for additional socio-demographic control variables, X_i. Coefficients of indicators for missing values of gender, race, and education are included but omitted in the table. Robust standard errors are in parentheses. *Level of significance*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Probit	Tobit	Tobit	OLS	OLS
Dependent variable:	Default (=1)		Amount in Default		FICO Score	
$\overline{IDF}$	-4.059***	-4.012***	-34517.994***	-36054.439***	235.141***	199.448**
	(1.273)	(1.377)	(12927.555)	(12501.664)	(74.663)	(80.692)
Ln(Disposable Income)		-0.324		993.588		6.788
		(0.221)		(1891.273)		(9.751)
# of Dependents		-0.179		-3733.597*		-0.469
		(0.188)		(1917.511)		(11.329)
College Experience (=1)		0.566		-908.371		19.287
		(0.371)		(3534.602)		(20.513)
Age		-0.014		562.770		8.998*
		(0.092)		(828.916)		(5.071)
Age Squared		0.000		-6.788		-0.105
		(0.001)		(10.624)		(0.066)
Gender (Male=1)		0.201		-3915.145		-0.483
		(0.335)		(3111.836)		(17.485)
Race (African-American=1)		-0.060		2640.659		-20.588
		(0.388)		(3805.986)		(27.087)
Constant	3.690***	6.458***	28506.395**	11817.554	404.781***	210.868*
	(1.154)	(2.286)	(11528.239)	(19269.692)	(65.441)	(111.190)
LL/R^2	-64.380	-60.523	-566.991	-563.912	0.085	0.177
N	99	99	99	99	90	90

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Table A2: Time Preferences and Defaulting in 2007: This table shows result of regressions of the following form: $Defaulting_i = \beta_0 + \beta_1 \overline{IDF}_i + \gamma X_i + \ _i$ for the 2007 sub-sample. Columns (1) and (2) show results of probit regressions where the dependent variable is an indicator variable which equals 1 if an individual has any amount in default and 0 otherwise. Columns (3) and (4) show results of tobit regressions using the amount in default as the dependent variable. Columns (5) and (6) show results of OLS regressions using FICO credit score as the dependent variable. All regressions control for an individual's discount factor ($\overline{IDF}$) and the year of study. Columns (2), (4) and (6) controls for additional socio-demographic control variables, X_i. Coefficients of indicators for missing values of gender, race, and education are included but omitted in the table. Robust standard errors are in parentheses. *Level of significance*: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Probit	Tobit	Tobit	OLS	OLS
Dependent variable:	Default (=1)		Amount in Default		FICO Score	
$\overline{IDF}$	-0.546	-0.627	-11438.304**	-12209.918**	64.236**	56.842*
	(0.432)	(0.474)	(4552.642)	(4744.792)	(31.178)	(31.027)
Ln(Disposable Income)		0.060		330.098		7.051
		(0.054)		(642.924)		(5.063)
# of Dependents		0.172*		625.941		-6.511
		(0.092)		(881.385)		(6.298)
College Experience (=1)		-0.008		1161.005		22.542**
		(0.155)		(1592.361)		(10.959)
Age		0.014		588.377*		0.669
		(0.030)		(313.361)		(1.899)
Age Squared		-0.000		-6.037*		0.004
		(0.000)		(3.641)		(0.022)
Gender (Male=1)		0.132		2046.323		-19.107*
		(0.163)		(1654.462)		(11.339)
Race (African-American=1)		-0.470**		-4663.142**		15.580
		(0.183)		(1802.773)		(12.613)
Constant	0.439	-0.201	6373.952	-6512.935	554.354***	445.617***
	(0.374)	(0.799)	(3907.574)	(8651.784)	(26.658)	(59.001)
LL/R^2	-239.648	-230.446	-1938.733	-1928.914	0.015	0.119
N	347	347	347	347	291	291

Table A3: Time Preference Intervals and Defaulting: This table presents interval regressions based on Stewart (1983) using the upper (IDF_{Ui}) and the lower (IDF_{Li}) bound of *IDF*s for each of the three choice sets as the dependent variable. As explanatory variables, the table uses an indicator for whether the individual has any amount in default (Columns (1) and (2)), the amount in default divided by 1000 (Columns (3) and (4)), and the FICO score divided by 10 (Columns (5) and (6)). All regressions control for the year of study and design elements of the choice sets by including indicator variables which equal 1 if the choice set involves the present, $Has\ Present$ ($t = 0$), and if the choice set involves a six month delay, $Six\ Month\ Delay$ ($\tau = 6$)). Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and indicators for missing values of gender, race, and education. Standard errors clustered on the individual level in parentheses. *Level of significance*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)
Amount in Default (=1)	-0.037**		
	(0.017)		
Amount in Default/1000		-0.004***	
		(0.001)	
FICO score /10			0.003***
			(0.001)
Six Months Delay (τ=6)	0.027***	0.027***	0.027***
	(0.002)	(0.002)	(0.002)
Has Present (t=0)	-0.072***	-0.072***	-0.067***
	(0.010)	(0.010)	(0.011)
Ln(Disposable Income)	0.031***	0.030***	0.027**
	(0.010)	(0.010)	(0.011)
# of Dependents	-0.002	-0.006	-0.005
	(0.011)	(0.011)	(0.012)
College Experience (=1)	0.039*	0.039*	0.028
	(0.020)	(0.020)	(0.023)
Age	-0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)
Age Squared	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Gender (Male=1)	-0.059***	-0.059***	-0.063***
	(0.020)	(0.020)	(0.023)
Race (African-American=1)	-0.018	-0.015	-0.028
	(0.021)	(0.021)	(0.023)
Constant	0.608***	0.576***	0.415***
	(0.109)	(0.108)	(0.126)
Year Dummy	Yes	Yes	Yes
LL	-3766.856	-3760.174	-3217.489
N	1338	1338	1143
# of Individuals	446	446	381

Table A4: The Effect of Buffers Against Adverse Life Events on Various Defaulting Outcomes: This table shows in Panel A results of probit regressions with an indicator dependent variable which equals 1 if individuals have any amount in default and 0 otherwise. Panel B presents results of OLS regressions using FICO score as the dependent variable. In addition to individual discount factor ($\overline{IDF}$), year controls and other control variables, the regressions control for potential buffers against adverse life events. Column (1) controls for revolving credit limit and the amount of non-deferred outstanding debt (both in natural logarithm). Column (2) controls for whether individuals report having health insurance. Column (3) controls for whether individuals have at least one bank account. And column (4) controls for all variables simultaneously. Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and dummies for missing variables on gender, race, education, no insurance, and no bank account. Robust standard errors are in parentheses. *Level of significance*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

	(1)	(2)	(3)	(4)
Year Control	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Panel A: Default (=1); Probit Regressions				
$\overline{IDF}$	-0.915**	-0.922**	-0.869**	-0.883*
	(0.447)	(0.441)	(0.442)	(0.451)
ln(Credit Limit)	-0.073***			-0.071***
	(0.020)			(0.020)
ln(Non-deferred outstanding balance)	-0.006			-0.006
	(0.019)			(0.019)
No Health Insurance (=1)		-0.303		-0.333
		(0.266)		(0.272)
No Bank Account (=1)			0.289*	0.162
			(0.167)	(0.173)
N	446	446	446	446
Panel B: FICO Score; OLS Regressions				
$\overline{IDF}$	63.019**	75.255***	71.987**	61.345**
	(26.055)	(28.824)	(28.255)	(25.639)
ln(Credit Limit)	10.095***			9.729***
	(1.230)			(1.242)
ln(Non-deferred outstanding balance)	-1.811			-1.963
	(1.226)			(1.236)
No Health Insurance (=1)		21.180		23.121
		(20.287)		(15.924)
No Bank Account (=1)			-44.726***	-27.780***
			(10.483)	(9.752)
N	381	381	381	381

Table A5: Different Choice Sets and Various Defaulting Outcomes: This table shows in Panel A results of probit regressions with an indicator dependent variable which equals 1 if individuals have any amount in default and 0 otherwise. Panel B presents results of OLS regressions using FICO score as the dependent variable. As a measure of individual discounting, the table controls for each of the three $IDF_{t,\tau}$ from the three different choice sets separately. All regressions control for the year of study. Control variables include ln(disposable income), number of dependents, age, age squared, gender, race, college experience, and indicators for missing values of gender, race, and education. Robust standard errors are presented in parentheses. *Level of significance*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)
Control Variables	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes
Panel A: Default (=1); Probit Regressions			
$IDF_{t=0,\tau=1}$	-0.305		
	(0.295)		
$IDF_{t=0,\tau=6}$		-1.016	
		(0.871)	
$IDF_{t=6,\tau=1}$			-0.946***
			(0.317)
N	446	446	446
Panel B: FICO Score; OLS Regressions			
$IDF_{t=0,\tau=1}$	45.388**		
	(19.365)		
$IDF_{t=0,\tau=6}$		92.068	
		(57.810)	
$IDF_{t=6,\tau=1}$			52.854***
			(20.167)
N	381	381	381

B Instructions of Study 1 (2006)

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

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

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

[Block 3; $t = 6$, $\tau = 1$]: 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**

C Instructions of Study 2 (2007)

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

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

RED BLOCK (Numbers 1 through 7): Decide between payment **today** and payment in **one month**
BLACK BLOCK (Numbers 8 through 15): Decide between payment **today** and payment in **six months**
BLUE BLOCK (Numbers 16 through 22): Decide between payment in **six months** and payment in **seven months**

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

[Red Block; $t = 0$, $\tau = 1$]
TODAY VS. ONE MONTH FROM TODAY WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 1 AND 7? Decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **one month**? Please answer for each possible number (1) through (7) by filling in one box for each possible number.
Example: If you prefer $49 today in Question 1 mark as follows: ✓ $49 today or $50 in one month
If you prefer $50 in one month in Question 1, mark as follows: $49 today or ✓ $50 in one month
If you get number (1): Would you like to receive $49 **today** or $50 in **one month**
If you get number (2): Would you like to receive $47 **today** or $50 in **one month**
If you get number (3): Would you like to receive $44 **today** or $50 in **one month**
If you get number (4): Would you like to receive $40 **today** or $50 in **one month**
If you get number (5): Would you like to receive $35 **today** or $50 in **one month**
If you get number (6): Would you like to receive $29 **today** or $50 in **one month**
If you get number (7): Would you like to receive $22 **today** or $50 in **one month**

[Black Block; $t = 0$, $\tau = 6$]
TODAY VS. SIX MONTHS FROM TODAY WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 8 AND 15? Now, decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **six months**? Please answer each possible number (8) through (15) by filling in one box for each possible number.
If you get number (8): Would you like to receive $49 **today** or $50 in **six months**
If you get number (9): Would you like to receive $47 **today** or $50 in **six months**
If you get number (10): Would you like to receive $44 **today** or $50 in **six months**
If you get number (11): Would you like to receive $40 **today** or $50 in **six months**
If you get number (12): Would you like to receive $35 **today** or $50 in **six months**
If you get number (13): Would you like to receive $29 **today** or $50 in **six months**
If you get number (14): Would you like to receive $22 **today** or $50 in **six months**
If you get number (15): Would you like to receive $14 **today** or $50 in **six months**

[Blue Block; $t = 6$, $\tau = 1$]
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**