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Present-Biased Preferences and Credit Card Borrowing†

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Some individuals borrow extensively on their credit cards. This paper tests whether present-biased time preferences correlate with credit card borrowing. In a field study, we elicit individual time preferences with incentivized choice experiments, and match resulting time preference measures to individual credit reports and annual tax returns. The results indicate that present-biased individuals are more likely to have credit card debt, and to have significantly higher amounts of credit card debt, controlling for disposable income, other socio-demographics, and credit constraints. (*JEL* D12, D14, D91)

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

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

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

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

A second approach measures individual time preferences directly with choice experiments, and correlates these measures to *self-reported* credit balances or spending problems. Glenn W. Harrison, Morten I. Lau, and Melonie B. Williams (2002) find that individual long-run discount factors do not correlate with borrowing behavior, though their study says nothing about the association between present bias and credit card borrowing.[3] Using measurement techniques similar to our own, Thomas Dohmen et al. (2006) show that present-biased individuals report having more problems restricting their spending.[4] Though these studies provide important indications that exponential discount factors alone do not correlate with borrowing, or that present bias is associated with spending problems, the accuracy of the self-reported measures from these studies is particularly difficult to assess. People generally either underreport their debt levels or lie altogether (for details, see David B. Gross and Nicholas S. Souleles 2002; Karlan and Zinman 2008; Zinman 2009). It is therefore critical to analyze objective data on credit card borrowing.

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

[2] Another set of studies show behavioral patterns in field data consistent with present-biased preferences (e.g., Dan Ariely and Klaus Wertenbroch 2002; Xavier Gine, Dean Karlan, and Jonathan Zinman 2008; Sharon M. Oster and Fiona M. Scott Morton 2005).

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

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

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

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

The paper proceeds as follows. Section I discusses the design of the field study, our methodology for eliciting time preferences, and the data. Section II presents results, and Section III concludes.

I. Data

A. *Field Study Design*

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

We obtained consent from all participants to access their credit reports and to retrieve income information from their tax returns. Additionally, we surveyed participants to obtain certain socio-demographic characteristics (most likely measured with more error than information from tax data), and elicited their time preferences using incentivized choice experiments. We obtain a usable measure of time

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

preferences for 541 of the 606 individuals who participated (see Section IC for details). These individuals represent our primary study sample.

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

As the summary statistics indicate, study participants were largely LMI/subprime borrowers. This nonstandard subject pool is of particular interest, as the less secure position of LMI and subprime households puts them at great financial risk (see Marianne Bertrand, Sendhil Mullainathan, and Eldar Shafir 2004). There are also very few experimental studies focusing solely on the behavior of LMI families in developed countries (an exception is Catherine Eckel, Cathleen Johnson, and Claude Montmarquette 2005). When interpreting the magnitudes of the presented results, the low income of participants should be taken into account. As in many experimental and survey studies, individuals select to come to the VITA sites and participate in our study. As we show in Meier and Sprenger (2008), study participants are more financially literate and more patient than individuals at the VITA site who elect not to participate. Though the direction of any potential bias is difficult to assess, one should keep the selection of the sample in mind when generalizing the results of this study.

B. *Credit Bureau Data*

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

We measure credit card borrowing as outstanding balances on revolving accounts.[8] Panel B of Table 1 illustrates the two stylized facts of credit card borrowing previously noted: high borrowing and substantial debt heterogeneity. The average credit card

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

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

[8] Though balances listed on credit reports are point-in-time measures, we argue that our borrowing measures closely reflect revolving balances and not convenience charges. In general, only around 5–10 percent of total balances are convenience charges (Kathleen W. Johnson 2004). Additionally, we implemented a companion survey with questions on credit card bill payment habits as worded in the Survey of Consumer Finances ($N = 174$). Individuals who report normally paying the full amount on their credit card at the end of the month (21 percent of the sample), have significantly lower balances on revolving accounts ($1,093 versus $3,086; $p < 0.05$ in a t-test).

Table 1—Summary Statistics

	All participants (1)	Primary sample (2)	Present-biased (3)	Not present-biased (4)
Panel A. Socio-demographic variables				
Age	35.8	35.9	33.8	37.1
	(13.8)[606]	(13.4)[541]	(12.9)[194]	(13.5)[347]
Gender (male=1)	0.36	0.35	0.41	0.32
	(0.48)[569]	(0.48)[510]	(0.49)[185]	(0.47)[325]
Race (African American=1)	0.80	0.80	0.81	0.79
	(0.40)[548]	(0.40)[491]	(0.39)[178]	(0.41)[313]
College experience (=1)	0.51	0.52	0.62	0.45
	(0.50)[522]	(0.50)[465]	(0.49)[173]	(0.50)[292]
Disposable income	18,084	18,516	17,361	19,162
	(13,695)[606]	(13,692)[541]	(14,151)[194]	(13,407)[347]
Dependents	0.51	0.52	0.41	0.58
	(0.84)[606]	(0.84)[541]	(0.72)[194]	(0.89)[347]
Panel B. Credit information				
Debt (=1)	0.41	0.41	0.45	0.39
	(0.49)[606]	(0.49)[541]	(0.50)[194]	(0.49)[347]
Revolving balance	1,162	1,059	1,565	776
	(2,838)[606]	(2,414)[541]	(3,216)[194]	(1,761)[347]
Having a revolving account (=1)	0.53	0.53	0.54	0.52
	(0.50)[606]	(0.50)[541]	(0.50)[194]	(0.50)[347]
Revolving credit limit	4,741	4,764	5,129	4,560
	(11,705)[606]	(11,850)[541]	(12,440)[194]	(11,520)[347]
FICO score	611	610	608	610
	(84)[437]	(84)[390]	(80)[133]	(86)[257]
Panel C. Time preferences				
IDF	0.84	0.83	0.85	0.81
	(0.19)[606]	(0.19)[541]	(0.11)[194]	(0.23)[347]
Present bias (=1)	0.36	0.36	1	0
	(0.48)[606]	(0.48)[541]	(0)[194]	(0)[347]
Future bias (=1)	0.11	0.09	0	0.14
	(0.31)[606]	(0.28)[541]	(0)[194]	(0.35)[347]

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

balance is $1,059 (*standard deviation* (SD) $2,414), with 40 percent of participants carrying credit balances.

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

C. *Measuring Time Preferences*

Methodology.—Individual time preferences are measured using incentivized choice experiments. (For similar approaches, see Maribeth Coller and Williams 1999; Harrison, Lau, and Williams 2002; McClure et al. 2004; Tomomi Tanaka, Colin Camerer, and Quang Nguyen 2007. For a survey on measuring time preferences, see Shane Frederick, Loewenstein and O'Donoghue 2002.) We analyze decisions from two multiple price lists in which individuals are asked to make a series of choices between a smaller reward ($\$X$) in period t and a larger reward ($\$Y > \$X$) in period τ. We keep $\$Y$ constant and vary $\$X$ in two time frames. In time frame 1, t is the present ($t = 0$) and τ is in one month ($\tau = 1$); and in time frame 2, t is six months from the study date ($t = 6$) and τ is seven months from the study date ($\tau = 7$).[9] The delay length, d, is one month in both time frames.

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

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

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

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

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

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

- *Individual discount factor* (*IDF*): We estimate monthly *IDF*s by observing the point in a given price list, X^*, at which individuals switch from opting for the smaller, earlier payment to opting for the larger, later payment. That is, a discount factor is taken from the last point at which an individual prefers the earlier, smaller payment, assuming that $X^* \approx IDF^d \times Y$, where d represents the delay length.[11] As the delay length, d, is one month for the time frames analyzed here, $IDF \approx (X^*/Y)^{1/1}$. For example, if an individual prefers \$75 today over \$80 in one month, but prefers \$80 in one month over \$70 today, then we take \$75 as the switching point and calculate the monthly discount factor as $(75/80)^{1/1} = 0.94$.[12] Making these calculations for the two multiple price lists yields two discount measures, $IDF_{t,\tau}$: $IDF_{0,1}$, $IDF_{6,7}$. We use the average of these calculated monthly discount factors as the *IDF* in the main analysis.

- *Present bias and future bias*: Using two time frames allows us to identify dynamic inconsistency. Dynamically inconsistent individuals exhibit a bias toward either present or future payments. An individual is present-biased if he is less patient (lower IDF) when the smaller, earlier payment is received in the present ($t = 0$). We classify an individual as present-biased if $IDF_{0,1} < IDF_{6,7}$, and

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

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

as future-biased if $IDF_{0,1} > IDF_{6,7}$. For our primary analysis, we use indicator variables *Present Bias* (=1) and *Future Bias* (=1) following these classifications.

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

In order to have useable measures of *IDF* and dynamic inconsistency, an individual must exhibit a unique switching point in each price list. In both years, about 11 percent of participants do not exhibit unique switching points. In the main analysis, we focus on a primary sample of the 541 individuals who do show unique switching points in all price lists. When we include individuals with multiple switching points in a robustness test, by using their first switching point, the results are maintained (see Section IB).

For participants in the primary sample (column 2 of Table 1), we measure a monthly discount factor, *IDF*, of 0.83 as shown in panel C of Table 1. This discount factor is low, but consistent with previous research, which tends to find low discount factors in experimental studies (see Frederick, Loewenstein, and O'Donoghue 2002). Decisions on payday loans or used cars often imply much lower discount factors for subprime borrowers than measured by our experiment (e.g., Skiba and Tobacman 2007; William Adams, Liran Einav, and Jonathan Levin 2009). Thirty-six percent of study participants are classified as present-biased, and 9 percent are classified as future-biased. Dohmen et al. (2006) find a similar proportion of present-biased individuals in their sample (28 percent), but more future-biased individuals (38 percent). Our levels of dynamic inconsistency are somewhat more comparable to Ashraf, Karlan, and Yin (2006) who classify 27.5 (19.8) percent of their sample as present (future)-biased.

D. *Measurement Validation*

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

The impact of extra-experimental borrowing and lending opportunities can be seen as an arbitrage argument. If an individual can borrow at a lower interest rate than the experimentally offered rate, then the individual should wait for later experimental payments, borrow outside the experiment, and repay with experimental earnings, thereby arbitraging the experiment with a "borrow low–save high" strategy. If an individual can lend (save) at a higher rate than the experimentally offered rate, a second arbitrage strategy is open, and the individual should take the earlier experimental payment and invest it at the available higher rate.

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

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

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

Table 2 presents regressions using measured time preferences as the dependent variables. Columns 1 and 2 present OLS models in which the dependent variable is the average discount factor measure (*IDF*). Columns 3 and 4 present interval regressions (Mark B. Stewart 1983) in which the dependent variable is the interval measure of an $IDF_{t,\tau}$. Columns 5 and 6 present OLS regressions in which *Present Bias* (=1) is the dependent variable. In each specification, we control for basic demographic characteristics of age, gender, and race. Columns 2, 4, and 6 additionally control for credit constraints (measured as the amount of available credit), for future

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

Table 2—Time Preferences

	IDF		Interval of $IDF_{t,\tau}$		*Present bias* (=1)	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Age	−0.002***	−0.002**	−0.002***	−0.002**	−0.005***	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Gender (male=1)	−0.057***	−0.057***	−0.070***	−0.070***	0.092**	0.076
	(0.018)	(0.019)	(0.022)	(0.023)	(0.045)	(0.049)
Race (African American=1)	−0.010	−0.013	−0.011	−0.015	0.031	0.028
	(0.020)	(0.019)	(0.024)	(0.023)	(0.049)	(0.049)
ln(disposable income)		0.023***		0.030**		−0.023
		(0.009)		(0.012)		(0.020)
Dependents		−0.008		−0.009		0.009
		(0.014)		(0.017)		(0.035)
College experience (=1)		0.042**		0.050**		0.181***
		(0.018)		(0.022)		(0.048)
ln(credit amount available)		0.004*		0.005*		−0.000
		(0.003)		(0.003)		(0.007)
Tax refund(liability) amount		0.000		0.000		−0.000*
		(0.000)		(0.000)		(0.000)
Direct deposit of refund (=1)		0.023		0.028		−0.026
		(0.016)		(0.020)		(0.043)
Insufficient credit to be scored (=1)		0.040*		0.048*		0.080
		(0.021)		(0.025)		(0.054)
Loan accounts		−0.001		−0.002		0.003
		(0.001)		(0.002)		(0.003)
Has present (=1)			−0.079***	−0.079***		
			(0.009)	(0.009)		
Constant	0.975***	0.697***	0.993***	0.647***	0.441***	0.539***
	(0.029)	(0.085)	(0.035)	(0.108)	(0.077)	(0.202)
R^2/log-likelihood	0.07	0.12	−2,928.99	−2,904.62	0.03	0.07
Observations	541	541	1,082	1,082	541	541
Individuals	541	541	541	541	541	541

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

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

liquidity (measured as future tax refund quantity and whether or not it will be direct deposited), and for credit experience proxies (measured as whether credit history is sufficient to receive a FICO credit score and the number of credit history loan accounts). In columns 2, 4, and 6, we also control for potentially endogenous demographics: income, number of dependents, and education. In the interval regression, whether or not the price list involves the present, *Has Present* (=1), is also controlled for, and standard errors are clustered on the individual level.

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

Table 2 also presents results relevant for the general discussion of time preferences and socio-demographic characteristics (see Harrison, Lau, and Williams 2002). Age is found to be negatively correlated with discount factors and whether or not individuals exhibit present bias. Men, though they have significantly lower discount factors than women, are equally likely to be present-biased. Individuals with higher income have higher measured discount factors, but are no more likely to be present-biased than others, while individuals of higher education have somewhat higher measured discount factors and are significantly more likely to be present-biased. The observed correlation between education and present bias seems counterintuitive and requires attention in future research. Interestingly, the results of the interval regressions in columns 2 and 3 support the claim that individuals, on average, discount nonexponentially. Measured discount factors decrease when the present is involved, a pattern consistent with present-biased preferences (Frederick, Loewenstein, and O'Donoghue 2002).

II. Results

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

$$(1) \qquad \mathit{Borrowing}_i = \alpha + \gamma_1 \mathit{IDF}_i + \gamma_2 \mathit{PresentBias}_i + \gamma_3 \mathit{FutureBias}_i + \gamma_4 Y_i + \gamma_5 \mathbf{X}_i + \varepsilon_i.$$

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

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

[14] *IDF* and *PresentBias*(=1) are also found to be uncorrelated with credit constraints in regressions in which credit card holdership and available credit limits are the dependent variables (results available on request).

Table 3—Present-Biased Preferences and Credit Card Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
IDF	1,591.4	1,653.3	413.2	2,998.2	247.2	520.3
	(1,167.4)	(1,181.2)	(1,183.5)	(3,978.8)	(844.4)	(1,095.3)
	[0.13; 477.9]	[0.14; 494.7]	[0.04; 121.2]	[0.26; 1,019.1]	[0.02; 53.2]	[0.05; 141.6]
Present bias (=1)	1,304.4**	1,611.0***	1,779.4***	2,885.3**	1,874.0***	2,013.6***
	(508.3)	(516.4)	(518.8)	(1255.8)	(402.9)	(492.2)
	[0.11; 402.2]	[0.14; 498.7]	[0.16; 542.9]	[0.25; 1047.1]	[0.20; 430.1]	[0.20; 576.5]
Future bias (=1)	−270.5	−48.0	−487.9	−389.4	−315.5	−689.8
	(811.7)	(786.6)	(776.5)	(1,341.0)	(666.9)	(732.1)
	[−0.02; −80.0]	[−0.004; −14.3]	[−0.04; −139.0]	[−0.03; −130.1]	[−0.03; −66.1]	[−0.06; −179.4]
Constant and year of study	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous control variables	No	Yes	Yes	Yes	Yes	Yes
Other socio-demographics	No	No	Yes	Yes	Yes	Yes
Credit card information	No	No	No	No	Yes	No
FICO score information	No	No	No	No	No	Yes
For reference group (Present Bias (=0) and Future Bias (=0)):						
Mean of DV	786.8	786.8	786.8	1,027.7	786.8	786.8
Mean of DV (if uncensored)	2,028.1	2,028.1	2,028.1	2,055.4	2,028.1	2,028.1
LL	−2,351.4	−2,340.5	−2,321.2	−663.34	−2,121.7	−2,259.8
Observations	541	541	541	122	541	541

Notes: Dependent variable: Outstanding balance on revolving accounts. In column 4, the dependent variable is the outstanding balance on revolving accounts one year after the experiment for the 2006 sample. Coefficient of tobit regressions. Robust standard errors are in parentheses. Marginal effects are in brackets [probability to be censored at 0; expected value of the dependent variable conditional on being uncensored]. *Exogenous control variables*: age, gender, race, and dummies for missing values. *Other socio-demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Credit card information*: dummy for having a revolving account and ln(credit limit). *FICO score information*: FICO score and a dummy for missing score.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

A. *Present Bias and Credit Card Borrowing*

Table 3 presents results from tobit regressions in which the dependent variable is total outstanding credit card balances. Column 1 presents results without control variables. To this basic specification, in column 2, we add exogenous control variables: age, gender, and race. Column 3 adds further socio-demographics which may be correlated with time preferences: income, number of dependents, and college experience. Across specifications, present-biased individuals are found to have substantially higher credit card balances. Controlling for demographics, the estimated relationship between present bias and card borrowing is economically important, given participants' low incomes, and statistically significant at the 99 percent level. Similar to Harrison, Lau, and Williams (2002), the results show that *IDF*s are not significantly correlated with credit card debt levels.[15]

Marginal effects computed from the tobit model, in column 3, indicate that present-biased individuals are more likely to borrow, and borrow more than dynamically

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

consistent individuals. Present bias is associated with a 16 percentage point increase in the probability of borrowing, and, conditional on borrowing, about $540 more debt. Examining the average balance on revolving accounts for the reference group (see bottom of Table 3) indicates that this $540 translates into approximately 27 percent higher credit card balances for present-biased individuals.[16]

In this study, time preferences and credit card debt are point-in-time measures. Recent shocks could potentially influence both card borrowing and measured preferences. A negative shock could increase credit card debt, and, if individuals were sufficiently liquidity constrained, could also impact measured preferences (see Meier and Sprenger (2009) for evidence that measured time preferences are stable over time and uncorrelated with changes in income or employment status). For this reason, we obtained the consent of the 2006 sample participants to analyze their credit report again in 2007.[17] Column 4 presents this follow-up analysis. Tobit models are estimated with the dependent variable of credit card borrowing observed one year after the original time preference experiment. The results indicate that present bias remains substantially and significantly correlated with card borrowing even one year after time preferences are measured. Present-biased individuals are, again, found to be more likely to borrow, and borrow more than dynamically consistent individuals. This follow-up analysis suggests that recent short-lived shocks are not driving the correlation between present bias and credit card debt.

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

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

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

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

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

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

FICO scores.[20] Controlling for FICO scores as a proxy for interest rates, present bias is associated with both a higher probability of borrowing and conditionally more debt.

In sum, the results indicate that individuals who exhibit present bias are between 15 and 20 percentage points more likely to borrow on their credit cards. Conditional upon borrowing, present-biased individuals have around \$400–\$580 (about 25 percent) more debt than dynamically consistent individuals. The relationship between present bias and credit card debt is maintained when controlling for demographics, credit constraints (both credit access and limits), and a proxy for interest rates. One year after the original time preference experiment, present bias remains significantly correlated with card borrowing.

B. *Robustness Tests*

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

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

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

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

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

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

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

Table 4—Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)
$IDF_{6,7}/IDF_{0,1}$	1,264.1**					
	(607.6)					
β		−2,516.6**				
		(1,019.4)				
δ		888.5				
		(1,190.4)				
$\overline{IDF}$			113.8			
			(1,533.5)			
$\overline{PresentBias}$ (=1)			1,588.6***			
			(581.3)			
$\overline{FutureBias}$ (=1)			273.9			
			(1,156.3)			
IDF				−533.6	1,804.6	528.5
				(1,281.1)	(1,360.7)	(1,426.3)
Present bias (=1)				1,895.0***	1,681.9***	1,418.1**
				(558.3)	(561.9)	(596.4)
Future bias (=1)				−308.4	−54.0	−1,086.1
				(818.8)	(801.1)	(844.7)
Constant and year of study	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous control variables	Yes	Yes	Yes	Yes	Yes	Yes
Other socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Risk attitudes	No	No	No	Yes	No	No
Including multiple switchers	No	No	No	No	Yes	No
Non-missing control variables	No	No	No	No	No	Yes
LL	−2,327.78	−2,325.60	−2,324.70	−2,033.28	−2,659.19	−1,797.90
Observations	541	541	541	463	606	420

Notes: Dependent variable: Outstanding balance on revolving accounts. Coefficient of tobit regressions. Robust standard errors are in parentheses. *Exogenous control variables*: age, gender, race, and dummies for missing values. *Other socio-demographics*: ln(disposable income), number of dependents, college experience, and a dummy for missing information for education. *Risk attitudes*: based on question *"How willing are you to take risks in general? (on a scale from 0 "unwilling" to 7 (in 2006) or 10 (in 2007) "fully prepared")*. The answers are rescaled to be on an 11-point scale for both years.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Column 6 excludes all individuals for whom any demographic control variables are missing, and the results do not change substantially.

III. Conclusions

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

We find that present-biased individuals are more likely to borrow and, conditionally, borrow more than dynamically consistent individuals. The relationship between present bias and credit card debt is maintained when controlling for demographics, credit constraints (both access and limits), and a proxy for interest rates. One year after the original time preference experiment, present bias remains significantly correlated with card borrowing. The results are unaffected by changes in the calculation of present bias or sample selection criteria.

The finding that directly measured present bias correlates with credit card borrowing gives critical support to behavioral economics models of present-biased preferences in consumer choice. This paper opens up a number of avenues for future research. First, the results presented here are correlative. Future research should focus on the more difficult problem of exploring the theoretically proposed *causal* link between present bias and borrowing. Second, our efforts focus exclusively on credit card borrowing and not other forms of debt (e.g., installment loans, mortgages, etc.). Credit card debt is identified as being psychologically different from other forms of debt (e.g., Drazen Prelec and Duncan Simester 2001), and, so, future work should determine whether or not our results extend to other borrowing behavior. Third, our analysis shows nothing with regard to the discussion of sophistication and naïvete in present bias. A number of policy implications with regard to card borrowing depend critically on borrower sophistication (see, for example, Colin Camerer et al. 2003). Research should investigate which present-biased consumers are and are not cognizant of their own present bias.

REFERENCES

Adams, William, Liran Einav, and Jonathan Levin. 2009. "Liquidity Constraints and Imperfect Information in Subprime Lending." *American Economic Review*, 99(1): 49–84.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and Elisabet E. Rutström. 2008. "Eliciting Risk and Time Preferences." *Econometrica*, 76(3): 583–618.

Ariely, Dan, and Klaus Wertenbroch. 2002. "Procrastination, Deadlines, and Performance: Self-Control by Precommitment." *Psychological Science*, 13(3): 219–24.

Ashraf, Nava, Dean Karlan, and Wesley Yin. 2006. "Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines." *Quarterly Journal of Economics*, 121(2): 635–72.

Avery, Robert B., Paul S. Calem, Glenn B. Canner, and Raphael W. Bostic. 2003. "An Overview of Consumer Data and Credit Reporting." *Federal Reserve Bulletin*, 89(2): 47–73.

Bernheim, B. Douglas, and Antonio Rangel. 2004. "Addiction and Cue-Triggered Decision Processes." *American Economic Review*, 94(5): 1558–90.

Bertaut, Carol, Michael Haliassos, and Michael Keiter. 2009. "Credit Card Debt Puzzles and Debt Revolvers for Self Control." *Review of Finance*. 13(4): 657–92.

Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir. 2004. "A Behavioral-Economics View of Poverty." *American Economic Review*, 94(2): 419–23.

Camerer, Colin, Samuel Issacharoff, George Loewenstein, Ted O'Donoghue, and Matthew Rabin. 2003. "Regulation for Conservatives: Behavioral Economics and the Case for 'Asymmetric Paternalism.'" *University of Pennsylvania Law Review*, 151(1): 1211–54.

Chabris, Christopher F., David Laibson, Carrie L. Morris, Jonathon P. Schuldt, and Dmitry Taubinsky. 2008. "Measuring Intertemporal Preferences Using Response Times." National Bureau of Economic Research Working Paper 14353.

Coller, Maribeth, and Melonie B. Williams. 1999. "Eliciting Individual Discount Rates." *Experimental Economics*, 2(2): 107–27.

Cubitt, Robin P., and Daniel Read. 2007. "Can Intertemporal Choice Experiments Elicit Time Preferences for Consumption?" *Experimental Economics*, 10(4): 369–89.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. 2006. "Dynamic Inconsistency Predicts Self-Control Problems in Humans." Unpublished.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner. Forthcoming. "Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey." *Journal of the Economic Association*.

Eckel, Catherine, Cathleen Johnson, and Claude Montmarquette. 2005. "Saving Decisions of the Working Poor: Short- and Long-Term Horizons." In *Field Experiments in Economics*, Vol. 10, ed. Jeffrey P. Carpenter, Glenn W. Harrison, and John A. List, 219–60. Greenwich, CT: JAI Press.

Fehr, Ernst. 2002. "The Economics of Impatience." *Nature*, 415(6869): 269–72.

Frederick, Shane, George Loewenstein, and Ted O'Donoghue. 2002. "Time Discounting and Time Preference: A Critical Review." *Journal of Economic Literature*, 40(2): 351–401.

Fudenberg, Drew, and David K. Levine. 2006. "A Dual-Self Model of Impulse Control." *American Economic Review*, 96(5): 1449–76.

Furletti, Mark. 2003. "Credit Card Pricing Developments and Their Disclosure." Federal Reserve Bank of Philadelphia Payment Cards Center Discussion Paper 03–02.

Gine, Xavier, Dean Karlan, and Jonathan Zinman. 2008. "Put Your Money Where Your Butt Is: A Commitment Contract for Smoking Cessation." Unpublished.

Gross, David B., and Nicholas S. Souleles. 2002. "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data." *Quarterly Journal of Economics*, 117(1): 149–85.

Gul, Faruk, and Wolfgang Pesendorfer. 2001. "Temptation and Self-Control." *Econometrica*, 69(6): 1403–35.

Harrison, Glenn W., Morten I. Lau, and Melonie B. Williams. 2002. "Estimating Individual Discount Rates in Denmark: A Field Experiment." *American Economic Review*, 92(5): 1606–17.

Harrison, Glenn W., Morten Igel Lau, Elisabet E. Rutström, and Melonie B. Sullivan. 2005. "Eliciting Risk and Time Preferences Using Field Experiments: Some Methodological Issues." In *Field Experiments in Economics*, Vol. 10, ed. Jeffrey P. Carpenter, Glenn W. Harrison, and John A. List, 125–218. Greenwich, CT: JAI Press.

Heidhues, Paul, and Botond Kőszegi. Forthcoming. "Exploiting Naivete about Self-Control in the Credit Market." *American Economic Review*.

Johnson, Kathleen W. 2004. "Convenience or Necessity? Understanding the Recent Rise in Credit Card Debt." Board of Governors of the Federal Reserve System Finance and Economics Discussion Series 2004–47.

Karlan, Dean, and Jonathan Zinman. 2008. "Lying About Borrowing." *Journal of the European Economic Association*, 6(2–3): 510–21.

Laibson, David. 1997. "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics*, 112(2): 443–77.

Laibson, David, Andrea Repetto, and Jeremy Tobacman. 2008. "Estimating Discount Functions with Consumption Choices over the Lifecycle." Unpublished.

Loewenstein, George, and Ted O'Donoghue. 2004. "Animal Spirits: Affective and Deliberative Processes in Economic Behavior." Unpublished.

McClure, Samuel M., David I. Laibson, George Loewenstein, and Jonathan D. Cohen. 2004. "Separate Neural Systems Value Immediate and Delayed Monetary Rewards." *Science*, 306(5695): 503–07.

McClure, Samuel M., Keith M. Ericson, David I. Laibson, George Loewenstein, and Jonathan D. Cohen. 2007. "Time Discounting for Primary Rewards." *Journal of Neuroscience*, 27(21): 5796–5804.

Meier, Stephan, and Charles Sprenger. 2008. "Discounting Financial Literacy: Time Preferences and Participation in Financial Education Programs." Unpublished.

Meier, Stephan, and Charles Sprenger. 2009. "Stability of Time Preferences." Unpublished.

O'Donoghue, Ted, and Matthew Rabin. 1999. "Doing It Now or Later." *American Economic Review*, 89(1): 103–24.

Oster, Sharon M., and Fiona M. Scott Morton. 2005. "Behavioral Biases Meet the Market: The Case of Magazine Subscription Prices." *B. E. Journal of Economic Analysis and Policy: Advances in Economic Analysis and Policy*, 5(1): 1–30.

Phelps, Edmund S., and Robert A. Pollak. 1968. "On Second-Best National Saving and Game-Equilibrium Growth." *Review of Economic Studies*, 35(3): 185–199.

Prelec, Drazen, and Duncan Simester. 2001. "Always Leave Home Without it: A Further Investigation of the Credit-Card Effect on Willingness to Pay." *Marketing Letters*, 12(1): 5–12.

Rabin, Matthew. 2000. "Risk Aversion and Expected-Utility Theory: A Calibration Theorem." *Econometrica*, 68(5): 1281–92.

Reuben, Ernesto, Paola Sapienza, and Luigi Zingales. Forthcoming. "Time Discounting for Primary and Monetary Rewards." *Economics Letters*.

Shui, Haiyan, and Lawrence M. Ausubel. 2005. "Time Inconsistency in the Credit Card Market." Unpublished.

Skiba, Paige Marta, and Jeremy Tobacman. 2007. "Payday Loans, Uncertainty, and Discounting: Explaining Patterns of Borrowing, Repayment, and Default." Unpublished.

Stewart, Mark B. 1983. "On Least Squares Estimation When the Dependent Variable Is Grouped." *Review of Economic Studies*, 50(4): 737–53.

Strotz, Robert H. 1956. "Myopia and Inconsistency in Dynamic Utility Maximization." *Review of Economic Studies*, 23(3): 165–80.

Tanaka, Tomomi, Colin Camerer, and Quang Nguyen. Forthcoming. "Risk and Time Preferences: Experimental and Household Data from Vietnam." *American Economic Review*.

Zinman, Jonathan. 2009. "Where Is the Missing Credit Card Debt? Clues and Implications." *Review of Income and Wealth*, 55(2): 249–65.