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Sticking to your plan: The role of present bias for credit card paydown[☆]

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We use data from an online financial service to show that many consumers fail to stick to their self-set debt paydown plans. This behavior is best explained by present bias. Our empirical approach is informed by a parsimonious model showing that the sensitivity of spending to paycheck receipt reflects a present-biased agents short-run impatience, and that this sensitivity is reduced by available resources only for agents who are aware (sophisticated) of their future impatience. Classifying users accordingly, we find that (i) sophisticated users debt paydown decreases with short-run impatience, and that (ii) planned paydown is most predictive of actual paydown for sophisticated users.

1. Introduction

In the United States, the majority of households have at least one credit card and more than half of these households roll over credit card debt from month to month. The average household with such credit card debt rolls over almost $13,000 each month, with typical annual interest rates well above 10% (Bricker et al., 2014; 2017). The substantial cost of this credit card borrowing makes the observed amount of credit card debt hard to rationalize with standard preferences in economic models (see, for

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instance, the discussions in Laibson et al., 2003; Agarwal et al., 2015; Keys and Wang, 2019; Agarwal and Mazumder, 2013; Agarwal et al., 2010; 2008).

In light of these difficulties, economists have proposed present-biased preferences as a potential explanation for the observed levels of household borrowing (e.g., Strotz, 1955; Akerlof, 1991; O'Donoghue and Rabin, 1999; Angeletos et al., 2001; Ausubel, 1991; Meier and Sprenger, 2010). According to this explanation, individuals are overly impatient in the short run relative to their long-run preferences. They borrow excessively and often fail to repay later, despite a genuine intention to reduce their debt levels. In these models, the effect of present bias on borrowing depends on the extent to which individuals are aware or unaware about the difference between their short-run and long-run preferences whether they are "sophisticated" or "naive" (O'Donoghue and Rabin, 1999). In this paper, we empirically evaluate the extent to which present bias can account for the observed household debt repayment behavior. We first propose empirical measures of both aspects of an individual's present bias the extent of the individual's short-run impatience as well as her sophistication based on high-frequency transaction-level data. We then apply our methodology to a sample of consumers struggling with credit card debt to analyze the role of present bias in explaining their debt paydown behavior. We find present-biased preferences play an important role, and document substantial differences in the debt repayment behavior of sophisticated and naive individuals with the same degree of present bias.

We study a sample of U.S. consumers who signed up for an online financial management service. The data contain the daily balances and transactions on all bank accounts and credit cards of the users. Upon joining the service, users make a plan of how much they would like to reduce their debt balances each month. It is this unique feature in our data, information on initially planned paydown, that allows us to measure each individual's success in debt paydown relative to her original intent. This allows us to interpret any failure to reduce debt levels as an actual deviation from planned behavior, rather than as ex ante optimal behavior given unobserved factors. We find that users' self-set debt paydown plans are, on average, predictive of their actual paydown behavior. In fact, no other characteristic, such as monthly income or original debt levels, significantly affects actual paydown once the user's original plan is controlled for. However, most users fall substantially short of their original paydown plans. Specifically, for each dollar of planned paydown, the average user only reduces her debt by 25 to 30 cents.

To understand whether present bias can explain this observed shortfall in actual paydown relative to originally planned paydown, we suggest a novel way to use high-frequency information on spending to measure an individual's short-run impatience as well as the degree to which she is aware (sophisticated) or unaware (naive) of her impatience. We theoretically ground our proposed methodology in a parsimonious model of present bias. Our model is consistent with a well-known empirical test for the degree of short-run impatience based on the co-movement of consumption and income: more impatient individuals consume more immediately after receiving their paychecks rather than smoothing their consumption over the pay cycle. In addition, our model suggests a novel empirical test for sophistication: unlike naive consumers, sophisticated consumers act more patiently when they have more available resources. The extent to which a consumer's consumption response to paycheck receipt is attenuated when she has relatively more resources thus provides a good measure of her sophistication.

The model also highlights that more present bias and larger naivete both imply that consumers are worse at sticking to their self-set debt paydown plans. Intuitively, it is attractive for present-biased individuals to delay paying down debt from the current to the next pay cycle to avoid reducing consumption in the current pay cycle when it is particularly valued. When faced with the same decision in the next pay cycle, however, delaying just one more pay cycle appears attractive again. Naive individuals underestimate their future impatience and future desire to continue to delay payments. They are therefore particularly prone to repeatedly delay making payments and end up not following through with their original plans. Unlike naives, sophisticated agents are aware of their future impatience, allowing them to recognize and avoid the temptation to repeatedly delay. This makes sophisticates relatively more successful at following through with their debt paydown plans.

We then implement our theoretical tests for present bias and sophistication empirically. First, we estimate each individual's level of impatience by analyzing their consumption response to paycheck receipt using expenditures for goods which are instantly consumed (e.g., restaurant meals).[1] We filter out the impact of possible alternative explanations for a correlation between spending and paycheck receipt, such as credit constraints. Second, we estimate how each individual's consumption response to paycheck receipt varies with available resources. Here, we exploit within-individual variation in resources over time. We address the potential endogeneity of available resources to consumption patterns by instrumenting with hypothetical balances based on regular, non-discretionary payments such as monthly rent payments. Based on these estimates, we classify approximately half of our users as sophisticated and the others as naive.

Consistent with our theoretical predictions, we find that higher impatience leads to lower debt paydown for sophisticated individuals. Moreover, we find that planned debt paydown is indeed significantly more predictive of actual paydown for sophisticates than it is for naives. The large difference between naive and sophisticated users in following through with their debt paydown plans provides a key piece of evidence for the role of present bias in explaining debt repayment behavior. Indeed, no alternative explana-

[1] Other papers have documented the sensitivity of consumption to the receipt of a paycheck (e.g., Shapiro, 2005; Stephens, 2006; Hastings and Washington, 2010; Gelman et al., 2014; Olafsson and Pagel, 2018; Zhang, 2017; Baugh et al., 2017) or other expected payments (e.g., Souleles, 1999; Parker, 1999; Browning and Collado, 2001; Hsieh, 2003; Scholnick, 2013; Baugh et al., 2014). Jappelli and Pistaferri (2010) survey this literature on consumption responses to income changes.

tion would predict the relationship between the consumption patterns used to measure present bias and the success in following debt paydown plans that we find in the data. Our empirical findings therefore serve a dual purpose. First, they validate our approach to measuring present bias and sophistication. Second, they further our understanding of the role of present bias in debt paydown, while highlighting the importance of distinguishing between the behavior of sophisticated and naive present-biased agents.

We consider and rule out a number of possible alternative explanations for the individual consumption sensitivity to paycheck receipt — our measure of short-run impatience — and the observed debt repayment behavior. We argue that, while some alternative explanations could be consistent with either one of the observed patterns — sensitivity of consumption spending to paycheck receipt or lack of following through with debt paydown plans — no competing explanation we considered can explain the joint patterns observed in the data. For example, some people might have developed a habit of going out for "date night" every two weeks. This behavior might, by chance, overlap with the receipt of their paycheck in a way that is unrelated to short-run impatience. However, if such behavior was driving the observed consumption responses to paycheck receipt, one would not expect these agents to also have the differential debt repayment behavior that we observe in the data. We discuss that, for similar reasons, the following factors also fail to explain the joint patterns of consumption spending behavior and debt paydown: non-separabilities in consumption or the social coordination of consumption spending; time-consistent preferences with high discount factors; loss of income; differences in the interpretation of what a "repayment plan" means (e.g., aspirational versus realistic planning); overoptimism; a lack of planning skills; and financial literacy. We also show that our empirical results are robust to different approaches of filtering out confounding factors, such as short-term credit constraints, and variations in measuring short-run impatience and sophistication.

We see our paper as making two main contributions. First, we propose and validate a novel methodology that uses high-frequency income and spending data to infer whether a person is present-biased and aware of their short-run impatience. While previous work has shown that the distinction between sophisticated and naive agents is theoretically important (e.g., Gabaix and Laibson, 2002; Heidhues and Kőszegi, 2010; Heidhues et al., 2016), researchers have struggled to measure sophistication in the data, which has limited our understanding of whether this theoretical distinction is quantitatively relevant for understanding behavior. For example, the prior empirical literature has sometimes attempted to identify sophisticated individuals as those who use costly commitment devices (e.g., John et al., 2019; Ashraf et al., 2006; Beshears et al., 2011). However, take-up rates of such costly commitment devices have been puzzlingly low in many areas (see Laibson, 2015). In addition, using commitment devices to identify sophisticated individuals does not allow researchers to explore the effect of sophistication on outcomes, since the commitment devices usually directly affect those outcomes of interest. Our approach of measuring sophistication sidesteps these issues. Moreover, the high-frequency financial data required to implement our approach are becoming increasingly available to researchers, (see recent work by Gelman et al., 2014; Baugh et al., 2014; Baker, 2018; Olafsson and Pagel, 2018; Ganong and Noel, 2019; 2018; Meyer and Pagel, 2019; Baugh et al., 2017). As a result, other researchers can use our approach to improve our understanding of the role of present bias and sophistication for household decision making across other settings.[2]

Second, our results directly expand our understanding of the role of present-biased preferences and sophistication for financial decision making. The prior literature has shown that models with present-biased agents, or quasi-hyperbolic discounting as in Laibson (1997), can often rationalize observed household behavior better than models with standard agents. For instance, Laibson et al. (2017) estimate a life-cycle model with credit card borrowing and illiquid wealth, and find that the simultaneous holdings of debt and assets can be explained by a model with present bias. Meier and Sprenger (2010) conduct experiments to measure consumer impatience and find that more present-biased individuals have higher levels of credit card debt.[3] Our methodological contribution in measuring sophistication allows us to show that, consistent with theoretical predicitons, the debt repayment behaviors of sophisticated and naive present-biased agents is quantitatively different, which has important implications, for example regarding what debt-reduction interventions might be successful.

The paper continues as follows: Section 2 describes the data and presents summary statistics. Section 3 shows the planned and actual paydown of users in our sample. Section 4 formally proposes empirical tests for both short-run impatience and sophistication, and validates those measures in simulated data. Section 5 implements the empirical tests and Section 6 presents and validates our measures of impatience and sophistication with actual debt paydown patterns. Section 7 discusses alternative explanations and provides robustness checks and Section 8 concludes.

[2] In this respect, our research emphasizes the increasingly important role of data from online services—such as Facebook, LinkedIn, Twitter, eBay, Mint, Trulia, Zillow, and ReadyForZero—in overcoming important measurement challenges across the social sciences (see, for example, Baker, 2018; Giglio et al., 2015a; 2015b; Einav et al., 2015; Piazzesi et al., 2015; Bailey et al., 2019a; 2018b; 2018a; 2019c; 2019b).

[3] Several other papers have also documented the influence of present bias on consumer's choices Shui and Ausubel (2005) show that present bias can explain consumer choices between different credit card offers. Skiba and Tobacman (2008) find that the behavior of payday loan borrowers is better captured by the hyperbolic model than the standard model. Madrian and Shea (2001), Choi et al. (2004), and Carroll et al. (2009) document the importance of default options in 401(k) savings plans, which can be attributed to the tendency of present-biased consumers to procrastinate. Present-biased preferences have also been shown to explain consumers' decisions regarding workouts (DellaVigna and Malmendier, 2006) or homework assignments (Ariely and Wertenbroch, 2002). Relatedly, Paserman (2008), Fang and Silverman (2009), and Fang and Wang (2015) show the effect of present bias on job searches, welfare program participation, and mammogram usage, respecitvely. DellaVigna (2009) provides an overview of the empirical evidence on the effects of present bias across a number of settings.

2. Data

2.1. Empirical setting

The data are obtained from the U.S. online financial management service ReadyForZero, which offers users free help in managing their debt. ReadyForZero's main service allows users to see all their financial accounts in one interface, which makes it easier to keep track of different accounts and to allocate payments to different accounts. When customers sign up, they are encouraged to link their bank accounts and credit cards. Additionally, they are prompted to make a plan of how much they want to reduce their debt each month. Hence, ReadyForZero collects two types of data as part of providing their services:

1. High-frequency transaction-level data
2. Users' planned debt paydown

The transaction-level data are automatically collected for all linked accounts and show the amount, date charged, and description (the same the customer sees on his bank account statement) for each transaction. It also contains a code from the data provider classifying the transactions into different categories. Finally, the data include daily snapshots of the balances and credit limits on all linked accounts. This type of high-frequency transaction-level data has become more widely available to researchers, either from other financial aggregators (Gelman et al., 2014; Baker, 2018; Baugh et al., 2014; Olafsson and Pagel, 2018) or from financial institutions directly (Ganong and Noel, 2019; 2018; Meyer and Pagel, 2019). The information contained in these data sets is very similar to ours. Hence, our proposed measures of short-run impatience and sophistication can be implemented in other data sets that researchers have access to.

What is unique to our data set is the information on users' planned debt paydown. ReadyForZero focuses on helping users allocate monthly payments among different credit card accounts, which requires asking users for their planned monthly debt paydown. The information on planned debt paydown allows us to compare actual debt paydown to a user's intent. It therefore allows us to directly relate our proposed measure of sophistication to one of the key differences between naive and sophisticated individuals, namely, the ability to follow through with planned behavior.

2.2. Sample selection

We focus on individuals who (i) have linked their checking accounts, (ii) receive regular biweekly paychecks, (iii) appear to have linked all their relevant accounts, and (iv) are observed for at least 180 days after sign-up. The first two conditions allow us to focus on users with regular, predictable, transitory fluctuations in income from week to week. The last two conditions ensure that the data contain information about user's debt paydown after sign up. The final sample includes a total of 516 U.S.-based users who fulfilled these criteria between September 2009 and September 2012. Appendix D.1 describes the sample selection in detail. Our final sample of users is a select group of individuals. First, all users in our sample signed up for ReadyForZero, a service targeted at individuals who want to reduce their credit card debt. While this does not allow us to draw conclusions about the population in general, it is a sample uniquely suited for studying the reasons why some individuals persistently struggle to reduce their debt. To be able to study how differences in short-run impatience and sophistication translate into behavior, we need individuals in our sample to differ along these dimensions. We believe the services offered by ReadyForZero — combining all accounts into one interface and helping with the allocation of payments — can appeal to a variety of individuals, irrespective of impatience or sophistication. It is therefore likely that we observe a diverse sample of individuals with credit card debt who seek help with reducing their debt. Second, we only study users for whom we are confident to observe all credit card and checking account information. We thus study a sample of users that chose to link all their accounts and stuck with the online service a certain amount of time. While the nature of missing data prevents us from comparing users with and without sufficient data coverage, there is no obvious reason to think that they differ systematically from the overall sample in terms of their present bias or that the conclusions we draw from these individuals cannot be generalized.

2.3. Income, assets, and debt paydown

The first panel of Table 1 shows that we observe the average user in the final sample for just over one year (415 days). During this time, the average user receives 28 paychecks, of which 21 are regular pay cycles during which the paycheck arrives on time and no additional payment is received. During regular pay cycles, the average user receives a paycheck income of $3,778 per month. This monthly income is comparable to incomes reported in the 2010 Survey of Consumer Finances, (SCF). Ackerman et al. (2012) find that roughly 70% of income are wages resulting in median wage income of about $32,000 ($45,800*0.7=$32,000) and average wage income of $55,000 ($78,500*0.7 = $55,000). The corresponding annual median wage income in our sample is about $45,336 (12*$3,779), which is higher than the median, but less than the average in the SCF.

The average credit card debt at sign-up is $13,942, almost four times the user's average monthly income. This debt level is slightly higher than the $12,900 of revolving debt carried by households with such debt in the SCF. Furthermore, the mean credit limits are $24,952 in our data and $22,210 in the SCF. Thus, users also have substantial borrowing capacity left on their cards. Overall, our sample is also comparable to other studies using financial aggregator data (such as Gelman et al., 2014; Baker, 2018; Olafsson and Pagel, 2018).

Data on interest rates are only available for a subset of accounts. Consumers face an average annual percentage rate (APR) of 16.7% on their credit card accounts. Users have an average cash balance of $5584 in their bank accounts; the median cash balance is $2099, equivalent to 64% of average monthly income, and comparable to the equivalent in the 2010 SCF ($4520 mean balance and a

Table 1
Summary statistics - Income and assets.

	Obs.	Mean	Income and assets Std. dev.	25th pctile	50th pctile
Users					
Days in sample	516	415	150	262	430
Days in sample after sign-up		392	231	274	401
Nr of paychecks		28	12	19	26
Nr of paychecks - regular pay cycles		21	14	12	20
Income					
Avg. monthly income- regular pay cycles	516	3805	1993	2469	3460
Median monthly income- regular pay cycles		3780	2027	2450	3440
Avg. monthly non-paycheck income		300	442	0	135
Median monthly non-paycheck income		72	276	0	0
Fraction of regular income		0.89	0.12	0.83	0.92
Assets					
Credit card Debt - $	516	13,942	14,029	4,582	9,777
Credit card debt - rel. to income		4.23	9.88	1.40	2.90
Cash balances - $		5584	15,063	911	2,099
Cash balances - rel. to income		1.42	3.48	0.31	0.64
Total credit - $		24,952	23,874	8573	18,000
Total credit - rel. to income		7.38	13.74	2.70	5.16
Available credit - $		11,010	16,157	1550	4973
Available credit - rel. to income		3.15	5.20	0.48	1.47
APR paid on debt - mean	401	16.70	5.69	13.24	16.33
APR paid on debt - median		16.78	6.59	13.24	16.24

The table shows mean, median, and the 25th and 75th percentiles for how long users are observed in the sample, their income, and assets of the users in the sample used throughout the paper. All variables are winsorized at the 1% level.

median of $1326). Furthermore, there is significant heterogeneity across users in debt levels, both in absolute and in relative terms. The 25th percentile's debt level is 140% of monthly income, while the 75th percentile user has almost five times as much debt as monthly income. This is comparable to the debt levels reported in the SCF. We thus observe a very diverse sample of indebted users who are comparable on observables to the average US household.

2.4. Spending

We measure spending as all purchases made with credit or debit cards. Each transaction is already classified into one of about 50 different spending categories, such as restaurant meals, groceries, utilities, or cash withdrawals. In our analysis, we focus on identifying two categories of payment flows.

As a proxy for consumption, we focus on discretionary spending that is likely consumed shortly after purchase. Specifically, we focus on what we call "short-run consumables," such as restaurant meals, entertainment, groceries, and gas. Appendix D.2 describes the classification in detail and the Online Appendix lists all types of expenditures included in each of these categories.

We also use regularly recurring and pre-scheduled payments as a source of variation in the overall resources available to a user. Regularly recurring payments include rent, mortgage and loan interest payments, and magazine subscriptions. A set of transactions is classified as regular if the payment amounts are about equal to each other, the payments are mostly 7, 14, or 30 days apart, and not more than one payment was missed. All remaining non-regular payments are classified as discretionary or non-discretionary based on the category assigned by the data provider.

Table 2 shows summary statistics of users' monthly expenditures. Total monthly discretionary spending is about $1800 for the average user, which corresponds to about 52% of the user's regular income. Within discretionary spending, 30% or $548, is spent on short-run consumables, of which $290 goes to restaurant meals and entertainment. Spending in the SCF is comparable, with $492 on average spent on food (of which $148 is restaurant spending). Regular monthly payments average $1205 per month, equivalent to 33% of users' regular income.

3. Planned and actual paydown

The information on planned monthly paydown reported by users is unique to our data set. Based on their reported planned paydown, users receive payment reminders and the website calculates how to optimally split monthly payments among the user's different accounts. To maximize the usefulness of the service provided by ReadyForZero, it is therefore in the user's interest to truthfully state how much they want to pay down when making their "plan." Table 3 shows that the average user plans to reduce their debt by $891 per month and the median user by $598. The average user, therefore, plans to spend 25% of monthly income on debt payments and to reduce balances by 12% of the original balance per month.

To understand what factors affect an individual's planned paydown, the first five columns of Table 4 show regression estimates of the effect of user characteristics on planned paydown. Planned monthly paydown is strongly related to income and original debt levels. For each dollar of additional monthly income users plan to spend between

Table 2
Summary statistics - Spending.

				Monthly spending		
	Obs.	Mean	Std. dev.	25th pctile	50th pctile	75th pctile
Discretionary spending						
Total						
Avg. $	516	1,795	939	1,127	1,593	2,271
Avg. relative to avg. income		0.52	0.24	0.35	0.47	0.63
Median $		1817	1,044	1117	1638	2311
Median relative to avg. income		0.52	0.26	0.35	0.49	0.65
Non-durable						
Avg. $	516	1,026	540	635	920	1291
Avg. relative to avg. income		0.30	0.15	0.20	0.28	0.36
Median $		1030	595	624	942	1314
Median relative to avg. income		0.30	0.15	0.21	0.28	0.37
Short-run consumables						
Avg. $	516	548	285	336	500	681
Avg. relative to avg. income		0.16	0.08	0.10	0.14	0.20
Median $		564	330	340	514	718
Median relative to avg. income		0.16	0.10	0.10	0.15	0.21
Restaurant&entertainment						
Avg. $	516	290	165	172	256	370
Avg. relative to avg. income		0.09	0.05	0.05	0.08	0.11
Median $		277	181	152	246	364
Median relative to avg. income		0.08	0.05	0.04	0.07	0.10
Regular payments						
Avg. $	516	1205	784	619	1050	1673
Avg. relative to avg. income		0.33	0.19	0.20	0.31	0.44
Median $		1264	965	475	1096	1902
Median relative to avg. income		0.35	0.24	0.15	0.33	0.50

The table shows mean, median, and the 25th and 75th percentiles for spending of the users in the sample used throughout the paper. All variables are winsorized at the 1% level.

Table 3
Summary statistics - Plans and paydown.

				Plans and debt paydown		
	Obs.	Mean	Std. Dev.	25th pctile	50th pctile	75th pctile
Plans						
Planned paydown - monthly - $	516	891	1,112	353	598	1,017
Planned paydown - monthly - % of debt		0.12	0.18	0.04	0.06	0.11
Planned paydown - monthly - % of income		0.25	0.37	0.11	0.18	0.30
Planned paydown - 90 days - $	516	2482	2710	926	1792	2992
Planned paydown - 90 days - % of debt		0.28	0.26	0.11	0.18	0.33
Planned paydown - 180 days - $	516	4650	4972	1785	3288	5951
Planned paydown - 180 days - % of debt		0.47	0.30	0.22	0.36	0.66
Debt Paydown						
Change in debt - 90 days - $	516	−734	3,041	−1,291	−222	292
Change in debt - 90 days - %		0.02	0.92	−0.14	−0.02	0.04
Change in debt - 180 days - $	516	−977	3,858	−2,087	−418	479
Change in debt - 180 days - %		0.26	4.04	−0.20	−0.04	0.06
Shortfall relative to plan - 90 days - $	516	1,748	3,466	429	1,417	2,986
Shortfall relative to plan - 90 days - %		0.85	2.45	0.39	0.84	1.19
Shortfall relative to plan - 180 days - $	516	3673	5224	970	2813	5410
Shortfall relative to plan - 180 days - %		1.16	4.28	0.50	0.88	1.15
Payments made - 90 days	516	3160	4398	660	1660	3957
Payments made - 180 days		5823	7324	1339	3490	7747

The table shows mean, median, and 25th and 75th percentile for planned and actual debt paydown of the users in the sample used throughout the paper. All variables are winsorized at the 1% level.

17 and 20 cents per month on debt reduction. Original debt levels also somewhat increase planned paydown: a $1000 increase in debt levels is associated with $25 of higher planned paydown each month. Cash balances, remaining available credit, total credit, discretionary spending, the interest rate paid, the number of credit cards owned, and credit card usage have no statistically significant effect on planned paydown. Next, we compare planned paydown to actual paydown. The second set of columns of Table 4 show that originally planned paydown

Table 4
Determinants of planned paydown and actual paydown after 90 days.

	Planned monthly paydown ($)					Actual paydown after 90 Days ($)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Planned Paydown						0.288***	0.287***	0.295***	0.283**	0.253**
($, over 90 days)						(0.109)	(0.109)	(0.109)	(0.111)	(0.117)
Monthly income ($)	0.174***	0.176***	0.136***	0.192***	0.200***	0.046	0.049	0.067	0.051	0.077
	(0.041)	(0.045)	(0.040)	(0.045)	(0.055)	(0.057)	(0.059)	(0.080)	(0.061)	(0.076)
Original debt ($)	0.025***	0.025***	0.024***	0.025***	0.026***	0.001	0.002	0.002	0.002	0.003
	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Cash balances ($)		−0.001	0.000	−0.004	−0.006		0.001	0.000	0.000	0.002
	(0.006)	(0.006)	(0.006)	(0.007)			(0.007)	(0.007)	(0.007)	(0.008)
Available credit ($)		0.000	−0.001	−0.006	−0.006		−0.001	−0.001	−0.002	−0.002
		(0.003)	(0.003)	(0.004)	(0.005)		(0.007)	(0.007)	(0.008)	(0.009)
Monthly discretionary			0.145					−0.037		
spending ($)			(0.123)					(0.097)		
Nr. of credit cards				−7.080	−2.889				−3.032	−9.233
				(23.85)	(27.92)				(18.72)	(22.30)
Credit card usage				786.53	776.62				54.672	271.005
(% of expenditures)				(268.81)	(334.18)				(187.75)	(224.00)
Avg. APR (%)					−1.518					0.391
					(6.895)					(8.956)
N	516	516	516	516	401	516	516	516	516	401

Note: standard erros in parenthesis, *** p<0.01, ** p<0.05, * p<0.1, winsorized 1%, sensitivity, robust standard error
The table shows estimates of the effect of various variables on planned paydown and actual paydown after 90 days with robust standard errors in parentheses. All variables are winsorized at the 1% level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

is the single most predictive factor for actual paydown in the 90 days after sign-up. Controlling for planned paydown, the user's income, debt levels, cash balances, available credit, total credit, interest rates, or spending behavior do not significantly affect actual debt reduction. This indicates that planned paydown already incorporates information about the user's ability to reduce debt captured by these other variables. Despite planned paydown's high predictiveness for actual paydown, however, users fall substantially short of their debt paydown plans. Each dollar in planned paydown is associated with only 25 and 30 cents in actual paydown. This substantial shortfall is also reflected in the summary statistics in Table 3. Based on monthly planned paydown of $891, the average user plans to reduce debt levels over the first 90 days by a total of $2482, but ends up reducing debt only by $734 an average shortfall of $1748, or 85% relative to the originally planned amount. A substantial fraction of users even increase their debt levels, as reflected in the increase in debt of $292 for the 75th percentile of changes in debt levels.

Overall, while plans predict actual paydown better than any other factor, many users fall substantially short of their plans to reduce credit card debt. Not following through with originally made plans is a key prediction of present bias, in particular for naive users that are not aware of their own present bias. The remainder of the paper analyzes to what extent present bias can indeed explain the observed failure of sticking with debt paydown plans.

4. Inferring present bias from consumption patterns

This section shows how consumption patterns can be used to measure an individual's short-run impatience and sophistication. In particular, we present a parsimonious model of present bias and validate the proposed measures in simulated data from that model.

4.1. Preferences

We study an agent with quasi-hyperbolic preferences, the most widely applied modeling approach for present bias popularized by Laibson (1997). In each period $t \in \{1, \dots, T\}$, the agent decides how much to consume, C_t, to maximize her lifetime utility given by

$$u(C_t) + \beta E_t\left[\sum_{\tau=1}^{T-t} \delta^{\tau} u(C_{t+\tau})\right]$$

where we assume a power-utility specification for all period utility functions, $u(C) = \frac{C^{1-\theta}}{1-\theta}$, with the constant relative coefficient of risk aversion denoted by $\theta > 0$. The agent's discount factor between periods is not constant over time. Between any two consecutive future periods, the agent discounts by a factor $\delta \in [0, 1]$. However, between the current period and all future periods, the agent is more impatient and applies an additional discount factor of $\beta \in [0, 1]$. For $\beta < 1$, the agent is more impatient in the short run relative to his or her long-run preferences. Such short-run impatience implies that the agent's preferences are time inconsistent, i.e., that her preferences over how much to consume change over time. For $\beta = 1$, the agent has standard time-consistent preferences.

Given time-inconsistent discount factors, an agent's expectation about the extent of her future short-run impatience, $\hat{\beta}$, matters for her current choices. We focus on two types of agents (in the absence of any time inconsistencies, when $\beta = 1$, this distinction is irrelevant):

1. A *sophisticated* agent who is perfectly aware of his or her short-run impatience, i.e., $\hat{\beta} = \beta$.
2. A *naive* agent who believes that her future preferences will be identical to her current preferences, not realizing that her future self will become impatient, i.e., $\hat{\beta} = 1$ irrespective of true β.

In the context of our model, the agent's "plan" corresponds to her own expectation of future consumption. Hence, for sophisticated and standard agents, planned and actual future consumption will be the same. A naive agent's planned consumption is her consumption under the mistaken assumption that her future impatience factor will be equal to 1, i.e., under her belief that $\hat{\beta} = 1$.

4.2. Model environment

All agents face a standard budget constraint where resources X_t are determined by past savings, A_{t-1}, and income, Y_t. Agents save at interest rate R^s or borrow at interest rate R^b, summarized by the function $R(A_{t-1})$. This yields the following budget constraint:

$$X_t = A_{t-1}R(A_{t-1}) + Y_t = (X_{t-1} - C_{t-1})R(X_{t-1} - C_{t-1}) + Y_t.$$

As in our empirical setting, the agent receives biweekly paychecks. In addition, the agent is subject to uncertain expense shocks which can increase or decrease her net income. In all odd periods, $T-1, T-3, T-5, \ldots, 1,$ the agent receives a paycheck and a shock to expenses. In period T and all even periods prior, the agent only receives a shock to expenses. In each period, the agent's net income in week t is denoted by Y_t and characterized by a deterministic growth rate G_t on top of the transitory shock $N_t^T = e^{s_t^T}$ with $s_t^T \sim N(\mu_T, \sigma_T^2)$. We model the income process by generating uncertain net income in each period, and by subtracting the certain paycheck from the uncertain net income generated for non-payperiods. Formally, income in each period t is given by

$$Y_t = \left\{ \begin{array}{l} G_t N_t^T = G_t e^{s_t^T} \text{ if } t \in \{T-1, T-3, T-5, \ldots, 1\} \\ G_t N_t^T - 1 = G_t e^{s_t^T} - 1 \text{ if } t \in \{T, T-2, T-3, \ldots, 2\} \end{array} \right\}.$$

Because the agent is certain to receive positive net income in every other future payperiod, she can borrow up until the discounted value of all future income.[4]

4.3. Model equilibrium

We can obtain the equilibrium solution by backward induction. For the standard and sophisticated agents, we derive the equilibrium consumption function under the premise that the agent enters period t, optimizes over consumption, and expects to behave in the same manner in the future. The naive agent, however, enters period t, optimizes over consumption, but expects to behave in a different manner in the future. Specifically, because $\hat{\beta} = 1$, the naive agent expects her future self to discount payoffs only by δ^{τ} instead of by $\beta\delta^{\tau}$. These equilibrium concepts correspond to those widely applied in the literature (for instance, Laibson, 1997). The model cannot be solved analytically but simulations using numerical backward induction suggest that a unique and stable equilibrium exists.[5]

4.4. Calibration and model simulation

We calibrate the environmental and preference parameters in line with the literature. For the stochastic net income components, we follow the fairly tight ranges suggested in the life-cycle literature such as Gourinchas and Parker (2002). Specifically, the transitory net income shocks are parameterized with $\mu_T = 0$ and $\sigma_T = 0.1$ on an annualized basis. We then estimate G_t from the Consumer Expenditure Survey (CEX) using a standard pseudo-panel approach following Gourinchas and Parker (2002). The interest rate on savings is $R^s = 1.008$, which equals the average Fed Funds rate over our sample period. The interest on borrowing is $R^b = 1.1677$, the average APR in our data (see Table 1). For the preference parameters, we assume an exponential discount factor of $\delta = 0.94$ and a coefficient of risk aversion of $\theta = 2$, both standard in the literature. Empirical estimates for the present-bias parameter typically range from $\beta = 0.6$ to $\beta = 0.9$ (see Angeletos et al., 2001, among others) when the exponential discount factor is close to one (as is our choice of $\delta = 0.94$). We will simulate our model for values of β in this range to show how varying values of β affect our estimates for present bias and sophistication.

We simulate consumption data from the model to run and validate our empirical tests in simulated data. To make the simulation exercise similar to our empirical setting, we simulate the model and run the regressions at a weekly frequency. The parameters δ, μ_T, σ_T, R^s, R^b, and G_t were calibrated to annualized statistics and we convert them to a weekly frequency for this purpose. For instance, an annualized transitory net income uncertainty of $\sigma_T = 0.1$ corresponds to a weekly net income uncertainty of $\sqrt{\frac{1}{52}} \times 0.1 = 0.0139$. Additionally, the agents' deterministic net income growth rate equals the average of those estimated for the years 25 to 40 in the CEX data, as we likely observe a younger user population with relatively high income growth (then converted to the weekly frequency). In period 1, agents have initial debt levels that correspond to our empirical setting. Specifically, for each agent, initial debt level A_0 is the rate of debt to weekly net income in our model $(-13,808/(3,778 \times 0.5))$ times the agent's first period paycheck (Y_1). We simulate data for the same number of agents, 516 (the number of individuals in our final sample), and for the same number of biweekly paychecks, 28 (the mean number of payweeks for users in our sample), to demonstrate that our empirical setting offers sufficient statistical power to detect short-run impatience and sophistication.

In Appendix A.1, we also discuss the model's implied life-cycle consumption paths using an annual frequency,

4 We omit permanent income uncertainty from the model for several reasons. First, in our empirical setting, we select individuals with stable employment and income over the sample period and are interested in inferring features of present bias from individual reactions to transitory income fluctuations. Second, Carroll (2001) and others have argued that household income processes are well approximated by a deterministic trend and a transitory shock.

5 The consumption functions are increasing and concave and the equilibrium appears easy to solve for and stable. Carroll (2011) and Harris and Laibson (2002) demonstrate the existence and uniqueness of equilibria for the standard and sophisticated hyperbolic-discounting agents in similar environments.

as is standard in the literature. The lifetime consumption profiles of present-biased agents look reasonably similar to the average consumption profile from CEX data, suggesting our calibration is appropriate. The simulation also shows that the consumption profiles look very similar for the sophisticated and naive present-biased agents. This confirms the findings in prior studies, such as Angeletos et al. (2001) and Laibson et al. (2017), that consumption profiles from standard data sources, such as quarterly survey consumption data, do not allow distinguishing sophisticated and naive individuals. This highlights the value of using the high-frequency responses to income fluctuations and how these responses vary with available resources to classify individuals as either sophisticated or naive.

4.5. Model insight I: measuring short-run impatience

The literature has argued that more impatient agents have a higher marginal propensity to consume out of current income (Campbell and Deaton, 1989; Attanasio, 1999). Based on this insight, we propose that cross-sectional differences in the estimated propensity to consume out of income fluctuations can be used as a measure of an individual's short-run impatience. To show that this is indeed the case, we use our model to simulate agents' consumption choices and estimate the following equation:

$$log(C_t) = a + b_1 payweek_t + e_t. \tag{1}$$

The variable $payweek_t$ is one for periods $t \in T-1, T-3, T-5, \dots, 1$ when the agent receives positive income net of expenses. This specification matches the empirical regression we run in our data (Eq. (3) below). Our first prediction, Prediction 1, suggests that the estimated propensity to consume out of transitory income fluctuations, b_1, increases with agents' short-run impatience (lower β). Hence, person-specific estimates of b_1 can be used as a proxy for individual-level short-run impatience.

Prediction 1. Agents with higher short-run impatience (lower β) have a higher sensitivity of consumption to income fluctuations, as captured by b_1 in Eq. (1).

As in our empirical exercise, we estimate Eq. (1) separately for each agent. The top two panels of Fig. 1 show the average estimates for b_1 for agents with different levels of short-run impatience, β. For both sophisticated and naive agents, higher impatience in the short-run (lower β) is indeed associated with higher estimated coefficients b_1, as they react more strongly to changes in income from period to period.

4.6. Model insight II: measuring sophistication

Next, we want to empirically classify whether an individual is naive or sophisticated. We propose that sophisticated present-biased agents, but not naive ones, will have a lower sensitivity of consumption to income when they have higher resources than when they have lower resources. Hence, we can estimate the extent of this behavior and classify individuals accordingly. The intuition for this insight comes from the Euler equation for present-biased agents. Tobacman (2007) derives the following Euler equation for fully naive agents:

$$u'(C_t) = \delta E_t[R\beta u'(\hat{C}_{t+1})].$$

In contrast, the Euler equation for fully sophisticated agents is:

$$u'(C_t) = \delta E_t\left[R\left(\beta\frac{\partial C_{t+1}}{\partial X_{t+1}} + \left(1 - \frac{\partial C_{t+1}}{\partial X_{t+1}}\right)\right)u'(C_{t+1})\right].$$

Unlike naive agents, sophisticated agents know that their future selves do not share their more patient long-run preferences. In other words, sophisticated agents know that their future selves will consume more than their current self likes. When considering whether to consume or save a marginal unit of resources, a sophisticated agent therefore considers his or her future self's use of such a unit of resources passed on. When the future self's propensity to consume is lower (lower $\frac{\partial C_{t+1}}{\partial X_{t+1}}$), the future self uses the marginal unit of resources more in line with the preferences of the current self, making it more worthwhile for the current self to pass on resources. That is, the sophisticated agent has a lower effective discount factor and will act more patiently when the expected marginal propensity to consume next period, $\frac{\partial C_{t+1}}{\partial X_{t+1}}$, is lower. This is not the case for the naive agent. The extent of this behavior therefore distinguishes sophisticated and naive agents.

Unfortunately, the expected future marginal propensity to consume is unobserved, so we cannot directly estimate its effect on discounting in the data. The marginal propensity to consume, however, depends on the level of available resources. With diminishing marginal utility of consumption, the marginal propensity to consume decreases with the level of resources. Hence, we would expect sophisticated agents to act more patiently when they expect next period's resources to be high due to high current cash on hand, X_t, and marginal utility to be low. This difference in behavior then allows us to distinguish between naive and sophisticated present-biased agents in our data.

We turn to our model to show that our intuition based on the Euler equation translates into agents' consumption choices in the simulated data as proposed. We estimate the following equation:

$$log(C_t) = \alpha + b_1 payweek_t + b_2 X_t + b_3 X_t payweek_t + \varepsilon_t, \tag{2}$$

which is again the equivalent to our empirical specification, Eq. (4). As outlined above, we expect higher resources (causing the future self to be more patient) to lead to a lower sensitivity of consumption to income for sophisticated agents, but not for naive ones, as suggested by Prediction 2.

Prediction 2. Unlike naive agents, sophisticated agents have a lower sensitivity of consumption to income fluctuations when they have higher resources, as captured by a negative estimate of b_3 in Eq. (2).

As in our empirical setting, we estimate each regression separately for each agent. The two bottom panels of

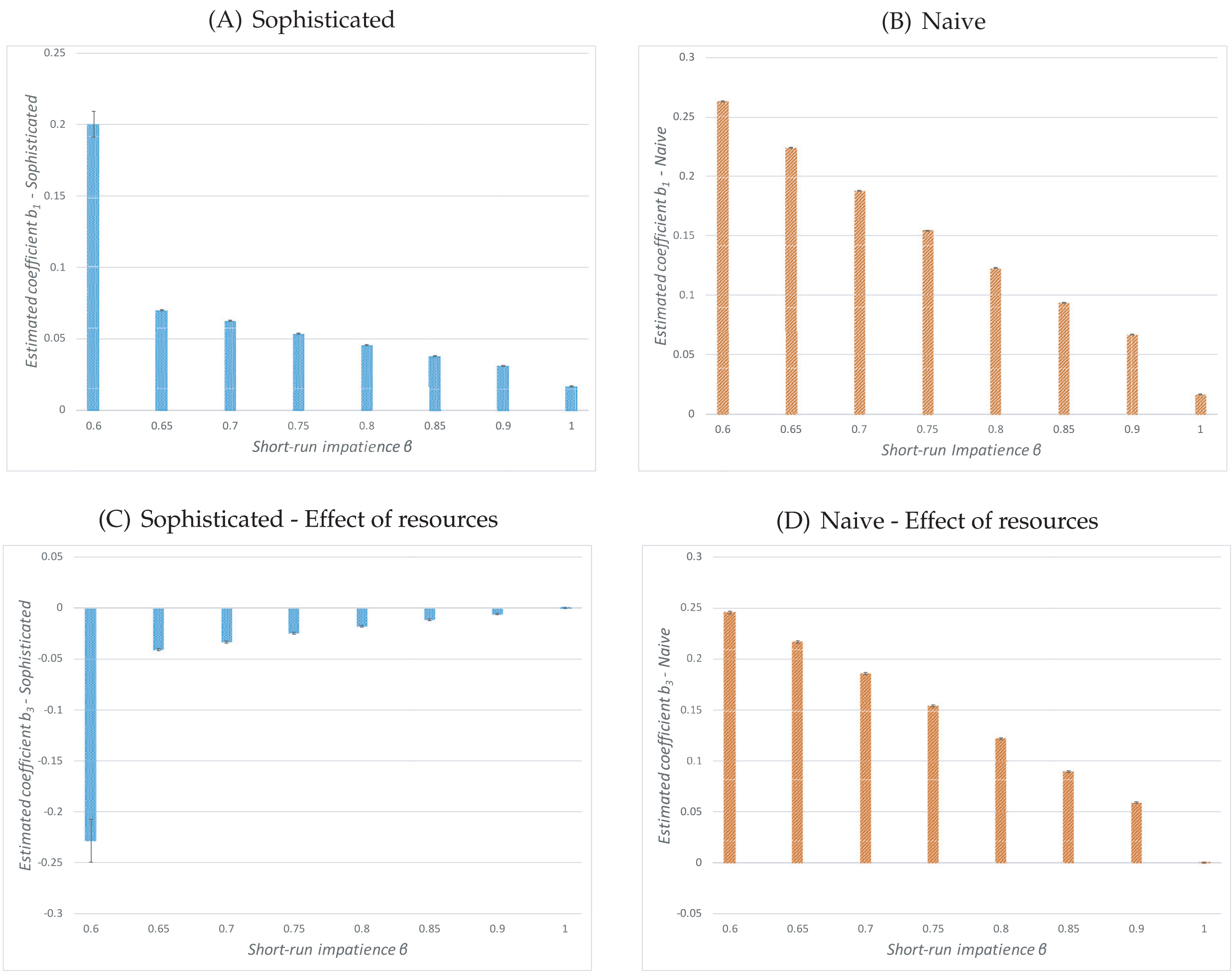

Fig. 1. Model consumption patterns and present bias. The top two panels show the estimated coefficient b_1 in regression Eq. (1) and standard errors for sophisticated (Panel A) and naive (Panel B) agents. The bottom two panels show the estimated coefficient b_3 in regression Eq. (2) and standard errors for sophisticated (Panel C) and naive (Panel D) agents. Throughout, we use simulated data of 516 agents with 28 periods.

Fig. 1 show the average regression estimates of Eq. (2). As suggested by Prediction 2, we find a negative coefficient b_3 for sophisticated agents with short-run impatience. For naive agents, the estimated coefficients are positive. For time-consistent agents ($\beta = 1$), we find small positive coefficients. In this case the distinction between sophisticated and naive is meaningless since they have no short-run impatience to be aware of.

The findings in Fig. 1 thus validate our proposed measures of short-run impatience and sophistication in simulated data using one of the most widely used ways of modeling present bias, hyperbolic discounting (Laibson, 1997). In turn, in our empirical exercise, we will classify users as sophisticated or naive based on whether or not we estimate a negative effect of resources on the propensity to consume out of income fluctuations. Because the simulations also suggest that agents who have only low short-run impatience (high β) are difficult to classify using our proposed measure, in our empirical exercise, we will also show robustness of our results to excluding agents with low short-run impatience.

4.7. Debt reduction

The purpose of our model is to demonstrate the validity of our measures of present bias. Furthermore, we can also evaluate the effect of present bias and sophistication on debt levels in our model. In the context of our model, we understand the agent's plan to be her own expectation of future debt levels. For naives, the agent's plan is therefore given by the debt paydown of the standard agent who does not have a time-inconsistency problem. Using this definition of planned paydown, we find that naive agents fail to meet their planned debt paydown. Over the simulation period, naives with a hyperbolic discount factor β of 0.6 fall short 92% on average. Naives who are less impatient in the short-run with a $\beta = 0.8$ (or $\beta = 0.95$) still fall short 40% (or 7.9%). For sophisticated agents, we can think about planned paydown in two ways. First, sophisticated agents correctly anticipate their own behavior perfectly and, therefore, by definition, fully follow through with their own debt paydown plans. Second, however, sophisticates would like to pay down more. For them the standard agent's debt paydown is an aspirational plan that they would like to follow if they could. More formally, the standard agent's plan would maximize sophisticates' overall lifetime utility. They would thus like to commit to this plan if they could. Relative to the standard agent's debt paydown, the sophisticated agent's shortfall is 50% for $\beta = 0.6$, 33% for $\beta = 0.8$, and 4.7% for $\beta = 0.95$. Therefore, even relative to the time-consistent agent's plan, the sophisticated agent's shortfall is substantially smaller than the naive agent's shortfall. Irrespective of whether sophisticates make perfectly realistic plans or entirely aspirational plans (or plans somewhere in the middle), we would therefore expect that sophisticates are substantially better in following through with their debt paydown plans than naives.

4.8. Discussion of the model and its match to the empirical setup

The goal of this section is to demonstrate the validity of our proposed measures for present bias in the most parsimonious model that still captures the key characteristics of our empirical setting: in particular, the initial indebtedness, high-frequency consumption and savings or borrowing decisions, biweekly income patterns, number of agents, and number of paychecks we observe. As a very parsimonious model, however, it abstracts from some features present in real life. First, the model abstracts from debt accumulation as we take the initial debt accumulation as given to match our empirical setting. This abstraction from how and why individuals accumulated this debt in the first place, is also reflected in our empirical analysis. Indeed, since we only observe individuals once they have accumulated debt, our empirical analysis also focuses on debt repayment taking initial debt levels as given. Second, the model does not feature any credit limits or liquidity constraints imposed by credit card providers or banks. The model features a natural borrowing constraint using the terminology in][]C2011 that equals the agent's discounted future minimum net income. In other words, agents in the model borrow against their future net income if they are impatient, but they would not borrow more than what they are expecting to earn in the future. This abstraction from bank-imposed credit limits is also reflected in our empirical analysis: we exclude all weeks in which users did not have enough capacity to borrow before they would hit their credit limits. We do so to not confound credit limits as an explanation for short-run impatience with present bias. In principle, however, the theoretical results would not be affected by the presence of provider-imposed credit limits in the model.

The third abstraction in the model concerns how we capture uncertainty. Agents in the model receive certain biweekly incomes but are subject to expense shocks that increase or reduce their net income available for consumption. That is, all uncertainty is captured by shocks to net income. The expense shocks in the model therefore capture that, in the actual data, consumption choices are more complex than in the model. Specifically, a substantial amount of consumption, such as housing, clothing, or electronics, is prepaid due the lumpy nature of expenditures on durables, especially over such short-term horizons as the two weeks considered in our setting. Similarly, individuals are required to occasionally prepay future consumption by acquiring durable goods, leaving less income for other discretionary consumption. We therefore think about the transitory shocks to net income in the model as capturing both fluctuations in actual income, as well as shocks to the amount of implicit income (in the form of pre-paid consumption minus required expenditure on durables for future consumption) due to the lumpiness of spending on durables as well as uncertain expenses.

It is important to note here that we deliberately illustrate our results in a very parsimonious life-cycle model, but that the results carry over to more elaborate models. In principle, the empirical tests for short-run impatience and sophistication we propose work at all simulation frequencies and a number of modifications of the model presented here. We have also considered a richer model, the one in Laibson et al. (2017), which includes many additional features such as illiquid savings and liquidity constraints. Simulating consumption choices in this model also generates Predictions 1 and 2 about how present bias and sophistication manifest in consumption patterns. We briefly present these results in Appendix A.2.[6]

5. Consumption patterns

This section estimates each user's sensitivity to paycheck receipt and how it is affected by varying resources over time. This allows us to implement the empirical measures of present bias we proposed and validated above. After estimating each user's level of short-run impatience and sophistication, we will relate these measures to debt paydown behavior in the next section.

5.1. Sensitivity of consumption to paycheck receipt

5.1.1. Regression equation

We estimate the following equivalent regression corresponding to Eq. (1) to obtain the sensitivity of consumption spending to paycheck receipt for user i :

$$log(E_{it}) = \alpha_i + payweek_{it}\gamma_{1i} + X_{it}\psi_i + \varepsilon_{it} \quad (3)$$

E_{it} are user i's consumption expenditures on day t. $payweek_{it}$ is an indicator that is equal to one on the day of paycheck receipt and the six subsequent days, and zero on all remaining days. X_{it} includes month fixed effects and day-of-week fixed effects. Estimating Eq. (3) separately for each user yields a user-specific estimate of her sensitivity of consumption spending to paycheck receipt, captured by the coefficient on payweek, γ_{1i}; this coefficient is the equivalent to b_1 in Eq. (1).

We focus on expenditures E_{it} for goods likely to be consumed shortly after purchase, which we call short-run consumables: restaurant and entertainment expenditures, and food and gas purchases.[7] Since food and gas can be

[6] We thank the authors for sharing their solution code to simulate the model.

[7] Measuring consumption by expenditures can lead to misleading conclusions, as shown by Aguiar and Hurst (2005). We focus on expendi-

Table 5
Sensitivity estimates.

	Obs.	Mean	Std. dev.	Sensitivity to paycheck receipt 25th pctile	50th pctile	75th pctile
Sensitivity (γ_1) - Pooled estimates						
Short-run consumables	516	0.061	0.009	t-stat = 6.94		
Restaurant & Entertainment	516	0.047	0.008	t-stat = 5.74		
Sensitivity (γ_1) - Individual estimates						
Short-Run consumables	516	0.061	0.211	−0.081	0.049	0.199
Restaurant & Entertainment	516	0.046	0.201	−0.086	0.052	0.172
Effect of Resources on Sensitivity (γ_3)						
Short-Run consumables	516	−0.473	8.932	−0.116	0.014	0.134
Restaurant & Entertainment	516	0.122	4.082	−0.135	0.012	0.170

The table shows summary statistics of the baseline estimates of each user's sensitivity to paycheck receipt and the effect of higher resources on this sensitivity. The first four rows reflect sensitivity to paycheck receipt as captured by the coefficient on *payweek* in Eq. (3), i.e., γ_1. The last two rows reflect the effect of higher resources on sensitivity as captured by the coefficient on *payweek*resources* in Eq. (4), i.e., γ_3. Both equations are estimated separately for each user and include day of week and month fixed effects. Resources are instrumented for with calculated balances based on regular payments.

stored for a while rather than immediately consumed, we also present results for just restaurant and entertainment spending and show that the consumption patterns look very similar.

5.1.2. Filtering out short-term credit constraints

We are interested in capturing the extent of sensitivity to paycheck receipt that reflects a user's level of short-run impatience. However, if expense shocks come at times when consumers are extremely credit constrained in their consumption spending, we may see increased consumption spending in payweeks in response to a relaxation of these credit constraints. To isolate the effect of short-run impatience from those of credit constraints, we thus restrict the sample to those pay cycles in which short-term credit constraints are unlikely to play a role. Specifically, we restrict the sample to those times in which the user had enough resources (cash in his account and available credit on his cards) to afford the payweek's worth of spending in the previous week.

This restriction excludes users with extremely tight short-term credit constraints — those that would not have been able to afford the week's consumption spending, $140 on average, in the prior week. It includes many users considered credit constrained in a broader sense. For instance, a user with liquid assets and available credit of only $300 would be included in our sample during those weeks where her consumption spending does not exceed her available resources of $300, despite the fact that we would not consider her financially unconstrained in general. In Section 7.4, we show that our results are robust to more conservative approaches to filtering out the effects of short-term credit constraints.

5.1.3. Estimated sensitivity to paycheck receipt

Table 5 shows estimates of the sensitivity γ_{1i} in our sample. On average, users indeed consume significantly more during payweeks than during non-payweeks, even if short-term credit constraints are unlikely to play a role. During payweeks, spending on short-run consumables is 6.1% higher, and spending on restaurants and entertainment is 4.7% higher. There is substantial variation across users. For instance, at the 75th percentile users increase consumption in both categories by almost 20% in payweeks.[8] Some of this variation is due to noise in the estimation and some due to true differences among individuals. We therefore bootstrap standard errors for all estimates below in which sensitivity to paycheck is used as an explanatory variable to account for the variation due to noise rather than actual differences between individual users. Bootstrapping the standard errors is the most conservative approach we can take and tends to yield larger standard errors than simply correcting for heteroskedasticity or other approaches.

5.2. Effect of resources on sensitivity to paycheck receipt

5.2.1. Regression equation

The effect of variation in resources on the sensitivity to paycheck receipt is estimated separately for each user by the following equation:

$$log(E_{it}) = \alpha_i + payweek_{it}\gamma_{1i} + resources_{it}\gamma_{2i} + resources_{it} * payweek_{it}\gamma_{3i} + X_{it}\psi_i + \varepsilon_{it}k \quad (4)$$

where, as in Eq. (3), E_{it} are each user's daily expenditures, $payweek_{it}$ is an indicator that is set equal to one on the day of paycheck receipt and the six subsequent days, and X_{it} includes month fixed effects and day-of-week fixed effects. $resources_{it}$ are a user's available resources, defined as the cash balances on her bank accounts plus the available credit on her credit cards. Again, we estimate Eq. (4) separately for each user, to obtain an individual ? specific estimate of γ_{3i}, the empirical equivalent of b_3 in Eq. (2).

ture categories that are likely to be a good proxy for actual consumption, such as restaurant meals and entertainment. We also estimate spending patterns over several pay cycles in which consumers do not experience income shocks. It is therefore unlikely that the estimates are driven by shifts in behavior from one regime to another in response to shocks.

[8] Appendix Fig. A2 plots the distribution of the estimated sensitivity for both categories of consumption. The two distributions look very similar and confirm the key insights of Table 5: The mean of the distributions is shifted upwards from zero, and a t-test confirms that it is significantly different from zero.

5.2.2. Wealth fluctuations due to regular payments

To estimate the effect of varying resources, we exploit within-agent variation in resources over time. However, the level of resources available to the agent at every point in time is not exogenous to the agent's consumption decision. There are two potential sources of endogeneity. First, expenditures in the beginning of the pay cycle reduce the resources available later in the pay cycle one-for-one. This can be addressed by measuring resources at the beginning of each pay cycle. Second, resources in the given pay cycle depend on past consumption. This is problematic if high prior spending not only reduces the agent's resources, but also his taste for consumption in the current period, leading to biased estimates. For instance, a user who regularly went to restaurants over the last weeks has lower resources in the current pay cycle. Additionally, she may have a lower taste for new consumption, having recently been to her favorite restaurants.

To address this endogeneity problem, we exploit variation in the agent's resources due to regular payments. Users in our sample are paid twice a month, but have regular *monthly* expenses, such as rent or mortgage payments. These monthly obligations lead to substantially lower resources during the two-week pay cycle when they are due relative to the other two weeks of the month.[9] Another example are months with three paychecks for users who are paid biweekly (rather than twice a month). We exploit the systematic fluctuations in the level of resources caused by such regular payments to construct an instrumental variable for the level of resources. Based on the agent's regular payments, we calculate what her resources would have been if all non-regular spending was split evenly across the sample period. These hypothetical balances isolate the variation caused by regular payments from the variation caused by prior discretionary spending. Fig. A3 in Appendix B.2 illustrates the intuition for these calculated balances. Section 7.3 discusses the implications of using (OLS) estimate rather than IV estimates of the effect of resources on sensitivity to paycheck receipt when classifying users as sophisticated or naive.

5.2.3. Measuring sophistication by effect of resources on sensitivity

We now estimate how fluctuations in resources affect the sensitivity of consumption spending to paycheck receipt, using the hypothetical balances based on regular payments as an instrumental variable. The user-specific estimates captured by γ_{3i} in Eq. (4) are shown in the bottom panel of Table 5.

As outlined in Section 4, additional resources lead sophisticated agents — but not naive ones — to act more patiently; as a result, the consumption of sophisticated agents reacts less to payment receipt when the agents have higher resources. We split the sample into two groups: "sophisticated" users for whom additional resources reduce

Table 6
Classification into sophisticated and naive.

	Restaurant & Entertainment		
	Naïve	Sophisticated	Total
Short-run consumables			
Naïve	210	75	285
Sophisticated	66	165	231
Total	276	240	516

This table shows the number of users classified as sophisticated or naive based on estimates using either short-run consumables or restaurant and entertainment spending. Users are classified as sophisticated if additional resources decrease sensitivity to paycheck receipt, i.e. if the coefficient on *payweek*resources* in Eq. (4) is negative.

sensitivity to paycheck receipt, i.e., those for whom γ_{3i} is negative, and "naive" users for whom this is not the case.

For the median user, the effect is close to zero for both short-run consumable spending and for restaurant and entertainment spending. There is substantial heterogeneity in γ_{3i}, allowing us to split the sample along this characteristic. Table 6 shows the classification of users into sophisticated and naive, approximately half of users are classified as sophisticated. We show the robustness of our results to variations in this classification approach in Section 7.3.

5.2.4. Summary statistics by differences in consumption patterns

One possible concern with our approach is that agents classified as sophisticated or naive could also differ along dimensions other than sophistication that are associated with outcomes, such as impatience, assets, or earnings. To assess the validity of such conerns, Table 7 shows average and median estimated sensitivity levels for naive and sophisticated users based on short-run consumables, as well as based only on restaurant and entertainment spending. When based on short-run consumables spending, estimated levels of sensitivity to paycheck receipt are somewhat larger for sophisticated agents. When based on restaurant and entertainment spending only, they are somewhat lower, but the differences between the two groups are not statistically significant in either case.

While the average differences in sensitivity across sophisticates and naives are relatively small, there are several factors that could lead sensitivity estimates to differ between the two groups. First, average sensitivity estimates are biased slightly downwards for sophisticated agents. When resource levels are high, sensitivity is lower for a sophisticated agent than it is for a naive agent with the same level of impatience. Therefore the average sensitivity, estimated for times of both low and high resource levels, will be lower for a sophisticated agent than for a naive one with the same level of impatience.[10] A second factor is measurement error in classifying users into sophisticated and naive. If sensitivity of consumption to paycheck receipt

[9] Individuals may purposefully set up regular payments to align with their paychecks. For the purpose of constructing our instrument, this is not a concern as long as regular payments are not rescheduled based on short-term variation in discretionary consumption spending.

[10] Instead of using the average sensitivity to paycheck receipt estimated by Eq. (3), an alternative measure would be the base level of sensitivity captured by the coefficient on *payweek* in Eq. (4). However, because of the additional variables and the need to instrument for them, the estimates are much more noisy. Because of this higher precision, we use the average sensitivity in the regression analysis, since the focus is on intra-, not inter-, group comparisons.

Table 7
Summary statistics by sophistication.

	Naïve	Sophisticated	*t-test for equality (p-value)*
Sensitivity to paycheck (short-run consumables)			
Average sensitivity	0.051	0.072	0.263
Median sensitivity	0.043	0.059	
Sensitivity to paycheck (restaurant & entertainment)			
Average sensitivity	0.046	0.045	0.969
Median sensitivity	0.058	0.034	
Income and Debt			
Income - Mean	3,808	3,802	0.975
Credit card debt - mean	14,144	13,693	0.713
Credit card debt - median	9,430	10,133	
Credit card debt / income - mean	3.786	4.773	0.306
Total Discretionary Spending			
Avg. $	1,844.0	1,755.8	0.307
Avg. % of income	52.9	51.6	0.598
Avg. % spend on credit cards	34.3	33.9	0.854
Short-run consumables			
Avg. $ - mean	560.9	537.0	0.503
Avg. % spend on credit cards	31.1	31.1	0.981
Restaurant & entertainment			
Avg. $ - mean	298.6	282.6	0.289
Avg. % spend on credit cards	32.4	32.4	0.978
Planned paydown - 90 days			
Mean	2,540.1	2,409.7	0.574
Median	1,795.1	1,723.3	
N	285	231	

The table shows summary statistics on estimated sensitivity to paycheck receipt, monthly income, debt and spending for users classified as naive or sophisticated based on estimates using short-run consumables.

is relatively low, any potential sensitivity changes (or lack thereof) due to resource fluctuations are also small in absolute terms and, when measured with error, less likely to be correctly detected. Users with low levels of impatience are therefore more likely to be misclassified than users with high levels of impatience. In the robustness checks, in Section 7.3, we therefore exclude users with low sensitivity who are most likely to be misclassified. Third, the level of impatience may be directly related to whether a user is aware of his short-run impatience. Users with high short-run impatience may be more likely to eventually become aware of their own time inconsistency relative to users with a relatively minor time-inconsistency problem.

In addition to estimated levels of sensitivity, Table 7 shows some key summary statistics on income and debt levels across naive and sophisticated users. Income and initial credit card debt levels are very similar between the two groups. Average income is almost identical. Average initial debt is slightly lower, $13,693 relative to $14,144, for sophisticated users, but median debt is higher for sophisticates. Table 7 also shows that sophisticated and naive agents have very similar spending habits across all categories, both in absolute terms and relative to their incomes. Both types also use their credit card in similar ways and charge 31% of total purchases on their credit cards. In general, the differences between sophisticated and naive agents in assets and spending are small and none are statistically significant. It is therefore unlikely that the classification into naive and sophisticated masks substantial differences between the two groups along other dimensions which could directly account for any differences in their debt repayment behavior. This conclusion is also consistent with the notion that the services provided by ReadyForZero appealed to a variety of users with credit card debt and did not target those with a specific form of present bias. The similarities in income, assets, and spending between sophisticated and naive users are also in line with our theoretical results. As pointed out in Section 4 and shown in Fig. A1, the life-cycle consumption profiles do not differ much between the two types of agents, reinforcing the need for our high-frequency-data-based measure of sophistication.

Finally, we also do not find substantial differences in the levels of planned paydown across sophisticates and naives. Appendix Table A2 shows that the main determinants of planned paydown are income and original debt levels, which are very similar across the two groups; there were no statistically significant effects from sensitivity or sophistication on planned paydown. Hence, planned paydown seems to be determined primarily by factors such as income, existing debt levels, and possible other considerations such as spending needs and ease of reductions in spending. We now turn to analyzing whether sophisticates are better in meeting their debt paydown plans.

6. The effect of present bias on debt repayment

Section 5 showed that consumption patterns over the pay cycle are consistent with users exhibiting short-run impatience and varying levels of sophistication. We now relate the measures of each user's present bias and his sophistication to the individual success in reducing debt levels.

6.1. Regression equation

To formally analyze the effects of our measures of present bias and sophistication on debt paydown, we estimate the following regression:

$$\begin{aligned} Paydown_i = \mu_0 &+ Sensitivity_i \mu_{1n} + PlannedPaydown_i \mu_{2n} \\ &+ Sensitivity_i * Sophist_i \mu_{1s} \\ &+ PlannedPaydown_i * Sophist_i \mu_{2s} \\ &+ X_i' \lambda + \nu_i \end{aligned} \tag{5}$$

where $Sensitivity_i$ is each user's sensitivity of spending to paycheck receipt, estimated by Eq. (3). $PlannedPaydown_i$ is the amount the user originally planned to pay down and $Sophist_i$ is an indicator for whether the user is classified as sophisticated. X_i is a set of control variables, including the user's monthly income and debt levels at sign-up. We measure debt paydown over two horizons: 90 and 180 days. To make estimates comparable, debt paydown and planned paydown are measured per day. Debt paydown is measured by the (linearly fitted) trend in debt balances over the given time horizon. Relative to the simple difference in debt levels, this measure filters out fluctuations in debt levels caused by the use of credit cards for transactions. The results are very similar using the simple difference in debt levels instead.

6.2. Regression results

Table 8 shows the regression estimates for Eq. (5) over time horizons of 90 and 180 days. Since the regressors $Sensitivity_i$ and $Sophist_i$ are themselves estimated from consumption patterns, standard errors in the second stage are bootstrapped to be most conservative.[11]

For naive agents, who constitute the omitted category, an additional dollar in planned paydown increases actual paydown by 18 cents over the first 90 days and by 13 cents over 180 days. For sophisticated users, planned paydown is substantially more predictive of actual paydown than it is for naive users. Specifically, over the first 90 days, sophisticated agents pay down 55 cents $(0.18 + 0.37)$ per dollar of planned paydown. Over the first 180 days, sophisticated users pay down 52 cents per dollar of planned paydown $(0.13 + 0.39)$. As shown below, these results are very similar and robust across different specifications.

In our baseline specification, sensitivity has a small positive effect on paydown for naive users. This estimate is insignificant over the 90-day horizon, but marginally significant over the 180-day horizon. In addition, this result is not robust across different specifications as shown throughout Section 7. We therefore interpret our results as

Table 8
Effect of impatience and planned paydown on actual debt paydown by naive and sophisticated agents.

	Paydown	
	90 Days	180 Days
Sensitivity	8.511	6.461*
	(7.253)	(3.921)
Planned paydown	0.179*	0.129
	(0.094)	(0.086)
Sensitivity * Sophisticated	−33.293***	−10.179*
	(11.638)	(5.861)
Planned paydown * Sophisticated	0.371*	0.391*
	(0.224)	(0.212)
Median paycheck (in 1,000s)	1.938	1.990*
	(1.503)	(1.150)
Original debt (in 1,000s)	0.173	−0.028
	(0.123)	(0.104)
Median paycheck * Sophisticated	−2.116	−2.412
	(3.148)	(2.280)
Original debt * Sophisticated	−0.346	−0.148
	(0.273)	(0.236)
Sophisticated	4.157	−1.099
	(5.747)	(4.271)
Constant	−12.035***	−8.585***
	(2.688)	(2.035)
Number of individuals	516	516

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

ambiguous regarding the effect of short-run impatience for naive users' paydowns. In contrast, for sophisticated users, the level of short-run impatience has a significant negative effect on paydown: more impatient agents reduce their debt by less. The difference relative to naive users, as well as the combined effect for sophisticates, is statistically significant (unreported test) and economically meaningful: moving from the 75th to the 25th percentile of estimated impatience levels increases debt paydown in the first 90 days after sign-up by \$623. This is a substantial fraction of the average paydown of \$711 over this time horizon.[12] There is no statistically significant difference in the effect of the control variables for sophisticated and naive users. In fact, most of the control variables have no substantial effect on actual paydown once planned paydown is included, consistent with the results presented in Table 4.

Overall, the estimated relationship between the characteristics of a user's consumption patterns and her debt paydown reflects what one would expect if both were caused by present bias: Sophisticated users are better in following through with their debt paydown plans, but higher short-run impatience leads them to pay down less. The results also reinforce the interpretation of sensitivity to paycheck receipt as a measure of impatience and validates the classification of users as naive or sophisticated —

[11] For each user, we draw a bootstrap sample from the observations of consumption spending and re-estimate the first stage variables for each draw. Then we use these estimates in the second stage estimation and compute bootstrapped standard errors based on the second stage results of all draws. Using robust standard errors to interpret the results would not change the overall conclusions though it would generally increase statistical significance.

[12] The difference between the 25th and 75th percentile for the estimated sensitivity based on short-run consumables is $0.28 = 0.20 + 0.08$, as shown in Table 5. Multiplying this difference by the total estimated effect for sophisticated agents yields an estimated effect of \$6.93 per day, or \$623 over 90 days.

after all, better ability to follow plans is a key prediction of sophistication as opposed to naivete.

7. Robustness and alternative interpretations

We interpret our results in Section 6 as support for our measures of present bias and sophistication, as well as evidence for an important role of present bias in determining households' ability to reduce their debt levels. We next discuss whether other factors could plausibly drive our collection of results. More specifically, this section shows robustness of our main results to a large number of data construction choices. We also show that potential alternative explanations for some of the patterns in the data fail to explain the *joint* behavior of debt paydown and consumption patterns.

7.1. Robustness of estimating effect on paydown

Estimates based only on restaurant and entertainment spending.
Our main results in Table 8 use spending patterns based on short-run consumables as proxies for short-run impatience and sophistication. Instead, the first two columns of Appendix Table A3 use spending patterns based only on restaurant and entertainment spending. The results are very similar to our baseline results: The level of short-run impatience has a significant negative effect for sophisticated users, but not for naive users, and planned paydown is substantially more predictive of actual paydown for sophisticated rather than naive users.

Regression specification. The remaining columns of Appendix Table A3 explore different regression specifications. A possible concern about the specification in Eq. (5) is that planned paydown and the estimated level of sensitivity to paycheck receipt are highly correlated. We, therefore, estimate separate specifications in which either the sensitivity to paycheck or planned paydown is interacted with sophistication, and the respective other variable is only included as a control (not interacted with sophistication). The results are very similar. Furthermore, our baseline specification allows the effect of the control variables to differ between sophisticated and naive users. Appendix C.1 shows that the estimates are very similar when income and original debt levels are not interacted with sophistication and the control variables are restricted to have the same influence for both types of users.

Direct relationship between paydown and consumption patterns. One potential concern is that the spending patterns we use as measures for present bias and sophistication are directly linked to debt paydown. After all, by definition, debt paydown requires a reduction in consumption spending. However, there is no mechanical relationship between the spending patterns and debt paydown. The sensitivity to paycheck receipt, which is used to measure present bias, only captures how evenly consumption is split over the pay cycle. It is thus unrelated to the *level* of consumption, which is what affects debt paydown. This leaves enough variation to identify potential differences in the amount of debt paid down. In other words, sensitivity of consumption captures the ratio of future to present consumption ($\frac{C_{t+1}}{C_t}$), but saving for debt paydown depends on the *level* of consumption spending ($saving = income - C_{t+1} - C_t$). Therefore agents can exhibit the same level of sensitivity to paycheck receipt, while having different levels of debt paydown. Similarly, agents with the same amount of debt reduction may choose to split the remaining resources differently between the two periods of the pay cycle, leading to different sensitivity of consumption spending, but equal debt reduction.[13]

Nevertheless, it could be the case that users who smooth consumption more when they have higher resources, which we label sophisticates, may also be those who consume a lower share of these additional resources, leading them to save more for debt paydown. A high reduction in sensitivity as resources increase (i.e., a more negative coefficient on the interaction of $payweek{*}resources$) would lead to higher debt paydown. Appendix C.2 explores this concern, and shows estimates of the direct relationship between the reduction in sensitivity to paycheck receipt and debt paydown. This direct relationship is far from statistically significant, and the point estimate is positive in several specifications the opposite of what would be expected under the hypothesis that a reduction in sensitivity as resources increase leads to higher debt paydown.

7.2. Robustness of estimating sensitivity

Appendix C.3 shows that our results are robust to different ways of estimating the sensitivity to paycheck receipt. In the baseline, we require 45 days of positive spending to include a user in our sample. In Appendix Table A5 we replicate the analysis requiring 40 or 50 days instead. The relationship between consumption patterns and debt paydown is unaffected.

In the baseline specification, spending is measured in logs and on a daily level. The first two columns of Table A6 instead use sensitivity estimates based on the actual amount spent and normalizes those estimates by average spending. The third and fourth columns use weekly spending instead of daily spending. The last two columns use sensitivity estimates based only on debit card spending, excluding any credit card spending. All results are very similar to the baseline estimates in Table 8.

7.3. Robustness of measuring sophistication

Low levels of sensitivity. From a theoretical perspective, the distinction between sophisticated and naive agents becomes meaningless when users have very low or no short-run impatience. As a result, users with low levels of sensitivity to paycheck receipt are difficult to classify

[13] Consider the following example to illustrate this point: An agent with a paycheck of \$100 saves \$50 and consumes \$30 in the first period and \$20 in the second period, leading to 50% higher consumption in payweeks. Alternatively, the agent can consume \$60 in the first period and \$40 in the second, leading to the same sensitivity of consumption spending but different paydown. Similarly, saving \$50 but consuming \$25 each period leads to the same savings as in the first case, but completely smooths consumption.

Table 9
Low impatience excluded.

	Paydown 90 days				Paydown 180 days			
		Exclude if sensitivity in the lowest				Exclude if sensitivity in the lowest		
	Baseline	10%	15%	20%	Baseline	10%	15%	20%
Sensitivity	8.511	9.471	10.684	10.626	6.461*	5.963	6.379	6.087
	(7.253)	(7.589)	(7.614)	(7.732)	(3.921)	(4.050)	(4.075)	(4.110)
Planned paydown	0.179*	0.152	0.129	0.153*	0.129	0.118	0.102	0.117
	(0.094)	(0.100)	(0.099)	(0.089)	(0.086)	(0.086)	(0.089)	(0.088)
Sophisticated * Sensitivity	−33.293***	−33.412**	−32.203**	−30.319**	−10.179*	−10.352*	−9.786	−8.326
	(11.638)	(12.088)	(12.332)	(13.049)	(5.861)	(6.172)	(6.247)	(6.465)
Sophisticated * Planned paydown	0.371*	0.398*	0.414*	0.402*	0.391*	0.368*	0.388*	0.384*
	(0.224)	(0.238)	(0.238)	(0.231)	(0.212)	(0.210)	(0.215)	(0.219)
Sophisticated	4.157	7.080	6.068	6.494	−1.099	0.712	0.726	0.538
	(5.747)	(6.364)	(6.570)	(6.838)	(4.271)	(4.628)	(4.869)	(5.148)
Median paycheck	Y	Y	Y	Y	Y	Y	Y	Y
Original debt	Y	Y	Y	Y	Y	Y	Y	Y
Constant	Y	Y	Y	Y	Y	Y	Y	Y
Number of individuals	516	465	439	413	516	465	439	413

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

as either sophisticated or naive: with a low initial level of sensitivity, any potential reduction in the observed sensitivity which could identify a user as sophisticated is relatively low. Therefore such a reduction is less likely to be picked up in the estimation. As a robustness check, Table 9 thus repeats our baseline analysis while excluding users with low levels of sensitivity. Starting with the baseline sample, we subsequently exclude users with estimated levels of sensitivity to paycheck receipt in the lowest 10%, 15%, and 20%. Despite the reduction in sample size, the estimated differences between sophisticated and naive agents remain statistically significant and of similar magnitude.[14] Consistent with our theoretical predictions, it appears that the differences between sophisticated and naive agents are indeed driven by those agents with higher levels of short-run impatience rather than those with relatively low or no short-run impatience.

Different classifications of users. Appendix C.4 provides additional robustness checks on the classification of users as sophisticated or naive. Ideally, users should be classified the same irrespective of whether estimates are based on short-run consumables or restaurant and entertainment spending only. Appendix Table A7 shows that results are very similar to the baseline when only consistently classified users are included. If anything, the point estimates are more similar across categories, supporting the notion that previously misclassified users cause additional noise in the estimation.

Classification as sophisticated and naive is based on the effect of higher resources on sensitivity to paycheck receipt. When estimating this effect, resources are instrumented for by hypothetical balances as outlined in Section 5.2. This addresses the concern that past consumption levels may affect both the level of resources, as well as spending, through unobservables such as a taste for consumption. This could lead to a negative coefficient absent any sophistication by the user. To understand the importance of this concern, we replicate the results classifying users as sophisticated or naive based on OLS estimates instead of IV estimates of the effect of resources. If the endogeneity concern is important, a substantial number of users will be misclassified when using OLS estimates and the estimated differences between the two groups should be smaller. Indeed, Appendix Table A7 finds smaller differences between sophisticated and naive individuals (though they are mostly statistically insignificant), reinforcing the need to instrument for the level of resources.

7.4. Alternative explanations for sensitivity to paycheck

Consumption spending may be sensitive to paycheck receipt for reasons other than short-run impatience. In this section we argue that alternative explanations cannot explain the joint patterns of consumption spending and debt paydown we observe.

Credit constraints. One possible cause of consumption spending sensitivity to paycheck receipt are short-term credit constraints. If users are credit constrained and suffer an expense shock, they have to wait until the next paycheck to incur the expense, making spending sensitive to paycheck receipt. Therefore, as discussed above, the baseline estimation of the sensitivity to paycheck receipt is based only on times when short-term credit constraints are unlikely to have played a role. Specifically, the baseline specification requires that spending in a given category be affordable in the pre-paycheck week. In this section, we replicate the main results using different approaches of excluding periods of potential credit constraints.

The first alternative approach takes into account that users may want to hold a buffer stock of resources at all times. Therefore, spending in a given category would have to have been affordable in the pre-paycheck week

[14] Note that the average level of sensitivity and its standard deviation in the sample also changes as we drop observations. So differences in the coefficients - or lack thereof - cannot be interpreted as implying a different sized effect (or lack thereof). The estimated coefficients across the different sample are not statistically different from each other.

Table 10
Debt paydown and consumption patterns - Different restrictions on sensitivity estimates.

	Baseline	Buffer stock	Total discretionary affordable	No restriction
Dependent variable: Paydown 90 says				
Sensitivity	8.511	6.135	8.934	8.362
	(7.253)	(6.823)	(6.330)	(6.833)
Planned paydown	0.179*	0.180*	0.180*	0.179*
	(0.094)	(0.095)	(0.095)	(0.102)
Sensitivity	−33.293***	−28.158***	−31.647***	−32.144***
* Sophisticated	(11.638)	(11.372)	(10.381)	(11.634)
Planned paydown	0.371*	0.380*	0.372*	0.368
* Sophisticated	(0.224)	(0.228)	(0.226)	(0.224)
Sophisticated	4.157	3.061	3.610	4.394
	(5.747)	(5.632)	(5.740)	(5.232)
Dependent variable: paydown 180 days				
Sensitivity	6.461*	4.428	3.920	5.593
	(3.921)	(4.065)	(3.988)	(3.655)
Planned paydown	0.129	0.139	0.139	0.139*
	(0.086)	0.094	0.093	(0.093)
Sensitivity	−10.179*	−8.115	−6.921	−8.567
* Sophisticated	(5.861)	(6.876)	(6.289)	(5.653)
Planned paydown	0.391*	0.420*	0.418*	0.416*
* Sophisticated	(0.212)	(0.232)	(0.232)	(0.225)
Sophisticated	−1.099	−1.455	−1.550	−1.260
	(4.271)	(4.322)	(4.373)	(4.299)
Controls				
Median paycheck	Y	Y	Y	Y
Original sebt	Y	Y	Y	Y
Nr of individuals	516	516	516	516

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

without reducing a consumer's resources below a buffer stock, specified as the 5th percentile of observed average resources. The second alternative approach requires that the payweek's total discretionary spending, rather than just category-specific spending would have been affordable in the previous week.

Across all users, the baseline specification excludes about 20% of days with positive spending as possibly credit constrained over the two-week pay cycle.[15] Requiring total discretionary spending to be affordable or taking a buffer stock into account increases the number of excluded days to 22% and 28%, respectively. Appendix Table A1 shows that the estimated sensitivity decreases slightly when filtering out these additional pay cycles. However, the estimated sensitivity would decrease even if credit constraints did not play any role, since the excluded pay cycles are those with the highest spending. Still, within each consumption category, the correlation between estimates with different restrictions is more than 90%. Across the two spending categories — short-run consumables or restaurant and entertainment spending only — the estimates are also very similar with correlations between 55% and 65%. Table 10 replicates the main results using sensitivity estimates based on these different restrictions. Throughout, the results are very similar to those from the baseline specification.

Habits, non-separabilities in consumption, or social coordination. Habits that coincide with payweeks are another possible alternative explanation for higher spending during payweeks. For instance, some people may have a habit of going out for "date night" every two weeks. For some of them, this might by chance overlap with the receipt of their paycheck. Alternatively, some people may rationally coordinate some purchases with when they get paid. Or they may coordinate consumption spending with their potentially credit-constrained or present-biased friends or colleagues. However, if the estimated sensitivity of consumption to paycheck receipt was caused by such habits, non-separabilities between consumption, or social coordination, there would be no reason to expect users to have differential sensitivity depending on their resources; one would also not expect them to differentially adhere to their debt repayment plans in the way observed in the data. Therefore, the estimated sensitivity to paycheck receipt is at least partially driven by short-run impatience. Otherwise, it would not relate to debt paydown in exactly the way predicted by present bias.

Time-consistent preferences with a high discount factor. For consumers who live paycheck to paycheck, time-consistent preferences with a very high discount factor can lead consumption spending to be higher early in the pay cycle. Similarly, consumers with a higher discount rate would also reduce their debt balances less. However, this is unlikely to be driving the results for the following reasons. First, the discount factor that would be necessary

[15] For comparison, in a representative sample of Icelandic financial aggregation app users, Olafsson and Pagel (2018) document that approximately 10% of individuals have less than 10 days of average consumption left in liquidity the mornings before their paychecks. Furthermore, we compare our summary statistics for debt levels and credit limits to the SCF in Section 2.

to lead to sensitivity of consumption spending over a two-week horizon is so high that it is generally considered to be implausible, given consumers' relative patience in the long-run (see Shapiro, 2005). Second, time-consistent consumers should have no issue sticking to their original plans. In our setting, a time-consistent consumer with a high discount factor is likely to be classified as naive. However, we find that these consumers follow their plans substantially less than consumers classified as sophisticated. Thus, time-consistent preferences with a high discount factor cannot explain why consumers whose consumption spending becomes less sensitive when resources are higher are more able to stick to their debt paydown plans.

7.5. Alternative explanations for failing to stick to plan

Loss of income. A substantial loss of income, for instance from unemployment, could render households unable to follow their original plan to reduce debt levels. However, all users in our sample have regular paychecks throughout the sample period. Therefore they do not experience a substantial reduction in their income which could force them to abandon their original plans.

Aspirational plans. When prompted by ReadyForZero to state how much they want to reduce their debt each month, users may differ in what they understand a "plan" to be. For instance, some users may view their planned paydown as an aspirational goal rather than as a realistic plan to which they are likely to stick. However, differences in interpreting what a plan means should not affect how consumers allocate consumption over the pay cycle and therefore cannot explain the systematic relationship between consumption patterns and the extent to which consumers follow their plan.

Better monitoring of financial situation. Some users may be paying more attention to their financial situation than others. This could lead them to allocate more of their spending to times when their resources are high, such as right after receiving a paycheck, and to generally have a higher marginal propensity to consume when resources are high. At the same time, paying more attention would also make them more successful in following through with planned paydown. However, such a story would predict that users pay down more when they are more responsive to paycheck receipt and when their marginal propensity to consume increases with resources. This is the opposite of our results: we classify users as sophisticated when they have a lower — not higher — marginal propensity to consume when overall resources are high and find that these users are better at following plans. At the same time, a higher propensity to consume after paycheck receipt is associated with lower debt reduction. Better monitoring and alignment of spending with times of high resources would predict the opposite of what we find and, therefore, cannot explain our results.

Lack of planning skills or overoptimism. A lack of planning skills or overoptimism could lead some users to make overly ambitious debt paydown plans and, hence, explain their failure to stick to their plans. Such bad planning either due to overoptimism or lack of planning skills in general could also lead to sensitivity of consumption spending to paycheck receipt. Users may be overoptimistic about the probability of receiving additional resources in the second week of a pay cycle or underestimate the cost of their first week's planned consumption. As a result, they might spend more of the paycheck when they receive it, and when additional resources fail to materialize, reduce expenditures. However, there is no reason why the extent of overoptimism or lack of planning skills should vary systematically with the week-to-week changes in an individual's level of resources. There is also no reason why variations in resources affecting sensitivity of consumption spending should relate to success in sticking to debt-paydown plans. Furthermore, it is not the case that sophisticated and naive users differ in the aggressiveness of their plans. Hence, overoptimism alone does not predict the systematic differences between users classified as sophisticated and naive in our data.

Lack of financial literacy. Several papers have shown that consumers' lack of basic financial literacy leads many to make suboptimal financial decisions (see Hastings et al., 2013, for an overview of this literature). A lack of financial literacy alone, however, cannot explain the results in this paper. Lack of financial literacy does not necessarily lead to sensitivity of consumption to paycheck receipt. However, consumers who better understand the implications of their financial decisions may also be better at planning and allocating resources over their two-week pay cycles, leading them to smooth consumption more. That being said, a lack of financial literacy would not predict that differences in the effect of resources on the sensitivity to paycheck receipt systematically relate to which consumers are better able to follow their plan and reduce their debt levels. Furthermore, one may argue that financially literate individuals should have a higher marginal propensity to consume when resources are high (see the argument above about better monitoring) rather than the other way around, which is what we observe for sophisticates. Nevertheless, the results are consistent with some — or even most — consumers lacking a thorough understanding of financial matters in addition to some having present-biased preferences.

8. Conclusion

This paper shows that differences in consumers' short-run impatience and their awareness about their own time-inconsistent preferences can help explain why some consumers plan to pay off expensive credit card balances but fail to stick to their plans and actually do so.

We first propose a new empirical methodology to detect short-run impatience and sophistication versus naivete in high-frequency transaction-level data of spending, income, balances, and credit limits. Our proposed methodology can easily be transferred to many other settings where spending and income data are available; indeed, given the proliferation of data from online aggregators or financial institutions, such data are becoming increasingly common. We then apply our methodology to understand the role of present bias in debt paydown. The unique feature of our data information on planned paydown allows us to show that sophisticated individuals are substantially better in following through with their debt paydown plans. Confirming this key prediction of present bias in the data, in turn, further validates our proposed empirical measure.

Documenting that present bias can help explain household debt repayment behavior, and highlighting the distinction in the behavior of sophisticates and naives, has important implications for the design of consumer financial regulation. For instance, a set of theoretical papers has shown that common features in credit card contracts, such as teaser rates, disproportionally hurt consumers with behavioral biases (see Heidhues and Kőszegi, 2010).[16] But whether credit markets should be regulated or not, depends on the extent to which individuals are aware of their behavioral biases or not. Regulations such as those in the (CARD) Act of 2009, for instance, prohibits issuers of subprime credit cards to backload fees, which would be very effective in preventing present-biased consumers from borrowing without fully internalizing the cost.[17] Similarly, our results have important implications for how to help consumers get out of debt. For instance, given the important role of present bias in explaining their behavior, any mechanism that makes commitment to long-term plans attractive to consumers could be a promising and cost-effective way to do so. One possibility would be to allow consumers to select a certain amount to be deducted from their regular paycheck to be put toward debt repayment, and to make it costly or complicated to change this selection.

Appendix A. Model validation and extensions

A.1. Consumption life-cycle profiles

We simulate the model in Section 4 at an annual frequency, as is standard in the literature. This allows us to compare the simulated consumption profiles to those estimated from CEX data. For this illustration, we set $\beta = 0.7$. We follow Gourinchas and Parker (2002) who assume that agents start their life at age 25 years. To match average US retirement age of 68 (according to the Organisation for Economic Co-operation and Development) and average US life expectancy of 79 (according to the United Nations), agents live for 54 years after they start life at age 25. At age 25, the mean ratio of liquid wealth to income equals one, $\frac{A_0}{P_0} = 1$.

Fig. A1 contrasts the consumption paths of the three types of agents considered standard, naive present-biased, and sophisticated present-biased - with the empirical consumption and income profiles estimated from CEX data. As in the data, sophisticated present-biased and naive present-biased preferences generate a hump-shaped consumption profile.[18] The calibrated lifetime consumption profiles look reasonably similar to the average consumption profile from CEX data suggesting our calibration is appropriate.

However, the calibration also shows that the consumption profiles look very similar for the sophisticated and naive present-biased agent. Thus, we cannot use standard data sources for consumption, such as quarterly or annual surveys, and the implied consumption profiles to tell whether individuals are sophisticated or naive.

A.2. Richer life-cycle models

We consider the life-cycle model in Laibson et al. (2017) that successfully explains the extent of credit card borrowing via illiquid savings and naive hyperbolic discounting (see, Laibson, 1997; O'Donoghue and Rabin, 1999).[19] The model features naive or sophisticated hyperbolic-discounting preferences and illiquid assets as well as revolving high-interest credit, liquidity constraints, stochastic labor income, social security, child and adult household dependents, retirement, and mortality.

More specifically, Laibson et al. (2017) consider the following model. The agent lives for $t = \{1, \dots, T\}$ periods. Each period the agent selects an optimal level of consumption C_t. Additionally, he decides how much to save in both the liquid and illiquid assets. The variable X_t represents liquid asset holdings in the beginning of period t before receipt of period t income Y_t. If $X_t < 0$ then uncollateralized high-interest debt, i.e., credit card debt, was held between t and $t-1$ at an interest rate of R^{CC}. The agent also faces a credit limit in period t of $\lambda > 0$ times average income at age t. If the agent saves instead of borrows, he earns an interest R. The stock variable $Z_t \geq 0$ represents illiquid asset holdings at the beginning of period t, earning interest R^Z and providing consumption value. However, illiquid assets can be liquidated only with a proportional transaction cost, which declines with age $\kappa_t = \frac{\frac{1}{2}}{1+e^{\frac{t-50}{10}}}$. Let $I_t^X$and I_t^Z represent net investment each period into the liquid and illiquid assets so that the budget constraint is given by

$$C_t = Y_t - I_t^X - I_t^Z + \kappa_t \min(I_t^Z, 0).$$

The consumer has constant relative risk aversion quasi-hyperbolic preferences and maximizes

$$\max_{I_t^X, I_t^Z} \left\{ n_t \frac{(\frac{C_t+\gamma Z_t}{n_t})^{1-\rho}}{1-\rho} + \beta E_t \left[\sum_{\tau=1}^{T-t} \delta^\tau \left(\prod_{j=1}^{\tau-1} s_{t+j}\right) \left(s_{t+\tau} \frac{(\frac{C_{t+\tau}+\gamma Z_{t+\tau}}{n_{t+\tau}})^{1-\rho}}{1-\rho} \right.\right.\right.$$
$$\left.\left.\left. + \ (1 - s_{t+\tau}) B(X_{t+\tau}, Z_{t+\tau}) \right) \right] \right\}$$

[16] Ponce-Rodriguez (2008) shows that banks in Mexico structure credit card contracts to exploit customers' potential behavioral biases. DellaVigna and Malmendier (2004) study how firms structure contracts with consumers who have self control issues. Several papers have explored the implications of behavioral biases for regulation and policy. Camerer et al. (2003) argue for the benefits of some paternalistic regulation in the face of behavioral biases, including potential present bias. Mullainathan et al. (2012) present a framework for the implications of potential behavioral biases for regulation and public finance. Gruber and Kőszegi (2004) study the implications of time-inconsistent preferences for the incidence of cigarette taxes.

[17] Agarwal et al. (2015) show that reductions in fees after the Credit CARD Act were not passed on to consumers. Agarwal et al. (2018) also show why reductions in the cost of funds may not be passed on to credit card borrowers.

[18] Power utility implies prudence, such that all agents have a standard precautionary-savings motive causing an initially increasing consumption path. But, the present-biased agents are also sufficiently impatient, such that consumption eventually decreases.

[19] We thank the authors for kindly sharing their solution code to simulate the model.

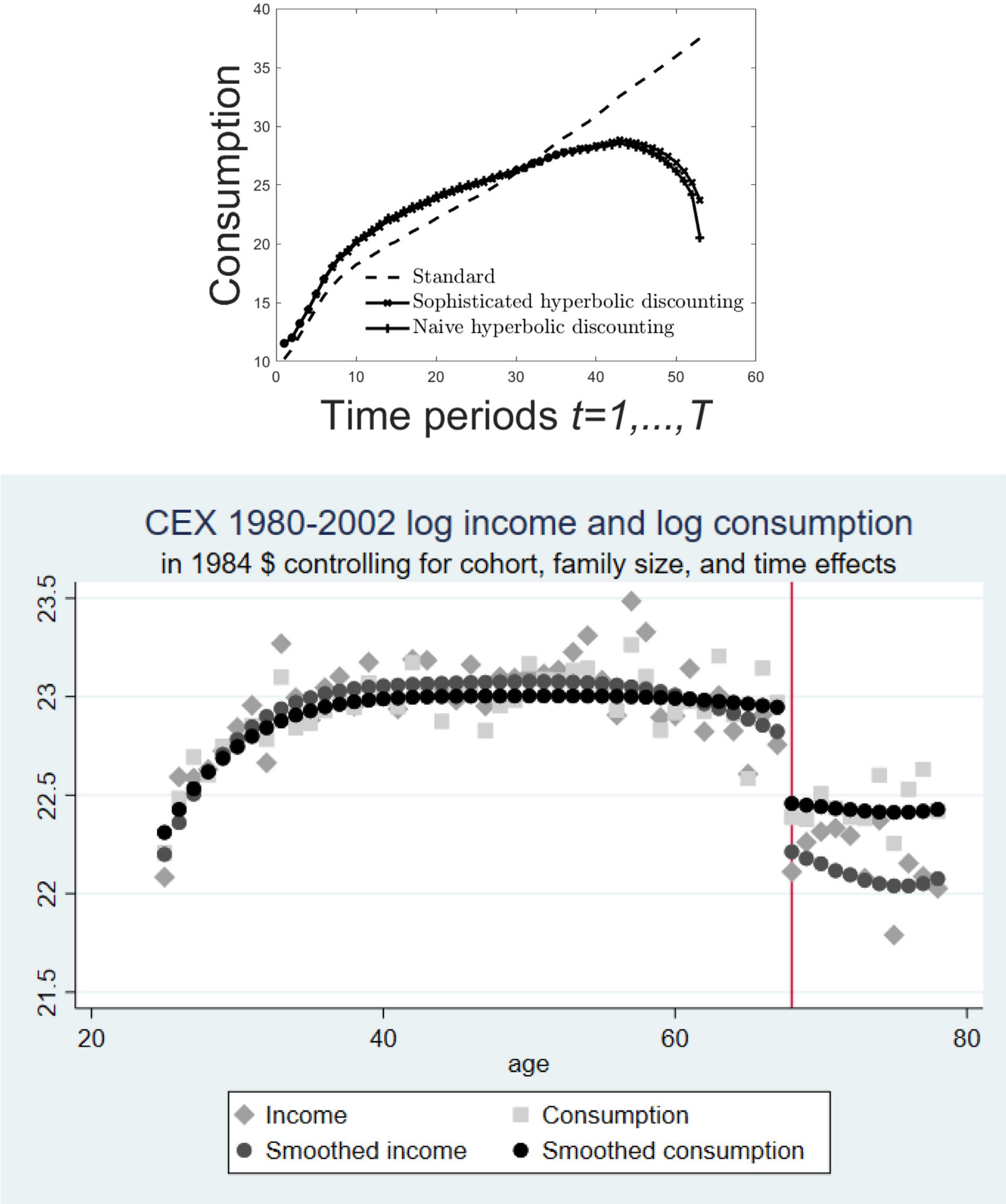

Fig. A1. Simulated life-cycle profiles and CEX consumption and income data.
This figure contrasts the average consumption profiles using the simulated data of 516 agents that have either sophisticated, naive, or standard preferences with the average CEX consumption and income data. For this illustration, we set $\beta = 0.7$. The unit of consumption and income is the log of 1984 dollars controlling for cohort, family size, and time effects.

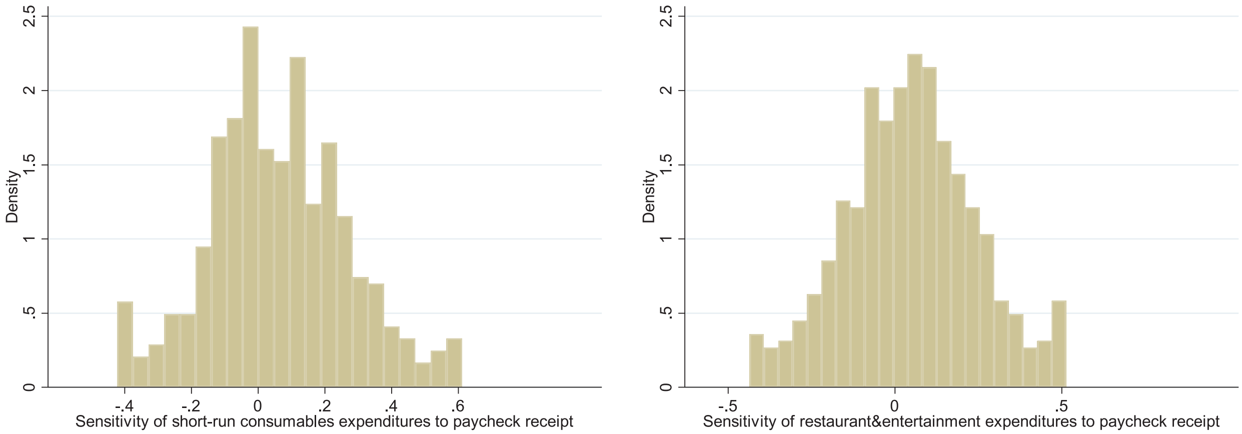

Fig. A2. Distribution of individual-level sensitivity to paycheck receipt.
The distribution of the estimates of each user's sensitivity to paycheck receipt, captured by γ_{1i} in Eq. (3).

each period t subject to the budget constraint. Here, n_t represents family size in period t, ρ is the coefficient of relative risk aversion, β is a hyperbolic discount factor, and δ is an exponential discount factor. $B(\cdot)$ incorporates the bequest motive in the death state which is represented by $s_t = 0$ instead of $s_t = 1$ when the agent survives. The agent can be sophisticated or naive, i.e., his period t self does or does not take into account that his period $t+1$ self is present-biased. More details can be found in Laibson et al. (2017) and the model is solved by numerical backward induction. Laibson et al. (2017) estimate the environmental parameters of the model using data from the American Community Survey of the U.S. Census Bureau, the Survey of Consumer Finances, and the Panel Study of Income Dynamics and the preference parameters of this model to match the patterns of wealth accumulation and credit card borrowing over the life-cycle and we adopt the parameters of their best fit for the naive hyperbolic agent. For the sophisticated hyperbolic agent, we assume the same calibration but the sophisticated agent knows that his β is the same in the current as well as all future periods. In turn, we consider a standard agent by setting $\beta = 1$.

We simulate the life-cycle consumption paths of 10,000 agents and then run the equivalent of our empirical specifications in the simulated data. Unlike main setting, this model does not feature biweekly paychecks specifically. We therefore cannot isolate the sensitivity of consumption to variation in income steming only from biweekly paychecks. Rather, we estimate how sensitive the agent's consumption is to income in general. That is, we first estimate the following equation

$$\log(C_{i,t}) = \alpha + b_1 \log(Y_{i,t}) + \phi age_{i,t} + \epsilon_{i,t}$$

where $\log(C_{i,t})$ is the amount consumed by agent i at age t, $\log(Y_{i,t})$ is the agent's i's realization of income at age t, and $age_{i,t}$ is a full set of age fixed effects to control for any trends over the life cyle. The income process is calibrated to include social security and unemployment benefits but does not specifically model the receipt of paychecks which is why we use the income amount as the explanatory variable. Second, to estimate the effect of resources, we estimate the following equation

$$\log(C_{i,t}) = \alpha + b_1 \log(Y_{i,t}) + b_2 \log(X_{i,t}) \\ + b_3 \log(X_{i,t}) \log(Y_{i,t}) + \phi age_{i,t} + \epsilon_{i,t}$$

where $\log(C_{i,t})$, $\log(Y_{i,t})$, and $age_{i,t}$ are the same variables as in the first specification and $\log(X_{i,t})$ are agent i's resources or cash-on-hand at age t (when the agent borrows then $X_{i,t} < 0$ and we use $-\log(abs(X_{i,t}))$). In turn, we estimate $b_1 = 0.8069$ with a standard error of 0.0005 in the first specification and $b_3 = 0.0055$ with a standard error of 0.0217 in the second specification for the naive agent. For the sophisticated agent, we estimate $b_1 = 0.7386$ with a standard error of 0.0005 in the first specification and $b_3 = -0.01442$ with a standard error of 0.0023 in the second specification. For the standard agent, we estimate $b_1 = 0.3703$ with a standard error of 0.0003 in the first specification and $b_3 = 0.8633$ with a standard error of 0.0049 in the second specification.

Appendix B. Estimating sensitivity to paycheck receipt

B.1. Distribution of estimated sensitivities

Fig. A2 plots the distribution of the estimated sensitivity to paycheck receipt of expenditures on short-run consumables in the left panel, and of expenditures on restaurant and entertainment spending only in the right panel. The plot complements the summary statistics on the estimated sensitivity to paycheck receipt in Table 5. As indicated by the summary statistics, the mean of the distributions is shifted upwards from zero. A t-test confirms that it is significantly different from zero that is the average user's expenditures react substantially to paycheck arrival. The two distributions also look very similar irrespective of whether expenditures on short-run consumables or restaurant and entertainment only were considered.

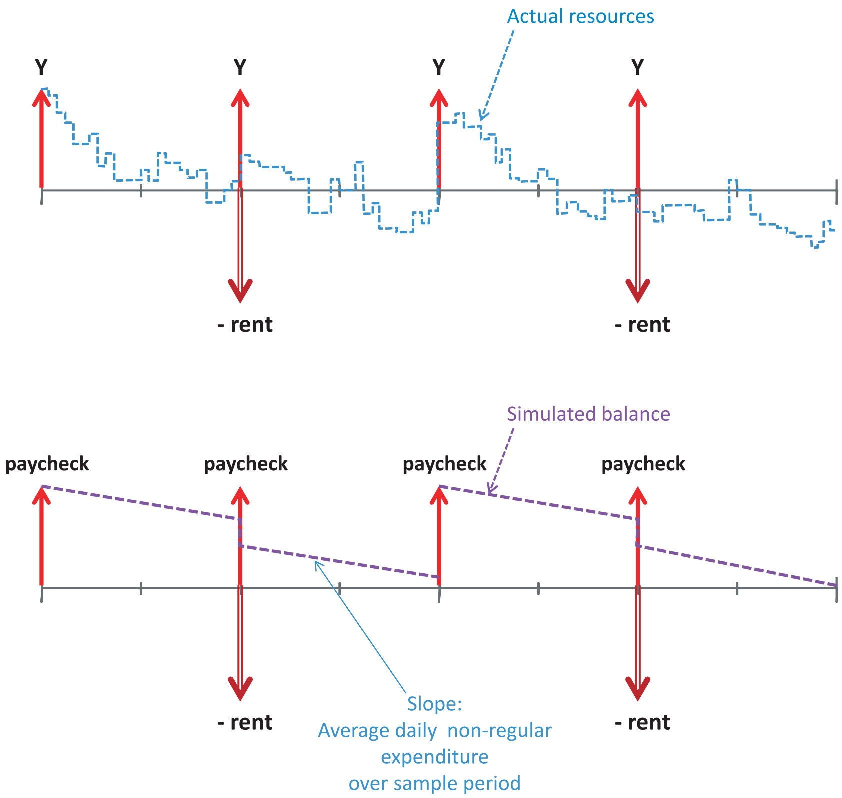

Fig. A3. Hypothetical balances based on regular payments.
The figure illustrates the construction of hypothetical balances based on regular payments. The upper panel shows actual balances for a hypothetical agent who receives regular biweekly paychecks (illustrated by upward pointing red arrows) and has to pay rent monthly every other pay date (downward pointing red arrows). The lower panel shows the agent's hypothetical balances based on regular payments and the assumption that spending is split equally across all days. Each day's balance is calculated based on the agent's regular paycheck, regular rent payment, and average daily spending.

B.2. Hypothetical balances based on regular payments

Section 5.2.2 estimates the effect of changing resources on the sensitivity to paycheck receipt. To do so, we isolate the variation in resources uncorrelated with an individual's prior spending by calculating hypothetical balances for each consumer. Fig. A3 illustrates the construction of these hypothetical balances. It shows actual (upper panel) and calculated balances (lower panel) for a hypothetical consumer who receives regular biweekly paychecks (illustrated by upward pointing arrows) and has to pay rent monthly every other pay date (downward pointing red arrows). The upper panel shows the agent's actual balances given her income, rent payments, and spending patterns. The lower panel shows the agent's calculated balances. Instead of using the agent's actual spending, nonregular spending is assumed to be split equally across all days. Each day's hypothetical balance is then calculated based on the agent's regular paycheck, regular rent payment, and average daily spending. The figure shows that the monthly regular rent payments lead to substantially lower resources during the pay cycle in which they have to be made compared to the pay cycle where no regular payment is due. The calculated balances isolate this exogenous variation in the agent's level of resources from the endogenous variation caused by prior discretionary spending.

B.3. Sensitivity to paycheck under different restrictions

Table A1 shows summary statistics of estimated sensitivity to paycheck under different restrictions in the top panel and the intra user correlation between these estimates in the bottom panel. The estimated sensitivity decreases as more pay cycles are filtered out in which the user may have been credit constrained. However, the estimated sensitivity would decrease even if credit constraints did not play any role, since the excluded pay cycles are those with the highest spending. On the individual level, the estimated sensitivities are highly correlated. Within a given consumption category (short-run consumables or restaurant and entertainment), the correlation between sensitivity estimates with different restrictions is more than 90%. Across the two spending categories, the estimates are also similar with correlations between 55% and 65%.

B.4. Planned paydown by differences in consumption patterns

Table A2 shows that planned paydown is similarly influenced by characteristics for naive and sophisticated individuals. There is no statistically significant effect of sensitivity or sophistication on planned paydown. Overall,

Table A1
Sensitivity estimates under different restrictions.

Panel A: Sensitivity Estimates

	Obs.	Mean	Std. dev.	25th pctile	50th pctile	75th pctile
	Sensitivity to paycheck receipt					
Short-run Consumables						
No restriction	516	0.074	0.211	−0.064	0.066	0.201
Category spending possible (baseline)		0.061	0.211	−0.081	0.049	0.199
Buffer stock (5th percentile)		0.052	0.227	−0.093	0.040	0.190
Total discretionary possible		0.057	0.216	−0.089	0.039	0.198
Restaurant & Entertainment						
No restriction	516	0.056	0.201	−0.070	0.056	0.192
Category spending possible (baseline)		0.046	0.201	−0.086	0.052	0.172
Buffer stock (5th percentile)		0.041	0.223	−0.108	0.050	0.179
Total discretionary possible		0.040	0.206	−0.089	0.042	0.163

Panel B: Correlation

	Short-run consumables				Restaurant & Entertainment			
	No restriction	Category baseline	spending with buffer	Total possible	No restriction	Category baseline	spending with buffer	Total possible
Short-run consumables								
No restriction	1							
Category spending (baseline)	0.976	1						
Category spending with buffer	0.903	0.927	1					
Total discretionary possible	0.948	0.964	0.933	1				
Restaurant & Entertainment								
No restriction	0.648	0.628	0.584	0.614	1			
Category spending (baseline)	0.629	0.632	0.587	0.617	0.983	1		
Category spending with buffer	0.553	0.564	0.624	0.574	0.885	0.900	1	
Total discretionary possible	0.580	0.586	0.575	0.623	0.933	0.951	0.910	1

The top panel shows summary statistics of each user's estimated sensitivity to paycheck receipt under restrictions other than the baseline estimates. The bottom panel shows the correlation between these estimates of each user's sensitivity to paycheck receipt. Throughout the table, the first row shows sensitivity estimates based on all pay cycles the user is observed. The second row shows the baseline estimates. The third row requires payweek spending in each category to have been affordable without reducing the user's resources below the 5th percentile of the user's observed resources. The fourth row requires total discretionary spending (rather than just spending in the respective category) to have been affordable. As in the baseline specification, sensitivity to paycheck receipt is captured by the coefficient on *payweek* in Eq. (3).

planned paydown seems to be determined primarily by factors such as income, existing debt levels, and possible other considerations such as spending needs and ease of reductions in spending.

Appendix C. Robustness of paydown results

C.1. Estimates based on restaurant and entertainment spending and regression specification

The first two columns of Table A3 show estimates of Eq. (5) when the sensitivity and sophistication are based only on spending on restaurant and entertainment rather than the broader category of short-run consumables. The last six columns of Table A3 show different regression specifications of the baseline results in Table 8. Unlike in the baseline, the control variables are assumed to have the same effect for both types of agents and are therefore not interacted with sophistication. In addition, the effect of sensitivity and planned paydown is estimated separately. Therefore, either sensitivity to paycheck or planned paydown is interacted with sophistication and the respective other variable is only included as a control (not interacted with sophistication). The results for each variable are very similar to the baseline results in Table 8.

C.2. Direct relationship between paydown and consumption patterns

To look for any direct relation between the reduction in sensitivity to paycheck receipt and debt paydown, we estimate the following regression equation:

$$Paydown_i = \mu_0 + (coefficient\_on\_payweek * resources)\mu_1 + X_i'\lambda + \nu_i \tag{A1}$$

The regressor of interest is $(coefficient\_on\_payweek * resources)$ estimated in Eq. (4), which captures how additional resources affect an agent's sensitivity to paycheck receipt. Eq. (A1) is estimated with and without including the explanatory variables from the baseline specification (Eq. (5)) as additional controls. Table A4 shows that the direct relationship between paydown and the reduction in sensitivity with additional resources is weak in all specifications. None of the coefficients are statistically significant and several are positive. That is the opposite of what would be expected under the hypothesis that a reduction in sensitivity as resources increase directly leads to higher debt paydown.

Table A2
Sensitivity, sophistication, and planned paydown.

	Planned Paydown	
	Short-run consumables	Restaurant& Entertainment
Sensitivity	145.538	186.976
	(131.181)	(170.901)
Sophisticated	32.648	140.571
	(113.646)	(104.431)
Sensitivity * Sophisticated	−70.542	−126.329
	(246.732)	(249.622)
Median paycheck ($)	194.5***	257.5***
	(51.312)	(55.614)
Original debt ($)	17.8***	15.8***
	(3.309)	(3.317)
Cash balances	3.247	2.283
	(4.462)	(4.485)
Available credit	2.435	3.641
	(2.116)	(2.779)
Median paycheck * Sophisticated	−2.058	−112.168
	(76.658)	(74.710)
Original debt * Sophisticated	1.296	4.279
	(4.541)	(4.553)
Cash balances * Sophisticated	−4.209	−1.390
	(6.642)	(6.632)
Available credit * Sophisticated	0.327	−1.986
	(3.786)	(3.552)
Constant	−123.076	−198.269
	(113.267)	(128.905)
Number of individuals	516	516

Note: standard erros in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, winsorized 1%, sensitivity, bootstrapped standard errors
The table shows estimates of the effect of short-run impatience and sophistication on planned paydown with bootstrapped standard errors in parentheses. All variables are winsorized at the 1% level. Short-run impatience is measured as the coefficient β_1 in Eq. (3) using expenditures on short-run consumables or restaurant and entertainment as the dependent variable. Median paycheck and level of original debt are measured in dollars. Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Table A3
Alternative regression specifications.

	Restaurant & entertainment only		Alternative regression specification					
	Paydown 90 days	Paydown 180 days	Paydown 90 days			Paydown 180 days		
Sensitivity	−2.876	8.937**	5.046	8.910		4.497	6.254	
	(6.552)	(4.279)	(6.800)	(7.358)		(3.935)	(4.255)	
Planned paydown	0.268***	0.194***	0.223***		0.216***	0.176***		0.168***
	(0.066)	(0.055)	(0.061)		(0.066)	(0.057)		(0.060)
Sensitivity *Sophisticated	−17.219*	−24.525***	−26.341**	−29.980***		−7.893	−10.137	
	(10.379)	(6.604)	(10.532)	(11.492)		(6.015)	(6.433)	
Planned paydown *Sophisticated	0.105	0.259*	0.268		0.262	0.338**		0.337***
	(0.166)	(0.140)	(0.175)		(0.172)	(0.168)		(0.161)
Median paycheck	1.317***	0.639***	1.199***	3.880***	1.547***	0.853***	2.663***	1.054***
	(0.220)	(0.177)	(0.243)	(0.141)	(0.221)	(0.217)	(0.079)	(0.216)
Original debt	0.029	−0.115***	0.030	0.327***	0.035*	−0.110***	0.188***	−0.115***
	(0.026)	(0.020)	(0.022)	(0.011)	(0.021)	(0.022)	(0.007)	(0.021)
Sophisticated	−1.621	−4.134***	−3.695	5.029	−3.821	−5.806	2.474	−6.388
	(4.263)	(3.472)	(4.729)	(3.296)	(4.755)	(3.983)	(2.071)	(3.945)
Constant	−12.609***	−8.998***	−9.357***	−16.577***	−11.239***	−6.590***	−12.611***	−6.880***
	(3.380)	(1.904)	(2.469)	(1.630)	(2.482)	(2.047)	(1.115)	(2.048)
Nr of individuals	516	516	516	516	516	516	516	516

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

C.3. Sensitivity estimates based on level of spending and weekly spending

To be included in the baseline sample, users are required to have at least 45 days of positive spending. Table A5 replicates the baseline results requiring either 40 or 50 days of positive spending instead. Throughout, the results are very similar to the baseline estimates in Table 8.

In the baseline specification, spending is measured in logs and on a daily level. Instead, the first two columns of Table A6 use sensitivity estimates based on the actual amount spent and normalizes those estimates by average spending (levels instead of logs). The third and fourth

Table A4
Direct effect of sophistication measure on debt paydown.

	Paydown 90 days				Paydown 180 days			
	I	II	III	IV	V	VI	VII	VIII
Short-run consumables								
Coefficient on	−0.439	0.114	−0.224	0.683	−0.497	−0.539	−0.376	−0.075
Resources*Payweek	(0.559)	(1.401)	(0.534)	(1.311)	(0.341)	(0.904)	(0.319)	(0.826)
Winsorized	1%	5%	1%	5%	1%	5%	1%	5%
Controls			Y	Y			Y	Y
N				516				
75th - 25th percentile				0.251				
Restaurant & entertainment								
Coefficient on	−0.070	0.185	−0.075	0.492	0.320	0.843	0.267	0.925
Resources*Payweek	(0.409)	(1.109)	(0.385)	(1.061)	(0.260)	(0.631)	(0.242)	(0.591)
Winsorized	1%	5%	1%	5%	1%	5%	1%	5%
Controls			Y	Y			Y	Y
N				516				
75th - 25th percentile				0.305				

The table shows regression estimates of Eq. (A1) with p-values based on bootstrapped standard errors in parentheses. The coefficient on the interaction of *payweek* and *resources* is estimated in Eq. (4). Full controls include all regressors included in Eq. (5), i.e., debt levels at sign up and user's monthly income. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A5
Paydown - Different requirements for days observed for sample inclusion.

	Paydown 90 days			Paydown 180 days		
	Baseline (45 obs)	40 obs	50 obs	Baseline (45 obs)	40 obs	50 obs
Sensitivity	8.511	8.260	2.825	6.461*	5.813	4.290
	(7.253)	(6.831)	(7.876)	(3.921)	(3.961)	(4.296)
Planned paydown	0.179*	0.180*	0.178*	0.129	0.103	0.127
	(0.094)	(0.093)	(0.094)	(0.086)	(0.084)	(0.086)
Sensitivity	−33.293***	−31.175***	−32.280***	−10.179*	−7.222	−10.515*
* Sophisticated	(11.638)	(10.972)	(12.504)	(5.861)	(5.531)	(6.358)
Planned paydown	0.371*	0.360	0.380*	0.391*	0.408**	0.401*
* Sophisticated	(0.224)	(0.222)	(0.227)	(0.212)	(0.208)	(0.213)
Median paycheck	1.938	1.817	1.752	1.990*	1.015	1.804*
	(1.503)	(1.413)	(1.572)	(1.150)	(1.149)	(1.202)
Original debt	0.173	0.177	0.187	−0.028	0.102	−0.029
	(0.123)	(0.116)	(0.126)	(0.104)	(0.111)	(0.106)
Median paycheck	−2.116	−1.083	−2.564	−2.412	−0.944	−2.571
* Sophisticated	(3.148)	(2.923)	(3.365)	(2.280)	(2.296)	(2.399)
Original debt	−0.346	−0.337	−0.358	−0.148	−0.244	−0.150
* Sophisticated	(0.273)	(0.255)	(0.278)	(0.236)	(0.250)	(0.238)
Sophisticated	4.157	2.728	4.664	−1.099	−3.063	−1.211
	(5.747)	(5.444)	(6.071)	(4.271)	(4.181)	(4.545)
Constant	−12.035***	−12.105***	12.622***	−8.585***	−8.012***	0.607
	(2.688)	(2.626)	(2.801)	(2.035)	(2.005)	(1.888)
Number of individuals	516	537	493	516	537	493

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

columns use weekly spending instead of daily spending. The last two columns use sensitivity estimates based only on debit card spending, excluding any spending on credit cards. Some users do not have enough spending on debit cards, so the sample is smaller 494 instead of 516 users. All results are very similar to the baseline estimates in Table 8.

C.4. Robustness to sophistication classification

The first four columns of Table A7 exclude users who get classified differently into naive and sophisticated based on short-run consumables or restaurant and entertainment spending. This reduces the sample size and therefore increases standard errors so that some of the estimates are outside standard significance bounds. Overall, the results are similar to the baseline results in Table 8. If anything, the point estimates are more similar across categories, supporting the notion that previously misclassified users lead to additional noise in the estimation. The last two columns of Table A7 classify users as sophisticated or naive based on OLS estimates of the effect of resources instead of using estimates when resources are instrumented for by hypothetical balances as outlined in Section 5.2. If the endogeneity concern motivating the use of IV estimates is important, we would expect a substantial number of users to be misclassified when using OLS estimates and, hence, to find fewer differences between the two groups. Indeed, Table A7 finds smaller differences between sophisticated and naive, which are mostly not statistically significant, reinforcing the need to instrument for the level of resources.

Table A6
Paydown - Sensitivity estimates based on levels, weekly spending and debit card spending only.

	Levels		Weekly		Debit card only	
	90 Days	180 Days	90 Days	180 Days	90 Days	180 Days
Sensitivity	4.844	1.426	11.585**	8.032***	16.731**	6.907*
	(5.186)	(2.594)	(4.672)	(3.035)	(6.509)	(3.844)
Planned paydown	0.179*	0.140	0.177*	0.106	0.149	0.125
	(0.093)	(0.093)	(0.092)	(0.083)	(0.119)	(0.115)
Sensitivity*Sophisticated	−13.557*	−4.919	−14.306**	−9.213**	−31.065***	−6.599
	(7.966)	(4.079)	(7.108)	(4.602)	(10.151)	(5.872)
Planned paydown*Sophisticated	0.354	0.415*	0.358	0.390**	0.458**	0.426*
	(0.225)	(0.232)	(0.223)	(0.196)	(0.231)	(0.229)
Median paycheck	1.835	2.092*	1.739	2.073*	1.556	1.961
	(1.516)	(1.186)	(1.549)	(1.203)	(1.722)	(1.329)
Original debt	0.175	−0.071	0.198	−0.001	0.219*	−0.044
	(0.124)	(0.113)	(0.123)	(0.098)	(0.127)	(0.119)
Median paycheck*Sophisticated	−1.441	−2.445	−1.252	−3.021	−3.121	−2.612
	(3.098)	(2.345)	(3.144)	(2.365)	(3.400)	(2.589)
Original debt*Sophisticated	−0.305	−0.129	−0.322	−0.112	−0.374	−0.144
	(0.273)	(0.258)	(0.273)	(0.215)	(0.280)	(0.254)
Sophisticated	2.467	−1.296	1.919	−0.312	5.933	−0.907
	(5.802)	(4.535)	(5.544)	(4.490)	(6.004)	(4.775)
Constant	−12.301***	−8.496***	−13.387**	−9.366***	−12.366	−8.845**
	(2.817)	(2.155)	(5.225)	(2.704)	(9.242)	(3.753)
Number of individuals	516	516	516	516	494	494

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table A7
Sophistication classification - Exclude inconsistently classified users and classification based on OLS estimates.

	Consistently classified users only				Classification based on OLS	
	Paydown 90 days		Paydown 180 days		Paydown 90 days	Paydown 180 days
	Short-run consumables	Restaurant & Entertainment	Short-run consumables	Restaurant & Entertainment	Short-run consumables	
Sensitivity	5.633	−4.140	1.973	6.480	6.741	2.351
	(8.959)	(8.184)	(4.754)	(5.390)	(6.463)	(3.525)
Planned paydown	0.243**	0.240**	0.133	0.144*	0.261***	0.194*
	(0.123)	(0.108)	(0.106)	(0.085)	(0.090)	(0.106)
Sensitivity*Sophisticated	−38.795***	−19.103	−9.739	−20.045**	−23.764**	−0.887
	(14.462)	(12.924)	(7.328)	(8.335)	(10.330)	(5.206)
Planned paydown*Sophisticated	0.331	0.316	0.456*	0.480**	0.141	0.261
	(0.291)	(0.262)	(0.256)	(0.241)	(0.235)	(0.241)
Median paycheck	−0.016	0.308	0.354	0.423	1.307	0.380
	(2.089)	(1.819)	(1.212)	(1.153)	(1.694)	(1.228)
Original debt	0.151	0.138	0.027	−0.008	0.198*	0.037
	(0.142)	(0.151)	(0.116)	(0.109)	(0.120)	(0.103)
Median paycheck*Sophisticated	2.653	3.070*	0.365	0.568	0.329	0.892
	(3.826)	(3.472)	(2.238)	(2.142)	(3.302)	(2.404)
Original debt*Sophisticated	−0.404	−0.326	−0.265	−0.249	−0.427	−0.362
	(0.323)	(0.306)	(0.262)	(0.246)	(0.261)	(0.239)
Sophisticated	−3.634	−6.876	−6.417	−6.818*	6.269	−2.309
	(6.688)	(6.323)	(4.481)	(4.072)	(6.224)	(4.148)
Constant	17.229***	10.582	0.240	−0.456**	−17.621***	−10.305***
	(7.486)	(8.388)	(2.882)	(2.994)	(3.142)	(2.014)
Number of individuals	375	375	375	375	516	516

This table shows regression estimates of Eq. (5) with bootstrapped standard errors in parentheses. Variables are winsorized at the 1% level. Paydown is the average daily reduction in debt levels. Sensitivity is the coefficient γ_1 in Eq. (3). Users are classified as sophisticated if additional resources reduce the sensitivity to paycheck receipt and as naive otherwise. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Appendix D. Data preparation and classifications

D.1. Sample selection

The following table illustrates how many users are lost at each step of the data selection process, starting with a random sample of users. To ensure that we observe all relevant activity for a given user, we restrict to users for whom spending over time appears to be primarily financed by the observed income and changes in account balances. This excludes users who most likely have additional sources of income that we do not observe, such as users with accounts that are not linked. For the same reason, we also exclude users who link more accounts later in the sample indicating that part of the earlier observed spending or debt balances were incomplete. We allow users to fulfill all sample criteria in four possible ways. First, they are included when all criteria are fulfilled considering all available data. Next, we restrict each user's data to one year, 270 days, and 180 days after sign-up and include them if they fulfill all criteria during this shorter sample horizon. This includes users who acquire additional accounts later in the sample or switch jobs, such that they miss more than one paycheck or no longer have a regular paycheck later in the sample. The vast majority of users, 470 out of 516 fulfill the sample criteria when all their data are considered.

Users with a linked checking account in original sample	3653
and observed for at least 180 days after sign-up	2558
and all accounts linked at sign-up	2051
and a credit card and plan to reduce debt	1845
and at least one paycheck deposited into a checking account	1590
and regular biweekly paychecks	1118
and regular paychecks account for more than 70% of all income	923
and appear to have all relevant accounts linked	897
and at least 8 regular, non-constrained pay cycles	698
and at least 45 days of positive spending	579
and fulfill all above criteria over the same horizon	516
fulfill criteria over full time observed	470
fulfill criteria during first year observed	21
fulfill criteria during first 270 days observed	12
fulfill criteria during first 180 days observed	13

D.2. Classifying transactions

The transaction data used in the paper include the amount, date charged, and description the customer sees on his bank account statement, as well as a code from the data provider which classifies transactions into different categories. Based on this information, we first identify transactions which are likely to be paychecks. The remaining transactions are classified as either regular or non-regular. Finally, we define two additional types of spending, short-run consumables and total discretionary spending. This online appendix explains how transactions are classified into each category.

Paychecks. Transactions are identified as paychecks when they are classified as such by the data provider or when their description contains one or more of the following words or word groups:

- "Payroll," "payroll," "PAYROLL," "PAYRLL," "PAYROL," "PAYPPD"
- "SALARY," "salary," "Salary," "FED SAL,"
- "PPD," plus one of the following: "DIR DEP," "DIRDEP," "DIRECTDEPOSIT," "DIRECT DEPOSIT," "DIRECT DEP," "DIR.DEPST," "CO ID," "PAYMENTPPD"
- "CO ID"and "INDN," plus one of following: "DIR DEP," "DIRDEP," "DIRECTDEPOSIT," "DIRECT DEPOSIT," "DIRECT DEP"

Even if they meet the above criteria, transactions are not classified as a paycheck if they contain any of the following words:

- "tax", "Tax", "TAX"
- "PAYPAL," "paypal," "HALF.COM," "Square Inc," "SQUARE INC"

Finally, we classify regular deposits (identified the same way as regular payments described below) of more than $500 as paychecks.

Regular Paychecks. To identify those users with regular paychecks, we first isolate transactions which are likely paychecks, as desribed above. A user is classified as receiving regular bi-weekly paychecks if he receives paychecks of similar amounts about every two weeks (13 to 16 days apart), at most one paycheck is missed, and these regular paychecks account for at least 70% of a user's income.

Spending. We first distinguish between regular and non-regular payments. Non-regular payments are further distinguished into discretionary spending and non-regular, non-discretionary spending. Discretionary spending is defined as an expense where at the time of the payment the consumer had discretion about (i) whether to incur the payment at all, or (ii) how much to spend. Payments are classified as discretionary based on the type of expenditure category. An example of discretionary spending is a restaurant meal. For non-discretionary spending, such as cell phone bills or utility bills, the amount due depends on past consumption, but there is no discretion once the bill arrives. We further consider short-run consumables, a subcategory of discretionary spending described below.

Regular and non-regular payments. To classify transactions as regular payments they are first grouped into sets which have the same

- exact amount
- amount when cents are truncated
- amount rounded to the next integer
- amount rounded to multiples of $10 when the transaction amount is more than $100

A set of transactions is classified as occurring regularly every two weeks if

- there are at least 7 transactions
- the median difference between payments is between 13 and 16 days
- at most one payment in the sequence was missed, i.e., the maximum amount of time between payments is 31 days

A set of transactions is classified as occurring regularly monthly if

- there are at least 5 transactions
- the median difference between payments is between 28 and 31 days
- at most one payment in the sequence was missed, i.e., the maximum amount of time between payments is 64 days

Non-regular payments are further classified into short-run consumables, non-durables or total discretionary spending. These three broad categories consist of the following sub-categories as assigned by the data provider:

- Short-run Consumables
  - gasoline/fuel

  - groceries
  - restaurant/dining
  - entertainment (movie tickets, Netflix, iTunes, video/DVD rental, computer games, party stores, etc.)
- Total discretionary expenditure
  - short-run consumables
  - travel
  - gifts
  - drugstore purchases/personal care
  - pet expenditures
  - general merchandise (Target, Walmart, Cosco, etc.)
  - automotive expenditures (excluding car purchases), primarily oil checks and the like
  - toys and other children's products
  - clothing and shoes
  - healthcare/medical products
  - home maintenance
  - non-regular cable and online services
  - hobby expenditures
  - electronics
  - credit reports or services
  - advertising or custom management services
  - non-regular bills
  - PayPal purchases
  - unclassified credit card purchases
  - non-regular uncategorized transactions

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