Time to Repay or Time to Delay? The Effect of Having More Time Before a Payday Loan is Due*

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Abstract

We examine the effect of state laws on minimum payday loan durations that give some borrowers an additional pay cycle to repay their initial loan with no other changes to contract terms. Neoclassical models predict this "grace period" would reduce borrowers' need for costly loan rollovers. However, in reality, borrowers' repayment behavior with grace periods is very similar to borrowers with shorter loans, merely pushed out a few weeks. Potential explanations include heuristic repayment decisions and naive present focus. A calibrated model suggests that present-focused borrowers get less than half the benefit from a grace period that time-consistent borrowers would.

Keywords: payday loans, present focus, loan duration, consumer finance
JEL classification: G51, D11, D12

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1 Introduction

A concern often raised about short-term subprime credit, such as payday loans, is that their short durations make it difficult for people to save for repayment and consumption smooth, leading to a cycle of repeat borrowing.[1] However, little is known empirically about how borrowers would actually respond to having more time to repay their loans.

We explore this question using a large administrative dataset on the repayment patterns of payday loan borrowers in Texas who faced different amounts of time to repay their loans. Laws in Texas during the timeframe of our data created variation in loan durations with no changes to other contract terms.[2] The duration of a payday loan had to be at least seven days - due on a payday. Since these loans mature on the borrower's payday, it meant that if a borrower originated a loan seven days before their next pay date, their initial loan would be seven days. A similar borrower who came in one day later, however, would have until the end of their next pay period before the loan was due (we call this a "grace period"). Importantly, the payday lender we study set the interest charges at 18% of the principal, irrespective of the length of the loan. For two borrowers paid biweekly, this scenario resulted in one borrower having an initial loan length of seven days, while the other had 20 days (and an intervening pay date), with no difference in their total interest charge. Any subsequent borrowing (i.e., loan rollovers) had loan durations of two weeks for both types of borrowers.

We exploit this variation in whether or not the initial loan has this "grace period" to explore how additional time before a loan payment is due affects repayment behavior. Borrowers have four options when their due date arrives: 1) Allow the lender to cash their collateral check which would result in full repayment (if the check clears) or delinquency (if the check bounces); 2) repay in full at the storefront; 3) repay interest only resulting in a "rollover" of the original or a larger loan balance to the next pay period; 4) "paydown" some principal plus full interest resulting in a "rollover" of the remaining principal balance plus interest to the next pay period. The question we ask here is: Does having extra time to repay affect these repayment behaviors?

In Section 3 we develop the simplest possible neoclassical model of consumption and debt repayment and show that in theory a "grace period" of this type should lead to an increase in the amount of the debt that is paid off at the initial due date and an overall reduction in repeat borrowing. The logic is simple: a borrower with a grace period can save some

[1] For example, Richard Cordray as director of the Consumer Financial Protection Bureau noted concern with repeat payday-loan borrowing: "Trouble strikes when [borrowers] cannot pay back the money and that two-week loan rolls over and over and turns into a loan that the consumer has been carrying for months and months." http://www.consumerfinance.gov/speeches/remarks-by-richard-cordray-at-the-payday-loan-field-hearing-in-birmingham-al/.

[2] 7 Tex. Admin. Code § 1.605 (2001)

money toward the debt repayment and will smooth consumption by doing so. The question of interest for our empirical exercise is whether this simple prediction is actually borne out in the data.

The primary challenge to the empirical exercise is that people choose when to come in for a payday loan. However, we present evidence that borrowers appear unsophisticated in their timing of arrival at the payday store front and that the variation in loan durations is plausibly exogenous. In particular, we show that there is no spike in borrowers taking advantage of longer loans by coming in after the threshold day when they would be afforded a grace period. We also find that borrowers who come in just before and just after the seven-day discontinuity point are very similar on a broad range of important characteristics, such as loan size, credit score, and income. Our results are also consistent when restricting to borrowers who are taking out a loan for the first time and thus are unlikely to know the differences of coming in six versus seven days before a pay day. These patterns give us confidence in using the variation in loan duration for borrowers around this cutoff to estimate the effect of having more time to repay an initial loan.[3]

Contrary to the simple theoretical predictions, we find that borrowers take little advantage of the grace period to accelerate their loan repayment. On average, borrowers with biweekly paychecks took out initial payday loans of \$300 with an initial interest charge of \$54. Borrowers with short loans due at their next pay date, on average, paid down around 30% of their initial loan balance at their first due date. These borrowers without grace periods slowly paid down their average debt balances across due dates, paying off 40% in total by their second pay date after loan origination, 50% by their third pay date, and so on. We might expect, then, that grace-period borrowers might pay down around 40% at their initial due date, which comes at their second pay date after loan origination, since short-duration borrowers paid off that amount at their second pay date. However, we find that grace-period borrowers do not accelerate their loan repayments and make initial loan repayments that are nearly identical on average to what we see for the short-duration borrowers. The 95% confidence intervals on our estimates exclude additional payments for grace-period borrowers at their first due date of more than \$3. Similarly, rollover frequencies and total accumulated interest charges were only modestly lower for borrowers who have more time to repay the initial loans. Overall, the key empirical finding is that the grace period leads borrowers to

[3] Hertzberg et al. (2018) find that borrowing behaviors are responsive to loan duration in the online lending context. We note that a key difference in our setting from theirs is that we think the borrowers in our sample are unlikely aware of the shorter loan option since it is not posted on the "menu" of loans as on an online lending platform. Therefore, our argument here does not contradict their finding that when borrowers are aware of the loan duration differences they are responsive to them. Additionally, in the online lending context, interest rates are tied to loan duration, which is not the case in our setting.

primarily "push off" their repayment cycle by a pay period.

We explore a number of potential explanations for this pattern of borrowers seemingly ignoring or wasting the grace period. We begin by considering factors that can be added to the neoclassical model that might affect debt repayment. We consider the possibilities that a) when borrowers first take out a loan they may be experiencing a period of temporarily low income (or equivalently high unavoidable expenditure shocks like a medical spending), b) borrowers may face highly volatile income or expenditure shocks, c) borrowers may be anticipating a positive income shock (e.g., a tax return) that they will use to repay debt, or d) borrows may have extremely high risk aversion leading to sharply diminishing utility from reducing consumption. Each of these possibilities can profoundly affect basic debt repayment patterns in the model, but none of them predict the patterns we see where borrowers with grace periods show the same repayment trajectories shifted out two weeks.

While modifications to the neoclassical model incorporating risk and income shocks do not provide an explanation for our finding, behavioral considerations including myopia, inattention, and repayment heuristics may help explain borrower behavior. These factors can help account for the fact that the empirical data is consistent with borrowers acting as if they ignore the loan during the grace period and then begin on the same repayment trajectory they would have had as the initial due date grows near.

This type of pattern could be consistent with simple debt-repayment heuristics. For example, Gathergood et al. (2019) find that for U.K. credit-card users appear to use a simple "balance-matching" heuristic to decide which credit cards to pay down. Similarly, Keys and Wang (2019) find that many people who make minimum payments on credit cards seem to be "anchoring" on the minimum amount suggested rather than having a true liquidity constraint. These exact heuristics do not apply naturally to the payday loan setting, but simple heuristics, such as repaying a fixed $20 of loan principal at each due date, can explain a subset of the behavior we observe. We explore the importance of this possible channel in Section 6 and conclude that heuristics could play a role in helping to explain the lack of response to the grace period, but we are unable to identify simple heuristic processes that offer a complete explanation.

Naive present focus (Laibson, 1997; O'Donoghue and Rabin, 1999) offers another potential explanation for observed borrower behavior. Adapting the simple neoclassical model of debt repayment to include naive present focus predicts the repayment "push-off" pattern we see with the grace period. The intuition for this result is that even modest levels of present focus cause short-run impatience that leads to procrastination so that most of the consumption reductions that go toward repaying debt occur next to loan repayment deadlines. When that procrastination effect is strong enough, adding additional time before the loan is due has very little effect on the debt-repayment patterns. However, present focus likely needs to be coupled with inattention to income and expenditure risk to explain the patterns. Awareness of income and expenditure risk should generate a precautionary savings motive even for present-focused agents and that would, in turn, mean that the grace period should lead to higher initial debt repayments.

We calibrate a version of our repayment model that combines naive present focus and inattention to expenditure risk, which allows us to quantify the potential borrower welfare benefits from grace periods. The simple model with homogeneous preferences can fit both targeted and untargeted moments in the data well, including predicting the empirical "push off" pattern with grace periods. The calibrated model implies that the welfare benefits of a grace period are only 45% of what they would be if borrowers were time consistent. These results suggest that myopic behavior may substantially reduce the benefits of policies aimed at providing borrowers with additional time to handle debt repayments.

These findings have implications for economic policy for subprime loan products. Some states have introduced laws that increase the length of time borrowers have to repay their loans.[4] Our results suggest that while these policies are net positive for borrowers, their benefits are more muted than standard theory would predict.

Our findings also contribute to understanding the behavioral foundations of subprime borrowing. While classical economic theory predicts that access to a voluntary credit source can only benefit fully-informed consumers, various forms of biases generating myopia might lead people to take on costly debt that is not in their own best interest (Caskey, 2012). Empirical research directly testing the question of whether access to payday loans is beneficial or detrimental comes to mixed conclusions.[5] However, research has documented important patterns of myopic behavior among payday-loan borrowers that helps to inform this debate. For example, a field experiment by Bertrand and Morse (2011) with payday loan borrowers

[4] For example, in 2009 Virginia began requiring that payday borrowers be given at least two pay cycles (rather than the typical one) to repay their loans. See: https://scc.virginia.gov/getattachment/ecd570b2-780e-4efc-9d61-dc985ba42934/payday_rept_09.pdf.

[5] Melzer (2011) concludes that access to payday loans exacerbates financial difficulties. Carrell and Zinman (2014) also find that access to payday loans harms the job performance of Air-Force personnel, and Skiba and Tobacman (2019) find that payday loans increase personal bankruptcy filings. On the other hand, Zinman (2010); Morgan et al. (2012) and Bhutta et al. (2016) provide evidence that limiting access to payday loans may push people toward other costly forms of subprime credit, such as overdrafts or pawnshop loans. Morse (2011) finds that payday loans help borrowers who suffered through a natural disaster. Bhutta et al. (2015) find that payday borrowers turn to these loans only after exhausting access to less costly forms of credit, consistent with classic models of liquidity constraints. Yet they also find that these borrowers tend to borrow at high rates for long periods of time suggesting that high-interest borrowing is not relieving temporary credit constraints. Zaki (2016) finds that access to payday loans helped military personnel better smooth their food consumption over the course of pay periods. Carter and Skimmyhorn (2017) find no effects of access to payday loans on credit or labor outcomes of Army personnel.

found that "information that makes people think less narrowly (over time) about finance costs results in less borrowing." Burke et al. (2015) find that behaviorally-informed disclosures like those used in the Bertrand and Morse experiment reduced payday loan borrowing in Texas. Skiba and Tobacman (2008) show that default typically occurs after making a long series of interest payments, which is most consistent with models of naive hyperbolic discounting. However, Allcott et al. (2020) survey payday loan borrowers about their beliefs about future borrowing and find evidence consistent with present-focus but conclude that only new borrowers appear naive about their present focus. Olafsson and Pagel (2016) find that many people borrow on payday loans for immediate consumption on alcohol and restaurants despite having cheaper sources of liquidity available, suggesting this borrowing may relate to self-control problems. The findings in this paper add new empirical evidence supporting the proposition that accounting for consumer myopia is important for those hoping to understand the behavior of subprime borrowers.

Finally, our findings add to a broader literature documenting empirical patterns of consumption and borrowing behavior that can be more easily rationalized with models of quasi-hyperbolic discounting incorporating time inconsistency than classic exponential-discounting frameworks. These studies include findings related to monthly patterns of food consumption for food-stamp participants (e.g. Shapiro, 2005; Hastings and Washington, 2010), financial shortfalls in response to variation in the timing of social security receipt (Baugh and Wang, 2018), saving and borrowing behavior (e.g. Laibson, 1997; Angeletos et al., 2001; Gross and Souleles, 2002; Meier and Sprenger, 2010), retirement-savings patterns (e.g. Loewenstein et al., 1999; Madrian and Shea, 2001), and monthly patterns of credit card debt repayment (Kuchler and Pagel, 2017). Our study is the first in this series to explore how consumers react to variation in the timing of predictable future expenditures. Like much of this literature, our study does not provide a test of the quasi-hyperbolic model of discounted utility versus other models of consumer myopia.[6] However, the findings here provide new evidence in support of the value of incorporating these behavioral factors into economic models. Our results also suggest that using variation in the time that people have to prepare for spending shocks and changes in credit conditions more generally may be a valuable direction for future research aimed at a better understanding of the behavioral foundations of consumption, borrowing, and savings dynamics. In the discussion at the end of the paper we highlight some other settings where exploring these dynamics might be valuable.

[6]Examples include, temptation (Gul and Pesendorfer, 2001), focusing effects (Kőszegi and Szeidl, 2012), or inattention (Shah et al., 2012). In fact, as we discuss below, even exponential discounting with extreme discount rates could help rationalize the lack of repayment response to a grace period. Within the exponential model, however, that degree of short-run impatience implies implausible discounting of the further future (e.g., a nearly complete discounting of utility one year out).

2 Background on Payday Loans

Payday lenders supply a few hundred dollars of cash on the spot in exchange for a personal check written to the lender by the borrower, post-dated to an upcoming payday.[7] The due date is typically set for the borrower's next payday or the payday after that, variation which we describe in more detail in Section 4. Unless the borrower comes in to renew and extend the loan, the lender then cashes the check, written for the principal plus fees (including interest), on that payday.[8] The typical $300 payday loan requires a $54 interest fee for its short term (e.g., two weeks). Hence, annualized interest rates for these loans are on the order of 400–600 percent.

A key feature of most payday loans, including the ones studied here, is that this interest charge is a fixed percentage of the loan balance over the course of a pay cycle. For example, the $300 loan has a $54 interest charge (18%) due at the next pay date, regardless of the length of time in the pay cycle. There is also no prepayment advantage, and as such, there is no true daily interest rate for these loans. This distinguishes payday loans from many other types of consumer credit.

When the loan comes due, the borrower has a number of options. She can allow the payday lender to cash her check and pay off the loan that way. She can also go to the lender and repay the loan in cash. Finally, borrowers can partially or fully "renew" or "roll over" a loan. A loan rollover allows the borrower to pay her interest charge on the due date and renew all or some of the principal. The renewal extends the maturation date of the loan, requiring an additional interest payment but giving the borrower a subsequent pay cycle to repay the principal (plus the additional interest). Many states restrict this practice, and there are a number of papers that study the chronic behavior of payday loan borrowers.[9] It is not clear, however, how effective those restrictions on repeat borrowing are since monitoring payday borrower behavior is difficult. The data we use comes from Texas during a time period where there were no such restrictions on repeat borrowing for payday loans.

[7]Repayment via direct withdrawal from the borrower's bank account has become common recently. Repayment with a physical check was the norm during the time frame we study. Most large lenders, including the one studied here, calculate a subprime credit score they use to approve and reject applications. About 15 percent of all loan applications are rejected based on this score. For more on the subprime scoring process, see Agarwal et al. (2009).

[8]Beyond requiring a checking account to obtain a payday loan, a borrower must also verify her employment, identity, and address by providing the lender a recent pay stub, a phone or utility bill, and a valid form of identification.

[9]See for example, Bertrand and Morse (2011); Burke et al. (2015); Fusaro and Cirillo (2011); Li et al. (2012); Skiba (2014) and Stegman and Faris (2003) for papers that discuss rollover behavior and borrowers who chronically use payday loans.

3 Standard Representative Agent Theoretical Model

We begin by establishing a benchmark prediction about the effect of grace periods by using a standard dynamic consumption-saving model with a representative agent. The representative agent receives income y at regular pay cycle intervals (e.g. every 14 days). Pay cycles are indexed by I and the days within the pay cycle by t. The final day of a pay cycle is denoted $t = T$. We then denote the consumption on day t of pay cycle I as c_t^I. The payday loan borrower in our model begins the first pay cycle of the model with an initial debt balance (i.e. the initial payday loan) of D^0. The re-borrowing limit at any time in the model is 50% of their income y, which roughly matches the empirical reality in our sample time period. This re-borrowing constraint implies that $D^I \leq 0.5y$ for all I. There is a periodic interest rate of r charged on the debt balance and this interest charge comes due at the end of each pay cycle.[10] Importantly, as mentioned, in payday lending this interest rate is charged on the entire balance for the pay period regardless of the length of the period and cannot be reduced by prepayment.

We consider first the "non-grace period" payday loan repayment schedule, in which the loan and interest charge come due at the end of every pay cycle. For the non-grace period borrowers, the budget constraint in each period is given by:

$$rD^I + (D^I - D^{I+1}) + \sum_{t=1}^{T} c_t^I = y \tag{1}$$

The first term is the interest payment due on the loan for that period. The second term is the net principal paid down on the loan that period. The final term on the left-hand side of the equation is simply the sum of daily consumption during the period. The model also assumes that the interest and principal must be repaid so that default is not an option.

In the "grace-period" case, the initial loan payment is due at the end of the second pay cycle, rather than the end of the first pay cycle as in the non-grace period case. The budget constraint for the initial "grace-period" pay cycle, $I = 0$, is:

$$S + \sum_{t=1}^{T} c_t^0 = y \tag{2}$$

where S denotes savings during the first pay cycle that can be used to help repay the payday loan at the end of the next pay cycle. The savings during the first pay cycle does not earn any interest, a feature of our model that matches the fact that interest payments due on an

[10] An equivalent interpretation is that the interest charge comes due at the immediate start of the following pay period.

initial payday loan are fixed and cannot be reduced by repaying part of the loan early.

For an individual with the grace-period, the budget constraint for the following pay cycle, $I = 1$, when the initial loan comes due, is then given by:[11]

$$rD^0 + (D^0 - D^2) + \sum_{t=1}^{T} c_t^1 = y + S \tag{3}$$

Because the grace period only applies to the initial loan repayment, the budget constraint for all subsequent pay cycles is then given by equation (1). The utility of the agent from the perspective of any day t of any pay cycle I is a discounted sum of the utility of (expected) consumption into the future and is given by:

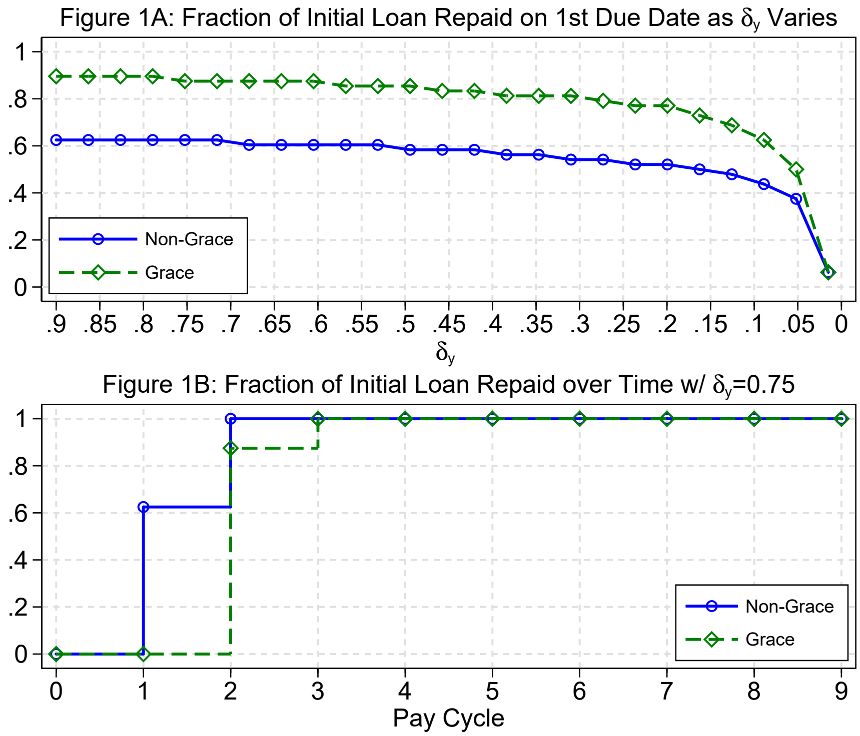
$$U_{t,I} = \sum_{Z \geq I} \sum_{k=t}^{T} \delta^{(k-t+(Z-I)T)} u(c_k^Z) \tag{4}$$

where δ is the daily discount factor that is calculated from the yearly discount factor δ_y. The agent maximizes $U_{t,I}$ by choosing daily consumption streams and payday loan balance for each pay period. We lay out the mathematical details of the agent's problem in the Appendix.

Figure 1 shows the model's predictions on repayment behaviors for both non-grace and grace period borrowers in terms of their fractions of initial loan principals repaid over time. The representative agent in the model is assumed to have a biweekly income ($900) and an initial payday loan balance ($300), which are both consistent with the average values observed in our data, and log utility over daily consumption. The top panel shows that the size of the initial debt repayment is substantially larger under a grace period for essentially any yearly exponential discount rate other than those that approach zero. The bottom panel shows a prediction for the debt repayment pattern under both the non-grace and grace-period cases for an example situation where the yearly exponential discount factor (δ_y) is set to 0.75. The grace period would be expected to increase the amount of debt repaid at the first due date substantially but not quite enough to lead to grace-period borrowers having the same outstanding debt after that first due date as the non-grace borrowers do after their second due date. Because the grace period borrowers pay off their loan with fewer total rollovers and less debt after their initial repayment, they end up paying fewer total interest charges over the course of the loan. These patterns provide our theoretical benchmark to which we compare the equivalent empirical realizations in the next sections.

[11] In Equation (3), the term $(D^0 - D^2)$ could be replaced by $(D^1 - D^2)$ because for the grace-period case $D^1 = D^0$.

Figure 1: Theoretical Predictions of the Baseline Model



Note: All calculations above assume a representative agent with biweekly income of \$900 and an initial payday loan balance of \$300. The borrowing limit is half of biweekly income, which is \$450.

4 Empirical Analysis

4.1 Administrative payday-loan data

Our data come from the administrative records of a large payday lender in Texas. We observe information obtained during the application process (take-home pay from latest paycheck, pay frequency, checking account balance, credit score, gender, etc.) and loan characteristics (origination and maturation date, loan size, interest paid, and whether the loan was renewed, repaid in full, or defaulted on). Our lender is active in 14 states, but we focus on loans originated in Texas because the majority of applications at this lender occur there. We also focus on loans originated between November 2001 and August 2004, during which time the lender used stable loan terms. Finally, we restrict our analysis to borrowers who are paid either every two weeks (main analysis sample) or semimonthly, i.e., every 15 days, (presented in the Appendix) because those borrowers are the ones for whom laws on minimum loan lengths allow us to employ our empirical strategy.

For our analysis, we focus on how initial loan durations affect the patterns of debt repayment. To facilitate that analysis, we identify a sample of "initial loans." Specifically, we look for loans taken out when the individual has not had a loan from the lender for some time (at least 32 consecutive days). We define an initial loan in this way to capture borrowers who have not been dependent on a loan for at least two pay cycles. We then analyze the patterns of repayment and rollovers for all the loans that follow this initial loan in a continuous fashion, what we label a "loan spell."[12]

We further focus our main analysis on borrowers who are paid biweekly. Most of these borrowers are paid every other Friday, though a small fraction are paid on Thursdays. In Section 2 of the Appendix, we replicate all of the main analyses, with similar results, for borrowers who are paid semi-monthly, typically on the 1st and the 15th day of the month, for whom there are similar discontinuities in loan lengths.

Table 1: Summary Statistics

	Biweekly Sample	Biweekly Sample (Restricted to 6 and 7 days before payday)
Borrower Characteristics for Initial Loans		
Age	36.19	36.19
	(10.00)	(9.99)
Female	64.85%	63.35%
White	21.83%	21.75%
Black	40.78%	40.68%
Hispanic	36.35%	36.63%
Race, other	1.05%	0.95%
Homeowner	37.26%	37.72%
Direct Deposit	75.92%	77.51%
Annualized Net Pay ($)	22,476.67	22,940.35
	(8,922.01)	(8,958.25)
Checking Balance ($)	265.04	269.39
	(423.39)	(422.72)
Credit Score ($)	558.97	555.94
	(210.77)	(208.92)
Initial Loan Characteristics		
Principal of Initial Loan ($)	312.48	299.93
	(133.41)	(134.78)
Interest Due on Initial Loan ($)	56.25	53.99
	(24.01)	(24.26)
Initial Loan Duration (days)	12.79	13.34

table continues to next page

[12] A subsequent loan is considered in the "loan spell" if someone took out another loan within 15 days of a previous loan.

	Biweekly Sample	Biweekly Sample (Restricted to 6 and 7 days before payday)
	(4.13)	(6.50)
Initial Loan Outcomes		
Principal paid on first due date ($)	85.74	88.84
	(150.57)	(152.54)
Rollover on first due date (%)	67%	64%
Number of Effective Rollovers in Loan Spell	3.11	2.98
	(4.70)	(4.71)
Total Finance Charges Paid in Loan Spell ($)	219.69	208.55
	(306.92)	(303.90)
Loan Spell Ended with Default (%)	22%	20%
Total Number of Initial Loans	79,098	15,491
Total Number of Loans (including Rollovers)	325,020	61,709

Note: Means of all variables shown, with standard deviations in parentheses for continuous variables. Data are based on authors' calculations from administrative data from a large payday lender in Texas from November 2001 - August 2004. Initial loans are loans where the borrower did not have a loan outstanding for at least 32 days prior to initiation. Our administrative records do not include demographic information for all borrowers, and we observe gender, race and homeownership information for about half the sample.

Table 1 provides summary statistics on the loan and borrower characteristics from our full sample of new loans for borrowers paid biweekly[13]. We have 79,098 initial loans (Col. 1). Including the total number of loans in a borrower's spell, this amounts to a total of 325,020 loans analyzed. Our main analysis will restrict this sample to those who arrive 6 or 7 days before the payday loan is due (Col. 2) which includes 15,491 initial loans.

The average loan was around $300. The borrowers taking out these loans had estimated annual take-home pay of around $23,000. The average checking account balance from their most recent bank statement prior to obtaining their initial loan was just $265-$270, which confirms that the majority of these borrowers are likely cash constrained as their payday arrives. The lender charged a per-period interest rate of 18 percent on loans during this time, which generates an average interest charge on these loans of $54. The average initial loan duration was 13 days for those paid biweekly. If we annualize interest charges of $50 paid every two weeks for a $300 loan, this would equate to an approximate annualized interest rate of 433%[14].

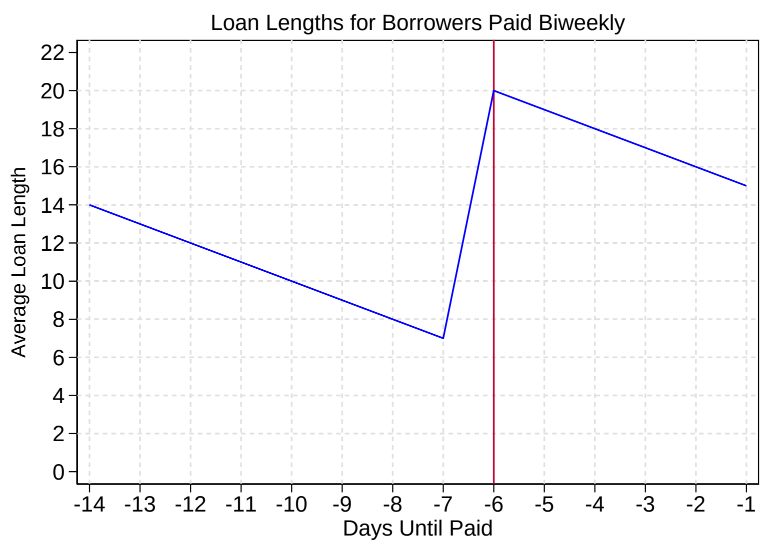
[13] The Appendix presents similar analysis for borrowers who are paid semimonthly in Appendix Table A3.

[14] $50 $\times$ 26 biweekly pay periods in a year = $1,300 in interest fees. $1,300/$300 = 4.33

4.2 Variation in initial loan durations

In Texas, payday loan maturities during this time were regulated to be "not less than seven days." This rule, when combined with the fact that payday loans come due on a borrower's payday, creates a unique opportunity for us to explore the effect of loan lengths on repayment and rollover behavior because it generates sharp discontinuities in loan lengths depending on when a borrower comes in to initiate a new loan. Because loans cannot have a maturation period of less than seven days, a borrower arriving at a lender six or fewer days before her next payday will receive an extra pay period to repay the loan. For example, a borrower paid biweekly on Fridays (i.e., every 14 days) who initiates a loan seven days prior to her payday, i.e., the Friday between paydays, will have a seven-day loan due on her next payday. However, a similar borrower who obtains a loan six days before her next payday, i.e., on Saturday, will not have to repay the loan on her next payday because that would create a loan shorter than the seven-day minimum. Instead, her loan will be due on her following pay date, implying that she will receive a loan with a 20-day duration.

Figure 2: Loan Length



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. Figure 2 reports the average loan length for borrowers paid biweekly. The minimum loan maturity is seven days. If a borrower arrives at the lender with fewer than seven days until her next payday, the loan length is equal to the number of days until that payday plus the time until the next payday (14 days for biweekly borrowers).

These effects are illustrated in Figure 2. Because we know when the payday loan is due and the frequency at which a borrower is paid, we can infer the next payday of the borrower for those paid biweekly. We plot on the x-axis the number of days until a borrower's next inferred (biweekly) payday. The most relevant part of this graph for our empirical design is the difference in maturation periods for borrowers who arrive at the lender six (seven) days before their payday and receive a 20 (7) day loan.

In the Appendix we document similar discontinuities in loan lengths for borrowers paid semimonthly. In those graphs, we show loan length based on day of the month the borrower initiates the loan. Borrowers paid semimonthly are typically paid on the 1st and 15th of the month, though some are paid on the 15th and last day of the month.

4.3 Results

In this section, we report the results of our empirical analysis investigating the effect of having more time to repay an initial payday loan. The goal of our empirical strategy is to exploit the exogenous variation in loan duration generated by binding minimum-loan-length laws to measure how borrower repayment will respond. Importantly, for this approach to be valid, the decision to come in six days versus seven days before a payday needs to be uncorrelated with other factors that affect the outcome variable. The concern in our setting is that borrowers control when they come in to initiate a loan, and as such borrowers receiving longer loans may be systematically different than those with shorter loans. In Section 4.3.1 we present evidence suggesting that this type of self-selection bias is likely not present in this setting and argue that we can therefore think of the loan lengths around the seven-day regulatory minimum as plausibly exogenous. In Section 4.3.2 we then present estimates of the effect that different loan lengths have on repayment behavior. Finally, in Section 4.3.3 we present robustness checks for these estimates.

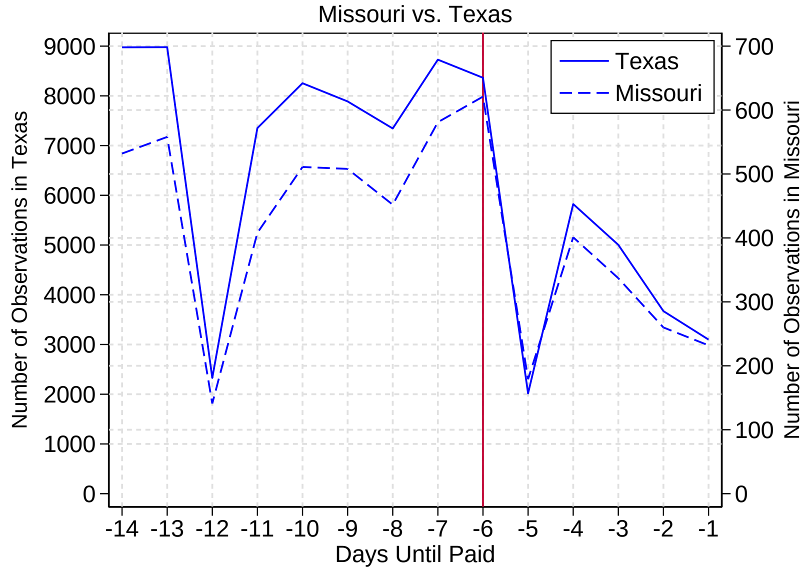
4.3.1 Evidence of similarity of borrowers around loan-length discontinuities

The primary endogeneity concern for this paper is that borrowers may understand that by waiting an additional day to obtain a loan they can get a much longer initial loan duration. If many borrowers take advantage of that opportunity, we would expect systematic differences in the density and characteristics of borrowers on either side of the discontinuity.

Figure 3 plots the number of loans disbursed by days until payday for borrowers paid biweekly. The solid line in the graph plots the number of loans for borrowers from our Texas sample. This graph suggests that there may not be very serious distortion based on borrowers' timing of obtaining a loan. There is little difference between the number of loans given to those with biweekly paychecks seven days before versus six days before their pay date. There is certainly no spike in lending six days before the cutoff, as we would expect if borrowers were strategic about the lending rules[15].

[15]The drops in loan volume seen in the figure at 5 days and 12 days prior to payday reflect the fact that

Figure 3: Loan Origination around the Cut-off



Note: Authors' calculations based on payday loan transaction data in Texas and MO from November 2001 until August 2004. The figure reports the number of observations for borrowers paid biweekly in Texas and Missouri, respectively, for each day. The vertical line represents seven days before a payday loan is due. A borrower arriving one day later (i.e., six days before payday) will receive an additional 14 days in loan length.

To further confirm that borrowers are not exploiting the opportunity for longer loan lengths, we compare the patterns of loan initiations for our Texas sample to patterns in Missouri during the same time period. In Missouri, the minimum loan duration during this period was 14, which means there was no discontinuity in loan lengths for initiations between six and seven days before payday.[16]. As such, the patterns of borrowing around the sixth and seventh day for biweekly borrowers in Missouri provide a counterfactual for what we might expect to see in the absence of loan-length incentives. The dashed line in Figure 3 shows the patterns for Missouri. The total volume of loans is much lower in Missouri (right-hand axis), but despite the very different loan-length rules in the two states, the patterns of loan initiations are very similar. In particular, there is no spike in the number of loans made in Texas six days prior to payday relative to what we see for Missouri.

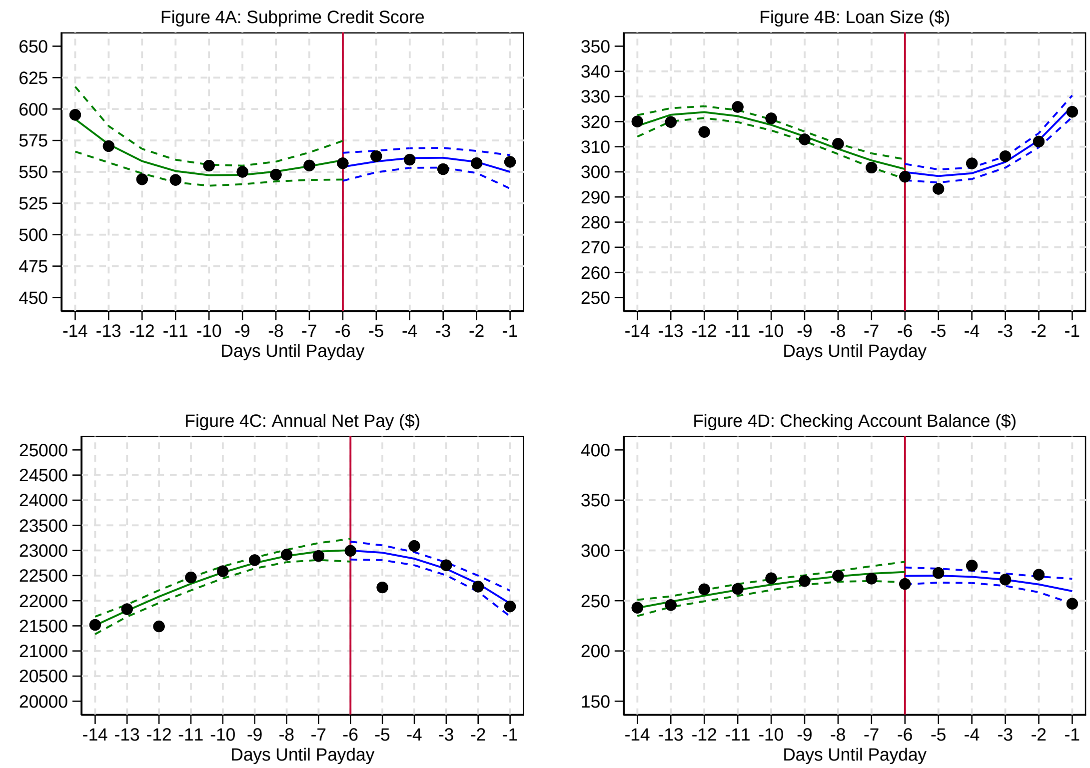
Our analysis of the characteristics of borrowers receiving longer and shorter loans also suggests that there is nothing unusual about borrowers receiving longer loans that would lead to a bias in our estimates. Figure 4 shows how important characteristics of borrowers vary as a function of how many days before payday the loan was initiated. We see that patterns

the majority of biweekly borrowers are paid on Fridays and payday loan outlets are closed on Sunday.

[16]During our sample period, Missouri's General Assembly passed a law governing small-dollar loans (2002 Mo. Laws 809-SB 884). This law codified within the Missouri statutory code (Section 408.505) already-existing administrative rules (Mo. Code Regs. Ann. tit. 4, § 140-11.010 (5)) including those governing borrowers' minimum loan lengths (to be not less than 14 days).

of average subprime credit scores, loan sizes, annual net pay magnitudes, and checking account balances are very similar and smooth across the discontinuity that generates the grace period in loan length. We plot a simple third-order polynomial function of the x-axis and its confidence interval allowing for a jump at the loan-length discontinuity point. In virtually every case the function estimates no discontinuity.

Figure 4: Key Control Variables around the Cut-off



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The vertical line marks six days until payday, i.e., the day in the pay cycle where the borrower experiences a discontinuous increase in loan length. Dots on the graph represent the averages of each outcome (in the figure heading) for each day until payday. The curve shows the predicted outcomes from the regression results of the outcome variable on the cubic form of days until payday as well as an indicator for a borrower taking out a loan six or fewer days before their next payday. The curve to the left of the line is the predicted outcome without an indicator for six or fewer days until payday. The curve to the right of the line maps the predicted outcomes including the dummy for less than six days until payday. 95% confidence intervals are represented by dashed bands.

In Table 2 we show regression results to quantify the magnitude of differences between these characteristics for borrowers who initiate loans either the day before or the day after the "grace-period" cutoff. For this analysis we limit the sample to only borrowers on either side of the cutoff, although we note that the results are very similar if we instead use the polynomial structure from Figure 4 and include all of the data in the regressions. We run a simple OLS regression of loan or borrower characteristics on the binary indicator of whether a borrower has a grace period for her initial loan. In addition to the four variables shown in Figure 4, we also test the correlation with age, gender, race, homeownership and the likelihood of having direct deposit. In all cases we see very little difference in the characteristics of borrowers on either side of the cutoff. These differences are statistically insignificant in most cases and have point estimates that are typically just 1% of the mean of the variable of interest.

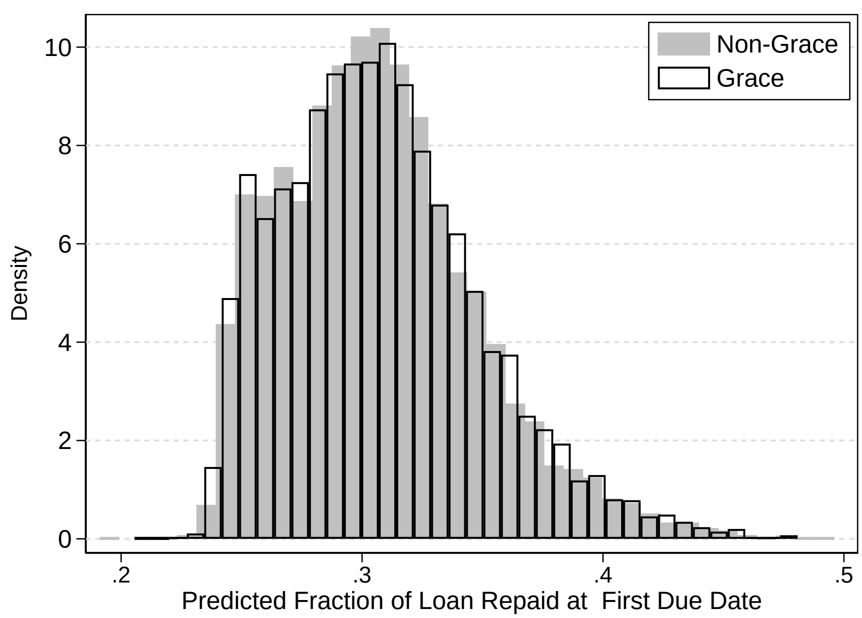
Table 2: Control Variables as Outcomes for Borrowers Paid Biweekly

	(1)	(2)	(3)
	Mean	Grace (Six Days until Payday)	Sample Size (Restricted to 6 and 7 days before payday)
Subprime Credit Score	555.94	1.79	15,491
		(3.41)	
Loan Amount	$299.93	-3.62^{*}	15,491
		(2.18)	
Net Pay	$22,940.35	103.21	15,491
		(147.25)	
Account Balance	$269.39	-5.34	15,491
		(6.87)	
Direct Deposit	0.78	-0.003	15,491
		(0.01)	
Age	36.19	0.28^{*}	15,480
		(0.16)	
Female	0.63	0.02	7,396
		(0.01)	
Black/Hispanic	0.77	0.01	7,358
		(0.01)	
Homewoner	0.38	-0.01	8,072
		(0.01)	

Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. Column 2 shows coefficients from individual linear regressions of being in the *Grace* group on each control variable listed. OLS regressions are shown for subprime credit score, loan amount, net pay, account balance, direct deposit indicator, age, female indicator, Black or Hispanic indicator, and homeowner indicator. The sample is restricted to borrowers paid biweekly who have an origination date six or seven days before their payday. We cluster the regressions at the individual level to account for the fact that some individuals initiate more than one new loan spell during our data time frame. The sample includes individuals who are missing information on age, gender, race, and home ownership, which is reflected in the changing number of observations in rows six through nine. Standard errors are clustered at the individual level and are reported in parentheses below the coefficients. $***$, $**$, and $*$ designate statistical significance at the 1%, 5%, and 10% level, respectively.

This type of check for balance on observables is valuable primarily if there is both meaningful variation in these characteristics within the population and if the characteristics are strongly related to the outcome of interest (i.e., repayment patterns). To check for these two qualifications, we run a regression to predict the fraction of the initial loan balance an individual would repay at their first due date as a function of their income, credit score, initial loan amount, and debt-to-income ratio, restricting the sample to borrowers with non-grace loans (i.e., initiated seven days before pay date). We then generate the predicted values from this regression for both non-grace and grace-period borrowers. We show the histograms of these predictions for both groups in Figure 5 below. We see that there is substantial heterogeneity in the expected repayment amounts based on these characteristics, ranging from a low of around 20% to a high of just over 40%. Consistent with the results for the similarity in average characteristics, we find that the distribution of these predicted values is nearly identical between grace and non-grace borrowers. We conclude from this result that these two groups of borrowers have similar distributions of characteristics that predict loan repayment patterns.

Figure 5: Predicted First Repayment

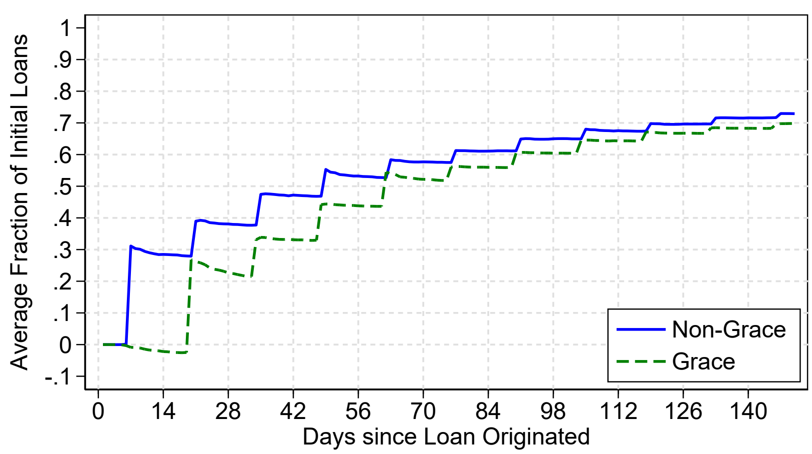


Note: This figure reports histograms of the predicted fraction of loan repaid on a borrower's first due date. The prediction comes from a regression of fraction of loan repaid on first due date on income, credit score, initial loan amount, and debt-to-income ratio estimated among those borrowers who initiated loans seven days before their payday (non-grace borrowers). Using the predicted values from this regression, we generate predicted fractions of loan repaid for both the grace and non-grace borrowers and plot them above.

Of course, this analysis cannot guarantee that there are not differences between borrowers who come in before and after the grace-period cutoff on unobservable dimensions. However, it is important to note that for unobservable differences to impact our analysis, any such variation would have to be uncorrelated with these observable characteristics, each of which are important predictors of payday loan repayment behavior and generally strong indicators of financial health. The assumption we make going forward in the analysis is that borrowers who receive loans right after the loan-length discontinuity point are otherwise similar to those who receive loans right before the discontinuity and that these differences in loan lengths are plausibly exogenous. This assumption is consistent with the data patterns reported in this subsection and is also plausible given our understanding of payday-borrower behavior. In particular, there is little reason to expect that most payday loan borrowers during this period were familiar with and sophisticated about the laws governing payday loan lengths. Furthermore, the main mechanism we have in mind is that borrowers who are paid on Fridays come in to initiate a loan the weekend in between paychecks and that whether they make it to the lender on Friday evening or Saturday morning is likely driven by a range of idiosyncratic constraints in their daily lives. In Section 4.3.3, we discuss some additional robustness tests to confirm that our results are not driven by potential selection into loan lengths.

4.3.2 The effect of a longer initial loan duration on repayment patterns

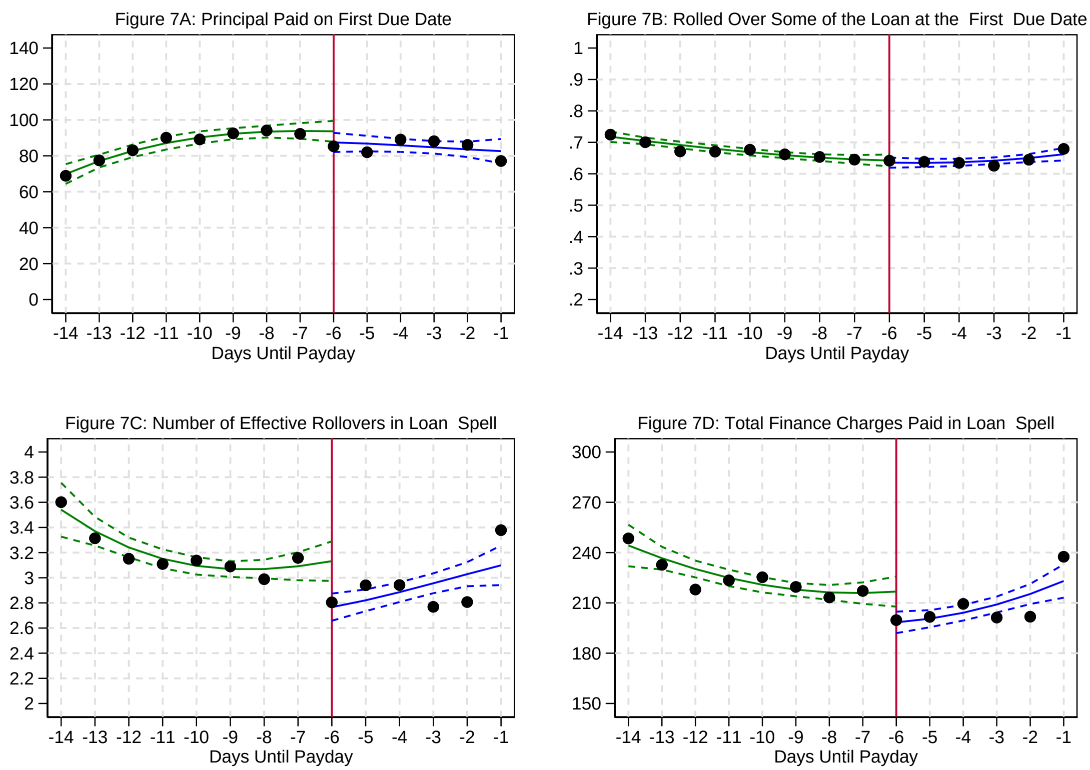
Figure 6: Average Fraction of Initial Debt Repaid



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The figure reports the average fraction of initial debt repaid by days since loan origination. We separate borrowers by the discontinuity in loan lengths. The solid line plots repayment patterns of borrowers who arrive seven days before their payday and get a seven day loan ("Non-Grace") and the dashed line plots behavior of borrowers who arrive six days before their payday and therefore receive a 20-day

Figure 6 shows the impact of the grace period on overall repayment patterns by graphing the average fraction of the initial loan balance that has been repaid by days since origination. This figure is the empirical analogue to the model predictions in Figure 1B. In contrast to the predictions of the baseline model, borrowers who receive grace periods have debt-repayment patterns that are roughly the same as those for borrowers without a grace period, simply shifted out by two weeks. In particular, notice that after their first due date the grace period borrowers have repaid just under 30% of their initial loan balance on average. That is nearly identical to the outstanding fraction of initial loans the non-grace period borrowers have right before their second due date and about 10% less than the non-grace period borrowers have repaid by their second due date.

Figure 7: Outcomes for Borrowers Paid Biweekly



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The vertical line marks six days until payday, i.e., the day in the pay cycle where the borrower experiences a discontinuous increase in loan length. Dots on the graph represent the averages of each outcome (in the figure heading) for each day until payday. The curve shows the predicted outcomes from the regression results of the outcome variable on the cubic form of days until payday as well as an indicator for a borrower taking out a loan six or fewer days before their next payday. The curve to the left of the line is the predicted outcome without an indicator for six or fewer days until payday. The curve to the right of the line maps the predicted outcomes including the indicator for less than six days until payday. 95% confidence intervals are represented by dashed bands.

In Figure 7 we analyze a number of summary measures of debt repayment patterns and graph them against the days until payday similar to how we analyzed the control variables. The key finding is that the principal paid on the first due date is almost exactly the same for those receiving a grace period as for similar borrowers whose initial loan is due after only seven days, and hence did not get a grace period (7A). We similarly see that receiving a grace period results in no reduction in the likelihood of rolling over at least some of the initial loan balance after the first due date (7B). There are, however, modest reductions in the number of total rollovers (7C) and the total finance charges (7D) paid by borrowers receiving the grace period.

Table 3: Regression Results

Biweekly Sample (Sample Restricted to Origination Date Six and Seven Days until Payday)				
	(1)	(2)	(3)	(4)
	Principal paid on first due date	Rolled over some of the loan at the first due date	Number of effective rollovers in loan spell	Total finance charges paid in loan spell
Mean	\$88.84	0.64	2.98	\$208.55
Grace	-4.04	-0.01	-0.35^{***}	-16.82^{***}
	(3.12)	(0.01)	(0.08)	(5.19)
Other Controls	Yes	Yes	Yes	Yes
N	15,491	15,491	14,073	14,073
R^2	0.13	0.07	0.05	0.08

Note: *Grace* is the indicator of having only six days until payday. Data are based on authors' calculations from administrative data of a large payday lender. OLS regressions are shown for four outcomes: Principal paid on first due date calculates the amount of the loan paid by the first due date; Rolled over some of the loan at first due date indicates that the borrower rolled over the loan at the first due date; Number of effective rollovers is a variable that counts the number of additional loans in succession by a borrower; and Total finance is the total finance charged over the loan cycle. Sample is restricted to borrowers paid biweekly who have an origination date six or seven days before their payday. Controls in all columns include loan size, gender, annual net pay, checking account balance, subprime credit score, and age bins. Dummies for race (White, Black, Hispanic, or other), having one's paycheck direct deposited, missing control variables, month-year, and each payday loan shop are also included. Columns 3-4 include fewer observations because we did not include loans initiated with less than five pay periods before the end of our sample so as to not artificially truncate these outcomes. Standard errors are clustered at the day the loan was initiated and are reported in parentheses below the coefficients. $***$, $**$, and $*$ designate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3 presents regression results to quantify these differences in outcome measures while restricting the sample to borrowers who initiated loans on either side of the grace-period cutoff.[17] We estimate that borrowers who got an additional pay period to repay their

[17]These regressions include controls for the borrower and loan characteristics we examined in the previous subsection. In Appendix Table A2, we show that the estimates are not sensitive to the inclusion of control variables.

initial loan paid down no more than those with shorter loan periods. The point estimate is actually negative, showing that on average borrowers with grace periods paid down \$4.04 less of their principal at the first due date (Col. 1). That small difference is not statistically significant, and more importantly, we can rule out increases in payment of more than \$2.07 (or 3% of the mean principal payment at first due date) at the 95% confidence level. Column 2 shows that borrowers are not substantially less likely to roll over a loan at their first due date (1 percentage point for borrowers paid biweekly, which represents 1.6% of the mean).

We also document modest reductions in total numbers of rollovers (Col. 3) and total finance charges (Col. 4) paid during the loan spell for borrowers getting grace periods. The reductions are around 10% for both measures. These findings suggest that while the initial impact of the grace period is quite small, there is at least a modest cumulative effect of increasing repayment tempo over the course of the loan spell. This is consistent with the visual evidence in Figure 6 that shows a modest shrinking of the gap between the two payment series over time.

4.3.3 Robustness and heterogeneity of main results

We perform a number of robustness checks to determine whether borrowers could be learning about the differential loan durations or whether lenders are pushing borrowers into arriving on different days of the month. Both forms of manipulation in loan length could affect our results.

In our analysis, we assume that borrowers are not strategic about the day that they arrive at the lender; rather, they take out a loan in response to an immediate need or when it is convenient. This assumption implies borrowers who have grace periods would not have subsequent borrowing habits that were different than borrowers without grace periods. We find that borrowers with a grace period in our sample on average take out their next new loan 8.09 days before their next payday. Borrowers without grace periods take out their next new loan 7.91 days before they are paid, a difference of only 0.18 days.[18] Given these facts, it does not appear that borrowers are learning or sophisticated on this front.

In Appendix Table A1 we replicate the regressions in Table 3, restricting the sample to the first loan a borrower obtained from this payday lender. By focusing on the borrower's first observed interaction with the lender, we reduce the likelihood that borrowers are selecting into either the sixth or the seventh day before their next payday as they learn more about

[18]Analogous statistics for semimonthly borrowers also confirm that the grace period is likely not associated with decisions about when to initiate a second new loan in the future: grace period borrowers take out their next new loan on the 15th (15.22) while non-grace come for their next new loan around the 15th (14.68) day of the month, as well.

how the payday loan process works.[19] As the table shows, the results are very similar to our main results: borrowers with more time pay only slightly less on their principal at the first due date, are only slightly less likely to roll over a loan, have modestly fewer total rollovers and thus pay less in total finance charges.

A final consideration on the validity of the results is that perhaps lenders are influencing who gets loans based upon the day of the month or the number of days until the potential borrower's next paycheck. Recall that lenders charge a fixed fee independent of the length of the loan, so underwriting shorter loans may be more desirable. If lenders prefer to underwrite shorter loans, we might expect a lower approval rate for borrowers obliged to be given a longer loan, encouraging borrowers to take out a loan on a different date. We can observe whether applicants are approved or denied a loan based on a subprime credit score and their pay frequency (biweekly, semimonthly, monthly, or weekly). We do not observe when an applicant's next payday is if she is denied a loan, so we restrict our analysis to borrowers paid semimonthly for whom we can easily infer pay dates. For the days that we are interested in, the 8th and the 9th day of the month, the approval rate is between 95.3 and 97.2 percent, respectively. While the approval rate does vary by 1.9 percentage points, the direction of the difference is the opposite sign we would expect if the lender was trying to influence borrowers into shorter loans. Applicants actually have, on average, a slightly higher probability of getting approved if they come in on the 9th of the month (receiving a longer loan duration) relative to coming in on the 8th day of the month.

Finally, it is worth investigating whether there is heterogeneity in the response to grace periods across the payday loan borrowers. In Appendix Section 1, we repeat the main analysis in Figure 6 splitting our sample along various characteristics. We explore whether the "push off" pattern in Figure 6 is similar across different levels of debt-to-income ratios, across median splits in financial metrics like income, subprime credit score, and checking balance, as well as demographics, including gender, race and age. The main result is highly robust and shows up similarly in virtually every cut we do in the data. The one exception is for those with very low initial debt-to-income ratios, a group which is typically borrowers with smaller initial loans. That population tends to increase borrowing over the first few weeks after getting their initial loan (both among non-grace and grace period borrowers). Within this group, the grace-period borrowers repay much less of their loans around their second and third pay periods and diverge more from the non-grace borrowers than in our full sample. Even in this case, though, the results are inconsistent with the baseline model

[19] We note, however, that we only observe the first interaction with this lender, not any lender. Our sample period was a time of rapid expansion of payday lending, so it is likely that the first observation we have for many (but not all) borrowers is their first interaction with any payday lender.

and overall in every other cut of the data we observe essentially the basic pattern of nearly full push-off of repayment patterns.

5 Modifying the Neoclassical Model Does Not Resolve the Empirical Puzzle

The empirical patterns of repayment when borrowers receive a grace period do not match the predictions of the baseline model from Section 3. While the baseline model predicts that initial loan repayments will be higher with a grace period, empirically we instead see that the overall debt repayment patterns are quite similar, merely just pushed out two weeks. In this section we consider whether there are modifications to the neoclassical model that could generate this type of "push off" pattern.

We investigate four possibilities: a) individuals may have very high risk aversion, b) loans might be initiated during a period of temporarily low income, c) people may face additional income (or equivalently expenditure) risk after the loan is initiated, and d) people may borrow in anticipation of a temporary income bump at a date in the future. The predictions of repayment of these modified baseline models are all shown in Figure 8 below. We discuss each one in turn and highlight that while all of them generate strong impacts on repayment patterns, none of them helps to explain the "push off" pattern we observe empirically with grace periods.

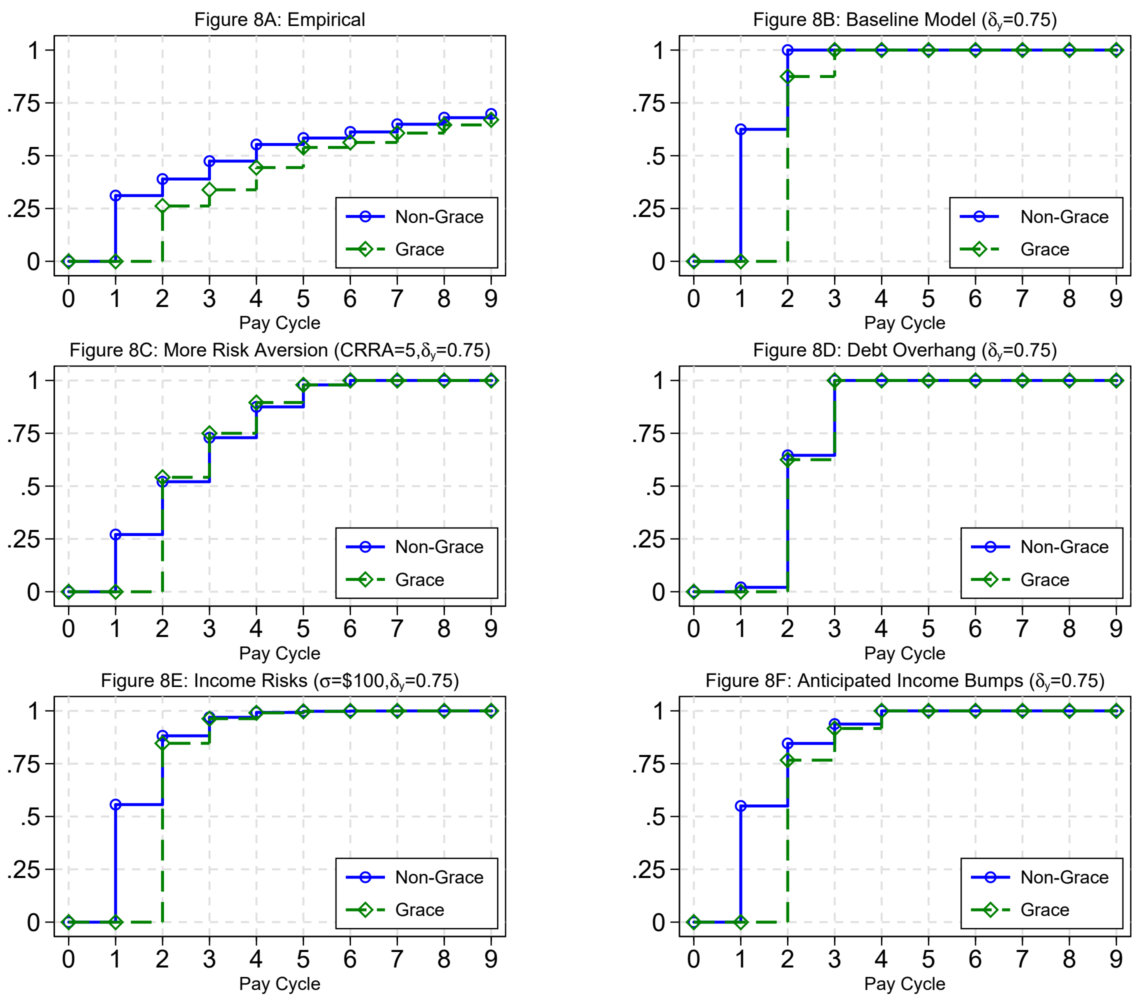
First, we explore the effects of risk aversion. In this exercise, we assume model agents have Constant Relative Risk Aversion (henceforth CRRA) preferences over daily consumption as represented by the following utility function:

$$u(c) = \frac{c^{1-\gamma} - 1}{1 - \gamma} \tag{5}$$

where γ represents the CRRA of the agent. Its reciprocal, $1/\gamma$, is the elasticity of intertemporal substitution. In our baseline model in Section 3, we assumed log utility, which is nested in the CRRA preferences family with a coefficient of relative risk aversion of one.

In Figure 8C we increase the coefficient of risk aversion to 5 and see that higher levels of risk aversion will make borrowers more reluctant to sacrifice large amounts to repay a loan in a given period and can help explain slow repayment patterns. The model with high risk aversion predicts much slower repayment over time, more in line with the repayment patterns we see empirically. However, higher risk aversion actually increases the consumption-smoothing motivation under the grace period and moves the model predictions further from the empirical reality. Borrowers with sharply diminishing marginal utility of consumption are predicted to save substantially in the grace period and would make much larger initial repayments under the grace period.

Figure 8: Average Fractions of Initial Loan Repaid over Time



Note: Figure 8A uses the same data as Figure 6 in our empirical section. The only difference is that Figure 8A abstracts from the daily balance dynamics by only plotting fraction repaid on the last day of each pay cycle (i.e., due dates). Therefore, unlike Figure 6, plots in Figure 8A looks flat between pay periods.

Second, we analyze the effects of having lower income in the first pay period. This captures the possibility that individuals take out the payday loan during a time of temporarily lower income, knowing that income will recover in the near future. For this model specification, shown in Figure 8D, we reduce the income during the first pay period for both grace and non-grace borrowers by 30%. Income returns to the baseline $900 for every pay cycle after the first one. In this case we observe that the borrowers without grace periods decide, rationally, not to repay any of their loan at their initial due date (simply rolling the loan over fully). At the same time, the grace borrowers hardly save anything over the grace period where income is lower. Therefore, both types start the second period with pretty much the same debt balance, which makes their repayment pretty much synchronized afterwards. So again, while this modification dramatically affects repayment patterns, it cannot explain the empirical "push off" pattern.

While the baseline neoclassical model assumes a deterministic income process, in reality payday loan users do face income fluctuations and expenditure shocks. In our third modification of the baseline model, we allow the representative agent's income path to be a stochastic process by adding a negative income shock (or equivalently an expense shock) at the beginning of each period. We assume rational expectations, which means the agent knows the possibility of the expense shocks and takes it into consideration when making repayment decisions.[20] For the illustration in Figure 8E we assume that the income shocks are drawn from an exponential distribution with mean $\sigma = \$100$. Adding income risks induces a strong precautionary motive, which makes the grace-period borrowers save more over the grace period. As result, the grace-period borrowers "catch up" with the non-grace borrowers after their first due date. So this modification again moves the theoretical predictions further from the empirical reality.

The last variation we add to the baseline neoclassical model is to introduce anticipated positive income shocks with heterogeneous timing. An example of this type of process could be if borrowers take out payday loans expecting they will receive a lump sum, like a tax return, at a known date in the near future, with some variation in that date across borrowers. For this exercise we assume that the positive shock equals the initial debt size. We solve and simulate the model five times with the anticipated "tax return" coming in at the beginning of the first through fifth pay cycles respectively. We then take the average of the repayment behaviors under these five different "tax return" timing scenarios to generate a model with representative-agent preferences but heterogeneous in the timing of the income bump. Figure 8E shows the average repayment behavior given these shocks. Again, this modification can predict slower overall debt repayment patterns but does not help generate the "push off" pattern we see empirically.

6 Possible Explanations

Given that the neoclassical model of debt repayment, including adaptations presented in the prior section, is unable to account for the empirical patterns, in this section we consider

[20] Appendix Section 3.4 presents the details of our modeling specifications of the expense shock process under agent awareness.

potential explanations that could help rationalize our findings. The core fact we need to explain is why borrowers who get a grace period appear *as if* they largely ignored that grace period and began whatever repayment sequence they would have had simply starting the following pay period. In this section we discuss two possibilities consistent with prior literature in behavioral economics that offer potential explanations: the use of repayment heuristics and naive present focus.

6.1 Repayment Heuristics

One possibility that could explain a lack of response to the grace period is that borrowers rely on repayment heuristics. Prior studies, such as Gathergood et al. (2019) and Keys and Wang (2019), have identified patterns of debt repayment in credit card markets that appear to be born from heuristics rather than decisions optimized based on the immediate circumstances. Borrowers basing repayment decisions on heuristics that are not responsive to the loan situation could help explain the empirical "push off" patterns we observe.

In our setting there is no obvious institutional heuristic that should dominate, but simple rules of thumb such as paying off in round dollar amounts could help explain our effect. For example, in the (extreme) case where every borrower simply planned to pay down $20 of their principal at each due date, there would be no effect of the grace period on accelerating loan repayments.

In order to better understand whether these simple rule-of-thumb repayment processes could explain the empirical findings, we tabulate in Table 4 the share of borrowers whose payments are consistent with various simple heuristics: defined as paying down the principal in an increment of $5 (e.g., $10, $15,...); paying in an increment of 10% of the initial loan balance; and making total payments of principal and interest in increments of $5.

Table 4: Heuristic Repayment Behavior

	(1)		(2)		(3)	
	Full Sample		Non-Grace		Grace	
	# of Obs.	% of Group	# of Obs.	% of Group	# of Obs.	% of Group
All	15,491	100%	7,936	100%	7,555	100%
Rolled over on 1st due date w/ partial principal repayment	6,822	44%	3,666	46%	3,156	42%
*among those who rolled over on **1st** due date with partial principal repayment*						

table continues to next page

	Full Sample		Non-Grace		Grace	
No apparent heuristic on 1st due date	1,889	28%	994	27%	895	28%
Made "heuristic" payment on 1st due date	4,933	72%	2,672	73%	2,261	72%
*among those who appeared to use heuristics on **1st** due date*						
Did not repeat same payment on the 2nd due date	3,778	77%	2,048	77%	1,703	77%
Repeated same payment on the 2nd due date	1,155	23%	624	23%	531	23%

Note: The sample includes individuals who came in either six (grace) or seven (non-grace) days before their next payday. Among borrowers who had any heuristic repayment behavior, the most common heuristics are $5 increment and 10% increment of principal reduction.

Using these generous definitions of heuristics, we find that 72% of borrowers who paid down some principal at the first due date could have been using a simple heuristic, and this is the same across borrowers with and without the grace period. Given that 44% of borrowers pay down some of the loan at the initial due date, this suggests that about a third of borrowers might be using this type of simple heuristic and might be unresponsive to loan duration. An additional 23% of borrowers in both grace and non-grace situations pay off their loans in full at the first due date, so there may be nearly a quarter of borrowers who have a source of funding for full repayment and are again not affected by the grace period. Finally, there are about 11% of borrowers who repay only the interest charge and rollover their loan fully at the first due date.[21] While the baseline model would predict that the grace period should reduce that number, we find the exact same share among the grace-period borrowers, and it is possible that "pay just the minimum due" is also a heuristic being used. All together, this suggests that perhaps almost 80% of borrowers may be using heuristics, which could largely explain the empirical findings.

On the other hand, relatively few borrowers show clear patterns of repeating the same heuristic. In the bottom of Table 4 we show that only 23% of borrowers who we classified as potentially using a heuristic to partially pay their initial loan balance made the same

[21] The remaining borrowers either increased their debt after the initial due date (9%), or had their collateralizing check bounce (12%). Among that latter group, 5% eventually repaid the debt, though we cannot observe exactly when the other 7% had the debt sent to collection and never repaid. The rates of all of these actions are similar across grace and non-grace borrower populations.

payment at their second due date. This is problematic for heuristics as an explanation for the empirical "push off" pattern from the grace period. It is not clear why grace-period borrowers would use the same distribution of heuristics as the non-grace borrowers at the first due date if non-grace borrowers are not using those heuristics consistently across payment periods. Ultimately, the results of this subsection suggest that borrowers' use of heuristics could help explain why there is such a small reaction to grace periods among payday loan borrowers, but it is not clear that this is a complete explanation.

6.2 Model with Naive Present Focus

An alternative possibility is that borrowers are engaging in an optimization process to decide on loan repayments, but are present focused and time inconsistent. As we show in this subsection, naive present-focus can help rationalize why grace-period borrowers might not take advantage of the additional time before the loan is due to save and smooth consumption. We first introduce naive present focus into the baseline model from Section 3 and show that it offers a simple explanation for the "push off" pattern. We then enrich the model to allow for income risk and show that borrowers would have to be not only present focused but also ignoring income risk to explain the "push off" pattern. Finally, we calibrate a version of the model incorporating these features and use the calibrated model to analyze the welfare benefits of grace periods for loan repayments. If one is comfortable with the assumptions in this naive present-focus model, our calibration exercise makes it possible to quantify how the benefits of a grace period compare to what we would expect them to be if borrowers were not present focused and responded as the baseline neoclassical model predicts.

6.2.1 The Baseline Model with Naive Present Focus

In this exercise, we introduce naive present focus into the baseline model presented in Section 3. With present focus, the objective function of an agent in the model becomes the following:

$$U_{t,I} = u(c_t^I) + \beta \sum_{Z \geq I} \sum_{k=t+1}^{T} \delta^{(k-t+(Z-I)T)} u(c_k^Z) \tag{6}$$

where β is the daily quasi-hyperbolic discount factor that ranges between 0 and 1. This discount factor represents the degree of present focus between the current day and all future days. Specifically, smaller β implies a higher degree of present focus.

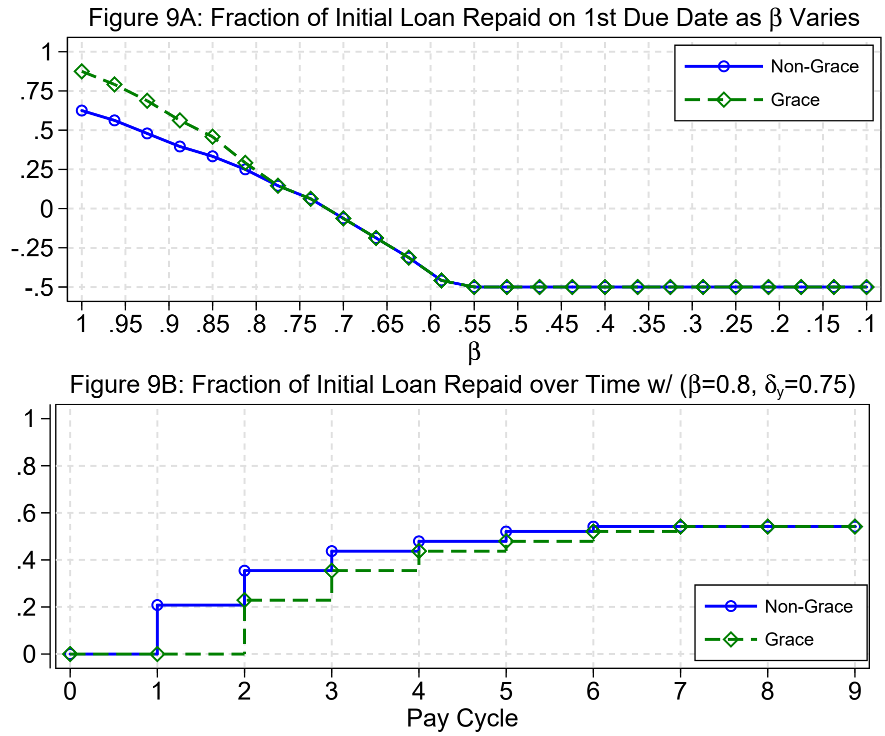
The naivete assumption about present focus here implies that our model agents know that their contemporaneous selves are present focused; nevertheless they believe that their future selves are not and therefore their future selves will behave in a time-consistent way (i.e., as in the benchmark neoclassical model). We focus on the naive version of the quasi-hyperbolic model rather than the sophisticated version (where the agent is accurately aware of her level of present focus in the future). We use this assumption primarily because Skiba and Tobacman (2008) show that broader patterns of payday loan borrowing behavior are most easily rationalized by the naive hyperbolic formulation.[22] All other details of the model setup are the same as the benchmark model in Section 3. We give the details of solving this model in Appendix Section 3, and focus here on some numerical examples to illustrate the effect of adding present focus on response to the grace period.

In Figure 9, we present the analogous figure to that in Figure 1 for the baseline model, but with variation in present focus rather than the yearly exponential discounting factor.[23] The top panel shows how the fraction of initial loan that is repaid at the first due date changes with present focus for both non-grace and grace-period borrowers. Not surprisingly, the amount repaid falls as the agent becomes more present focused. The key thing to note, though, is that the grace-period and non-grace repayment amounts converge around present focus of 0.8, with both types repaying about 25% of the initial loan balance. Figure 9B shows an example of the full repayment schedules when we set present focus to 0.8. In this case, we replicate the nearly full "push off" pattern we observe empirically.

[22]We also note that solving this model under sophistication is challenging due to the binding credit constraints in the payday loan environment, which change the effective interest rates periodically. For a sophisticated agent this creates a sequential game structure where the different daily "selves" are playing a finite game during a pay period, but that finite game structure is embedded within a larger infinite game across pay periods.

[23]We assume for this example that the yearly exponential discount factor is set at 0.75, but the results are qualitatively the same at different levels of exponential discounting.

Figure 9: Theoretical Predictions of Naive Present Focus Model



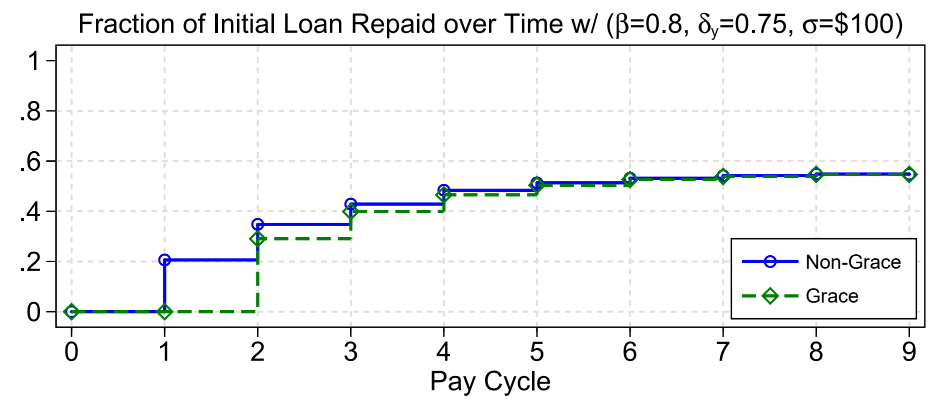
Note: All calculations above assume a representative agent with biweekly income of \$900 and an initial payday loan balance of \$300. The borrowing limit is half of biweekly income, which is \$450. Note that when one increases the present focus level, all borrowers would start to re-borrow more on their first due date and therefore have negative "repayment" as shown in Figure 9A. Since in the representative agent context, the borrowing limit is 50% of biweekly income (\$900) with initial debt balance of \$300, the most one can re-borrow on their first due date is \$150 which would increase their total balance to \$450. This translates into agents repaying -0.5 of their initial loan on the first due date which explains why first repayment size clusters on the -0.5 floor in Figure 9A as β becomes smaller than 0.55.

The intuition for this result is that the naive-present-focused agents are procrastinating on sacrificing consumption to repay the debt. Present-focused agents prefer to delay sacrifices to the near future. Further, a naive agent believes that in upcoming days she will pull back on consumption to help repay the debt by more than she actually will. When the due date is far away, these naive beliefs lead the agent to wrongly conclude that there are low returns to reducing immediate consumption. However, as the due date approaches, the fact that consumption on prior days was high becomes apparent and it is clear that sacrifices are needed to repay the loan. As such, a naive present-focused agent engages in most of the consumption reductions that help to repay the loan in the days immediately leading up to the loan due date. When agents are sufficiently present focused, adding additional time before the loan is due in the form of a grace period does not result in any additional saving to help repay the loan. Ultimately, then, the model helps to highlight that to the extent that naive present-focus can rationalize slow repayment of high-interest debt and other consumer behavior, it simultaneously predicts that policies aimed at affording people more time to engage in consumption smoothing may have little effect.

6.3 Adding Income Risks

While the preceding subsection demonstrates that naive present focus offers a simple explanation for the lack of response to grace periods, this simple result holds in the fully deterministic setting of our stylized neoclassical baseline model. Here we show that in a more realistic environment with negative income shocks (or equivalently expense shocks), even a naive present-focused agent would be expected to take advantage of the grace period.

Figure 10: Theoretical Predictions of Naive Present-Focus Model with Income Risks



We add simple income shocks to the model from the prior subsection and assume initially that agents in the model are aware of these income risks. Furthermore, we copy the setup of negative income shocks presented in Section 5 and for our numerical example leave β at 0.8. Similar to the results of the neoclassical model with income risks, when coupled with income risks and rational expectation of them, the present-focus model's ability to account for data patterns is eroded as demonstrated in Figure 10. The economic rationale for this is again the precautionary motive induced by awareness of expense shocks. During the grace period the borrower is worried about the possibility of a negative income shock in the next period and will use the grace period to engage in some precautionary saving. That saving, in turn, allows the grace period borrower to repay more of the loan at the initial due date. This analysis suggests that naive present focus can account for the apparent "wasting" of the grace period we observe empirically, but only if borrowers are also inattentive to the potential for negative income (or expense) shocks.

6.4 Calibrated Model

In this subsection we combine the forces discussed above in a model that incorporates naive present focus, income risk, and inattention to that income risk. We calibrate the parameters of the model to match a few basic moments in the repayment patterns of borrowers without grace periods. We then show whether the calibrated model can fit the "out-of-sample" moments regarding repayment and specifically the empirical "push off" pattern of grace-period borrowers. The purpose of this exercise is to explore whether a simple and tractable version of the present-focus model can quantitatively, and not just qualitatively, rationalize the patterns we see in the data.

Before presenting these results, it is worth noting, however, some limitations of this exercise. The model we are calibrating remains quite simplistic and omits a number of realistic considerations for payday loan borrowers. For example, it is likely that a fair number of borrowers have anticipated income windfalls that they will use to repay loans. We do not include this in the model because we have no simple way of identifying such a process from the data we observe. As a consequence, the model will be able to capture average repayment rates, but will miss some of the lumpiness of the actual repayment distributions. We also are calibrating a model of homogeneous preferences and shock processes, though we do allow for cross-sectional variations in initial debt-to-income positions. So this calibrated model should be thought of as a rough approximation for a representative agent at our payday lender. We discuss some analysis of heterogeneous preferences below, but note that they are limited and for the most part this is a representative-agent modeling exercise.

The setup of the calibrated model is as follows. As in the baseline model setup, agents have separable utility over daily consumption values and we assume log utility for the daily utility function. They discount between days with a present-focus parameter β and exponentially over time with an annual discount factor we assume to be $\delta_y = 0.9$, though we note that results are not meaningfully affected by the assumption on exponential discounting. Agents are naive about their present focus, as discussed in the prior subsections.

The calibrated model uses an exponential expense shock process, as discussed in the previous subsection, with a parameter σ giving the mean of the shock distribution. The expense shock each period is subtracted from the available income without entering the daily consumption utility. We assume that agents are fully inattentive to the expense shock process and make their consumption decisions during the current period assuming (wrongly) that they have full income y at their disposal.

Nevertheless, the shocks still occur so that there are still fluctuations of disposable income. Since the agents consume without anticipating these shocks, they will sometimes have a shock large enough that they cannot make even the required interest payment on the loan.

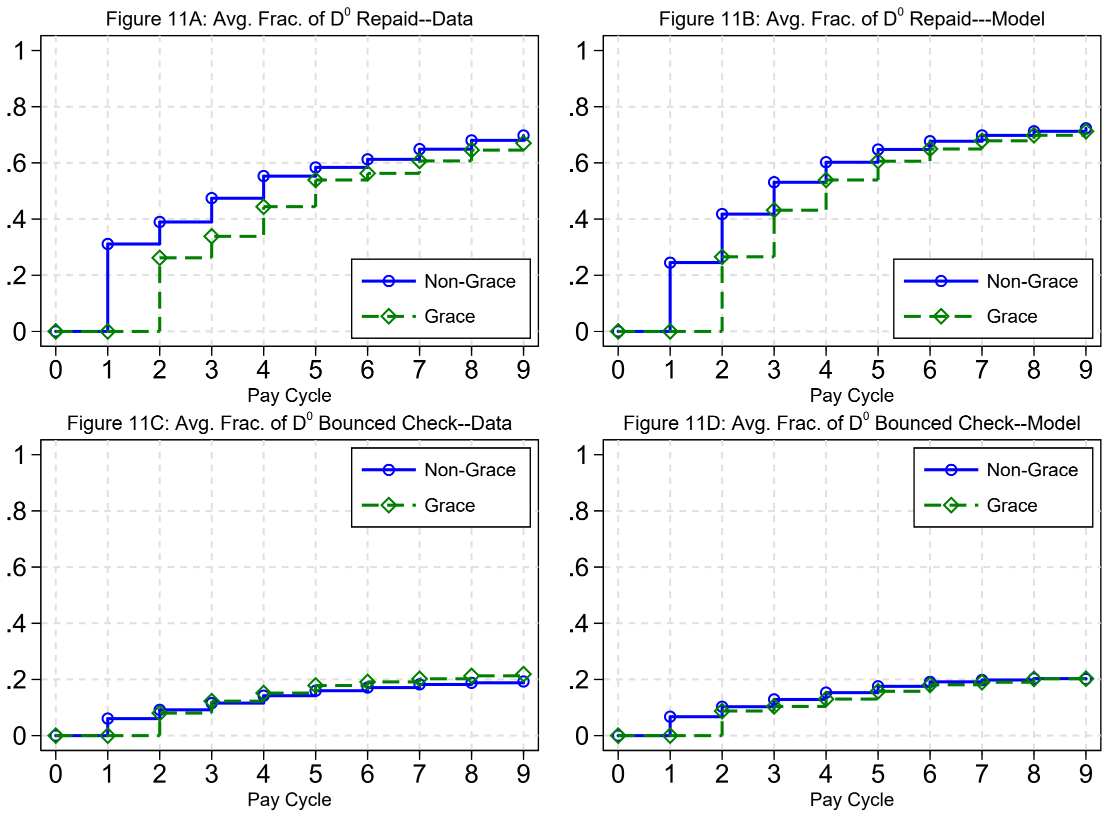
We assume in these cases that the agents are allowed to rollover the loan without additional penalty and simply start the next period with a lower available net income after first repaying the interest payment from the prior loan.[24] This assumption is somewhat simplistic, but roughly matches the idea that a borrower may temporarily have too little cash on hand to make interest payments, but then will receive their next paycheck which can be used to rectify the shortfall.

The model formulated in this way allows us to capture non-strategic instances of temporary "default" in the form of bounced checks. We are abstracting from the reality that these bounced checks would carry additional fees, but since agents in the model are unaware of the possibility of these expense shocks, this abstraction does not meaningfully affect the consumption decisions in the model. The model also abstracts from the possibility of full (strategic) default. While incorporating strategic default into the model would add richness, it would significantly complicate the model and require a range of additional assumptions. Further, the institutional details of payday loans, where borrowers have to show proof of an existing checking account and write a check to collateralize the loan, mean that truly strategic default requires a somewhat costly process of closing out a bank account before the lender has the chance to cash the check, which is likely fairly rare in practice.

In our calibration procedure, values of β and σ are jointly selected by minimizing the mean squared error between model moments and data moments. We endow a set of agents in the model with the same distribution of periodic baseline income and initial debt that we observe in the empirical sample. As such, the model allows for heterogeneity in initial conditions matching the empirical sample, but imposes homogeneity in the expense shock process and present focus. The three moments we target in this process are: the means of the first, second, and third repayment of non-grace borrowers as fractions of their initial debt. We then apply the calibrated values of β and σ to both grace and non-grace borrowers in the model and analyze their repayment patterns, with the predictions for non-grace borrowers after pay period three and all of the grace borrowers' predictions coming from "untargeted moments" in the data. We also trace out the predictions of the model for "bounced check" rates as well. Table 5 describes results of our calibration, while Figure 11 presents the calibrated model's predictions on repayment and bounced checks for both types of borrowers.

[24] The Appendix presents details regarding how we operationalize this assumption in the calibrated model.

Figure 11: Repayment Behavior—Data vs. Calibrated Model's Predictions



Note: The model predictions are computed using the parameter values of $\beta = 0.86$ and $\sigma = \$27.43$ deriving from our calibration. δ_y is fixed at 0.9. The model averages are computed off a 20-pay-cycle simulation of 14,073 individuals who are heterogeneous in their initial payday loan balance and biweekly income. The joint cross-sectional distribution initial payday loan balance and biweekly income in the simulation is specified according to the observed distribution in our data. Simulation sample size for each pay cycle is chosen to match the data sample size.

As shown in Table 5, the calibrated values of β and σ are both empirically reasonable, with a modest present focus of $\beta = 0.86$ and the mean periodic expense shock $\sigma = \$27.43$. These calibrated parameters do a decent job of fitting the targeted moments in the data (Panel A) and also most of the untargeted moments for the non-grace period borrowers. For example, the average fraction of debt repaid after the tenth pay cycle for these borrowers in the data is 0.72, which matches exactly what the model calibrated from the first three pay periods would predict. The rates of borrowers who have bounced checks predicted by the model, driven here primarily by the calibrated σ, also match quite closely to the data, even though the model is not calibrated with information on bounced check rates.

Most notably, Figure 11 shows that the out-of-sample predictions of the model for grace-period borrowers are quite good and the calibrated model is able to account for the "push off" of repayment among grace borrowers. Overall, the fit of this simple calibrated model suggests that naive present-focus combined with inattention to income risks can potentially quantitatively account for the repayment patterns we see.[25]

Table 5: Naive Present-Focus Model Calibration for the Non-Grace Case

Panel A: Targeted Moments (All Moments are Calculated as Fractions of Initial Debt)		
	Data Mean	Model Mean
Non-Grace 1^{st} Cycle Repayment	0.31	0.26
Non-Grace 2^{nd} Cycle Repayment	0.39	0.42
Non-Grace 3^{rd} Cycle Repayment	0.47	0.52

Panel B: Calibrated Parameter Values		
Notation	**Definition**	**Value**
β	Degree of Naive Present Focus	0.86
σ	Mean of Expense Shock	\$27.43

Panel C: Untargeted Moments (All Moments are Calculated as Fractions of Initial Debt)		
	Data Mean	Model Mean
Non-Grace 4^{th} Cycle Repayment	0.55	0.60
Non-Grace 5^{th} Cycle Repayment	0.58	0.64
Non-Grace 6^{th} Cycle Repayment	0.61	0.67
Non-Grace 7^{th} Cycle Repayment	0.65	0.69
Non-Grace 8^{th} Cycle Repayment	0.68	0.70
Non-Grace 9^{th} Cycle Repayment	0.70	0.71
Non-Grace 10^{th} Cycle Repayment	0.72	0.72
Non-Grace 1^{st} Cycle Check Bounced	0.06	0.07
Non-Grace 2^{nd} Cycle Check Bounced	0.09	0.10
Non-Grace 3^{rd} Cycle Check Bounced	0.12	0.13
Non-Grace 4^{th} Cycle Check Bounced	0.14	0.15
Non-Grace 5^{th} Cycle Check Bounced	0.18	0.18
Non-Grace 6^{th} Cycle Check Bounced	0.19	0.19
Non-Grace 7^{th} Cycle Check Bounced	0.20	0.20
Non-Grace 8^{th} Cycle Check Bounced	0.21	0.20
Non-Grace 9^{th} Cycle Check Bounced	0.22	0.20
Non-Grace 10^{th} Cycle Check Bounced	0.22	0.21

Note: δ_y is set to be 0.9 in this calibration. Repayment is the amount of payday loan principal paid down. In other words, it is the money a borrower repays in addition to the mandatory interest charges. The model averages are computed off a 20-pay-cycle simulation of 14,073 individuals who are heterogeneous in their initial payday loan balance and biweekly income.

We also check whether there is cross-sectional heterogeneity in β and σ among borrowers with different initial debt-to-income ratios. To do that, we repeat the above calibration

[25] In Appendix Section 5, we repeat the above calibration procedure for a time-consistent model. There we calibrate the yearly exponential discount factor, δ_y, assuming $\beta = 1$. That calibration yields an extreme rate of discounting, $\delta_y = 0.13$, and much higher mean expense shock, $\sigma = \$86$. The calibrated time-consistent model fits the empirical patterns less well than the calibrated present-focus model.

process within a sub-sample defined by a range of initial debt-to-income ratios (e.g. those borrowers whose debt-to-income ratio is greater than 20% but less than 30%). Results of these sub-sample calibrations are presented in Appendix Section 6. We find very modest differences in calibrated values of β and σ across sub-samples. The model's fit to targeted and untargeted moments of repayment and the push-off pattern of grace borrowers look similar for all sub-samples.

However, it is worth noting that this parsimonious model with homogeneous preferences does not fully explain borrower behavior. In particular, while the model fits aggregate repayment patterns well, it does not capture the cross-sectional distribution of repayment amounts. Empirically people show a fairly bimodal distribution of repayment amounts, often making either very small or very large principal reductions, while our simple model predicts more intermediate payoff amounts. It may be that people face a different distribution of income shocks that we do not capture in our model, such as period positive income windfalls, that generates this more bimodal pattern.

6.5 Welfare Implications of the Grace Period

One of the benefits of having a calibrated model of repayment behavior is that it allows us to quantify the value borrowers get from a grace period given the calibrated level of present focus and shock processes. We can also compare this value of the grace period to what it would be if borrowers were not present focused (but still had the same inattention to expense shocks). Of course, an important caveat is that these quantifications are sensitive to the assumptions of this simple model.

We measure the borrower welfare gains from a grace period using a measure of *consumption equivalent variation* (CEV). We measure the fraction of daily consumption that a non-grace borrower is willing to pay (if positive) or would have to be paid (if negative) in all future days to get the utility level that borrower would have with a grace period within the model. We first compute the 20-cycle utility for each individual borrower in our simulation sample. The utility for borrower n with no grace period is $U_n^{Non-grace}$ and for that borrower with a grace period is U_n^{Grace}.[26] We compute these utilities for each borrower n in our simulated sample by as follows:

$$U_n = \sum_{t=1}^{280} \delta^t \ln(c_{nt}) \tag{7}$$

where t is the index for days of the 20 cycles in our simulation. Based on the definition of

[26] Recall that borrowers in the simulation sample vary in their level of income and initial debt balances.

of our welfare measure, we derive the following mathematical expression for CEV:

$$U_n^{Grace} = \sum_{t=1}^{280} \delta^t \ln((1 + \lambda_n) c_{nt}^{Non-grace}) \tag{8}$$

where λ_n is the fraction of daily consumption that the non-grace borrower n is willing to pay for all future days. Since λ_n is a constant over time, we may express it in closed form as follows:[27]

$$\lambda_n = exp\Big(\frac{U_n^{Grace} - U_n^{Non-grace}}{\sum_{t=1}^{280} \delta^t}\Big) - 1 \tag{9}$$

To get the total 20-cycle CEV for borrower n in dollar amount, we simply multiply λ_n by the daily consumption in the simulation as follows:[28]

$$\Lambda_n = \sum_{t=1}^{280} \lambda_n c_{nt} \tag{10}$$

Table 6 shows the results of this welfare comparison. Columns 1 through 3 show the model's predictions of total interest charges paid under both non-grace and grace scenarios while column 4 shows the welfare benefit of having a grace period in terms of CEV.

Table 6: Welfare Results

	(1) Non-grace Total Interests Paid	(2) Grace Total Interests Paid	(3) Interest Savings w/ Grace	(4) Welfare Benefit of Grace (CEV)
Present Focused ($\beta = 0.86$)	\$340.42	\$325.33	\$15.09	\$15.69
Time Consistent ($\beta = 1.0$)	\$116.96	\$96.28	\$20.68	\$34.79

Note: All calculations above are based on a 20-cycle simulation of our calibrated model. All statistics reported above are the means of the simulated sample.

For present-focused agents, the grace period leads them to reduce total interest payments by \$15.09. Their CEV measure of the benefit of the grace period is nearly identical to this value, at \$15.69, revealing that for present-focused agents there is little additional

[27] We lay out the detailed derivation of this expression in the Appendix.

[28] While the CEV measure depends on the total pay cycles we include in the calculation, the final dollar amount does not change much once we go beyond 15 cycles in the calculation. This is because the repayment behavior and debt balance—and therefore also consumption—between non-grace and grace borrowers synchronize after 15 cycles. Welfare results for a range of different simulation horizons are available upon request.

consumption-smoothing benefit of the grace period. Time-consistent borrowers would have a CEV value of the grace period more than double this value at \$34.79. The additional value of grace periods for time-consistent borrowers in the model comes partly from the fact that they see larger interest savings with a grace period. However, there is a meaningful gap between the CEV measure and the interest savings for time-consistent borrowers, which highlights that time-consistent borrowers get an additional consumption-smoothing benefit from the grace period. Approximately 70% of the additional borrower welfare value of the grace period for the time-consistent borrowers relative to present-focused borrowers comes from this consumption-smoothing benefit. In Appendix Section 4.1 we provide a plot of the average daily consumption levels in the model simulation that helps to visualize the sources of these results.

7 Conclusion

This paper documents that payday loan borrowers receiving a grace period take only modest advantage of the additional time before repayment to engage in saving to help repay the loan. These patterns are difficult to reconcile with anticipated consumption-smoothing behavior for forward-looking exponential discounters. The repayment patterns can be potentially rationalized both by borrowers who use repayment heuristics and a model combining naive present focus with inattention to expense shocks. We cannot clearly distinguish the relative importance of these two forces, and we suspect that both heuristics and borrower myopia likely play a role in determining borrower repayment patterns.

These findings have implications for policy makers who are interested in improving subprime credit markets. Our results suggest that having more time to repay a loan will not, by itself, meaningfully improve repayment behavior or result in smoother consumption profiles. Borrowers who are using heuristics or are naively present focused may benefit more from policies that target the creation of regular repayment paths, such as minimum repayment plans, than simply unconstrained time to repay.

Finally, we note that our results from the present-focus model highlight a potentially important dynamic to consider in future research. Prior research on consumption dynamics in the quasi-hyperbolic model shows that predictable changes in income or credit conditions can lead to corresponding consumption changes for present-focused individuals that would be smoothed out more fully by time-consistent agents (e.g. Angeletos et al., 2001; Laibson, 1997; Stephens and Unayama, 2011; Gross and Tobacman, 2014). In our setting we document a new and related empirical pattern: a lack of response to the length of time to prepare for a future expenditure. The broader literature on consumption dynamics incorporating time inconsistency has not yet systematically explored questions related to the timing of when people are aware of future shocks and how consumption responses relate to that timing. Considering these issues more fully might be valuable for our understanding of a range of different consumer credit products, including mortgage lending and credit-card borrowing.

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Appendix

1 Robustness and Heterogeneity of Main Results

In this section, we repeat the baseline analysis as in Table 3 and Figure 6 of Section 4.3.2 in the main text for different groups of borrowers to check for robustness and heterogeneity of our main empirical results. Additionally, we show that our regression results in Table 3 are robust to the exclusion of control variables.

First, we demonstrate the robustness of our main regression results in Table A1. We use the same biweekly sample as in Table 3 but focus only on the first observation for each borrower. Specifications of the underlying regressions are identical to those in Table 3.

Table A1: Regression Results

Biweekly Sample Restricted to First Observations				
	(1)	(2)	(3)	(4)
	Principal paid on first due date	Rolled over some of the loan at the first due date	Number of effective rollovers in loan spell	Total finance charges paid in loan spell
Mean	$79.02	0.66	3.14	$218.72
Grace	-1.82	-0.02	-0.38^{***}	-19.04^{**}
	(4.52)	(0.01)	(0.12)	(8.15)
Other Controls	Yes	Yes	Yes	Yes
N	6,778	6,778	6,019	6,019
R^2	0.17	0.11	0.08	0.12

Note: *Grace* is the indicator for having only six days until payday. Data are based on authors' calculations from administrative data from a large payday lender. OLS regressions are shown for four outcomes: Principal paid on first due date calculates the amount of the loan paid by the first due date; Rolled over some of the loan at first due date indicates that the borrower rolled over the loan at the first due date; Number of Effective Rollovers is a variable that counts the number of additional loans in succession by a borrower; and Total Finance is the total finance charged over the loan cycle. Sample is restricted to first observations of borrowers paid biweekly. Controls in all columns include loan size, gender, annual net pay, checking account balance, subprime credit score, and age bins. Dummies for race (White, Black, Hispanic, or other), having paycheck direct deposited, missing control variables, month-year, and each payday loan shop are also included. Columns 3-4 include fewer observations because we did not include loans initiated with less than five pay periods before the end of our sample so as to not artificially truncate these outcomes. Standard errors are clustered at the day the loan was initiated and are reported in parentheses below the coefficients. $***$, $**$, and $*$ designate statistical significance at the 1%, 5%, and 10% level, respectively.

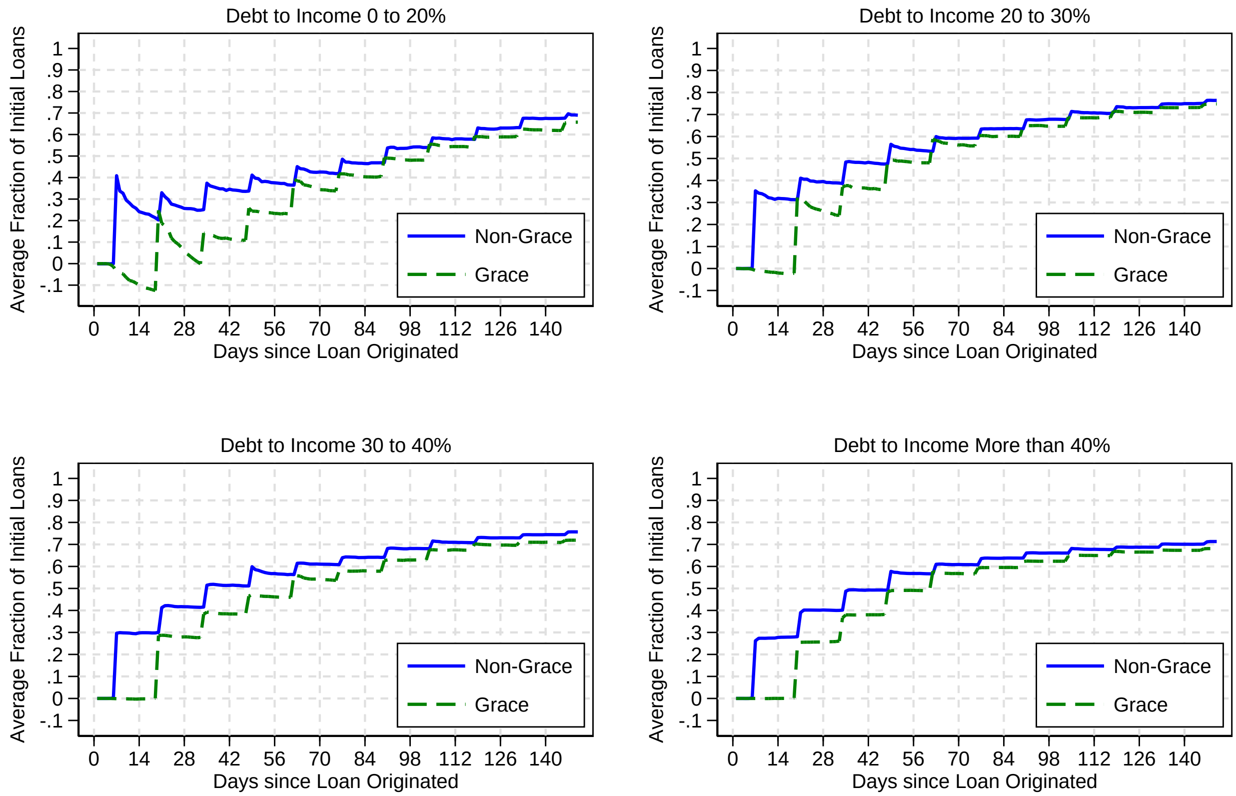
Table A2: Regression Results without Controls

	Biweekly Sample (Sample Restricted to Origination Date Six and Seven Days until Payday)			
	(1)	(2)	(3)	(4)
	Principal paid on first due date	Rolled over some of the loan at the first due date	Number of effective rollovers in loan spell	Total finance charges paid in loan spell
Mean	\$88.84	0.64	2.98	\$208.55
Grace	-6.92	-0.00	-0.35^{***}	-17.40^{***}
	(4.23)	(0.01)	(0.09)	(5.54)
Other Controls	No	No	No	No
N	15,491	15,491	14,073	14,073
R^2	0.00	0.00	0.00	0.00

Note: The above table repeats the regression analysis in Table 3 of the main manuscript, excluding all the control variables. Everything else in the regression specification remains unchanged.

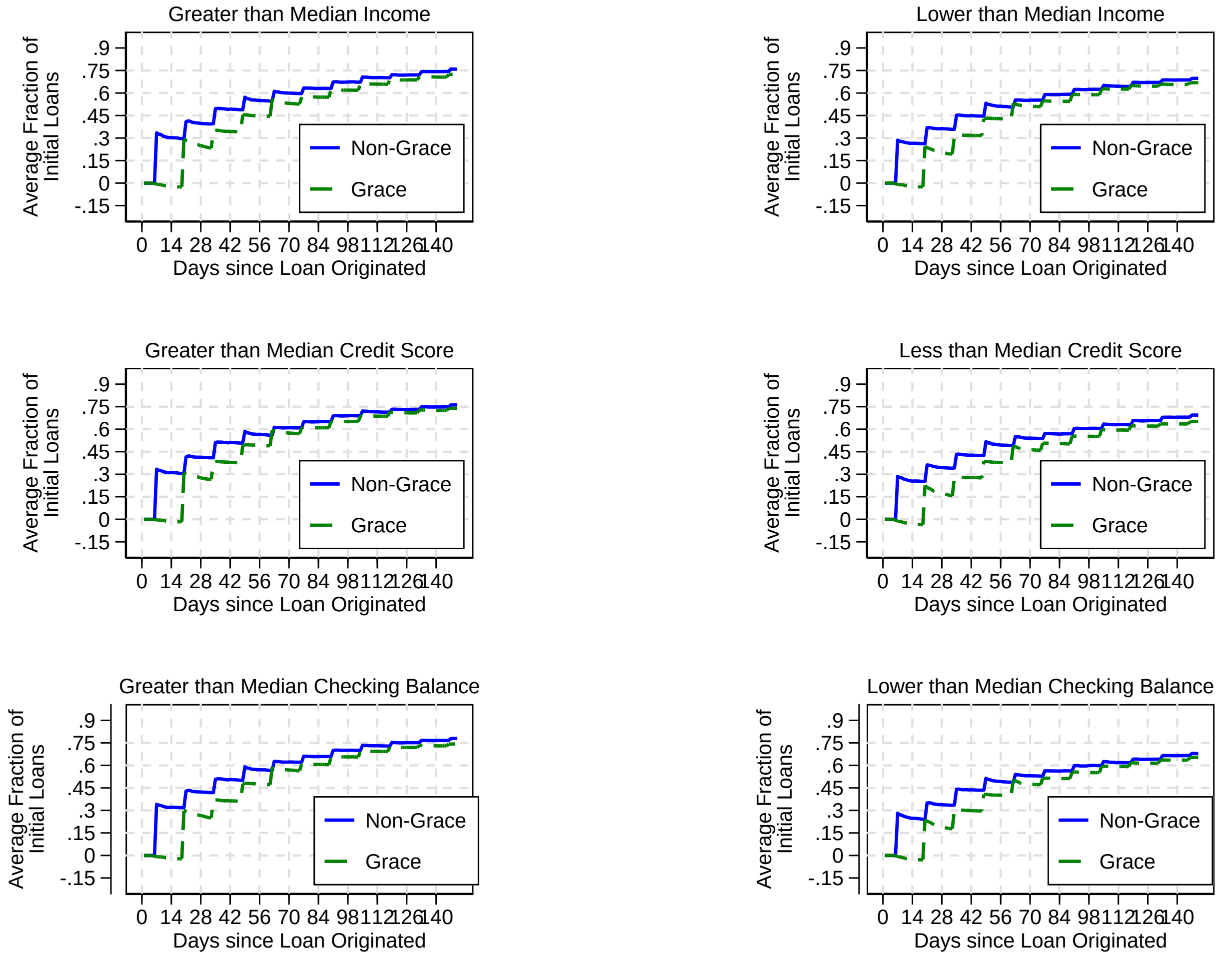
Secondly, we show in Table A2 that our main empirical results concerning the impact of a grace period on a range of repayment behavior are robust when we take out all the control variables in our regression model. Furthermore, the figures below examine the average fraction of initial loan that is repaid every day since the initial loan was taken out. The main purpose here is to investigate whether there is heterogeneity in the response to grace periods across the payday loan borrowers.

Figure A1: Average Fraction of Initial Load Repaid by Debt-to-Income Ratios



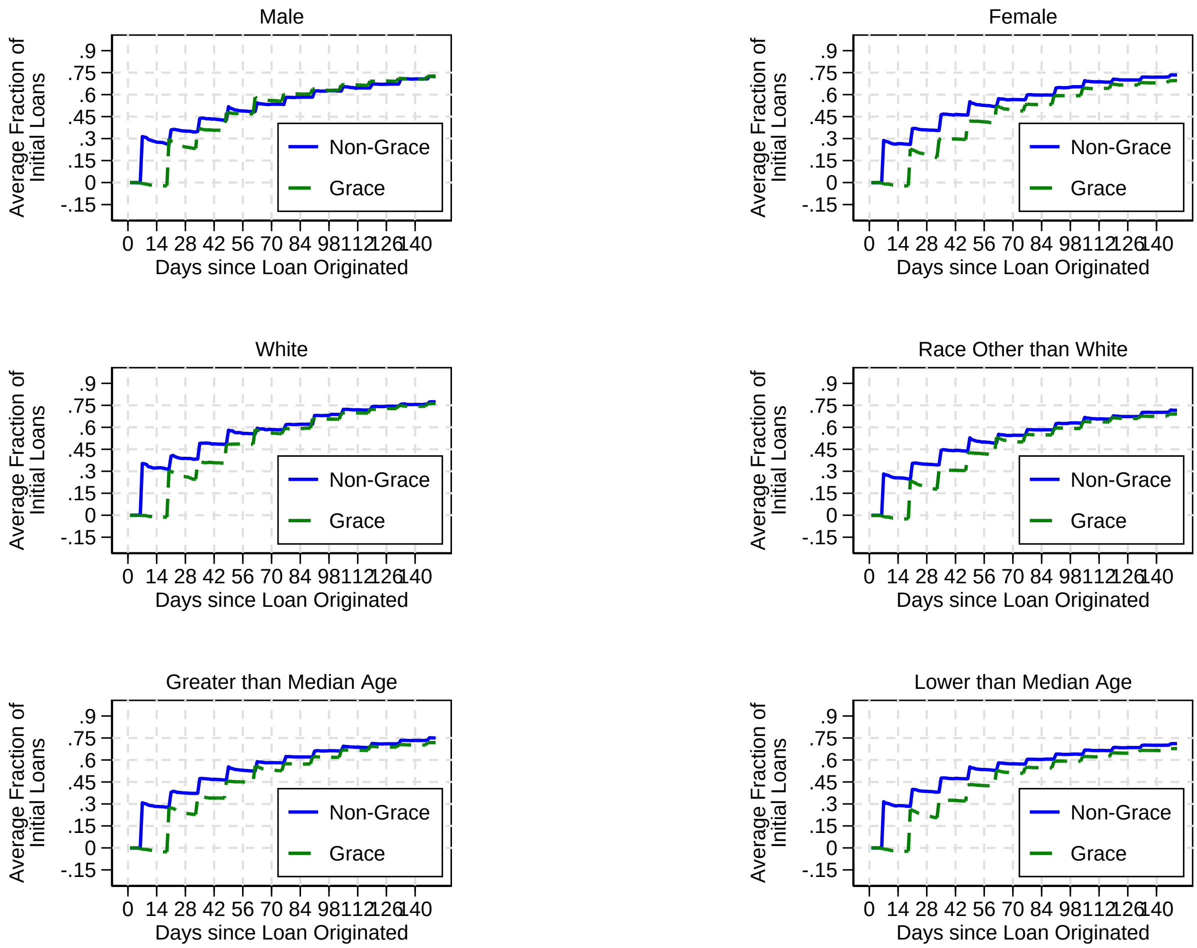
In Figure A1, we split the groups by the payday loan debt-to-income ratio, i.e., the amount of the loan divided by their income for the period. We split the groups into 0 to 20%, 20 to 30%, 30 to 40%, and 40% or more debt-to-income ratio. There are differences in repayment behavior by group: Those who took out lower percentages of debt to income are more likely to take out larger loans. However, the push-off of repayment by those with a grace period in their repayment remains consistent.

Figure A2: Average Fraction of Initial Load Repaid by Financial Conditions



In Figure A2 we categorize groups by financial characteristics: income, credit score, and checking account balance. For each of these groups we split them by above and below median. We again find similar patterns between the grace and non-grace groups as those found in Figure 6.

Figure A3: Average Fraction of Initial Load Repaid by Demographics



Finally, in Figure A3 we split the groups by demographics: gender, race, and age. Again, in each group we find that the grace-period individuals push off their repayment by a pay period. Altogether, we find that repayment differences between those with grace and non-grace loans do not vary by demographic characteristics, and it does not appear our results are driven by a subset of our population.

2 Empirical Analysis for Borrowers Paid Semimonthly

Borrowers paid semimonthly typically receive paychecks on the 15th of the month and either the end of the month or the first of the month. Therefore, borrowers who come in on the 8th of the month will typically receive a seven-day loan, while those who come in on the 9th of the month (six days before their next payday) will get an extra pay cycle to repay their loan. This creates a similar discontinuity to borrowers paid biweekly. There is a similar discontinuity around the 24th of the month, although it is less clean given variation in the number of days in a month and the exact day borrowers are paid. Below we present analogous figures and tables for borrowers paid semimonthly as those shown for borrowers paid biweekly in the main text.

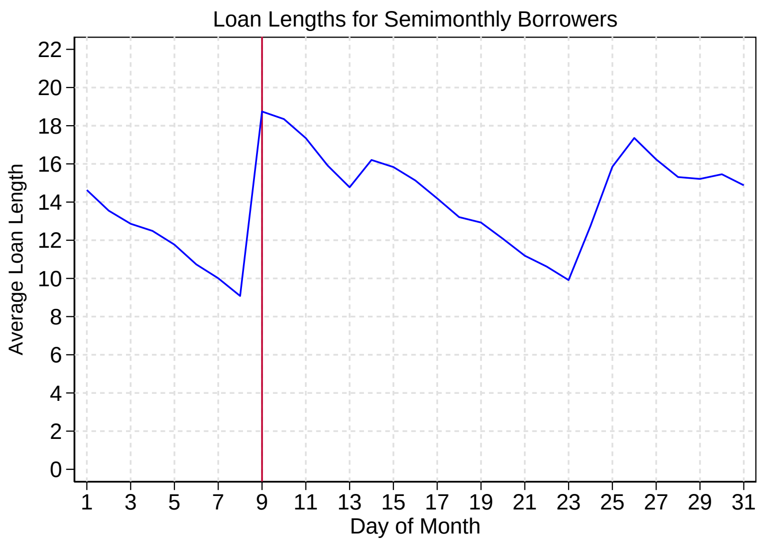
Table A3: Summary Statistics for Borrowers Paid Semimonthly

	Semimonthly Sample	Semimonthly Sample (restricted to the 8th and 9th of the month)
Borrower Characteristics for Initial Loans		
Age	35.98	35.85
	(9.96)	(9.92)
Female	69%	67%
White	25%	29%
Black	40%	40%
Hispanic	33%	30%
Race, other	1%	1%
Homeowner	38%	35%
Direct Deposit	75%	77%
Annualized Net Pay ($)	24,238.66	24,415.79
	(9,622.45)	(9566.44)
Checking Balance ($)	329.10	328.92
	(482.99)	(467.57)
Credit Score ($)	543.75	545.63
	(210.13)	(208.29)
Initial Loan Characteristics		
Principal of Initial Loan ($)	324.87	311.71
	(139.96)	(140.74)
Interest Due on Initial Loan ($)	58.48	56.11
	(25.19)	(25.33)
Initial Loan Duration (days)	13.67	13.66
	(4.61)	(6.66)
Initial Loan Outcomes		
Principal paid on first due date ($)	92.92	92.27
	(159.63)	(160.29)
Rollover on first due date (%)	66%	64%
Number of Effective Rollovers in Loan Spell	2.90	2.82
	(4.27)	(4.26)
Total Finance Charges Paid in Loan Spell ($)	217.34	205.89
	(287.58)	(273.01)
Loan Spell Ended with Default (%)	19%	20%
Total Number of Initial Loans	28,213	2,072
Total Number of Loans (including Rollovers)	110,042	7,920

Note: Means of all variables shown, with standard deviations in parentheses for continuous variables. Data are based on authors' calculations from administrative data from a large payday lender in Texas from

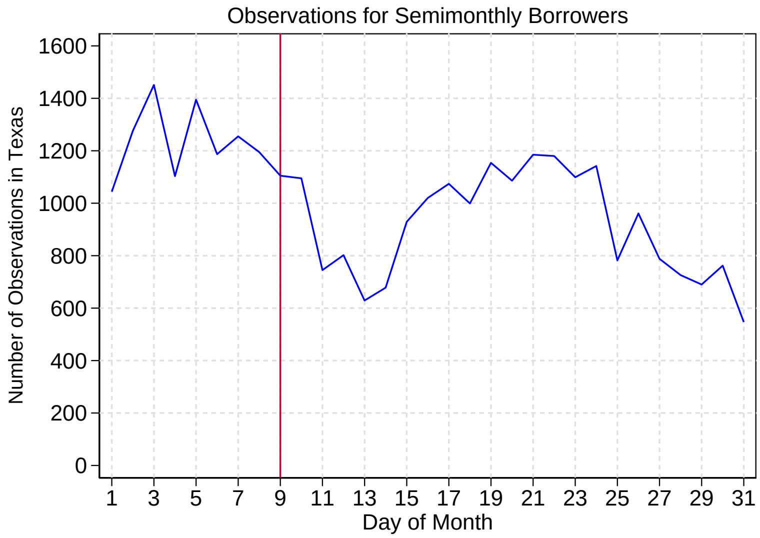
November 2000-August 2004. Initial loans are loans where the borrower did not have a loan outstanding for at least 32 days prior to initiation. Our administrative records do not include demographic information for all borrowers, and we have gender, race, and home ownership information for around 50% of the sample.

Figure A4: Loan Length
Borrowers Paid Semimonthly



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 to August 2004. The figure reports the average loan length for borrowers paid semimonthly. If workers paid semimonthly arrive at the lender on the 8th day of the month, they will typically receive a loan lasting seven days. If, however, they arrive on the 9th day of the month, there are only six days until their next pay date; hence they will instead have 21 days to repay their loan (six days until next payday plus the 15 days of their next pay cycle). Since there is some variation in exact pay dates (e.g., months when the 15th falls on a Sunday), the observed variation does not exactly match the hypothetical case outlined above. However, there is a clear jump in average loan length between loans originated on the 8th and loans originated on the 9th day of the month. Borrowers obtaining loans on the 8th day of the month have on average 9 days to repay that initial loan, while borrowers on the 9th day have an average of 19 days to repay their loan. Because the number of days in a month varies and some borrowers paid semimonthly get paid at the end of the month rather than the first of the month, the second jump in loan lengths (between the 23rd and 24th of the month) is less precise and therefore we do not use it in our subsequent analyses for borrowers paid semimonthly.

Figure A5: Loan Observations
Borrowers Paid Semi-monthly



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The figure reports the number of observations for borrowers paid semimonthly for each day of the month.

Table A4: Control Variables as Outcomes for Borrowers Paid Semimonthly

	(1) Mean	(2) Grace (9th Day of the Month)	(3) Sample Size (Restricted to Origination Date on 8th and 9th Day of Month)
Subprime Credit Score	545.63	-2.46	2,072
		(9.11)	
Loan Amount	\$311.71	-3.06	2,072
		(6.24)	
Net Pay	\$24,415.79	510.57	2,072
		(421.75)	
Account Balance	\$328.92	14.43	2,072
		(20.83)	
Direct Deposit	0.77	0.004	2,072
		(0.02)	
Age	35.85	0.39	2,071
		(0.43)	
Female	0.67	0.01	899

table continues to next page

		(0.03)	
Black/Hispanic	0.70	-0.04	894
		(0.03)	
Homeowner	0.35	-0.02	967
		(0.03)	

Note: Column 2 shows coefficients from individual linear regressions of being in the Grace group on each control variable listed. Data are based on authors' calculations from administrative data from a large payday lender. OLS regressions shown for subprime credit score, loan amount, net pay, account balance, direct deposit indicator, age, female indicator, Black or Hispanic indicator, and homeowner indicator. The sample is restricted to borrowers paid semimonthly with a payday loan origination date on the 8th or 9th day of the month. The sample includes individuals who are missing information on age, gender, race, and home ownership, which is reflected in the changing number of observations in rows six through nine. Standard errors are clustered at the individual level and are reported in parentheses below the coefficients. $***$, $**$, and $*$ designate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5: Regression Results for Semimonthly Sample

Panel A: Semimonthly Sample (Sample Restricted to Origination Date on 8th and 9th Day of Month)				
	(1)	(2)	(3)	(4)
	Principal paid on first due date	Rolled over some of the loan at the first due date	Number of effective rollovers in loan spell	Total finance charges paid in loan spell
Mean	\$92.27	0.64	2.82	\$205.89
Grace	2.17	-0.05^{**}	-0.35^{**}	-26.18^{***}
	(5.97)	(0.02)	(0.14)	(8.22)
Other Controls	Yes	Yes	Yes	Yes
N	2,072	2,072	1,847	1,847
R^2	0.24	0.16	0.18	0.19
Panel B: First Observations of Semimonthly Sample				
	(1)	(2)	(3)	(4)
	Principal paid on first due date	Rolled over some of the loan at the first due date	Number of effective rollovers in loan spell	Total finance charges paid in loan spell
Mean	\$88.66	0.63	2.86	\$201.46
Grace	1.89	0.00	0.06	1.44
	(10.12)	(0.03)	(0.22)	(15.49)

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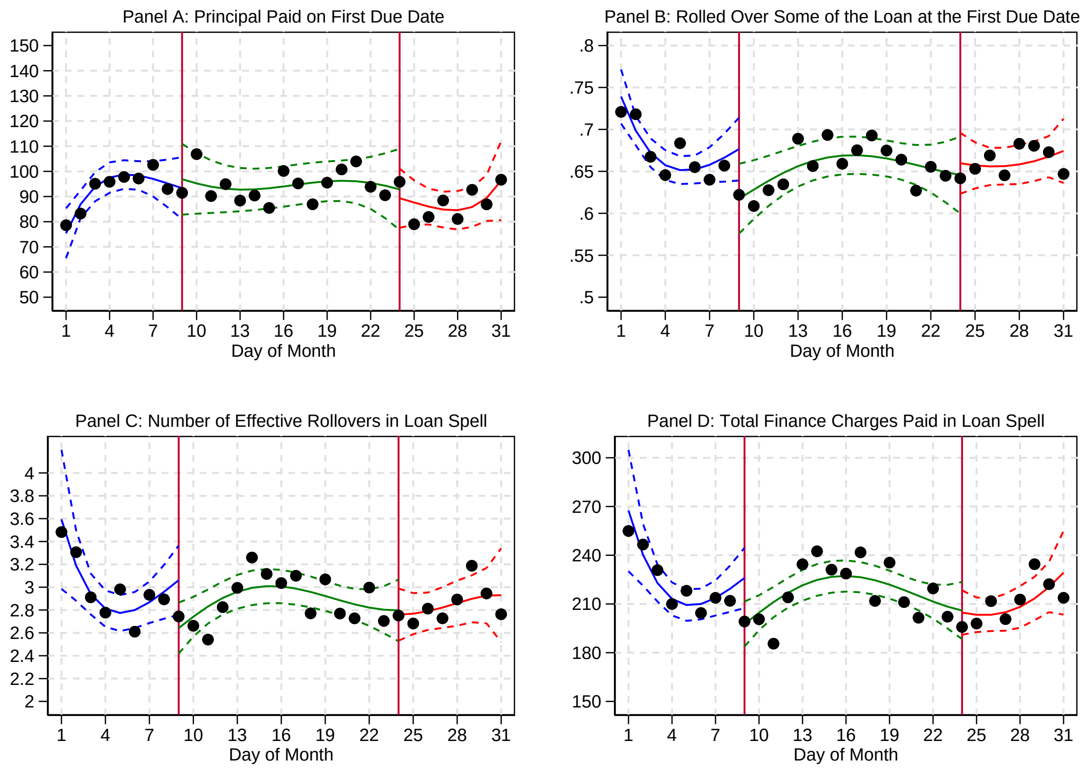
Other Controls	Yes	Yes	Yes	Yes
N	944	944	821	821
R^2	0.36	0.29	0.29	0.29

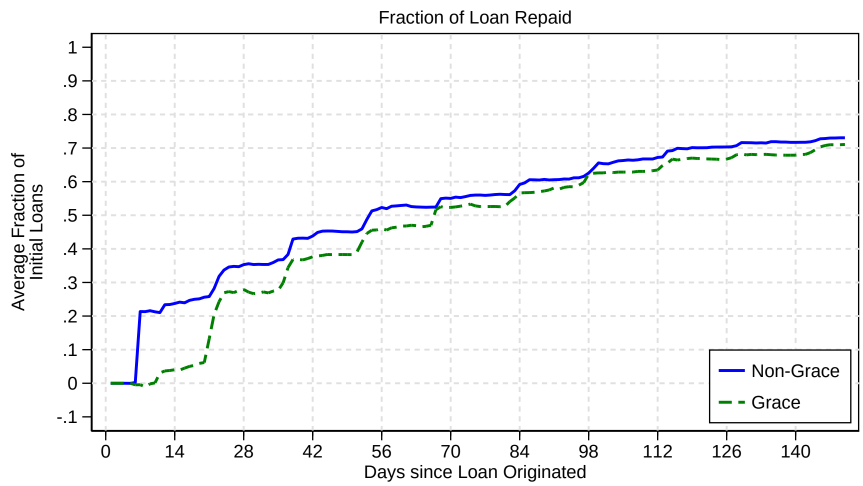
Note: *Grace* is the indicator of having only 6 days until payday. Data are based on authors' calculations from administrative data from a large payday lender. OLS regressions shown for four outcomes: Principal Paid on first due date calculates the amount of the loan paid by the first due date; Rolled over some of the loan at first due date indicates that the borrower rolled over the loan at the first due date; Number of Effective Rollovers is a variable that counts the number of additional loans in succession by a borrower; and Total Finance is the total finance charged over the loan cycle. Panel A includes borrowers paid semimonthly and restricts the sample to loans with an origination date on the 8th or 9th day of the month. Panel B includes the sample in Panel A but only uses the first observation for each borrower. Controls in all columns include loan size, gender, net pay per year, checking account balance, subprime credit score, and age bins. Dummies for race (White, Black, Hispanic, or other), having paycheck direct deposited, missing control variables, month-year, and each payday loan shop are also included. Columns 3-4 include fewer observations because we did not include loans initiated with less than five pay periods before the end of our sample so as to not artificially truncate these outcomes. Standard errors are clustered at the day the loan was initiated and are reported in parentheses below the coefficients. ***, **, and * designate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure A6: Outcomes for Borrowers Paid Semi-monthly



Note: Data are based on authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The vertical lines marks six days until payday, i.e., the day in the pay cycle where the borrower experiences a discontinuous increase in loan length on either the 9th of the month or the 24th of the month. Dots on the graph represent the averages of each outcome (in the figure heading) for each day of the month. The curve shows the predicted outcomes from the regression results of the outcome variable on the day of the month raised to the fifth, as well as an indicator for a borrower taking out a loan after the 9th or 24th of the month. The curve to the left of the line is the predicted outcome without an indicator for six or fewer days until payday. The curve to the right of the line maps the predicted outcomes including the dummy for less than six days until payday. 95% confidence intervals are included in dotted lines.

Figure A7: Average Fraction of Initial Debt Repaid
Borrowers Paid Semimonthly



Note: Authors' calculations based on payday loan transaction data in Texas from November 2001 until August 2004. The figure shows the average fraction of initial debt repaid by days since loan origination. We separate borrowers by the discontinuity in loan lengths. We show borrowers who arrive seven days before their payday and get a seven-day loan (”Non- Grace”) and borrowers who arrive six days before their payday and therefore receive a 20-day loan (”Grace”).

3 Model Solution Details

We solve the model using recursive methods. To fully characterize optimal decisions of agents in the model, we use a two-step procedure. The first step is to find the solution to a time-consistent (i.e. exponential discounting) version of the agent's dynamic programming problem. The second step is to solve a time-inconsistent version of the agent's problem. The source of time-inconsistency in our model is that agents exhibit quasi-hyperbolic discounting. In addition, we assume that the agents are naive as opposed to sophisticated. Thus in the time-inconsistent problem, agents incorrectly think that their future selves would behave in a time-consistent manner. In the following section, we write out formally the dynamic programming problems of the two-step procedure for the non-grace period case and the grace period case respectively. After that we describe the algorithm used to solve the dynamic programming problems.

3.1 Borrower's Problem—Non-Grace Period Case

In the non-grace borrower's case the time-consistent problem for a day t agent is as follows:

$$V(D^I) = \max_{\{\hat{c}_i^I\}_{i=t}^T, \hat{D}^{I+1}} \ln(\hat{c}_i^I) + \sum_{i=t+1}^{T} \delta^{i-t} \ln(\hat{c}_i^I) + \delta^{T+1-t} V(\hat{D}^{I+1}) \tag{A1}$$

subject to

$$\hat{D}^{I+1} \leq \frac{1}{2} y$$
$$\sum_{i=1}^{T} \hat{c}_i^I + rD^I = y - (D^I - \hat{D}^{I+1})$$

T is the terminal day of one pay cycle and we set it to 14 to match a biweekly payday loan repayment schedule. D^0 denotes the initial level of debt. y is the biweekly income. The index for days within a pay cycle is i while I is the index for pay cycles. In addition, δ is the exponential discount factor while β is the quasi-hyperbolic discount factor. The *hat* notation denotes the beliefs of the agent, which are equal to the true values if the agent is time consistent. The solution of the above problem consists of a value function, $V(D^I)$, and a policy function for next period debt, $f(D^I) = D^{I+1}$. They are both time-consistent in the sense that the solutions from different t agents are the same. In other words, the two functions $V(D^I)$ and $f(D^I)$ are not time dependent. Having obtained the solutions of the time consistent problem, the second step is to solve the time-inconsistent problem, which is the one we ultimately focus on in this paper. Note that because agents are assumed to be naive, they incorrectly believe that their future selves would adopt the time-consistent behavior. Through the lens of the time-consistent model, this means that they think they will follow the time-consistent solutions in the future. Formally, we write a day t agent's problem as follows:

$$W(D^I, t) = \max_{c_t^I, \{\hat{c}_i^I\}_{i=t+1}^{14}, \hat{D}^{I+1}} \ln(c_t^I) + \beta \Big\{ \sum_{i=t+1}^{14} \delta^{i-t} \ln(\hat{c}_i^I) + \delta^{15-t} V(\hat{D}^{I+1}) \Big\} \tag{A2}$$

subject to

$$\hat{D}^{I+1} \leq \frac{1}{2} y$$
$$\sum_{i=1}^{t} c_i^I + \sum_{i=t+1}^{14} \hat{c}_i^I + rD^I = y - (D^I - \hat{D}^{I+1})$$

Note that consumption before and including today does not have a *hat* because these are the actual choices made by the agent. However, consumption beyond today has a *hat* due to the naive agent's incorrect beliefs. Given our time convention, the actual level of next cycle's debt, D^{I+1} is determined on day 14. Thus the day 14 agent's problem is

$$W(D^I, 14) = \max_{c_{14}, D^{I+1}} \ln(c^I_{14}) + \beta\delta V(D^{I+1}) \tag{A3}$$

subject to

$$D^{I+1} \leq \frac{1}{2}y$$
$$\sum_{i=1}^{14} c^I_i + rD^I = y - (D^I - D^{I+1})$$

The solution to the above time-inconsistent problem is a set of value functions: $\{W(D^I, t)\}_{t=1}^{14}\}$, and a set of policy functions for next period debt:

$$\left\{\{f(D^I, t) = \hat{D}^{I+1}\}_{t=1}^{13} \text{ and } f(D^I, 14) = D^{I+1}\right\}$$

One thing worth noting is that due to her naive quasi-hyperbolic discounting, the agent revises her expectations each day about the level of debt she will hold next period. Timing is summarized as follows:

- on each day before the 14th day of a pay cycle, an agent makes decisions on her daily consumption and on how much money to leave for tomorrow;
- on the 14th day of a pay cycle, an agent makes decisions on how much to consume for that day and how much to pay down her payday loan principal;
- on the 15th day, an agent receives a new pay check and the next pay cycle begins.

Figure A8 below puts the timing convention in perspective.

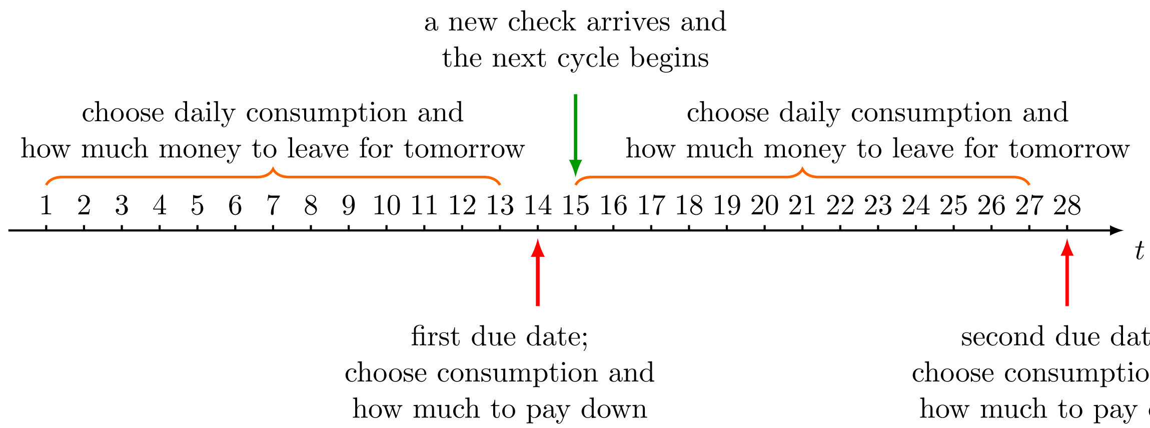


Figure A8: Model Timing—Non-Grace Period Case

3.2 Borrowers' Problem—Grace Period Case

The grace period case differs from the above non-grace period case in that there is no payment required for the first pay cycle. Figure A9 below puts this difference in perspective by outlining the timing convention of the grace period case.

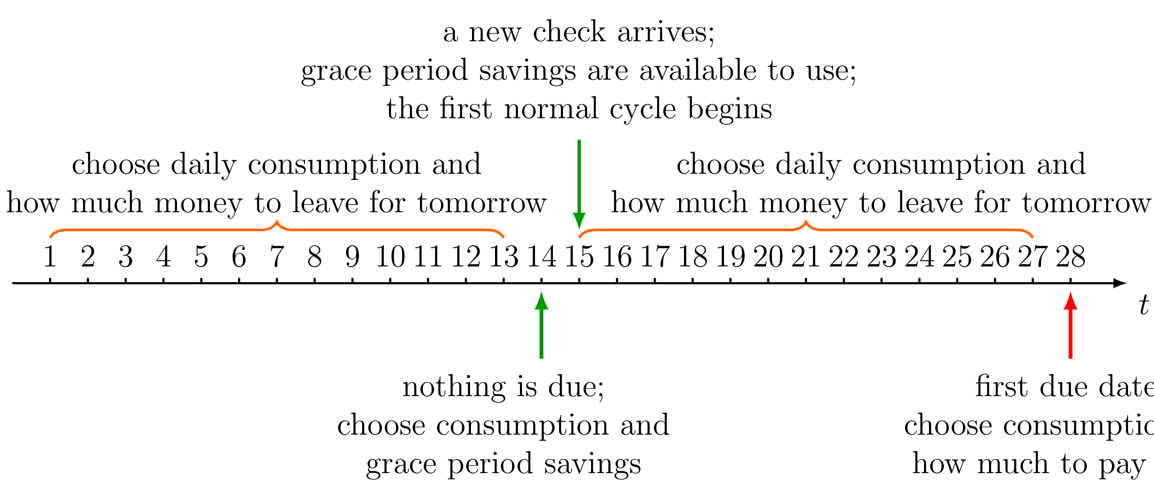


Figure A9: Model Timing—Grace Period Case

To properly reflect this difference in the model, we need to solve two separate Bellman equations for the grace period (i.e. the first 14 days since debt initiation) and the first normal period (i.e. the second 14 days since debt initiation) in addition to the one in the non-grace period case. Each of the two Bellman equations needs to be solved using a two-step procedure that is similar to the one in the non-grace period case. Before writing them down formally, we shall describe what the agent's problems are in these two special cycles. During the grace period the agent makes decisions on her daily consumption and grace-period saving.

Grace-period saving is the money saved for next period. Thus during the first normal cycle, the agent's total disposable income is increased by the amount of grace-period saving while the decisions she needs to make are the same as in any other normal cycle. Formally, the additional dynamic programs for these two special periods are as follows:

3.2.1 Borrower's Problem in the Grace Period

$$W^g(t) = \max_{c_t^g, \{\hat{c}_i^g\}_{i=t+1}^{14}, \hat{G}} \ln(c_t^g) + \beta\Big\{ \sum_{i=t+1}^{14} \delta^{i-t} \ln(\hat{c}_i^g) + \delta^{15-t} V^1(D^0, \hat{G}) \Big\} \tag{A4}$$

subject to

$$\hat{G} \geq 0$$
$$\sum_{i=1}^{t} c_i^g + \sum_{i=t+1}^{14} \hat{c}_i^g + \hat{G} = y$$

where G is the level of grace period saving and $V^1(D^0, G)$ is the time-consistent value function of the agent in the first normal cycle. We highlight that the actual level of grace-period savings is determined on day 14. Hence when $t = 14$, *hat* variables in the above program are replaced with actual values. To obtain the solution to the above problem, we first solve for $V^1(D^0, G)$ in the following way.

$$V^1(D^0, G) = \max_{\{\hat{c}_i^1\}_{i=t}^{14}, \hat{D}^2} \ln(\hat{c}_i^1) + \sum_{i=t+1}^{14} \delta^{i-t} \ln(\hat{c}_i^1) + \delta^{15-t} V(\hat{D}^2) \tag{A5}$$

subject to

$$\hat{D}^2 \leq \frac{1}{2} y$$
$$\sum_{i=1}^{14} \hat{c}_i^1 + rD^0 = y + G - (D^0 - \hat{D}^2)$$

where $V(\cdot)$ on the right-hand side of the above Bellman equation is the time-consistent value function obtained from solving equation (A1). Again, due to naive quasi-hyperbolic discounting, the policy functions for consumption and next-period debt from equation (A5) are not the actual values the agent would choose. To obtain those actual values, we proceed to solve the time-inconsistent problem of the first normal cycle as follows:

$$W^1(D^0, G, t) = \max_{c_t^1, \{\hat{c}_i^1\}_{i=t+1}^{14}, \hat{D}^2} \ln(c_t^1) + \beta\Big\{ \sum_{i=t+1}^{14} \delta^{i-t} \ln(\hat{c}_i^1) + \delta^{15-t} V(\hat{D}^2) \Big\} \tag{A6}$$

subject to

$$
\begin{aligned}
&\hat{D}^2 \leq \frac{1}{2} y \\
&\sum_{i=1}^{t} c_i^1 + \sum_{i=t+1}^{14} \hat{c}_i^1 + rD^0 = y + G - (D^0 - \hat{D}^2)
\end{aligned}
$$

Once equation (A4) and equation (A6) are solved, the rest of the problem is exactly the same as in the non-grace period case (i.e. equation (A2)). In the following section, we provide the algorithm for solving equations (A1), (A2), (A4) and (A6).

3.3 Algorithm

We begin by highlighting that one can write the optimal consumption of any day within a cycle as a function of the (perceived) 14th-day's optimal consumption per the first order conditions (FOCs) for daily consumption. These FOCs are characterized by the following two Euler's equations:

$$
\begin{aligned}
u'(c_t^I) &= \beta\delta u'(\hat{c}_{t+1}^I) \text{ for } t < 14 \\
u'(c_t^I) &= \beta\delta(1+r) u'(\hat{c}_1^{I+1}) \text{ for } t = 14
\end{aligned}
$$

Doing so reduces the number of choice variables in the dynamic programming problem to just the 14th-day's consumption and next-period debt (and grace-period saving in the grace-period case). The following algorithm we use assumes that this simplification has been done.

1. Create a grid for the debt level D^I. In the grace-period case, create another grid for grace-period saving G;
2. Solve equation (A1) on the grid for D^I using the value function iteration method below;
   (a) take a continuous function $V_0(D^I)$ as the initial guess for $V(\cdot)$;
   (b) solve the maximization problem on the right-hand side of equation (A1) using $V_0(D^I)$;
   (c) use the obtained solution to calculate the value function on the left-hand side of equation (A1); call the result $V_1(D^I)$;
   (d) calculate the sup norm between $V_0(D^I)$ and $V_1(D^I)$ over D^I grid;
   (e) if the sup norm is less than some tolerance level, stop; otherwise, update $V_0(D^I)$ using $V_1(D^I)$ and return to step (b);

3. Solve the maximization problem in equation (A2) using $V(D^I)$ on the right-hand side of the Bellman equation;

4. If there is a grace period, solve equation (A5) and equation (A6) using $V(D^I)$ to obtain $V^1(D^0, G)$. Then solve equation (A4) using $V^1(D^0, G)$.

Below we summarize the specifications of the evenly-spaced discrete grids of the state variables used to solve our models. The notations for these state variables are D (payday loan balance), G (savings over grace period), and y (biweekly income).[A1]

Table A6: Grid Specifications

Variable	Min	Max	Increment	No. of Points
D	\$0.00	\$1000.00	\$6.25	161
G	\$0.00	\$800.00	\$3.20	250
y	\$330.00	\$2100.00	\$50.00	36

Note: The upper (lower) bound of D and y grids are chosen to match the largest (smallest) value we observe in our data sample. The upper bound of G is chosen such that there is no one in the model who would ever endogenously decide to save more than that number.

3.4 Income Risks with Awareness

In the modification of our baseline representative model that incorporates income risks, we assume that borrowers in the model are aware of these risks. This assumption means that we need to add another state variable to the above Bellman equations. Specifically, let s^I denote the expense shocks of pay cycle I and the non-grace borrower's problem becomes the following:

$$V(D^I, s^I) = \max_{\{\hat{c}_i^I\}_{i=t}^T, \hat{D}^{I+1}} \ln(\hat{c}_t^I) + \mathbb{E}_s \Big\{ \sum_{i=t+1}^{T} \delta^{i-t} \ln(\hat{c}_i^I) + \delta^{T+1-t} V(\hat{D}^{I+1}, s^{I+1}) \Big\} \tag{A7}$$

subject to

$$\hat{D}^{I+1} \leq \frac{1}{2} y \tag{A8}$$

$$\sum_{i=1}^{T} \hat{c}_i^I + rD^I = y - s^I - (D^I - \hat{D}^{I+1}) \tag{A9}$$

[A1]The grid for y is only used in the calibrated model where we add cross-sectional heterogeneity in income and initial payday loan balance. In the representative models we set $y = \$900$, which is the average biweekly income of our data sample.

There are two key differences in the above from the problem without income risks. First, because we assume awareness, the representative borrower in the model will form expectations over future expense shocks using the probability distribution of the expense shock. This is why we must use the expected continuation value in the Bellman equation above. Secondly, since the model agent is aware of the expense shock, she knows that her disposable income has already been reduced by s^I for cycle I after the expense shock hits. This explains why we must subtract s^I in the budget constraint. While we have only laid out the details of this variant of the baseline model for the non-grace borrowers above, the modifications for the grace borrowers are highly analogous.

To operationalize the addition of income risks as described above, we first postulate that s^I follows an exponential distribution with scale parameter σ and is independently distributed over time. Given the exponential-distribution assumption, the expected expense shock in dollar value is σ. In the numerical exercises of this variant of the baseline model, we assume that $\sigma = \$100$, which means that on average the magnitude of the expense shock is \$100. Furthermore, to make the expense-shock process compatible with the above Bellman equations, we discretize the exponential stochastic process s^I into a five-point process with support [\$50 \$162.5 \$275 \$387.5 \$500] and associated probability of [0.68 0.22 0.07 0.022 0.008] respectively. For a given value of s in the discrete support, the associated probability is calculated using the below formula:

$$Prob(s_i) = \frac{exp(-(\frac{1}{\sigma})s_i)}{\sum_{j=1}^{5} exp(-(\frac{1}{\sigma})s_j)} \tag{A10}$$

4 Model Simulation Details

This section describes in detail our procedure for simulating the calibrated model based on the solutions obtained in the previous section. This simulation is used to generate repayment predictions. Simulations of the representative agent models are similar. Since unlike the calibrated model, we abstract from ex-ante cross-sectional heterogeneity in initial loan balance and biweekly income in all representative agent models in this paper, steps involved in simulating the representative agent models is a subset of the steps involved in the calibrated model simulation. The following description of our simulation procedure assumes a 20-cycle horizon.

1. Construct the cross-sectional joint distribution of initial payday loan balance and biweekly income for the model borrowers in the simulation.

   (a) we simulate 14,073 borrowers in the model to match the number of observations in our biweekly sample used in our empirical analysis;

(b) for each simulated borrower, we take her initial loan balance and biweekly income values observed in her data counterpart as the initial conditions. That is, suppose the observed loan balance and income of the first borrower in our data is \$350 and \$900 respectively; then the first borrower in the simulation will have a initial debt balance D^0 of \$350 and a biweekly income y of \$900;

(c) since we have two discrete grids for D^0 and y in solving the model, when the data numbers are off our grids, we use the closest points on the grids for the simulation;[A2]

2. For each borrower in the simulation, draw a 20-period time series of expense shocks from the exponential distribution with scale parameter σ;

3. Solve the decision problems laid out in Section 3 of this appendix at every possible state on the grids to obtain decision rules of repayment, consumption, and savings over the grace period in the grace-borrower case. Note that in the calibrated model we assume that agents are not aware of the expense shocks, which means that unlike what is in equation (A7), we solve the Bellman equations without the expense shock s^I as a state variable and s^I is no longer a part of the budget constraint;

4. Begin each borrower in the simulation with the initial conditions set up in step 1 and apply the decision rules from step 3 as well as the randomly-drawn expense shocks to simulate each borrower's repayment behavior. In the case of a grace borrower, apply the decision rule of savings over the grace period to obtain money saved during their first pay cycle.

   (a) obtain the total consumption within a 14-day pay cycle for each borrower using the decision rule of daily consumption;

   (b) for each borrower obtain the post-consumption and post-expense shock net disposable income by subtracting 14-day total consumption and the expense shock;

   (c) if the net disposable income is less than the mandatory interest charges given the debt balance, record it as a check bounce and carry the interest charges over to next period;[A3] In the case of a bounced check, repayment is zero;

[A2]We also use this method to deal with debt balance, grace-period savings, and disposable-income numbers that are off the grid in the subsequent steps.

[A3]The particular way we implement this carry-over is to subtract the amount of interest charges from income of next period. We think of this as the payday loan lender drafting whatever amount interest charges that are past due as soon as a new pay check is deposited into a borrower's account.

(d) if the net disposable income is larger or equal to the the mandatory interest charges, apply the decision rule of repayment to obtain debt balance of next period[A4];

(e) in the case of a grace borrower, obtain the savings over the grace period using the decision rules and the drawn expense shock in similar ways as described above; Add grace period savings to disposable income of the second pay cycle;

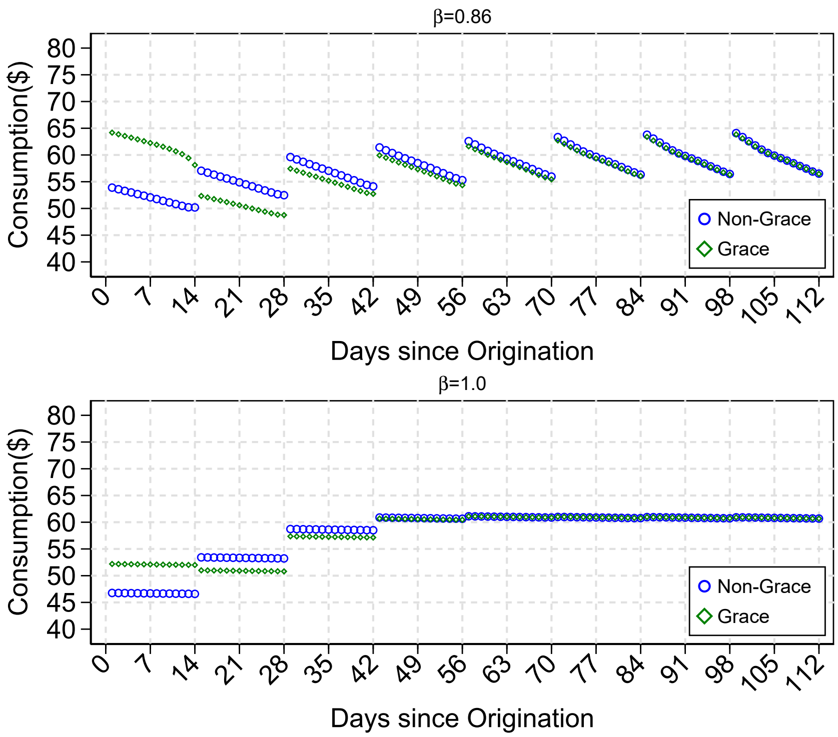
5. Repeat step 4, except for the grace-period saving part, for every subsequent pay cycle after the first one; The only difference is that instead of starting with the initial loan balance like in step 4, the loan balance at the beginning of each subsequent period is determined by the simulated repayment decisions in the previous pay cycle.

4.1 Average Daily Consumption in Model Simulation

One way to see where the welfare results in Section 6.5 of the main manuscript come from is to look at the average consumption of both types of borrowers on a daily basis, as shown in Figure A10 below. First, regardless of whether the borrowers are present focused or not, the grace borrowers consume more than the non-grace borrowers during the first pay cycle because there is no due date for the grace borrowers during this cycle. However, when borrowers are time consistent, the consumption differential between grace and non-grace borrowers is significantly smaller during the first pay cycle. This means that time-consistent grace borrowers save more over the grace period and therefore are able to pay down more of their balance on their first due date and pay less interest charges going forward. Consequently, compared to present-focused non-grace borrowers, present-focused grace borrowers on average have a much lower consumption profile during the second pay cycle, which makes having a grace period less beneficial.

[A4]Note that due to the lack of awareness in solving the decision problem, the decision rule does not account for the existence of the expense shocks. Therefore the expense shock is subtracted from the repayment decision rule to obtain the actual amount of repayment in the simulation.

Figure A10: Calibrated Present-Focus Model Daily Consumption Profiles



4.2 Derivation of the CEV Welfare Measure

As mentioned in Section 6.5 in the main text, we compute the total utility for each borrower n in our simulated sample as follows.

$$U_n = \sum_{t=1}^{280} \delta^t \ln(c_{nt})$$

where t is the index for days of the 20 cycles in our simulation. Based on the definition of of our welfare measure, we derive the following mathematical expression for CEV.

$$U_n^{Grace} = \sum_{t=1}^{280} \delta^t \ln((1+\lambda_n)c_{nt}^{Non-grace})$$

where λ_n is the fraction of daily consumption that the non-grace borrower n is willing to pay for all future days. Since λ_n is a constant over time, we may re-write the above as:

$$\begin{aligned}
U_n^{Grace} &= \sum_{t=1}^{280} \delta^t \ln(1+\lambda_n) + \sum_{t=1}^{280} \delta^t \ln(c_{nt}^{Non-grace}) \Rightarrow \\
U_n^{Grace} &= \sum_{t=1}^{280} \delta^t \ln(1+\lambda_n) + U_n^{Non-grace} \Rightarrow \\
U_n^{Grace} - U_n^{Non-grace} &= \sum_{t=1}^{280} \delta^t \ln(1+\lambda_n) \Rightarrow \\
U_n^{Grace} - U_n^{Non-grace} &= \ln(1+\lambda_n) \sum_{t=1}^{280} \delta^t \Rightarrow \\
\ln(1+\lambda_n) &= \frac{U_n^{Grace} - U_n^{Non-grace}}{\sum_{t=1}^{280} \delta^t} \Rightarrow \\
1+\lambda_n &= exp\Big(\frac{U_n^{Grace} - U_n^{Non-grace}}{\sum_{t=1}^{280} \delta^t}\Big) \Rightarrow \\
\lambda_n &= exp\Big(\frac{U_n^{Grace} - U_n^{Non-grace}}{\sum_{t=1}^{280} \delta^t}\Big) - 1
\end{aligned}$$

Note that λ_n is the constant fraction of daily consumption for all days in the 20 cycle. Therefore, the total 20-cycle CEV for borrower n in dollar amount is:

$$\Lambda_n = \sum_{t=1}^{280} \lambda_n c_{nt}$$

We then use the simulation sample mean of Λ_n to measure the benefits of having a grace period. That is, our final measure is:

$$\bar{\Lambda} = \frac{\sum_{n=1}^{N} \Lambda_n}{N}$$

where N is our sample size.

5 Calibration over δ_y

In this section we calibrate a time-consistent model and compare the calibrated model's predictions on repayment with data observations. The purpose of this exercise is to find out whether there is any plausible parameter values of δ_y and σ such that the model can fit the data well absent present focus. We introduce ex-ante cross-sectional heterogeneity in biweekly income and initial payday loan balance to the baseline neoclassical model. In addition, we also assume away awareness of the expense shocks as we do in the calibration of the present focus model. Table A7 below presents the results of this calibration.

Table A7: Time-Consistent Model Calibration for the Non-Grace Case

Panel A: Targeted Moments (All Moments are Calculated as Fractions of Initial Debt)		
	Data Mean	Model Mean
Non-Grace 1^{st} Cycle Repayment	0.31	0.23
Non-Grace 2^{nd} Cycle Repayment	0.39	0.41
Non-Grace 3^{rd} Cycle Repayment	0.47	0.55

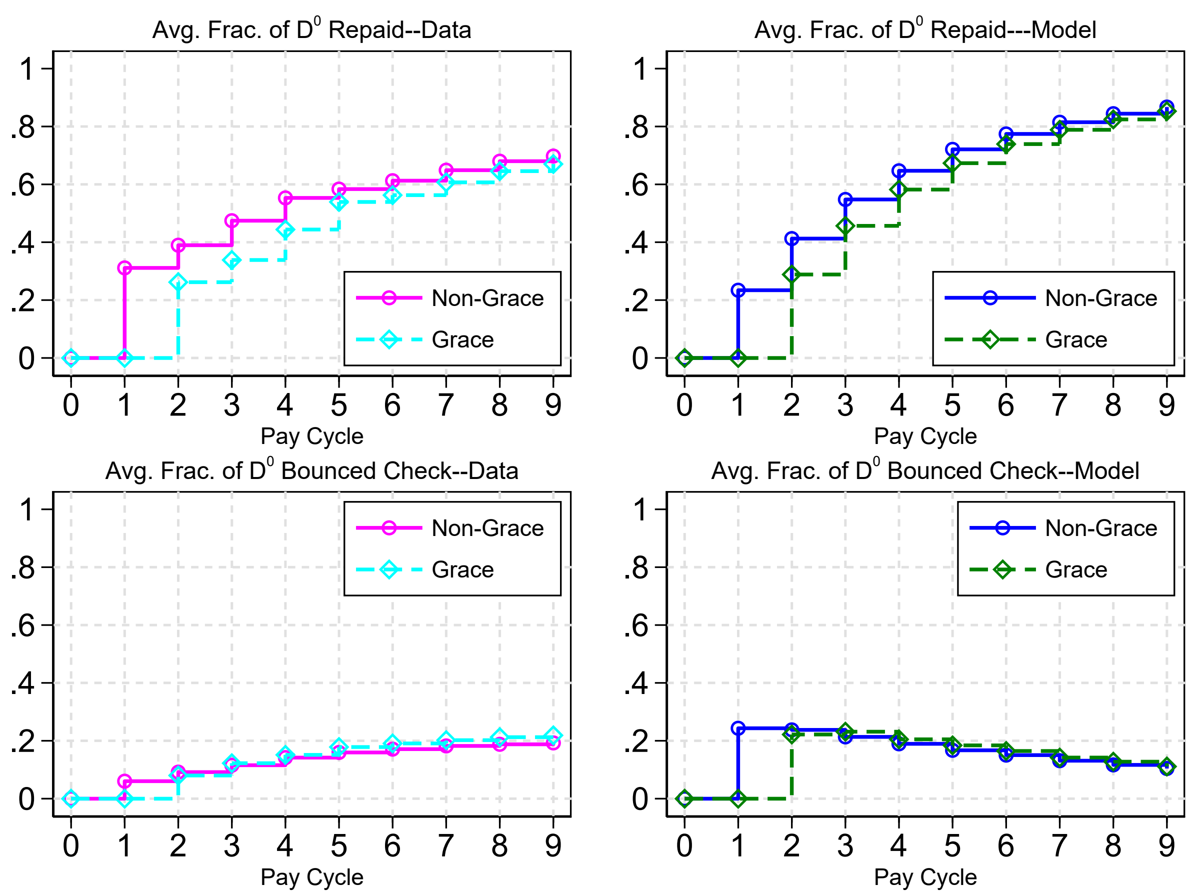
Panel B: Calibrated Parameter Values		
Notation	**Definition**	**Value**
δ_y	Yearly Exponential Discount Factor	0.13
σ	Mean of Expense Shock	\$85.62

Panel C: Untargeted Moments (All Moments are Calculated as Fractions of Initial Debt)		
	Data Mean	Model Mean
Non-Grace 4^{th} Cycle Repayment	0.55	0.65
Non-Grace 5^{th} Cycle Repayment	0.58	0.72
Non-Grace 6^{th} Cycle Repayment	0.61	0.77
Non-Grace 7^{th} Cycle Repayment	0.65	0.81
Non-Grace 8^{th} Cycle Repayment	0.68	0.84
Non-Grace 9^{th} Cycle Repayment	0.70	0.87
Non-Grace 10^{th} Cycle Repayment	0.72	0.89
Non-Grace 1^{st} Cycle Check Bounced	0.06	0.22
Non-Grace 2^{nd} Cycle Check Bounced	0.09	0.23
Non-Grace 3^{rd} Cycle Check Bounced	0.12	0.20
Non-Grace 4^{th} Cycle Check Bounced	0.14	0.18
Non-Grace 5^{th} Cycle Check Bounced	0.18	0.16
Non-Grace 6^{th} Cycle Check Bounced	0.19	0.14
Non-Grace 7^{th} Cycle Check Bounced	0.20	0.13
Non-Grace 8^{th} Cycle Check Bounced	0.21	0.11
Non-Grace 9^{th} Cycle Check Bounced	0.22	0.10
Non-Grace 10^{th} Cycle Check Bounced	0.22	0.09

Note: Agents are assumed time consistent in this calibration. Repayment is the amount of payday loan principal paid down. In other words, it is the money a borrower repays in addition to the mandatory interest charges. The model averages are computed off a 20-pay-cycle simulation of 14,073 individuals who are heterogeneous in their initial payday loan balance and biweekly income.

Panel A of Table A7 shows the model fit to targeted data moments. As Panel B indicates, the way a time-consistent model tries to capture the targeted data moments is very different from a present-focus model. First, we have to make model agents ultra impatient (i.e. δ_y=0.13) so that they do not payoff the initial balance altogether within a short amount of time, as suggested by the results of the representative agent neoclassical model in Section 3. On top of that, we also need a much higher mean expense shock to prevent non-grace borrowers in the model from paying down a lot more than the data suggests during the first three periods.

Figure A11: Data v.s. Calibrated Time-Consistent Model's Predictions



Note: The model predictions are computed using the estimates of $\delta_y = 0.13$ and $\sigma = \$85.62$ coming out of our calibration. β is fixed at 1.0 so agents are time consistent. The model averages are computed off a 20-pay-cycle simulation of 14,073 individuals who are heterogeneous in their initial payday loan balance and biweekly income. The joint cross-sectional distribution of initial payday loan balance and biweekly income in the simulation is specified according to the observed distribution in our data.

Secondly, the model fit for both targeted as well as untargeted moments are significantly worse than the calibrated present-focus model. Since model borrowers are time consistent, they manage debt balances in ways that are consistent with the goal of achieving a smoother consumption path. This is revealed by the fact that the grace-period borrowers do save over the grace period and then repay more on their first due date, although the salience of this grace-period saving channel is largely suppressed by high expenses shocks (i.e. σ=\$85.62). Additionally, without any present focus, the model agents keep paying down their debt over time such that they end up with much lower balances than the data suggests after nine pay cycles. This channel together with high mean expense shock explains why the check-bounce rate in this model is decreasing in time: agents are more likely to have a bounced check when they get a larger expense shock and their debt balance is relatively high (e.g. before they make the first repayment). As they pay down their balance over time, their interest charges go down so that the same of amount of expense shocks are less likely to make them unable to afford the charges and therefore less likely to have a check bounce. This is in sharp contrast to the data observation where borrowers keep rolling over part of their initial debt for an extended period of time.

6 Heterogeneity in Welfare Results

In this section, we use the present-focus model to explore quantitatively whether the welfare impact of having a grace period is heterogeneous across borrowers who differ in initial debt-to-income ratios. We start off by dividing the borrowers into four groups according to their initial debt-to-income ratios. We then obtain group-specific values of the parameters β and σ by re-calibrating the present-focus model separately for each group of borrowers. We follow the same calibration procedure as in the main text; the only difference here is that the three targeted moments are calculated within each group instead of at the whole-sample level. Table A8 below presents the calibrated parameter values for each debt-to-income group. We note that the degree of present focus needed (i.e. β) to fit the targeted repayment behavior is decreasing in debt-to-income ratio. This is because in the model, as one's debt-to-income ratio increases, the marginal benefit of repaying becomes higher. As a result, high debt-to-income-ratio borrowers are more driven to pay down their balances in the model. Therefore, one would need more present focus to offset the enhanced marginal benefit of repaying as debt-to-income increases.

Table A8: Calibration Results for Different Groups of Borrowers

Panel A: Borrowers with Debt-to-Income ratio $\in (0.2, 0.3]$		
Notation	**Definition**	**Value**

table continues to next page

β	Degree of Naive Present Focus	0.871
σ	Mean of Expense Shock	\$31.13
Panel B: Borrowers with Debt-to-Income ratio $\in (0.3, 0.4]$		
Notation	**Definition**	**Value**
β	Degree of Naive Present Focus	0.858
σ	Mean of Expense Shock	\$31.51
Panel C: Borrowers with Debt-to-Income ratio $\in (0.4, 0.5)$		
Notation	**Definition**	**Value**
β	Degree of Naive Present Focus	0.856
σ	Mean of Expense Shock	\$32.04
Panel D: Borrowers with Debt-to-Income ratio ≥ 0.5		
Notation	**Definition**	**Value**
β	Degree of Naive Present Focus	0.845
σ	Mean of Expense Shock	\$32.04

Note: δ_y is fixed at 0.9 for all of the above calibrations. Unlike what we do in the main text, we leave out tables that detail each calibration process for the benefit of space. However, we follow the same calibration process as in the main text. The only difference here is that moments—including both targeted and untargeted—from the data as well as the model are calculated at the corresponding sub-sample. Detailed information such as model fit to targeted and untargeted moments is available upon request.

As in the main text, we use CEV to gauge the welfare benefit of a grace period for each deb-to-income group. As shown below in Table A9, a grace period is more beneficial for higher debt-to-income borrowers in both the present-focus and time-consistent cases. This is again due to the economic mechanism that marginal benefit of repaying is higher when debt-to-income is higher. Having a grace period provides an opportunity to realize these enhanced benefits for borrowers with a higher debt-to-income ratio. Furthermore, as initial debt-to-income ratio decreases, present-focused borrowers "waste" more of the welfare benefit associated with a grace period relative to time-consistent borrowers.

Table A9: Welfare Results for Different Groups of Borrowers

	(1) Non-grace total interest paid	(2) Grace total interest paid	(3) Interest savings with grace	(4) Welfare benefit of grace (CEV)
Panel A: Borrowers with Debt-to-Income ratio $\in (0.2, 0.3]$				
Present Focused ($\beta = 0.871$)	\$310.51	\$299.63	\$10.88	\$6.10
Time Consistent ($\beta = 1.0$)	\$98.19	\$84.27	\$13.92	\$19.95
Panel B: Borrowers with Debt-to-Income ratio $\in (0.3, 0.4]$				
Present Focused ($\beta = 0.858$)	\$395.01	\$379.52	\$15.49	\$15.86
Time Consistent ($\beta = 1.0$)	\$128.07	\$104.71	\$20.65	\$33.75
Panel C: Borrowers with Debt-to-Income ratio $\in (0.4, 0.5)$				
Present Focused ($\beta = 0.856$)	\$399.03	\$380.40	\$18.64	\$23.24
Time Consistent ($\beta = 1.0$)	\$151.08	\$120.88	\$30.20	\$42.93
Panel D: Borrowers with Debt-to-Income ratio ≥ 0.5				
Present Focused ($\beta = 0.845$)	\$409.24	\$391.08	\$18.16	\$20.27
Time Consistent ($\beta = 1.0$)	\$151.86	\$120.54	\$31.32	\$43.98

Note: All calculations above are based on a 20-cycle simulation of our calibrated model. All statistics reported above are the means of the simulated sample.