Timing to the Statement: Understanding Fluctuations in Consumer Credit Use

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Abstract

We show that consumers spend 15% more per day in the first week following the receipt of a credit card statement than in the days just prior to the statement. This increase in spending includes both an increase in the likelihood that they use the credit card in the first weeks following their statement and an increase in transaction amount on days they use the credit card. In contrast to the effect on credit card spending, debit card spending is unaffected by credit card statement issuance, suggesting that consumers are not simply switching among modes of payment. Our estimates are based on exogenous variation from bank-assigned statement dates. We propose and test several alternative explanations to this spending puzzle: optimization of the free float, salience effect of the credit card statement, mental accounting, liquidity constraints, and automatic payments. We find that the consumers most apt to spend early in the credit card cycle tend to be those who do not revolve balances and are not close to their credit limit. Thus, this paper documents a puzzle with mixed support for several alternative explanations.

1. Introduction

Consumers often do not follow rational models of behavior: they sign up for credit cards with relatively high interest rates in response to a temporary "teaser" rate (Ausabel, 1999, Agarwal, Liu Chomssiengphet 2010); accept payday loans with high APRs when cheaper forms of credit are available (Agarwal, Skiba, and Tobacman, 2009); those with multiple credit card offers fail to optimally choose the right credit card (Agarwal et. al., 2015); discretionary spending increases just after the receipt of income that was perfectly forecast (Gelman et al, 2014); and savings in retirement accounts is highly dependent on default savings rates (Choi, Laibson, Madrian, and Metrick, 2003). A growing literature has shown various environments in which consumers do not view money as fungible between sources (Abeler and Marklein, 2017; Beatty et al., 2014; Hastings and Shapiro, 2013 and 2017; Milkman and Beshears, 2009). We highlight another puzzle in consumer spending decisions: consumers spend more on their credit cards in the first days following their statement dates.

A simple model of credit card use would suggest that credit card statement dates should have little impact on credit card usage or its timing since they do not directly affect consumers' income or liquidity (Gross and Souleles, 2002). However, we present evidence that consumers increase spending on their credit cards by 15% in the week following their credit card statement. This paper contributes to a growing literature on factors that may have strong effects on consumer behavior. Consumer behavior may be affected through salience and limited attention (Akerlof, 1991; Bordalo et al. 2013; Karlan et al, 2016; Taubinsky and Rees-Jones 2016), small costs or nudges (O'Donoghue and Rabin, 1999; Duflo, Kremer, and Robinson, 2011), setting optimal defaults (Choi et al, 2003; Carroll et al, 2009), and anchoring and reference dependence (Tversky and Kahneman, 1991).

We suggest and test several potential explanations for this timing of spending anomaly. A rational optimization model suggests that since credit cards allow customers to delay payment between the time that a purchase is made and the time that the consumer has to pay their bill for up to a month (a "free float"), they can be an attractive way to fund expenditures against future income. The float is most

valuable in the initial days after the credit card statement is issued when the "free float" period is maximized. Additional potential explanations include: pre-determined spending among customers who have set automatic payments to occur early in the credit cycle; liquidity constraints; and mental accounting through self-imposed limits to the "credit account" which are reset each statement period. Salience of the statement's information content (e.g., previous spending or limit used) is another potential explanation. We show evidence on the extent to which these factors explain the puzzle of consumers increasing spending following the issuance of their credit card statement.

We analyze detailed transactions level data from one of the largest banks in India. Statement dates at this bank are exogenous to the consumers: the bank sets the statement date at the time it issues the credit card, and the date changes only when it coincides with a Sunday or a holiday. The issuing bank from which we collected the data has full discretion in determining each cardholder's statement date, and assigns statement dates at the time the account is opened to maximize its own liquidity and cash flow considerations rather than adjusting the statement date to consumer preferences or characteristics. The bank does not allow its customers to change the statement date nor does it reset the date after the account has been opened.

We use detailed monthly statement data for the period January 2006 to May 2008 for 5,797 credit card account holders of which 2,882 hold a debit card as well. The dataset contains demographic information about the account holder, statement date, date of payment made on the credit card account,[1] credit limit, amount spent on the card, minimum payment due, actual amount paid, and information on the size and date of each transaction.

We begin by presenting empirical evidence that customers time purchases to occur just after their account statement date. We run a distributed-lag model with credit card statement as the exogenous event and observe the impulse response of credit card spending to the date of issuance of the credit card statement. Consumers increase the use of their credit card in the first days following the issuance of the credit card

[1] The credit card payment date is only available for the subset of consumers who pay their credit card bill using their checking accounts.

statement: credit card spending is 15% higher per day in the first week after the credit card statement is issued compared with spending in the few days prior to the statement date. This is a combination of an increased probability of using the credit card, and an increase in transaction size when the consumer uses the credit card. Our results are robust to controlling for credit card payment dates, account holder fixed effects, calendar dates or weeks (as a proxy for salary payday which tends to be clustered around the beginning of the month) and calendar month, and to estimating the model separately for customers with statement dates in each of the weeks across the month.

The monthly timing of spending is not a mechanical effect of automatic payments set on the cards. While this could potentially still be consumer optimization of the free float, it would suggest a one-time optimization decision by the account holder and a mechanical effect thereafter. This is a mechanism suggested by Gelman et al (2014) as a large force in fluctuations in spending with paychecks in the U.S. To check whether a mechanical pre-determined billing effect might drive our results, we compare credit cardholders' spending response between discretionary categories (retail, leisure, and all discretionary) and other non-discretionary bills (school fees). We find that in the discretionary sub-categories, credit card spending increases following the statement date but not in the less discretionary category of school fees. Automating other types of periodic payments such as utility bills, house rental and mortgages using a credit card was not typically feasible in India during our sample period. In contrast to Gelman et al (2014), we show that automated bill payments do not appear to be the primary driving force in intra-month variation in credit card use in our data.

We investigate heterogeneity in the response to credit card statement date across consumer types and use this to better understand the mechanisms for the effect. We provide suggestive evidence that one component of this timing effect is consumer optimization of the free float, implying a basic level of sophistication among consumers. The free float, i.e., the ability to access funds interest-free by spending early in the credit cycle and paying close to the due date, is only available to people who have paid off the credit card in the prior cycle. To the extent that households are timing the purchases in order to maximize

the free float, we would expect the timing effect to be driven primarily by "transactors"--those who pay their bill off every month and therefore do not expect to pay interest on current purchases. Our results show that transactors do respond 50-57% more to the statement than the revolvers who do not benefit from the timing of spending.

One way to test potential explanations for this timing behavior is to analyze the effect by other, related information about the account holders. Consumers optimizing the free float should also wait to pay their bills until just before the payment due date in order to take full advantage of the float. Therefore, we should see more timing behavior among those who pay their bills just before the credit card statement is due than from those that pay early in the cycle. Surprisingly, we find that earlier payers are no more likely to time their spending to the statement date than those who wait until the due date to pay off their credit card. Liquidity constraints are an alternative potential explanation for the effect. If liquidity constraints were driving the reaction of cardholders to the statement date, then we would expect the largest effects to be among those who are most credit-constrained and who are close to their credit limit. We test this directly and reject that liquidity constraints drive this effect: there is no differential timing effect between those who are close to their limit and those have spent little of their available limit within the current credit card cycle. However, those who spent a large percentage of their limit in the preceding statement-month are less likely to exhibit the timing effect. Those who may be concerned about needing to revolve a balance temporarily reduce spending in the beginning of the month. This result is in line with the salience explanation: the statement serves as a reminder to those with low spending in the previous statement-month to increase spending.

Mental accounting generates at least two suggestive, but by no means conclusive, predictions for spending behavior: first, spending from different accounts should be independent, and second, spending accumulates until a self-imposed threshold for an account is reached, at which point the consumer stops spending (Thaler, 1990). In accordance with the first prediction, we show that consumers do not treat money across all of their accounts as fungible. The increase in credit card spending is not matched by a

decrease in spending in the debit card account, suggesting consumers are not just substituting across financial products. In contrast to credit card spending, debit card spending does respond to calendar dates—spending at the beginning of the month on debit cards is higher than later in the month. Thus, consumers appear to be spending on debit cards in response to the receipt of paychecks, but timing credit card spending to follow the statement. This difference in timing across financial instruments suggests that consumers may not be treating money in different accounts as fungible.

For the second prediction of mental accounting models, that there will be a decrease in spending after a threshold is reached, we test several threshold levels and find that contrary to the predictions of mental accounting, account holders spend more in the remaining weeks of the month when they hit a threshold early than when they hit a threshold late. Mental accounting may play a role in the tradeoff between debit and credit cards for consumers, but it does not appear to be driving the timing of the consumer's spending on their credit card in the early days of the statement-month. It is important to note that while we are able to rule out several likely mental accounting thresholds of 50%, 75%, and 100% of the consumer's mean spending in a month, we are unable to reject that consumers are responding to some other rule. Overall, the paper documents an interesting puzzle in consumer spending, i.e., an increase in spending in response to the timing of the credit card bill. We find suggestive but not conclusive evidence in support on a number of alternative theories we consider for explaining the phenomenon.

This paper proceeds as follows. Section 2 discusses the context for our study: a large bank engaged in the rapidly growing credit market in an emerging market, India. We provide summary statistics from the data and explain our event-study empirical strategy. Section 3 discusses the main result documenting the effect of credit card statement dates on spending and shows that the results are robust to a variety of specifications and spending types. Section 4 examines heterogeneity in the response to statement date across several customer types. Section 5 examines the implications of mental accounting theories on cardholders' response to the statement date. Section 6 concludes and discusses the policy implications of our findings.

2. Institutional Details, Data and Methodology

Credit cards in India were introduced by public sector banks in the 1980s but were little used until the entry of foreign banks in the 1990s. ANZ Grindlays introduced a credit card in India in 1989, Citibank in 1990 and HSBC in 1992. The credit card market was initially focused on the high-income consumer market, but it is now expanding across the salaried and professional worker categories.

In 2008-09, India had 0.2 credit cards per capita compared with about 2.7 per capita in the U.S. during this time.[2, 3] While the starting base of credit cards in India was very low, the growth in credit cards has been substantial. Credit cards are an increasingly important category of consumer credit in India. Between 2005-06 and 2008-09, the growth in credit card receivables was the largest contributor to the growth in commercial banks' portfolios of total loans and advances (Reserve Bank of India (RBI), various issues). The total value of all credit card transactions at the points of sale, as a proportion of GDP, doubled between 2003-04 and 2008-09, rising from 0.6% in 2003-04 to 1.2% in 2008-2009. Over the period from 2006-07 to 2008-09, the number of outstanding credit cards issued in India grew at an average annual rate of 12.5%; the average annual growth in the number and value of credit card transactions at the point of sale were 18.5% and 24.5%, respectively.

There has also been an increased use of debit cards, both in terms of number and value of transactions. As of 2011-12, there were 17.65 million credit cards and 278.28 million active debit cards. According to the World Bank's Global Findex Database, in 2011 debit card ownership (as a percentage of

[2] More recently, as of 2017, while 3% of the Indian population had a credit card, the corresponding number in the U.S. as of 2008 was 78%. The ownership of credit cards was and remains skewed in India. As of 2008-09, credit cards per head in the urban population was more than three times the national average. For data on India, see Reserve Bank of India database and World Bank database. For the U.S., see Federal Reserve of Boston (2010), "The 2008 Survey of Consumer Payment Choice," Public Policy Discussion Papers, No. 09-10, April, Table 7.

[3] According to a U.S. Department of Commerce report, market penetration (credit and charge cards per capita) in 2005 was similar in China, India and Russia, at about 0.02. By comparison, it was 2.53 in the U.S. but with much slower growth than in the emerging markets.

people aged 15 or more) was 8% in India versus 72% in the U.S. However, by 2017, it had increased four-fold, to 33%, in India, as compared to 80% in the U.S.[4]

2.1 Data

We use a proprietary dataset of retail account holders in one of the five largest domestic private commercial banks in India, which is also one of the biggest issuers of credit and debit cards. The dataset includes 10,000 savings account holders and all of their related accounts and account activity at the bank during our sample period, January 2006 to May 2008. It includes information on the type of account, account holders' age, marital status, gender and city of residence. In addition, it provides data on the card(s) attached to an account for the duration of our sample period. The issuance of debit and credit cards is not automatic for the account holders at the bank with which we are working. The consumers in our data have specifically applied for these accounts. We use transaction-level data for credit and debit cards that come from the monthly statements of these accounts. These provide data on transaction dates as well as the amount spent on each transaction. We aggregate spending to daily totals in most specifications, but also investigate within-spending category effects. In addition to daily spending data, we have data on credit card statement dates, payment dates for a sample of accounts, minimum payment amounts, and credit limits.[5]

In some of our tests, we compare results across consumers who have both debit and credit cards, as these cards are close substitutes, and the decision to systematically use one over the other reveals information about intra-month spending.[6] There are 2,882 account holders in our sample with both a credit card and a debit card, and transactions occur over the two and a half year sample period. Table 1 provides summary statistics for these account holders at the beginning of the sample period. While our sample is

[4] https://globalfindex.worldbank.org/

[5] We are somewhat limited in our analysis in that we do not have data on APR, changes in customer credit limits over time, differences in features of cards across account holders in the sample, or the number of other credit or debit cards the account holder has from other banks.

[6] Zinman (2009) compares the consumer's choice of debit and credit card. We focus on credit card use but we use debit card spending response to credit card statement date both as a robustness test as well as to explore the implication for total spending.

not representative of the general population, it is typical of financial services clients in India. Most account holders are married men and the average account holder age is 30. A comparison of demographic characteristics of consumers holding debit cards only, credit cards only, and both debit and credit cards shows that they are similar along observable characteristics.

Summary statistics on credit and debit card spending and frequency of use at the *person-day level* are provided in Table 2a. Average daily spending is Rs.133 ($3.03) on credit cards and Rs.31 ($0.71) on debit cards; these numbers increase to Rs.2,061 ($47.05) on credit cards and Rs.1,247 ($28.47) on debit cards when we restrict the sample only to days the card was used.[7] Credit card transactions are twice as frequent as debit card transactions. There is substantial heterogeneity in the use of the credit cards—many consumers have very few debit and credit transactions, but some consumers use both cards frequently. The mean statement balance is Rs.12,723 ($290.48) while mean credit limit is Rs.67,632 ($1,544.11) suggesting that on average account holders use about 18% of the credit limit in a month. The average consumer has had a credit card for 1.7 years, but some consumers acquire their credit cards over the sample period.

2.2 Exogeneity of Credit Card Statement Dates

Our identification strategy relies on differences in statement dates that are exogenous to the consumers. Managers at the bank explained that the bank chooses statement dates at the time the account is opened based on its operational convenience and its need to optimize bank liquidity and cash flow within a month, not based on consumer preferences. This reduces concerns about potential endogeneity of the statement date which would arise if customers chose their dates based on their own cash flow and spending needs or other customer preferences or characteristics. Figure 1 shows the distribution of statement dates over the course of a month across accounts in percentage terms. A few dates (the 18th, 20th, and 28th) have

[7] According to the Reserve Bank of India, the exchange rates (Rupees/USD) for 2006-2008 were 45.3, 40.2, and 45.9, respectively, or an average of 43.8. (https://www.rbi.org.in/scripts/PublicationsView.aspzid=15268).

larger masses than the others; we test the robustness of the main specification to dropping these dates and find the results remain.[8]

The exogeneity of the statement date is crucial to our identification: we provide non-parametric evidence that the bank does not base its decision about statement dates for different consumers on the information that it has on the consumers. In Figure 2, we chart the statement date frequency across sub-groups of consumers based on key demographic and account-level characteristics including gender, marital status, location (rural or urban), account holder age, age of the account, and different levels of credit limits. Although statement dates are not uniformly distributed, we observe no major differences across the distributions, suggesting that the bank is not basing statement dates on readily observable information about the customers.

Credit card statement dates are salient to customers. One potential concern is the length of time that it takes for a statement to reach an account holder, but the bank has used email for billing purposes since the early 2000s, and this was the most common mode of delivery the bank used during our sample period (2006-2008) for sharing the credit card statement on the date the cycle ended.[9] Unfortunately, we cannot identify the delivery mode in our data, and it is possible that some account holders did not receive electronic statements. However, hard-copy statements from the bank in question are always sent through speed post (private couriers). To the extent that some customers may receive statements later, our results would be attenuated.

Figure 3 further investigates credit card use across the month. We plot the frequency of credit card transactions of a card holder on each day of the month, as a percentage of the total number of transactions in the month, averaged across all card holders. We see that just over 3% of transactions occur on any given

[8] The credit card grace period is 25 days, with the exception of when a date falls on weekends or holidays in which case the date is moved up. There is, therefore, very little separate variation between the statement date and the payment due date.

[9] Presently, most account holders receive both short message service (SMS on mobile phones) and email with information about the credit card statement on the date the cycle ends. This information comes from multiple conversations with bank management personnel.

day of the month, and the level is extremely steady across the month (standard deviation is 0.21%). The absence of overall large swings in credit card use across the month is further suggestive evidence that the bank's effort at smoothing cash flow and liquidity across the month is relatively successful.

2.3 Empirical Specification

Our analysis exploits the disaggregated nature of our data. We use intra-month account-level data, focusing on daily spending on credit cards and debit cards on each additional day following the credit card statement date.

Let $S_{i,t}$ represent the amount of daily spending on credit or debit card by account holder *i* at the end of each day *t*, $I_{i(t)}$ be an indicator for *i* if the bank issued her credit card statement on day t, $I_{i(t-2)}$ be an indicator for *i* if the observation is from the second day of the statement-month (i.e., the day after the statement is issued). Our tables show the regressions at the weekly level, where I(1) is daily spending during the first week following the issuance of the credit card, I(2)-I(4) are daily spending in the second through 4th weeks following the issuance of the credit card. $I_{i(0)}$, or the day that the statement is issued is the excluded variable in the daily regressions, so all coefficients are in comparison to the day the statement is issued.[10] In the weekly regressions, the excluded variable is the day the statement is issued and the days just before the statement is issued (days 30, and 31 depending on the number of days in the month). Our estimation equation is given by:

$$S_{i,t} = \alpha_i + \sum_{j=2}^{n} \beta_{(t-j)} I_{i(t-j)} + \gamma' X_t + \varepsilon_{it} \qquad (1)$$

The *marginal* coefficients $\beta_2, \ldots, \beta_{31}$ measure the *additional* spending each day after the issuance of the credit card statement (i.e., day 2 to day 31) relative to the day of the issuance of the statement (day 1). In the weekly regressions, the marginal coefficients measure the additional spending for a day during a given week following the issuance of the statement. The identification in the main specification is based on variation in the statement date which, since set by the bank, is exogenous to the consumer.

[10] We follow the event study literature see, Agarwal, Liu and Souleles (2009), Agarwal and Qian (2014, 2017).

Although the bank sets the statement date according to their cash flow considerations and does not use consumer characteristics in the determination of the statement date, we are particularly careful about the possibility of omitted variables that could potentially be correlated with the indicator variable, $I_{i(t)}$. As a robustness test, we include a full set of account fixed effects, α_i, to control for potential omitted variable bias related to customer-specific spending, and find that the results remain. Within-account variation in statement dates (the basis of identification in the fixed effects specifications) is based on statement dates falling over weekends and holidays, and is therefore equally unrelated to consumer characteristics once we have controlled for day of the week. The correct interpretation of the marginal coefficients for each day after the statement date in the specification with account level fixed effects is the spending relative to each customer's average spending during the excluded period. The excluded period is the statement date in estimation equation (1) for daily spending. X_t is a vector of controls, which include day of the week, day-of-the-month and month-year fixed effects, and standard errors are clustered by account holder. Any spending related to the calendar date rather than the days from the statement date will be controlled for with the day-of-the-month fixed effects.

In order to estimate the heterogeneous effects, we add interactions between the heterogeneity terms and the week indicators, using the following specification:

$$S_{i,t} = \alpha_i + \sum_{w=1}^{4} \beta_{(t-w)} I_{(t-w)} + \sum_{w=1}^{4} \theta_{(t-w)} * H_i * I_{(t-w)} + \varphi H_i + \gamma' X_t + \varepsilon_{it} \qquad (2)$$

The coefficient φ measures the average daily spending for the group of interest relative to the rest of the sample. $\theta_1, \theta_2, \theta_3$ and θ_4 measure the *additional* daily spending by week for the group of interest relative to the rest of the sample.

For ease of exposition, we focus on the results of week-based regressions and report them in the main tables. We report the daily level regression results for credit cards in Figures 6 and 11 which show the coefficients in solid lines and the standard errors in dotted lines. The corresponding results for debit cards are shown in Figure 10.

3. The Response of Spending to Credit Card Statement Dates

We provide nonparametric evidence that spending responds to statement dates and show that this relationship is robust across multiple specifications. Our main specification shows an increase in spending of 15% in the days just following the statement date. We run a battery of robustness tests including controlling for payment dates, estimating the effects separately by the week of the month in which the statement falls, and confining the sample to discretionary spending, and find that the results still hold.

3.1 Non-parametric Results on Daily Spending

As mentioned before, Figure 3 shows the percentage of a person's credit card transactions that fall on a particular day of the month, averaged across cardholders. In this figure, we see that there is little variation in timing of when consumers use credit cards across the month; each day accounts for 2.9% to 3.9% of a cardholder's credit card transactions with no obvious pattern although a general increase in spending toward the end of the month. Figure 4 plots credit card use over the days following the statement date at the person-month level. This shows non-parametrically the main effects that we estimate. There is noticeable variation by statement date in Figure 4. Frequency of daily credit card use in a month by a cardholder goes from an average of 4.0% on days 2-4 to 3.2% on days 29-31.. In Figure 5, the percent of the cardholder's monthly spending (which combines both the frequency of use and the size of the purchases) shows a similar decline from 4.0% to 3.1% during those days.. Overall, there is higher daily credit card spending by a card holder in the first week following the statement date (approximately 3.7%) than in the remaining weeks of the statement-month (approximately 3.2%).

3.2 Response to Statement Date in Credit Card Use

In Figure 6, we plot the daily coefficients from our main specification (equation (1)). These regressions summarize the outcome noted in Figures (4) and (5): the daily spending increases on average following the receipt of the credit card statement. The regression specification allows us to control for specific factors about the account holder, the day of the week on which the spending occurred, and the

month-year combination, reducing the potential that the effect could be confounding another variable with the account holder's reaction to the statement date. The coefficients in panel (a) provide estimates of the total additional spending per day as compared to spending on the day of the statement. As seen in the overall distributions, we find that credit card spending spikes up in the first days of the statement month—by Rs.24.3 on day 2 (an 18.3% effect at the mean of Rs. 133 per day) and does not dip to zero until day 13, even controlling for the day of the calendar month. By the end of the second week, this effect dies out, and spending in most days is not statistically significantly different from the day the statement is issued. In panel (b), we estimate the increased propensity to use the credit card in the days following the statement date. In line with the raw data investigated in Figures (4) and (5), we find that cardholders are 0.6-0.8 percentage points more likely to use their credit card in each of the 7 days following the credit card statement issuance than on the day that the statement is issued.

While the daily spending regressions make it possible to observe intra-week fluctuations in spending, weekly regressions allow us to look at overall effects across a month between different groups and different categories of spending more easily. We repeat the main daily regressions at the week level, and use the weekly format in order to further investigate the drivers of the effect.

Table 3 presents the results for daily spending across weeks in a month following the credit card statement date. As outlined in Section 2, the results can be interpreted as an event study, with the omitted (comparison) variable being the day of the statement and the days immediately before the statement (i.e., the few days between the end of week 4 from the statement date and the next statement date which follows after a month). In column (1) of the table, account holders spend Rs.20.6 more (or approximately 15.5% based on mean daily spending of Rs.133, from Table 2a) in the days of the first week following the receipt of their credit card statement. We break this into its two separate components: spending per day on days in which there is non-zero spending and the probability of spending on their credit card, and present the results in columns (3) and (5), respectively. Daily transaction amount on days on which there are transactions increases by Rs.107.6, or approximately 5.2% (with a mean of Rs.2,061 on days with non-zero

spending) in the first week of the month. Consumers are 0.7 percentage points more likely to use their credit cards in the days following the receipt of their statements (an effect of approximately 10% at the mean of a 7% chance of using the credit card) when controlling for week of the month. Combining these results on increased daily spending and daily usage suggests that the impact on total spending comes from an increased likelihood of shopping and not uniquely from an increased propensity to purchase large items in the beginning of the statement-month.

Results of the fixed effects specifications are shown in columns 2, 4, and 6 of Table 3. In these specifications, we see that the results are robust to the inclusion of account-holder fixed effects: as predicted since the account's statement date is exogenous to the consumer, we see that regressions are relatively unchanged when we include account fixed effects.[11]

One may be concerned that statement dates are correlated with paycheck receipts. This is unlikely since, as we have shown, statement dates are exogenous to the consumer. However, we investigate this possibility directly. Figure 7 shows the distribution of paycheck deposits into individual bank accounts by day of the month. Unlike statement dates (Figure 1) which are distributed through the month, paycheck deposit dates are clustered around month-end or beginning of the month.[12] We find that credit card spending does not respond to the calendar week of the month. Our results remain qualitatively unchanged when we explicitly control for days since the paycheck in the subsample where we observe information about the account holders' paycheck deposits.[13]

One could also be concerned that while statement dates are distributed across the month by the bank, customers choose the dates on which they pay their credit card bills and they may time spending to their payments. This suggests a potential omitted variable bias if bill payment dates are not included in the specification. Figure 8 shows the distribution of payment dates by calendar date. We see that payment

[11] As additional robustness, we run the specifications (2) and (4) of Table 3 after excluding the more common statement dates (the 18th, 20th, and 28th). Our results are qualitatively unchanged and are included in the online appendix. We thank the referee for this suggestion.
[12] Most firms in India pay salaries monthly rather than bi-monthly.
[13] Results are available in an online appendix.

dates are highest during the first 10 days of the month and drop off somewhat towards the end of the month. Figure 9 shows the distribution of days between the credit card statement date and the bill payment date. The distribution peaks at 23 days, which matches the grace period of 25 days (except when a date falls on weekends or holidays) and suggests that a large proportion of account holders wait to pay their credit card bills closer to the payment due date. Since payment dates could have an impact on spending responses, Table 4 includes controls for each week following the payment date.[14] Specifications 1, 2, 5, and 6 control for the customer's actual payment date (and specifications 2 and 6 include account fixed effects). As specification 1 shows, credit card bill payment does appear to affect spending -- in the week following the credit card payment, spending increases by Rs.49, or approximately 37%. Controlling for payment dates also increases the magnitude of the observed impact on spending following the statement date. Daily spending in the week following the statement date increases by 20% at the mean of Rs.133 per day after controlling for weeks after payment of the credit card bill. Consumers are also 0.8 percentage points more likely to use their credit cards in the days following the receipt of their statements controlling for payment date. So the timing effect continues to hold after we control for the credit card payment date.

The days on which clients choose to pay their credit card bills are endogenous. So instead of the actual payment date, we consider the due date, which is 25 days after the customer's statement was issued but moved forward in cases of Sundays and holidays, in order to observe the effect with an exogenous control for payment date.[15] Specifications 3, 4, 7, and 8 show the results. We find that the results are statistically similar when we control for the payment due date: spending increases in each of the three weeks following the issuance of the statement. We control for all time invariant characteristics of the customers by adding account fixed effects in specifications 4 and 8, and find that the results are still unchanged.

[14] In our dataset, information about credit card bill payment date is only available for account holders who have both credit and debit cards and pay their credit card bill from their debit card account. This accounts for the smaller sample size.

[15] As a consequence, variation in payment due date is limited.

3.3 Statement Date Timing

We show above that the spending following the credit card statement is robust to the timing of the payment within the month. One potential concern is that results may be driven by accounts with statement dates that fall at the end of the month, in which case the timing of the spending would be a reflection of consumers with late statement dates switching to credit cards toward the end of the month. We test this directly by estimating the model separately across each of the calendar weeks. If the results were driven by customers with statement dates at the end of the month switching to the credit card at the end of the month, we should expect the effects to be quite large for those with statement dates in week 4 of the calendar month and we should not see significant effects for account holders with statement dates in earlier weeks of the calendar month. Table 5 shows that our results are the inverse: we continue to find evidence of intra-month shifting in spending for weeks 1, 2, 3, and 4, and the timing effect is actually largest among customers with statement dates at the beginning of the month.

3.4 Timing of Discretionary and Non-discretionary Expenses

One explanation for the increased spending could be that account holders time pre-determined bills and expenses to immediately follow the statement date rather than pursue deliberate spending after the statement. The spending response we document would then be a reflection of mechanical spending on these pre-determined expenses. In order to test whether this is driving our results, we use vendor-level categories in our data to group purchases by type. Unfortunately, vendor information for transactions is noisy and allows only for relatively crude product-category classifications. We separate transactions across broad vendor types, and focus on retail spending, leisure spending, overall discretionary spending, and school-related fees. The retail category includes shops such as gift shops, luggage stores, piece goods stores, stationary stores, bicycle shops, and sporting goods stores. Leisure spending includes movie theaters, pool halls, golf courses, and music. School-related fees include expenditures associated with universities, vocational schools, childcare services, and correspondence schools. Retail and leisure spending across months are relatively discretionary, so these are combined in All Discretionary Spending,

while overall school spending may be able to be timed within a month but is relatively non-discretionary in size. School spending is among the types of spending we would expect consumers to use if they were timing bill payments within the month according to statement dates.

Specifications 1 - 4 in Table 6 present the results for the timing of spending in each of these four product categories. Customers who have not spent in a particular category have been dropped from the sample in order to reduce the possibility of attenuation bias from inclusion of a large number of customers never using their credit card for a certain spending type. Retail spending (specification (1)) responds significantly in the first two weeks following the statement but does not respond to the calendar week. A daily increase of Rs.7.43 in the first week translates to an average impact of 15.5% per day (mean daily retail spending is Rs.47.9). We similarly see increases in leisure spending (specification (2)) as well as when we aggregate the two discretionary spending categories (specification (3)). However, school-related spending, which is the least discretionary category, shows no evidence of significant fluctuation in payments across the statement month (specification (4)). Therefore, the spending increase does not appear to be driven by account holders setting up regular (i.e., non-discretionary) payments to match the statement date. As a robustness test, we exclude all repeat transactions (i.e., an account holder's transactions of the same amount within each category) across all categories of purchases. The results, in specification 6 of Table 6, continue to show that there is a timing effect immediately following the credit statement date, although the magnitude of the coefficient is slightly smaller than in specification (5) where repeat transactions have not been removed.

Increased discretionary spending in the first week following the statement relative to subsequent weeks would allow account holders to maximize the use of the free float. These results are in line with consumer optimization. They are also in line with salience about the card resulting in increased spending following the credit card statement.

4. Heterogeneity across customer types

In this section, we analyze the implications for spending response based on customer heterogeneity. We observe differences in the strength of the timing to the statement effect based on three versions of customer types: (i) revolvers who maintain debt on their credit cards and therefore will not benefit from a free-float versus transactors who pay the card off each month, (ii) early payers who pay the card soon after they receive their statement versus just-in-time payers who pay close to the due date, and (iii) the extent to which account holders are liquidity constrained.

We estimate the daily effect on those who pay off their balances each month and those who revolve balances on their credit cards separately, and plot the daily coefficients in Figure 11. Panel (a) shows that the effect is larger and more significant when the sample is restricted to those that pay off their balance each month (transactors) while we see no such effect for the revolvers. Transactors spend an extra Rs.46 on the day after the receipt of their statement, and their spending does not return to their average levels until day 12. Transactors benefit from the free float, and therefore have the incentive to spend early in the credit cycle, while revolvers receive no benefit from accumulating more of their spending in the first part of the statement month. These regressions show that the consumers react to these incentives and provide support for the free float hypothesis, i.e., consumers seek to optimize their benefits.

Specifications (1) and (2) in Table 7 show the regression results for transactors and revolvers by week. In specification (1), we define transactors and revolvers based on the last statement, while specification (2) defines the consumers based on whether they are transactors or revolvers in the majority of months over their history in our sample (i.e., customer "type"). The un-interacted coefficients in these specifications (i.e., week following the statement) should be interpreted as the spending response for the transactors, while the interacted coefficients should be interpreted as the *additional* response of revolvers to being in that statement-week. Under specification (1), we find that transactors on average spend Rs.75 more than revolvers each week, and have significantly more time variation in their spending. Transactors spend an additional Rs.40 (approximately 30% at the mean of Rs.133 spent per day) in days in the first week following the statement date, while revolvers have a Rs.23 lower timing response than the transactors.

The results exhibit qualitatively similar effects in specification (2) based on customer type. These results provide support for the optimization hypothesis that sophisticated consumers may choose to spend earlier in the credit card monthly cycle in order to maximize the free float.

Heterogeneity in consumers' bill payment decisions is another way in which we can separate consumers into those most likely to optimize and those who do not appear to be taking advantage of the free float. Customers interested in optimizing the free float may also pay their statements just before the due date in order to maximize the length of time they receive an interest-free grace period on the spending. As seen in Figure 8, consumers are heterogeneous in terms of when in the month they pay their credit card bill. For each credit card holder, we determine the days between the statement date and the bill payment date. We characterize those who make their bill payments less than two weeks after the statement date as "Early Payers," and those who pay between two weeks after the statement date and the due date as "Late Payers." Those who are optimizing the float would be expected to pay their credit card bill as late as possible to increase the number of days for which they have free credit. If the impulse response in spending is stronger among consumers who care about float, we should expect the late payers to exhibit a greater increase in spending after the statement date than the early payers.

Specifications (3) and (4) in Table 7 show the credit card spending response following the statement date for early versus late payers.[16] While specification (3) defines early/late payers based on the last statement, specification (4) defines these categories of consumers based on whether the customer is an early payer in more than half of the months of the sample (i.e., customer "type"). Under specification (3), late payers spend Rs.23 more in days during the first week following the statement, i.e., about 17% of the mean of Rs.133 spent per day. However, the interaction of early payer with week 1 shows no statistically significant difference in timing of spending between early payers and late payers. Early payers in the previous statement month (i.e., specification (3)) spend Rs.4 more than the late payers in days during the

[16] In our dataset, information about credit card bill payment date is available, if at all, only for account holders who have both credit and debit cards. So, the sample size is smaller.

first week after the statement, and customers who are usually early payers (i.e., specification (4)) spend Rs.10 less than late payers in the first week, but neither of these differences between the two groups is statistically significant. While the results on revolvers and transactors provide some support for the hypothesis that households are optimizing their use of the grace period, we would expect households that were optimizing the use of the grace period to pay later in their billing cycle in order to retain the funds for the maximum number of days possible. We do not find a statistically significant larger timing response for those paying toward the end of their statement period. Therefore, there must be reasons in addition to or other than the optimization of the grace period for this timing effect in credit card spending.

An alternative hypothesis is that the timing effect is a result of liquidity constraints, i.e., those who spend a large amount of their credit line may be constrained toward the end of the statement-month, so the reduction in spending could be a mechanical effect of hitting their credit limit. We determine the degree of liquidity constraint of any account holder as the percent of credit limit used. Specification (5) in Table 7 considers the account holders' liquidity constraint as of the date of the observation. We find that more liquidity constrained consumers have no statistically significantly different timing response relative to the unconstrained consumers—unconstrained consumers spend on average Rs 23 more in the days just following the statement, and there is no statistically significant difference for constrained customers. This suggests that liquidity constraints do not drive the measured effects—if they did, we would expect to see the constrained customers have much larger spending in the first weeks following the statement.

Alternatively, if the statement serves to provide information about the remaining limit on the card from the past statement period or if the amount that they spent in the past period was made more salient by the arrival of the statement, it would lead to increased spending among those who spent less of their credit limit in the previous statement-month. We do see some evidence of this in specification (6) in which we interact the percent of the consumer's credit line that they have spent with the week of the statement-month. Cardholders who spent more on their credit cards in the past statement month spend significantly less in the first weeks following the statement. Unconstrained card holders based on the past statement spend an

additional Rs.33 daily during the first week after the statement. Relative to this group, the more constrained consumers spend significantly less, by Rs.22 daily in the first week after the statement. This may be an impact of the salience of the information that the statement provides about how much credit they have remaining or the salience of the amount that they have already spent and must now repay.

5. Debit Card Spending and Spending Thresholds

5.1 Debit Card Responses to Credit Card Statement Date

If consumers substitute across payment methods, it is possible that even with an increase in credit card spending after the statement date, total spending remains unchanged. While we lack information on account holders' cash spending, we do have information on debit card spending, and debit cards are the financial tool most likely to be directly substitutable with credit spending. We estimate the effect of the statement date on debit card spending using the sample of account holders with *both* credit and debit cards. In contrast to the effect of statement date on credit card purchases, the two panels in Figure 10 show that debit card spending does not respond to the credit card statement date.

Table 8 shows the daily estimates of debit card spending response to credit card statement date aggregated by week. We include a full set of week, day of the week, week of the month, and month-year dummies in order to control for any relationship between spending across the month and the statement date in consumers' accounts. Specifications (1) and (2) in Table 8 estimate the response of spending on debit cards to the statement date, with specification (2) including account fixed effects. In contrast to the effect of issuance of the statement on the consumer's credit spending (shown in Table 3), issuance of the credit card statement does not have a similar impact on the consumer's debit spending. There is no significant effect of statement date on debit card spending across the statement-month. Similarly, the probability of spending on the debit card does not respond to statement date (specifications (3) and (4)). While the credit

card spending was unaffected by calendar day, debit card spending shows a strong increase in the first weeks of the calendar month—a 0.4 percentage point increase or 13.3% increase in the probability of a transaction at the mean of a 3 percentage point probability of a transaction in a day. Since paychecks are clustered around the end of the calendar month (Figure 7), our results suggest that while paycheck receipts do not increase credit card spending, customers do respond by increasing debit card spending in the period immediately following receipt of their paychecks. Overall, while there is an increase in daily spending on the credit card following the statement date, the credit card spending is not offset by a decrease in debit card spending. This lack of fungibility of spending across accounts is in line with one prediction of a mental accounting model.

5.2 Spending Thresholds

We examine whether the timing effect is affected by thresholds of spending and present the results in Table 9. We assume that consumers use a threshold that is somewhat constant over time, and so it should be some percentage of their average statement balance in months in which they spend on their credit cards. We test thresholds of 50%, 75%, and 100% of their mean statement balance, and run separate regressions based on the week in which the threshold is reached during the statement-month. In all the regressions, we find that credit card spending is higher in the remaining weeks of the statement-month once the account holder reaches the threshold. This is contrary to a mental accounting model that may predict that card holders would reduce spending significantly once they reach a reference point thresholds of 50%, 75% or 100% of average spending, but does not preclude the possibility that account holders are using mental accounting with a threshold that we have not tested.

6. Conclusion

We document an empirical puzzle in consumer spending: consumers have a strong spending response to the receipt of their credit card statement. There is a sharp increase in spending in the week following the credit card statement, with little or no substitution away from debit card spending. The timing effect is limited to categories which are the most discretionary, suggesting that the timing behavior is one

that account holders are choosing with some frequency rather than just setting automatic bill payments to occur at a certain time and forgetting about them. These findings add to a broader literature on factors that may affect consumer behavior.

We suggest and find mixed evidence in support of several potential explanations. The customers most likely to engage in timing are those who benefit from it most directly: those without past outstanding balances, and those with relatively low balances from the prior period. These results are in line with consumer optimization and salience of information in credit card statements. Given the early stages of credit card adoption in India in our analysis, it is likely that the relatively sophisticated consumers in our sample bias are among the more financially-savvy in India as they are early adopters of credit cards. Additional research is needed to determine whether this sophisticated behavior among the transactors in our sample would be found among the general population as the availability of credit cards expands throughout the wider population of India. We also find mixed evidence for mental accounting. However, we find little support for liquidity constraints as an explanation for the observed spending following the credit card statement.

Understanding the behavior of credit card spending and the degree of consumer sophistication is important, particularly in emerging markets. It sheds light on the necessity of increasing financial regulations as these markets expand. While free access to new financial products cannot reduce the welfare of consumers who understand the financial products and make informed decisions about their use, policy makers may be concerned about less knowledgeable consumers becoming trapped in cycles of debt after incorrectly using consumer credit. We provide early evidence on consumer use of new financial instruments from a large and growing market. In particular, there is some evidence of sophistication among credit card holders.

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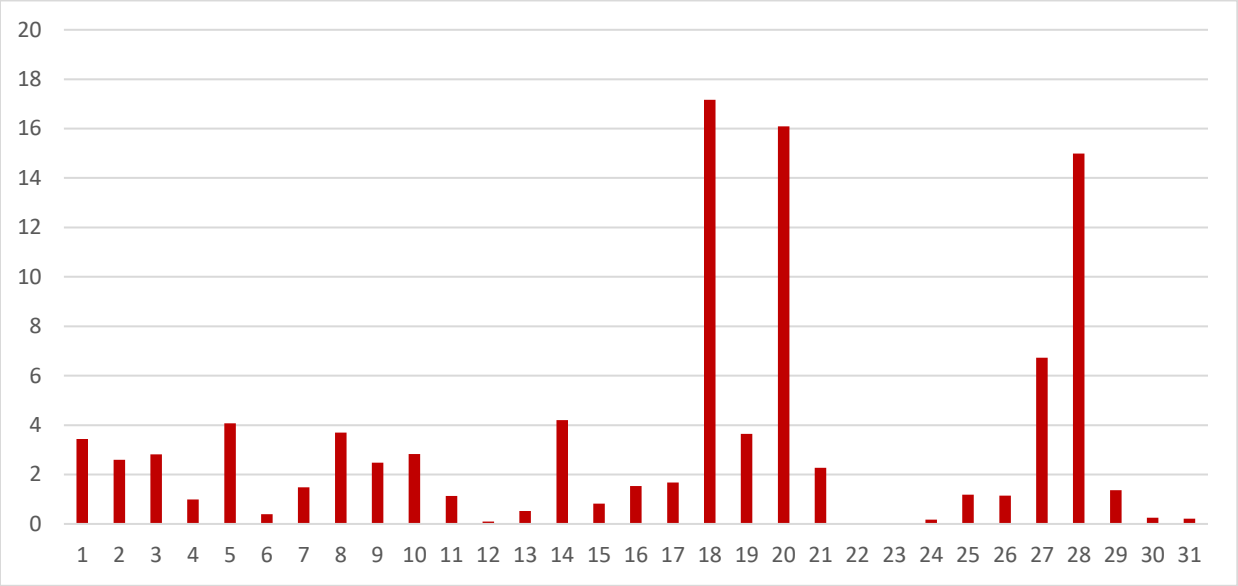
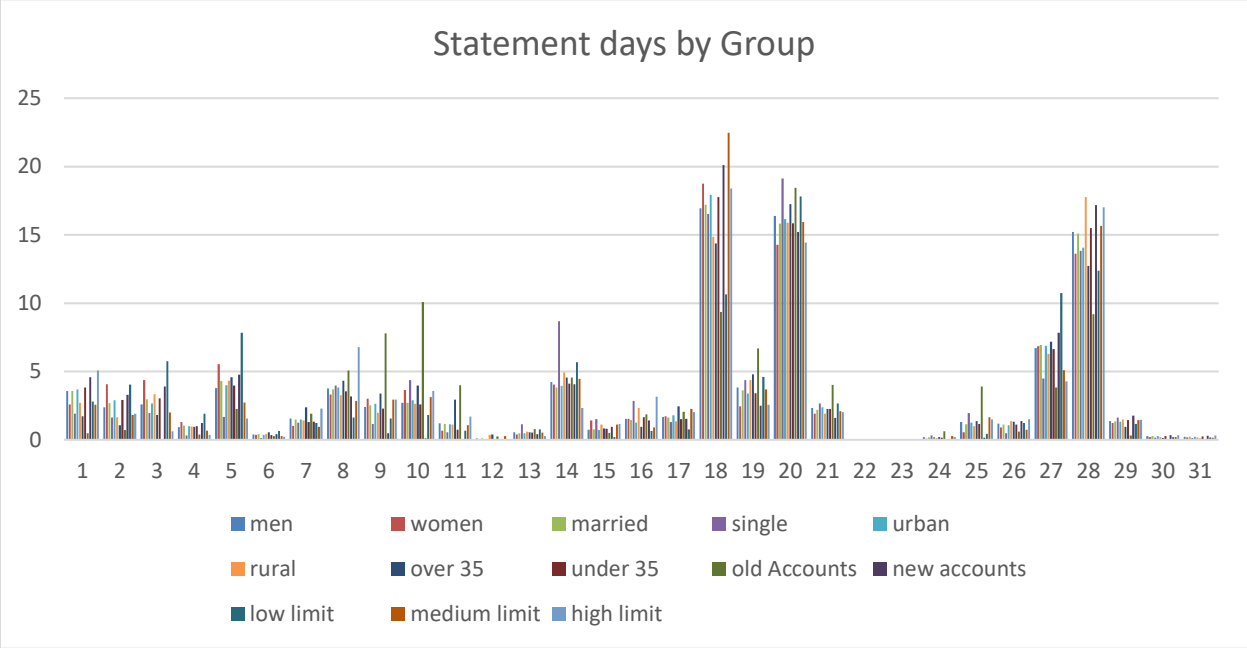
Figure 1: Distribution of Statement Dates



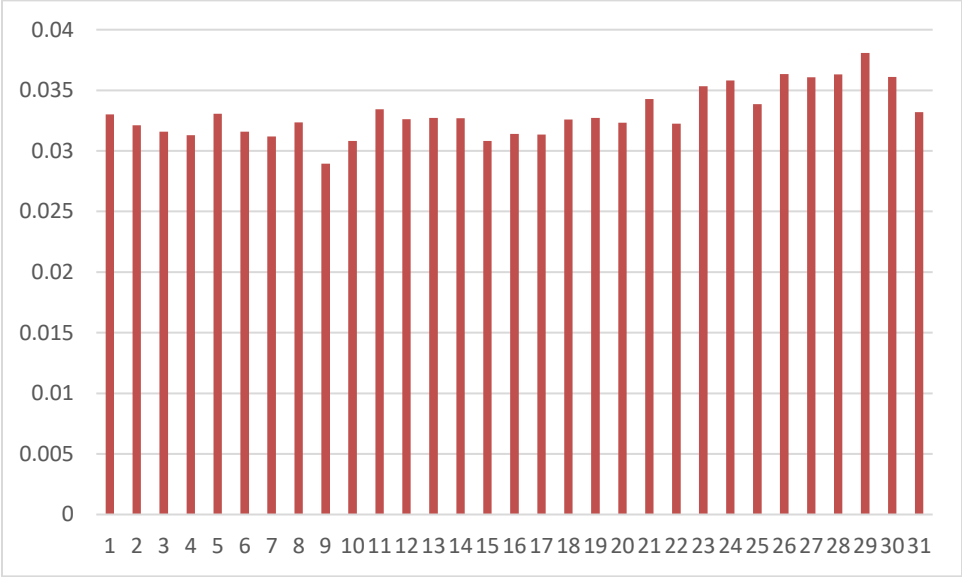
Notes: The figure plots the percentage of credit card statements (y-axis) that are issued on each day of the month (x-axis).

Figure 2: Distribution of Statement Dates by Subgroups



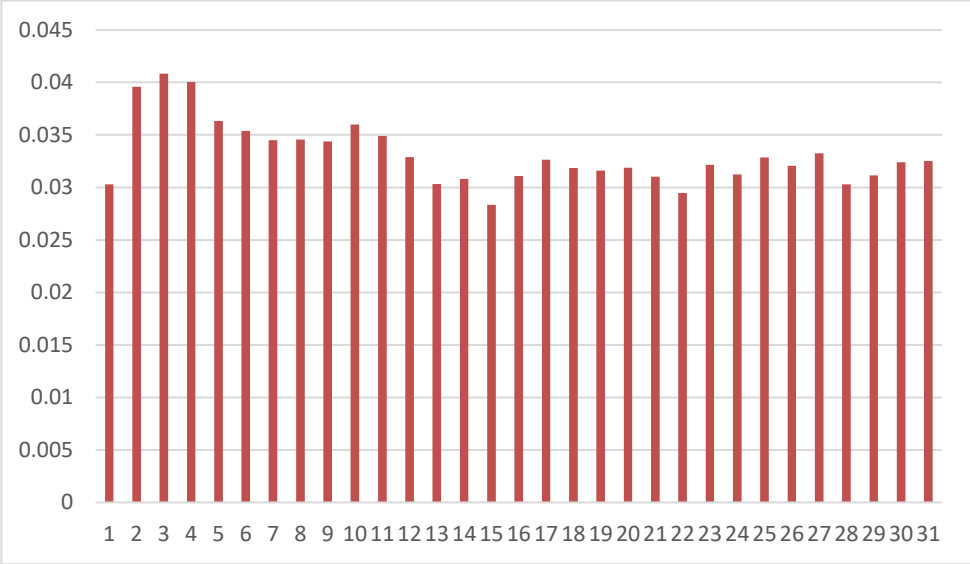
Notes: The figure plots, by account holder characteristics, the percentage of credit card statements (y-axis) that are issued on each day of the month (x-axis).

Figure 3: Credit Card Usage by Date of the Month



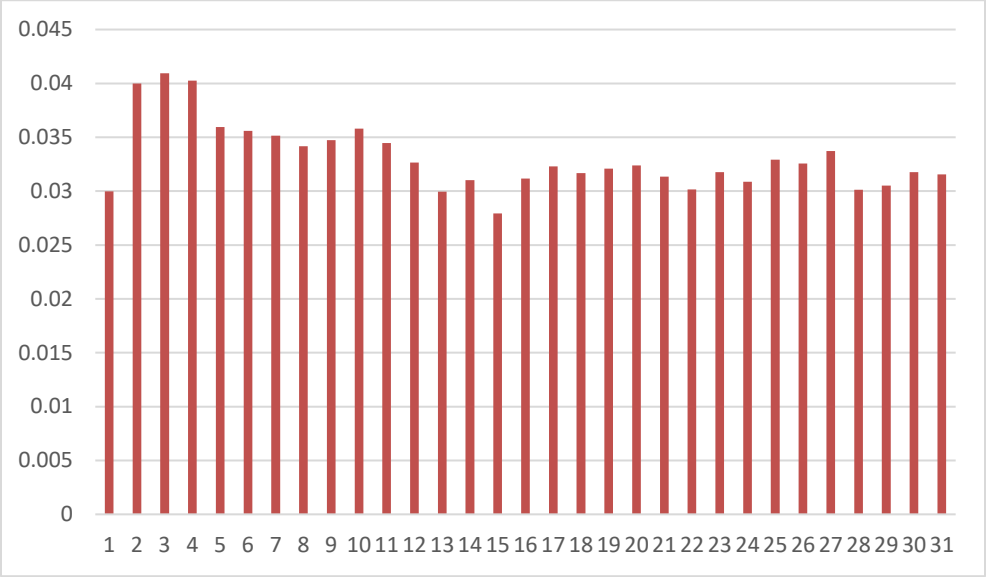
Notes: This figure plots the percentage of a given person-month's credit card transactions that occur on each day of the calendar month.

Figure 4: Credit Card Usage by Days from the Statement Date



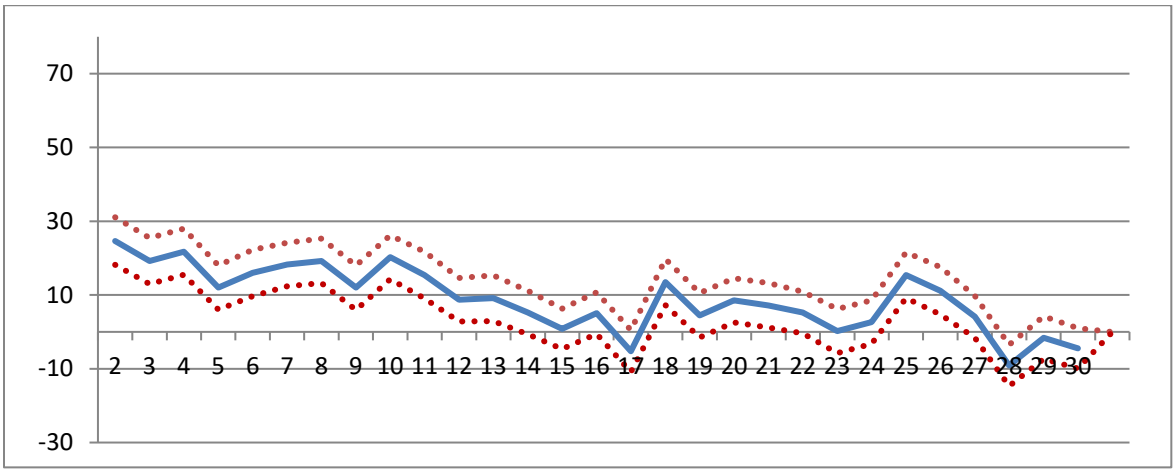
Notes: This figure plots the percentage of a given person's daily credit card transactions in the 28-31 days following the statement (depending on the month) from the statement date.

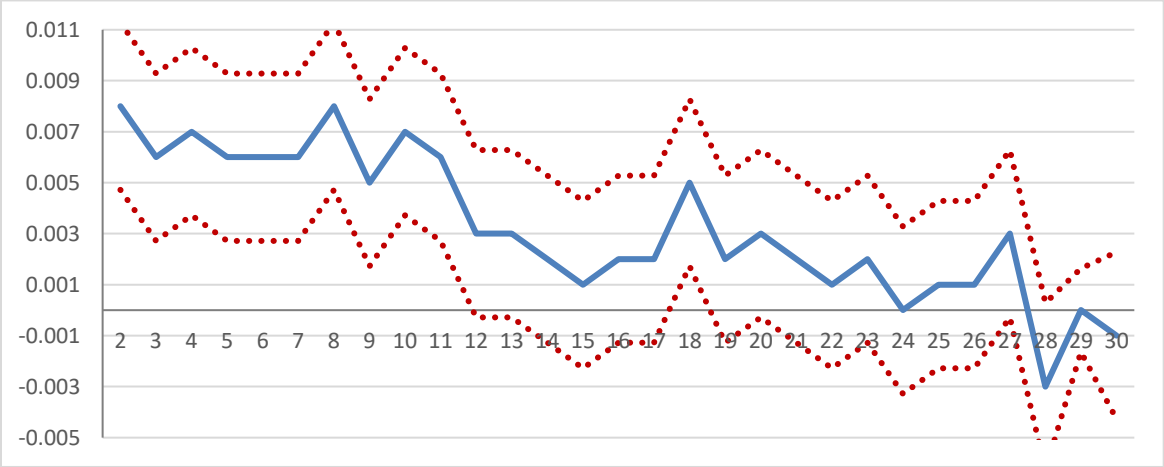
Figure 5: Credit Card Spending by Days from the Statement Date



Notes: This figure plots the percentage of a given person's daily credit card spending in the 28-31 days following the statement (depending on the month) from the statement date.

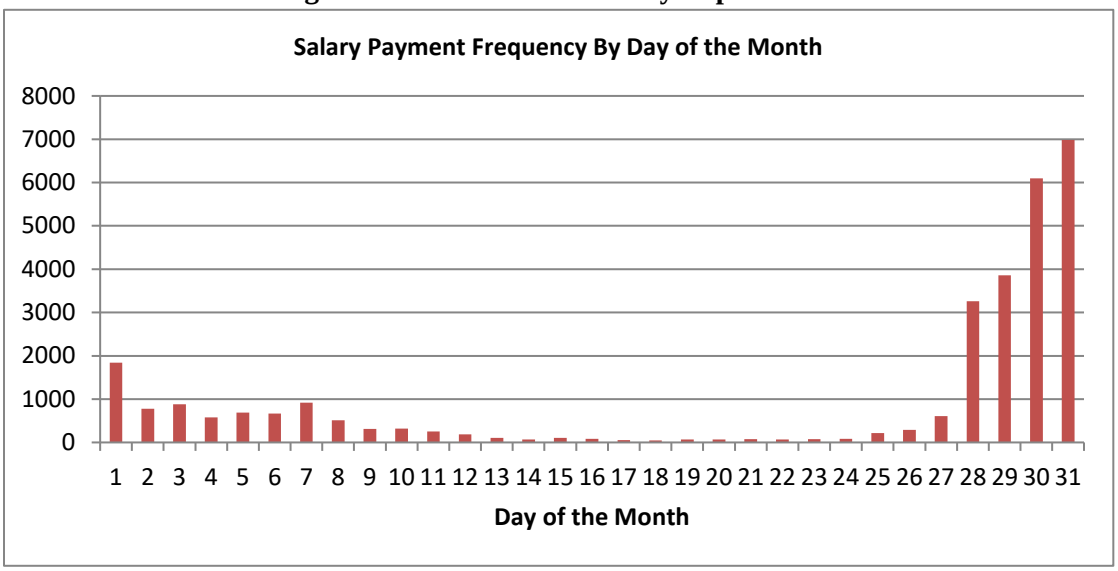
Figure 6: Daily Level Regressions – Coefficients of (a) Credit Card Spending and (b) Credit Card Use





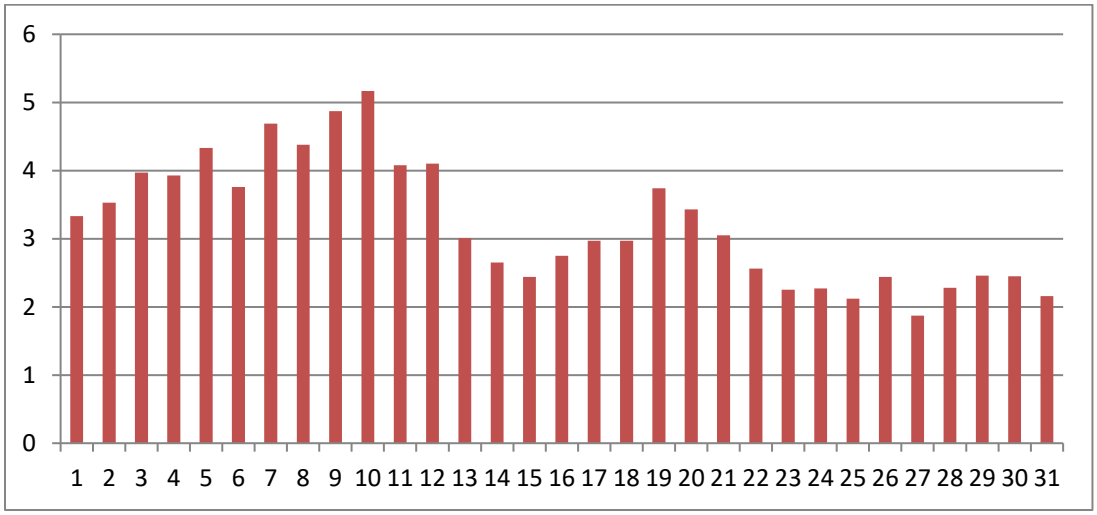
Notes: The figures plot the marginal coefficients (solid line) and the corresponding confidence interval (dotted lines) from a distributed lag model based on daily-level data. The sample has account holders who have both credit and debit cards. The level of observation is person-day. The regression specification includes fixed effects for each account holder, day of the week, day of the month and month-year. Figures (a) – (b) plot specifications where the dependent variable is credit card spending and credit card usage. Units for the top panel are in rupees spent per day, units for the bottom panel are probability that household uses the credit card in a given day.

Figure 7: Distribution of Salary Deposit Date



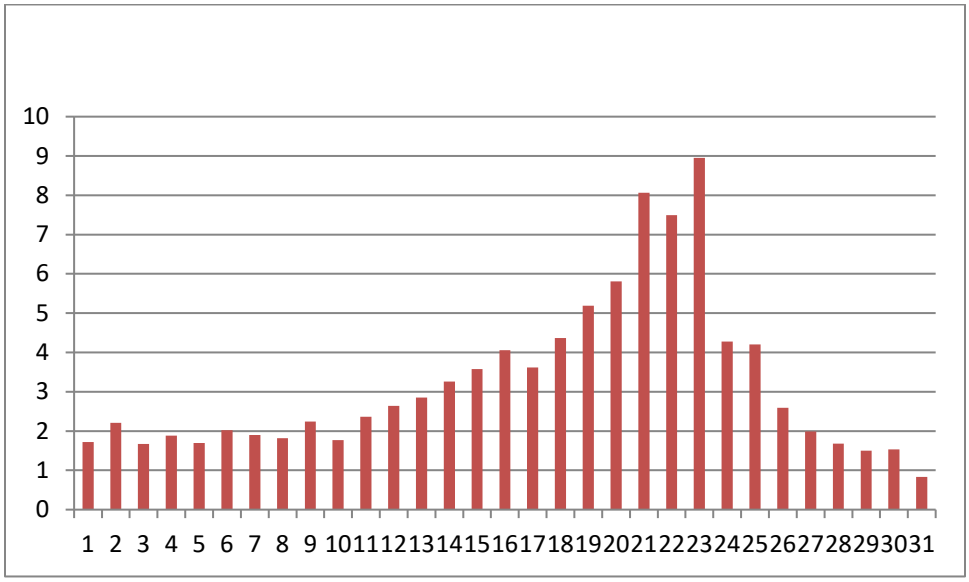
Notes: The figure plots the frequency of salary deposits made on each day of the month for our sample of credit card account holders.

Figure 8: Distribution of Credit Card Payment Date



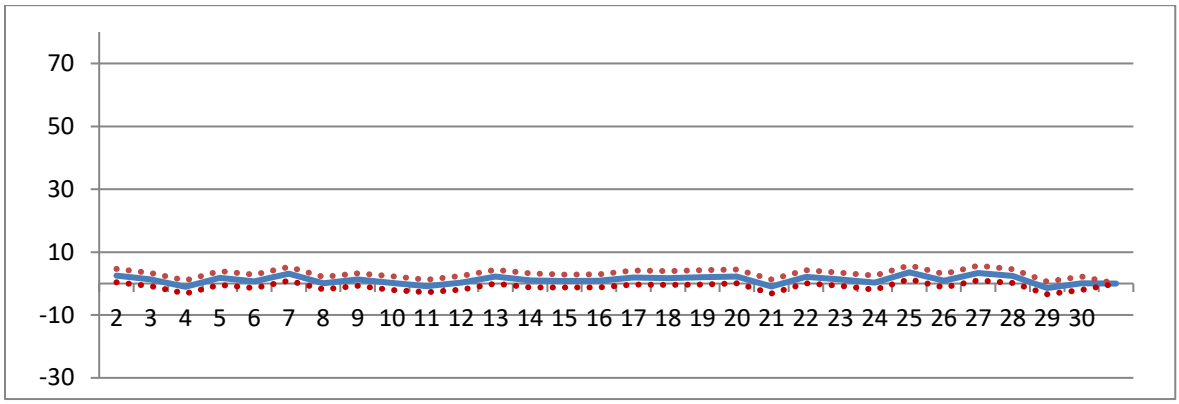
Notes: We aggregate the number of credit card payments made on each date of the month for all account holders with a credit card. The figure plots the percentage of credit card payments made by date of the month.

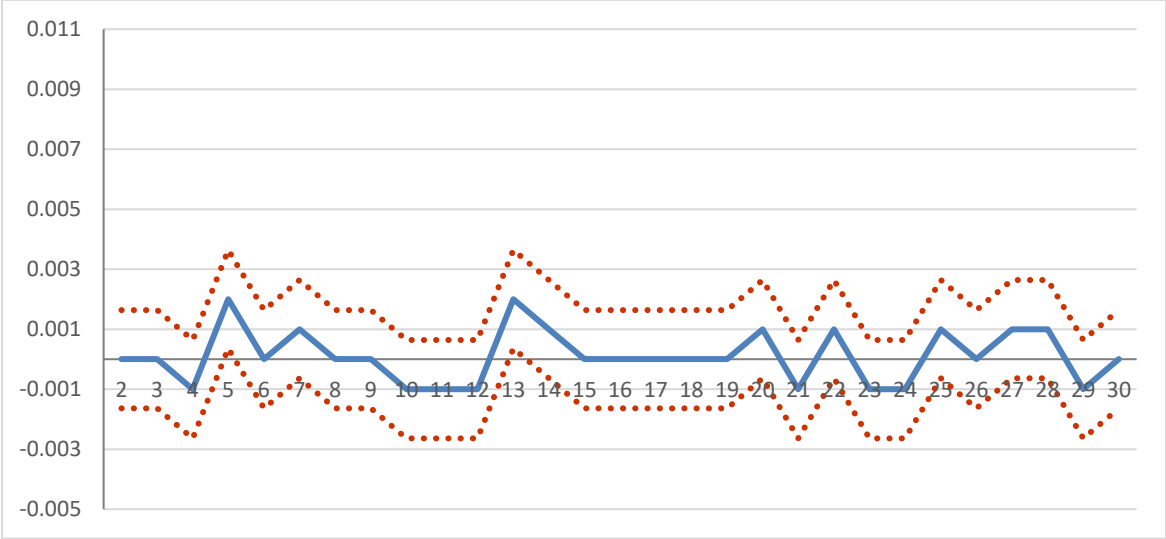
Figure 9: Credit Card Payment by Days from the Statement Date



Notes: We aggregate the number of credit card payments made based on the number of days since the statement date for all account holders with a credit card. The figure plots the percentage of credit card payments made by days from the statement date.

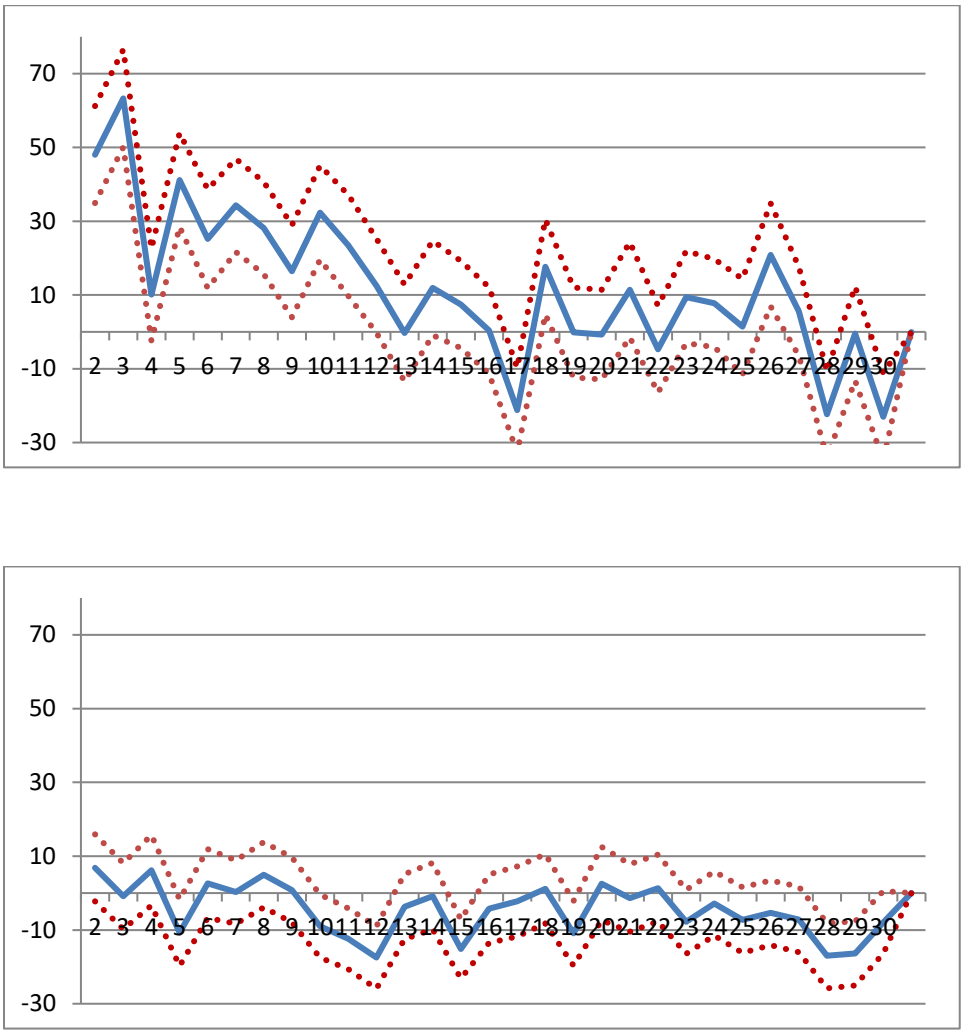
Figure 10: Daily Level Regressions – Coefficients of (a) Debit Card Transactions and (b) Debit Card Usage.





Notes: The figures plot the marginal coefficients (solid line) and the corresponding confidence interval (dotted lines) from a distributed lag model based on daily-level data. The sample has account holders who have both credit and debit cards. The level of observation is person-day. The regression specification includes fixed effects for each account holder, day of the week, day of the month and month-year. Figures (a) – (b) plot specifications where the dependent variable is debit card spending and debit card usage. Units for the top panel are in rupees spent per day, units for the bottom panel are probability that household uses the credit card in a given day.

Figure 11: Daily Level Regressions – Coefficients of (a) Credit Card Transactors and (b) Credit Card Revolvers



Notes: The figures plot the marginal coefficients (solid line) and the corresponding confidence interval (dotted lines) from a distributed lag model based on daily-level data. The sample has account holders who have both credit and debit cards. The level of observation is person-day. The data is split between those who pay their previous credit bill in full (transactors), and those who do not (revolvers). Figures (a) and (b) plot specifications where the dependent variable is credit card spending for transactors and revolvers, respectively. The regression specification includes fixed effects for each account holder, day of the week, day of the month and month-year.

Table 1: Demographic Summary Statistics

Debit and Credit Account Holders	Observations	Mean	Std. Dev.
Age	2882	30	6.499
Married	2882	0.899	0.301
Male	2882	0.851	0.356
Credit Card Accounts			
Age	5797	32.4	8.98
Married	5797	0.8165	0.387
Male	5797	0.8519	0.357
Debit Card Accounts only			
Age	862	30.162	6.676
Married	862	0.9095	0.287
Male	862	0.7865	0.410

Notes: The table presents demographic summary statistics for three different categories of accounts – account holders that have both a debit and a credit card, account holders with a credit card (who may or may not have a debit card) and account holders with only a debit card.

Table 2a: Summary Statistics – Daily Financial Transactions and Credit Card Account

	Obs (millions)	Mean	Std. Dev.
Daily Credit Transactions (#)	2.73	0.07	0.25
Daily Credit Spending (Rs.)	2.73	133	800
Daily Credit Spending above 0 (Rs)*	0.08	2,061	3168
Daily Debit Transactions (#)	1.24	0.03	0.21
Daily Debit Spending (Rs.)	1.24	31	337
Daily Debit Spending above 0 (Rs)*	0.03	1,247	1748
Credit Limit (Rs.)	2.73	67,632	92,272
Number of years credit account open	2.72	1.69	1.36

**Restricted to observations with both credit and debit.*

Table 2b: Summary Statistics - Financial Transactions, by Week From Credit Card Statement

	Week 1 Following Statement	Week 2 Following Statement	Week 3 Following Statement	Week 4 Following Statement
Credit Card Use	0.0779	0.0758	0.0719	0.0703
Credit Spending (Rs.)	192	173	165	169
Debit Card Use	0.0244	0.0245	0.0253	0.024
Debit Spending (Rs.)	34	35	37	35
Retail Spending (Rs)	49.5	39.2	36.0	35.3

Notes: Table 2a presents summary statistics (mean and standard deviation) on daily credit and debit card usage and spending, as well as the credit limit and the age of the account. In Table 2b, we present the likelihood of an account holder using her credit card or debit card per day as well as the daily amount an account holder spends on her credit card or debit card, in *Week t, t=1,..,4*, following the statement date, averaged across all account holders. There are several days a week in which an account holder does not use either card. Observations in Table 2b are limited to customers who have both a credit card and a debit card.

Table 3. Spending Following the Receipt of the Credit Card Statement

Dependent Variable:	Credit spending		Credit spending >0		Credit Usage	
	(1)	(2)	(3)	(4)	(5)	(6)
Week 1 Following Statement	20.604***	20.502***	107.574**	92.229**	0.007***	0.007***
	(3.596)	(3.600)	(48.773)	(45.262)	(0.001)	(0.001)
Week 2 Following Statement	11.334***	11.121***	44.957	11.549	0.004***	0.004***
	(3.518)	(3.529)	(48.570)	(47.612)	(0.001)	(0.001)
Week 3 Following Statement	7.567**	7.574**	35.788	23.773	0.003***	0.003***
	(3.426)	(3.436)	(46.980)	(45.031)	(0.001)	(0.001)
Week 4 Following Statement	4.63	5.239	49.731	34.612	0.001	0.001
	(3.387)	(3.392)	(47.437)	(44.982)	(0.001)	(0.001)
First Week of Month	-2.979	-2.298	20.639	35.295	-0.002*	-0.002
	(3.646)	(3.643)	(47.738)	(44.906)	(0.001)	(0.001)
Second Week of Month	0.755	0.934	31.814	15.433	-0.001	0.000
	(3.705)	(3.701)	(47.534)	(45.381)	(0.001)	(0.001)
Third Week of Month	2.732	2.672	31.487	10.071	0	0
	(3.716)	(3.714)	(48.613)	(46.479)	(0.001)	(0.001)
Fourth Week of Month	2.296	2.198	-34.888	-46.382	0.002**	0.002**
	(3.700)	(3.703)	(47.401)	(45.600)	(0.001)	(0.001)
Constant	13.405**	-9.757	2107.94	1147.34	0.065***	0.058***
	(6.501)	(19.777)	(9406789)	(1305.482)	(0.011)	(0.011)
Account FE	N	Y	N	Y	N	Y
Observations	1,246,925	1,246,925	78,708	78,708	1,246,925	1,246,925

Notes: The table reports OLS estimates of our baseline weekly level specification, equation (1), based on the sample of account holders with a both a credit card and debit card. The observations are at the person-day level. The dependent variable is the daily credit card spending, except in specifications (5) and (6) where a dummy variable takes the value 1 if credit card was used. The indicator variable, *Week t Following Statement, t=1,..,4,* takes the value 1 if the observation lies in *Week t* following the statement date, and 0 otherwise. In all specifications, we control for each of the 4 weeks of the calendar month. Sample restricted to days with non-zero spending in specifications (3) and (4). In specifications (2), (4), and (6), we include fixed effects for account holder; all specifications include fixed effects for day of the week, and month-year, which are not shown for brevity. 1% of outliers for days in which spending was non-zero have been removed. Robust standard errors, clustered at the account holder level, are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4: Spending Following Statement, Controlling for Payment Date

	Dependent Variable: Credit Spending				Dependent Variable: Indicator used Credit Card			
	Payment date customer's actual pmt		Payment date 25 days following statement		Payment date customer's actual pmt		Payment date 25 days following statement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week 1 following statement	26.937***	25.534***	25.77***	25.85***	0.011***	0.011***	0.008***	0.008***
	(7.227)	(7.26)	(5.908)	(5.895)	(0.002)	(0.002)	(0.002)	(0.002)
Week 2 following statement	20.640***	17.542**	18.45***	18.27***	0.009***	0.008***	0.007***	0.007***
	(7.084)	(7.126)	(6.479)	(6.480)	(0.002)	(0.002)	(0.012)	(0.002)
Week 3 following statement	12.176*	11.206*	12.68**	12.62**	0.005***	0.005**	0.005***	0.005***
	(6.690)	(6.770)	(5.782)	(5.791)	(0.002)	(0.002)	(0.002)	(0.002)
Week 4 following statement	0.308	1.949	4.346	5.022	0.000	0.000	0.001	0.002
	(6.762)	(6.800)	(4.413)	(4.423)	(0.002)	(0.002)	(0.001)	(0.001)
First week following Payment	49.172***	34.249***	-5.781	-6.358	0.016***	0.009***	0.001	0.001
	(7.952)	(7.544)	(4.867)	(4.855)	(0.002)	(0.002)	(0.001)	(0.001)
Second week following Payment	26.354***	15.211**	-11.20*	-11.98*	0.009***	0.004**	0.000	-0.001
	(7.342)	(7.281)	(6.669)	(6.633)	(0.002)	(0.002)	(0.002)	(0.002)
Third week following Payment	17.772**	10.348	-14.66**	-15.20**	0.006***	0.003	-0.003*	-0.003*
	(7.163)	(7.114)	(6.865)	(6.836)	(0.002)	(0.002)	(0.002)	(0.002)
Fourth week following Payment	6.388	2.638	-11.43**	-11.65**	0.001	-0.001	-0.003*	-0.003*
	(6.942)	(6.849)	(5.612)	(5.607)	(0.002)	(0.002)	(0.001)	(0.001)
First week of the month	-3.593	-4.569	-3.548	-3.207	-0.003	-0.002	-0.002	-0.001
	(7.516)	(7.494)	(4.247)	(4.243)	(0.002)	(0.002)	(0.001)	(0.001)
Second week of the month	-6.571	-6.908	1.74	1.552	-0.001	-0.001	0.000	0.000
	(7.570)	(7.537)	(4.321)	(4.319)	(0.002)	(0.002)	(0.001)	(0.001)
Third week of the month	-0.769	-1.064	3.545	3.066	0.000	0.001	0.001	0.001
	(7.550)	(7.522)	(4.309)	(4.307)	(0.002)	(0.002)	(0.001)	(0.001)
Fourth week of the month	-2.695	-2.906	2.075	1.76	0.003	0.003	0.003**	0.003**
	(7.492)	(7.461)	(4.299)	(4.298)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	4.113	241.368***	15.93*	171.8***	0.065**	0.110***	0.081***	0.079***
	(19.768)	(13.962)	(8.722)	(8.970)	(0.030)	(0.004)	(0.015)	(0.003)
Account FE	N	Y	N	Y	N	Y	N	Y
Observations	401,707	401,707	956,185	956,185	401,707	401,707	956,185	956,185

Notes: The table reports OLS estimates of our baseline weekly level specification, equation (1), based on the sample of account holders with a credit card and debit card. The observations are at the person-day level. The dependent variable is the daily credit card spending in specifications (1)-(4), and a dummy variable takes the value 1 if credit card was used in specifications (5)-(8). The indicator variable, *Week t Following Statement*, *t=1,..,4,* takes the value 1 if the observation lies in *Week t* following the statement date, and 0 otherwise. In all specifications, we control for each of the 4 weeks of the calendar month. Sample is restricted to clients whose credit card payment came from their debit card account in specifications (1), (2), (5) and (6). In specifications (2), (4), (6) and (8), we include fixed effects for account holder; all specifications include fixed effects for day of the week, and month-year, which are not shown for brevity. 1% of outliers for days in which spending was non-zero have been removed. Robust standard errors, clustered at the account holder level, are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively

Table 5: Weekly Credit Card Spending – by week of Statement Date in Calendar Month

		Credit Card Spending
For statement dates in week 1 of calendar month:		
	Week 1 following statement	26.821***
		(4.951)
	Week 2 following statement	21.834***
		(5.466)
	Week 3 following statement	13.261**
		(5.659)
	Week 4 following statement	12.095**
		(4.937)
For statement days in week 2 of month:		
	Week 1 following statement	21.134***
		(4.994)
	Week 2 following statement	10.476**
		(5.046)
	Week 3 following statement	6.490
		(4.861)
	Week 4 following statement	-1.892
		(4.447)
For statement days in week 3 of month:		
	Week 1 following statement	17.880***
		(3.465)
	Week 2 following statement	7.369**
		(3.688)
	Week 3 following statement	4.527
		(3.583)
	Week 4 following statement	5.005
		(3.116)
For statement days in week 4 of month:		
	Week 1 following statement	14.375***
		(4.440)
	Week 2 following statement	13.394***
		(4.448)
	Week 3 following statement	5.972
		(4.458)
	Week 4 following statement	3.044
		(3.893)
Statement Date in Last Few Days of Month		
	Week 1 following statement	3.423
		(2.771)
	Week 2 following statement	4.998
		(3.114)
	Week 3 following statement	173.887
		(146.359)
	Week 4 following statement	3.720
		(2.829)
Controls for all regressions:	First week of Month	-3.753
		(2.457)
	Second week of month	-5.351*
		(2.882)
	Third week of month	-4.428
		(3.035)
	Fourth week of month	-4.145
		(2.651)
Observations		2,730,531

Notes: The table reports OLS estimates of our baseline weekly level specification (equation (1)) based on the sample of account holders with a credit card. The observations are at the person-day level. The dependent variable is the daily credit card spending. The indicator variable, *Week t Following Statement, t=1,..,4,* takes the value 1 if the observation lies in week *t* from the statement date, and 0 otherwise. This set of 4 indicator variables is different for each of the 4 calendar weeks in which a credit card statement is issued. In all specifications, we include fixed effects by day of the week, and month-year, which are not shown for brevity. Robust standard errors, clustered at the account holder level, are in parentheses. Regression is run on full sample of credit account holders. 1% of outliers for days in which spending was non-zero have been removed. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Weekly Credit Card Spending Across a Statement Month--Product Categories

	Retail	Leisure	All Discretionary	School Fees	Total	Total w/o repeats
	(1)	(2)	(3)	(4)	(5)	(6)
Week 1 Following Statement	7.429***	2.327***	9.096***	-0.351	23.096***	17.970***
	(1.624)	(0.687)	(2.066)	(3.805)	(2.686)	(1.869)
Week 2 Following Statement	4.722***	2.078**	5.348**	-1.684	13.974***	10.593***
	(1.584)	(0.874)	(2.153)	(3.811)	(2.792)	(1.923)
Week 3 Following Statement	0.484	0.988	0.971	-5.608	7.096***	4.998***
	(1.419)	(0.834)	(1.981)	(3.613)	(2.666)	(1.853)
Week 4 Following Statement	1.187	1.059	1.271	-0.556	3.326	2.062
	(1.461)	(0.664)	(2.001)	(3.719)	(2.459)	(1.707)
First week of month	2.755	-1.407	0.408	1.351	-4.793*	-3.824**
	(1.722)	(0.992)	(2.388)	(2.56)	(2.887)	(1.921)
Second week of month	2.299	-0.881	-0.733	3.966	-2.482	-1.972
	(1.603)	(1.394)	(2.297)	(2.991)	(3.038)	(2.096)
Third week of month	1.652	-0.828	-1.293	-1.586	-1.241	-0.107
	(1.768)	(1.16)	(2.385)	(2.57)	(3.201)	(2.201)
Fourth week of month	2.467	-1.332	-0.639	2.898	-3.562	-1.797
	(1.813)	(1.064)	(2.428)	(2.986)	(2.978)	(2.036)
Constant	36.836***	4.440***	41.235***	4.775	195.657***	158.597***
	(2.844)	(1.26)	(3.563)	(7.753)	(10.142)	(6.972)
Mean Dep Variable	47.9	13.1	61.6	17.2	104.6	69.8
Observations	2,376,953	1,814,780	2,731,203	442,628	2,756,017	2,756,017

Notes: The table reports OLS estimates of our baseline weekly level specification (equation (1)) based on the sample of account holders with a credit card, with the outcome variable changed to spending of each transaction type (retail, leisure, all discretionary (retail, leisure, travel, jewelry), and school expenses. The observations are at the account-day level. The indicator variable, Week t Following Statement, t=1,..,4, takes the value 1 if the observation lies in Week t from the statement date, and 0 otherwise. We control for each of the 4 weeks of the calendar month. In all specifications, we include fixed effects for day of the week, and month-year, which are not shown for brevity. The sample for each regression is restricted to observations from account holders who had transactions of each type recorded at least once during the period. In specification (6) transactions which occur on the same day of the month and are the same amount are changed to 0. Robust standard errors, clustered at the account holder level, are in parentheses. The top 1% of outliers for days in which spending was non-zero have been removed in the total spending regressions (5) and (6), but not in the disaggregated purchases (1)-(4). ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 7: Weekly Credit Card Spending in a Statement Month, Consumer Heterogeneity

	Revolver		Early payer		Liquidity--Pct Limit	
	Last Period	Type	This Period	Type	This Period	Last Period
	(1)	(2)	(3)	(4)	(5)	(6)
Week 1 following Statement	40.318***	29.240***	23.454***	22.681***	23.648***	32.920***
	(9.956)	(5.853)	(8.211)	(5.042)	(3.612)	(5.128)
Week 2 following Statement	21.970**	23.736***	12.598	10.818**	16.036***	26.849***
	(9.305)	(5.528)	(7.977)	(4.882)	(3.594)	(4.907)
Week 3 following statement	20.567**	14.043**	9.546	7.785	9.803***	21.185***
	(9.040)	(5.538)	(7.658)	(4.786)	(3.518)	(4.725)
Week 4 following statement	16.654*	10.432*	6.116	3.689	3.476	11.197**
	(9.260)	(5.421)	(7.999)	(4.772)	(3.436)	(4.637)
Statement week1* Interaction term	-23.196**	-15.940**	4.511	-10.436	2.781	-22.281***
	(11.390)	(7.373)	(14.986)	(10.037)	(6.941)	(8.597)
Statement week2 * Interaction term	-13.491	-23.402***	22.200	3.189	-8.204	-33.953***
	(10.987)	(7.088)	(14.306)	(8.904)	(6.746)	(7.697)
Statement week3* Interaction term	-14.589	-11.586	6.235	-2.218	0.587	-27.441***
	(10.571)	(7.056)	(14.118)	(9.072)	(7.339)	(7.963)
Statement week 4* Interaction term	-19.579*	-10.667	-0.955	2.902	5.124	-14.291**
	(10.665)	(6.959)	(13.251)	(9.207)	(6.852)	(7.281)
Interaction Term	-75.779***	-36.886***	-20.625	-20.789	40.172***	-9.089
	(9.734)	(8.304)	(16.329)	(12.646)	(8.551)	(8.947)
First week of Month	5.422	-4.530	0.833	-4.815	-2.526	-2.904
	(5.902)	(3.758)	(6.828)	(4.395)	(3.833)	(3.834)
Second week of Month	6.665	0.093	4.651	-1.369	1.876	1.645
	(6.063)	(3.825)	(7.011)	(4.517)	(3.903)	(3.905)
Third week of Month	15.614**	1.998	9.886	1.978	3.635	3.596
	(6.083)	(3.820)	(6.909)	(4.466)	(3.897)	(3.900)
Fourth week of month	12.069**	1.382	6.128	1.987	2.900	2.840
	(5.886)	(3.837)	(6.953)	(4.541)	(3.898)	(3.897)
Observations	444,757	1,200,474	440,054	935,471	1,128,034	1,128,034

Notes: The table reports OLS estimates of our weekly spending baseline weekly level specification with interactions for different subsamples (equation (2)), based on the sample of account holders with both credit and debit cards. The observations are at the account-day level. Interaction terms are: an indicator for revolver (did not pay the previous credit bill in full)--(1) the payment for the most recent statement while (2) refers to the modal behavior over the course of the study period; early payers (payment of the credit card bill within 2 weeks of the statement date)—in (3) early payer refers to the payment for the most recent statement, while in (4) early payer refers to whether the account was paid in the first two weeks in the modal cycle); and liquidity constraints (the percentage of the credit limit used--(5) refers to the percent of credit used as of the date of the observation, while (6) refers to the maximum used in the prior cycle). Samples are restricted to observations for which we have the relevant information on prior payments and credit limits. The dependent variable is the daily credit card spending. The indicator variable, Week t Following Statement, t=1,..,4, takes the value 1 if the observation lies in Week t from the statement date, and 0 otherwise. We control for each of the 4 weeks of the calendar month. In all specifications, we include fixed effects for day of the week, and month-year, which are not shown for brevity. Robust standard errors, clustered at the account holder level, are in parentheses.

Table 8: Weekly Debit Card Spending

	Debit Spending		Debit Usage	
	(1)	(2)	(3)	(4)
Week 1 Following Statement	0.596	0.566	0.000	-0.000
	(1.237)	(1.244)	(0.001)	(0.001)
Week 2 Following Statement	0.455	0.445	0.000	0.000
	(1.292)	(1.300)	(0.001)	(0.001)
Week 3 Following Statement	0.602	0.64	-0.000	0.000
	(1.329)	(1.336)	(0.001)	(0.001)
Week 4 Following Statement	0.669	0.694	-0.000	-0.000
	(1.253)	(1.257)	(0.001)	(0.001)
First Week of Month	5.462***	5.539***	0.004***	0.004***
	(1.428)	(1.422)	(0.001)	(0.001)
Second Week of Month	-0.743	-0.694	0.001	0.001*
	(1.367)	(1.367)	(0.001)	(0.001)
Third Week of Month	-3.977***	-3.990***	-0.001**	-0.001**
	(1.344)	(1.346)	(0.001)	(0.001)
Fourth Week of Month	-5.536***	-5.546***	-0.003***	-0.003***
	(1.333)	(1.329)	(0.001)	(0.001)
Constant	18.673***	21.400***	0.015***	0.017***
	(2.203)	(5.42)	(0.002)	(0.004)
Account FE	N	Y	N	Y
Observations	1,246,925	1,246,925	1,246,925	1,246,925

Notes: The table reports OLS estimates of our baseline weekly level specification, equation (1), based on the sample of account holders with both credit and debit cards. The observations are at the person-day level. The dependent variable is the spending only on debit card in specifications (1) and (2), and an indicator variable with value 1 for debit card use in a day, 0 otherwise in specifications (3) and (4). The indicator variable, *Week t Following Statement*, *t=1,..,4*, takes the value 1 if the observation lies in *Week t* from the statement date, and 0 otherwise. We control for each of the 4 weeks of the calendar month. In all specifications, we include fixed effects for day of the week, and month-year, which are not shown for brevity. Robust standard errors, clustered at the account holder level, are in parentheses. 1% of outliers for days in which spending was non-zero have been removed. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 9: Weekly Credit Card Spending Across a Statement Month – Threshold Spending

	Spending after week…			
	Week 1	Week 2	Week 3	Week 4
	(1)	(2)	(3)	(4)
Indicator for 50% of mean balance spent by week…	849.538***	762.778***	525.924***	375.043***
	(239.935)	(109.394)	(60.522)	(22.988)
Indicator for 75% of mean balance spent by week…	737.174**	756.318***	472.445***	379.713***
	(335.882)	(133.772)	(71.634)	(25.401)
Indicator for 100% of mean balance spent by week…	311.463	577.532***	429.614***	401.444***
	(438.119)	(129.183)	(87.141)	(29.312)
Observations	86,054	86,054	86,054	86,054

Notes: Observations are at the person-statement month level. We run different regressions based on three alternative thresholds of spending during the statement month, i.e., 50%, 75% and 100% of an account holder's mean balance on the credit card. For each threshold *P*, we run 4 different regressions based on whether the account holder reaches the specific threshold *P* in week 1, 2, 3 or 4 of the statement-month. The estimates reported above reflect results from 12 different regressions. In each regression, for threshold *P* and week *t*, the dependent variable is the daily credit card spending after *Week t*, *t=1,..,4* following the credit card statement date. The independent variable is an indicator variable that takes the value 1 if the observation spent the threshold amount *P* by Week *t* of the statement-month, and 0 otherwise. We include fixed effects for account holder, day of the week, week of the month and month-year, which are not shown for brevity. Robust standard errors, clustered at the account holder level, are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.