Timing to the Statement: Understanding Fluctuations in Consumer Credit Use[1]

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Abstract

The within-month timing of credit card spending provides evidence on the smoothing of consumption and consumer sophistication in the use of financial products; consumers manage their credit card spending in order to optimize their use of the free float that the card provides. Using exogenous variation in the statement date, we show that consumers spend 20-27% 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 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, debit card spending is unaffected by credit card statement issuance. These effects are strongest among discretionary spending categories. The consumers most apt to spend early in the credit card cycle tend to be those who benefit most from the free float: those who do not revolve balances and those who are not close to their credit limit. We test and reject several alternative explanations: timing to credit card payment dates, mental accounting, and automatic payments.

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[2]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 percent; the average annual growth in the number and value of credit card

1. Introduction

There are mounting calls for increased consumer protection in financial markets due to concerns about the potential for exploitation of consumers with limited financial acumen. There is evidence that consumers make significant financial mistakes (Campbell, 2006; Choi, Madrian, and Laibson, 2012), many of which appear in credit card use: when using credit cards, consumers increase spending on discretionary items (Hirschman, 1979; Feinberg, 1986), and choose the wrong credit card contracts (Agarwal et. al 2007a). The least educated consumers are those most likely to make financial mistakes (Cole and Shastry, 2007). The possibility of negative effects of access to credit cards on less financially savvy consumers is particularly pronounced in developing countries such as India and Brazil where the consumer credit market is growing quickly and consumers may be less familiar with consumer finance products.[2] Improved information on the financial management ability of credit card consumers in developing countries will help to identify likely effects of this increased access to credit and the importance of increased consumer protection.[3] We show that consumers optimize the timing of their credit card expenditures in order to take advantage of the free float offered by credit cards. To our knowledge, this is the first paper that provides evidence on consumer sophistication in credit card use in a developing country.

This paper adds to a growing literature on the timing of consumption spending. There is substantial evidence that contrary to the Permanent Income Hypothesis, consumption and spending are not well-smoothed across time--even when income shocks are predictable (see, for example: Gelman et al, 2013; Stephens, 2003; Shapiro, 2005; Hastings and Washington, 2010; Baker, 2014; Huffman and Barenstein, 2004).[4] Changes in spending in response to predictable income changes may be composed of

[2]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 percent; the average annual growth in the number and value of credit card transactions at the point of sale were 18.5 percent and 24.5 percent, respectively.

[3] Kapoor and Ravi, 2009 show a large increase in savings following an increase in interest rates in India from a natural experiment which exogenously changed interest rates for those over 60. See Campbell, Jackson, Madrian, and Tufano, 2011 for a full review of the literature on consumer financial management.

[4]Stephens (2003) documents that consumers spend significantly more in the days following the receipt of their social security check. Shapiro (2005) finds that U.S. food stamp recipients' daily caloric intake

two factors—the impact of the change in income and a timing effect. By focusing on an event that has no impact on income but incentivizes differences in when purchases are made, we are able to isolate the timing component and show that households change their spending in response to billing changes. This suggests that the pure timing effect is an important component of the overall intra-month fluctuations in spending that have been investigated in other settings.

In the context of credit cards, most analyses of intra-month spending rely on shocks in the form of changes to credit card terms such as credit limits or APRs. These credit card-based variations may be related to changes in the consumer's financial profile. Therefore, the spending effects could be picking up the impact of other income-related factors besides the direct impact of changes in terms.[5] In this paper, we consider the implications of credit card statement dates. Statement dates are exogenous to the consumers: the bank sets the statement date at the time it issues the credit card, and the date does not change in most months. 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. Statement dates only change when the date coincides with a Sunday or a holiday. We show that there is a 20-27% increase in spending during the week following the statement over the days just prior to the statement.

We employ a unique transaction-level dataset from one of the largest financial institutions in India. 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, payment due date, date of payment made on the

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declines between monthly food stamp payments and finds evidence of quasi-hyperbolic discounting in the use of food stamps, inconsistent with the permanent income hypothesis (see also, Hastings and Washington, 2010). Huffman and Barenstein (2004) use paydays as predictable income shocks and find declining daily expenditure between paydays in the Family Expenditure Survey data of U.K families.

[5] Gross and Souleles (2002) are able to identify the effects of changes in credit terms through exogenous changes in APRs and credit limits.

credit card account,[6] credit limit, amount spent on the card, minimum payment due, actual amount paid, and information on the size and date of each transaction.

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 statement: credit card spending is 20-27% 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 falsification tests using randomized statement dates.[7]

This increase in credit card spending is not a general increase in spending across all financial products: unlike the increase in consumer credit use following the issuance of the credit card statement, debit card use is uncorrelated with the credit card statement date. While it is possible that the account holder has other credit cards or accounts in other banks, there is no evidence that she directly substitutes spending from debit card to credit card within the same bank. 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.

We show that this timing effect is a result of consumer optimization of the free float which suggests a basic level of sophistication among consumers. A rational optimization model suggests that since credit cards offer a free float for up to a month, it is 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

[6] The credit card payment date is only available for the subset of consumer who pay their credit card bill using their checking accounts.
[7] Falsification test results not shown, but are available upon request.

the float period is maximized. We find that these incentives are most taken advantage of by the types of consumers who perceive the largest benefits from the free float: transactors who pay off their credit card balances each month, those who are not liquidity constrained, and those who wait until the due date to pay off their credit card.

The monthly optimization of the timing of spending is not a mechanical effect of automatic payments set on the cards. While this would 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 (2013) as a large force in fluctuations in spending with paychecks in the US. 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 jewelry) and the other more likely to be pre-determined monthly 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 (2013), automated bill payments do not appear to be the primary driving force in intra-month variation in credit card use in our data.

We consider two alternative explanations for spending changes caused by credit card dates: liquidity constraints and mental accounting. Liquidity constraints have been shown in other settings to create differences in intra-month spending (Aaronson et al, 2012; Gross and Souleles, 2002). However, the issuance of credit card statements does not affect the available credit balance (or "liquidity") on the card. Available credit is adjusted at the time the cardholder pays the credit card bill which need not be on the statement date. Therefore, if the liquidity constraint were binding, we would expect the consumer to be spending close to their credit limit in each billing cycle, and for their payment of the credit card bill to "release" them to spend more. The documented spending response to credit card statement dates is robust to controlling for the credit card payment date, suggesting that the credit limit is not binding for many consumers.

We also estimate heterogeneity in the timing effects by whether the customer's last statement amount was more than 80% of their credit limit. 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, or close to their credit limit. We test this directly and reject that liquidity constraints drive this effect: those who are not near their credit limit react significantly more to the statement date than those who have spent 80% of their credit limit during the past billing cycle. Therefore, while liquidity constraints may be an important component of spending in other contexts, timing appears to matter even without liquidity constraints.

Mental accounting suggests two predictions for spending behavior: first, spending from different accounts should be independent, and second, spending accumulates until a mental threshold for an account is reached, at which point the consumer stops spending. The fact that credit card and debit card spending are separately timed suggests some support for mental accounting models: consumers seem to be spending on debit cards during the early calendar days of the month, while they use credit cards in the early days following their credit card statement, particularly for discretionary purposes. Following the payment of their credit card—when the credit card "mental account balance" is low, consumers increase their credit card spending by a large percentage, in accordance with the predictions of a mental accounting model.

For the second prediction of mental accounting models: 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.

This paper proceeds as follows. Section 2 chronicles the vast expansion in credit card use in India in the past decade and the institutional details of the bank from which our data originate. 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, including a falsification test. Section 4 considers tests for a number of alternative hypotheses to explain the intra-month spending variation following the credit card statement. Section 5 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.

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' portfolio of total loans and advances (Reserve Bank of India (RBI), various issues). The use of credit cards is growing quickly: there is increased availability of the cards and improved acceptance at points of sale. The total value of all credit card transactions at the points of sale, as a proportion of GDP, has doubled between 2003-04 and 2008-09, rising from 0.6 percent in 2003-04 to 1.2 percent 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 percent; the average annual growth in the number and value of credit card transactions at the point of sale were 18.5 percent and 24.5 percent, respectively. There has also been an increased use of debit cards, both in terms of number and value of transactions.[8]

[8] 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.

As of 2011-12, the total number of active credit and debit cards in India was 17.65 million and 278.28 million, respectively.

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 account holders at the bank with which we are working. The consumers in our data have specifically applied for these accounts. We have 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 category effects. In addition to daily spending data, we have data on credit card statement dates, payment due dates for a sample of accounts, minimum payment amounts, and credit limits.[9]

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.[10] 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

[9] 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.

[10] 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.

sample is 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. 101 on credit cards and Rs. 31 on debit cards; these numbers increase to 2061 on credit cards and 1,247 on debit cards when we restrict the sample only to days the card was used. Credit card transactions are twice as frequent as debit card transactions. There is substantial heterogeneity in use of the credit cards—many consumers have very few debit and credit transactions, but some consumers use both cards frequently. The mean credit limit is Rs. 55,981 suggesting that an average account holder only uses about 11 percent 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 is 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, 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.

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. 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 dates are salient to customers. 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.[11] Unfortunately, we cannot identify the delivery mode in our data, and it is possible that some account holders did not receive electronic statements. However, statements from the bank in question are always sent through speed post. This minimizes concerns about a distortion between the statement date (end of credit card cycle) and the actual receipt of the statement.

Figure 3 further investigates credit card use across the month. We plot the frequency of credit card transactions on each day of the month, as a percentage of the total number of transactions across all accounts. We see that just over 3% of transactions occur on any given day of the month, and the level is extremely steady across the month (standard deviation is 0.27). 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 the 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, $I_{i(t-1)}$ be an

[11]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.

indicator for i if the bank issued her credit card statement 1 day prior to day t, $I_{i(t-2)}$ be an indicator for i if the bank issued her credit card statement 2 days prior to day t, and so on. $I_{i(0)}$ is the excluded variable, so all coefficients are in comparison to the day the statement is issued. Our estimation equation is given by:

$$S_{i,t} = \alpha_i + \sum_{d=2}^{31} \beta_{i(t-d)} I_{i(t-d)} + \gamma' X_t + \varepsilon_{it} \tag{1}$$

The *marginal* coefficients $\beta_2, \ldots, \beta_{31}$ measure the *additional* spending each day after the issuance of the credit card statement (day 2 to day 31) relative to the day of the issuance of the statement (day 1). 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.

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. 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 account level fixed effects mean that the correct interpretation of the marginal coefficients for each day after the statement date 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 the account fixed effects regressions, identification comes from variation within account on the day on which the statement date falls (primarily from the statement date falling on a Sunday or holiday).

We also run the regressions by week, with four weeks per statement month, the first week beginning the day after the issuance of the statement, the second week beginning the 8^{th} day following the statement, the third week beginning on the 15^{th} day following the statement, and the fourth week beginning on the 21^{st} day following the statement; the statement day and the remaining three to four days per statement month are the excluded group. Our baseline specification in this case is:

$$S_{i,t} = \alpha \quad + \sum_{w=1}^{4} \beta_{i(t-w)} I_{i(t-w)} + \gamma' X_t + \varepsilon_{it} \qquad (2)$$

Here $I_{i(t-1)}$ is an indicator for *i* if the bank issued her credit card statement in the week prior to the current week, $I_{i(t-2)}$is an indicator for *i* if the bank issued her statement 2 weeks prior to day t, and so on. In the week level regressions we include week of the month fixed effects, day of the week fixed effects, and month-year fixed effects. Standard errors are clustered by account. The *marginal* coefficients β_1, β_2,β_3, and β_4 measure the *additional* spending each day of week 1, 2, 3 or 4 after the issuance of the credit card statement relative to the excluded period which is the final days prior to the issuance of the statement.

For ease of exposition, we focus on the results of week-based regressions (equation (2)) and report them in the main tables. We report the daily level regression results in figures 6 and 7 which show the coefficients in solid lines and the standard errors in dotted lines. Aggregating spending over weeks tends to smooth the large temporary effect across the week and reduces the magnitude of the coefficients.

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. We then examine the difference in account holders' response between credit card and debit card, and show that the statement date relationship does not hold in debit card spending.

3.1 Non-parametric Results on Daily Spending

Figure 3 shows the percentage of credit card transactions that fall on a particular day of the month. In figure 3, we see that there is little variation in timing of when consumers use credit cards across the month; approximately three percent of credit card transactions occur on each day. Figure 4 plots credit card use over the days following the statement date. This shows the main effects that we estimate non-parametrically. In contrast to the lack of variability in credit card use by calendar date in figure 3, there is noticeable variation by statement date in figure 4. Frequency of credit card use goes from 3.7% in the first eleven days following the statement date to 2.7% close to the next expected statement. In figure 5, the percent of the monthly spending (which combines both the frequency of use and the size of the purchases) shows a similar, though somewhat more limited, decline from over 1.5% in the first few days following the statement, to 1.3-1.4% toward the end of the statement-month, with greater variability through the course of the month. There is higher daily credit card spending in the first week following the statement date than in each of the subsequent three weeks of the statement-month.

3.2 Response to Statement Date in Credit Card Use

In Figure 6, we plot the coefficients of the daily coefficients from our main specification (equation 1). The coefficients in panel (a) provide estimates of the total additional spending made per day as compared to spending on the day of the statement. As seen in the overall distributions, we see that credit card spending spikes up in the first days of the statement month—by 24.3 rupees on day 2 and not dipping 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. We find that people are 0.6-0.8% 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 mechanism for 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. Account holders spend 20.6 rupees more (or approximately 20% based on mean daily spending of 101 rupees) 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. Daily transaction amount on days on which there are transactions increases by 107 rupees, or approximately 5.2% (with a mean of 2,061 rupees on days with non-zero spending) in the first week of the month. Consumers are 0.7% 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, 6, and 8 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. In all specifications, we include controls for calendar-ordered week of the month and day of the week in order to allow for the possibility that credit card use increases during certain periods of the month (particularly the beginning of the month following the paycheck date).

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 week of the month. The coefficient on the first week following the statement date continues to be significant and positive. Combining the above results on increased daily spending as well as 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.

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 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 average grace period of about 25 days 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, specifications 7 and 8 in Table 3 include controls for each week following the payment date.[13] Credit card bill payment does appear to affect spending -- in the week following the credit card payment, spending increases by 49 rupees, or approximately 49%. 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 27% after controlling for weeks after payment of the credit card bill.

We find strong empirical evidence of increased credit card spending and use following issuance of the credit card statement. The results are robust to controlling for the day or week of the month to

[12] Most firms in India pay salaries monthly rather than bi-monthly.

[13] 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.

account for possible paycheck receipts as well as for bill payment dates. Account holder fixed effects capture all time-invariant observable and unobservable characteristics so that the results reflect spending responses to within-account variation in statement dates, and the results are robust to the fixed-effects specifications.

3.3 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, figures 10 (a) and (b) show that debit card spending does not respond to the credit card statement date. The coefficients on days since credit card statement in the debit card spending regressions are small in magnitude, and are not significantly different from 0. Figures 10 (a) and (b) show that debit card spending and usage are invariant to statement day.

Table 4 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 4 estimate the response of spending on debit cards to the statement date. While issuance of the statement affected the consumer's credit spending as shown in table 3, it 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 month. Similarly, probability of spending on debit card does not respond to statement date. 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 17.4% increase the first week with an increase in the probability of transaction of 10%. 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, the evidence points to an increase in daily spending on the credit card following the statement date, and the spending is not offset by debit card spending.

4. Tests of Alternative Hypotheses

We test whether the data support other potential explanations for the credit card spending response to the statement date documented in the previous section. These include optimization of the free float, timing of pre-determined or non-discretionary expenses, and mental accounting. We take advantage of heterogeneity in the types of account holders and features of their accounts to test these alternative hypotheses.

4.1 Optimization of the Free Float

Credit cards offer users interest-free credit (a free float) between the purchase date and the bill payment date. Sophisticated consumers may choose to spend earlier in the credit card monthly cycle in order to maximize their use of the free float. We rely on three types of variation in order to test whether optimization of the free float plays a role in driving consumer's variation in intra-month spending: the timing of the statement date within the calendar month; the variation between those revolving debt on their credit cards (revolvers) and those paying them off monthly (transactors); and the variation in how long following their statement dates account holders pay their bills.

If optimization of the free float is the primary driver of intra-month changes in spending, then we should see that the first week's increased spending effect is not dependent on the timing of statement dates within the calendar month. If, on the other hand, the intra-month spending changes are primarily a reflection of timing of spending across the month and consumers with late statement dates switch to credit cards toward 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 credit card spending responses by week following credit card statement issuance, where each issuance date is categorized in one of four calendar-month weeks. We continue to find evidence of intra-month shifting in spending. There is increased spending in the first week following the statement date for statement dates across each of the four weeks of the calendar-month. This increase in spending is smooth across weeks in which the statement date is issued: spending in the first week following the statement is 10-16 rupees higher than just before the statement is issued for those with statements issued in the first through fourth weeks of the month. It is only statistically significantly different from the measured increase for those with statements in the last days of the month.

Next, we consider groups of account holders who may differentially benefit from variation in intra-month spending in order to optimize the free float. We separate account holders into groups of *transactors* and *revolvers*. A transactor is a credit card customer who pays off the statement balance of his credit card from the preceding month each month. Revolvers carry at least a part of the total outstanding amount over to the next period. Only transactors benefit from the free float so if the free float is an important factor, we should see larger fluctuations in intra-month spending response for transactors than for revolvers.

We estimate the 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 figures 11 (a) and (b). Panel (a) shows that the effect is larger and even more significant when the sample is restricted to those that pay off their balance each month (transactors). Transactors spend an extra 46 rupees 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: this provides additional support for the free float hypothesis.

Specification (1) in Table 6 shows the regression results for transactors and revolvers by week. The un-interacted coefficients 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. Transactors spend on average 68 rupees more than revolvers each week, and have significantly more time variation in their spending. Transactors spend 33 rupees more (approximately 33% at the mean of 101 rupees spent per day) in days in the first week following the statement date, while revolvers have no statistically significant impact from the date of the statement (this can be seen by adding the interaction term to the point estimate for week 1 following the statement).

Heterogeneity in consumers' bill payment decisions is another way in which we can separate consumers into those most likely to be optimizing and those who do not appear to be taking advantage of the free float. One could argue that customers who are most interested in optimizing the free float should be those who also pay their statements just before the due date in order to maximize the length of time they have an interest-free grace period on the spending. As seen in Figure 8, consumers spread bill payments across the month. 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. So, 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.

Specification (2) in Table 6 shows the credit card spending response following the statement date for early and late payers, respectively.[14] While both groups experience an increase in spending in the first week after the statement date, the increase is somewhat smaller for early payers (although not statistically significantly so).

Finally, one might think that this 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 month, so the reduction in spending could be a mechanical effect of them hitting their credit limit. In fact, we see the opposite: those who are not close to their credit limit exhibit the large timing response. Those who are credit constrained are more likely to smooth their spending across the month.

4.2 Timing of Discretionary and non-Discretionary Expenses

Account holders may time pre-determined bills and expenses to immediately follow the statement date. This would also allow them to maximize the use of the free float. 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, jewelry spending, and school-related fees. The retail category includes shops such as gift shops, luggage stores, piece goods stores, stationary stores, bicycle shops, sporting goods stores, etc. School-related fees include expenditures associated with universities, vocational schools, childcare services, and correspondence schools. Retail spending across months is relatively discretionary 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.

[14] 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.

Table 7 presents the results for spending response in each of these four product categories. Retail spending responds significantly in the first two weeks following the statement but does not respond to the calendar week. A daily increase of Rs. 5.73 in the first week translates to an average impact of 14% per day (mean daily retail spending is Rs. 42). However, school-related spending, which is the least discretionary category, shows no evidence of significant fluctuation in payments across the statement month. 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.

4.3 Mental Accounting

Mental accounting poses a potential alternative explanation for the timing of intra-month spending. Cardholders may have different mental accounts for credit cards and debit cards. Within the credit card mental account, the statement date marks a natural end of a spending cycle to the consumer and the balance is reset to zero. Account holders reset their mental account only for credit cards, leaving their mental account for debit cards unchanged.

One key result of a mental accounting hypothesis is that consumers not treat their accounts as fungible, switching between them across the month. There is empirical support for this in the data, since we show that debit and credit card spending do not appear to change in the same way across the month. Debit spending draws down on current income while credit cards allow for spending from future income. Table 4 provides evidence that consumers increase their debit card use immediately following the beginning of the month (when they receive their paychecks), and decrease their debit card use towards the end of the month when the account may be getting lower. However, the coefficient on the calendar date is statistically insignificant for credit card spending. Conversely, credit card spending responds to the statement date but there is no effect on debit card spending. In other words, consumers do not treat current and future incomes as fungible.

Another key prediction of mental accounting models is that consumers spend until they reach a certain threshold, their reference point, and after they reach that point they reduce spending significantly.

This suggests that spending within the statement-month before and after the threshold will be negatively correlated if consumers are timing their spending based on a mental accounting model. We test this hypothesis directly in table 8. 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.[15] This is contrary to the prediction of the mental accounting model.

5. Conclusion

This paper provides evidence on the extent to which consumers optimize their use of closely substitutable financial products. We exploit exogenous assignment of the credit card statement dates to study the intra-month smoothing of credit card spending by consumers. We use a distributed lag model to estimate the daily response of credit card spending to credit card statement date at the daily and weekly levels. Consumers have a strong 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. We find support for optimization of the free float as the explanation for the intra-month fluctuations in spending, and are able to reject several alternative explanations.

The existing literature studying consumption response to income shocks typically combines the timing and income effects. The focus on credit card statement dates where there is no change in income allows us to isolate the implication of the timing effect from the effect of a change in income and is an important contribution to the literature.

[15] We find similar results without thresholds, when we separately regress spending after each of the 4 weeks of the statement month on spending in the period before during the same statement period.

Understanding the extent of financial literacy and sophistication among consumers in developing countries is important in determining the necessity of increasing financial regulations in these new markets. 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.

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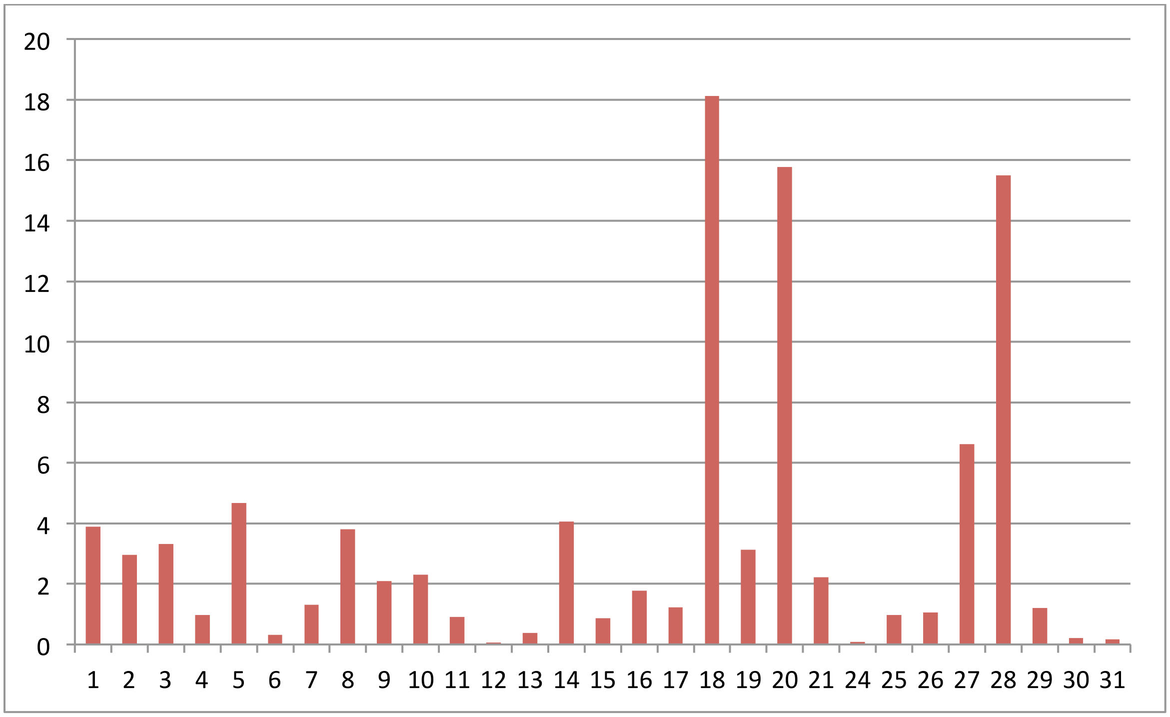
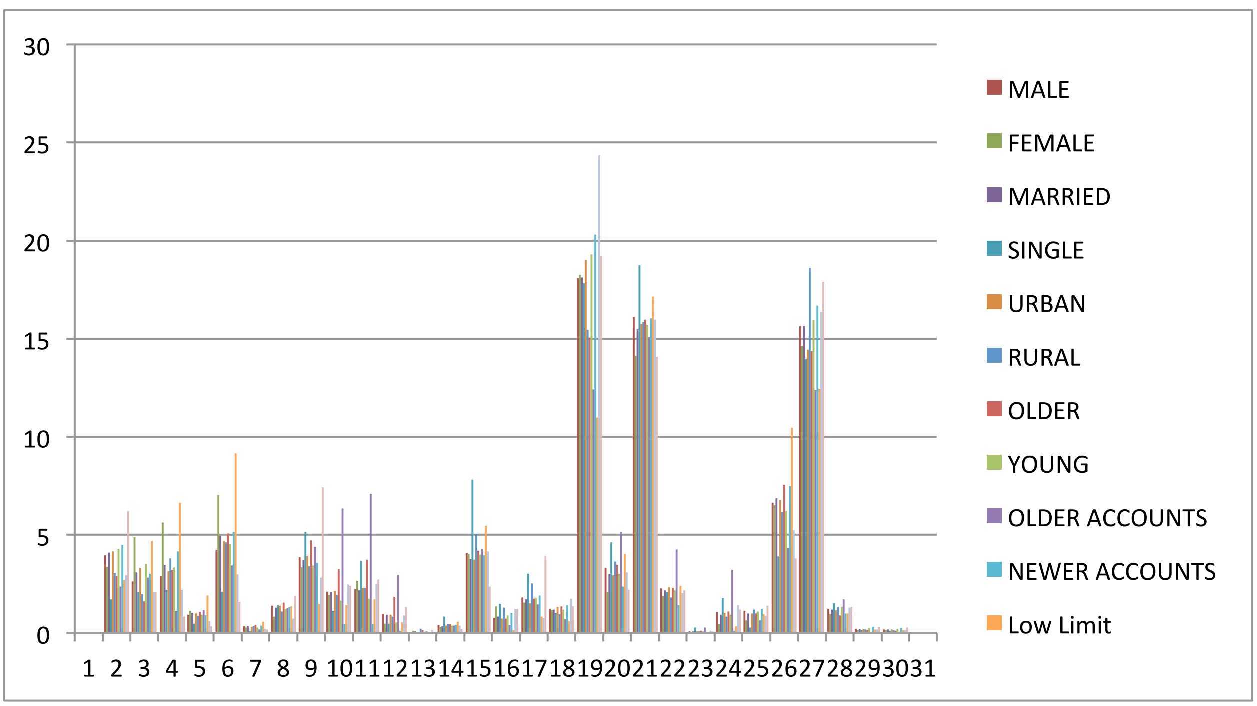
Figure 1: Distribution of Statement Dates



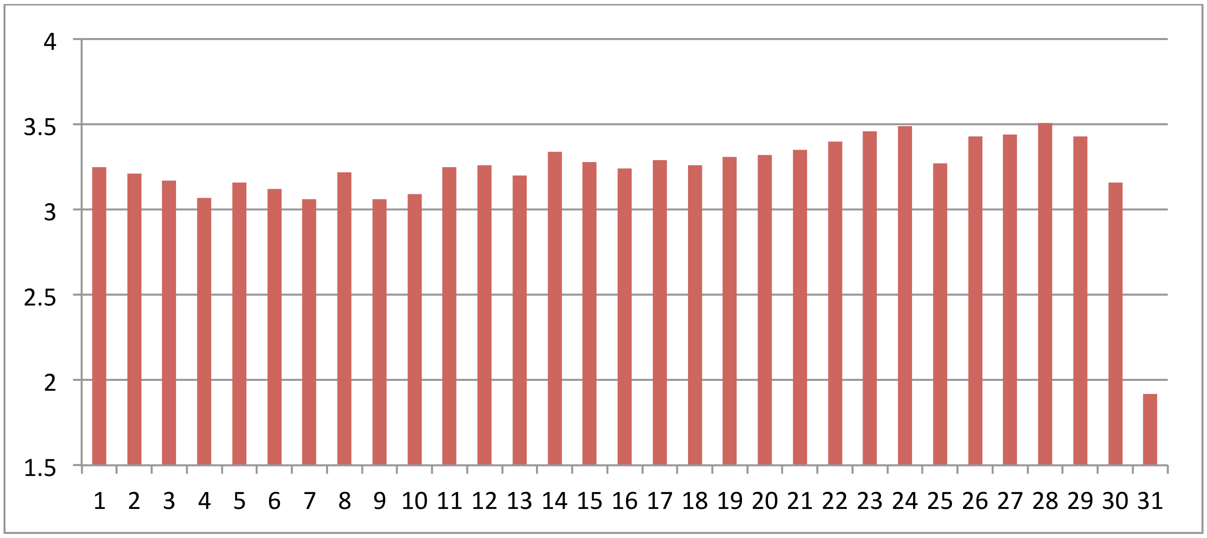
Notes: The figure plots the percentage of credit card statements (y-axis) that are issued on each day of the month (x-axis).

Figure 2: Distribution of Statement Dates by Subgroups



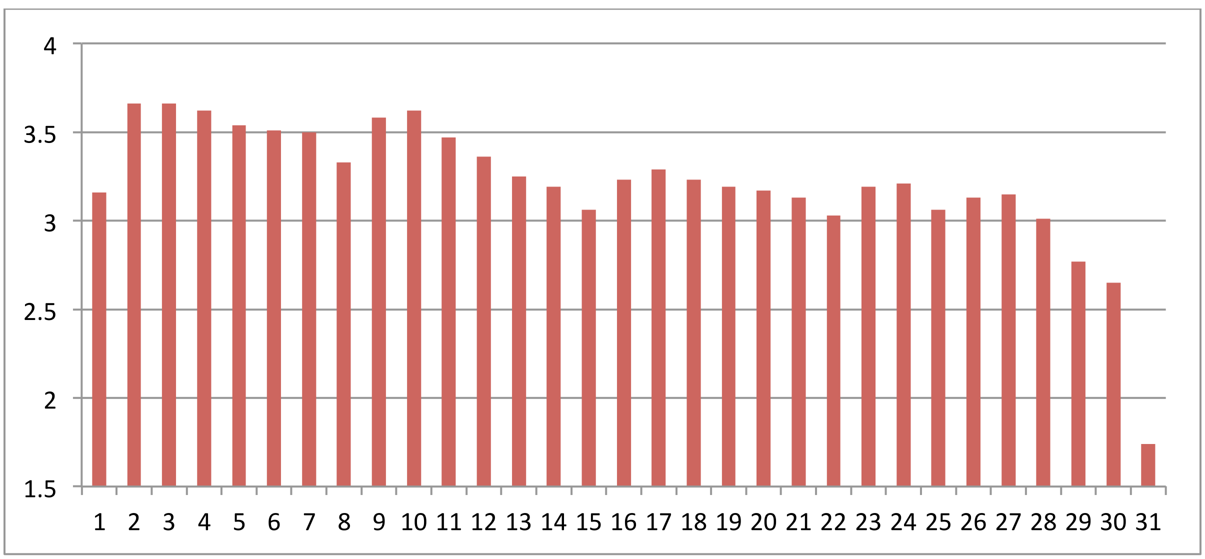
Notes: The figure plots, by account holder characteristics, the percentage of credit card statements (y-axis) that are issued on each day of the month (x-axis).

Figure 3: Credit Card Use by Date of the Month



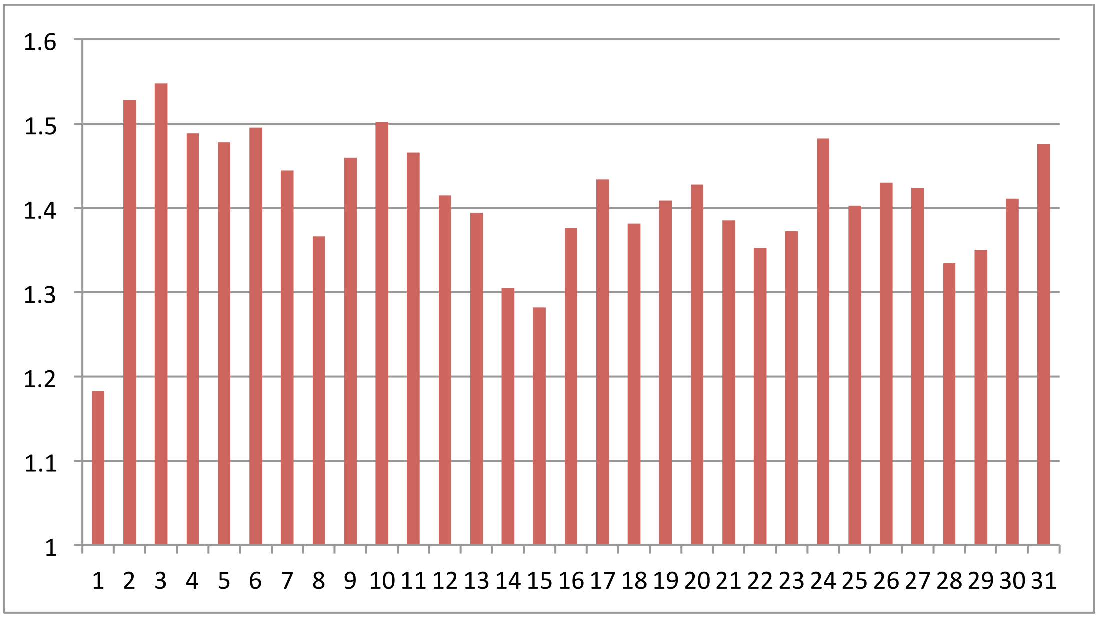
Notes: This figure plots the percentage of credit card use by day of the month for all account holders with a credit card.

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



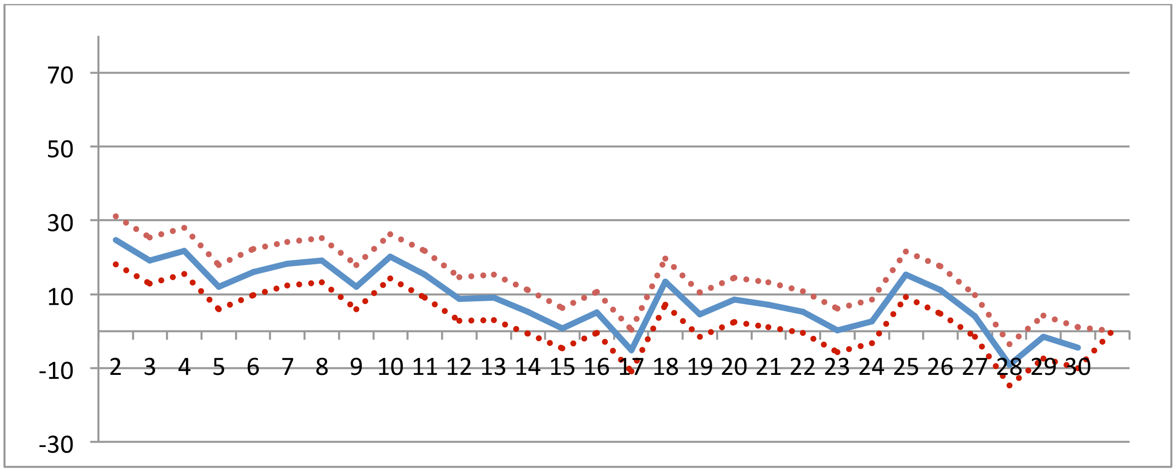
Notes: This figure plots the percentage of credit card use by days from the statement date following the day of the credit card statement for all account holders with a credit card.

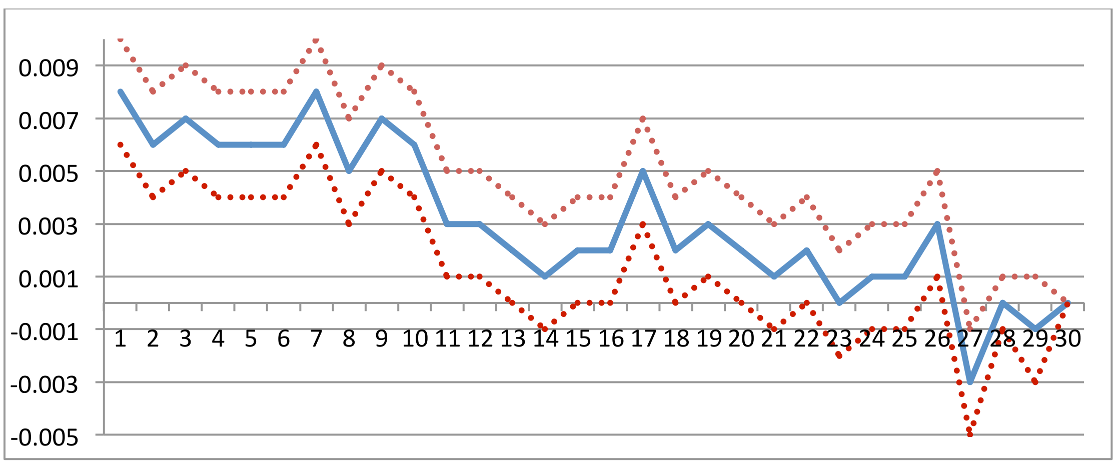
Figure 5: Credit Card Spending by Days from the Statement Date



Notes: We aggregate the amount spent on credit cards on each day following the date of the credit card statement for all account holders with a credit card. The figure plots the percentage of credit card spending by days from the statement date.

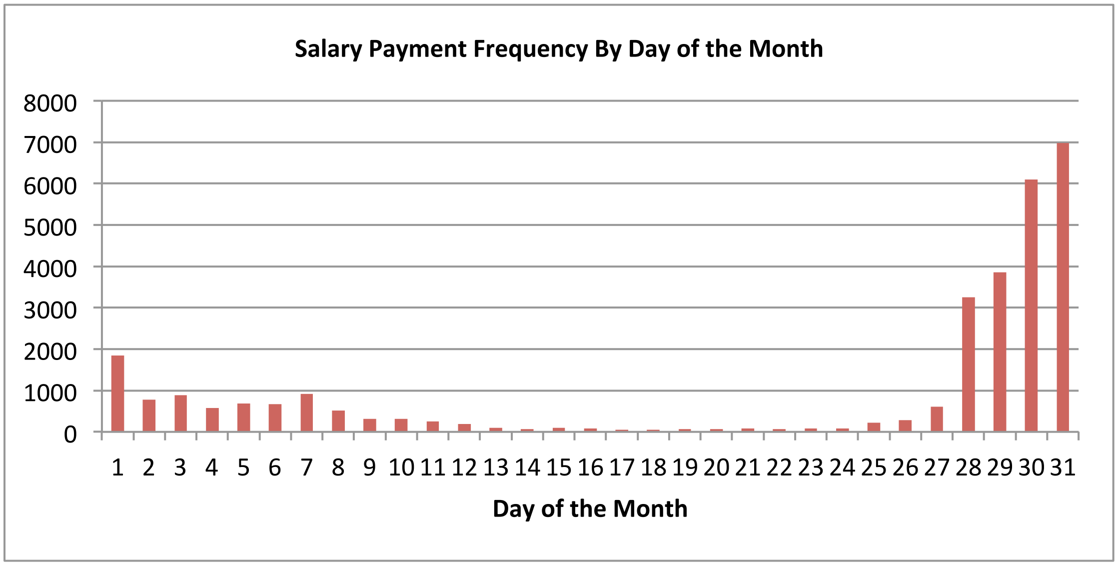
Figure 6: Daily Level Regressions – Coefficients of (a) Credit Card Spending and (b) Credit Card Use





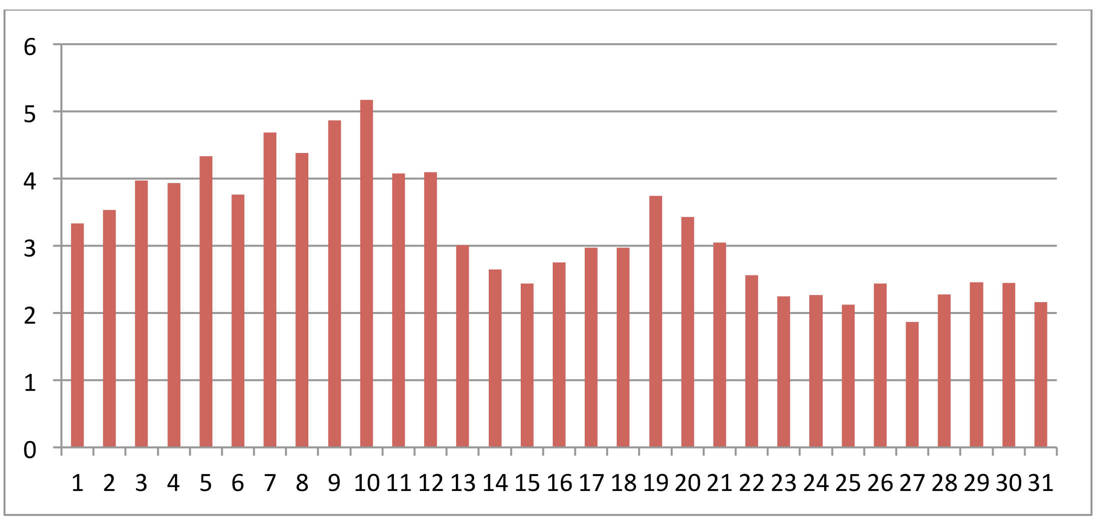
Notes: The figures plot the marginal coefficients (solid line) and the corresponding confidence interval (dotted lines) from a distributed lag model based on daily-level data. The sample has account holders who have both credit and debit cards. The level of observation is person-day. The regression specification 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.

Figure 7: Distribution of Salary Deposit Date



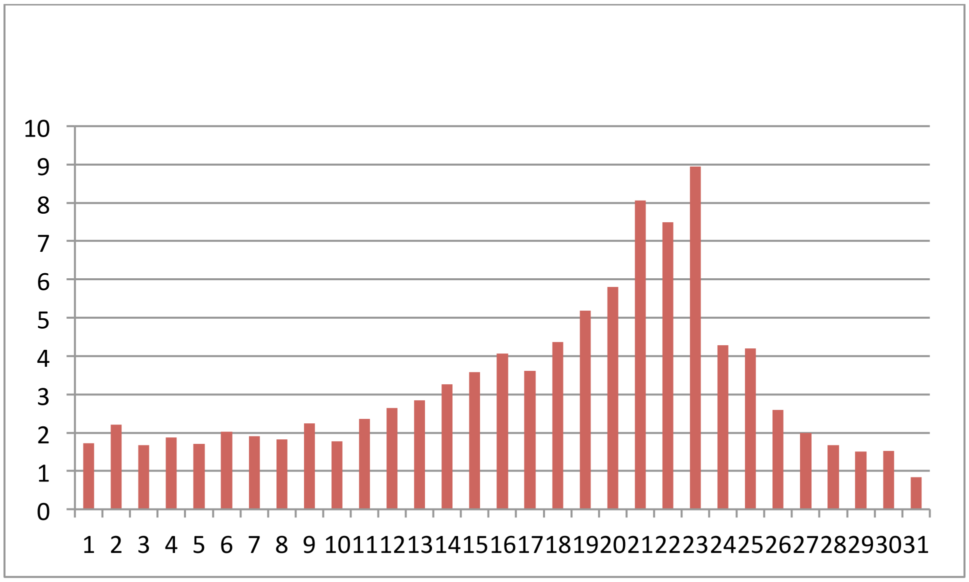
Notes: The figure plots the frequency of salary deposits made on each day of the month for our sample of credit card account holders.

Figure 8: Distribution of Credit Card Payment Date



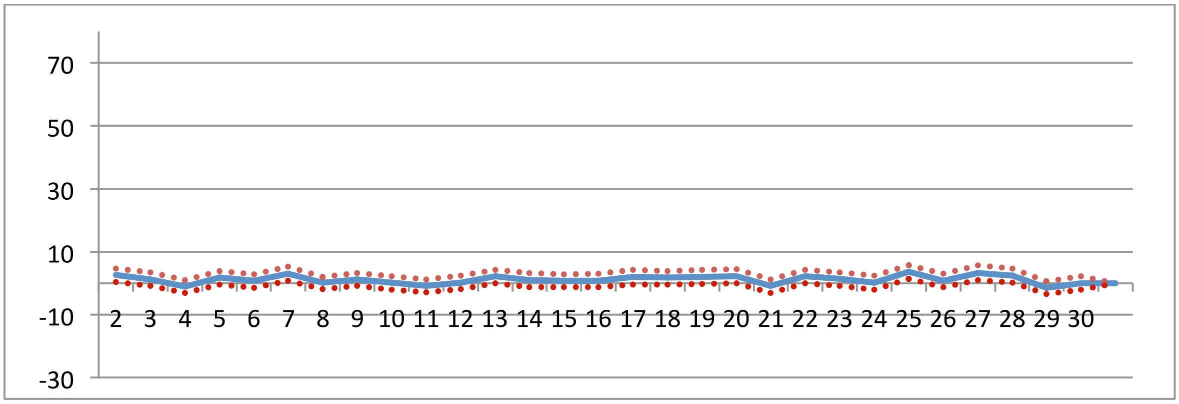
Notes: We aggregate the number of credit card payments made on each date of the month for all account holders with a credit card. The figure plots the percentage of credit card payments made by date of the month.

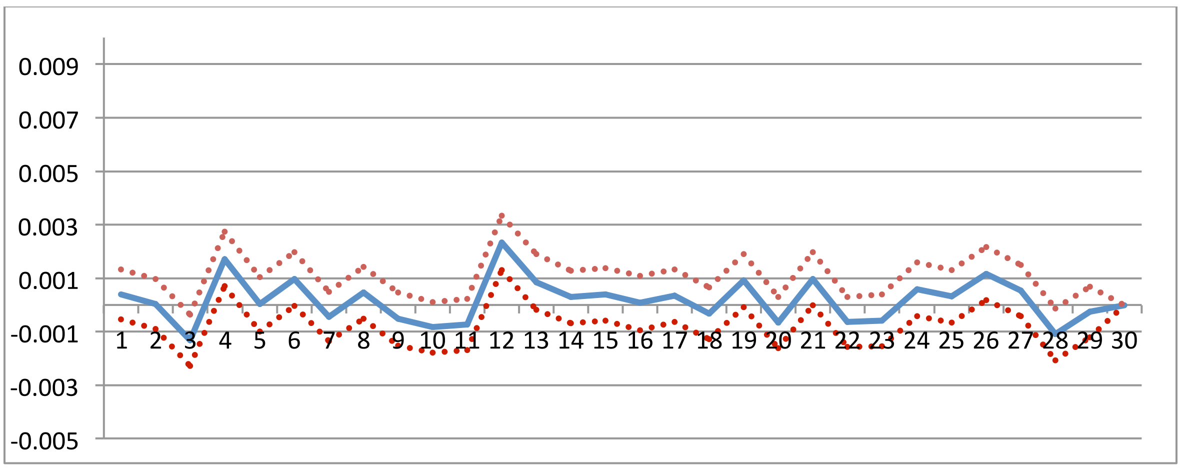
Figure 9: Credit Card Payment by Days from the Statement Date



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.

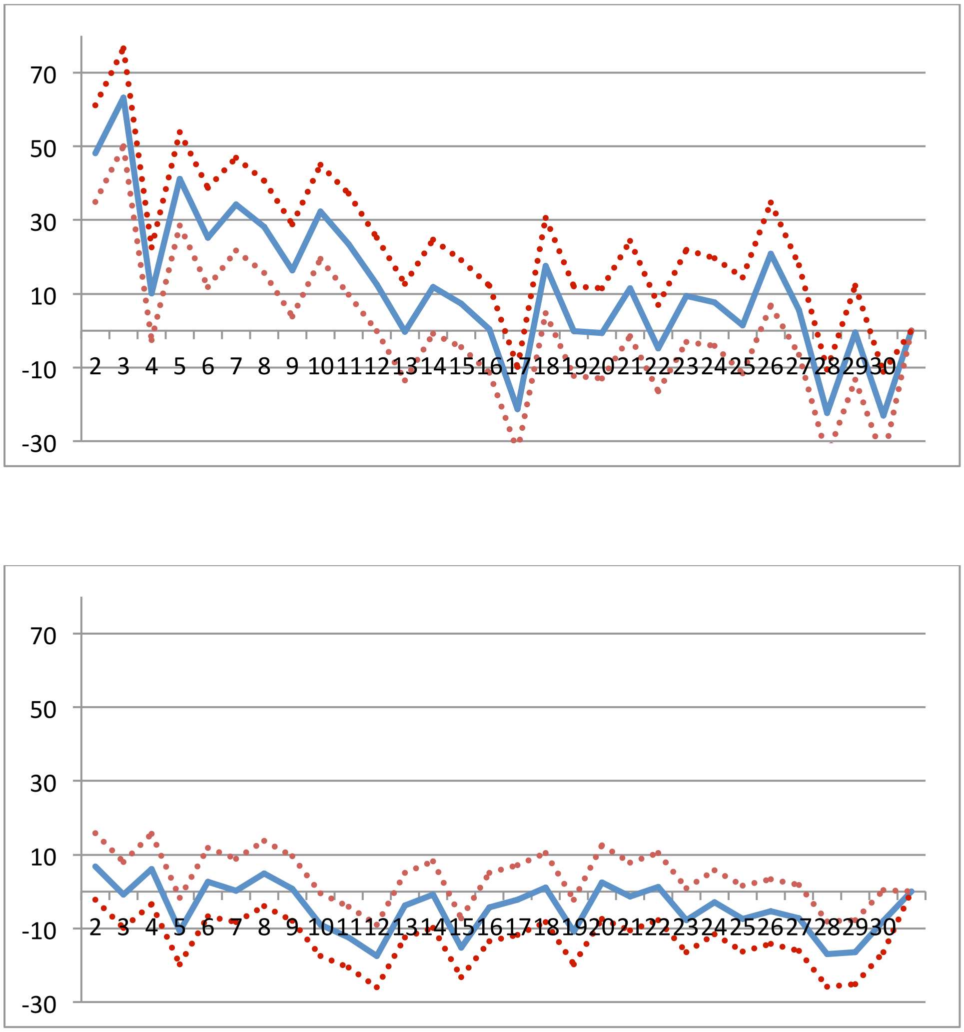
Figure 10: Daily Level Regressions – Coefficients of (a) Debit Card Transactions and (b) Debit Card Usage.





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.

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 (#)	2.72	0.07	0.25
Daily Credit Spending (Rs.)	2.72	101	587
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.)	2.72	55,981	99,016
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

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: Weekly Credit Card Spending

Dependent Variable:	Credit spending		Credit spending >0		Credit Usage		Credit Spending	
Week 1 Following Statement	20.604***	20.502***	107.574**	92.229**	0.007***	0.007***	27.232***	25.814***
	(3.596)	(3.600)	(48.773)	(45.262)	(0.001)	(0.001)	(7.208)	(7.241)
Week 2 Following Statement	11.334***	11.121***	44.957	11.549	0.004***	0.004***	20.730***	17.610**
	(3.518)	(3.529)	(48.57)	(47.612)	(0.001)	(0.001)	(7.062)	(7.105)
Week 3 Following Statement	7.567**	7.574**	35.788	23.773	0.003***	0.003***	12.336*	11.394*
	(3.426)	(3.436)	(46.98)	(45.031)	(0.001)	(0.001)	(6.675)	(6.754)
Week 4 Following Statement	4.630	5.239	49.731	34.612	0.001	0.001	0.020	1.660
	(3.387)	(3.392)	(47.437)	(44.982)	(0.001)	(0.001)	(6.747)	(6.787)
First Week of Month	-2.979	-2.298	20.639	35.295	-0.002*	-0.002	-1.921	-2.903
	(3.646)	(3.643)	(47.738)	(44.906)	(0.001)	(0.001)	(7.462)	(7.439)
Second Week of Month	0.755	0.934	31.814	15.433	-0.001	-0.000	-5.106	-5.442
	(3.705)	(3.701)	(47.534)	(45.381)	(0.001)	(0.001)	(7.518)	(7.483)
Third Week of Month	2.732	2.672	31.487	10.071	0.000	0.000	0.426	0.142
	(3.716)	(3.714)	(48.613)	(46.479)	(0.001)	(0.001)	(7.473)	(7.443)
Fourth Week of Month	2.296	2.198	-34.888	-46.382	0.002**	0.002**	-1.050	-1.279
	(3.700)	(3.703)	(47.401)	(45.600)	(0.001)	(0.001)	(7.456)	(7.426)
First Week Following Payment							49.352***	34.498***
							(7.932)	(7.522)
Second Week Following Payment							26.643***	15.611**
							(7.324)	(7.264)
Third Week Following Payment							18.143**	10.862
							(7.140)	(7.094)
Fourth Week Following Payment							6.700	3.062
							(6.899)	(6.811)
Constant	13.405**	-9.757	2107.94	1147.340	0.065***	0.058***	187.652**	31.584**
	(6.501)	(19.777)	(9406789)	(1305.482)	(0.011)	(0.011)	(77.383)	(14.694)
Account FE	N	Y	N	Y	N	Y	N	Y
Observations	1,246,925	1,246,925	78,708	78,708	1,246,925	1,246,925	401,592	401,592

Notes: The table reports OLS estimates of our baseline specification, equation (2), 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, 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 specifications (2) and (3), we control for each of the 4 weeks of the month. Sample is restricted to account holders that own both a debit and a credit card account, and further restricted to days with non-zero spending in specifications (3) and (4) and clients whose credit card payment came from their debit card account in specifications (7) and (8). 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 4: Weekly Debit Cards Spending

	Debit Spending		Debit Usage	
	0.596	0.566	0.000	-0.000
Week 1 Following Statement	(1.237)	(1.244)	(0.001)	(0.001)
	0.455	0.445	0.000	0.000
Week 2 Following Statement	(1.292)	(1.300)	(0.001)	(0.001)
	0.602	0.640	-0.000	0.000
Week 3 Following Statement	(1.329)	(1.336)	(0.001)	(0.001)
	0.669	0.694	-0.000	-0.000
Week 4 Following Statement	(1.253)	(1.257)	(0.001)	(0.001)
	5.462***	5.539***	0.004***	0.004***
First Week of Month	(1.428)	(1.422)	(0.001)	(0.001)
	-0.743	-0.694	0.001	0.001*
Second Week of Month	(1.367)	(1.367)	(0.001)	(0.001)
	-3.977***	-3.990***	-0.001**	-0.001**
Third Week of Month	(1.344)	(1.346)	(0.001)	(0.001)
	-5.536***	-5.546***	-0.003***	-0.003***
	(1.333)	(1.329)	(0.001)	(0.001)
Fourth Week of Month				
	18.673***	21.400***	0.015***	0.017***
Constant	(2.203)	(5.420)	(0.002)	(0.004)
Fixed Effects by Account holder?	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 specification, equation (2), 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 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. Observations above the 99^{th} percentile for daily spending have been trimmed. ***, **, * denote significance at the 1%, 5% and 10& levels, respectively.

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

		Credit Card Spending
For statement dates in week 1 of calendar month:		
	Week 1 following statement	16.076***
		(3.493)
	Week 2 following statement	13.633***
		(3.991)
	Week 3 following statement	6.917
		(4.432)
	Week 4 following statement	6.983*
		(3.767)
For statement days in week 2 of month:		
	Week 1 following statement	15.563***
		(3.870)
	Week 2 following statement	7.350**
		(3.742)
	Week 3 following statement	6.522*
		(3.795)
	Week 4 following statement	-1.509
		(3.440)
For statement days in week 3 of month:		
	Week 1 following statement	14.099***
		(2.502)
	Week 2 following statement	8.241***
		(2.723)
	Week 3 following statement	3.855
		(2.641)
	Week 4 following statement	3.093
		(2.386)
For statement days in week 4 of month:		
	Week 1 following statement	9.969***
		(3.350)
	Week 2 following statement	6.007*
		(3.146)
	Week 3 following statement	1.390
		(3.220)
	Week 4 following statement	-0.366
		(2.787)
Statement Date in Last Few Days of Month		
	Week 1 following statement	1.572
		(1.740)
	Week 2 following statement	1.423
		(2.104)
	Week 3 following statement	0.748
		(2.115)
	Week 4 following statement	-0.021
		(1.895)
	First week of Month	-0.992
		(1.758)
	Second week of month	-1.016
		(2.143)
	Third week of month	0.577
		(2.245)
	Fourth week of month	0.542
		(1.947)
Observations		2,721,321

Notes: The table reports OLS estimates of our baseline specification (equation (2)) 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 for account holder, 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, observations above the 99th percentile for daily spending have been trimmed. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Weekly Credit Card Spending Across a Statement Month--Consumer Heterogeneity

Dependent variable:	Credit Spending		
Interaction term:	Revolvers	Early payers	Liquidity Constrained
Week 1 following Statement	33.653***	21.156***	32.859***
	(7.179)	(4.946)	(6.160)
Week 2 following Statement	23.862***	11.821**	13.876**
	(6.548)	(4.944)	(5.863)
Week 3 following Statement	11.729*	7.626	8.618
	(6.576)	(4.802)	(5.690)
Week 4 following Statement	11.302*	3.610	2.414
	(6.354)	(4.820)	(5.672)
Statement week1*interaction term	-24.594***	-2.912	-21.696***
	(8.151)	(9.902)	(7.086)
Statement week2* interaction term	-25.236***	-0.377	-6.753
	(7.532)	(8.749)	(7.012)
Statement week3*interaction term	-6.526	-0.198	-3.785
	(7.861)	(8.898)	(6.892)
Statement week4*interaction term	-13.022*	4.516	0.184
	(7.433)	(8.953)	(6.810)
Interaction Term	-68.344***	9.742	-60.557***
	(8.639)	(11.504)	(6.627)
First week of Month	-4.910	-6.005	-3.713
	(4.066)	(4.368)	(3.836)
Second week of month	1.228	-2.210	1.050
	(4.113)	(4.476)	(3.909)
Third week of month	2.215	1.241	3.092
	(4.127)	(4.432)	(3.890)
Fourth week of month	2.375	1.407	2.223
	(4.122)	(4.521)	(3.913)
Observations	943,594	1,129,602	976,716

Notes: The table reports OLS estimates of our baseline specification (equation (2)), with interactions for different subsamples, based on the sample of account holders with both credit and debit cards. The observations are at the person-day level. Subsamples are based on transactor/revolver (those who pay/do not pay their previous credit bill in full), and early/late payers (those who pay their credit card bill within/after 2 weeks of the statement date), and liquidity constrained (those who are at or near their credit card limit). 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 month. In all specifications, we include fixed effects for account holder, 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. Observations above the 99th percentile for daily spending have been trimmed. ***, **, * denote significance at the 1%, 5% and 10& levels, respectively.

Table 7: Weekly Credit Card Spending Across a Statement Month--Product Categories

	Retail Spending	Leisure Spending	Jewelry Spending	School Fees
	(1)	(2)	(3)	(4)
Week 1 Following Statement	5.728***	1.538***	7.887***	0.257
	(1.147)	(0.355)	(1.392)	(0.368)
Week 2 Following Statement	3.838***	1.170***	5.633***	0.187
	(1.133)	(0.372)	(1.392)	(0.372)
Week 3 Following Statement	0.966	0.337	1.253	-0.122
	(1.057)	(0.346)	(1.314)	(0.357)
Week 4 Following Statement	0.478	0.848**	1.016	-0.003
	(1.058)	(0.376)	(1.323)	(0.342)
First week of month	2.240*	-0.397	1.282	-0.015
	(1.158)	(0.377)	(1.428)	(0.315)
Second week of month	2.357**	-0.202	1.938	-0.061
	(1.201)	(0.397)	(1.482)	(0.331)
Third week of month	1.414	0.089	1.734	-0.104
	(1.215)	(0.404)	(1.487)	(0.326)
Fourth week of month	2.291*	-0.139	1.313	0.100
	(1.185)	(0.384)	(1.453)	(0.342)
Constant	29.889***	1.986***	35.289***	-0.568
	(1.850)	(0.551)	(2.269)	(0.561)
Observations	2,728,618	2,728,618	2,728,618	2,728,618

Notes: The table reports OLS estimates of our baseline specification (equation (2)) based on the sample of account holders with a credit card. The observations are at the person-day level. The dependent variable is daily credit spending on retail, leisure, jewelry, and school product categories (specifications (1) (2), (3), and (4) respectively). 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 month. In all specifications, we include fixed effects for account holder, 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. In contrast to the other specifications, the top 1% of observations have not been dropped, since purchases of interest may be quite large, particularly in the jewelry category. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 8: Weekly Credit Card Spending Across a Statement Month – Threshold Spending

	Spending after week…			
	Week 1	Week 2	Week 3	Week 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)
Other Controls	Day of the week, Week of the month, Month-year			
Fixed Effects	Account holder			
Observations	86,054	86,054	86,054	86,054

Notes: The table reports OLS estimates of our baseline specification (equation (2)) based on the sample of account holders with a credit card. The 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. So, 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 which 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.