

Why do financially unconstrained individuals respond to higher credit limits?*

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Abstract

This paper uses unique bank-account-level panel data to examine why credit limit increases boost consumption among financially unconstrained households. Despite low ex-ante credit utilization and substantial liquid savings, consumers spend 7.8 cents per \$1 of increased credit limit, funded by drawing down savings rather than borrowing. The response is stronger for individuals with higher income, liquidity, and lower uncertainty, inconsistent with liquidity constraints or precautionary motives. Instead, we propose and document a novel cue-based mechanism: credit limit increases act as psychological triggers, enhancing the salience of available credit and stimulating spending.

JEL Classification: D14, E21, E51, H31

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1 Introduction

Understanding how financially unconstrained households respond to credit limit changes remains a critical yet understudied question in household finance. While the literature on marginal propensities to consume (MPCs) extensively examines liquidity-constrained households, it largely assumes that unconstrained individuals exhibit negligible or predictable consumption responses.¹ Yet, U.S. banks consistently extend substantial credit lines to wealthier households with low credit utilization rates and marginal propensity to borrow (Agarwal et al., 2018), raising a puzzling question: why? Data from the Federal Reserve’s 2023 report on the economic well-being of US households highlights this trend: credit card penetration is increasing in income and highest at 97% for those with an income exceeding \$100,000. While only 46% of individuals in the lowest income group have a credit card. In contrast, credit utilization is decreasing in income.² This apparent targeting of high-income, low-utilization consumers suggests a behavioral explanation: higher credit limits may stimulate consumption even among liquidity-unconstrained individuals. Policymakers, including the Consumer Financial Protection Bureau (CFPB), have expressed concerns about these dynamics, warning that rising credit limits could encourage overspending and lead to higher household debt. Yet, empirical evidence regarding behavioral drivers of credit card usage remains scarce. By focusing on the overlooked segment of financially unconstrained individuals, our findings provide the first direct evidence of a psychological driver of credit-induced consumption.

Leveraging a unique panel dataset of high-frequency bank transactions that enables us to disentangle the roles of liquidity constraints, precautionary savings, and behavioral factors with high precision, we provide novel empirical findings that extend the literature on MPC out of credit. We find that financially unconstrained individuals—on average holding liquid savings exceeding three months of expenses, utilizing only 20% of available credit limits, and negligible credit card debt rollover rates (less than 3%)—significantly increase consumption following credit limit hikes. Strikingly, this increased consumption is not funded by additional borrowing but by a reduction in the savings rate. This response is inconsistent with traditional explanations tied to liquidity constraints or precautionary motives, as spending increases are more pronounced among those with higher income, higher liquid savings, higher unused credit buffers, and lower income volatility.

Instead, we propose and provide evidence that supports a novel cue-based mechanism, where credit limit increases act as behavioral triggers that enhance the salience of available credit and stimulate consumption (Laibson, 1997, 2001; Addoum et al., 2015; Pennesi, 2021; Banker et al., 2021; Ilut and Valchev, 2023). Laboratory experiments and neural studies show that credit-related cues activate reward pathways in brains, thereby increasing the motivation to spend (Feinberg, 1986;

¹See Deaton (1991); Gross and Souleles (2002); Jappelli et al. (2008); Bursztyn et al. (2018); Carroll et al. (2019); D’Acunto et al. (2020); Aydin (2022); Agarwal et al. (2023); Gomes et al. (2021); Ghosh and Vats (2022); Boehm et al. (2024)

²37% of those in the highest income group carry a credit card balance while this number ranges between 52%–60% for those with lower income. Overall, 56% of US credit card holders use credit cards only for payment convenience and do not carry any debt, as per the Federal Reserve’s Survey of Consumer Finances (2022).

Banker et al., 2021). Building on this idea, we present a conceptual framework in Section 6.3.1 that explicitly incorporates the role of cues in a household’s utility function and illustrates how credit limit changes may act as cue triggers that stimulate consumption. Using several proxies to test the cue theory, we document evidence consistent with the idea that credit limit hikes serve as cues that trigger consumption. These findings have significant implications for understanding credit policy’s impact on consumption and welfare, particularly in emerging economies, and suggest that changes in credit availability can influence aggregate demand through psychological cues rather than liquidity effects.

We use a sample of consumers randomly selected from the clients of one of the largest private banks in India to study how their spending, credit card borrowing, and savings change in response to an automatic increase in credit card limits (*treatment*). Our sample is representative of the lower to upper-middle-class salaried population in India.³ Specifically, the baseline analysis is based on a staggered difference-in-differences identification that exploits the exogenous variation in the timing of the credit limit increase for a group of similar consumers. We also perform a propensity score-matched difference-in-differences analysis (PSM-DID) for robustness. Each treated individual is matched to a user in the control group based on age, gender, occupation, city of residence, marital status, *ex-ante* monthly spending, *ex-ante* saving account balance, salary, *ex-ante* growth rate of spending and *ex-ante* ratio of cash expenditure and credit card expenditure to control for observable determinants of credit card usage.

In line with previous research, we begin by tracking the spending responses to credit limit increases. After the credit limit increase, the total cumulative MPC is 7.8%, suggesting that consumers spend 7.8 cents on average for every \$1 increase in credit limit. The MPC is lower than 12%-15% reported by prior studies for developed countries such as the US (Gross and Souleles, 2002). The dynamic responses suggest the positive effect on total spending lasts for at least 24 months, and the MPC in 24 months is above 15%. Credit card transactions account for most of the increase in monthly spending, with the 24 months MPC equal 19.3%. Cash withdrawals decrease by approximately ₹16 for each thousand rupee of limit increases within 24 months, and the coefficient is statistically insignificant, whereas MPC of debit cards falls significantly by approximately ₹28 for each thousand rupee of limit increases within 24 months. Thus, individuals substitute credit cards for debit cards and cash. Our results suggest that examining the impact of spending response only through credit cards may overestimate the MPC by 23%.

Further, we don’t find any economically meaningful increase in credit card utilization or the propensity to roll over credit card debt. After the credit limit increase, credit utilization falls by 6 percentage points from 20% before the increase, suggesting that the credit card line usage grows slower than the limit increase. Nevertheless, there is a 7 percentage point increase in the probability of rolling over credit card debt. While this increase is significant relative to the average propensity to roll over in the pre-treatment period of 3%, the probability remains economically small.

³Section 4.1 discusses the representativeness of our sample.

These numbers are in sharp contrast to developed countries like the USA, where approximately 44% of the consumers roll over their credit card debt (U.S. Survey of Consumer Finances 2020).⁴ Importantly, the treatment effect estimates remain robust if we restrict the sample to only those individuals who do not roll over their credit card debt. Thus, inconsistent with currently binding liquidity constraints, the consumption response is not completely financed by additional borrowing. We observe a quantitatively and statistically equivalent decline in savings following a credit limit increase, which is consistent with the consumption response estimates. This result shows that the consumers are liquid and finance the higher consumption mainly by reducing their savings rate instead of additional borrowing.

To further nail down whether the impulse response to credit increase is driven by liquidity constraints, we examine the spending responses by the categories of expenditure through credit cards and debit cards. Discretionary expenditure accounts for approximately sixty percent of the total expenditure response. This pattern suggests that the demand for necessities is largely satisfied and not constrained by liquidity shortage so that extra credit can be used for discretionary goods. These results strengthen our thesis that the increase in consumption is unlikely to be driven by a relaxation of currently binding liquidity constraints. Rather, these results point to precautionary savings motives or cue triggers as potential explanations for the consumption response.

Next, we examine the heterogeneity in response based on income. Insofar as MPC is decreasing in income, individuals with high-income inflows relative to their expenses are less likely to feel constrained in their ability to spend as they face both lower liquidity constraints and precautionary motives. To test this thesis, we investigate the heterogeneity of consumer responses by the average pre-treatment income scaled by average pre-treatment monthly expenditure. We find that the impulse response in consumption is 146% higher for individuals in the high-income group relative to those in the lower-income group.

To examine the behavior of consumers with varying needs for buffer savings, we proxy the precautionary motive with the degree of labor income uncertainty (*salary volatility*), which is calculated by scaling the *ex-ante* standard deviation of salary by the average monthly income in the pre-treatment period (Carroll et al., 2019). Contrary to precautionary savings and in line with behavioral explanations, we find that the consumption response is 38% lower in the highest tercile of salary volatility compared to the low volatility groups. The result is similar if we proxy for future uncertainty with the *ex-ante* standard deviation of monthly consumption expenditure.

While an individual may have sufficient income to cover necessary expenditures, the additional credit may still relax liquidity constraints, allowing them to spend more on discretionary consumption such as vacations. To test this idea, we utilize cross-sectional variation in *ex-ante* liquidity buffer as alternative measures of household liquidity as robustness tests. Specifically, we construct three measures of liquidity buffer: unutilized credit card balance, cash holdings in savings accounts, and the sum of these two, all normalized by average monthly expenditure (Olafsson and

⁴See <https://www.federalreserve.gov/publications/files/scf20.pdf> [Accessed in November 2024]

[Pagel, 2018](#)). Consistent with our findings regarding income tier, we find that the consumption response is increasing in liquidity buffer. These results are inconsistent with liquidity constraints. Specifically, the impulse response is 138% and 194% higher for individuals in the highest tercile of *ex-ante* cash holdings and unutilized card balance credit relative to those in the bottom two terciles. The results remain robust to other measures of liquidity constraints that combine cash holdings in savings accounts, unutilized card balances, and term deposits.

Collectively, the consumption response across income, liquidity, and salary volatility subsamples is difficult to rationalize with standard models of precautionary savings or liquidity constraints. Moreover, the estimated increase in consumption is not financed through borrowing and was financially feasible for individuals even in the lowest (highest) tercile of income and liquidity (credit utilization) distribution even before the credit limit increase. Overall, our findings are difficult to reconcile with conventional models of rational household behavior. Rather, the evidence suggests that increases in credit limits serve as stimuli that induce a response in consumption due to behavioral reasons, especially for those who have ample liquidity to cover the higher spending. Our findings align more with recent research that shows that predictable income events like payday can trigger consumption, even without a change in permanent income, due to psychological reasons ([Addoum et al., 2015](#); [Olafsson and Pagel, 2018](#); [Ilut and Valchev, 2023](#)).

To illustrate the effect of cues, we present a conceptual framework in Section 6.3.1 and solve a two-period household consumption optimization model that explicitly incorporates the role of cues ([Laibson, 1997](#); [Pennesi, 2021](#)). Formally, the household’s utility function includes a cue component that gets triggered when the credit limit increases, thus increasing the marginal utility of consumption and prompting households to consume more even if they are not liquidity-constrained. For instance, consistent with our evidence on the increase in discretionary spending, prior research shows that status-seeking customers may derive greater prestige from the credit limit increase, thereby causing them to spend more on visible discretionary consumption such as restaurants and tourism ([Bursztyn et al., 2018](#)). Our conceptual framework illustrates that the MPC out of saving or income is higher with cue triggers. Households with higher initial savings finance this increased consumption by drawing down their savings rather than borrowing, but the effect of the cue on consumption behavior remains significant across different levels of initial savings. Likewise, cue-triggers may also lead households to consume a larger portion of their income and reduce their savings rate. Importantly, the implications of the model are in line with our empirical findings, which show a higher consumption response to credit limit increases for those with higher *ex-ante* savings buffer and income.

Next, using a few proxies, we empirically examine whether the cue theory can explain the consumption response to credit limit changes. Building on [Olafsson and Pagel \(2018\)](#) and [Laibson \(2001\)](#), we conjecture that the same underlying psychological characteristics may drive spending responses to paydays and credit limit increases, so we sort individuals based on the fraction of

the salary consumed within 5 days⁵ following payday. Consistent with our thesis, we find that individuals with a higher propensity to spend around paydays also exhibit a 108% higher MPC to increased credit limits. The result is robust to using subsamples of consumers with similar level of liquidity.

Further, a credit card statement, which is sent to the customers by email and/or SMS at the end of each billing cycle, may also act as repeated cues that trigger spending, driving persistence in consumption response. First, we find a significant spending response on credit cards during the statement week. Second, the consumption response to a credit limit increase is 46% higher in the statement week. Further, insofar as the credit card statements may draw attention to the credit limit increase, limit increases followed by a statement may serve as a stronger cue. Indeed, the limit increases followed by statements have an MPC out of credit card 52% higher than otherwise. These results suggest that credit limit increases likely serve as cue triggers that stimulate consumption.

Finally, an additional possibility is that the credit limit changes serve as signals of future income growth (Yin, 2022). Unfortunately, in our data, we do not observe any change in income *ex-post* credit limit increase for the individuals, which makes it less likely that the income expectation hypothesis holds in our setting. Nonetheless, for robustness, we control for income in our tests. Furthermore, to understand if individuals in our sample perceive credit limit increases as positive signals of future income prospects, we examine the impact of limit increases on financial risk-taking, as measured by equity market investments. Insofar as labor income is a substitute for bonds, an expected increase in income should increase ownership of risky assets (Calvet and Sodini, 2014; Gomes et al., 2021). In contrast to credit limits affecting beliefs regarding expected labor income, mutual funds and equity investments do not change significantly after credit limit increases. Thus, the income expectations channel is unlikely to fully account for the consumption responses in our setting.

We observe data from just one bank for each participant in our sample, which is a significant caveat to our findings. There could be another explanation for the findings we report if an individual has banking relationships with different banks. First, an increase in the credit limit on a certain card may make it more visible, causing consumers to shift their spending from other credit cards (“unobservable”) to the one with the credit limit increase. There may not be an increase in consumption in such a circumstance. Our focus on salary accounts alleviates part of this concern because these accounts are more likely to be the primary account (Loos et al., 2020). Moreover, the monthly expenditure of the average individual in our sample is approximately ₹33,200, which is 87% of the average monthly salary of ₹38,000. Thus, it is unlikely that individuals in our sample use an alternate account as the primary one for their consumption.

Nonetheless, we do a battery of robustness tests to address the issue of substitution among credit cards issued by different banks. We repeat our tests with the subsample of consumers with above pre-treatment median monthly expenditure in our sample. The underlying premise is that

⁵The result is robust to different choice of different thresholds, including 3 and 7 days.

the bank accounts in our sample are likely to be the primary account for individuals with high *ex-ante* expenditures. Our findings remain robust if we restrict attention to the subsample.

A related issue is a substitution of spending and savings across bank accounts of different members within the same household. To address this concern, we examine the differential effect on married and single individuals. The underlying assumption is that it is more difficult for single individuals to shift their spending to and from the cards of other family members. Reassuringly, we do not find an economically and statistically significant difference between the treatment effect across the two subsamples.

Finally, a key empirical challenge for research on credit expansion is that access to credit is not random. First, when consumers desire to borrow or anticipate an increase in spending, they may request an increase in credit limit. Second, the bank is likely to raise limits for people with a stronger ability to pay or who are more inclined to consume more. To address the first concern and reduce the potential confounding effects of such selection biases on our estimation of treatment effects, we follow [Gross and Souleles \(2002\)](#) and restrict the sample to “automatic” credit line increases initiated by the bank, which is less prone to the selection issue that comes with the consumer initiated limit increases. Until October 2022, banks could unilaterally increase loan limits without the borrower’s consent or approval, so the bank-initiated limit increases will not be subject to borrowers’ endogenous choice regarding limit retention. The bank notifies the borrower of the increased limit by SMS and email. The notification simply mentions the limit adjustment but does not include any other content that may stimulate expenditure.

Related to the second issue, per our conversations, the bank increases the credit limit periodically for all clients whose credit limit is below a threshold. Therefore, it is possible for two similar consumers to receive the limit increase in different months. Moreover, we find that the expenditure and salary in the previous year are not correlated with the limit increase.

Furthermore, we only include credit limit increases on existing cards to avoid potential selection bias in new credit card applications. Importantly, we limit our focus to salary accounts in order to account for monthly income, which might alter both credit demand and the ability to repay debt. All our specifications include account fixed effects, which control for any time-invariant differences across accounts, and year \times month fixed effects, which absorb time-varying aggregate shocks. Reassuringly, we do not find any pre-trends, which is critical for identification given our empirical design. We repeat all of our tests for robustness using the alternate PSM-DID design by matching on a comprehensive set of covariates mentioned above. The control group in this analysis comprises individuals who did not experience a credit limit change during our sample period.

Overall, our findings are inconsistent with either currently binding liquidity constraints or precautionary savings motives. Our results are also unlikely to be explained by myopic consumption-binging ([Garber et al., 2024](#)) as consumers in our sample do not seem to borrow beyond their means to finance their consumption. Moreover, individuals maintain sufficient liquidity buffers, suggesting that they are forward-looking. Collectively, the low credit utilization and high liquid holding before

the limit increase suggest that Indian consumers appear to be more prudent or debt-averse. Our evidence suggests heuristic behavior on the part of individuals, wherein credit limit changes act as cues that trigger a consumption response (Laibson, 2001).

The documented behavior is in line with recent studies that also document consumption responses to income shocks and MPC estimates, which are inconsistent with conventional models of rational household agents (Olafsson and Pagel, 2018; Garber et al., 2024; Boehm et al., 2024). In our context, a rise in credit limit may act as cues that improve an individual’s marginal utility of consumption (Laibson, 2001), causing them to spend more. More work is needed to examine if such impulse responses increase or decrease consumer welfare.

These findings have significant implications for understanding credit policy’s impact on consumption and welfare, particularly in emerging economies, and suggest that changes in credit availability can influence aggregate demand through psychological cues rather than liquidity effects (Hall, 2012; Mian et al., 2017; Mian and Sufi, 2018). In particular, if individuals in developing economies are unduly prudent in their savings and borrower behavior, then any cue that increases consumption will improve welfare by nudging individuals toward their optimal consumption and savings rate (Gopalan et al., 2024; Martínez-Marquina and Shi, 2024). In such a setting, policies that expand credit access can significantly boost consumption and improve welfare without increasing default risk or indebtedness. In contrast, if financially unsophisticated borrowers “overborrow” and “overconsume” in response to increased credit access, the optimal policy response would call for restricting credit access (Garber et al., 2024).

2 Related Literature

Our study is most closely related to Olafsson and Pagel (2018) and Garber et al. (2024). Olafsson and Pagel (2018) study spending response to regular and irregular income payments and find a significant increase in consumption by individuals in Iceland on paydays despite no change in permanent income and paydays being perfectly anticipated. They find a similar response to unpredictable, irregular income. Importantly, the impulse response is large and economically significant throughout the income and liquidity distributions. They conclude that the evidence is inconsistent with conventional models of optimal household behavior. Instead, their evidence points to heuristic behavior consistent with a cue effect. Our study complements their work by uncovering very comparable household behavior in India in response to expanded credit card limits. Despite high cash holdings and unutilized credit card balances, households in our environment boost expenditures following a rise in credit limit. Garber et al. (2024) study a large credit expansion plan for public sector workers and find an increase in borrowing and consumption for individuals across the distribution of expected income growth. Their evidence is also difficult to rationalize with conventional models of rational households. Rather, the results are driven by financially unsophisticated individuals who sub-optimally borrow beyond their means and become “overindebted.” In contrast,

in our setting, we show that individuals do not significantly increase their borrowing but increase their consumption following an increase in credit card limits. Moreover, credit utilization rates fall, and the fraction of consumers who roll over debt remains low. Thus, the concern among Indian policymakers over the risk of consumer overindebtedness is likely misplaced.

Our research also adds to the relatively limited empirical evidence on the impulse reaction to credit shocks (Zeldes, 1989; Gross and Souleles, 2002; D’Acunto et al., 2020; Aydin, 2022; Agarwal et al., 2023).⁶ Gross and Souleles (2002) also study MPC out of liquidity using automatic credit line increases and find a large consumption response for individuals with binding liquidity constraints with *ex-ante* credit utilization close to the limit. MPC, on the other hand, is significant, albeit subdued for those closer to the limit. In a similar vein, a recent significant study is Aydin (2022). Using a large-scale randomized control trial in Turkey, Aydin (2022) documents a significant marginal propensity to borrow and consume out of credit increase. Consistent with precautionary savings motives, the response is highest for individuals with currently binding constraints. Nevertheless, our findings extend to those with substantial liquid assets and those who are far from the limit. In contrast, we document a significant consumption response that is higher for individuals with high liquid assets and low credit utilization. Notably, the increase in consumption in our environment is not financed by borrowing. Consistent with this, the credit utilization ratio falls by a large magnitude following credit limit increases. Moreover, the majority of the consumers in our sample pay their credit card balance in full at the end of the month. Thus, our findings are inconsistent with liquidity constraints and buffer-stock models of consumption (Deaton, 1989; Carroll, 1997; Jappelli et al., 2008; Kaplan and Violante, 2014; Carroll et al., 2019). Instead, our study highlights that credit limit increases act as cue triggers that stimulate a consumption response.

Our findings are more in line with D’Acunto et al. (2020), who examine the spending reaction to an extensive margin of credit increase caused by an extension of an overdraft facility via a fintech application. They also show a long-term rise in consumption, with the most liquid persons benefiting the most. In contrast, we investigate the impact of an increase in the *intensive* margin of credit through an increase in credit card limits for *traditional bank* customers. Importantly, the typical borrower in our sample has enough cash and an unutilized credit card debt. Nonetheless, a rise in credit limit leads to a permanent increase in consumption and a decrease in savings rate.

Finally, as noted in Deaton (1989) and Deaton (1991), our findings emphasize the importance of understanding household finance behavior in developing countries. Our paper documents several interesting empirical facts. First, credit card usage in our sample is substantially lower than in the United States. Similarly, when compared to the general US population, individuals in our sample have a considerably lower proclivity to roll over credit card debt. Furthermore, the MPC for credit-

⁶Our paper also complements the large literature on consumption response to income and wealth shocks such as those caused by unanticipated increase in the wage rate, tax rebates, housing wealth, etc. See, for example, Lettau and Ludvigson (2004); Johnson et al. (2006); Agarwal et al. (2007); Stephens Jr (2008); Adams et al. (2009); Gan (2010); Leth-Petersen (2010); Aaronson et al. (2012); Mian et al. (2013); Agarwal and Qian (2014); Paiella and Pistaferri (2017); Baker (2018); Christelis et al. (2019); Granja et al. (2021).

constrained individuals is much smaller. Our findings imply that Indian consumers appear to be more prudent or debt-averse (Prelec and Loewenstein, 1998; Meissner, 2016; Gopalan et al., 2024). Lastly, we show that the consumers switched the payment method from debit card and cash to credit card, which suggests that there could be a significant overestimation of the MPC if only credit card spending is observed. This is likely due to the low penetration rate of credit cards in India, and our comprehensive data, including both cash withdrawal and spending on debit cards, enables us to estimate the MPC more accurately. This pattern may also be the case in other countries where credit cards are not the dominant payment instrument. These findings underscore the need for additional research into household behavior in developing economies. Our findings have important policy implications because they suggest that credit-based fiscal interventions, such as those launched by the government of India during and after COVID-19, can stimulate consumption without increasing indebtedness or defaults.⁷

3 Credit Card Market in India

Aiming to move towards a cashless payment system, the Indian government has issued different policies to encourage the usage of cashless payments since 2009 (Das 2010). The use of cashless payment has increased dramatically. As of the end of 2012, India had 331 million and 20 million debit and credit cards, respectively; which grew to 925 million and 47 million, respectively, as on March 2019. Nearly 30% of all retail transactions are conducted with cards as of 2017 (RBI 2019). For the middle-income group, with proof of regular salary and tax filing, application for a credit card is not difficult.

When using a credit card for a retail transaction, the customers must pay the card issuer, and the merchant must pay their banks. The fees and charges paid by the customers vary from bank to bank. The annual fee can range from as little as ₹500 to as high as a few thousand, or sometimes waived by the issuers. The annual percentage rate of credit cards ranges from 20% to above 50%. The late payment fee is waived for a low outstanding balance and can be as high as ₹1,000 for a higher outstanding balance. Cash advances and cash withdrawals from credit cards are charged 2 to 3% of the transaction amount. The merchants have to pay a Merchant Discount Rate (MDR) to issuers of their bank account when the customer pays with a credit card or debit card. The MDR on credit cards is up to 2 to 4% of the transaction volume. The MDR on debit cards is up to 0.75 to 1% of the transaction volume (Das 2020).

Given the potential profit that the bank could earn from credit cards, the banks have an incentive to encourage the clients to increase their usage of credit cards. One way is to increase the credit limit. The bank periodically increases the credit limit of the clients whose limit is below

⁷The RBI declared a debt moratorium on all loans, including credit card dues, in March 2020 to address COVID-19's financial impact. See <https://economictimes.indiatimes.com/news/economy/finance/repayment-moratorium-covers-all-loans-including-credit-card-dues-rbi/articleshow/74852570.cms> [Accessed in November 2024].

a threshold, and the decision is made using a built-in model that is rarely adjusted. Priority is given to clients who have a lower utilization rate, while total expenditure and salary do not affect the banks’ decision on credit limit increases for *existing* credit cards. More importantly, due to the limitation in the lending capacity, the bank does not increase the limit of all the clients that meet the requirement concurrently. As such, it is possible for two similar accounts that are both qualified for the limit increase to get the limit increase in different weeks or even months. Given the complex decision rule employed by the bank, the clients can hardly predict the exact timing of the limit change.

To qualify for the limit increase, the clients do not need to provide any extra documents. Once the banks have decided to increase the limit for a client, they will notify the clients through their registered mobile number via SMS, email, monthly statement, and online banking system. The monthly statement is sent to the consumers at the end of the billing cycle. The statement usually includes the current credit limit, the transactions conducted in the billing cycle, and minimum repayment amount. We include a sample of the statement in Figure A1 of Online Appendix A.

As long as the clients check these notifications regularly, they will be aware of the increase shortly after they are notified. Until October 2022, banks could unilaterally increase loan limits without the borrower’s consent or approval.⁸ While the clients can choose to decrease their limit, they usually do not, as it may negatively affect their credit score, as a lower credit utilization ratio is associated with a higher credit score. This ensures that credit limit change is not an endogenous choice made by consumers. In the empirical section, we employ the automatic limit increases together with other empirical strategies for causal inference. More details will be introduced in Section 5.

Other than the bank-initiated credit limit changes (or “automatic” increase), the clients could also approach the bank and apply for the limit increase (“manual” increase). Unlike automatic limit increases, manual increases are likely endogenous to clients’ credit demand. In Table A4, we show that the consumption response is similar to the automatic limit increases. However, consistent with endogeneity in the customer’s credit needs, Figure A4 shows that the total expenditure has a clear pre-trend before the manual limit increase.

Other than increasing the credit limit, the bank uses the welcome bonus, low fees or charges, cashback, and other non-monetary benefits to attract customers. However, these features are mostly for new credit cards. For existing credit cards, these terms are usually unchanged.

⁸In a master circular dated April 21, 2022, the RBI revised regulatory guidelines governing credit and debit cards and notified a new rule that went into force from October 1, 2022, requiring that cardholders cannot increase the credit limit without the cardholder’s explicit consent. The master circular (RBI/2022-23/92) can be accessed at <https://rbidocs.rbi.org.in/rdocs/notification/PDFs/92MDCREDITDEBITCARD423AFFB5E7945149C95CDD2F71E9158.PDF>. Also, see a news article in the leading Indian economic news daily summarizing the key changes - <https://economictimes.indiatimes.com/wealth/spend/3-new-credit-card-rules-will-come-into-effect-on-october-1-how-it-will-impact-card-holders/articleshow/94476420.cms> [Accessed in November 2024].

4 Data and Summary Statistics

Our data is obtained from a leading retail bank in India, which is one of the four largest banks, with more than 18,000 branches and ATMs. The bank offers a plethora of banking products and financial services, such as credit and debit cards, saving accounts, term deposit accounts, mutual funds, and equity investment accounts. Our baseline sample contains around 8,000 randomly selected sample of accounts from the bank’s clients in 9 cities (Ahmedabad, Bangalore, Bhubaneswar, Chennai, Delhi, Gurgaon, Kolkata, Mumbai, and Surat) from the period of January 2012 to December 2019. Each account is registered by a unique client, and one client holds one account only. For the credit card fees and charges, the annual percentage rate of credit cards in this bank is nearly 30%. The late payment fee is ₹500 for a card balance between ₹501 to ₹10,000, and ₹700 for a balance ₹10,001 or above.

The data includes a comprehensive breakdown of monthly expenditures through both credit cards and debit cards by merchant categories. The data also includes cash withdrawals from ATMs, allowing us to examine substitution away from cash and, thus, more precisely estimate the MPC. Further, the data includes information regarding credit card balance per billing cycle, credit limit, and liquid assets, including savings account balance, term deposits, and holdings of risky financial assets, including mutual funds and equity investments. We also obtained information regarding the demographic characteristics of the account holders, including age, gender, address, occupation categories, marital status, and city. Furthermore, the dataset captures the monthly salary deposits.

In summary, to study the effect of credit limit changes on spending, credit card usage, and the holding of liquid assets, we employ the dataset that is representative of the bank’s consumers in the 9 cities, spanning January 2012 to December 2019, with each account owned by a unique consumer. We then construct a monthly panel, which includes the following information at the account level: (1) the amount of expenditure through credit card and debit card during the month, (2) the amount of cash withdrawal, (3) the month-on-month changes in liquid asset holding, and (4) the using of credit card in each billing cycle, including the utilization rate and whether the credit card debt is paid in full. We winsorize the data for all dependent variables at 1% and 99%. For the baseline analysis, we focus on the sample of 1,843 salary accounts associated with an automatic credit limit increase during our sample period.⁹ We also obtained information on a matched sample of 1,308 accounts with no credit limit increase during our sample period. For each account, we examine the period from 5 months before the line increases to 24 months after unless the account opens less than 5 months before the line increases.

⁹We also obtained a sample of 2,930 account holders with a self-selected manually initiated increase in credit limit. Their spending responses are reported in Figure A4

4.1 Summary Statistics

Table 1 summarizes the data. Panel A reports the demographic information of the account holders and basic account information. Our sample is representative of the lower to upper-middle-class salaried population in India. While there is no clear consensus on the definition of middle and high-income group among policymakers, academics, or the public at large (Atkinson and Brandolini, 2013; Gornick and Jäntti, 2014), several studies define those with a daily income in the range of \$10-\$50 (2011 ppp) per person as belonging to the middle class (Meyer and Birdsall, 2012; Jolliffe et al., 2015; Birdsall, 2015; Kochhar, 2020). Consistent with our sample comprising of the middle-income group in India, the average monthly salary is ₹38,250 (US\$ 455)¹⁰, which translates into approximately \$15 per day. The account holder with the median salary of ₹17,713 belongs to the low-income group, while those with a salary higher than ₹38,000 belong to the upper-middle income group. The median person holds substantial liquid savings equal to 2.5 months of expenses. In Panel A of Figure A3 in Online Appendix A, we compare the distribution of bank deposits in our sample to the 2019 “All India Debt & Investment Survey (AIDIS)”. This figure provides more supporting evidence that our sample is representative of the low- to upper-middle-income group.

The average consumer in our sample is 39 years old. In Panel B of Figure A3 in Online Appendix A, we compare the age distribution of our sample to the National Family Health Survey (NFHS) 2019 -2021. This figure shows that our sample has a larger fraction of the younger population below 45 and underrepresents the older population over 50. This aligns with the fact that our sample comprises the salaried group, so the older retired population constitutes a smaller proportion. The proportion of male account holders is 88%, which is high. This is because of labor force participation, and consequently, salary accounts are significantly higher for males in India. Consistent with our sample being representative of the low- to upper-middle-income population, we find that 39% and 24% of the accounts have mutual funds and equity trading accounts, respectively. We do not find a significant difference in the monthly salary before and after the credit limit increase.

Panel B of Table 1 summarizes the credit limit changes. The credit limit before the increase (treatment) is ₹105,925 (US\$ 1,259), while after the change, the limit increases by five times to ₹530,467 (US\$ 6,306). Thus, the increase in credit limit is unlikely to be driven by an increase in borrowers’ debt repayment ability.

Panel C summarizes the spending variables. The total spending is comprised of cash withdrawals, debit card transactions, and credit card transactions. The total spending before the line increases is ₹33,203 rupees (US\$ 395) per month. The magnitude of total monthly spending is marginally lower but very close to the monthly salary, suggesting that this account is likely the main account for spending. 70% of the spending is through cash, 15% through credit cards, and 13% through debit cards. After the limit increase, the total spending increases by 15%, to ₹38,027 (US\$ 451) per month. The spending through credit cards increases by 153% from ₹5,072 (US\$ 60)

¹⁰Exchange rate of US\$ 1= ₹84.11 in November 2024.

to ₹12,814 (US\$ 152). The debit card transactions decrease by 19% from ₹4,380 (US\$ 52) to 3,529 rupees (US\$ 41). Monthly cash withdrawals decrease by 9% from ₹23,096 (US\$ 275) to ₹20,994 rupees (US\$ 250). The huge increase in total spending relative to the salary increment suggests that the consumers increase consumption not because of better income prospects. Further, the payment method switches from debit cards to credit cards when extra credit is available. However, these numbers are only indicative and could just be reflecting time trends. Thus, we control for time trends in our empirical analysis and find these patterns to be robust.

Panel D summarizes the change in credit card usage and liquid asset holdings. The average utilization rate, which is the credit card balance at the end of each billing cycle divided by the credit limit, is 13 percentage points after the limit increase, significantly lower than the average utilization rate in developed countries like the USA ([Gross and Souleles, 2002](#)), suggesting some degree of aversion to debt. $1_{revolve}$ is an indicator variable that is equal to zero if the beginning-of-billing cycle credit card balance is paid in full (i.e., “transactor”). Otherwise, it is equal to one (i.e., “revolver”). An economically small 3% of the cardholders carry forward some debt on their card in the pre-treatment period. This fraction increases to 15% post-treatment. The credit card utilization rate decreases from 20% to 13% after the line increase, suggesting the extra credit line further lowers their credit constraints. The average savings balance at the end of each month is ₹138,576 (US\$ 1,648), and the average term deposit balance is ₹103,922 (US\$ 1,236). On average, the savings account balance increases by ₹3,958 (US\$ 47) in the pre-treatment period, while in the post-treatment period, the amount drops significantly to close to zero. Similarly, the monthly net deposit in term deposits decreases by 60% from ₹2,062 (US\$ 25) to ₹831 rupees (US\$ 10). The significant drop in the growth rate of savings suggests that the increased credit limit reduces saving amount by increasing the expenditure.

[Insert Table 1 here]

In summary, while our data doesn’t perfectly capture the entire spectrum of the Indian population, it provides useful insights for the subset who are more likely to possess and use credit cards. Given the rapid development of consumer finance in India, as well as in other developing countries, this population is gaining importance in many emerging economies. Importantly, there is significant variation in liquid assets in our sample, with individuals in the tenth and ninetieth percentiles of the distribution having 0.5 and 4 months of expenditure, respectively. Furthermore, with an *ex-ante* credit usage ratio of 20%, the average individual is not credit limited. Credit utilization ratios are 0 and 15% in the 25th and 75th percentiles of the income distribution. Importantly, only 3% of the individuals in our sample rolled over their debt before the limit increase. Rather, most individuals pay off their balances in full before the due date. [Olafsson and Pagel \(2018\)](#) document a similar behavior by the Icelandic population. The high liquid savings, combined with low credit utilization, are difficult to rationalize with theoretical predictions ([Kaplan and Violante, 2014](#); [Olafsson and Pagel, 2018](#)). Importantly, unlike [Yin \(2022\)](#), credit limit increase is not associated with

an expected increase in consumer income.

5 Empirical Methodology

To investigate the consumers' expenditure responses to the credit line changes, we run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i + \beta_2 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (1)$$

As explained in Section 3, we examine the responses to the automatic limit increases on existing credit cards to address the endogeneity issue related to the consumers' self-selected choice of applying for a credit limit increase. The dependent variables include measures of spending and liquid asset holding. Measures of spending consist of credit card expenditure, debit card expenditure, cash withdrawals, and the aggregate total spending, which is the sum of these three variables made by individual i through his or her bank account during period t . For liquid asset holding, we use the month-on-month change in the savings account (Δ Saving Balance) and term deposit balance (Δ Term Deposit). Following [Agarwal et al. \(2007\)](#) and [Aaronson et al. \(2012\)](#), the monthly expenditure and changes in liquid asset holding are measured in levels.

The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period, which spans from the month after the treatment to 24 months after the treatment and zero otherwise. Because our bank, as well as most retail banks in India, rarely decreases the credit limits, we only include the limit increases as the treatments. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. To estimate the marginal changes in spending and savings as a fraction of the credit limit increase, we interact the indicator variables $1_{after_{it}}$ and $1_{during_{it}}$ with the increases in credit limit measured in 1,000-rupee ($\Delta Limit_i$). We control for the monthly salary, account fixed effects (δ_i), and year-month fixed effects (τ_t). Thus, our estimates are not driven by differences in income, time-invariant characteristics of consumers, and time-varying aggregate shocks. Standard errors are clustered by account. The coefficients β_1 and β_2 represent the marginal responses in the outcome variable per thousand rupees line increase after and during the month of treatment. For example, the coefficient β_1 represents the MPC out of credit when the dependent variable is spending.

We then use equation (2) to estimate the total effect of the credit limit increase on credit card usage. We use the change in the credit utilization rate and probability to carry forward credit card debt to reflect the credit card usage. Credit utilization rate is defined as the ratio of credit card balance at the end of each billing cycle to the credit limit. To examine the propensity to carry forward credit card debt, we define a binary variable $1_{revolve_{it}}$ that is equal to one if the consumers did not fully repay the credit card debt in a billing cycle before the due date, i.e. "revolver."

All other variables in equation (2) have the same definition as in equation (1). Therefore, γ_1 and γ_2 capture the differential change in credit card usage for the treated accounts relative to the pre-treatment period after the line increase and during the month of line increase, respectively.

$$Y_{it} = \gamma_1 1_{after_{it}} + \gamma_2 1_{during_{it}} + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (2)$$

Another key empirical challenge of this study is that the consumers who are offered a credit limit increase may be different from other consumers. Thus, in our baseline empirical strategies specified in equations (1) and (2), we perform a within-treated group comparison where the treatment effects are identified through variation in the timing of the credit limit increase, rather than through the variation in receiving the limit increase or not. Therefore, our estimation is not confounded by the unobservable attributes that may lead to the selection of being offered the credit limit increase by the bank.

However, the timing may be endogenous if the bank increases the credit supply when they expect credit demand to increase. We believe that it is unlikely that the bank strategically chooses the timing of credit limit adjustments for two reasons. Firstly, in our conversation with the bank, they claimed that they periodically increase the credit limit mainly for the purpose of consumer retention. They adjust the credit limit for a sub-portfolio of the credit cards whose limit is below a threshold using a pre-specified in-house model that is rarely adjusted. They make the limit changes for all the consumers chosen by the model. Consequently, two consumers who are similar in all aspects are likely to get credit limit adjustments in different months. In Table A1, we provide suggestive evidence that total expenditure and salary in the previous year are not correlated with the bank’s decision to increase the credit limit, so it is unlikely that the bank increases the limit because they expect a higher demand for credit or higher debt repayment ability. We also show that the *ex-ante* credit card utilization is negatively correlated with the limit increase, consistent with our conjecture that the bank increases the credit limit to encourage the usage of credit cards.

Secondly, we find that the number and rupee value of credit limit increases are distributed evenly across the years, which suggests that any changes from the demand side do not drive the credit supply. Figure A2 plots the amount of credit line increase by year and month during our sample period. The total amount of the monthly increase in credit limit aggregated across all accounts is on average ₹10 million per month (US\$ 119,000). The number and rupee value of credit limit increases are very similar across the years. Even during the demonetization in November 2016, when the demand for credit increased significantly, the pattern of credit limit increase was identical to November in other years. These patterns help assuage concerns regarding endogeneity in the timing of credit limit increases.

To further eliminate the effect of endogenous credit demand on credit limit increases, we focus exclusively on automatic limit increases initiated by banks for existing cards. This approach eliminates potential biases arising from endogeneity in borrower-initiated limit increases and the

opening of new cards. Before October 2022, the banks were permitted to increase the limit unilaterally without borrowers' consent. While the clients can choose to decrease their limit, borrowers typically refrain from adjusting the increased limits downward because this may hurt their credit scores, as an abrupt increase in credit utilization ratio is associated with a lower credit score. Thus, the automatic credit limit changes that we study are not an endogenous choice made by consumers. In addition, we control for the cardholder's salary in all our tests, which may influence both credit demand and the ability to repay debt. Lastly, we confirmed with the bank that they rarely adjust the interest rate or other benefits for existing credit card accounts.

We provide further evidence on the quasi-exogenous timing of the limit adjustments by examining the dynamics of the responses in spending and liquid asset holding using equation (3). We assign an indicator variable $1_{month_{ij}}$ ($j \in [-5, 24]$) for each of the 30 months from 5 months before the limit increase until 24 months after and interact $1_{month_{ij}}$ with $\Delta Limit_i$ to estimate the marginal effect. The coefficient $b_k = \sum_{j=1}^k \beta^j$ captures the marginal spending or savings responses for every ₹1,000 increase in credit limit aggregated over k months. For example, when Y_{it} is total spending, $b_{12} = \sum_{j=1}^{12} \beta^j$ measures the cumulative MPC over the 12 months following the credit limit increase.

$$Y_{it} = \sum_{j=-5}^{24} \beta^j 1_{month_{ij}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (3)$$

For measures of credit card usage, including the credit utilization rate and probability to revolve, we employ a similar event-study design specified in equations (4). The coefficients γ^j estimate the monthly responses in credit card usage.

$$Y_{it} = \sum_{j=-5}^{24} \gamma^j 1_{month_{ij}} + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (4)$$

As mentioned above, the treatment effects are identified through variation in the timing of the credit limit increase, so selection in receiving the credit limit increase does not confound our estimation. Nonetheless, to show the robustness of our results, we conduct a Propensity Score Matching algorithm to match the consumers in our current sample to the individuals who do not experience a credit limit change during the sample period. To implement the PSM method, we obtain a counterfactual group of untreated consumers matched on age, gender, occupation, city of residence, marital status, savings balance, salary, total monthly spending, growth rate of total spending and proportion of spending on credit card and by cash. Our covariates capture observable determinants of one's socio-economic status, spending habits and credit card usage. Further, the potential consumers to be matched to the treated group satisfy the following conditions: (1) they had debit card and credit card expenditures during our sample period; (2) the total debit card expenditure, credit card expenditure, and average investment balances are within 1st to 99th

percentile; (3) they had no credit limit change during the sample period from January 2012 to December 2019. One consumer from the treated sample is matched to at most one consumer in the control group.

The underlying assumption of the PSM method is that the consumers who are similar in the comprehensive set of observable covariates are also similar along other unobserved dimensions. Table A2 provides a comparison of the means for the matched control and treated sample. The treated and control groups are observationally similar.

We then use standard difference-in-differences empirical design, where the treatment is the credit limit change of the treated consumer. Formally, we run the following regression specifications:

$$Y_{it} = \mu_1 1_{after_{it}} * \Delta Limit_i * 1_{treated_{it}} + \mu_2 1_{during_{it}} * \Delta Limit_i * 1_{treated_{it}} + \mu_3 1_{after_{it}} * \Delta Limit_i + \mu_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (5)$$

$$Y_{it} = \eta_1 1_{after_{it}} * 1_{treated_{it}} + \eta_2 1_{during_{it}} * 1_{treated_{it}} + \eta_3 1_{after_{it}} + \eta_4 1_{during_{it}} + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it} \quad (6)$$

Y_{it} in equation (5) includes measurements for spending and liquid asset holding, and in equation (6) includes the measurements of credit card usage. The indicator variable $1_{treated_{it}}$ is a binary variable that equals one for the treated group and zero for the matched control group. All other variables in equations (5) and (6) have the same definition as in equations (1) and (2). Therefore, μ_1 captures the marginal treatment effect on spending and liquid asset holding, and η_1 captures the total effect on credit card usage. We also examine the dynamics of the responses by the matched control group using the event-study design specified in equations (3) and (4). Specifically, we expect to find the matched control group to have little or no response in the spending, saving and card usage. Therefore, the treatment effect estimated with η_1 and μ_1 should be of similar magnitude as β_1 and γ_1 .

6 Main Results

6.1 Consumption Response

We begin by analyzing consumption responses to credit limit increases. Table 2 reports these estimates. Panel A reports the estimates of $\beta_{s \in [1,2]}$ and $\gamma_{s \in [1,2]}$ based on equations (1) and (2) respectively. Focusing on column 1, we find that the monthly total MPC out of credit is approximately 0.9% in the 24 months after treatment. The monthly MPC through credit card is 0.9%. In contrast, the marginal propensity to spend through debit cards is -0.078%, implying that the

consumers substitute part of their spending through debit cards with credit cards following credit expansion. The marginal propensity to use cash is not affected.

[Insert Table 2 here]

The key underlying assumption of our empirical design is the absence of pre-trends in spending. Figure 1 plots the coefficients $b_k = \sum_{j=-5}^k \beta^j$ estimated using equation (3). The dependent variables include total spending, debit card spending, credit card spending, and cash withdrawal. Reassuringly, we do not find any pre-trends in any of these variables.

[Insert Figure 1 here]

In Panel B of Table 2, we repeat these tests using the propensity score matching method. The reported coefficients are based on equations (5) and (6). Reassuringly, Panel B of Figure 1 shows no contemporaneous change in spending for the control group, alleviating the concern that some aggregate time trend could drive our results. Overall, the results are qualitatively similar using the PSM approach.¹¹

In Table A3, we test the robustness of the staggered DID specification using the method in [de Chaisemartin and D’Haultfoeuille \(2020\)](#). The coefficients in Table A3 are larger than in Table 2, but still comparable.

Table 3 presents the cumulative changes in monthly MPC to the credit limit increase. The total cumulative MPC is 4.8%, 7.8%, and 15.7% in the 6-month, 12-month, and 24-month periods following the credit limit increase. The MPC from credit cards is 10.6% in 12 months and 19.3% in 24 months. However, the debit card spending decreases by 1.7% of the limit increase in 12 months and 2.8% in 24 months post-treatment. This suggests that focusing on credit cards alone to estimate the spending responses may overestimate the consumption responses by 23% ($=19.3/15.7-1$). The cumulative response estimates for cash withdrawal are statistically indistinguishable from zero, while the magnitude is comparable to the decrease in debit card spending. The results suggest for every ₹1,000 credit limit increase, the users switch ₹17 of their monthly spending from the debit cards to the credit cards within 12 months after the line increases. The results of the PSM-DID method reported in Panel B are very similar.

[Insert Table 3 here]

In summary, our results confirm a positive spending response to credit increase, consistent with the prior literature in other settings ([Gross and Souleles, 2002](#)). Importantly, we add a few novel findings to the literature. First, credit increases result in substitution between debit cards and

¹¹For robustness, we repeat our tests with manual credit line increase, which may be endogenous, and find the effect on total spending is much smaller. The results are in Figure A4, and Table A4 in Online Appendix A.

credit cards. Thus, ignoring expenditures through debit cards may result in an overestimation of MPC. Second, the MPC of credit is significantly lower in India as compared to 12%-15% reported by [Gross and Souleles \(2002\)](#) and [Aydin \(2022\)](#). This fact, coupled with low credit card utilization rates, suggests some degree of prudence or debt aversion. These findings underscore the importance of new research in household finance focusing on developing economies, as the insights based on research on the developed world may not necessarily be generalizable to the rest of the world.

6.2 Tests for Liquidity Constraints and Precautionary Motives

6.2.1 Credit card debt

We next examine whether the consumption response is financed by increased borrowing. If individuals are credit-constrained, an increase in credit limit relaxes constraints and allows them to borrow and consume more. We plot the inter-temporal dynamics of credit card usage estimated using equation (4) in Figure 2. The utilization rate immediately decreases by nearly 15 percentage points, then marginally increases and stabilizes at around 7 percentage points lower than the pre-treatment level. Before the credit limit increase, the utilization rate was stable, implying that customers did not increase spending through credit cards before the pre-treatment period.

[Insert Figure 2 here]

Table 4 reports the regression estimates based on our baseline equation (2). Panel A reports the results using the staggered DID specification. Focusing on column 1, we find that the credit utilization rate decreases by 6%. Focusing on column 2, consistent with the inter-temporal dynamics, we find that the average propensity to roll over the credit card debt increases by 7 percentage points, which is a significant increase over the pre-treatment level. Nevertheless, the fraction of individuals who roll over remains economically small. These numbers are in sharp contrast to developed countries like the USA, where approximately 44% of consumers roll over their credit card debt. The results are qualitatively similar using our alternate PSM-DID empirical strategy in Panel B.

[Insert Table 4 here]

Notably, the impulse response estimates reported in Table 2 remain qualitatively and quantitatively similar if we restrict our sample to those cardholders who do not roll over debt both *ex-ante* and *ex-post*. These results are reported in Table A5 of Online Appendix A. In Table A8 of Online Appendix A, we show that the savings accounts decrease by a similar magnitude as the spending increase, further corroborates our argument that the higher spending is not financed by borrowing. Thus, credit limit increases do not stimulate borrowing too much but boost consumption for most individuals in our sample. Moreover, the average credit card utilization rate of 20% before

treatment indicates that users have ample unused credit and are not credit-constrained. Overall, inconsistent with currently binding liquidity constraints, the consumption response is not financed by additional borrowing.

6.2.2 Consumption categories

To further examine whether currently binding liquidity constraints drive the impulse response to credit increase, we decompose the card spending into different categories of expenditure. Based on the Merchant Category Code, we categorize the expenditures through credit and debit cards into durable goods, non-durable goods, services, and discretionary spending, where the first three categories are mutually exclusive. We define the discretionary spending following [Garmaise et al. \(2021\)](#) and define the durable goods and non-durable goods following [Aydin \(2022\)](#).¹² We then re-run the baseline regressions specified in equations (1) and (5) to examine the responses in discretionary spending, non-durable goods, durable goods, and services.

Table 5 reports the results. Among the first three categories, spending on credit and debit cards increases the most for services by ₹2.6 (=2.7-0.1). Discretionary spending increases by ₹5.3 (≈ 5.95 -0.66) or 60% of the total spending increase. Figure 3 shows that the spending increases the most for tourism by more than ₹1.5 for each thousand dollars in limit increase. These results corroborate our conjecture that the consumers do not face liquidity constraints, as we expect the consumers who face tight liquidity constraints such that their demand for necessities is not satisfied should have a higher propensity to borrow for non-discretionary necessities, such as food and grocery, instead of discretionary items, such as tourism.

[Insert Table 5 here] [Insert Figure 3 here]

One concern with the interpretation of these results is that we do not observe the categories of goods purchased in cash. However, we do not expect credit card usage to change the composition of cash spending significantly. Importantly, we do not find an economically meaningful and statistically significant effect of credit limit increase in cash withdrawals. So, the switch from cash to cards cannot completely explain the significant increase in various categories of consumption through credit cards.

¹²Following [Aydin \(2022\)](#), durable goods include apparel, electronics, jewelry, and furniture; non-durable goods include retail/grocery, restaurant, recreation, hobbies, cosmetics and personal care, and stationary; service includes tourism, insurance, and financial services, health care, education, and other services. Following [Garmaise et al. \(2021\)](#), discretionary spending includes automotive expenses, cable services, charitable giving, child expenses, apparel, subscriptions, electronics and jewelry, recreational spending, gifts, hobbies, furniture, home appliances and maintenance, cosmetic and personal care, pets and pet care, restaurant, and tourism.

6.2.3 Heterogeneity in labor income and labor income volatility

Next, we examine the heterogeneity in response based on income normalized by average monthly expenditure. Insofar as MPC is decreasing in income, individuals with high-income inflows relative to their expenses are less likely to feel constrained in their ability to spend as they face both lower liquidity constraints and precautionary motives.

We define an indicator variable 1_{high_i} equal to 1 for the top tercile consumers of average pre-treatment income scaled by average pre-treatment monthly expenditure and equal to 0 otherwise. We interact 1_{high_i} with $1_{after_{it}} * \Delta Limit_i$ to separately estimate the responses of the high-income group and the low-income group. Column 1 of Table 6 reports the results. We find that the consumption response is increasing in income. Specifically, the impulse response is ₹7.5 or 146% ($=7.51/5.16$) higher in the high-income group compared to the low-income group. These results are not consistent with currently binding liquidity constraints, as do our findings on expenditure categories and credit card debt. Instead, precautionary savings or cue triggers may explain the consumption response.

[Insert Table 6 here]

To further examine the effect of the precautionary saving motive on consumer behavior, we employ a proxy for the precautionary saving motive, labor income volatility, and the volatility of spending and assume that the consumers with high income and consumption volatility also have a higher precautionary saving motive (Carroll et al., 2019).

We measure income volatility using the standard deviation of consumer salary divided by the average salary in the five months before the credit limit increase. We use the indicator variable 1_{high_i} to identify the top tercile consumers of *ex-ante* salary volatility. The results are reported in column 2 of Table 6. Inconsistent with the buffer-stock model and in line with behavioral explanations, we find that the impulse response is ₹4.1 or 38% ($=-4.1/10.91$) lower in the high volatility group compared to the low-to-medium volatility group. Specifically, the low-to-medium volatility consumers' monthly MPC out of credit card is 1.09%, while the high volatility consumers' monthly MPC is 0.68% ($=1.09-0.41$).

Similarly, we measure the spending volatility using the standard deviation of total expenditure divided by the average total spending in the five months before the credit limit increase and use 1_{high_i} to identify those in the top tercile of *ex-ante* consumption volatility. The results are reported in column 3. We find that the high volatility group increases spending 59% ($=-6.13/10.29$) less than the low-to-medium volatility group. In summary, these results are not consistent with precautionary saving motives.

6.2.4 Heterogeneity in liquidity buffers

In this section, we utilize cross-sectional variation in *ex-ante* liquidity buffers to further distinguish between liquidity constraints and behavioral reasons that may account for the observed rise in consumption in response to credit limit increases. Specifically, we construct three measures of liquidity constraints: cash holdings in savings accounts, unutilized credit card balances, and cash holdings in savings accounts plus unused credit. We normalize all measures of liquidity constraints by average monthly expenditure (Olafsson and Pagel, 2018) and define an indicator variable 1_{high_i} equal 1 for the consumers that are within the high liquidity tercile, and equal 0 otherwise.¹³ We interact 1_{high_i} with $1_{after_{it}} * \Delta Limit_i$ to separately estimate the responses of the high liquidity group versus the low liquidity group.

Table 7 reports the results. Focusing on column 1, the monthly MPC out of credit is 0.73 percentage points or 138% ($=7.25/5.23$) higher for the consumers in the top tercile of savings balance distribution. The results remain qualitatively similar if we proxy for liquidity buffers using unused credit card balances in column 2. For robustness, in column 3, we repeat the test by combining the two measures of liquidity buffers (savings balance and unused credit card balance). The results remain robust.

[Insert Table 7 here]

The higher impulse response for the high savings balance group is inconsistent with Gross and Souleles (2002) and Aydin (2022). These results are closer to Olafsson and Pagel (2018), who find that impulse response to anticipated income inflows is increasing in liquidity. Along similar lines, using the provision of overdraft facilities, D’Acunto et al. (2020) find that an extensive margin of credit access spurs consumption, especially for those with high *ex-ante* liquid savings. In our context, we document similar household behavior in response to an increase at the intensive margin of credit. Overall, our findings presented above are difficult to rationalize with the commonly used models of rational consumer behavior, such as currently binding liquidity constraints and precautionary motives.

6.3 Cue-triggered Impulse Response

This section presents evidence that suggests that part of the impulse response to credit limit changes may be explained by the cue theory of consumption. We begin by first providing a conceptual framework that helps rationalize our empirical findings.

¹³In Table A6 of Online Appendix A, for robustness, we classify consumers into liquidity terciles based on the amount of liquid savings plus the relatively illiquid term deposits and repeat the tests. The results remain similar qualitatively and quantitatively using the alternate classification.

6.3.1 Conceptual framework

We present a two-period household optimal consumption problem that incorporates the role of *cues* (Laibson, 1997; Pennesi, 2021), specifically credit limit increases, which affect consumption behavior. Formally, the household’s utility function includes a cue component that gets triggered when the credit limit increases, thus increasing the marginal utility of consumption. For instance, prior research shows that status-seeking customers may derive greater prestige from the credit limit increase, thereby causing them to spend more on visible discretionary consumption such as bars, restaurants, and tourism (Bursztyn et al., 2018). Consistent with this idea, Table 5 shows that discretionary spending accounts for 60% of the increase in consumption following credit limit increases, with tourism showing the biggest increase.

This implies that credit limit increases can alter optimal consumption, savings, and borrowing decisions, even for households with ample liquidity. We focus on consumption out of saving in this conceptual framework because, in the empirical results, we find that the increase in credit card debt is marginal, and most of the consumption increase is financed with savings. The same conceptual framework can also rationalize a higher propensity to consume out of income conditional on credit-limit-induced cue triggers, as we demonstrate in Online Appendix B. Detailed proofs are presented step-by-step in Online Appendix B.

Model Setup

We consider a stylized model where households maximize their utility over two periods, incorporating the role of cues that are functions of the credit limit. Period 0 is the current period, and period 1 is the future period. The household maximizes lifetime utility, which includes both standard consumption utility and additional utility derived from cues dependent on the credit limit.

Utility function:

$$U = u(c_0) + \beta u(c_1) + \gamma S_0(L_0)v(c_0) \quad (7)$$

where:

- $u(c_t) = \ln(c_t)$: Standard utility from consumption in period t .
- $v(c_t) = \ln(c_t)$: Additional utility from consumption when a cue is present.
- β : Time preference discount factor ($0 < \beta < 1$).
- γ : Sensitivity to cues ($\gamma \geq 0$).
- $S_0(L_0)$: Cue function dependent on the credit limit L_0 .

The cue function, $S_0(L_0)$, is defined below:

$$S_0(L_0) = \phi(L_0 - L_{-1}) = \begin{cases} 1, & \text{if } L_0 > L_{-1} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Budget constraints are defined below:

$$A_1 = A_0(1 + r) + y_0 - c_0 \quad (9)$$

$$A_2 = A_1(1 + r) + y_1 - c_1 \quad (10)$$

$$A_2 \geq 0 \quad (\text{Terminal condition}) \quad (11)$$

$$A_t \geq -L_t \quad (\text{Borrowing constraint}) \quad (12)$$

where:

- A_t : Assets at the beginning of period t .
- y_t : Income in period t .
- c_t : Consumption in period t .
- r : Interest rate.
- L_t : Credit limit in period t .

The consumers maximize the utility, subject to the above budget constraints.

The marginal propensity to consume (MPC) out of saving is:

$$\frac{\partial c_0}{\partial A_0} = \frac{(1 + \gamma S_0)(1 + r)}{(1 + \gamma S_0) + \beta} \quad (13)$$

When $S_0 = 0$, MPC without the cue effect (MPC_0) is:

$$\frac{\partial c_0}{\partial A_0} = \frac{1 + r}{1 + \beta} \quad (14)$$

When $S_0 = 1$, MPC with the cue effect (MPC_1) is:

$$\frac{\partial c_0}{\partial A_0} = \frac{(1 + \gamma)(1 + r)}{1 + \gamma + \beta} \quad (15)$$

Note that $\frac{(1+\gamma)(1+r)}{1+\gamma+\beta} > \frac{1+r}{1+\beta}$, which implies the MPC with the cue effect is larger than the MPC without the cue effect. Similarly, MPC out of income is higher with cues. Figure 4 visualizes the consumption level at different levels of initial savings, including \$0, \$500, and \$1,000, with and without the cue effect. The figure shows that consumption increases with initial savings, both with and without the cue effect caused by the credit limit increase. The gap between the two lines represents the additional consumption induced by the cue. The gap widens as initial savings increase, indicating that households with more savings respond more strongly to the cue. Next, using a few proxies, we empirically examine whether the cue theory can explain the consumption response to credit limit changes.

[Insert Figure 4 here]

6.3.2 Payday as cues

Recent research documents significant spending responses on paydays of perfectly predictable regular income (Addoum et al., 2015; Olafsson and Pagel, 2018) despite no change in permanent income on paydays. This behavior manifests when positive income shock and consumption are complementary goods. The income flow may act as a cue that triggers higher utility for consumption (Laibson, 2001). Similarly, the higher credit limits may also trigger the feeling of having the “license to spend” and consequently increase the inclination to consume. Building on Olafsson and Pagel (2018), we conjecture that the same underlying psychological characteristics may drive spending responses to paydays and credit limit increases.

Following this rationale, we sort individuals based on the fraction of the salary consumed within 5 days following payday¹⁴. We define an indicator variable, $1_{\text{payday_reponse}}$, which equals one if the average ratio of salary spent in the first 5 days after the payday is more than 17% (=5/30 days). We interact $1_{\text{payday_reponse}}$ with $1_{\text{after}_{it}} * \Delta \text{Limit}_i$ and $1_{\text{during}_{it}} * \Delta \text{Limit}_i$ to estimate the heterogeneous effect of limit increases by the tendency to respond to payday cues. These results are reported in columns 1 to 2 in Table 8.

[Insert Table 8 here]

Consistent with our thesis, individuals with a higher propensity to consume around paydays also exhibit a more pronounced response to increased credit limits. Their monthly MPC is 0.2 percentage points higher than that of individuals with lower response around paydays in the month of the limit increase and 0.8 percentage points higher over the subsequent 24 months, indicating stronger habit formation for these individuals. These results point to the role of cues and dynamics of self-control in the consumption behavior of individuals. In Table A12, we repeat the analysis in Table 8 and split the consumers based on their *ex-ante* saving balance as a proxy for liquidity.

¹⁴We repeat the test using 3 and 7 days as the threshold. The results are similar.

The result shows that liquidity is not a confounding factor, and for consumers with similar levels of liquidity, the response is still higher for those who have a stronger response around paydays.

6.3.3 Credit card statements as cues

Other than receiving the salary, a credit card statement, which highlights the available credit limit and is sent to the customers by email and/or SMS at the end of each billing cycle, may also act as a cue that triggers spending.

In Table 8, we examine consumption response during credit card statement week. Recall that most customers have abundant unused credit limits and liquid savings in our sample. Thus, rather than reminding consumers of their credit card debt, the credit card statements may serve as cues that make the credit limit salient.

In these tests, we structure the credit card and debit card expenditure into event-weeks before or after each credit card statement. We define a variable $1_{statement_week}$ that equals one for the first event week after a credit card statement. $1_{after_{iw}}$ equals to one if an event week is after a credit limit increase.

Columns 3-4 in Table 8 report the results. First, in column 3, we examine the cue effect on the total spending on card, which is the summation of credit card and debit card transactions. We exclude cash withdrawal because most customers withdraw cash on a monthly basis. Because our baseline results show that the cash spending is not affected, we do not expect cash spending to change here. We find a significant spending response on cards in the statement week, indicating a cue-triggered response. In the statement week, the total card spending increased by nearly ₹800 more than in later event weeks, suggesting that the statements act as cues that trigger spending. Consistent with the baseline results, $1_{after_{iw}} * \Delta Limit_i$ has a positive coefficient. Further, we also find a positive and statistically significant coefficient on the interaction term, $1_{statement_week} * 1_{after_{iw}} * \Delta Limit_i$. The positive coefficient suggests that the effect of a higher credit limit is stronger in the week immediately after a statement than other weeks and that the statements that include information on the higher credit limit may amplify the effect of credit limit increases by 46% ($=0.38/0.83$). Note that the statement is sent in every billing cycle. Hence, credit limit changes can have a long-term effect on consumption behavior by triggering consumption every time the customer receives a statement. We find similar cue-triggered effect on credit card spending, reported in column 4.

To further strengthen our argument that statements may draw attention to the credit limit increase and limit increases followed by a statement may serve as a stronger cue, we show that the credit limit increases followed by cues have stronger effect on spending. We categorize all credit limit increases based on whether a statement is issued subsequently and examine whether the consumption response is differentially higher in such cases using our baseline empirical setup – equation (1). Specifically, we re-run our baseline regression as specified in equation (1), in-

incorporating an indicator variable, $1_{statement_follow_i}$, which is interacted with $1_{after_{it}} * \Delta Limit_i$ and $1_{during_{it}} * \Delta Limit_i$. The variable $1_{statement_follow_i}$ equals one if a statement is issued within 5 days after the limit increase.¹⁵ These results, reported in Table A7, suggest that limit increases followed by statements have an MPC through the credit card that is 50%(=1.78/3.57) higher in the month of the limit increase and 52%(=4.33/8.39) higher over the subsequent 24 months, with the latter being significant at 10% level. In unreported robustness test, we show that the loan repayment is not significantly higher after receiving the statements, suggesting that the statements do not affect consumption by incurring more debt. These results are consistent with our thesis that credit limit increases likely stimulate consumption through a cue-trigger effect.

6.4 Credit Limit Changes Signal Income Prospects?

One alternate explanation for the consumption response is that credit limit changes contain information regarding expected future income (Yin, 2022). While credit limit increases do not affect permanent income, they may change people’s expectations of future income, causing them to consume more. However, Table 1 shows no increase in monthly salary before or after the credit limit increase. Further, for robustness, we exploit the predictions of the standard life-cycle model on labor income and risky asset ownership. Insofar as labor income is a substitute for bonds, an expected increase in income should increase ownership of risky assets (Gomes et al., 2021). Using detailed Swedish registry data, Calvet and Sodini (2014) document that expected labor income is positively correlated with financial risk-taking, as measured by equity market investments. Thus, equity investments should increase if credit limit increases indicate positive income prospects. Table A9 investigates the impact of credit limit changes on cardholder investments in mutual funds and stocks. In contrast to credit limits affecting beliefs regarding expected labor income, mutual funds and equity investments do not increase significantly after credit limit increases. Thus, the increase in consumption response is not driven by any contemporaneous or expected increase in income.

[Insert Table A9 here]

6.5 Robustness Tests

Since we observe data from just one bank for each individual in our sample, one concern regarding our analysis is that our findings may be driven by the substitution of expenditure from other credit cards (“unobservable”) to the one with the credit limit increase. For instance, an increase in the credit limit on a certain card may make it more salient, increasing the usage of the card. Thus, our results may be accounted for by a substitution involving credit cards issued by various institutions. This concern is partially alleviated by our emphasis on salary accounts, which are more likely to

¹⁵For robustness, we also repeat these tests with 3-day and 7-day windows after the limit increase.

serve as the primary account (Loos et al., 2020). Moreover, the monthly expenditure of the average individual in our sample is approximately ₹33,500, which is 88% of the average monthly salary of ₹38,000. Thus, it is unlikely that individuals in our sample use an alternate account as the primary one for their consumption. Nonetheless, we perform a battery of robustness tests to address the issue of substitution among credit cards issued by different banks.

6.5.1 Savings response

First, we look at the savings reaction because savings are income minus consumption, and there is no reason to expect savings to be transferred across bank accounts in response to a credit limit rise. Table A8 shows the saving responses. On average, consumers save ₹6.5 ($=6.18+0.36$) less for every additional thousand rupees of credit limit increase, or 7.8 cents for every \$1 of limit increase in 12 months after limit increase. Change in savings balance accounts for most of the reduction in saving growth, falling on average by ₹6.2 per month for every additional thousand rupees of limit increase. The decrease in saving is marginally lower but comparable to the increase in spending as reported in Table 2.

6.5.2 High expenditure accounts

Next, we repeat our tests with the subsample of consumers with above pre-treatment median monthly expenditure in our sample. The underlying premise is that the bank accounts in our sample are likely to be the primary account for individuals with high *ex-ante* expenditures. The results are reported in Table A10 of Online Appendix A. Our findings remain robust if we restrict attention to the sample of customers with above median pre-treatment monthly expenditure.

6.5.3 Marital status of clients

A related concern is the possibility of substitution of spending across bank accounts of different members within the same household. For example, after the credit limit increases, couples may use the higher limit credit card for daily expenditure, so we will naturally observe that consumption through this account increases. To address this concern, we repeat our tests with the subsample of married and single individuals. The underlying idea is that single individuals are unlikely to shift their expenditures to and from the cards of other family members. The results are reported in Table A11. Reassuringly, we find that the increase in spending is of similar magnitude for single and married customers. These results alleviate the concern that the documented treatment effects are driven by the substitution of expenditure across credit cards.

7 Conclusion

This study uses a unique bank-account-level proprietary panel dataset with detailed information on credit card spending, debit card spending, cash withdrawals, savings, term deposits, and income for a representative sample of consumers from a leading Indian bank to investigate the determinants of consumers’ responses to credit expansion. We document significant and persistent responses to credit limit increases and find that the most liquid consumers and those facing lower uncertainty increase their spending the most. Our results are inconsistent with the explanations of liquidity constraints or precautionary saving motives.

Our results are also unlikely to be explained by myopic behavior or consumption-binging ([Garber et al., 2024](#)) because consumers in our sample do not appear to borrow beyond their means to finance their consumption. Furthermore, individuals retain enough liquidity buffers, indicating that they are forward-looking. Collectively, the low utilization and high cash holdings indicate that Indian consumers are more careful or debt-averse. Rather, our findings imply that individuals engage in heuristic behavior, with credit limit fluctuations serving as cues that stimulate a consumption reaction. The documented behavior is consistent with recent research on the behavior of license-to-spend individuals ([Addoum et al., 2015](#); [Olafsson and Pagel, 2018](#)). In our case, an increase in credit limit may act as cues that increase an individual’s marginal utility of consumption, prompting them to spend. A simple conceptual framework that explicitly incorporates cues in an individual’s utility function is able to rationalize our empirical findings.

More research is required to determine if such impulse responses boost or reduce consumer welfare. Our findings also offer a potential explanation for why banks periodically raise credit limits for unconstrained individuals. Such limits serve as cues, causing them to spend more. Even if the additional consumption is not financed by increased borrowing, banks profit from the interchange fees generated by such expenditures.

Our work also emphasizes the importance of new research in household finance focusing on developing economies, as the insights based on research on the developed world may not necessarily generalize to the rest of the world. Our findings suggest that individuals in India are prudent in their savings and borrower behavior. Thus, a common concern among policymakers regarding “overborrowing” and “overconsumption” by financially unsophisticated borrowers in response to increased credit access may not be applicable in developing economies. Rather, policies that expand credit access can significantly boost consumption and improve welfare without increasing default risk or indebtedness.

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Figure 1: Dynamics of Spending Response

This figure plots the cumulative MPC, $b_k = \sum_{j=-5}^k \beta_j$, where β_j is estimated with the event study model specified below:

$$Y_{it} = \sum_{j=-5}^{24} \beta_j 1_{month_{ij}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

Panel A is estimated using the consumers that experienced the credit limit increase. The dark lines in Panel B are estimated using the consumers that experienced the limit increase and are matched to a consumer from the control group. The grey lines in Panel B are estimated with the consumers from the matched control group. The dashed lines are the 95% confidence intervals. The dependent variables include total spending, debit card spending, credit card spending, and cash withdrawal, each labeled at the top of the figures. The x-axis denotes the event months from T-5 to T+24, where event month T=0 denotes the month of credit limit increase. Event month T-1 is the omitted reference group.

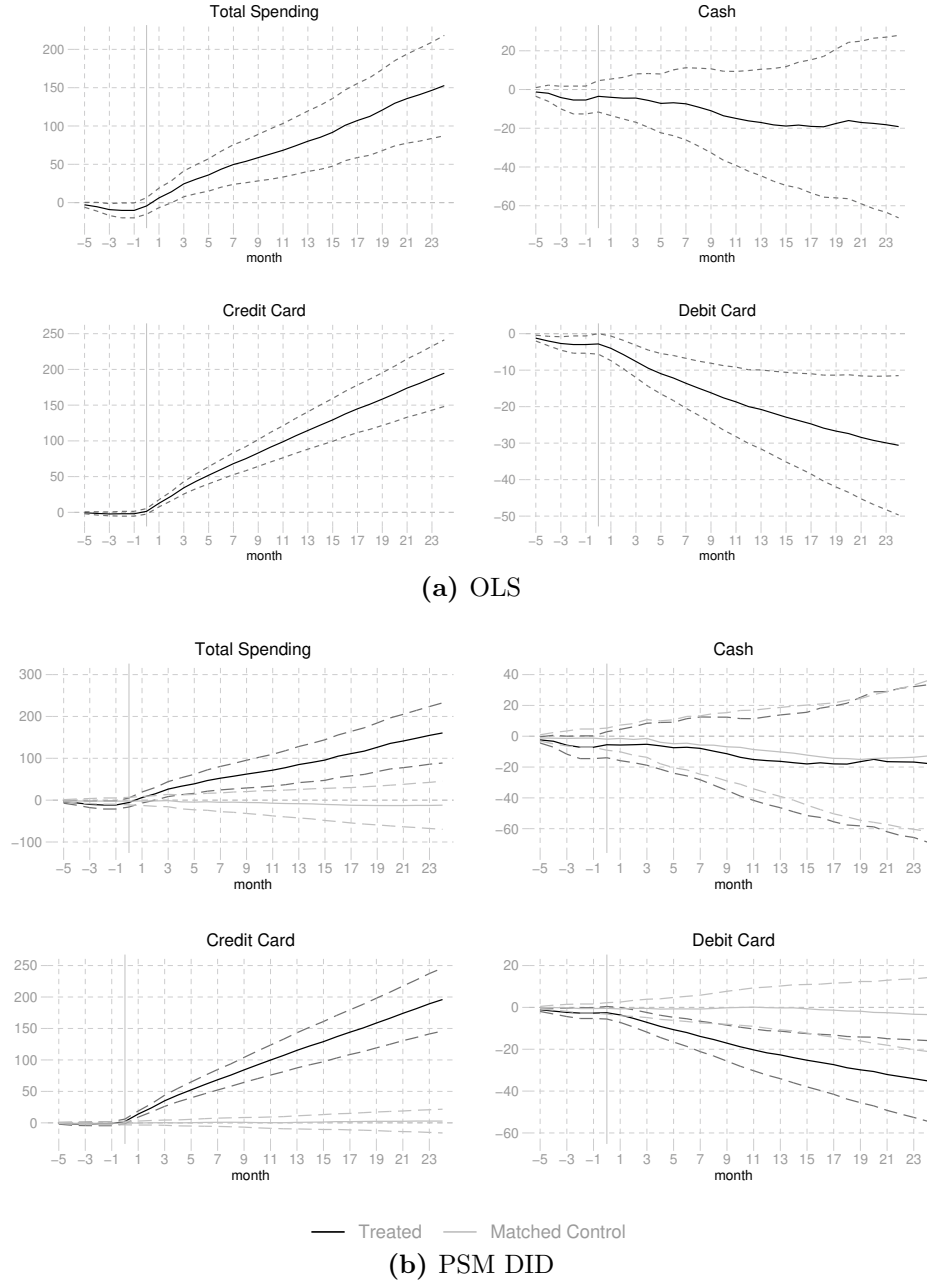


Figure 2: Dynamics of Credit Card Usage

This figure plots the coefficients β^j estimated with the event study model specified below:

$$Y_{it} = \sum_{j=-5}^{24} \beta^j 1_{month_{ij}} + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

Panel A is estimated using the consumers that experienced the credit limit increase. The dark lines in Panel B are estimated using the consumers that experienced the limit increase and are matched to a consumer from the control group. The grey lines in Panel B are estimated with the consumers from the matched control group. The dashed lines are the 95% confidence intervals. The dependent variables include the credit card utilization rate and the indicator variable identifying if the credit card balance at the end of the billing cycle is not paid in full ($1_{revolve}$), each labeled on the top of the figures. The x-axis denotes the event months from T-5 to T+24, where event month T=0 denotes the month of credit limit increase. Event month T-1 is the omitted reference group.

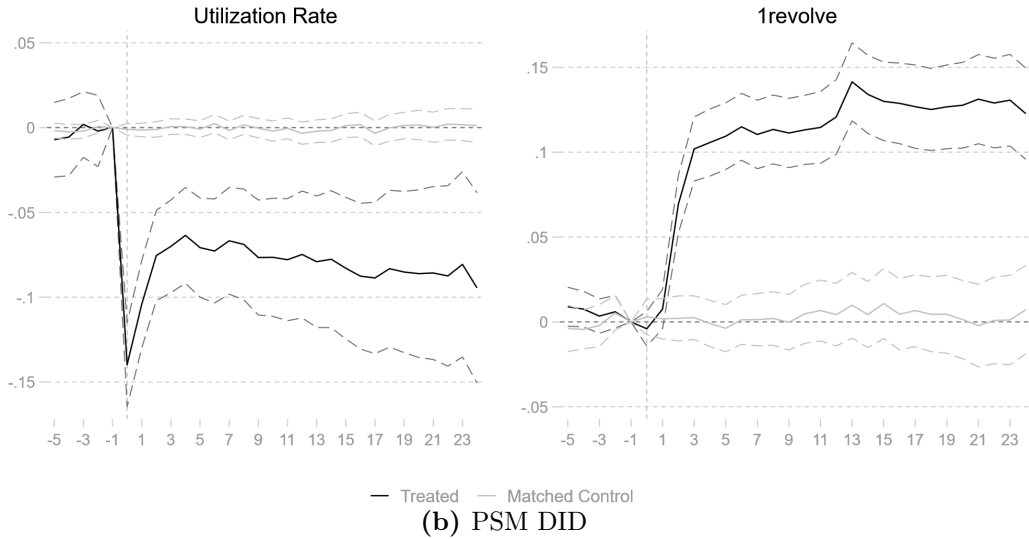
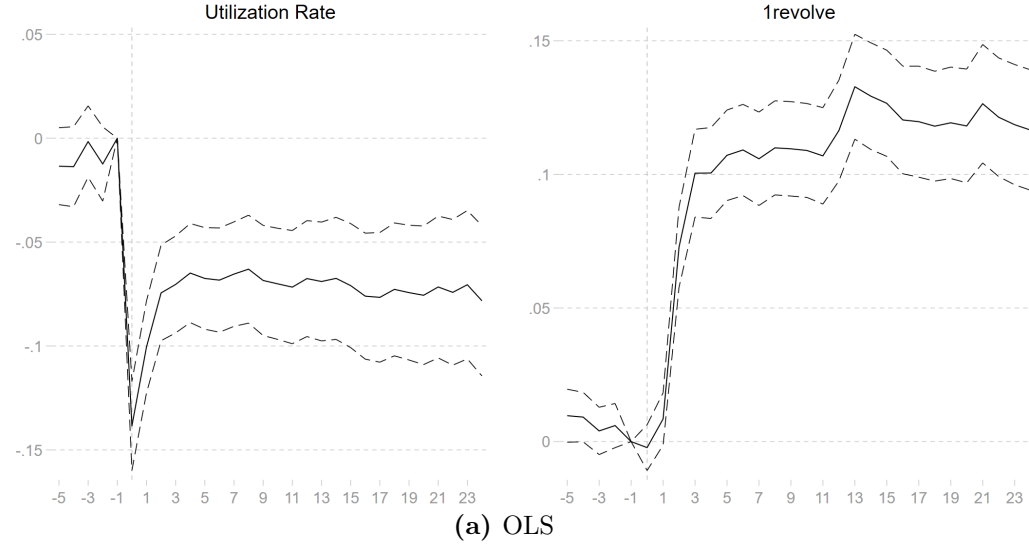


Figure 3: Card Spending Response by Merchant Categories

This figure plots the marginal response of credit card and debit card spending by merchant category. The estimates are based on the following regression specification:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i + \beta_2 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

For each merchant category, we run a separate regression to estimate the spending response. The coefficients reported represent β_1 , where $1_{after_{it}}$ is equal to one for the months T+1 to T+24, and $1_{during_{it}}$ is equal to one for the month of credit line increases. $\Delta Limit_i$ is the magnitude of the credit limit increase in ₹1,000. The vertical lines indicate 95% confidence intervals of the point estimates.

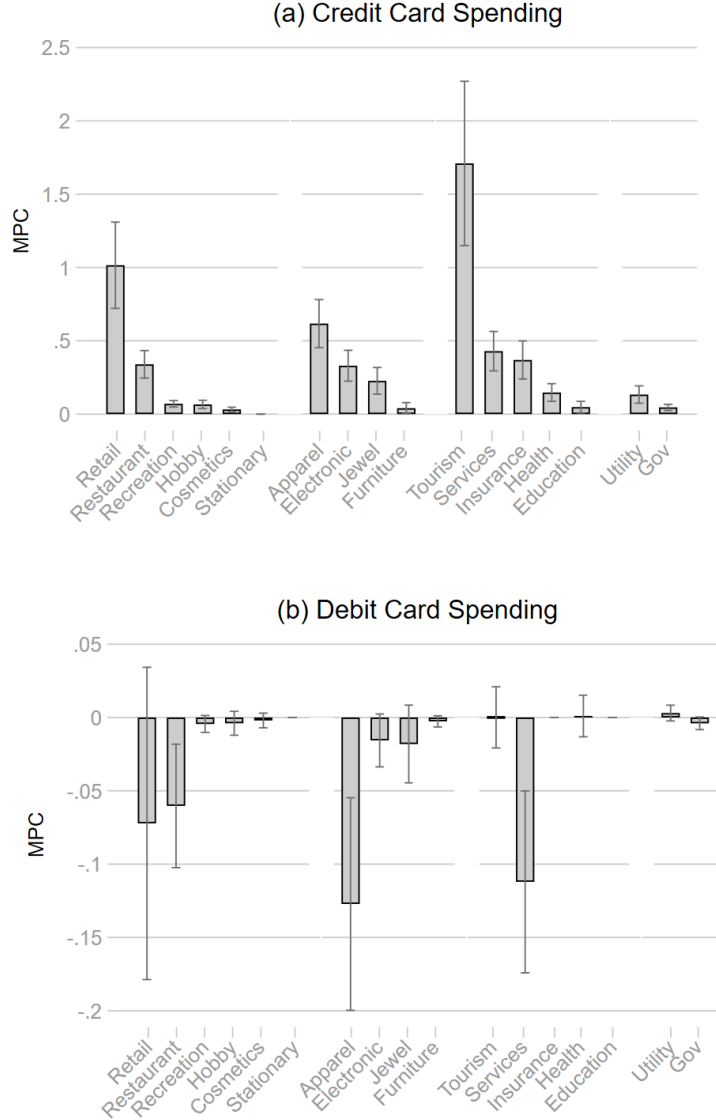


Figure 4: Consumption Response to Credit Limit Changes at Different Levels of Initial Savings

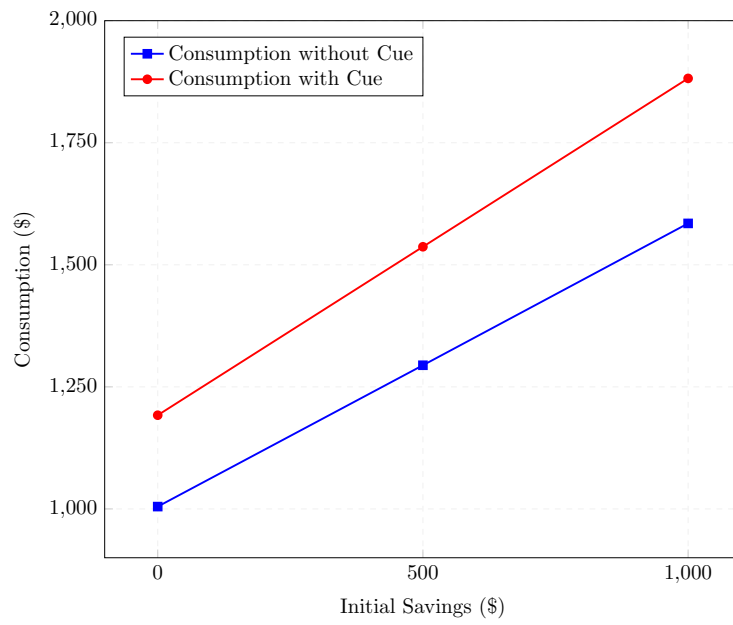


Table 1: Summary Statistics

The table summarizes the data. Panel A reports the demographic information of the clients and the basic account information. Panel B summarizes the credit limit changes. Panel C summarizes the spending variables, including total spending and expenditures, through the three payment methods: credit card, debit card, and cash. Panel D summarizes the credit card usage and liquid asset holding, including utilization rate and the indicator variable of revolving credit card debt ($1_{revolve}$), saving, and term deposit.

| Variables | (1) N | (2) Mean | (3) Std. Dev. | (4) p25 | (5) Median | (6) p75 |
|---|----------|-------------|------------------|------------|---------------|------------|
| <i>Panel A: Demographic Information</i> | | | | | | |
| Age | 1,838 | 39.46 | 7.69 | 34.00 | 38.00 | 43.00 |
| Salary | 1,843 | 42,357.26 | 48,081.78 | 0.00 | 23,721.17 | 59,154.48 |
| Male | 1,843 | 0.88 | 0.33 | 1.00 | 1.00 | 1.00 |
| Married | 1,843 | 0.58 | 0.49 | 0.00 | 1.00 | 1.00 |
| Have Saving Account | 1,843 | 1.00 | 0.02 | 1.00 | 1.00 | 1.00 |
| Have Term Deposit | 1,843 | 0.54 | 0.50 | 0.00 | 1.00 | 1.00 |
| Have Mutual Fund | 1,843 | 0.24 | 0.43 | 0.00 | 0.00 | 0.00 |
| Have Equity | 1,843 | 0.39 | 0.49 | 0.00 | 0.00 | 1.00 |
| Salary, Before | 10,461 | 38,255.43 | 59,439.06 | 0.00 | 17,713.00 | 57,586.00 |
| Salary, After | 42,207 | 38,404.74 | 65,086.73 | 0.00 | 0.00 | 58,988.00 |
| <i>Panel B: Credit Limit (₹1,000)</i> | | | | | | |
| Magnitude of Limit Increases | 1,843 | 424.54 | 499.45 | 162.00 | 288.00 | 506.00 |
| Limit Before Increases | 1,843 | 105.93 | 160.54 | 30.00 | 60.00 | 125.40 |
| Limit After Increases | 1,843 | 530.47 | 534.19 | 240.00 | 390.00 | 625.00 |
| <i>Panel C: Spending</i> | | | | | | |
| Total Spending, Before | 10,461 | 33,203.47 | 36,743.65 | 8,207.50 | 22,685.84 | 45,489.00 |
| Total Spending, After | 42,207 | 38,027.68 | 40,178.13 | 10,416.00 | 26,357.44 | 51,624.00 |
| Cash Withdrawal, Before | 10,461 | 23,096.30 | 28,312.57 | 3,000.00 | 14,600.00 | 31,197.49 |
| Cash Withdrawal, After | 42,207 | 20,993.82 | 27,453.61 | 1,100.00 | 12,000.00 | 29,000.00 |
| Credit Card Spending, Before | 10,461 | 5,071.98 | 13,380.71 | 0 | 0 | 3,155.00 |
| Credit Card Spending, After | 42,207 | 12,813.84 | 20,879.18 | 0 | 4,259.00 | 16,719.00 |
| Debit Card Spending, Before | 10,461 | 4,380.58 | 10,037.29 | 0 | 0 | 3,551.00 |
| Debit Card Spending, After | 42,207 | 3,529.68 | 8,998.46 | 0 | 0 | 2,350.00 |
| <i>Panel D: Balance Sheet</i> | | | | | | |
| Saving Balance | 52,668 | 138,576.00 | 265,473.00 | 17,763.00 | 55,733.00 | 139,991.00 |
| Term Deposit Balance | 52,668 | 103,922.00 | 325,345.00 | 0 | 0 | 50,000.00 |
| Δ Saving, Before | 10,312 | 3,958.40 | 117,057.00 | -16,634.57 | 0.93 | 20,247.95 |
| Δ Saving, After | 42,207 | -160.10 | 115,926.60 | -19,603.20 | 0 | 19,392.23 |
| Δ Term Deposit, Before | 10,281 | 2,062.17 | 32,619.71 | 0 | 0 | 0 |
| Δ Term Deposit, After | 42,207 | 831.13 | 32,701.30 | 0 | 0 | 0 |
| Utilization Rate, Before | 10,461 | 0.20 | 1.22 | 0 | 0 | 0.04 |
| Utilization Rate, After | 42,207 | 0.13 | 0.24 | 0 | 0.04 | 0.15 |
| $1_{revolver}$, Before | 10,461 | 0.03 | 0.18 | 0 | 0 | 0 |
| $1_{revolver}$, After | 42,207 | 0.15 | 0.35 | 0 | 0 | 0 |

Table 2: Consumption Response

This table reports the spending response to the automatic credit limit increases. Formally, the coefficient estimates in Panel A are from the estimation of equation (1), and the coefficients in Panel B are from the estimation of equation (5).

The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. The indicator variable $1_{treated_{it}}$ is a binary variable that equals one for the treated group and zero for the matched control group. $\Delta Limit_i$ is the magnitude of the credit limit increase in ₹1,000. The dependent variables include total spending (column 1), credit card spending (column 2), debit card spending (column 3), and cash withdrawal (column 4). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|--|-----------------------|--------------------|--------------------|------------------------|
| <i>Panel A: Staggered DID</i> | | | | |
| $1_{after_{it}} * \Delta Limit_i$ | 8.79*** (1.22) | 9.04*** (1.00) | -0.78*** (0.28) | 0.28 (0.66) |
| $1_{during_{it}} * \Delta Limit_i$ | 7.83*** (1.44) | 3.85*** (0.80) | 0.71** (0.34) | 2.96*** (0.98) |
| Observations | 52,668 | 52,668 | 52,668 | 52,668 |
| R-squared | 0.37 | 0.32 | 0.38 | 0.39 |
| Num Consumer | 1,843 | 1,843 | 1,843 | 1,843 |
| Mean DV | 37,616.24 | 4,027.54 | 11,539.57 | 22,049.13 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |
| <i>Panel B: PSM DID</i> | | | | |
| $1_{after_{it}} * 1_{treated_i} * \Delta Limit_i$ | 7.98*** (1.29) | 9.36*** (0.99) | -1.59*** (0.32) | -0.46 (0.84) |
| $1_{during_{it}} * 1_{treated_i} * \Delta Limit_i$ | 7.67*** (1.82) | 3.58*** (0.89) | 0.33 (0.44) | 2.99** (1.28) |
| Observations | 83,734 | 83,734 | 83,734 | 83,734 |
| R-squared | 0.40 | 0.41 | 0.38 | 0.39 |
| Num Consumer | 2,767 | 2,767 | 2,767 | 2,767 |
| Mean DV | 33717.36 | 3602.1 | 8248.8 | 21098.66 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Table 3: Cumulative Response Estimates

This table reports the cumulative changes in monthly spending based on the following regression specifications:

$$Y_{it} = \sum_{j=-5}^{24} \beta^j 1_{month_{ij}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

The coefficients β^j ($j \in [0, 24]$) capture the response of the dependent variables in the month of limit changes ($j = 0$) and each of the 24 months after. Similarly, the coefficients β^j ($j \in [-5, -1]$) capture the trend in the dependent variables in the five pre-treatment months. Event month $T = -1$ is the omitted reference group. The coefficient $b_k = \sum_{j=1}^k \beta^j$ captures the marginal spending response for every ₹1000 increase in credit limit aggregated over k months ($k \in [1, 24]$) after the line increase. For example, $b_{12} = \sum_{j=1}^{12} \beta^j$ measures the cumulative response of the dependent variables over the 12 months following the credit limit increase. The dependent variables are labeled at the top of each column. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|---|-----------------------|----------------------|----------------------|------------------------|
| <i>Panel A: Staggered DID (per ₹1,000 Limit Change)</i> | | | | |
| b_6 | 47.90*** (8.25) | 58.58*** (6.09) | -9.34*** (1.96) | -3.32 (5.35) |
| b_{12} | 78.45*** (15.52) | 105.54*** (11.63) | -17.17*** (4.09) | -12.68 (10.05) |
| b_{24} | 157.11*** (30.20) | 193.33*** (23.09) | -27.78*** (8.84) | -15.65 (21.05) |
| <i>Panel B: PSM DID (per ₹1,000 Limit Change)</i> | | | | |
| b_6 | 49.89*** (11.19) | 58.94*** (6.70) | -10.67*** (2.77) | -2.77 (8.29) |
| b_{12} | 78.47*** (20.56) | 110.23*** (12.49) | -24.06*** (5.70) | -12.99 (15.37) |
| b_{24} | 149.68*** (39.07) | 215.29*** (24.39) | -45.21*** (11.51) | -33.28 (30.45) |

Table 4: Credit Card Usage

This table reports the response of credit card usage to the automatic credit limit increases. Formally, the coefficient estimates reported in Panel A are from the estimation of equation (2), and the coefficients reported in Panel B are from the estimation of equation (6).

The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. The indicator variable $1_{treated_{it}}$ is a binary variable that equals one for the treated group and zero for the matched control group. The dependent variables include the credit card utilization rate (column 1) and the indicator variable of revolving credit card debt (column 2). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Utilization Rate | (2) $1_{revolve}$ |
|-----------------------------------|-------------------------|----------------------|
| <i>Panel A: OLS</i> | | |
| $1_{after_{it}}$ | -0.06*** (0.01) | 0.07*** (0.01) |
| $1_{during_{it}}$ | -0.13*** (0.01) | -0.01*** (0.00) |
| Observations | 52,668 | 52,668 |
| R-square | 0.42 | 0.46 |
| Mean DV | 0.13 | 0.12 |
| YM FE | Y | Y |
| Customer FE | Y | Y |
| <i>Panel B: PSM DID</i> | | |
| $1_{after_{it}} * 1_{treated_i}$ | -0.03*** (0.01) | 0.11** (0.01) |
| $1_{during_{it}} * 1_{treated_i}$ | -0.13*** (0.01) | -0.01* (0.01) |
| Observations | 83,734 | 83,734 |
| R-square | 0.44 | 0.53 |
| Mean DV | 0.10 | 0.12 |
| YM FE | Y | Y |
| Customer FE | Y | Y |

Table 5: Heterogeneity in Consumption Response by Salary and Degree of Uncertainty

The table reports the spending response after the automatic credit limit increases by the categories of goods consumed. Based on the Merchant Category Code, we categorize the transactions through credit cards and debit cards into durable goods, non-durable goods, service, and discretionary spending. Durable goods include furniture and home appliances, apparel, electronics, and jewelry. Non-durable goods include retail, hobbies, restaurants, cosmetic and personal care, recreational spending, and stationery. Services include insurance and finance, tourism, health care, education, and other services. Discretionary spending includes automotive expenses, cable services, charitable giving, child expenses, apparel, subscriptions, electronics and jewelry, recreational spending, gifts, hobbies, furniture, home appliances and maintenance, cosmetic and personal care, pets and pet care, restaurants, and tourism. We re-run the baseline regression specified in equations (1) and (5) for each of the four categories of the goods consumed by the payment method.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. Columns 1-4 (5-8) report the results for credit card (debit card) transactions. The dependent variables in columns 1 and 5 represent the expenditure on durable goods through credit cards and debit cards, respectively. The dependent variables in columns 2 and 6 are the expenditure on nondurable goods through the two payment methods. The dependent variables in columns 3 and 7 are the expenditure on services, and in columns 4 and 8 are the discretionary spending through the two payment methods. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|-------------------|-------------------|-------------------|-------------------|--------------------|--------------------|--------------------|--------------------|
| | Credit Card | | | | Debit Card | | | |
| | Durable | Nondurable | Service | Discretionary | Durable | Nondurable | Service | Discretionary |
| <i>Panel A Staggered DID</i> | | | | | | | | |
| $1_{after_{it}} * \Delta Limit_i$ | 1.22*** (0.16) | 1.52*** (0.20) | 2.70*** (0.37) | 5.95*** (0.78) | -0.16*** (0.05) | -0.14** (0.07) | -0.11*** (0.04) | -0.66*** (0.23) |
| $1_{during_{it}} * \Delta Limit_i$ | 0.61*** (0.15) | 0.28*** (0.11) | 0.79*** (0.28) | 2.46*** (0.73) | 0.01 (0.06) | 0.16* (0.09) | 0.14** (0.07) | 0.65 (0.40) |
| Observations | 52,668 | 52,668 | 52,668 | 52,668 | 52,668 | 52,668 | 52,668 | 52,668 |
| R-squared | 0.19 | 0.34 | 0.27 | 0.22 | 0.26 | 0.47 | 0.28 | 0.21 |
| Mean DV | 1,734.74 | 2,191.36 | 3,376.81 | 6,388.8 | 537.51 | 890 | 471.51 | 2,146.44 |
| YM FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y | Y | Y | Y | Y |
| <i>Panel B PSM DID</i> | | | | | | | | |
| $1_{after_{it}} * \Delta Limit_i * 1_{treated_i}$ | 0.64*** (0.20) | 0.98*** (0.25) | 1.60*** (0.28) | 2.76*** (0.69) | -0.13*** (0.04) | -0.18*** (0.07) | -0.09** (0.04) | -0.42*** (0.12) |
| $1_{during_{it}} * \Delta Limit_i * 1_{treated_i}$ | 0.09 (0.20) | -0.11 (0.19) | 0.23 (0.25) | 0.11 (0.61) | 0.02 (0.07) | 0.12 (0.08) | 0.13** (0.05) | 0.25 (0.16) |
| Observations | 83,734 | 83,734 | 83,734 | 83,734 | 83,734 | 83,734 | 83,734 | 83,734 |
| R-squared | 0.25 | 0.42 | 0.34 | 0.37 | 0.26 | 0.46 | 0.30 | 0.38 |
| Mean DV | 959.43 | 1355.52 | 1904.35 | 3589.3 | 407.03 | 755.71 | 387.27 | 1266.43 |
| YM FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y | Y | Y | Y | Y |

Table 6: Heterogeneity in Consumption Response by Salary and Degree of Uncertainty

This table examines the heterogeneity in spending response to the automatic credit line increase based on salary and proxies for uncertainty. We run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{high_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{high_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where 1_{high_i} is an indicator variable equal to one for the top tercile of consumers divided by the following measurements: monthly salary divided by the expenditure in the five months before the limit change (column 1), salary volatility measured by the ratio of standard deviation to the mean of salary in the five months before the limit change (column 2) and spending volatility measured by the ratio of standard deviation to the mean of spending in the five months before the limit change (column 3), and 0 otherwise.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variable is total spending. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) | (2) | (3) |
|---|-------------------|--------------------|---------------------|
| | Total Spending | | |
| 1_{high_i} indicates | Salary | Salary Volatility | Spending Volatility |
| $1_{high_i} * 1_{after_{it}} * \Delta Limit_i$ | 7.51*** (2.27) | -4.10** (2.04) | -6.13** (2.44) |
| $1_{high_i} * 1_{during_{it}} * \Delta Limit_i$ | 5.29* (2.79) | -3.91 (2.76) | -3.73 (3.19) |
| $1_{after_{it}} * \Delta Limit_i$ | 5.16*** (1.41) | 10.91*** (1.55) | 10.29*** (1.41) |
| $1_{during_{it}} * \Delta Limit_i$ | 5.62*** (2.00) | 9.93*** (1.90) | 8.76*** (1.65) |
| Observations | 50,411 | 51,209 | 52,668 |
| R-squared | 0.37 | 0.38 | 0.37 |
| Mean DV | 37,976.81 | 37,151.92 | 37,616.24 |
| YM FE | Y | Y | Y |
| Customer FE | Y | Y | Y |

Table 7: Heterogeneity in Consumption Response by *Ex-ante* Liquidity Buffers

This table examines the heterogeneity in spending response to the automatic credit line increase based on measurements of liquidity. We run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{high_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{high_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where 1_{high_i} is an indicator variable equal to one for the top tercile of consumers divided by the following measurements: cash holdings in a savings account (column 1), unutilized credit card balance (column 2), cash holdings in savings account plus unused credit (column 3). All liquidity measures are scaled by average *ex-ante* monthly expenditure.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variable in these tests is total spending. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) | (2) | (3) |
|---|-------------------|-------------------|---------------------------------|
| | Total Spending | | |
| 1_{high_i} indicates | Savings Balance | Unused Credit | Savings Balance + Unused Credit |
| $1_{high_i} * 1_{after_{it}} * \Delta Limit_i$ | 7.25*** (2.21) | 9.05*** (2.25) | 8.71*** (2.21) |
| $1_{high_i} * 1_{during_{it}} * \Delta Limit_i$ | 1.64 (2.74) | 9.76*** (2.92) | 5.65** (2.80) |
| $1_{after_{it}} * \Delta Limit_i$ | 5.23*** (1.45) | 4.65*** (1.37) | 4.35*** (1.47) |
| $1_{during_{it}} * \Delta Limit_i$ | 7.15*** (2.14) | 3.84** (1.69) | 5.28** (2.06) |
| Observations | 50,411 | 50,411 | 50,411 |
| R-squared | 0.37 | 0.37 | 0.37 |
| Mean DV | 37,058.28 | 37,058.28 | 37,058.28 |
| YM FE | Y | Y | Y |
| Customer FE | Y | Y | Y |

Table 8: Salary and Credit Card Statements as Cues

This table reports the evidence of consumption responses to cues. From columns 1 to 2, we proxy the tendency to respond to cues using the consumption responses on payday, and identify those with stronger payday response with $1_{\text{payday_response}_i} = 1$. We run the following regression:

$$Y_{it} = \beta_1 1_{\text{after}_{it}} * \Delta \text{Limit}_i * 1_{\text{payday_response}_i} + \beta_2 1_{\text{during}_{it}} * \Delta \text{Limit}_i * 1_{\text{payday_response}_i} \\ + \beta_3 1_{\text{after}_{it}} * \Delta \text{Limit}_i + \beta_4 1_{\text{during}_{it}} * \Delta \text{Limit}_i + \lambda \text{Salary}_{it} + \delta_i + \tau_t + \epsilon_{it}$$

From columns 3 to 4, we employ credit card statement as an alternative proxy of cues of limit increases. We run the following regressions:

$$Y_{it} = \beta_1 1_{\text{after}_{it}} * \Delta \text{Limit}_i + \beta_2 1_{\text{after}_{it}} * \Delta \text{Limit}_i * 1_{\text{statement_week}_{it}} + \beta_3 1_{\text{statement_week}_{it}} + \lambda \text{Salary}_{it} + \eta_{im} + \epsilon_{it}$$

where t represents the event weeks before or after receiving the credit card statement. $1_{\text{statement_week}_{it}}$ is an indicator variable equal 1 if week t is the first 7 days after the statement. η_{im} represents customer by calendar month fixed effects. We also control for monthly salary. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) | (2) | (3) | (4) |
|---|-------------------|-------------------|----------------------|----------------------|
| | Total Spending | Credit Card | Card Spending | Credit Card |
| | Salary as Cue | | Statement as Cue | |
| $1_{\text{payday_response}} * 1_{\text{after}_{it}} * \Delta \text{Limit}_i$ | 8.46*** (3.25) | 5.12** (2.10) | | |
| $1_{\text{payday_response}} * 1_{\text{during}_{it}} * \Delta \text{Limit}_i$ | 2.48 (3.44) | 1.96 (1.95) | | |
| $1_{\text{statement_week}_{it}} * 1_{\text{after}_{it}} * \Delta \text{Limit}_i$ | | | 0.38*** (0.07) | 0.38*** (0.07) |
| $1_{\text{after}_{it}} * \Delta \text{Limit}_i$ | 7.83*** (1.18) | 8.20*** (0.95) | 0.83** (0.36) | 0.78** (0.35) |
| $1_{\text{during}_{it}} * \Delta \text{Limit}_i$ | 7.51*** (1.46) | 3.44*** (0.73) | | |
| $1_{\text{statement_week}_{it}}$ | | | 790.40*** (44.49) | 718.09*** (43.37) |
| Observations | 52,668 | 52,668 | 646,627 | 646,627 |
| R-squared | 0.38 | 0.33 | 0.37 | 0.37 |
| YM FE | Y | Y | N | N |
| Customer FE | Y | Y | N | N |
| YM*Customer FE | N | N | Y | Y |

Internet Appendix A

This appendix reports additional details and robustness tests that are referred to in the main text.

Figure A1: Sample of Credit Card Statement

This figure shows a sample of the credit card statement sent to the email of clients at the end of each billing cycle.

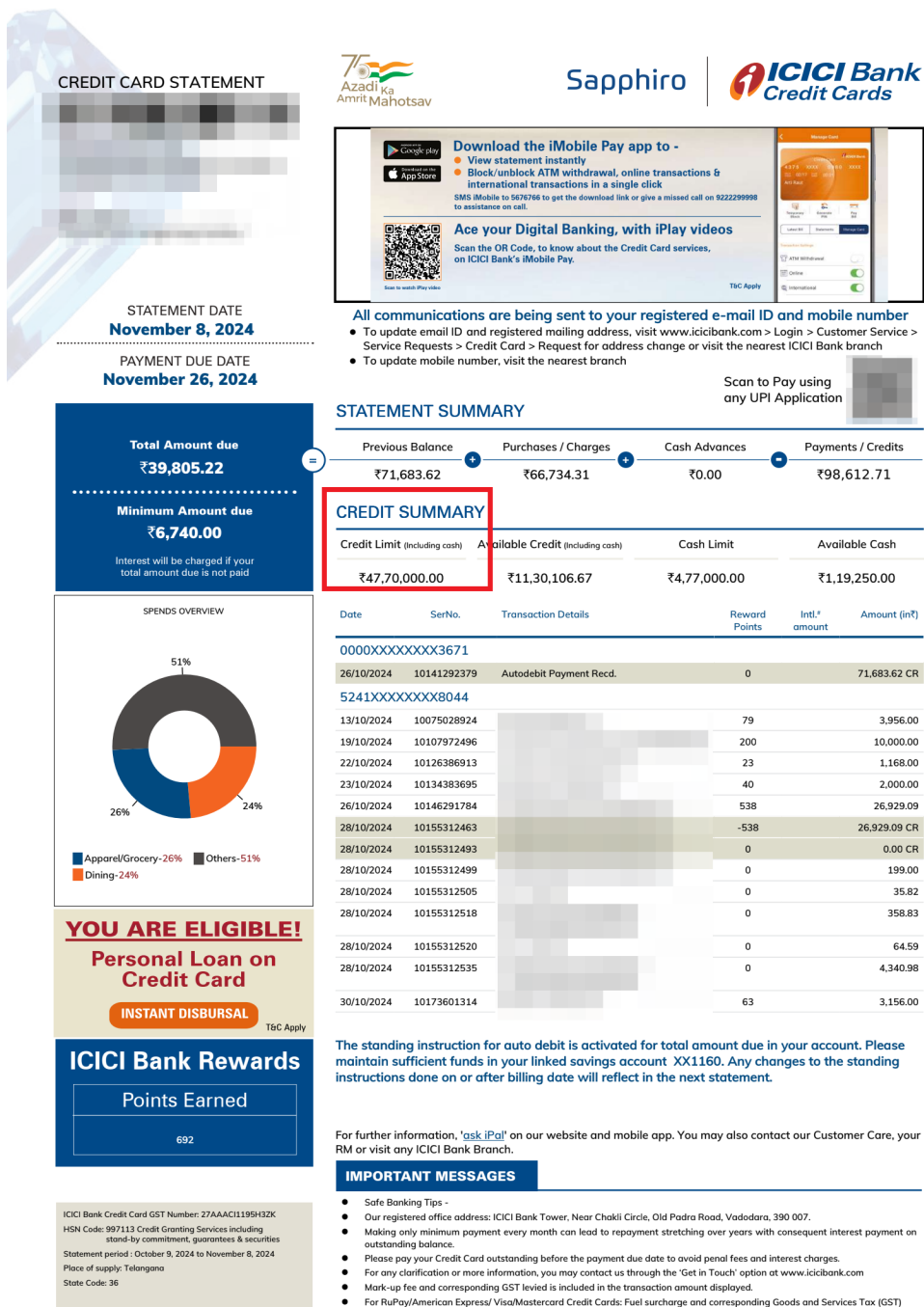


Figure A2: Credit Line Changes Overtime

This figure plots the amount of credit line increases by year and month during the sample period for the 1,843 bank accounts in the main sample. The x-axis is the 12 months from January to December. Each year is indicated with a different line.

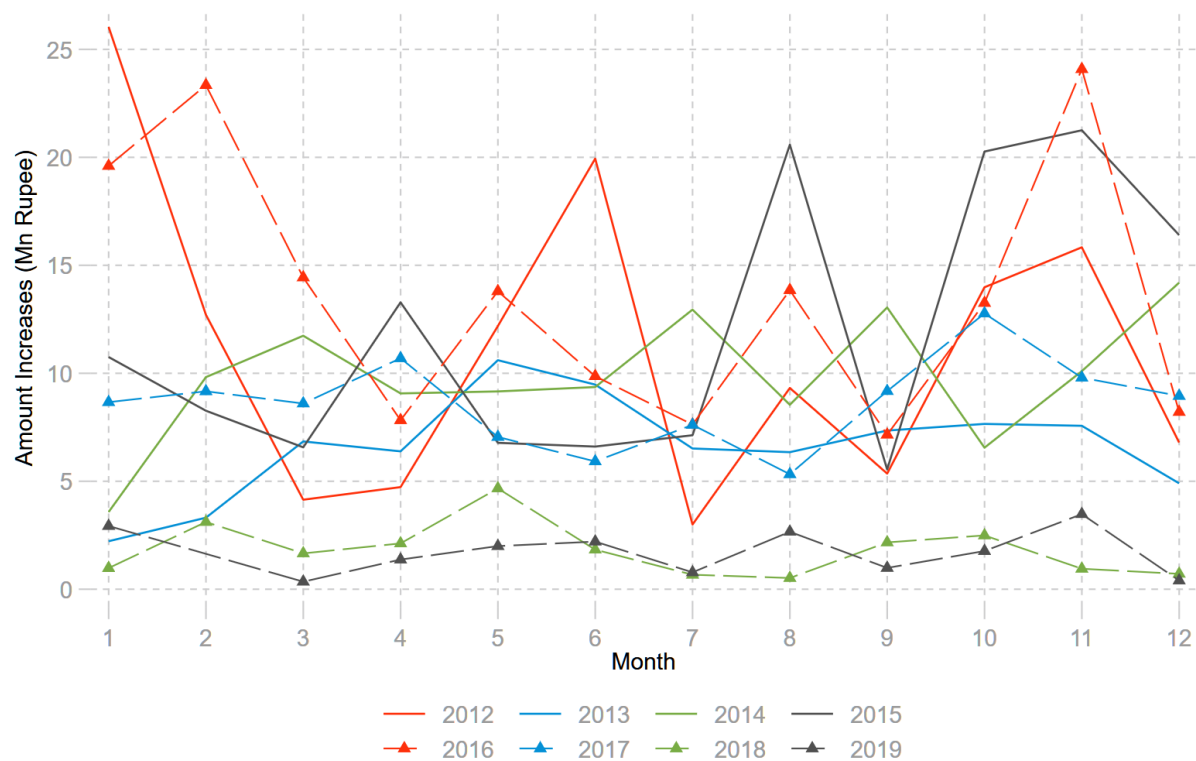


Figure A3: Comparison of Distributions

This figure compares the age and income distribution in the bank-level data with survey datasets.

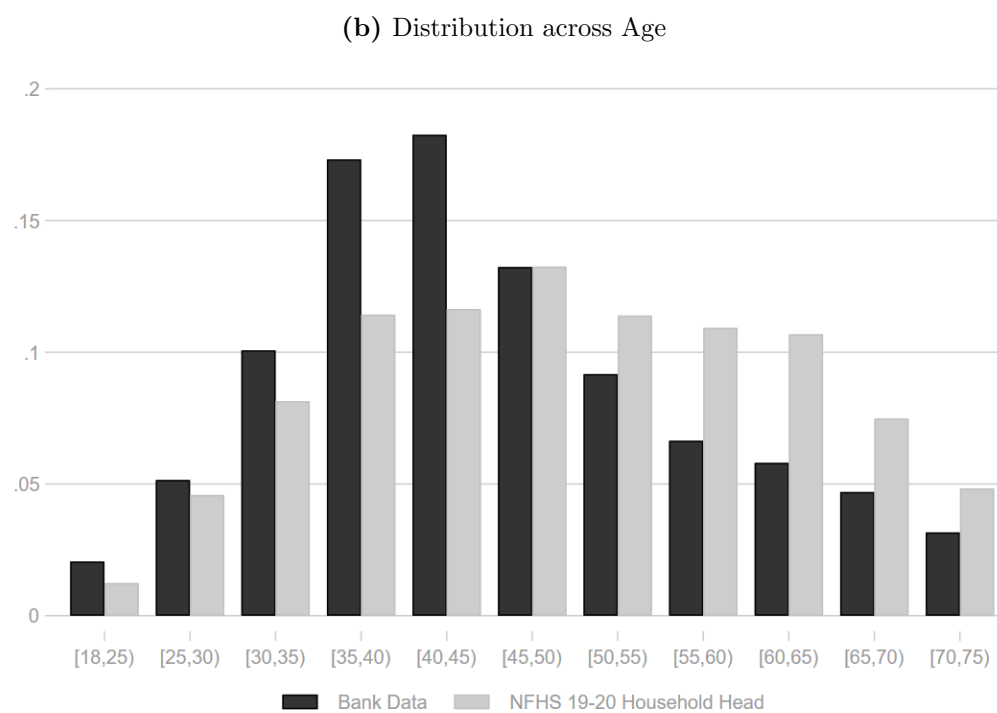
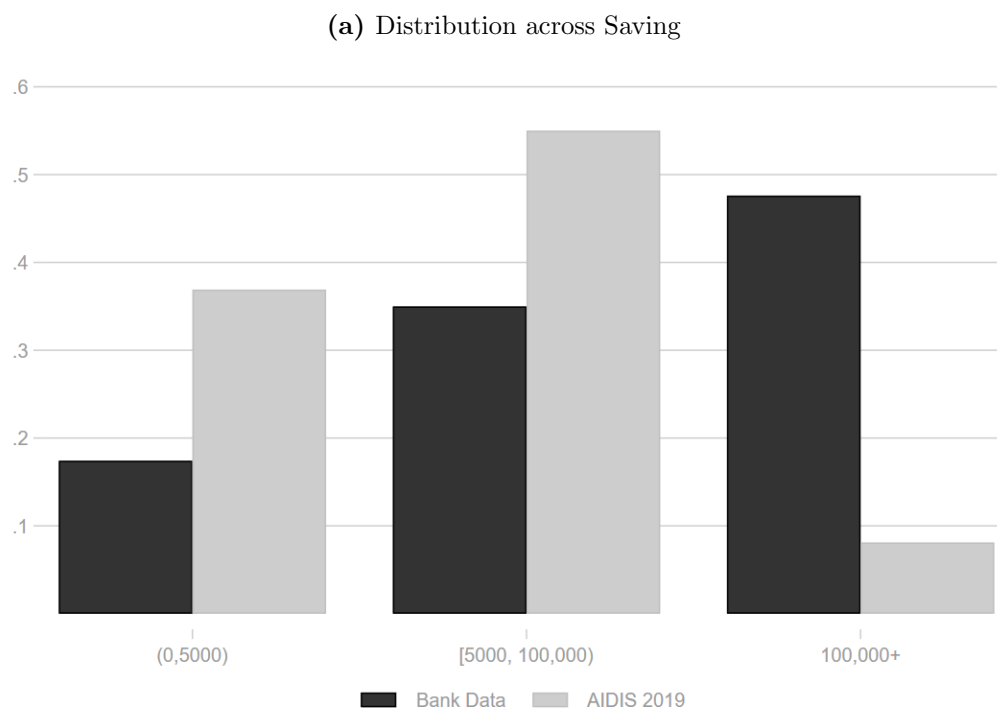


Figure A4: Dynamic Response in Expenditure After Manual Limit Increase

This figure plots the accumulated MPC, $b_k = \sum_{j=-5}^k \beta^j$, where β^j estimated with the event study model specified below:

$$Y_{it} = \sum_{j=-5}^{24} \beta^j 1_{month_{ij}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

The coefficients are estimated using the consumers who experienced the manual credit limit increase. The dependent variables include total spending, debit card spending, credit card spending, and cash withdrawal, each labeled at the top of the figures. The x-axis denotes the event months from T-5 to T+24, where event month T=0 denotes the month of credit limit increase. Event month T-1 is the omitted reference group.

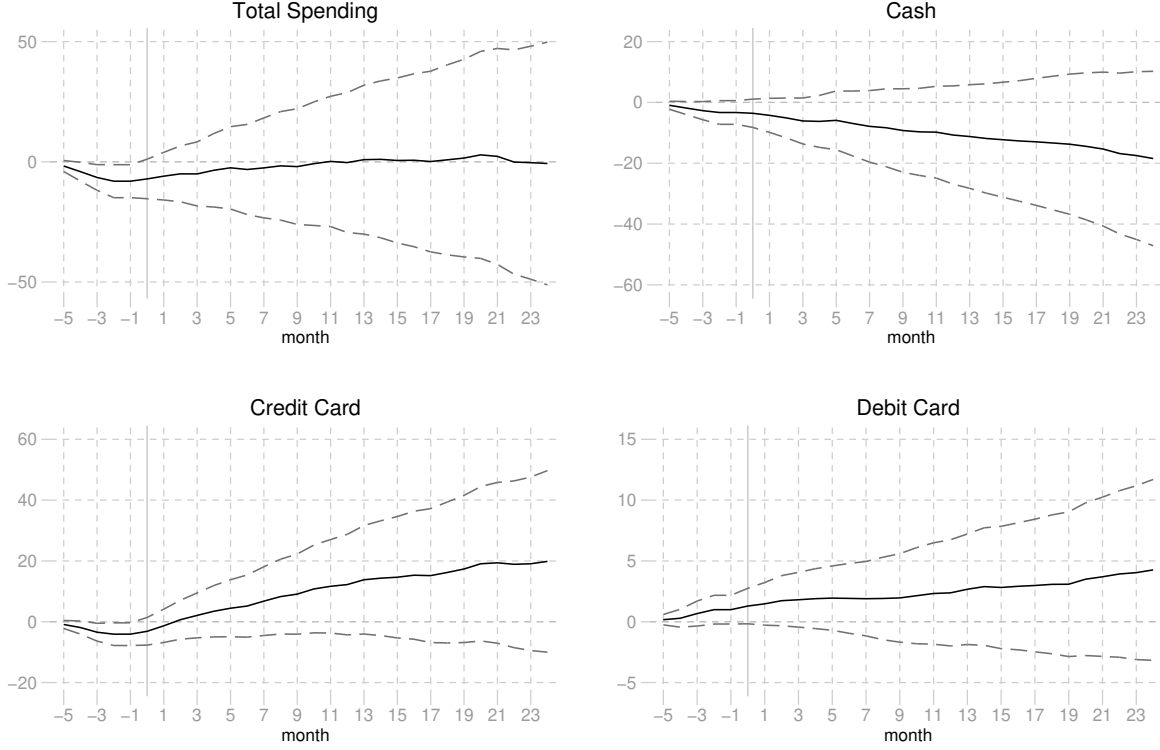


Table A1: Association Between Automatic Limit Increases and Account Activities

The dependent variable indicates if the bank increases the credit limit for the client in month t . The independent variables include total expenditures in the previous year, average monthly salary in the previous year, and the average utilization rate in the previous year. Account age in months, consumer age in years, and the square of these two variables are also included. The data structure is a monthly panel, starting from the later of the month after the first credit limit increase or January 2012 and ending in December 2019. We control for year-by-month fixed effects but do not include consumer fixed effects. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. (*1000) | (1) | (2) | (3) |
|--------------------------|--------------------|--------------------|--------------------|
| | $1_{Increase_t}$ | | |
| $\ln(Total_{lastyear})$ | 0.02 (0.08) | | 0.03 (0.08) |
| $\ln(Salary_{lastyear})$ | | -0.01 (0.02) | -0.02 (0.03) |
| $UR_{lastyear}$ | -0.00*** (0.00) | -0.00*** (0.00) | -0.00*** (0.00) |
| $acct_age$ | -0.09*** (0.01) | -0.09*** (0.01) | -0.09*** (0.01) |
| $acct_age^2$ | 0.00*** (0.00) | 0.00*** (0.00) | 0.00*** (0.00) |
| $consumer_age$ | -0.10*** (0.02) | -0.10*** (0.02) | -0.10*** (0.02) |
| $consumer_age^2$ | 0.00*** (0.00) | 0.00*** (0.00) | 0.00*** (0.00) |
| Observations | 261,430 | 261,430 | 261,430 |
| R-squared | 0.01 | 0.01 | 0.01 |
| Mean DV | 0.01 | 0.01 | 0.01 |
| Year * Month FE | Y | Y | Y |
| Consumer FE | N | N | N |

Table A2: Comparison of Means (Propensity Score Matching)

This table reports of a comparison of means for observable characteristics of the matched control and treated sample.

| | (1) Treated | (2) Control | (3) Treated-Control | (4) p-value |
|------------------------------------|------------------------|------------------------|----------------------------|----------------|
| Age | 38.925 (8.327) | 38.959 (7.611) | -0.0347 (0.3035) | 0.909 |
| Male | 0.871 (0.336) | 0.867 (0.34) | 0.0038 (0.0129) | 0.770 |
| Married | 0.587 (0.493) | 0.574 (0.495) | 0.0135 (0.0188) | 0.474 |
| Saving & Term Deposit Balance | 218328.2 (396398.7) | 223753.4 (404305.5) | -5425.2010 (15253.5300) | 0.722 |
| Total Expenditure | 34690.4 (20612.37) | 34553.19 (27195.56) | 137.2143 (925.5579) | 0.882 |
| Salary | 34433.52 (41279.99) | 35426.23 (41360.96) | -992.7151 (1573.482) | 0.528 |
| Growth of Total Expenditure | 1.258 (0.947) | 1.263 (3.709) | -0.0059 (0.1055) | 0.956 |
| Proportion of Cash Spending | 0.673 (0.206) | 0.677 (0.287) | -0.0037 (0.0096) | 0.702 |
| Proportion of Credit Card Spending | 0.191 (0.191) | 0.177 (0.275) | 0.0139 (0.0091) | 0.126 |
| Observations | 1,459 | 1,308 | 2,767 | |

Table A3: Robustness of Staggered DID Specification

This table replicates the baseline results reported in Table 2 using the estimator in [de Chaisemartin and D'Haultfœuille \(2020\)](#).

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|-----------------------------------|-----------------------|----------------------|----------------------|------------------------|
| $1_{after_{it}} * \Delta Limit_i$ | 12.837*** (0.915) | 16.681*** (0.270) | -3.220*** (0.085) | -1.117 (2.121) |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Table A4: Response After Manual Credit Line Increases

This table reports the responses to the manual credit line increases that are initiated by the customers. The coefficient estimates are from the estimation of equations (1) and (2). The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. The dependent variables are labeled on the top of each column. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal | (5) UR | (6) $1_{revolver}$ |
|------------------------------------|-----------------------|--------------------|-------------------|------------------------|--------------------|-----------------------|
| $1_{after_{it}} * \Delta Limit_i$ | 2.04*** (0.60) | 1.95*** (0.39) | -0.08 (0.10) | 0.05 (0.35) | | |
| $1_{during_{it}} * \Delta Limit_i$ | 2.55*** (0.86) | 1.79*** (0.48) | 0.10 (0.13) | 0.40 (0.52) | | |
| $1_{after_{it}}$ | | | | | -0.33*** (0.01) | 0.07*** (0.01) |
| $1_{during_{it}}$ | | | | | -0.40*** (0.01) | 0.00 (0.01) |
| Observations | 81,250 | 81,250 | 81,250 | 81,250 | 81,250 | 81,250 |
| R-squared | 0.39 | 0.41 | 0.38 | 0.38 | 0.45 | 0.49 |
| Number Consumer | 2,931 | 2,931 | 2,931 | 2,931 | 2,931 | 2,931 |
| Mean DV | 38,508.86 | 3,304.29 | 14,069.13 | 20,118.57 | 0.26 | 0.20 |
| YM FE | Y | Y | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y | Y | Y |

Table A5: Response of Non-revolvers

This table reports the spending response to the automatic credit limit increases for a subsample of consumers who neither revolve on their credit card *ex-ante* nor *ex-post*. Formally, the coefficients are from the estimation of equation (1).

The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ is the magnitude of the credit limit increase in ₹1,000. The dependent variables include total spending (column 1), credit card spending (column 2), debit card spending (column 3), and cash withdrawal (column 4). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|------------------------------------|-----------------------|--------------------|-------------------|------------------------|
| $1_{after_{it}} * \Delta Limit_i$ | 6.90*** (1.42) | 7.16*** (1.09) | -0.27 (0.33) | -0.25 (0.81) |
| $1_{during_{it}} * \Delta Limit_i$ | 7.55*** (1.73) | 3.36*** (0.97) | 0.88** (0.43) | 2.92** (1.23) |
| Observations | 27,213 | 27,213 | 27,213 | 27,213 |
| R-squared | 0.36 | 0.34 | 0.40 | 0.38 |
| Mean DV | 33,361.05 | 10,571.3 | 3,024.75 | 19,108.52 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Table A6: Heterogeneity in Spending Response by Alternative Measurements of *Ex-ante* Liquidity Buffer

This table examines the heterogeneity in spending response to the automatic credit line increase by alternative measurements of liquidity buffer. We run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{high_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{high_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where 1_{high_i} is an indicator variable equal to one for the top tercile of consumers divided by three measures of liquidity, including the sum of saving account and term deposit account balance (column 1), the sum of unused credit on the credit card, saving account and term deposit account balance (column 2), and the sum of unused credit on the credit card, saving account and term deposit account balance, and monthly salary (column 3). All liquidity measures are scaled by average *ex-ante* monthly expenditure.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variable in these tests is total spending. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) | (2) | (3) |
|---|--------------------|----------------------|-----------------------------|
| | Total Spending | | |
| 1_{high_i} indicates | SB+TD | Unused Credit +SB+TD | Unused Credit +SB+TD+Salary |
| $1_{high_i} * 1_{after_{it}} * \Delta Limit_i$ | 8.74*** (2.11) | 10.75*** (2.12) | 10.98*** (2.11) |
| $1_{high_i} * 1_{during_{it}} * \Delta Limit_i$ | 6.06** (2.77) | 5.04* (2.85) | 5.42* (2.85) |
| $1_{after_{it}} * \Delta Limit_i$ | 4.83*** (1.35) | 4.23*** (1.32) | 3.98*** (1.34) |
| $1_{during_{it}} * \Delta Limit_i$ | 75.34*** (1.92) | 5.83*** (1.89) | 5.61*** (1.90) |
| Observations | 50,411 | 50,411 | 50,411 |
| R-squared | 0.37 | 0.37 | 0.37 |
| Mean DV | 37,058.28 | 37,058.28 | 37,058.28 |
| YM FE | Y | Y | Y |
| Customer FE | Y | Y | Y |

Table A7: Heterogeneous Consumption Response by Strength of Cues

This table examines how consumer spending responds to the limit increases with different strengths of the cue, measured by whether a credit card statement is issued after the limit increases. We run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{statement_follow_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{statement_follow_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where $1_{statement_follow_i}$ is an indicator variable that equals 1 if a credit card statement is issued within 5 days after the limit increases initiated by the bank.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variables in these tests are total spending (column 1), credit card spending (column 2), debit card spending (column 3) and cash withdrawal (column 4). Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|--|-----------------------|--------------------|--------------------|------------------------|
| $1_{statement_follow_i} * 1_{after_{it}} * \Delta Limit_i$ | 5.21* (3.02) | 4.33* (2.30) | 0.48 (0.91) | 0.40 (2.11) |
| $1_{statement_follow_i} * 1_{during_{it}} * \Delta Limit_i$ | 5.10 (3.81) | 1.78 (1.75) | 0.58 (0.84) | 2.15 (2.47) |
| $1_{after_{it}} * \Delta Limit_i$ | 8.00*** (1.25) | 8.39*** (1.02) | -0.85*** (0.27) | 0.21 (0.62) |
| $1_{during_{it}} * \Delta Limit_i$ | 7.00*** (1.53) | 3.57*** (0.88) | 0.61 (0.38) | 2.59** (1.07) |
| Observations | 52,668 | 52,668 | 52,668 | 52,668 |
| R-squared | 0.37 | 0.32 | 0.38 | 0.39 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Table A8: Savings Response

This table reports the responses in saving to the automatic credit limit increases. Formally, the coefficient estimates reported in Panel A are from the estimation of equation (1), and the coefficients reported in Panel B are from the estimation of equation (5).

The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. The indicator variable $1_{treated_{it}}$ is a binary variable that equals one for the treated group and zero for the matched control group. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variables include the month-on-month changes in the savings account balance (column 1) and term deposits (column 2). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Δ Saving Balance | (2) Δ Term Deposit |
|--|--------------------------------|------------------------------|
| <i>Panel A: OLS</i> | | |
| $1_{after_{it}} * \Delta Limit_i$ | -6.18*** (2.29) | -0.36 (0.51) |
| $1_{during_{it}} * \Delta Limit_i$ | 8.75 (7.26) | 0.83 (1.22) |
| Observations | 52,519 | 52,488 |
| R-squared | 0.01 | 0.05 |
| Mean DV | 648.56 | 1,072.25 |
| YM FE | Y | Y |
| Customer FE | Y | Y |
| <i>Panel B: PSM DID</i> | | |
| $1_{after_{it}} * 1_{treated_i} * \Delta Limit_i$ | -3.82* (2.02) | -1.08* (0.59) |
| $1_{during_{it}} * 1_{treated_i} * \Delta Limit_i$ | 1.65 (7.18) | -0.47 (1.25) |
| Observations | 83,581 | 83,538 |
| R-squared | 0.02 | 0.06 |
| Mean DV | 829.69 | 1,129.75 |
| YM FE | Y | Y |
| Customer FE | Y | Y |

Table A9: Risky Asset Holdings

This table reports the portfolio response to the automatic credit limit increase. Formally, the coefficient estimates are from the estimation of the difference-in-differences regressions specified in equations (1) and (5). The indicator variable $1_{after_{it}}$ is a binary variable that equals one in the post-treatment (credit increase) period and zero otherwise. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. The indicator variable $1_{treated_{it}}$ is a binary variable that equals one for the treated group and zero for the matched control group. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variables include the month-on-month changes in the total investments in mutual funds in column 1 and equity investments in column 2. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1% respectively.

| Dep. Var. | (1) Δ Mutual Fund | (2) Δ Equity |
|--|-----------------------------|------------------------|
| <i>Panel A: Staggered DID</i> | | |
| $1_{after_{it}} * \Delta Limit_i$ | -0.03 (0.04) | 0.93* (0.50) |
| $1_{during_{it}} * \Delta Limit_i$ | -0.04 (0.07) | 0.07 (1.05) |
| Observations | 52,474 | 52,481 |
| R-square | 0.08 | 0.10 |
| Mean DV | -185.11 | 1,310.78 |
| YM FE | Y | Y |
| Customer FE | Y | Y |
| <i>Panel B: PSM DID</i> | | |
| $1_{after_{it}} * 1_{treated_i} * \Delta Limit_i$ | -0.04*** (0.01) | 0.51 (0.56) |
| $1_{during_{it}} * 1_{treated_i} * \Delta Limit_i$ | -0.02 (0.02) | 1.55 (1.55) |
| Observations | 83,514 | 83,522 |
| R-square | 0.18 | 0.09 |
| Mean DV | -68.23 | 951.07 |
| YM FE | Y | Y |
| Customer FE | Y | Y |

Table A10: Primary Bank Accounts

This table examines the response to the automatic credit line increase of the subsample of main spending accounts, where main accounts are the accounts that have high *ex-ante* expenditure through the account. We keep the accounts that spend more than ₹27,000 monthly before the limit increases. We re-run the baseline regression specifications in equation (1) from columns 1-4 and equation (2) from columns 5-6.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variables include total spending (column 1), credit card spending (column 2), debit card spending (column 3), cash withdrawal (column 4), utilization rate (column 5), and revolver or not (column 6). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal | (5) Utilization Rate | (6) $1_{revolve}$ |
|------------------------------------|-----------------------|--------------------|-------------------|------------------------|-------------------------|----------------------|
| $1_{after_{it}} * \Delta Limit_i$ | 6.43*** (1.77) | 9.28*** (1.59) | -1.35** (0.54) | -1.58 (1.15) | | |
| $1_{during_{it}} * \Delta Limit_i$ | 6.81*** (2.31) | 4.27*** (1.35) | 0.66 (0.58) | 1.72 (1.62) | | |
| $1_{after_{it}}$ | | | | | -0.21*** (0.07) | 0.08*** (0.01) |
| $1_{during_{it}}$ | | | | | -0.28*** (0.06) | -0.01 (0.01) |
| Observations | 26,130 | 26,130 | 26,130 | 26,130 | 26,130 | 26,130 |
| R-squared | 0.30 | 0.32 | 0.39 | 0.33 | 0.25 | 0.47 |
| Mean DV | 51,016.88 | 14,013.41 | 5,343.45 | 30,684.63 | 0.19 | 0.15 |
| YM FE | Y | Y | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y | Y | Y |

Table A11: Heterogeneous Response by Marital Status

This table examines heterogeneous response to the automatic credit line increase by the marital status of the clients. We run the following regression:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{married_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{married_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where $1_{married_i}$ is an indicator variable equal to 1 for the married individuals and 0 otherwise. The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| Dep. Var. | (1) Total Spending | (2) Credit Card | (3) Debit Card | (4) Cash Withdrawal |
|--|-----------------------|--------------------|-------------------|------------------------|
| $1_{married} * 1_{after_{it}} * \Delta Limit_i$ | 3.20 (2.17) | 2.30 (1.90) | -1.20 (0.74) | 2.10 (1.39) |
| $1_{married} * 1_{during_{it}} * \Delta Limit_i$ | 2.78 (3.26) | -3.34* (1.98) | 0.41 (0.87) | 5.72** (2.39) |
| $1_{after_{it}} * \Delta Limit_i$ | 7.71*** (1.54) | 8.56*** (1.52) | -0.03 (0.65) | -0.81 (1.22) |
| $1_{during_{it}} * \Delta Limit_i$ | 6.93*** (2.35) | 6.05*** (1.78) | 0.67 (0.59) | 0.22 (1.29) |
| Observations | 52,668 | 52,668 | 52,668 | 52,668 |
| R-squared | 0.34 | 0.29 | 0.28 | 0.33 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Table A12: Heterogeneity in Spending Response by Payday-Cues

This table examines the heterogeneity in spending response to the automatic credit line increase based on the intensity of consumption response around paydays. We run the following regression separately for consumers with high savings and low to medium savings:

$$Y_{it} = \beta_1 1_{after_{it}} * \Delta Limit_i * 1_{payday_response_i} + \beta_2 1_{during_{it}} * \Delta Limit_i * 1_{payday_response_i} + \beta_3 1_{after_{it}} * \Delta Limit_i + \beta_4 1_{during_{it}} * \Delta Limit_i + \lambda Salary_{it} + \delta_i + \tau_t + \epsilon_{it}$$

where $1_{payday_response_i}$ is an indicator variable equal to 1 for the consumers who tend to spend more right after receiving the salary.

The indicator variable $1_{after_{it}}$ is equal to one for the months T+1 to T+24, where T denotes the month of credit line increase. The indicator variable $1_{during_{it}}$ is a binary variable that equals one in the month of credit limit increase. $\Delta Limit_i$ represents the magnitude of credit limit increases. The dependent variables in these tests are total spending (column 1), credit card spending (column 2), debit card spending (columns 3), and cash withdrawal (columns 4). We control for monthly salary, account fixed effects, and year-month fixed effects in all specifications. Robust standard errors clustered at the account level are reported in parentheses. *, **, *** denote statistically significant levels at 10%, 5% and 1%, respectively.

| | (1) | (2) | (3) | (4) |
|---|--------------------------|-------------------|-------------------|------------------|
| | Panel A High Saving | | | |
| Dep. Var. | Total Spending | Credit Card | Debit Card | Cash Withdrawal |
| $1_{payday_response_i} * 1_{after_{it}} * \Delta Limit_i$ | 6.32** (3.03) | 4.93** (2.11) | 1.14* (0.68) | -0.70 (1.73) |
| $1_{payday_response_i} * 1_{during_{it}} * \Delta Limit_i$ | 0.89 (4.31) | 4.52 (2.97) | -1.09* (0.62) | -2.41 (3.00) |
| $1_{after_{it}} * \Delta Limit_i$ | 8.64*** (1.77) | 6.64*** (1.40) | -0.81** (0.35) | 2.28** (1.03) |
| $1_{during_{it}} * \Delta Limit_i$ | 7.91*** (2.73) | 4.24*** (1.40) | 0.43 (0.43) | 2.64* (1.51) |
| Observations | 17,043 | 17,043 | 17,043 | 17,043 |
| R-squared | 0.35 | 0.31 | 0.35 | 0.37 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |
| | Panel B Low & Mid Saving | | | |
| $1_{payday_response_i} * 1_{after_{it}} * \Delta Limit_i$ | 7.40* (3.98) | 5.38** (2.70) | 0.93** (0.46) | -0.04 (1.76) |
| $1_{payday_response_i} * 1_{during_{it}} * \Delta Limit_i$ | 4.91 (3.67) | 2.20 (2.24) | -0.87 (0.55) | 3.70 (3.93) |
| $1_{after_{it}} * \Delta Limit_i$ | 10.02*** (1.43) | 8.16*** (1.15) | -0.60** (0.26) | 1.95** (0.78) |
| $1_{during_{it}} * \Delta Limit_i$ | 8.71*** (2.04) | 4.47*** (0.98) | 0.88** (0.40) | 2.87** (1.20) |
| Observations | 34,128 | 34,128 | 34,128 | 34,128 |
| R-squared | 0.37 | 0.31 | 0.36 | 0.38 |
| YM FE | Y | Y | Y | Y |
| Customer FE | Y | Y | Y | Y |

Online Appendix B

This appendix reports more details about the conceptual framework reported in Section 6.3.1.

We consider a two-period model where households maximize their utility over two periods, incorporating the role of cues that are functions of the credit limit.

B1 Model Setting

There are two time periods, current period 0 and future period 1. The household maximizes lifetime utility, which includes both standard consumption utility and additional utility derived from cues dependent on the credit limit.

The utility Function is defined below:

$$U = u(c_0) + \beta u(c_1) + \gamma S_0(L_0)v(c_0) \quad (\text{B1})$$

where:

- $u(c_t) = \ln(c_t)$: Standard utility from consumption in period t .
- $v(c_t) = \ln(c_t)$: Additional utility from consumption when a cue is present.
- β : Time preference discount factor ($0 < \beta < 1$).
- γ : Sensitivity to cues ($\gamma \geq 0$).
- $S_0(L_0)$: Cue function dependent on the credit limit L_0 .

We define the cue as a function of the change in the credit limit:

$$S_0(L_0) = \phi(L_0 - L_{-1})$$

The function is defined below:

$$S_0(L_0) = \begin{cases} 1, & \text{if } L_0 > L_{-1} \\ 0, & \text{otherwise} \end{cases} \quad (\text{B2})$$

B1.1 Budget Constraints

$$A_1 = A_0(1 + r) + y_0 - c_0 \quad (\text{B3})$$

$$A_2 = A_1(1 + r) + y_1 - c_1 \quad (\text{B4})$$

$$A_2 \geq 0 \quad (\text{Terminal condition}) \quad (\text{B5})$$

$$A_t \geq -L_t \quad (\text{Borrowing constraint}) \quad (\text{B6})$$

where:

- A_t : Assets at the beginning of period t .
- y_t : Income in period t .
- c_t : Consumption in period t .
- r : Interest rate.
- L_t : Credit limit in period t .

The consumer optimize the utility function shown in equation (B1), subject to the budget constraints.

B2 Solving the Model

Since $u(c_0) = v(c_0) = \ln(c_0)$, the total utility simplifies to:

$$U = (1 + \gamma S_0(L_0)) \ln(c_0) + \beta \ln(c_1) \quad (\text{B7})$$

Set Up the Lagrangian:

$$\begin{aligned} \mathcal{L} = & (1 + \gamma S_0(L_0)) \ln(c_0) + \beta \ln(c_1) \\ & - \lambda_0 [A_1 - A_0(1 + r) - y_0 + c_0] \\ & - \lambda_1 [A_2 - A_1(1 + r) - y_1 + c_1] + \mu(-A_2) \end{aligned}$$

where:

- λ_0, λ_1 : Lagrange multipliers for the budget constraints.
- μ : Lagrange multiplier for the terminal condition ($\mu \geq 0$).

B2.1 First-Order Conditions

FOC with respect to c_0 :

$$\frac{\partial \mathcal{L}}{\partial c_0} = \frac{1 + \gamma S_0(L_0)}{c_0} - \lambda_0 = 0 \quad (\text{B8})$$

FOC with respect to c_1 :

$$\frac{\partial \mathcal{L}}{\partial c_1} = \beta \frac{1}{c_1} - \lambda_1 = 0 \quad (\text{B9})$$

FOC with respect to A_1 :

$$\frac{\partial \mathcal{L}}{\partial A_1} = -\lambda_0(-(1+r)) - \lambda_1 = 0 \quad (\text{B10})$$

$$\implies \lambda_1 = \lambda_0(1+r) \quad (\text{B11})$$

FOC with respect to A_2 :

$$\frac{\partial \mathcal{L}}{\partial A_2} = -\lambda_1(-1) + \mu = 0 \quad (\text{B12})$$

$$\implies \lambda_1 = \mu \quad (\text{B13})$$

Complementary Slackness Condition:

$$\mu \geq 0, \quad A_2 \geq 0, \quad \mu A_2 = 0 \quad (\text{B14})$$

From the first-order conditions, we can derive the Euler equation:

$$\lambda_0 = \frac{1 + \gamma S_0(L_0)}{c_0} \quad (\text{B15})$$

$$\lambda_1 = \beta \frac{1}{c_1} \quad (\text{B16})$$

$$\lambda_1 = \lambda_0(1+r) \quad (\text{B17})$$

Substitute:

$$\beta \frac{1}{c_1} = \left(\frac{1 + \gamma S_0(L_0)}{c_0} \right) (1+r) \quad (\text{B18})$$

Rewriting:

$$\beta(1+r) \frac{1}{c_1} = \frac{1 + \gamma S_0(L_0)}{c_0} \quad (\text{B19})$$

B3 Optimal Consumption with Respect to Initial Saving

Based on the model above, we then derive the cross derivative of optimal current consumption (c_0) with respect to initial savings (A_0) in a two-period household portfolio optimization model, where the cue parameter (S_0) is set to 0 and 1. The analysis assumes logarithmic utility and interprets the results, explaining the intuition behind the effect of cues on consumption behavior.

As before, we make the following assumptions:

- Logarithmic Utility: $u(c_t) = \ln(c_t)$.

- Interest Rate: r is constant.
- Incomes and Credit Limits: y_0, y_1 , and L_t are given.
- Borrowing Constraints: Not binding (for simplicity).

Assuming the terminal condition $A_2 = 0$ (binding), the intertemporal budget constraint becomes:

$$A_0(1+r) + y_0 + \frac{y_1}{1+r} = c_0 + \frac{c_1}{1+r} \quad (\text{B20})$$

Define total wealth W as:

$$W = A_0(1+r) + y_0 + \frac{y_1}{1+r} \quad (\text{B21})$$

From the Euler Equation:

$$c_1 = \beta(1+r) \frac{c_0}{1+\gamma S_0} \quad (\text{B22})$$

Substitute c_1 into the intertemporal budget constraint:

$$W = c_0 + \frac{c_1}{1+r} \quad (\text{B23})$$

$$= c_0 + \frac{\beta(1+r) \frac{c_0}{1+\gamma S_0}}{1+r} \quad (\text{B24})$$

$$= c_0 + \frac{\beta c_0}{1+\gamma S_0} \quad (\text{B25})$$

Solving for c_0 :

$$W = c_0 \left(1 + \frac{\beta}{1+\gamma S_0} \right) \quad (\text{B26})$$

$$\Rightarrow c_0 = \frac{W}{1 + \frac{\beta}{1+\gamma S_0}} \quad (\text{B27})$$

Simplify the denominator:

$$1 + \frac{\beta}{1+\gamma S_0} = \frac{(1+\gamma S_0) + \beta}{1+\gamma S_0} \quad (\text{B28})$$

Therefore:

$$c_0 = \frac{W(1 + \gamma S_0)}{(1 + \gamma S_0) + \beta} \quad (\text{B29})$$

We aim to find $\frac{\partial c_0}{\partial A_0}$ when $S_0 = 0$ and $S_0 = 1$.

Recall that W depends on A_0 :

$$W = A_0(1 + r) + C \quad (\text{B30})$$

where C represents constants independent of A_0 :

$$C = y_0 + \frac{y_1}{1 + r} \quad (\text{B31})$$

Thus:

$$c_0 = \frac{(1 + \gamma S_0)[A_0(1 + r) + C]}{(1 + \gamma S_0) + \beta} \quad (\text{B32})$$

Simplify:

$$c_0 = \frac{(1 + \gamma S_0)(1 + r)A_0}{(1 + \gamma S_0) + \beta} + \frac{(1 + \gamma S_0)C}{(1 + \gamma S_0) + \beta} \quad (\text{B33})$$

Differentiate c_0 with respect to A_0 :

$$\frac{\partial c_0}{\partial A_0} = \frac{(1 + \gamma S_0)(1 + r)}{(1 + \gamma S_0) + \beta} \quad (\text{B34})$$

When $S_0 = 0$:

$$\frac{\partial c_0}{\partial A_0} = \frac{1 + r}{1 + \beta} \quad (\text{B35})$$

When $S_0 = 1$:

$$\frac{\partial c_0}{\partial A_0} = \frac{(1 + \gamma)(1 + r)}{1 + \gamma + \beta} \quad (\text{B36})$$

Denote:

$$MPC_0 = \frac{1+r}{1+\beta} \quad (\text{Marginal Propensity to Consume without Cue}) \quad (\text{B37})$$

$$MPC_1 = \frac{(1+\gamma)(1+r)}{1+\gamma+\beta} \quad (\text{Marginal Propensity to Consume with Cue}) \quad (\text{B38})$$

Note that $MPC_1 > MPC_0$, implies that the propensity to consume is higher in the presence of cues.

B3.1 Numerical Example

We parameterize the model and consider different levels of initial savings A_0 to show how consumption changes.

Parameters are defined below:

- Income:

$$y_0 = \$1,000$$

$$y_1 = \$1,000$$

- Interest Rate:

$$r = 10\% \quad (1+r = 1.10)$$

- Discount Factor:

$$\beta = 0.90$$

- Cue Sensitivity:

$$\gamma = 0.5$$

- Credit Limits:

$$L_{-1} = \$500$$

$$L_0 = \$1,000$$

- Cue Indicator:

$$S_0(L_0) = 1 \quad \text{since } L_0 > L_{-1}$$

- Initial Savings (A_0) Cases:

- Case 1: $A_0 = \$0$
- Case 2: $A_0 = \$500$
- Case 3: $A_0 = \$1,000$

B3.2 Case 1: $A_0 = \$0$ (No Initial Savings)

B3.2.1 Euler Equation

$$\beta(1+r)\frac{1}{c_1} = \frac{1+\gamma}{c_0} \quad (\text{B39})$$

Substitute values:

$$\begin{aligned} 0.90 \times 1.10 \times \frac{1}{c_1} &= \frac{1+0.5}{c_0} \\ 0.99 \times \frac{1}{c_1} &= \frac{1.5}{c_0} \end{aligned}$$

Therefore:

$$c_1 = \frac{0.99c_0}{1.5} \approx 0.66c_0 \quad (\text{B40})$$

B3.2.2 Intertemporal Budget Constraint

$$\begin{aligned} A_0(1+r) + y_0 + \frac{y_1}{1+r} &= c_0 + \frac{c_1}{1+r} \\ 0 + \$1,000 + \frac{\$1,000}{1.10} &= c_0 + \frac{0.66c_0}{1.10} \\ \$1,000 + \$909.09 &= c_0 + 0.60c_0 \\ \$1,909.09 &= 1.60c_0 \end{aligned}$$

Solve for c_0 :

$$c_0 = \frac{\$1,909.09}{1.60} = \$1,193.18 \quad (\text{B41})$$

Compute c_1 :

$$c_1 = 0.66c_0 = 0.66 \times \$1,193.18 = \$787.50 \quad (\text{B42})$$

B3.2.3 Compute Assets and Borrowings

Period 0 Assets (A_1):

$$\begin{aligned}
A_1 &= A_0(1 + r) + y_0 - c_0 \\
&= 0 \times 1.10 + \$1,000 - \$1,193.18 \\
&= -\$193.18
\end{aligned}$$

Period 1 Assets (A_2):

$$\begin{aligned}
A_2 &= A_1(1 + r) + y_1 - c_1 \\
&= (-\$193.18) \times 1.10 + \$1,000 - \$787.50 \\
&= \$0
\end{aligned}$$

B3.3 Case 2: $A_0 = \$500$ (Moderate Initial Savings)

B3.3.1 Euler Equation

Same as before:

$$c_1 = 0.66c_0 \tag{B43}$$

B3.3.2 Intertemporal Budget Constraint

$$\begin{aligned}
A_0(1 + r) + y_0 + \frac{y_1}{1 + r} &= c_0 + \frac{c_1}{1 + r} \\
\$500 \times 1.10 + \$1,000 + \frac{\$1,000}{1.10} &= c_0 + 0.60c_0 \\
\$550 + \$1,000 + \$909.09 &= 1.60c_0 \\
\$2,459.09 &= 1.60c_0
\end{aligned}$$

Solve for c_0 :

$$c_0 = \frac{\$2,459.09}{1.60} = \$1,536.93 \tag{B44}$$

Compute c_1 :

$$c_1 = 0.66c_0 = 0.66 \times \$1,536.93 = \$1,014.38 \tag{B45}$$

B3.3.3 Compute Assets

Period 0 Assets (A_1):

$$\begin{aligned}
A_1 &= \$500 \times 1.10 + \$1,000 - \$1,536.93 \\
&= \$550 + \$1,000 - \$1,536.93 \\
&= \$13.07
\end{aligned}$$

Period 1 Assets (A_2):

$$\begin{aligned}
A_2 &= \$13.07 \times 1.10 + \$1,000 - \$1,014.38 \\
&= \$14.38 + \$1,000 - \$1,014.38 \\
&= \$0
\end{aligned}$$

B3.4 Case 3: $A_0 = \$1,000$ (Sufficient Initial Savings)

B3.4.1 Euler Equation

$$c_1 = 0.66c_0 \tag{B46}$$

B3.4.2 Intertemporal Budget Constraint

$$\begin{aligned}
A_0(1+r) + y_0 + \frac{y_1}{1+r} &= c_0 + \frac{c_1}{1+r} \\
\$1,000 \times 1.10 + \$1,000 + \frac{\$1,000}{1.10} &= 1.60c_0 \\
\$1,100 + \$1,000 + \$909.09 &= 1.60c_0 \\
\$3,009.09 &= 1.60c_0
\end{aligned}$$

Solve for c_0 :

$$c_0 = \frac{\$3,009.09}{1.60} = \$1,880.68 \tag{B47}$$

Compute c_1 :

$$c_1 = 0.66c_0 = 0.66 \times \$1,880.68 = \$1,241.25 \tag{B48}$$

B3.4.3 Compute Assets

Period 0 Assets (A_1):

$$\begin{aligned}
A_1 &= \$1,000 \times 1.10 + \$1,000 - \$1,880.68 \\
&= \$1,100 + \$1,000 - \$1,880.68 \\
&= \$219.32
\end{aligned}$$

Period 1 Assets (A_2):

$$\begin{aligned}
A_2 &= \$219.32 \times 1.10 + \$1,000 - \$1,241.25 \\
&= \$241.25 + \$1,000 - \$1,241.25 \\
&= \$0
\end{aligned}$$

B3.4.4 Comparison of cases with and without Cue

$$MPC_0 = \frac{1+r}{1+\beta} = \frac{1.10}{1+0.90} = \frac{1.10}{1.90} \approx 0.5789 \quad (\text{B49})$$

$$MPC_1 = \frac{(1+\gamma)(1+r)}{1+\gamma+\beta} = \frac{(1+0.50)(1.10)}{1+0.50+0.90} = \frac{1.65}{2.40} \approx 0.6875 \quad (\text{B50})$$

Table B1: Consumption Changes at Different Levels of Initial Savings

| Initial Savings (\$) | Consumption without Cue (\$) | Consumption with Cue (\$) | Change in Consumption (\$) | Savings at Period 1 (A_1) with Cue |
|----------------------|------------------------------|---------------------------|----------------------------|---|
| | (1) | (2) | (3) | (4) |
| 0 | 1,004.78 | 1,191.93 | 187.15 | -\$193.18 |
| 500 | 1,294.26 | 1,536.93 | 242.67 | \$13.07 |
| 1,000 | 1,584.78 | 1,881.81 | 297.03 | \$219.32 |

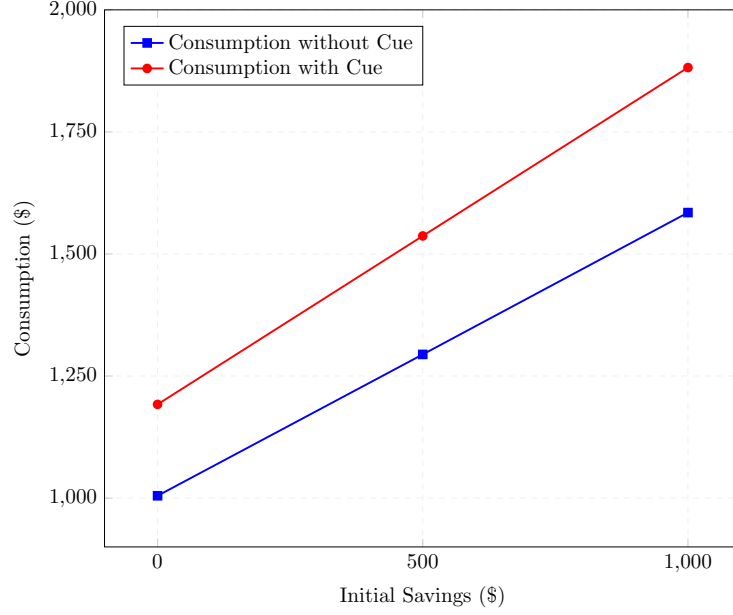


Figure B1: Consumption Response to Credit Limit Changes at Different Levels of Initial Savings

The table and figure above show that consumption increases with initial savings, both with and without the cue-induced by the credit limit increase. Column 3 of the table and the gap between the two lines represent the cue-induced additional consumption. The gap widens as initial savings increase, indicating that households with more savings respond more strongly to the cue. Column 4 of the table shows that those with no initial savings partly finance their period-0 consumption by borrowing. Those with higher savings draw down on their savings to fund the additional consumption.

B4 Optimal Consumption with Respect to Income

Based on the model defined in Section B1, we aim to find $\frac{\partial c_0}{\partial y_0}$ and $\frac{\partial c_0}{\partial y_1}$ when $S_0 = 0$ and $S_0 = 1$.

Recall that W depends on y_0 and y_1 :

$$W = A_0(1 + r) + y_0 + \frac{y_1}{1 + r} \quad (\text{B51})$$

Thus:

$$c_0 = \frac{(1 + \gamma S_0)}{(1 + \gamma S_0) + \beta} \left[A_0(1 + r) + y_0 + \frac{y_1}{1 + r} \right] \quad (\text{B52})$$

Differentiate c_0 with respect to y_0 and y_1 :

$$\frac{\partial c_0}{\partial y_0} = \frac{(1 + \gamma S_0) \times 1}{(1 + \gamma S_0) + \beta} \quad (\text{B53})$$

$$\frac{\partial c_0}{\partial y_1} = \frac{(1 + \gamma S_0) \times \frac{1}{1+r}}{(1 + \gamma S_0) + \beta} \quad (\text{B54})$$

When $S_0 = 0$:

$$\frac{\partial c_0}{\partial y_0} = \frac{1}{1 + \beta} \quad (\text{B55})$$

$$\frac{\partial c_0}{\partial y_1} = \frac{1}{(1 + \beta)(1 + r)} \quad (\text{B56})$$

When $S_0 = 1$:

$$\frac{\partial c_0}{\partial y_0} = \frac{1 + \gamma}{1 + \gamma + \beta} \quad (\text{B57})$$

$$\frac{\partial c_0}{\partial y_1} = \frac{1 + \gamma}{(1 + \gamma + \beta)(1 + r)} \quad (\text{B58})$$

Note that

$$\frac{\partial c_0}{\partial y_0} \text{ with } S_0 = 1 > \frac{\partial c_0}{\partial y_0} \text{ with } S_0 = 0 \quad (\text{B59})$$

$$\frac{\partial c_0}{\partial y_1} \text{ with } S_0 = 1 > \frac{\partial c_0}{\partial y_1} \text{ with } S_0 = 0 \quad (\text{B60})$$

B4.1 Numerical Example

Again let:

- $\beta = 0.90$
- $\gamma = 0.50$
- $r = 10\%$ ($1 + r = 1.10$)

B4.1.1 Calculate $\frac{\partial c_0}{\partial y_0}$ and $\frac{\partial c_0}{\partial y_1}$

For $S_0 = 0$:

$$\frac{\partial c_0}{\partial y_0} = \frac{1}{1 + 0.90} = \frac{1}{1.90} \approx 0.5263 \quad (\text{B61})$$

$$\frac{\partial c_0}{\partial y_1} = \frac{1}{1.90 \times 1.10} = \frac{1}{2.09} \approx 0.4785 \quad (\text{B62})$$

For $S_0 = 1$:

$$\frac{\partial c_0}{\partial y_0} = \frac{1 + 0.50}{1 + 0.50 + 0.90} = \frac{1.50}{2.40} \approx 0.6250 \quad (\text{B63})$$

$$\frac{\partial c_0}{\partial y_1} = \frac{1.50}{2.40 \times 1.10} = \frac{1.50}{2.64} \approx 0.5682 \quad (\text{B64})$$

The table below shows the consumption response at different income levels with and without the cue effect.

Table B2: Consumption Changes at Different Income Levels

| Income Level (\$) | Consumption without Cue (\$) | Consumption with Cue (\$) | Change in Consumption (\$) |
|-------------------|------------------------------|---------------------------|----------------------------|
| 500 | 792.92 | 940.34 | 147.42 |
| 1,000 | 1,294.26 | 1,536.93 | 242.67 |
| 1,500 | 1,796.65 | 2,135.27 | 338.62 |

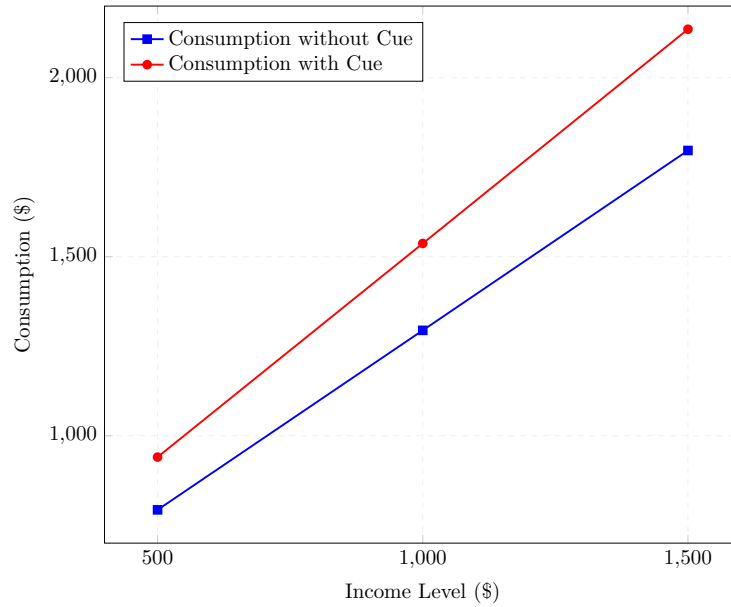


Figure B2: Consumption Response to Credit Limit Changes at Different Income Levels

The figure illustrates that consumption increases with income levels both before and after the credit limit increase. The gap between the lines widens with higher incomes, indicating a stronger consumption response to the cue among higher-income households. The presence of the

cue increases the MPC out of both current and future income.

B5 Implications

This two-period model demonstrates that households adjust their consumption in response to credit limit increases acting as cues, even when they have sufficient initial savings. The cue increases the marginal utility of current consumption, prompting households to consume more in the present period. Households with higher initial savings finance this increased consumption by drawing down their savings or reducing their savings rate rather than borrowing, but the effect of the cue on consumption behavior remains significant across different levels of initial savings.

The derivative of optimal current consumption with respect to initial savings ($\frac{\partial c_0}{\partial A_0}$) is higher when the cue parameter S_0 is set to 1 compared to when it is set to 0. This indicates that the presence of a cue amplifies the household's responsiveness of current consumption to their initial savings. The cue increases the marginal utility of current consumption, leading households to consume a larger portion of any additional savings.

The cross derivative of optimal current consumption with respect to income is higher when the cue parameter S_0 is set to 1 compared to when it is set to 0. This indicates that the presence of a cue amplifies the household's responsiveness of current consumption to their income. The cue increases the marginal utility of current consumption, leading households to consume a larger portion of any additional income.

This behavior highlights the significant role of psychological factors in financial decision-making and how cues can disrupt traditional consumption patterns, even for households with sufficient liquidity.