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MANAGING MENTAL ACCOUNTS: PAYMENT CARDS AND CONSUMPTION EXPENDITURES

Michael Gelman Nikolai Roussanov

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ABSTRACT

Does mental accounting matter for total consumption expenditures? We exploit a unique setting in which individuals exogenously received a new credit card, without requesting one. Using random variation in the time of receipt we show that individuals temporarily increase total consumption expenditure by making purchases with the new card without reducing spending on the others. We do not observe a corresponding increase in indebtedness. Total consumption expenditure rises even for the least liquidity-constrained individuals. The evidence is consistent with consumers treating methods of payment as nonfungible budget categories, as suggested by models of mental accounting and narrow bracketing.

Michael Gelman University of Delaware 42 Amstel Ave Newark, DE 19716 gelmanm@udel.edu

Nikolai Roussanov University of Pennsylvania 2400 Steinberg-Dietrich Hall 3620 Locust Walk Philadelphia, PA 19104-6367 and NBER nroussan@wharton.upenn.edu Permanent income hypothesis (PIH) suggests that only persistent changes in household income should alter the path of consumption expenditures. Combined with the fact that money is fungible it makes the analysis of household budgeting conceptually simple, but also renders attempts at stimulating aggregate demand via fiscal policy largely ineffective, as transfers from the government simply crowd out spending out of existing wealth for all but the most liquidity constrained households.¹ In contrast, mental accounting heuristic posits that consumers use separate "mental" accounts rather than the sum of their available resources when making consumption expenditure decisions. Households divide spending into non-fungible budget categories and money in one mental account is not a perfect substitute for money in another account (Thaler, 1985, 1999). This facilitates tradeoffs between competing uses for funds in a way that potentially violates the PIH. While there is evidence that mental accounting affects spending on individual budget categories (Hastings and Shapiro, 2013, 2018), little is known about its role in driving households' total consumption expenditures.

We document novel evidence that individuals manage non-fungible budgets using different payment cards in a fashion consistent with the mental accounting heuristic. Analyzing the expenditure response of individuals when they exogenously receive a new credit card, we show that they perceive it as a new budget category beyond the existing categories managed using other payment methods. Therefore, they temporarily increase total expenditure on the new card, without changing the spending pattern on their pre-existing cards, as they preserve the pre-existing budget categories. Importantly, we do not observe a corresponding increase in debt balances, implying that the effect is driven by the new mental account rather than availability of credit. While the new card does increase liq-

¹A large literature investigates the effect of stimulus payments on total consumption and the consumption response following tax refunds, e.g. Baker et al. (2023), Johnson, Parker, and Souleles (2006); Kan, Peng, and Wang (2017); Kim and Lee (2021); Parker (2017); Parker and Souleles (2019). In order to ensure that households use stimulus payments for current consumption rather than saving, governments increasingly turn to timed payment programs, such as a recent experiment in Hong Kong - see https://www.economist.com/finance-and-economics/2021/08/07/does-perishable-e-money-represent-the-future-of-fiscal-stimulus.

uidity available to the household, we observe a substantial effect even among consumers that do not appear to be liquidity constrained.²

We use a unique setup where individuals received a new general purpose store credit card at a random time, without requesting it. A large retail chain in Israel signed an agreement with a card provider to start distributing a new store card. It notified members that, after a three-month transition period, they would be able to continue enjoying the store's special member discounts only on purchases made with the new card. However, 70% of the members did not apply for the card. Therefore, the retailer decided to require those members to use the store card in order to take advantage of the store discounts starting from the expiration date of their previous membership card (which was not a payment method). On the first purchase in the expiration month, each member was notified by the cashier that the membership had expired, and the only way to continue enjoying the special discounts would be by obtaining the new store card. Members who chose to do so filled out the application forms on spot and the card was delivered to them by mail within 7-10 business days. By the end of this staggered process, most of the members that had not previously applied for the new card nevertheless ultimately received it.

The process was not advertised and members were not notified in advance. Memberships expired three years from a previous renewal or issuing date. Members were not required to present their previous membership cards at the store, as the identification was conducted using the individual's state ID number. Thus, the probability that individuals remembered the membership expiration date and anticipated to get offered the new credit card is negligible, especially given that the previous membership benefits were

²Recent research shows that even relatively wealthy households tend to have a large portion of their assets held in highly illiquid forms, such as real estate and retirement accounts, leading to high propensities to consume out of liquidity injections such as tax rebates/stimulus payments - e.g., Kaplan and Violante (2014); Kaplan, Violante, and Weidner (2014); Olafsson and Pagel (2018). Baugh, Ben-David, Park, and Parker (2021) argue that the observed response to expected tax refund receipts by households with ample liquidity is consistent with mental accounting.

not associated with a payment method. Indeed, analyzing spending patterns close to the membership expiration, we do not find evidence of anticipation.

This staggered process presents an important advantage for identification, as the timing of customers receiving the new credit card is independent of their spending needs. It enables us to isolate the effect of the new card from the individuals' motivation to apply and use it, and from an increase in credit supply when issuers expect credit demand to rise (Gross and Souleles, 2002).

The setup offers several additional advantages. First, we observe most of the individual's daily private consumption— credit card transactions and cash withdrawals.³ In addition, the setting enables us to avoid card-specific implications of receiving a new payment card (Bachas, Gertler, Higgins, and Seira, 2021), as credit cards serve as a central means of payment, used on a daily basis and held by the majority of the population with bank accounts. Further, individuals did not receive any promotions or rewards for using the new card. The only incentive they had to use it was to continue enjoying this specific store's special discounts, not transferable or redeemable in other stores. Therefore, the decision to use the new card for out-of-store purchases is isolated from any benefits. Moreover, during the years of the sample, no credit scoring was conducted by dedicated agencies. This enables us to remove credit score considerations that could motivate individuals to use multiple cards (but not too many cards) and control the balance on each card. Additionally, to accrue credit card debt, consumers may opt for an interestfree installment payment plan, chosen at the time of purchase.⁴ Hence, we observe an individual's consumption decisions that is unaffected by borrowing costs.

³Debit cards are not common and the usage of checks accounted for 10% of the total household's spending (Israel Central Bureau of Statistics for 2013).

⁴Most of the credit cards are general-purpose deferred debit cards that have to be paid off every month. The only way in which they extend credit in any meaningful sense is via payment plans, whereby merchants allow cardholders to pay for their purchases (usually for transactions above 25\$) through interest-free installments. When an individual makes a purchase, she can decide to how many interestfree installments to divide this specific purchase into (up to the number of installments that the merchant offers), subject to the available credit line on the card.

Our sample includes only store members that applied for the new card on the spot at the first store visit during the membership expiration month. As individuals could apply for the new card at any time, we construct the sample to avoid endogeneity concerns relating to the timing of application. Among these individuals, we focus on members with purchasing histories of at least one year with the card issuer as to prior to the membership expiration, and those that use only the issuer's cards (based on the issuer's internal assessment). The idea is to observe all the credit card expenditure, mitigate unobserved influences related to the card characteristics or the issuer, and to gather enough data to demonstrate the budget categories management. Finally, we exclude members that have not started using the card close to its activation. In that way, we avoid endogeneity issues with regard to the starting point of using the new card.

We utilize three different estimation strategies to investigate the influence of receiving the new card on the consumer's budget categories and total expenditure. First, we perform a Differences-in-Differences analysis with staggered adoption (Athey and Imbens, 2021). In each month during the first two years, the treated group is classified as individuals whose memberships expired during the month, while the control group consists of individuals whose membership have not expired yet. Next, we employ a regression discontinuity in time (RDiT) approach (Lee and Lemieux, 2010; Hausman and Rapson, 2018). The RDiT is a quasi-natural experimental econometric technique, a special case of the classical regression discontinuity design (RDD), where time is the running variable. We use the membership expiration as the running variable, analyzing expenditure changes in a narrow window of five months around it. Finally, we examine a standard Differences-in-Differences analysis. The treated group includes individuals whose memberships expired during the first two years of the staggered process, while the control group consists of those with membership expiration during the last year. In all the specifications, we find that individuals change total consumption after receiving the new card only on the new card, while the spending pattern on the pre-existing payment methods remains similar.

In a staggered Diff-in-Diff analysis, we find that total expenditure increases over the 12 months after receiving the new card by 25.9% relative to the control group. The elevated expenditure starts moderating within few months after the receipt of the new card, and declines to the level of the control group after 11-12 months. Our results remain consistent in the other two estimation strategies and in varied robustness tests. The results are driven by out-of-store expenditure, as spending at the retailer accounts for less than 2% of the total monthly expenditure (for the 90th percentile). Thus, the retailer's requirement to use the new card for in-store purchases—which leads to a shift from the pre-existing cards to the new one—cannot explain the results.

These findings provide first non-experimental evidence that households use different payment cards to manage non-fungible budgets. The new card is perceived as a new budget category beyond the existing ones managed on the other cards. Individuals increase expenditure only on the new card, without changing the spending pattern on the preexisting cards as they preserve the other categories. Decision makers facing cognitive load and complex situations are more prone to use choice rules, heuristics and mental shortcuts, as implied by models of bounded rationality (Simon, 1955; Salant, 2011; Banovetz and Oprea, 2020). Associating and grouping expenses by card can be a helpful tool for mitigating the complexity of tracking various expenditures and optimizing consumption decisions at the level of the entire household budget. Consistent with the idea of "narrow bracketing" (Read, Loewenstein, and Rabin, 1999), it enables individuals to instead manage card-specific budgets, as spending is traceable on the monthly statements and the credit line on each card serves as an observable binding limit. Thus, cognitive constraints might drive consumers to maintain their spending habits their pre-existing cards, while adding spending only on the new one, instead of optimizing their total expenditure across cards, in line with models of mental accounting that are based on narrow framing of decisions or "narrow thinking" (Kőszegi and Matějka, 2020; Lian, 2021).

Thaler (1999) defines mental accounting as "the set of cognitive operations used by

individuals and households to organize, evaluate, and keep track of financial activities". The cognitive load of budget management is likely higher in larger households that are characterized by a wide variety of spending needs, such as couples and families with children. As mental accounting is generally hypothesized to reduce the computational cost for spending decisions, facilitate self-control, and prevent overspending (Heath and Soll, 1996), larger households with more complex budgeting management should be more susceptible to the mental accounting heuristic or "narrow bracketing" of expenses. We do not observe the marital status of the individual, nor the household size or the total expenditures of the household. We conduct additional analysis to show that our results also hold for subsamples of individuals who are more likely to be "single", as they typically face lower spending needs with simpler budget management.

We impute "single" status using age as well as by matching consumption characteristics of individuals in our sample with representative consumption by industry of oneearner/one-person households from the Household Expenditure Survey. Performing the staggered Diff-in-Diff analysis on those subsamples, we find that the increase in consumption is 11.3%-15.8% relative to the control group. As expected, those magnitudes are smaller relative to the ones in our main specification, but consistent with prior experimental evidence (Milkman and Beshears, 2009). The complexity of budgeting for larger households with a variety of spending needs makes the mental accounting heuristic a more powerful driver of consumption behavior. Indeed the effect that we document is strongest for the individuals in the middle of their life-cycle, who are more likely to have new families with young children. Comparing older consumers with the young "singles," we find a larger effect among the former group, as their budgets tend to be more complex, yet it is weaker than for the middle-aged consumers. This analysis also helps us to rule out a potential concern that the observed increase in total expenditure on the new card is driven only by intra-household substitution from cards held by other household members that we do not observe. The reason is that "single" individuals are naturally less likely to reallocate expenditure in this fashion.

We argue that income shocks or changes in liquidity constraints cannot explain our results in full. This is a central concern, as shocks to income or liquidity might correlate with the receipt of the new card and affect the decision to what extent to use it. In our setup, the timing of receiving the new card is unlikely to coincide with the households' specific consumption or liquidity needs, as the sample includes only members who applied for the new card on spot on the first purchase in the membership expiration month. Those individuals represent the majority of the members, reducing the probability of selection bias of our results. Given that they could apply for the card any time but have not done it, suggests that they did not experience or anticipate significant monetary shocks. We also address this concern more directly. First, we show that the total consumption response and the management at the card level are widely spread among individuals. Performing our standard Diff-in-Diff analysis using a quantile regression for the 25th, 50th and 75th percentiles response in consumption, we find an increase of 17.8%, 27.4%and 35.9%, respectively. On the pre-existing card, a similar trend in expenditure relative to the control group is observed. These results are similar to the standard Diff-in-Diff analysis, indicating that managing mental accounts is not a behavior that is confined to a small subset of "outlier" individuals.

The budget constraint that most influences behavior under the mental accounting heuristic is the current income flow rather than the present value of lifetime income, i.e. total wealth (Thaler, 1985). Therefore, the fact that after the initial spike in consumption, it decreases towards the consumption level of the control group suggests that income has not significantly changed over time and the budget constraint remains similar. If the initial rise in consumption expenditure corresponds to a decrease in savings, consumers are likely to notice the decline in wealth after several billing cycles. Some theories of mental accounting suggest that individuals might revise the goals in response to such information, in this case shifting away from narrow towards broader bracketing of expenditures (e.g. Koch and Nafziger (2016)).

Alternatively, individuals could fund the additional consumption by accruing debt. We show that this is not the case. Separating between non-installment and installment spending, we find an increase in non-installment payments, while installment spending the only way to accumulate debt beyond the next billing cycle — remains similar to the control group. There is no revolving credit, while the use of intra-period credit that is paid off in full at the end of each monthly billing cycle exhibit a similar pattern as the change in total expenditure: it rises sharply following receipt of new card, and declines subsequently, essentially returning to the original level after 12 months.

We also show that our effect is not driven by individuals who are likely to be liquidity constrained, as inferred from the credit utilization ratio prior to receiving the new card. In fact, both liquidity constrained and non-constrained consumers increase by expenditure by using the new card, while maintaining similar spending patterns on their pre-existing cards. The fact that unconstrained individuals increase expenditure after receiving the new card may indicate that standard buffer stock consumption models (Carroll, 1997) are a plausible explanation of the results. The new card provides an additional credit line, which may increase the spare borrowing capacity and reduce the individual's precautionary savings motive, increasing consumption. However, the observed response is not consistent with precautionary concerns being the dominant factor because non-constrained consumers reduce expenditure after a few months, instead of maintaining them at a permanently higher level.

Present-biased consumers as described by models of hyperbolic discounting (Angeletos, Laibson, Repetto, Tobacman, and Weinberg, 2001) might be more sensitive to the additional credit line on the new card and thus increase their consumption upon receiving one. However, if this were the case, we would expect these individuals to apply for the new card when they were offered to do so during the transition period. While mental accounting can help consumers with self-control problems, an exogenous creation of a new mental account might undermine such efforts. Thus, we do not rule out the possibility of present bias contributing to the evidence that we find, since some form of mental accounting would still need to be present to explain it.

Existing literature show evidence of fungibility violations with respect to narrow consumption categories in response to benefits or price shocks (Beatty, Blow, Crossley, and O'Dea, 2014; Hastings and Shapiro, 2018, 2013; Kooreman, 2000), or how small "windfalls' from gift cards or coupons affect purchases (Reinholtz, Bartels, and Parker, 2015; Milkman and Beshears, 2009). Other studies show broader implications of non-fungible budget categories on savings and debt (Argyle, Nadauld, and Palmer, 2020; Baugh, Ben-David, Park, and Parker, 2021; Bernstein and Koudijs, 2021; Medina and Pagel, 2021). Our paper extends these studies by showing that consumers treat payment methods as non-fungible budget categories.

The management of non-fungible mental accounts could help explain the mixed evidence on the success of different stimulus programs around the world and the consumption response following tax refunds, e.g. Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2023), Johnson, Parker, and Souleles (2006); Kan, Peng, and Wang (2017); Parker (2017). We show in a clean setting that a new payment card is enough to generate additional temporary spending. Hence, programs that provide income in a way that could be perceived by recipients as non-fungible (e.g., a pre-paid debit card) are more likely to generate a temporary increase in total consumption.

Finally, this study extends previous work on the impact of changes in credit limits (Gross and Souleles, 2002; Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2018; Aydin, 2022), using a credit card rather than cash (Prelec and Simester, 2001), or an initiation of overdraft facilities (D'Acunto, Rauter, Scheuch, and Weber, 2020) on total spending. Our focus on the card level contributes to a better understanding of how individuals manage the increase in spending, as it is not conducted only on the new card. Further, we show that the increase in expenditure is temporary if it is not funded by accruing debt or additional income, as the total budget of the household does not change.

This paper proceeds as follows. Section I outlines the institutional background regarding the new credit card that the store members received and regarding the Israeli credit card market. We also present the data and our sample of individuals. Section II demonstrates the budget categories management at the card level and the total expenditure response following the receipt of the new card. We also analyze how different household spending needs affect the total expenditure response following the creation of a new mental account. Section III deals with alternative explanations, in which we discuss positive income shocks, changes in liquidity constraints, precautionary savings or heterogeneity in consumption preferences. In Section IV we present robustness tests of our specifications, while Section V presents our main conclusions.

I Data and Institutional Background

I.A The New Store Card

We use a unique setup where individuals received a new general purpose store credit card at a random time, without requesting it. A large retail chain in Israel signed an agreement with a card provider to start distributing a new store card. It notified members that, after a three-month transition period, they would be able to continue enjoying the store's special member discounts only if they pay for them with the new card. Membership enabled enjoying this specific store's special discounts, not transferable or redeemable in other stores. Members were not charged membership fees.

However, by the end of the transition period, 70% of the members did not apply for the card. After the end of the transition period, the retailer did not want to "force" customers to apply in order to avoid adverse impact on customer satisfaction. Instead, the retailer and the card provider decided to require those members to use the store card in order to

take advantage of the store discounts starting from the expiration date of their previous membership card (which was not a payment method).

On the first purchase in the expiration month, each member was notified by the cashier that their membership had expired, and the only way continue enjoying the special discounts is by paying for them with the new store card. Members filled in the application forms on spot and the card was delivered to them by mail within 7-10 business days. By the end of this staggered process, most of the members that had not previously applied for the new card nevertheless ultimately received it.

The process was not advertised and members were not notified in advance. The card provider and the retailer did not notify customers in advance since the notification during the transition period was not effective enough in the first place. Individuals did not receive any promotions or rewards for using the new card. The only incentive they had to use it was to continue enjoying this specific store's special discounts, not transferable or redeemable in other stores.

Memberships expired three years from previous renewal or issuing date. Members were not required to present their previous membership cards at the store, as the identification was conducted using the individual's state ID number. Thus, the probability that individuals remembered the membership expiration date and anticipated to get offered the new credit card is negligible, especially given that the previous membership benefits did not involve any payment methods. Indeed, analyzing spending patterns close to the membership expiration, we do not find evidence of anticipation, as presented in section II.

I.B The Israeli Credit Card Market

The Israeli credit card market is characterized by several distinctive features. Credit cards are a very common means of payment for most consumption expenditures. In contrast, debit cards are not common; it was only after recent regulations that financial institutions began distributing them in 2016, i.e. after the end of our sample. Personal checks accounted for 10% of total purchases during the relevant time period (Israel Central Bureau of Statistics for 2013). Therefore, most of the individual's daily private consumption is conducted by credit cards or cash. Credit cards serve as a major means of payment, held by the majority of the population with bank accounts and many use them on a daily basis.⁵

Most of the credit cards are general-purpose deferred debit cards that have to be paid off every month. To accrue credit card debt, consumers may opt for an interest-free installment payment plan, chosen at the time of purchase. The only way in which they extend credit in any meaningful sense is via payment plans, whereby merchants allow cardholders to pay for their purchases (usually for transactions above 25\$) through interest-free installments. This type of credit is provided by the merchant, not the credit card company. When an individual makes a purchase, she can decide to how many interest-free installments to divide this specific purchase into up to the number of installments that the merchant offers, and subject to the available credit line on the card. Cardholders can also ask merchants to register specific transactions as "credit transactions," which carries interest, but this accounted for less than 4% of the total transactions. In this case, the credit is provided by the credit card issuer, but the cardholder needs to choose the number of installments when making the transaction, instead of deciding at the end of each month how much to revolve.

Moreover, during the years of the sample, no credit scoring was conducted by dedicated agencies. Regulators started to develop credit scores systems only in 2018. Thus, the decision upon receiving a new card was conducted mainly based on the internal model of the card issuer. The only external data source that existed was information on customers

⁵The number credit cards in circulation was six million in 2011 (Knesset Research and Information Center, 2012) out of total population of 8 million.

that do not meet their obligations. Banks, credit card companies, courts, government institutions, and some commercial companies (such as cellular companies) are required to share this information. In our sample, a small proportion of the members were not approved during the screening process for another regular credit card. Those individuals received a general-purpose prepaid card. We include those members in our sample, although our results do not change if we exclude them.

Consumers usually apply for a new credit card when they seek a liquidity cushion for emergencies, anticipate future consumption needs that requires accruing new debt, or expect to benefit from better rewards, lower interest rates and fees, or improved credit scores by building a credit history.⁶ Our setting is unique in that individuals exogenously received a new credit card without requesting one, which, together with the Israeli credit card market characteristics, enables us to overcome the potential endogeneity concerns.

I.C Sample Selection

Our main sample consists of 13,291 individuals who satisfy the following conditions. We include only store members who applied for the new card on spot on the first purchase of the membership expiration month. As individuals could apply for the new card at any time, we construct the sample to avoid endogeneity concerns regarding the timing at which the person applied for the card. Among these individuals, we focus on members with purchasing histories with the card provider of at least one year prior to the membership expiration, and those that use only the issuer's cards (based on the issuer's internal assessment), which is the majority of consumers. The idea is to mitigate unobserved influences related to the card characteristics or the issuer, as well as to have sufficient data coverage and accuracy of baseline consumption expenditures. Finally, in our main

⁶Empirically, the cost of debt service is not necessarily the main factor that affects how individuals split consumption and repayments across cards (Prelec and Loewenstein, 1998; Amar, Ariely, Ayal, Cryder, and Rick, 2011; Gathergood, Mahoney, Stewart, and Weber, 2019; Keys and Wang, 2019; Ponce, Seira, and Zamarripa, 2017).

analysis we include only members that started using the new card within three months from its activation. This allows us to avoid endogeneity issues with regard to the starting point of using the new card. We do not filter by expenditure conducted after receiving the new card.

The unit of analysis in the data is an individual, not a credit card account that multiple individuals (e.g., spouses) can use. We use monthly proprietary data for the years 2010-2013 from a leading financial institution in Israel. The payment system is concentrated and composed of few leading financial institutions, each with a substantial market share.

The data includes the total and per card monthly expenditure (including ATM withdrawals conducted on the card), outstanding balance, credit line, installment and noninstallment spending for each individual on a monthly basis. Additionally we observe the gender, age, residence and an internal credit score of each individual. The card issuer uses a proprietary internal credit scoring model based on socio-economic indicators and estimated default risk to decide whether to issue a new card and under what terms. Additionally, the card issuer assesses whether an individual uses only its cards or also holds cards of other issuers based on a proprietary internal model.

I.D Summary Statistics

Table I presents the summary statistics of few of the main characteristics of the individuals in our sample in comparison to the overall Israeli population older than the age of 15 (the minimum age to apply for a credit card is 16, only with parental consent). We are limited in the amount of information we are able to disclose due to strict restrictions of the financial institution that provided the proprietary data. Table I presents the summary statistics.

The gender composition of the individuals in our sample is similar to the general adult population. Our sample consists of slightly older consumers that held slightly more credit cards (prior to receiving the new one). Further, individuals in our sample held an average of cards 1.57 prior to receiving the new card, generally similarly although slightly more than the adult Israeli population.

We also show the average total expenditure of individuals in our sample out of the average household consumption expenditure (excluding housing and vehicles), and out of one-person household consumption expenditure. The aggregate Israeli expenditure data is gathered from the Household Expenditure Survey (collected by The Israeli Central Bureau of Statistics). The expenditure on an average card of individuals in our sample accounts for 53% from the average household expenditure. As the average number of adults in a typical household is 1.7, this indicates the common usage of credit cards for current consumption, and the representation of the results of the individual's daily expenditure. Consistently, the expenditure out of a one-person household is 81%. Given that the on average, payments with checks account for about 10% of spending, we observe most of the individual's monthly spending.

The expenditure at the retailer accounts for less than 2% of the total monthly expenditure (for the 90th percentile). This indicates that the retailer accounts for a non-negligible portion of the consumer's spending, but not too high. Thus, we are not concerned that individuals felt special pressure to apply for the new card, which is also indicated in the fact that most of the members have not applied for the new card during the transition period.

II Evidence on Budget Categories and Expenditure after Receiving a New Payment Card

To study how receiving a new credit card influences the individual's budget management, our empirical methodology includes three different specifications. In Section II.A we show the results of our main specification— Diff-in-Diff analysis with staggered adoption. In Section II.B a regression discontinuity in time (RDiT) approach is presented, and in Section II.C we perform a standard Diff-in-Diff analysis. Our results are consistent across the three estimation strategies. Then, in Section II.D we demonstrate how household characteristics affect the spending response after receiving the new card.

II.A Staggered Differences-in-Differences

Exploiting the fact that individuals started using the new card at different points in time, we start the empirical analysis by performing a Diff-in-Diff specification with staggered adoption (Athey and Imbens, 2021). In each month during the first two years, the treated group is classified as individuals whose memberships expired during the month, while the control group consists of individuals whose membership has not expired yet. We estimate the following specification:

$$Y_{it} = \sum_{k=-11}^{12} \beta_k \text{Treated}_{it+k} + \alpha_i + \alpha_t + \varepsilon_{it}.$$
 (1)

Where Y_{it} represents the natural logarithm of total spending and the expenditure on the pre-existing cards for individual *i* in year-month *t*. We handle outliers by winsorizing the monthly expenditures at 1%. *Treated*_{*it+k*} is an individual-level dummy that is equal to 1 at time t + k and 0 otherwise, where k = 0 when individual *i* receives the new card at time *t*. We estimate the effect 12 months following the month in which the individual received the new card relative to the 12 preceding months, thus the treated group includes individuals whose memberships expire during the first two years on the staggered process. α_i is the consumer fixed effects, included to absorb time-invariant systematic differences in consumption spending across individuals, such as differences in occupation, gender, cultural background, or education. α_t is the time fixed effects that controls for any year-month specific effects on consumption. Standard errors are clustered by individual and

time.

Column 1 in Table II presents the results of the staggered Diff-in-Diff for the response in total expenditure. We find that total expenditure increases over the 12 months after receiving the new card by 25.9% relative to the control group.

In Figure 1 we show the changes in consumption on a monthly basis during a timewindow of 24 months around the membership expiration. During the first few months after the receiving the new card, total expenditure rises relative to the period prior to its receipt. However, then, over the following 10 months it gradually declines to the level of the control group.

Under the assumption of random assignment of adoption and no anticipation effects, the Diff-in-Diff estimator β_1 is a weighted average of the monthly treatment effects. As our identification strategy relies on the random timing of receiving the new card, we verify the assumption of no anticipation by analyzing whether expenditure exhibits parallel trends prior to receiving the new card. The trends found in the outcome variable must be the same in both the treatment and the control groups. We provide supporting evidence for this assumption based on a visual inspection of Figure 1. Observing the expenditure of the treated and control individuals, we find no significant differences in trends during the 12 months prior to the expiration of the membership, and specifically in the last few months prior to the expiration of the membership. Therefore, the parallel trends assumption appears to hold.

We also do not observe changes in expenditure prior to receiving the new card among individuals that received it (see further discussion in the next Section). Additionally, the membership issuance or previous renewals did not involve any payment requirement, hence members could not anticipate it to be part of the process this time. This enables us to rule out anticipation effects around the expiration date.

Separating between the new credit card and the pre-existing cards, we find no significant difference between the groups in spending on the pre-existing cards (Column 3). The similar expenditure pattern of both groups on the pre-existing cards is also observed in Figure 2. Consistent with non-fungible budget categories, households treat the new card as a new budget category, while preserving the other categories on the pre-existing cards. Hence, changes in total spending are managed only on the new card, while the spending pattern on the pre-existing cards remains similar.

In Columns 2 and 4 we consider each year-month as a separate cohort, focusing on specific time windows around each cohort. The cohort approach for the staggered Diffin-Diff allows us to identify a common treatment effect over multiple treatment events while avoiding influence of potential overlaps between events on the estimate, and mitigate potential biases from "bad comparisons" problems with multiple treatment events (Baker, Larcker, and Wang, 2022; Gormley and Matsa, 2011). To this end, we replace the individual fixed effects with individual-cohort fixed effects in the Diff-in-Diff specification. We find similar results as above, but with higher magnitudes for total expenditure, as now we control for individuals that may appear in the control group in a specific month and after receiving the new card in the treated group.

Although the retailer's requirement that the new card be used for in-store purchases in order to obtain the in-store discount does lead to a potential reallocation from the pre-existing cards that the household might have access to in favor of the new one, the in-store purchases account for less than 2% of the total monthly expenditure (for the 90th percentile). Thus, the use of the card for in-store discounts alone, and the resulting substitution away from other cards held by the household, cannot explain our results.

Further, we show that both the total and the card-level consumption responses do not vary substantially across individuals. We perform our staggered Diff-in-Diff analysis using quantile regression for the 25th, 50th and 75th percentiles of consumption response and find very similar (albeit, naturally, increasing) magnitudes across these percentiles. Table III presents the results. In Columns 1-3 of Table III, we find an increase of 17.8%, 27.4% and 35.9% in total expenditure, respectively. These results are similar to the baseline staggered Diff-in-Diff analysis, where the magnitude was 25.9%. In Columns 4-6, we find no difference in the expenditure on the pre-existing cards, similar to the baseline specification. The results indicate that our findings are not driven by a subset of "outlier" individuals.

As total spending of treated consumers declines to the level of the control group about 12 months after receiving the new card, we are also interested in exploring a longer period. Therefore, we study the expenditure pattern 13-24 months after receiving the new card (relative to the control group) for a subsample of individuals with early membership expiration, thus were the first to receive it. Figure A.1 presents the spending pattern for up to 24 months after receiving the new card. Focusing on months 13-24, we observe a similar expenditure pattern for the treated and control individuals, but with a somewhat higher variability among the treated consumers. They spend slightly less in months 14-17, but the difference between the groups disappears over the subsequent months. Consistent with our expectation, as the budget constraint has not changed, those individuals might have temporarily lower available resources due to the increased expenditure in the previous months.

As mentioned in Section I.C, we also observe ATM cash withdrawals since they are performed almost entirely via credit cards, given that debit cards are not common in Israel. Analyzing cash withdrawals after receiving the new card, we find that 91% of the individuals continue to use the pre-existing card at ATMs, and do not substitute towards using the new card. While this behavior is consistent with mental accounting individuals use the same card for the same purpose—we believe that the main driver in this case might be a simpler cognitive constraint: remembering the new card's PIN code requires additional effort, thus it is just easier to continue using the same card as before for cash withdrawals (in Israel, as in the US, the PIN code is not used for payments, but is necessary for cash withdrawals).

As a robustness test, in Section IV.A we mirror our results above after excluding indi-

viduals with early or late expiration dates, as they may react differently to the requirement to use the new card due to specific potential unobserved influences. Our results remain robust also after including in the specification for all the individuals that applied for the new card during the staggered process, including those that did it not on spot on the first purchase (Section IV.B).

II.B Regression Discontinuity in Time

An alternative estimation approach that naturally fits our empirical setting and identification strategy is Regression Discontinuity in Time (Lee and Lemieux, 2010; Hausman and Rapson, 2018). RDiT is a quasi-natural-experiment econometric technique, a special case of the classical regression discontinuity design, where time is the running variable. We use the time around membership expiration as the running variable, studying the total spending response and the behavior at the card level in a narrow window around the receipt of the new card. We estimate the following specification:

$$Y_{it} = \beta_{RDiT} \text{Post}_{it} + \alpha_i + \alpha_t + \varepsilon_{it}, \qquad (2)$$

where Y_{it} represents the natural logarithm of total spending and the expenditure on the pre-existing cards for individual *i* in year-month *t*. Post_{it} is an individual-level dummy that is equal to 1 after receiving the new card and 0 before. β represents the local average treatment effect (LATE), i.e., the relative difference in consumption after receiving the new card compared to the "normal" spending of those individuals before receiving the new card. Typically, smaller bandwidths provide less biased estimates of the effect of interest. Thus, we use a narrow window of 5 months before and after receiving the new card. In the robustness tests, we show that changing the time window to 3 months does not change the results (Section IV.B). α_i is the consumer fixed effects, α_t is the time (year-month) fixed effects. Standard errors are clustered by individual and time. Next, we visually explore the total expenditure among individuals that received the new card in a short time window before and after the membership expiration (Figure A.2). We observe an immediate increase in expenditure of 17% in the month of the membership expiration. We attribute the next month as the first full one for all the consumers, as the calendar months do not necessarily coincide with the billing cycles. Here we witness an additional increase of 9%. However, we do not observe any changes in expenditure prior to receiving the new card, indicating the lack of any anticipation effect or earlier change in spending.

In Column 1 of Panel A in Table IV we find that this increase in expenditure is notable with a coefficient of 27.3% in the RDiT analysis. At the same time, the increase on the pre-existing cards is not statistically significant (Column 2). These results are in line with the results of the Diff-in-Diff specifications and serve as an evidence of managing budget categories by payment cards. The new card is perceived as a new category, thus used by individuals to increase consumption while keeping the expenditure on the other categories similarly.

II.C Standard Differences-in-Differences Analysis

We supplement the analyses presented in sections II.A-II.B by performing a standard Diffin-Diff approach. This specification enables us to present more clearly the treated and the control group separately. The treated group includes individuals whose memberships expired during the first two years of the staggered process. The control group consists of those whose memberships expired during the last year, i.e. they have not received the new card during the first two years. We perform the following Diff-in-Diff specification:

$$Y_{it} = \beta_1 \text{After}_t \times \text{Treat}_i + \alpha_i + \alpha_t + \varepsilon_{it}.$$
(3)

Here Y_{it} represents the natural logarithm of total expenditure and the spending on the

pre-existing cards for individual *i* in year-month *t*. After is a dummy variable taking the value of one for the 12 months after the membership expiration and zero for the prior 12 months. Treat is an indicator equals one for individuals in the treatment group as defined above and zero for the the control group. α_i is the consumer fixed effects, α_t is the time (year-month) fixed effects. Standard errors are clustered by individual and time.

Panel B in Table IV presents the results of the standard Diff-in-Diff. In Columns 1-3 we find that total expenditure increases over the 12 months after receiving the new card by 27% relative to the prior period, while consumers that did not receive the new card experience a moderate rise of 3.9% in spending over the same period. Thus, the coefficient *After*×*Treat* is significantly positive with a magnitude of 23.4%.

Separating between the new credit card and the pre-existing cards, we find no significant difference between the groups in spending on the pre-existing cards (Columns 4-6 of Panel B in Table IV). A similar increase of 3.2%-3.7% in both groups indicates that the consumption on the pre-existing cards is not affected by the new card. Respectively, the coefficient *After*×*Treat* is insignificant. Consistent with non-fungible budget categories, households treat the new card as a new budget category, without changing the spending pattern on the rest of the categories managed on the other cards.

II.D Household Characteristics

The findings in the previous section provide first non-experimental evidence that households use different payment cards to manage non-fungible budgets. The new card is perceived as a new budget category beyond the existing ones managed on the other cards. Individuals increase expenditure only on the new card, without changing the spending pattern on the pre-existing cards as they preserve the other categories. Decision makers facing a greater cognitive load and complex situations are more prone to use heuristics and mental shortcuts, as associating and grouping expenses by card could help mitigate the complexity of optimizing consumption decisions. Consistent with the idea of "narrow bracketing" (Read, Loewenstein, and Rabin, 1999), it enables individuals to instead manage card-specific budgets, as spending is traceable on the monthly statements and the credit line on each card serves as an observable binding limit. Thus, cognitive constraints might drive consumers to maintain their spending habits their pre-existing cards, while adding spending only on the new one, instead of optimizing their total expenditure across cards, in line with models of mental accounting that are based on narrow framing of decisions or "narrow thinking" (Kőszegi and Matějka, 2020; Lian, 2021).

The cognitive load of budget management is likely higher in larger households that are characterized by a wide variety of spending needs, such as couples and families with children. As mental accounting is generally hypothesized to reduce the computational cost of making spending decisions, facilitate self-control, and prevent overspending (Heath and Soll, 1996), larger households with more complex budgeting management should be more susceptible to the mental accounting heuristic or "narrow bracketing" of expenses. We do not observe the marital status of the individual, nor the household size or the total expenditures of the household. Therefore, we conduct three types of analyses to show that our results also hold for subsamples of individuals who are more likely to be "single", as they typically face lower spending needs with simpler budget management.

The first set of tests restricted to a subsample of consumers younger than the average age of married for the first time—27 years for men and 25 for women (Israeli Central Bureau of Statistics, 2018). Columns 1-2 in Panel A of Table V present the results of our baseline staggered Diff-in-Diff specification for the total expenditure of this subsample.

We find that over the 12 month period following the receipt of the new card, total expenditures of young individuals increase by 11.7%-13.8% relative to the control group. These magnitudes are smaller relative to the ones in our main specification in Table V, but consistent with prior experimental evidence (Milkman and Beshears, 2009). We consider them to be a robust lower bound of the "true" effect of mental accounting, as the magnitudes among non-"single" households are expected to be higher.

Additionally, we use characteristics of consumption expenditure to proxy for family size. Using data on the aggregate 2012 expenditure by main merchant-coded industries for the individuals in our sample, we estimate the individual's expenditure share by industry. Then, we construct representative consumption shares by industry of households with one-earner/person (excluding housing expenditures) using data on consumption categories by number of earners in household and by number of persons in household from the 2012 Household Expenditure Survey.⁷ We use propensity score matching based on the expenditure shares for different consumption categories by household size. "Singles" are defined as those falling in the top decile of the respective probability distribution.Unlike the age analysis, here we are able to capture "single" consumers regardless of their age.

Columns 3-6 in Panel A of Table V present the results of the baseline Diff-in-Diff specification for the total expenditure of those two subsamples. We find that total expenditure of "singles," as proxied by the number of earners in household, increases by 11.3%-12% relative to the control group. When using the number of persons in the household (Columns 5-6), we observe an increase of 14.1%-15.8% in total expenditure among "singles" relative to the control group.

As expected, those magnitudes are smaller relative to the ones in our main specification, as the complexity of budgeting for larger households with a variety of spending needs makes the mental accounting heuristic a more powerful driver of consumption behavior.

In Panel B of Table V we verify that the pattern of expenditure on pre-existing cards documented above also holds among "singles." In all of the Columns—across the different types of analysis—we do not find statistically or economically significant change in spending relative to the control group, indicating that individuals in those subsamples preserve the rest of the budget categories managed on their other cards.

⁷The data are collected by The Israeli Central Bureau of Statistics annually on the expenses and income of households in Israel and on the products they own. The survey is used to estimate the weights for the consumer basket of the CPI, and the component of private consumption in GDP.

We further explore the role of budget complexity by extending the age-based analysis. We split the rest of the individuals in our sample into two subsamples: those aged between the average age of first marriage and the median age in the sample; and consumers older than the median age. Table VI presents the results for each of those two groups. Panel A shows the results for the total expenditure, while Panel B for the pre-existing cards. Then, we compare the magnitudes between the three groups by age—"singles", the "middle" group, and older individuals.

We find the largest effect among individuals in the middle of their life-cycle. Those consumers are more likely to be recently married or have established new households with newborns and young children. Compared to the "single" individuals, their budgets are more complex to manage due to the growing variety of spending needs, as they start purchasing new consumer goods from unfamiliar categories, such as products for babies and children, need to pay for childcare, etc. The lack of life experience and the steep learning curve to acquire budget management skills should make them more susceptible to "narrow bracketing" of expenses or the mental account heuristic, which helps them to reduce the cognitive load by compartmentalizing expenditures, in particular at the level of method of payment.

At the same time, the effects that we find among the oldest individuals are lower. Comparing directly between individuals in the middle group and older consumers, we find in Column 1 of Panel C in Table VI that younger individuals' total expenditure increased 26.7% more than the older ones after receiving the new card (relative to the control group). Both groups maintain their spending patterns on the pre-existing card similarly (Column 2). They are more experienced in managing budgets, have more time to plan, and have fewer demands on their time and resources, as the children in many cases have reached adulthood and are no longer dependent members of the household.

All of this suggests that the older households face a lower cognitive load than the middle-aged ones. Yet, the magnitudes that we find for the oldest individuals are still

higher than among "singles", as their budgets are typically more complex relative to "singles". Some of those individuals are also likely to be one-person households, similarly to "singles", but the non-monotonic effect in age indicates that the the complexity dimension has to be considered when analyzing the true effect of a new mental account.

III Alternative Explanations

In this section we address directly alternative explanations to the results. Section III.A explains that expenditure reallocation from other unobserved cards is not the main channel that drives our results. Section III.B shows that income shocks, liquidity constraints, and reduction in precautionary saving cannot fully explain our results. Section III.C explains why nonstandard consumption preferences are not a sufficient explanation either.

III.A Intra-Household Reallocation

We start the discussion of alternative explanations by analyzing potential intra-household substitution from other cards that we do not observe, held by the individual or other household members. This concern may explain the high magnitudes we observe in the full sample. Although we cannot fully exclude the existence of substitution, we discuss in this section that this is not the main driver of the results.

First, although the retailer's requirement that the new card be used for in-store purchases in order to obtain the in-store discount does lead to a potential reallocation from the other cards that the household might have access to in favor of the new one, the in-store purchases account for less than 2% of the total monthly expenditure (for the 90th percentile). Hence the resulting substitution away from other cards held by the household and the use of the new card for in-store discounts alone cannot fully account for our results.

Additionally, there is no specific motivation for individuals to reallocate out-of-store

purchases to the new card, as no benefits are associated with using it. It is also hard to believe that households shift expenditure so "efficiently" across cards in such a short time window. As total expenditure of the individual becomes similar to the control group after one year, it means that the entire consumption expenditure that was transferred to the new card is subsequently reallocated back (not that such a behavior would make sense if there were any benefits for spending a certain amount on the card during a short period after opening, as is often the case in the U.S. credit card market; however, there were no such incentives in our case).

Further, consumers included in our sample hold only this issuer's cards (as per the issuer's assessment), hence it is highly unlikely that the observed results are driven entirely by substitution from cards that we cannot observe.

Finally, the analysis of "single" households helps us to address the issue of intrahousehold substitution more directly. As "single" households are naturally less likely to reallocate expenditure from other unobserved cards in the household, the results in section II.D—by consumption characteristics and by age—demonstrate that creation of a new mental account has a meaningful impact on the consumer's total expenditure, which is not driven solely by reallocation.

III.B Income and Liquidity

Shocks to income or liquidity needs might correlate with the timing of receiving the new card and the extent to which it is used for consumption expenditure. Additionally, even if the receipt of the new card is fully exogenous, it could still lead to an increase in consumption expenditures under PIH if it relaxes consumers' liquidity constraints. We address these concerns in several ways.

First, we can rule out that the increase in consumption is driven by a coincidental increase in permanent income or anticipated consumption needs. A central feature of the setup is that we are able to include in our analysis only members who applied for the new card on the spot during their first purchase in the membership expiration month. Therefore, the timing of receiving the new card is unlikely to coincide with the households' consumption needs. Those individuals represent the majority of the members, which makes it unlikely that our results are subject to selection bias. Given that these consumers had the option to apply for the card at any time prior to expiration of their store membership but had not done so suggests that they did not experience or anticipate significant liquidity needs. We also find no evidence of anticipation by individuals prior to receiving the new card in (see Section II.A).

The fact that after the initial spike in consumption, it decreases towards the consumption level of the control group (see Figure 1) suggests that income has not significantly changed over time and the budget constraint remained similar. If individuals had received a positive permanent income shock that coincided with receiving the new card, their consumption expenditures would increase to a new level that would be maintained until the next (unpredictable) change in permanent income. Thus, the fact that consumption expenditure drifts back to its original level rules out the standard consumption-smoothing behavior that is implied by the PIH.

Second, one could imagine a lumpy consumption expenditure that produces a (smooth) stream of consumption services, such as an expensive durable good, that is funded by the new card. This could potentially explain the temporary spike in expenditure as liquidity constraints are relaxed. The typical way to fund such additional temporary (or lumpy) consumption needs is by accruing debt, which allows for better smoothing of payments and, thus, other consumption expenditures. In our Israeli setting, the main way to accumulate consumer debt beyond the next billing cycle is to make installment payments when purchasing products or services. Such installment loans are interest-free to the borrower (i.e., implicitly subsidized by the lender), and hence attractive to consumers who seek to smooth expenditures across consumption categories subject to their budget

constraint and limited liquidity. In order to analyze installment borrowing behavior, we perform the baseline staggered Diff-in-Diff analysis in equation (1) while separating non-installment and installment spending. When individuals make a purchase, they can choose the number of installment payments the purchase should be divided into (up to the maximum set by the merchant), subject to the available credit line on the card. Thus, our data includes the total monthly expenditure by installment vs. non-installment purchases.

Panel A in Table VII presents the results for total expenditure. We find that after receiving the new card, the increase in consumption is only observed in non-installment payments, while installment payments remain similar to the control group. In Panel B of Table VII we verify that individuals do not choose to increase installment borrowing on their pre-existing cards. We find a similar result, i.e., individuals' change in noninstallment payments is similar to the change in expenditure on the pre-existing cards, while installment payments do not change. This indicates that individuals do not accrue debt to temporarily increase expenditure. A natural increase in debt that occurs during the billing cycle could result in a temporary relief of potential liquidity needs. However, the entire balance of non-installment debt is paid off at the end of the monthly cycle, and the billing dates vary across consumers in a manner that is exogenous to their temporary liquidity needs.

The fact that individuals do not accrue debt might indicate that the increase in total expenditure on the new card is attributed to nondurable goods. Models of mental accounting predict faster debt repayment for nondurable goods (Quispe-Torreblanca, Stewart, Gathergood, and Loewenstein, 2019; Prelec and Loewenstein, 1998). To study the spending segments, we utilize partial data of expenditure breakdown by main merchant-coded industries in 2012 for a subsample of individuals. We compare the share of each segment on the new card relative to the consumer's pre-existing cards, and then relative to the control group. Figure 3 reports relative expenditure shares for the new card spending relative to spending on pre-existing cards (or the control group) for each main merchant

coded industry, where a ratio above one indicates that the share of spending for a specific segment is higher on the new card. We do not observe more granular data, thus we cannot separate between different products within each segment, but we find that the new card is used across a large variety of segments, for consumption expenditures on both durable and nondurable goods as well as services.

Consumers are more likely to use the new card on the more frequent types of expenditures (such as food and clothing) as well as less frequent purchases typically done at retail stores (electronics, appliances, and furniture), as evidenced by ratios of expenditure shares that are greater than unity. At the same time they largely continue using the pre-existing cards for expenditures that are infrequent but likely with the same vendor where the credit card might be saved in a customer's online profile (e.g. travel, insurance), as well as regular payments that might have prior pre-authorization to be made automatically (e.g. utilities or telecommunication services), since the ratios of expenditure shares on the new card for these categories are well below one. Again, this evidence is not consistent with the spike in spending after receipt of the new card being driven by lumpy consumption expenditures (e.g. of durable goods or expensive services, such as travel) as could be expected under PIH with liquidity constraints.

Even though the card receipt is exogenous, it could lead to an increase in consumption expenditure in standard buffer stock consumption models (Carroll, 1997). The new card provides an additional credit line, which may increase the spare borrowing capacity and thus mitigate one's concern about perceived uncertainty about future ability to absorb unexpected income shocks or consumption needs. This effect would reduce the consumers' precautionary savings motive, thus enabling them to increase current consumption and debt. However, the observed consumption response is not consistent with precautionary concerns being the dominant factor. As shown earlier in Figure 1, the increase in total expenditure is temporary. A few months following the receipt of the new card, consumers start reducing expenditure and eventually it decreases to the level of the control group. Thus, the additional liquidity cushion does not provide a *permanent* boost to consumption by reducing the need for precautionary saving, as would be predicted by buffer-stock models.

Next, in order to further investigate the potential role of relaxed credit constraints we study credit utilization ratios. To this end, we estimate the staggered Diff-in-Diff specification in equation (1) but changing the outcome variable to the utilization ratio. Panel A of Table VIII presents the results for the total utilization ratio on all the cards the individual holds, while Panel B presents the results for the utilization ratio on the pre-existing cards. In Columns 1-2 of each Panel, the outcome variable is the actual utilization ratio, while in Columns 3-4 of Panel A we follow Aydin (2022) and present the results for normalized utilization ratio, calculated at total outstanding balance relative to the credit limit *prior* to receiving the new card. As reported in Columns 1-2 of Panel A, after receipt of the new card the utilization ratios among treated individuals decline, since the increase in total expenditure is lower than the additional credit limit that comes with the new card (naturally, given the increase in total expenditure, the normalized utilization ratios increased, Columns 3-4). As individuals did not accrue more installment debt, the observed change in total utilization ratios stems from the rise in expenditure on the new card. At the same time, the utilization ratios on the pre-existing cards presented in Panel B do not change, in line with the evidence that expenditure on pre-existing cards does not decrease.

We also show visually in Figure 4 the patterns in the current and normalized utilization ratios on all the cards (we recode the spending levels of the control group as 100 at the beginning of the time window, i.e., 12 months before receiving the new card). The patterns in the normalized utilization are similar to the total expenditure—following an initial spike in the utilization ratio, it almost fully converges back to the original level. This is in contrast to other settings where reduced precautionary demand is the main driver of increased consumption expenditures following a raise in the credit limit (Aydin, 2022) or an initiation of overdraft facilities (D'Acunto, Rauter, Scheuch, and Weber, 2020), as credit utilization (relative to its previous limit) permanently increases (even though utilization relative to the total limit does revert back after the initial spike).

In addition, we show that both liquidity constrained and non-constrained consumers (as inferred from the credit utilization ratio prior to receiving the new card) increase consumption when receiving the new card. We perform the baseline staggered Diff-in-Diff analysis in equation (1), separating between individuals by quartiles of utilization ratios. Column 1 present the top utilization ratio quartile, and Column 4 the bottom. Panel A in Table IX presents the results of this specification for total expenditure, Panel B for spending on the pre-existing cards. We find that all of the groups increased total consumption in the 12 months after receiving the new card relative to the comparable control group, while the spending on the pre-existing cards remains similar to the control, as the coefficients in Panel B are statistically insignificant.

In order to further address the role of liquidity needs and credit constraints we return to the analysis based on consumer age, comparing younger and older individuals as presented in Table VI. An increase in total consumption occurs in all age groups, with a bigger magnitude among younger consumers (around 30% vs. 21% among older ones). The spending on the pre-existing cards remains similar to the control group in both age groups. As younger individuals are on average more liquidity constrained (in general and in our sample) and exhibit higher uncertainty in future income, we observe a stronger impact on younger individuals. These results are consistent with the mental accounting theory, by which the tighter the budget, the more explicit and strict are the budgeting rules (Thaler, 1999). However, these results show that although liquidity and uncertainty in future income are important factors, they do not fully explain our findings, especially in regard to the expenditure management at the card level.

Finally, we verify that the results are not driven by temporary liquidity needs. To this end, we rerun our staggered Diff-in-Diff analysis in equation (1), but this time exclude periods with increases in spending above the previous limit, which might be an ad-hoc binding constraint that motivated individuals to apply for the new card. Table X presents the results for total spending (Panel A) and spending on the pre-existing cards (Panel B) only among the treated individuals. In Column 1 of each Panel in Table X we include only months in which the consumer's expenditure is below the previous limit. We find that the effect remains significant at 24.7% (relative to 27% in the full sample) with no significant change in spending on the pre-existing cards. In Columns 2-4 of each Panel we include months with expenditures below 90%, 80% and 60% of the previous limit, respectively. The increase in total spending after receiving the new card holds in all Columns, although the magnitudes slightly decrease. However, spending on the preexisting cards remains stable, indicating that temporary liquidity needs are not the main driver of the results. Overall, the evidence presented above is not consistent with the relaxation of credit constraints being the sole driver of our results.

III.C Non-standard Preferences

Can "non-standard" consumption preferences explain our empirical results? Consumers exhibiting present bias as captured by models of hyperbolic discounting might be more sensitive to the new card with its available new credit line (Angeletos, Laibson, Repetto, Tobacman, and Weinberg, 2001), increasing their consumption immediately after the card receipt. However, if this were the case, we would expect these individuals to apply for the new card earlier, especially when they were offered to do so during the transition period, as minimal effort on their part would be required to obtain the card.

Impatient consumers might have less stable consumption over time, as they fail to smooth their consumption as PIH predicts, spending too much out of transitory increases in income and leaving too little of a savings buffer to cushion against shortfalls (Laibson, 1997). Such individuals might be more willing to take up the new card when it is offered to them on the spot as they might see it as a an easy way to increase consumption in the near term. To address this possibility, we rely on the analysis presented in section II.A of the spending trends in the treated and the control groups before receiving the new card. We find parallel trends both in spending level and spending volatility. Further, the change in expenditure is concentrated on the new card, while spending on the pre-existing cards remains similar— indicating some extent of self control— and consistent with preserving mental accounts. Finally, all our specification include individual fixed effects, which are meant to capture individual-specific long-term consumption patterns.

Impatient consumers might have higher risk of default as they are likely to spend beyond their means, falling into a "debt trap." Table XI presents the results of our baseline staggered Diff-in-Diff separating between high and low risk consumers, as estimated based on the card issuer's proprietary internal credit scoring model. We define high-risk consumers as those with the below-median scores and low-risk consumers as those with the above-median scores. Studying the individual's consumption response as a function of risk, we find no significant difference between high-risk and low-risk consumers. Both groups conduct expenditures of a similar magnitude on the new card (Panel A), while also maintaining (likewise similar) levels of expenditure on the pre-existing cards (Panel B) relative to the comparable control groups. As shown in Column 1 of Panel C in Table XI, high-risk and low-risk individuals have similar total expenditure responses. Moreover, both groups maintain their spending patterns on the pre-existing cards equally, as indicated by Column 2.

Our evidence does not rule out the presence of present bias. It is possible that consumers rely on the mental accounting heuristic to defeat their self-control problems, however the former is necessary to explain our results demonstrating the apparent nonfungibility of payment methods.

IV Robustness Tests

In this section we present additional robustness tests. In Section IV.A, we verify that our results are not driven by members with early or late expiration dates. In Section IV.B, we conduct our three estimation strategies with different treatment and control groups. In addition, to ensure that our estimates reflect individuals' response to the new card, we discuss placebo tests.

IV.A Early and Late Expiration Dates

We conduct two robustness tests to check whether the timing of receiving the new card affects the consumers' responses.

First, we compare the consumers who received the new card in the last two quarters of the implementation process with the rest of the consumers. We hypothesize that these consumers might have been more aware of the new policy and less surprised by the new card, either because they were informed by the cashier or by their friends or family members who had already received the new card. However, we find no evidence of such effects on their on-the-spot application rates or their usage patterns of the new card.

Second, we compare the consumers who received the new card in the first two quarters of the implementation process with the rest of the consumers. Although they did not apply for the new card during the transition period, the closeness of receipt to the transition period could be a concern. These consumers are more likely to be less surprised by receiving the new card, as it had been advertised only recently. However, we find no evidence of such effects on their on-the-spot application rates or their usage patterns of the new card.

We also test whether excluding the consumers with late or early expiration dates affects our results on the expenditure and the budget categories management. We run our specifications in equations 1-3 for each group separately and compare them with the rest of the consumers. Table XII shows the results of each specification in different panels: Panel A for the staggered Diff-in-Diff analysis, Panel B for the RDiT analysis, and Panel C for the standard Diff-in-Diff analysis.

We find that our results are robust to excluding either group of consumers. The effects on total spending and the expenditure on the pre-existing cards are similar to our previous results. The effects are slightly larger when we exclude both groups across all three specifications, implying that receiving the new card has a smaller impact on these consumers than on the rest of the consumers.

IV.B Alternative Groups

To check the robustness of our staggered Diff-in-Diff analysis, we use two alternative ways of defining the treatment and control groups. In Table XIII, Columns 1 and 2, we include all the consumers who applied for the new card during the implementation process, regardless of whether they did it on the spot or later, and whether they started using the card within three months or later. We obtain similar results to those in Table II.

To check the robustness of our RDiT specification, we narrow down the time window from 5 months to 3 months around the membership expiration. Smaller bandwidths reduce the bias in estimating the effect of interest. They also allow us to exclude the extra spending that happens on average 5 months after the membership expiration (see Figure A.2). Table XIII, Columns 3 and 4, show the results of this specification. We confirm the results of Table II for total spending and the expenditure on the pre-existing cards.

We also change the definition of the treatment and control groups in the standard Diff-in-Diff analysis. We define the treatment group as the consumers whose memberships expired in the first 18 months of the implementation process, and the control group as those whose memberships expired in the last 18 months. Table XIII, Columns 5 and 6, show the standard Diff-in-Diff results for total expenditure and spending on the preexisting cards, respectively. We obtain similar results to those in Table IV.

Lastly, to ensure that our estimates reflect the consumers' response to the new card, we could perform a placebo test using a random date to show that only the actual membership expiration date captures the effect of a new budget category. However, our Diff-in-Diff strategies already include consumers who have not received the new card yet as the control groups, because their membership expiration happens later. When we analyze the control groups (see Section II), we do not find a similar change in expenditure as in the treatment group. We consider these analyses as placebo tests in which we assign an earlier date for receiving the new card than the real date.

V Conclusions

This paper demonstrates that consumers use different payment cards to manage nonfungible budgets. We examine how consumers' spending behavior changes when they receive a new credit card and find that they perceive it as a new budget category, distinct from the existing categories on the pre-existing cards. They adjust their total expenditure only on the new card, while keeping the other budget categories unchanged. Therefore, introducing a new payment method leads to a temporary rise in total consumption expenditure, without increasing indebtedness.

Our results have potential implications for various contexts beyond our specific setting. The non-fungibility of mental accounts could inform the design of fiscal policies, such as stimulus programs that aim to boost household consumption during economic slumps. We show in a clear setting that a new payment card can induce additional temporary spending, as it acts as a budgeting tool and creates a new mental account. Thus, programs that provide income in a seemingly non-fungible way might have a larger impact on consumption expenditure than, for instance, a direct deposit into a household's bank account.

Moreover, the non-fungibility of mental accounts could have interesting implications for monetary policy. If central banks launch a form of digital money, it would become a new payment method and possibly occupy a new and separate budget category for consumers. This might affect consumption patterns at the aggregate level, at least temporarily.

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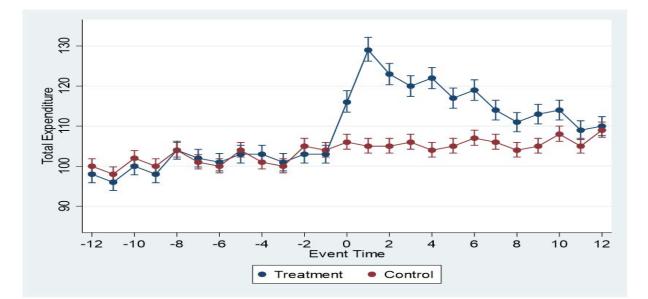


Figure 1: The figure plots the total expenditure of the treated vs. control individuals as defined in the staggered Diff-in-Diff with 95% confidence intervals. We recode the spending levels of the control group as 100 at the beginning of the time window (12 months before receiving the new card). Time 0 is defined as the membership expiration month.

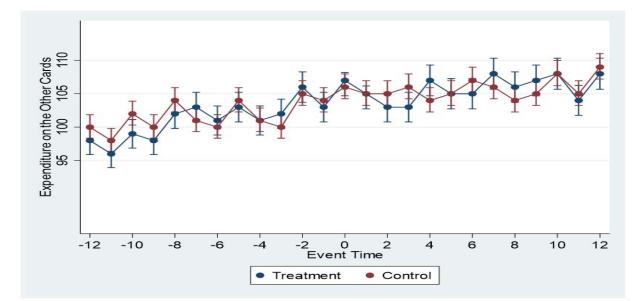


Figure 2: The figure plots the expenditure on the pre-existing cards of the treated vs. control individuals as defined in the staggered Diff-in-Diff with 95% confidence intervals. We recode the spending levels of the control group as 100 at the beginning of the time window (12 months before receiving the new card). Time 0 is defined as the membership expiration month.

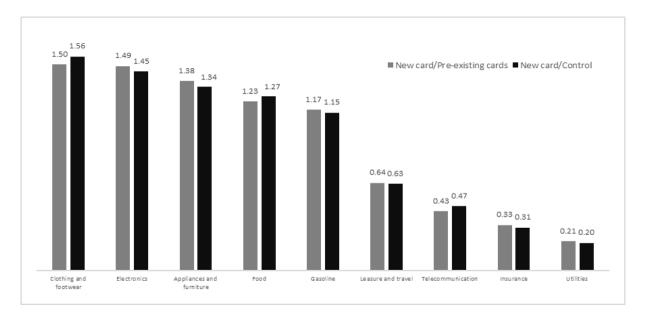


Figure 3: The figure plots the ratios of expenditure shares of spending on the new card to the corresponding shares of spending on the consumer's pre-existing cards (in gray), or to the control group (in black), for the main expenditure types. The ratios are calculated based on partial data of expenditure breakdown by main merchant coded industries in 2012 for a subsample of individuals.

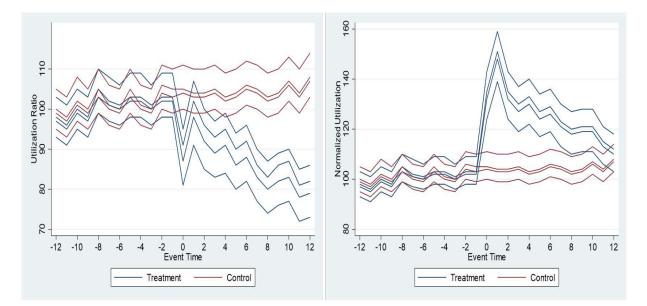


Figure 4: The figure plots the credit line utilization ratios (left panel), and the normalized utilization ratios (right panel) calculated as total outstanding relative to the credit limit prior to receipt of new card, by quartile of credit card utilization at time 0. In both panels, we recode the spending levels of the control group as 100 at the beginning of the time window (12 months before receiving the new card). Time 0 is defined as the membership expiration month.

Table I: Summary Statistics

This table presents the summary statistics for the average age, gender composition, and the number of held cards of individuals in our sample and in the overall Israeli population older than the age of 15 in 2012. We also present the share of expenditure of the individuals in our sample out of the average and one-person household consumption expenditure (excluding housing and vehicles). Finally, we present the share of expenditure at the retailer out of the total monthly expenditure for the 90th percentile.

	Sample	General Population
General Characteristics		
Age	44.33	42.83
Fraction of women	50.6%	51.2%
Number held cards (prior to receiving the new one)	1.57	1.35
Expenditure		
Expenditure/average household consumption expenditure	53.05%	
Expenditure/one-person household consumption expenditure	81.03%	
Share of expenditure at the retailer (90th percentile)	1.99%	

Table II: Expenditure Response After Receiving the New Card

The table presents the results of the staggered Diff-in-Diff analysis according to Equation (1). In Columns 1,2 the outcome variable is total expenditure, and in Columns 3,4 the expenditure on the pre-existing cards. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. In Columns 1,3 we include individual and year-month fixed effects, and in Columns 2,4 we include cohort-individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

	(1)	(2)	(3)	(4)
	Total S	pending	Pre-existi	ing Cards
Treated	0.259^{***}	0.264^{***}	0.00211	0.0093
	(0.0399)	(0.096)	(0.0024)	(0.0066)
Individual Fixed Effects	YES		YES	
Year-month Fixed Effects	YES	YES	YES	YES
Cohort-Individual Fixed Effects		YES		YES
Observations	5394000	5394000	5394000	5394000
Adjusted R^2	0.489	0.554	0.517	0.587

Table III: Difference-in-Differences with Quantile Regression

The table presents the results of the Diff-in-Diff analysis according to Equation (1) using a Quantile regression for the 25th, 50th and 75th percentiles response in total spending (Columns 1-3) and spending on the pre-existing cards (Columns 4-6). We present the results of the natural logarithm of each outcome variable. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. We include individual fixed effects.

	Total Spending			Spending on Pre-existing Cards			
	(1)	(2)	(3)	(4)	(5)	(6)	
	p(25%)	p(50%)	p(75%)	p(25%)	p(50%)	p(75%)	
Treated	0.178^{***}	0.274^{***}	0.359^{***}	-0.0125	0.0044	0.0195^{*}	
	(0.0618)	(0.0422)	(0.0587)	(0.00921)	(0.00399)	(0.0113)	
Individual Fixed Effects	YES	YES	YES	YES	YES	YES	
Observations	5394000	5394000	5394000	5394000	5394000	5394000	

Table IV: Alternative Specifications

Panel A presents the results of the regression Discontinuity in time analysis according to Equation (2) for total expenditure (Column 1) and the expenditure on the pre-existing cards (Column 2). We present the results of the natural logarithm of each outcome variable. *Post* is a dummy variable taking the value of one during the first 5 months after receiving the new card and zero for the prior 5 months. We include individual and year-month fixed effects. Panel B presents the results of the standard Diff-in-Diff analysis according to Equation (3) for total spending (Columns 1-3) and spending on the pre-existing cards (Columns 4-6). We present the results of the natural logarithm of each outcome variable. After is a dummy variable taking the value of one for the 12 months after receiving the new credit card and zero for the 12 months before. Treat is a dummy variable taking the value of one for individuals in the treatment group and zero for the individuals in the control group. Columns 2-3 and 5-6 present the results of the panel regression separately for the treatment and the control group with After as the explanatory variable and including individual fixed effects. In Columns 1,4 we include individual and year-month fixed effects. In Columns 2-3 and 5-6 we include individual fixed effects. In both Panels, standard errors (in parentheses) are clustered by individual and time.

Panel A: RDiT					
	(1)	(2)			
	Total Spending	Pre-existing Cards			
Post	0.273^{***}	0.00556			
	(0.0650)	(0.0552)			
Individual Fixed Effects	YES	YES			
Year-month Fixed Effects	YES	YES			
Observations	111530	111530			
Adjusted R^2	0.592	0.616			

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

Panel B: Standard Difference-in-Differences						
	То	tal Spendi	ng	Spending	on Pre-exis	sting Cards
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Treated	Control	All	Treated	Control
After×Treat	0.234^{***}			-0.00313		
	(0.0368)			(0.0330)		
After		0.270***	0.0387**		0.0319	0.0366^{*}
		(0.0233)	(0.0135)		(0.0251)	(0.0145)
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Year-month Fixed Effects	YES			YES		
Observations	332275	224450	107825	332275	224450	107825
Adjusted R ²	0.571	0.523	0.644	0.585	0.539	0.636

Table V: Expenditure Response Among "Singles"

The table presents the results of the staggered Diff-in-Diff in Equation (1) for total spending (Panel A) and spending on the pre-existing cards (Panel B) of subsamples of individuals likely to be "singles" based on age (Columns 1,2), number of earners (Columns 3,4) and household size (Columns 5,6). *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. Columns 1,3,5 include individual and year-month fixed effects, while Columns 2,4,6 include cohort- individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

Panel A: Total Spending							
	(1)	(2)	(3)	(4)	(5)	(6)	
	Age Earners Siz			ze			
Treated	0.117^{***}	0.138***	0.113^{***}	0.120***	0.141***	0.158^{***}	
	(0.0179)	(0.0408)	(0.0221)	(0.0324)	(0.0264)	(0.0388)	
Individual Fixed Effects	YES		YES		YES		
Year-month Fixed Effects	YES	YES	YES	YES	YES	YES	
Cohort-Individual Fixed Effects		YES		YES		YES	
Observations	350700	350700	539700	539700	543900	543900	
Adjusted R^2	0.474	0.512	0.481	0.535	0.457	0.486	

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

Panel B: Spending on Pre-existing Cards						
	(1)	(2)	(3)	(4)	(5)	(6)
	Ag	ge	Earners		Size	
Treated	0.008	0.007	0.009	0.011	0.006	0.008
	(0.0093)	(0.012)	(0.012)	(0.013)	(0.011)	(0.015)
Individual Fixed Effects	YES		YES		YES	
Year-month Fixed Effects	YES	YES	YES	YES	YES	YES
Cohort-Individual Fixed Effects		YES		YES		YES
Observations	350700	350700	539700	539700	543900	543900
Adjusted R^2	0.514	0.572	0.507	0.561	0.484	0.496

Table VI: Consumer's Age

Panels A,B present the results of the Diff-in-Diff analysis according to Equation (1) for total spending (Panel A) and spending on the pre-existing cards (Panel B). We present the results of the natural logarithm of each outcome variable. Columns 1-2 in each Panel present the results of individuals younger than the median age. Columns 3-4 present the the results of older individuals. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. Columns 1,3 include individual and year-month fixed effects, while Columns 2,4 include cohort- individual and year-month fixed effects.

In Panel C we change the explanatory variable to the interaction term of *Treated* with *Younger*. *Younger* is a dummy variable equals one for younger individuals, and zero for older.

Panel A: Total Spending						
	(1)	(2)	(3)	(4)		
	Younger	Consumers	Older Co	onsumers		
Treated	0.298^{***}	0.309***	0.215^{***}	0.202***		
	(0.0184)	(0.0473)	(0.0508)	(0.0746)		
Individual Fixed Effects	YES		YES			
Year-month Fixed Effects	YES	YES	YES	YES		
Cohort-Individual Fixed Effects		YES		YES		
Observations	2346300	2346300	2697000	2697000		
Adjusted R^2	0.548	0.603	0.389	0.444		

Standard errors (in parentheses) are clustered by individual and time.

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** * p < 0.001

Panel B: Spending on the Pre-existing Cards							
	(1)	(1) (2) (3)					
	Younger Consumers Older Consumers						
Treated	-0.0253	-0.0286	0.0038	0.0106			
	(0.0494)	(0.0145)	(0.0101)	(0.0141)			
Individual Fixed Effects	YES		YES				
Year-month Fixed Effects	YES	YES	YES	YES			
Cohort-Individual Fixed Effects		YES		YES			
Observations	2346300	2346300	2697000	2697000			
Adjusted R^2	0.634	0.675	0.452	0.524			

Panel C: Comparing between the Groups					
	(1)	(2)			
	Total Spending	Pre-existing Cards			
Treated×Younger	0.267^{***}	-0.0093			
	(0.0436)	(0.0227)			
Individual Fixed Effects	YES	YES			
Year-month Fixed Effects	YES	YES			
Observations	5043300	5043300			
Adjusted R^2	0.59	0.596			

Table VI - Continued

Table VII: Spending by Installments

The table presents the results of the Diff-in-Diff analysis according to Equation (1) for total spending (Panel A) and spending on the pre-existing cards (Panel B). We present the results of the natural logarithm of each outcome variable. Columns 1-2 in each Panel present the results of non-installment payments, while Columns 3-4 present the installment payments. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. In Columns 1,3 we include individual and year-month fixed effects, and in Columns 2,4 we include cohort-individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

Panel A: Total Spending						
	(1)	(2)	(3)	(4)		
	Non Inst	allments	Instal	lments		
Treated	0.254^{***}	0.287^{***}	0.00295	0.0074		
	(0.0276)	(0.0833)	(0.0035)	(0.0086)		
Individual Fixed Effects	YES		YES			
Year-month Fixed Effects	YES	YES	YES	YES		
Cohort-Individual Fixed Effects		YES		YES		
Observations	5394000	5394000	5394000	5394000		
Adjusted R^2	0.623	0.684	0.612	0.66		

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

Taner D. Spending on the Tre-existing Cards						
	(1)	(2)	(3)	(4)		
	Non Inst	allments	Install	ments		
Treated	-0.0201	-0.0184	0.0012	0.0016		
	(0.032)	(0.0291)	(0.006)	(0.007)		
Individual Fixed Effects	YES		YES			
Year-month Fixed Effects	YES	YES	YES	YES		
Cohort-Individual Fixed Effects		YES		YES		
Observations	5394000	5394000	5394000	5394000		
Adjusted R^2	0.668	0.733	0.616	0.671		

Panel B: Spending on the Pre-existing Cards

Table VIII: Utilization Analysis

The table presents the results of the staggered Diff-in-Diff analysis according to Equation (1), changing the outcome variable to utilization ratio. Panel A presents the results for the total utilization ratio on all the cards the individual holds. In Columns 1-2, the outcome variable is the actual utilization ratios, while in Columns 3-4 the explanatory variable is the normalized utilization ratios, calculated at total outstanding out of the limit prior to receiving the new card. Panel B presents the results of the utilization ratio on the pre-existing cards. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. In Columns 1,3 of Panel A and Column 1 in Panel B we include individual and year-month fixed effects. In Columns 2,4 of Panel A and Column 2 in Panel B we include cohort-individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

Panel A: Utilization Ratios on All Cards						
	(1)	(2)	(3)	(4)		
	Total Ut	tilization	Normalize	d Utilization		
Treated	-0.216***	-0.229***	0.414^{***}	0.432***		
	(0.0207)	(0.0316)	(0.0304)	(0.0283)		
Individual Fixed Effects	YES		YES			
Year-month Fixed Effects	YES	YES	YES	YES		
Cohort-Individual Fixed Effects		YES		YES		
Observations	5394000	5394000	5394000	5394000		
Adjusted R^2	0.432	0.485	0.449	0.456		

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

	(1)	(2)
Treated	-0.0071	-0.0093
	(0.013)	(0.0058)
Individual Fixed Effects	YES	
Year-month Fixed Effects	YES	YES
Cohort-Individual Fixed Effects		YES
Observations	5394000	5394000
Adjusted R^2	0.42	0.481

Panel B: Utilization Ratios on Pre-existing Cards

Table IX: Liquidity Constraint

The table presents the results of the Diff-in-Diff analysis according to Equation (1) for total spending (Panel A) and spending on the pre-existing cards (Panel B). We present the results of the natural logarithm of each outcome variable. Columns 1-4 in each Panel present the results by quartiles of utilization ratios. Column 1 present the top utilization ratio quartile, and Column 4 the bottom. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. We include individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

	Panel A: Total Spending					
	(1)	(2)	(3)	(4)		
	Top Quartile	2nd Quartile	3rd Quartile	Bottom Quartile		
Treated	0.322**	0.304***	0.292**	0.318**		
	(0.178)	(0.0782)	(0.164)	(0.175)		
Individual Fixed Effects	YES	YES	YES	YES		
Year-month Fixed Effects	YES	YES	YES	YES		
Observations	1348500	1348500	1348500	1348500		
Adjusted R^2	0.324	0.328	0.341	0.337		

Panel A: Total Spending

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

Panel Ba	Panel B: Spending on the Pre-existing Cards						
	(1)	(2)	(3)	(4)			
	Top Quartile	2nd Quartile	3rd Quartile	Bottom Quartile			
Treated	-0.0502	-0.0255	-0.0148	0.0071			
	(0.0865)	(0.0732)	(0.0522)	(0.0637)			
Individual Fixed Effects	YES	YES	YES	YES			
Year-month Fixed Effects	YES	YES	YES	YES			
Observations	1348500	1348500	1348500	1348500			
Adjusted R^2	0.375	0.361	0.372	0.354			

Table X: Expenditure Below Previous Limit

The table presents the results of the staggered Diff-in-Diff analysis according to Equation (1) for the natural logarithm of total spending (Panel A) and spending on the pre-existing cards (Panel B) only among the treated individuals. In Column 1 we present the results only for months when the individual's expenditure is lower than the limit prior to receiving the new card. Columns 2-4 present the results for months when the expenditure is lower than 90%, 80% and 60% respectively. Treated is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. We include individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

Panel A: Total Spending						
	(1)	(2)	(3)	(4)		
	Up to 100%	Up to 90%	Up to 80%	Up to 60%		
Treated	0.247^{***}	0.224^{***}	0.206***	0.188***		
	(0.0237)	(0.0295)	(0.0306)	(0.0351)		
Individual Fixed Effects	YES	YES	YES	YES		
Individual Fixed Effects	YES	YES	YES	YES		
Observations	180373	152664	138452	100229		
Adjusted R^2	0.527	0.531	0.542	0.558		

Standard errors in parentheses.^{*} p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001

Panel B: S	Panel B: Spending on the Pre-existing Cards						
	(1)	(2)	(3)	(4)			
	Up to 100%	Up to 90%	Up to 80%	Up to 60%			
Treated	0.00718	0.00554	-0.00013	-0.0044			
	(0.0283)	(0.0262)	(0.0302)	(0.0386)			
Individual Fixed Effects	YES	YES	YES	YES			
Individual Fixed Effects	YES	YES	YES	YES			
Observations	180373	152664	138452	100229			
Adjusted R^2	0.542	0.549	0.560	0.573			

Table XI: Consumer Default Risk

Panels A,B present the results of the Diff-in-Diff analysis according to Equation (1) for total spending (Panel A) and spending on the pre-existing cards (Panel B). We present the results of the natural logarithm of each outcome variable. Columns 1-2 in each Panel present the results for the top 50% of individuals by risk (as evaluated based on an internal scoring model of the card issuer), while Columns 3-4 present the results of less risky individuals. *Treated* is a dummy variable taking the value of one for individuals whose memberships expire each month, and zero for individuals whose memberships have not expired yet. In Columns 1,3 of each Panel we include individual and year-month fixed effects, and in Columns 2,4 we include cohort-individual and year-month fixed effects. In Panel C we change the explanatory variable to the interaction term of *One Card Holder* with *High Risk. High Risk* is a dummy variable that equals one for above-median-risk individuals, and zero otherwise.

Panel A: Total Spending					
	(1)	(2)	(3)	(4)	
	Highe	r Risk	Lower	r Risk	
Treated	0.233***	0.242^{***}	0.257^{***}	0.264^{***}	
	(0.0567)	(0.0746)	(0.0433)	(0.0892)	
Individual Fixed Effects	YES		YES		
Year-month Fixed Effects	YES	YES	YES	YES	
Cohort-Individual Fixed Effects		YES		YES	
Observations	2697000	2697000	2697000	2697000	
Adjusted R^2	0.673	0.712	0.648	0.677	

Standard errors (in parentheses) are clustered by individual and time.

Panel B:	Spending	on the	Pre-existing	Cards

			0	
	(1)	(2)	(3)	(4)
	Highe	r Risk	Lower	r Risk
Treated	0.0114	0.0256	-0.0083	-0.0106
	(0.0422)	(0.0537)	(0.0542)	(0.0511)
Individual Fixed Effects	YES		YES	
Year-month Fixed Effects	YES	YES	YES	YES
Cohort-Individual Fixed Effects		YES		YES
Observations	2697000	2697000	2697000	2697000
Adjusted R^2	0.704	0.733	0.732	0.786

Panel C: Comparing between the Groups					
	(1)	(2)			
	Total Spending	Pre-existing Cards			
Treated×High Risk	-0.0133	0.0059			
	(0.0484)	(0.0886)			
Individual Fixed Effects	YES	YES			
Year-month Fixed Effects	YES	YES			
Observations	5394000	5394000			
Adjusted R^2	0.691	0.752			

Table XI - Continued

Table XII: Excluding Early and Late Expiration Dates

The table presents the results of various robustness tests. Panel A presents the results of the staggered Diff-in-Diff analysis, Panel B for the RDiT specification, and Panel C for the standard Diff-in-Diff. In Columns 1-2 of Panels A and B we exclude members with expiration dates during the last 2 quarters of the staggered implementation process, and in Columns 3-4 we exclude members whose membership expired during the first 2 quarters. In Columns 1,3 of each Panel the outcome variable is the natural logarithm of total spending. In Columns 2,4 of each Panel the explanatory variable is the natural logarithm of spending on the pre-existing cards. All Panels include individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Panel A: Staggered Diff-in-Diff						
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$		Excl. Late Dates Excl. Early Dates					
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$		(1)	(2)	(3)	(4)		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		All Cards	Pre-existing	All Cards	Pre-existing		
	Treated	0.264***	0.0321	0.267***	0.0333		
Year-month Fixed Effects YES YES YES YES YES Observations 5267425 5267425 5267425 4738800 4738800 Adjusted R^2 0.495 0.548 0.514 0.563 Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ $Panel B: RDiT$ Excl. Late Expirations Excl. Early Expirations (1) (2) (3) (4) All Cards Pre-existing All Cards Pre-existing Alt_Post 0.287^{***} 0.00162 0.274^{***} 0.00325 Individual FE YES YES YES YES Year-month FE YES YES YES YES Year-month FE YES YES YES YES Year-month FE YES YES YES YES Adjusted R^2 0.588 0.615 0.533 0.617 Standard errors in parentheses.* $p < 0.05, ** p < 0.01, *** p < 0.001$ Excl. Early Dates (1) (2) (3) (4) All Cards Pre-existing All Cards		(0.0416)	(0.0561)	(0.0408)	(0.0545)		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Individual Fixed Effects	YES	YES	YES	YES		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Year-month Fixed Effects	YES	YES	YES	YES		
Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Panel B: RDiTExcl. Late Expirations(1)(2)(3)(4)All CardsPre-existingAll CardsPre-existingAlt_Post 0.287^{***} 0.00162 0.274^{***} 0.00325 (0.0693)(0.0553)(0.0651)(0.0552)Individual FEYESYESYESYear-month FEYESYESYESAdjusted R^2 0.588 0.615 0.533 0.617 Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Excl. Late DatesExcl. Early Dates(1)(2)(3)(4)All CardsPre-existingAll CardsPre-existingAll CardsPre-existingAfter×Treat 0.234^{***} -0.00178 0.234^{***} -0.00379 (0.0301)(0.0234)(0.0422)(0.0400)Individual Fixed EffectsYESYESYESYESYear-month Fixed EffectsYESYESYESYESYear-month Fixed EffectsYESYESYESYESYear-month Fixed EffectsYESYESYESYESYear-month Fixed EffectsYESYESYESYESObservations249175249175248625248625	Observations	5267425	5267425	4738800	4738800		
Panel B: RDiTExcl. Late Expirations(1)(2)(3)(4)All CardsPre-existingAlt_Post 0.287^{***} 0.00162 0.274^{***} 0.00325 (0.0693) (0.0553) (0.0651) (0.0552) (0.0693) (0.0553) Individual FEYESYESYear-month FEYESYESYear-month FEYESYESYear-month FEYESYESYear-month FEYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYear-month Fixed EffectsYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYESYESYear-month Fixed EffectsYESYear-month Fi	Adjusted R^2	0.495	0.548	0.514	0.563		
$\begin{tabular}{ c c c c c } \hline Excl. Late Expirations & Excl. Early Expirations \\ (1) & (2) & (3) & (4) \\ \hline All Cards & Pre-existing & All Cards & Pre-existing \\ \hline Alt_Post & 0.287^{***} & 0.00162 & 0.274^{***} & 0.00325 \\ \hline & (0.0693) & (0.0553) & (0.0651) & (0.0552) \\ \hline & Individual FE & YES & YES & YES & YES \\ \hline Year-month FE & YES & YES & YES & YES \\ \hline Adjusted R^2 & 0.588 & 0.615 & 0.533 & 0.617 \\ \hline & Standard errors in parentheses.* $p < 0.05, ** $p < 0.01, *** $p < 0.001 \\ \hline & Fanel c: Standard Diff-in-Diff \\ \hline & Excl. Late Dates & Excl. Early Dates \\ \hline & (1) & (2) & (3) & (4) \\ \hline & All Cards & Pre-existing & All Cards & Pre-existing \\ \hline & All Cards & Pre-existing & All Cards & Pre-existing \\ \hline & After \times Treat & 0.234^{***} & -0.00178 & 0.234^{***} & -0.00379 \\ \hline & (0.0301) & (0.0234) & (0.0422) & (0.0400) \\ \hline & Individual Fixed Effects & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES & YES & YES & YES & YES & YES \\ \hline & Year-month Fixed Effects & YES \\ \hline & Year-month Fixed Effects & YES & YES$	Standard errors in parenthese	s.* $p < 0.05$, **	p < 0.01, *** p < 0.01	0.001			
$\begin{tabular}{ c c c c c c } \hline (1) & (2) & (3) & (4) \\ \hline All Cards & Pre-existing & All Cards & Pre-existing \\ \hline Alt_Post & 0.287^{***} & 0.00162 & 0.274^{***} & 0.00325 \\ \hline (0.0693) & (0.0553) & (0.0651) & (0.0552) \\ \hline Individual FE & YES & YES & YES \\ Year-month FE & YES & YES & YES & YES \\ \hline Adjusted R^2 & 0.588 & 0.615 & 0.533 & 0.617 \\ \hline \hline Standard errors in parentheses.* $p < 0.05, ** $p < 0.01, *** $p < 0.001 \\ \hline Fanel c: Standard Diff-in-Diff \\ \hline \hline Fanel c: Standard Diff-in-Diff \\ \hline \hline Fanel c: Standard Diff-in-Diff \\ \hline \hline Fanel Cards & Pre-existing & All Cards & Pre-existing \\ \hline After \times Treat & 0.234^{***} & -0.00178 & 0.234^{***} & -0.00379 \\ \hline \hline (0.0301) & (0.0234) & (0.0422) & (0.0400) \\ \hline Individual Fixed Effects & YES & YES & YES & YES \\ Year-month Fixed Effects & YES & YES & YES & YES \\ \hline Observations & 249175 & 249175 & 248625 & 248625 \\ \hline \end{tabular}$		- ·					
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	E	ccl. Late Exp	irations Exc	l. Early Exp	pirations		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$		(1)	(2)	(3)	(4)		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Al	l Cards Pre	-existing All	Cards Pre-	-existing		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Alt_Post 0.	287*** 0	.00162 0.2	74*** 0	.00325		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	(0	.0693) (0	(0.0553) (0.0	(0.0651) (0.0000)	0.0552)		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Individual FE	YES	YES Y	ΈS	YES		
Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Panel c: Standard Diff-in-DiffExcl. Late DatesExcl. Early Dates(1)(2)(3)(4)All CardsPre-existingAfter × Treat 0.234^{***} -0.00178 0.234^{***} (0.0301)(0.0234)(0.0422)(0.0400)Individual Fixed EffectsYESYESYESYear-month Fixed EffectsYESYESYESObservations249175249175248625	Year-month FE	YES	YES Y	ΈS	YES		
$\begin{tabular}{ c c c c } \hline Panel c: Standard Diff-in-Diff \\ \hline Excl. Late Dates & Excl. Early Dates \\ (1) & (2) & (3) & (4) \\ \hline All Cards & Pre-existing & All Cards & Pre-existing \\ \hline After \times Treat & 0.234^{***} & -0.00178 & 0.234^{***} & -0.00379 \\ \hline & (0.0301) & (0.0234) & (0.0422) & (0.0400) \\ \hline Individual Fixed Effects & YES & YES & YES \\ Year-month Fixed Effects & YES & YES & YES \\ Observations & 249175 & 249175 & 248625 & 248625 \\ \hline \end{tabular}$	Adjusted R^2	0.588	0.615 0.	.533	0.617		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Standard errors in parer	theses.* $p < 0.$	05, ** p < 0.01, *	** $p < 0.001$			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Pa	nel c: Stan	dard Diff-in-	Diff			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					arly Dates		
$\begin{array}{c cccccc} \begin{tabular}{c ccccc} After \times Treat & 0.234^{***} & -0.00178 & 0.234^{***} & -0.00379 \\ \hline & & (0.0301) & (0.0234) & (0.0422) & (0.0400) \\ \hline & Individual Fixed Effects & YES & YES & YES & YES \\ Year-month Fixed Effects & YES & YES & YES & YES \\ Observations & 249175 & 249175 & 248625 & 248625 \\ \hline \end{array}$		(1)	(2)		•		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$							
Individual Fixed EffectsYESYESYESYESYear-month Fixed EffectsYESYESYESYESObservations249175249175248625248625	After×Treat	0.234***	0		<u> </u>		
Year-month Fixed EffectsYESYESYESYESObservations249175249175248625248625		(0.0301)	(0.0234)	(0.0422)	(0.0400)		
Observations 249175 249175 248625 248625	Individual Fixed Effects	YES	YES	YES	YES		
	Year-month Fixed Effects	YES	YES	YES	YES		
Adjusted R^2 0.5740.5780.5830.588	Observations	249175	249175	248625	248625		
	Adjusted \mathbb{R}^2	0.574	0.578	0.583	0.588		

Table XIII: Alternative Groups

The table presents the results of the estimation strategies for alternative treatment and control groups. Columns 1,2 present the results for the staggered Diff-in-Diff specification in Equation (1) for all the individuals that applied for the new card during the staggered process, including those that did it not on spot on the first purchase of the membership expiration month, and those that started using the card later than three months after its activation. Columns 3,4 present the RDiT specification in Equation (2) changing the period around the expiration months from 5 to 3 months. In Columns 5,6 we change the treated group in the standard Diff-in-Diff specification in Equation (3) to individuals with expiration dates in the first 18 months of the staggered implementation process, while the control group includes those with expiration dates during the last 18 months. In Columns 2,4,6 the natural logarithm of spending on the pre-existing cards. All Columns include individual and year-month fixed effects. Standard errors (in parentheses) are clustered by individual and time.

	Staggered Diff-in-Diff		RDiT		Standard Diff-in-Diff	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Cards	Pre-existing	All Cards	Pre-existing	All Cards	Pre-existing
Alt_Treated	$\begin{array}{c} 0.256^{***} \\ (0.0403) \end{array}$	$\begin{array}{c} 0.0026 \\ (0.0078) \end{array}$				
Alt_Post			0.275^{**}	0.0012		
			(0.0844)	(0.0226)		
$Alt_After \times Treat$					0.235^{***}	-0.0110
					(0.0472)	(0.0434)
Individual FE	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Adjusted \mathbb{R}^2	0.468	0.502	0.637	0.641	0.558	0.553

Appendix

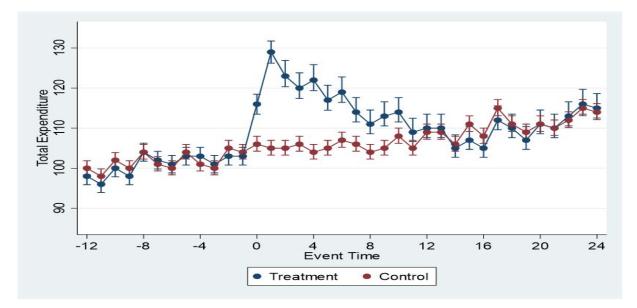


Figure A.1: The figure plots the total expenditure of the treated vs. control individuals over a period of 36 months (12 months prior to receiving the new card and 24 months after) for a subsample of individuals that received the new card during the first year of the implementation of the staggered process. We recode the spending levels of the control group as 100 at the beginning of the time window. Time 0 is defined as the membership expiration month.

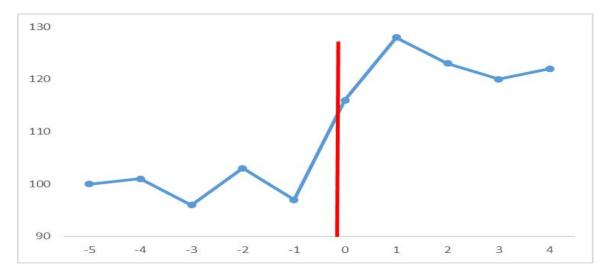


Figure A.2: The figure plots the total expenditure of all the individuals in our sample that received the new card. We recode the spending levels of the control group as 100 at the beginning of the time window (5 months before receiving the new card). Time 0 is defined as the membership expiration month.