WORKING PAPER · NO. 2019-140

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DECEMBER 2019

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FOR ECONOMICS AT UCHICAGO

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December 4, 2019

Abstract

We study the consumption response to the provision of credit lines to individuals that previously did not have access to credit combined with the possibility to elicit directly a large set of preferences, beliefs, and motives. As expected, users react to the availability of credit by increasing their spending permanently and reallocating consumption from non-discretionary to discretionary goods and services. Surprisingly, though, liquid users react more than others and this pattern is a robust feature of the data. Moreover, liquid users lower their savings rate, but do not tap into negative deposits. The credit line seems to act as a form of insurance against future negative shocks and its mere presence makes users spend their existing liquidity without accumulating any debt. By eliciting preferences, beliefs, and motives directly, we show these results are not fully consistent with models of financial constraints, buffer stock models with and without durables, present-bias preferences, uncertainty about future income, bequest motives, or the canonical life-cycle permanent income model. We label this channel the *perceived* precautionary savings channel, because liquid households behave as if they faced strong precautionary savings motives even though no observables suggest they should based on standard theoretical models.

JEL Codes: D14, E21, E51, G21

Keywords: Household Finance, Consumption, Behavioral Finance

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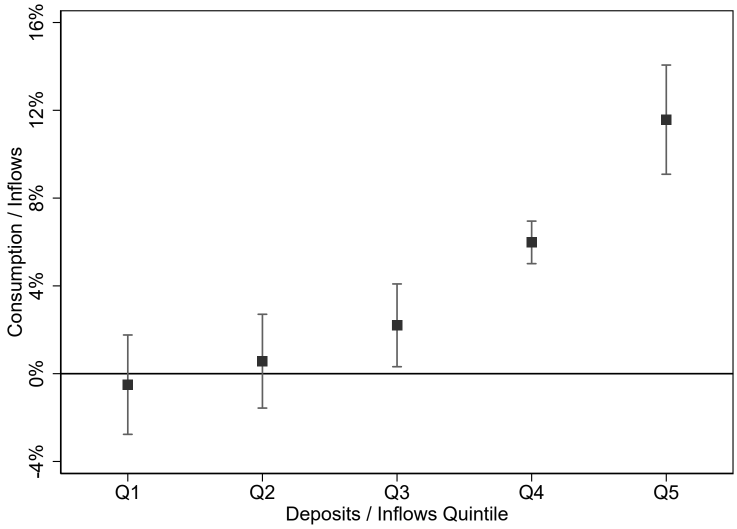
1 Introduction

In times of economic downturn, monetary and fiscal policy aim to stimulate consumption through credit, because household consumption comprises the largest share of gross domestic product (Agarwal et al., 2017). At the same time, household credit growth has been a major and often unforeseen driver of financial crises (Schularick and Taylor, 2012; Baron and Xiong, 2017; Di Maggio and Kermani, 2017; Mian and Sufi, 2015; Mian et al., 2017). Identifying the micro-level channels through which household credit affects consumption and saving decisions is thus important to understand the dynamics of business cycles as well as to inform the design of effective credit-based expansionary policies.

In this paper, we introduce a unique FinTech setting in which we observe the extensive margin of credit—initiation of overdraft facilities to first-time borrowers—combined with the possibility to elicit *directly* a set of preferences, beliefs, and individual perceptions that theoretical and empirical research typically relate to households' saving and consumption behavior. These dimensions, which are typically unobserved in large-scale micro data, include risk preferences, patience, expectations about future employment status, future large expenses, medical expenses, bequest motives, subjective life expectancy, as well as financial literacy and generalized trust in others. We use this setting to estimate the consumption effects of providing households with credit and to test directly for a broad set of typically unobserved channels that based on earlier theoretical and empirical research might explain the effects of credit on spending.

In our baseline analysis, we estimate a set of double-differences specifications in which we compare bank users' change in consumption spending after activating the overdraft facility relative to before and relative to users whose overdraft facilities are not yet activated. We find the average individual increases her spending by 4.5 percentage points of income inflows after credit is available relative to before and to users whose overdraft facility is not yet active. This positive effect on spending does not revert fully over time—we detect a permanent increase in spending and a drop in savings for the average user.

Figure 1: Consumption Response by Deposit-to-Income Quintile



Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate the plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles of deposits to income from lowest to highest. We then interact the resulting grouping variable with a binary indicator that equals 1 if a user has access to a mobile overdraft in given month. Vertical bands represent 95% confidence intervals for the point estimates in each quintile. We double cluster standard errors at the NUTS2 and year-month level.

The surprising result is that the baseline effect is heterogeneous across users, but not based on dimensions that earlier research proposed. We find that variation in motives to smooth consumption or liquidity constraints do not explain the effect. Instead, as Figure 1 shows, the effect increases monotonically with the liquidity of users. The higher the ratio of liquid deposits to income inflows, the stronger is the spending reaction to the provision of credit. Below, we also show that the higher this ratio, the more permanent is the effect over time.

Liquid users seem to behave as if they have strong precautionary savings motives, and hence accumulate liquid savings before the overdraft facility is available. Once the overdraft becomes available, consistent with an insurance effect of the facility, liquid users start to spend more of their existing liquid savings and decrease their savings rate permanently. Interestingly, liquid users do *not* use the overdraft facility, in the sense that only 10% of them ever tap into negative deposits and use the credit line. The availability of an overdraft facility makes these users spend their existing savings but not more than that, again consistent with strong precautionary savings motives that are reduced once the facility is available.

These results are puzzling to the extent that typically liquidity constraints are thought to be crucial in driving households' reaction to the availability of credit, which would predict that the least liquid users react most in terms of consumption spending—the opposite of our finding. For instance, research that studied the increase in the intensive margin of credit, such as increasing existing credit card limits, finds that users at the constraint (i.e., that maxed out their previous limit) react more to the increase in credit lines (see, e.g., Aydin, 2015; Agarwal et al., 2017; Gross and Souleles, 2002). In our setting in which a credit line is provided to borrowers that had no access to credit before, we find the opposite.[1]

The pattern of reaction by liquidity is a robust feature of the data. First, we rule out that the amount or volatility of inflows into the account before the credit line is available drives our results. For instance, one might worry that liquid users have other bank accounts and move liquidity to our provider when planning large expenses. Instead, liquid users do not differ from less-liquid users in terms of inflows in the year before the credit line is active. What differs across these groups is the amount of monthly outflows, which determines a higher saving rate for liquid users relative to illiquid users. Moreover, the pattern is unchanged if we only consider individuals that consume large parts of the inflows, for alternative definitions of deposits-to-inflows, for users in areas that have high versus low savings rates—and hence potentially different social norms about the importance of savings—for urban versus rural households, or individuals living in former communist countries and others.

To understand whether standard determinants of precautionary savings motives explain these results, we exploit the fact that our FinTech provider allows us to reach users directly through their app and elicit their preferences, beliefs, and motives. First, risk aversion and/or prudence are important potential drivers of savings behavior independent of income volatility (Gomes and Michaelides, 2005). We detect no economic or statistical differences in the levels of risk aversion and patience across users based on their liquidity. Moreover, users who have high subjective beliefs about future large expenses, such as medical expenses, or about future income uncertainty (Guiso et al., 1992; Ben-David et al., 2018) might save a larger fraction of

[1] We discuss the detailed institutional setting below.

their income. Even here, we find no systematic differences in the cross section of deposit-to-inflows. We do not find systematic differences in terms of subjective life expectancy, beliefs about future employment status, health conditions, or bequest motives, either. Finally, we do not find any systematic differences in terms of financial literacy or generalized trust—liquid users understand the incentives to borrow and save similarly as others.

Ultimately, a large fraction of users—all those above the bottom 40% by liquidity—behave as if they have strong precautionary savings motives before credit lines are available to them. These motives disappear with the activation of credit lines, which might thus be interpreted as a form of insurance against future negative states.

At the same time, none of the standard explanations for precautionary savings motives appear to have the potential to explain our results, either individually or jointly. For this reason, we label our mechanism "perceived precautionary savings"—users perceive they have strong precautionary savings motives, but neither their preferences, subjective or objective beliefs, or other characteristics we elicit directly explain these motives.

We argue that buffer stock consumption (Deaton, 1991; Carroll, 1997), buffer stock consumption with durables (Guerrieri and Lorenzoni, 2017; Aydin, 2015), the standard life-cycle permanent income model of Friedman (1957), or heterogeneous-agents models with assets of different liquidity (Kaplan et al., 2014) cannot explain our results in full. Non-standard preferences such as present-biased preferences are also unlikely to explain all our results. If the individuals that react the most to overdraft activation were present-biased, they would have consumed out of their higher deposits even *before* activating the overdraft facility, which we do not observe in the data. Our results are closer to Olafsson and Pagel (2018), who document users of a FinTech app that hold wealth in deposit accounts and use overdraft facilities at the same time increase consumption spending on paydays. In our setting, we show individuals with the highest ratio of deposits to income react the most in terms of spending once they activate the overdraft facility, whereas in Olafsson and Pagel (2018) individuals with lower amounts of deposits spend more in reaction to income payments. Ultimately, our results call for further theoretical and empirical evidence on potential alternative drivers of precautionary savings motives, either based on standard or non-standard beliefs.

One might wonder why we detect perceived precautionary savings motives in our setting, but earlier research studying the effect of credit provision to households did not find this result. The crucial difference is that we study the provision of credit lines to households that did not have access to credit beforehand (extensive margin of credit). Most of the earlier research, instead, is based on changing credit limits provided to households that were already borrowing (intensive margin of credit). The insurance feature of obtaining a credit facility already exists for borrowers that previously had access to credit, and hence the effect we document could not arise in those earlier settings. Moreover, we find that liquid users do not tap into negative deposits but only consume their existing savings, which suggests that changes in the credit limits or intensive margin of credit would have no effect on them. That is to say, these users do not make use of the credit limits at all.

A remaining concern with our baseline double-differences analysis is that users might activate the overdraft facility endogenously when they know they are about to make a large expense. The facts that the spending effect for liquid households is permanent, that elicited expectations about upcoming large expenses do not differ across liquid and illiquid users, and that we detect similar effects when limiting the analysis to users that had an account open at least one year before the overdraft was available, reduce this concern.

To address this concern directly, in the last part of the paper we also propose a sharp regression-discontinuity design (RDD) that exploits the rule with which the FinTech provider computes the maximum limit of the overdraft facility. This limit is a rounded function of users' income based on a set of pre-specified income bandwidths of which users are not aware. The FinTech application computes the limits automatically, with no role for bank officers to change the approved limits—this is why the app allows users to open the approved line of credit automatically in just a few seconds—and hence there is no scope for manipulating one's assignment to the high- or low-treatment group in design.

In this sharp RDD, we compare users that are observationally indistinguishable, as we document directly, but end up being assigned different overdraft limits based on small differences in their income inflows. This assignment combines the extensive margin of credit, so that the insurance effect of the facility exists for everybody, with a higher or lower intensive margin in terms of credit limit. The sharp RDD confirms our results. Note that we do not use this RDD for the baseline analysis and the heterogeneity tests, because by construction the RDD only uses a small subset of users who are close to the sharp threshold. The RDD results thus do not refer to the average user in our sample, and the statistical power for heterogeneity tests in this setting is minimal by construction given that the treated and control users are almost identical in most characteristics.

Ultimately, our results might provide novel insights about the effects of providing credit to households along the business cycle. Providing insurance against potential negative future spending shocks appears to increase the spending of households with high deposit-to-income ratios, but this policy intervention would not increase their debt positions or interest payments, because these households would not draw down from the overdraft facilities. If anything, providing insurance to these households at times of economic slumps might increase aggregate demand swiftly, because households that hoard cash due to perceived precautionary savings motives might end up spending parts of their savings. Importantly, providing insurance to perceived precautionary savers might be virtually costless based on our results, because these individuals would not end up paying any interest, would not accumulate debt over time, and would not worsen their credit position.

The main challenge to policies based on our findings might be political in nature. At times of economic crisis, policy-makers would provide virtually costless insurance to *wealthier* households (in terms of liquid wealth) to nudge them to spend more instead of providing costly subsidies to poorer households, who might become risky borrowers over time. Whether institutions might find enough political support in parliaments and among voters for this type of policy is a matter for future research.

Methodologically, the paper suggest a compelling reason for macroeconomists to use FinTech settings for research on household borrowing, saving, and spending. Such providers allow the researcher to access users directly in a logisitically simple way that barely involves any costs, because users can be contacted interactively through the FinTech lenders' apps. Easy direct access to users allows the elicitation of typically unobserved characteristics, as in this paper, as well as the potential to run field experiments to gauge the causal effects of theoretical channels that act through preferences, beliefs, and perceptions on actual high-stake choices.

2 Institutional Setting

We cooperate with a leading European FinTech bank to test for the effects of introducing a mobile overdraft facility on consumption spending behavior. The digital-only bank does not operate a branch network and provides all its services through an Android or iOS mobile app. The bank currently operates under a European banking license in several countries and has more than 1 million customers. Users can open a bank account within 10 minutes by entering their personal information into the app. They are required to verify their identity by providing a copy of their passport or personal ID through video conferencing before the bank confirms the account and users obtain their debit card by mail. The free mobile checking account is the bank's baseline product. The bank does not offer credit cards. Customers manage their account entirely via the bank's mobile app, which provides monthly consumption statistics and allows users to set their daily payment and withdrawal limits, lock their card, or change their pin in real time.

The bank also offers a mobile credit line in several European countries. Residents of these countries with a sufficiently high credit score are eligible for the mobile overdraft facility. Customers can activate the credit line directly in their mobile app within one minute and receive a maximum overdraft amount that ranges between 500 and 5,000 Euros depending on their credit score and other financial and personal characteristics. The bank uses a fully automated algorithm to allocate maximum credit amounts to users. In Section 6, we describe the bank's loan granting and credit allocation process in detail. Users that are granted a mobile credit line specify their desired credit amount, which they can change in real time via the mobile app depending on their consumption needs. However, customers cannot select an amount that exceeds the maximum overdraft limit granted to them by the bank. Users pay an annual interest rate of approximately 10 percentage points on their used overdraft amount, which the bank charges once every calendar quarter. The mobile app provides daily updated information on users' accrued interest costs. Customers can turn on push notifications that remind them whenever their account balance turns negative and they start using the overdraft. The bank cancels the mobile credit line if users default on their interest payments, receive unemployment benefits, or experience direct debit reversals.

3 Data and Descriptive Statistics

3.1 Data Sources and Sample Selection

We obtain detailed consumption data, credit line information, and personal user characteristics from a major European FinTech bank. Our sample consists of users that received an overdraft between February 2015 and September 2017. We focus on individuals that the bank classifies as "main account users" based on their consumption and inflow history to alleviate the concern that customers might have additional accounts with other banks, which we cannot observe. Main account users are individuals that receive a regular monthly salary or incoming standing order into their mobile checking account for at least two consecutive months. Prior research shows that European bank clients satisfy approximately 70% of their daily consumption needs through their primary salary account and that the majority of individuals only have one main account (Bain, 2017; ING, 2018). As a result, our consumption and overdraft data cover most if not all financial activities that main account users carry out via their mobile bank account.

We obtain information about the type, amount, and timestamp of all financial transactions that pass through users' checking account between February 2015 and March 2019. To protect the identity of its customers, the bank rounded all transaction amounts to the nearest Euro and only provided us with the day but not the exact time of each transaction. The financial transactions covered by our dataset can be classified into six broad categories: (*i*) cash deposits and withdrawals, (*ii*) incoming or outgoing wire transfers within the Single Euro Payments Area (SEPA), (*iii*) foreign wire transfers from or to non-SEPA countries, (*iv*) direct debit withdrawals (including reversals), (*v*) bank-imposed fees, and (*vi*) card-based electronic payments. The bank categorizes each electronic payment that a user makes with her debit card into one of seventeen merchant category code (MCC) groups. MCC groups specify the merchant's industry and allow us to identify which type of good or service the account holder purchased. The seventeen MCC groups cover the full range of users' consumption behavior and include both discretionary (e.g., entertainment, shopping, or gastronomy) and non-discretionary consumption types (e.g., groceries, family, or utilities/furniture). Our raw dataset contains 58,310,004 individual financial transactions, which we aggregate into user-month observations. Each within-user time series starts with the month in which the user signed up on the mobile app, verified her identify, and the bank then opened the account, and ends with the closing of the account or the last month of our sample period (March 2019). We code observations of our flow variables as zero if the user did not have any corresponding financial transaction in the given month.

The credit line dataset contains granular information about the application date, granted overdraft amount, and financial characteristics of users that activated the mobile overdraft facility. We observe all user-specific input parameters that enter the bank's credit allocation algorithm, including each individual's credit score, employment status, regular salary, and other credit-relevant inflows. Since the bank shared the precise inner workings of its overdraft granting process with us, we are able to perfectly replicate the credit allocation decision for all mobile credit line users in our sample. Moreover, the credit dataset contains the complete history of all overdraft setting changes that users made once they activated the credit facility. We observe any changes in the actual overdraft usage amount and whether an individual activated push notifications that pop-up whenever the account balance turns negative and users start drawing on the credit line.

The bank also provides us with demographic and personal information about each main account user. We obtain data on users' gender, year of birth, and residential zip code. To ensure data anonymity, the bank does not share the name, address, or precise date of birth of its account holders with us. In Appendix Table A1, we define all variables that we use in our empirical analysis.

3.2 Descriptive Statistics

Table 1 provides descriptive statistics for our main overdraft sample. We trim all ratios that involve consumption-related variables at the 5^{th} and 95^{th} percentile to mitigate the impact of outliers due to data errors or extreme values.[2] Our dataset contains 603,157 user-month observations of 36,005 individuals who obtained a mobile credit line between February 2015 and October 2017. The user base of the FinTech bank consists primarily of male Millennials who live in urban areas. The average user in our sample is 34 years old, has monthly inflows of 2,220 Euros, and opened the mobile bank account 1.6 years ago. 79% of our sample users are male and 53% live in large cities with more than 500,000 inhabitants. All overdraft users combined spent a total of 441 million Euros via their mobile checking account over our sample period. On average, these individuals consume 48% of their monthly inflows, of which approximately two thirds are attributable to electronic card transactions and the remainder is cash consumption. For each Euro that users spend electronically on non-discretionary goods, they purchase 61 cents of discretionary items. Main account users have access to the bank's mobile overdraft facility in 91% of all user-months. The average maximum overdraft amount equals about 1,561 Euros.

4 The Effect of Mobile Overdrafts on Users' Consumption Behavior

In this section, we first assess how the average user changes her spending behavior once she activates an overdraft facility on her mobile phone. We then move on to document a set of

[2] We obtain similar results when we instead winsorize our regression variables at the 5^{th} and 95^{th} percentile or when we use alternative trimming approaches (e.g., trimming at the 1% level in each tail).

heterogeneity patterns in the reaction to the availability. We find that users with higher ratios of deposits to income flows are the ones reacting the most in terms of increasing their spending after they obtain access to the overdraft facility.

4.1 Overall Consumption Response

Our baseline analysis considers users' monthly consumption expenditures and uses a double-differences (DD) design. The DD estimator compares changes in the level of spending around the activation of mobile overdrafts between individuals that already have and the ones that have not yet used the credit line. We restrict the analysis to mobile overdraft users only to address the endogeneity of being eligible for the overdraft facility, which by construction depends on a set of demographic characteristics that might also relate to changes in spending patterns over time. Moreover, the DD design allows us to exclude the possibility that individuals who never activate the overdraft despite being eligible might differ systematically from active users based on unobserved characteristics that also predict their spending patterns over time, such as users' inattention to their financial situation or the possibility that some users use the bank account we observe only for the purpose of depositing their money and do not use such deposits for regular consumption activities.

At the same time, the baseline DD design does not account for the possibility that unobserved shocks at the individual level determine the *timing* of the overdraft facility activation as well as consumption patterns over time. We tackle this concern directly below using a sharp RDD that only compared users at the time they activate their facilities, relative to before. Despite the endogeneity of the timing of activation, we use the DD design for the baseline analysis, because this design allows us to make assessments based on the full population of users in our sample. Instead, by construction, the RDD is based on estimating local treatment effects among a restricted subsample of the users in the overall population, based on their closeness to the regression discontinuity we exploit.

For the DD analysis, we estimate the following OLS regression model:

$$\text{Consumption}_{i,t} = \beta \times \text{Overdraft Available}_{i,t} + \text{Fixed Effects}_{i,t} + \varepsilon_{i,t}. \quad (1)$$

The dependent variable is the sum of all cash withdrawals and debit-card transactions by individual i in month t, divided by the amount of the user's account inflows in month $t-1$. Our main variable of interest, *Overdraft Available*, is an indicator variable that equals 1 at the beginning of the month in which the account holder got access to the credit facility on her mobile phone. We include user fixed effects to control for time-invariant variation in consumption patterns across overdraft users, such as differences in occupation, gender, cultural background, or education. We also include NUTS3×year-month fixed effects to account for concurrent but unrelated time-varying economic or institutional changes within local, sub-national districts, called NUTS3 in the European Union, which correspond to US counties. We double cluster standard errors at the NUTS2 (region) and year-month levels because consumption patterns are likely to be correlated cross-sectionally and over time within closeby locations.[3]

In Table 2, we present the estimated effects of mobile overdraft availability on consumption behavior. Column (1) documents an average positive consumption effect of mobile overdraft. In terms of magnitude, overall cash and card-based consumption normalized by the user's lagged account inflows increases by 4.572 percentage points (t-statistic: 11.11), which corresponds to an increase of approximately 9.5% relative to the sample mean (4.572/48.11). Columns (2) and (3) propose a split between different means of spending. We differentiate between cash withdrawals, i.e. cash spending, and debit-card spending. We find account holders increase their spending significantly through both payment types. In relative terms, the increase in card-based spending (coefficient: 3.152; t-statistic: 9.71) is larger than the increase in cash withdrawals (coefficient: 1.345; t-statistic: 7.73), and accounts for approximately 70% of users'

[3]We use a broader geographic definition for the spatial clustering of standard errors, because the NUTS2 level fully includes the NUTS3 level in the European Union administrative classification. This level of clustering is more conservative than NUTS3, because it allows for correlation of unknown form across the residuals not only across users in the same county, but also across users in neighboring counties that belong to the same region.

overall consumption response. Finally, in column (4), we study the change in the ratio between discretionary and non-discretionary spending and find users increase their discretionary spending by 3% relative to their non-discretionary spending.

Besides the timing of access to the online facility, our DD estimates can only be interpreted causally subject to a parallel-trends assumption—the spending behavior of treated and control users would have followed parallel trends after the overdraft facility was available had this shock not happened. This assumption is untestable, but we can directly test for whether the spending behavior of treated and control users followed parallel trends before the shock. In Figure 2, we provide graphical evidence that treated and control users have parallel and almost identical consumption patterns during the time period leading up to the mobile overdraft activation. To this aim, we repeat the estimation of equation (1) by adding a set of interactions of month dummies with the baseline covariate of interest, the availability of the overdraft facility. Treated users sharply increase their spending during the first two months in which they can access the credit line. Subsequently, the treatment effect stabilizes at around 2% higher consumption relative to inflows and does not fully revert in the long run. We can reject the null of no differences between the spending of treated and control users throughout the sample period and at any horizons we observe in the data after activation. As we will discuss below, this timing of the effect masks substantial heterogeneity—some groups of users face a permanent spending effect of the availability of the overdraft facility, whereas for other users the effect dissipates over time.

5 Heterogeneity and Perceived Precautionary Savings

Our results so far have focused on average effects across users. To better understand the economic channels that might drive our results and to assess the extent to which existing consumption models might explain them, we turn on to study the heterogeneity of the results in the cross section of users (Jappelli and Pistaferri, 2017).

Our baseline observational data do not include direct information about a set of economic mechanisms that are crucial to assess the relevance of different models, such as risk aversion, bequests motives, and beliefs. This lack of information typically makes it hard for empirical studies to pin down exact channels. To solve this problem, we exploit the unique feature that our FinTech bank can communicate with users through the online app to elicit a set of crucial features of their preferences and beliefs *directly* through a survey instrument. This elicitation is a methodological contribution of our paper and represents the main reason for why the FinTech nature of the lender with which we cooperate is central to our analysis. Indeed, accessing traditional bank users to elicit characteristics directly would require either inviting these individuals to a human-subjects laboratory or sending surveys via mail or phone call, which would limit substantially the scope and possibility of the intervention. We see our paper as one of the very first that emphasizes the potential use of app-based online banks to elicit characteristics of borrowers that would otherwise be barely observable in most real-time studies of borrowing and spending.

5.1 Consumption Smoothing? Income Growth, Volatility, and Age

We start by assessing the heterogeneity of the baseline effect across two characteristics we can observe in the field data, that is, (*i*) the growth of income inflows 6 months after overdraft activation relative to 6 months before activation; and (*ii*) users' age.

The permanent income hypothesis (PIH) suggests agents want to smooth their consumption over time. Empirically, income paths are increasing early in life before flattening out. Hence, the PIH predicts younger users and users with a steeply increasing income path should be more likely to use the overdraft facility to smooth their consumption and borrow against their higher future income to increase their spending on impact relative to other users.[4]

To assess this prediction, we split the sample in quintiles based on each of the three observable characteristics listed above. We then repeat the baseline DD analysis of equation (1) adding a set of interactions between a dummy for whether the user belongs to each quintile of

[4]Not only the level, but also the uncertainty of the future income path might be relevant to predict spending (Guiso et al., 1992). We will tackle this point directly below using past income volatility as well as with a survey instrument to elicit uncertainty about future income flows.

each characteristic with the treatment variable for observations before and after activation. To make the results easier to visualize, we report the estimated coefficients and 95% confidence intervals for each interaction in graphical form in Figure 3.

The top panel reports the effects across quintiles of income inflows growth around activation. The estimated effect is larger for users in the first quintile relative to users in the top 3 quintiles, although we do not reject the null hypothesis that the effects are equal across any of the quintiles, including when we compare the size of the effect in the first and fifth quintiles. This heterogeneity result if anything is the opposite of what the PIH would predict.

In the bottom panel of Figure 3, we split the sample into quintiles by age. Despite the fact that our users are on average younger than the broader population, we still detect substantial differences in age between the bottom quintile and the top quintile, whose averages are about 20 years old and 45 years old. We can plausibly argue that users across these quintiles are on different consumption life-cycle paths. The bottom panel of Figure 3, though, shows vividly the lack of nonlinear heterogeneities of the effect in the age distribution, but instead the effect is stable across the whole distribution. In terms of magnitudes, we estimate coefficients that range between 3% and 4% in each quintile. Moreover, we do not reject the null that the effects are the same across all quintiles at any plausible level of significance and if anything, the point estimates are slightly larger for older users with plausibly more stable income processes.

5.2 Liquidity Constraints? Deposits over Income Flows

We then move on to consider the potential role of liquidity constraints in explaining our results (Deaton, 1991). For this analysis, we split the sample by quintiles based on the deposits-to-income ratio in the month before activation. We use deposits-to-income as a proxy for liquidity constraints. If liquidity constraints explained our results, we would expect that users with lower deposits-to-income ratios would increase their spending after accessing the overdraft facility more relative to otherwise similar users with higher deposits-to-income ratios. Indeed, if liquidity constraints explained our baseline results, we would expect that those users with low levels of liquid wealth would increase their spending once they can tap into negative deposits, whereas users with large levels of liquid wealth would barely react to the availability of the overdraft facility.

Figure 4 reports the results for estimating the interaction coefficients across quintiles by deposits-to-income. We detect substantial heterogeneity in this case, but the heterogeneity of the effects goes in the *opposite* direction relative to the predictions of liquidity constraints. In fact, the effect of overdraft on spending is (insignificantly) negative for users in the bottom quintile—the most liquidity-constrained users—and is zero for those in the second quintile. The effect increases nonlinearly and is disproportionally higher the higher the quintile. The estimated effect is about 2% for users in the third quintile, 5% in the fourth quintile, and 12% in the top quintile. In fact, it is the *least* liquidity-constrained users who increase their spending over income flows more after having access to the overdraft facility. Although the positive association is largest for the top quintile by deposits over income inflows, the effect is economically and statistically significant for the median user, which suggests that specific peculiarities of the top quintile group cannot explain the effect.

In Figure 5, we report the estimated coefficients across the deposit-to-inflows quintiles over time. The red dashed line reports the estimated coefficients for users in the top quintile by deposits-to-inflow, the blue solid line refers to users in the first quintile, and grey lines to users in other quintiles. We see that not only the users in the top quintile increase their spending more than others on impact, but their spending increases permanently and does not revert over time. The same permanent effect is detected for users in the fourth quintile, whereas the increase in spending reverts to zero for other users. Importantly, we detect no different trends in the spending ratio of any users before the overdraft facility is available to them.

At first sight, the results in Figure 4 and Figure 5 might appear puzzling, because the association between users' pre-overdraft liquidity and their spending after overdraft activation seems to go in the opposite direction of what we would have expected under a liquidity-constraints explanation. Before digging deeper into the drivers of this empirical regularity, we therefore perform a large set of robustness tests to verify that this pattern is a robust feature of the data.

First, in Figure 6, we assess the robustness of the baseline pattern by liquidity quintiles across a set of relevant subsamples and specifications. In the top left panel, we compare the estimated coefficients and confidence intervals for the baseline specification and for the specification in which we include the full set of controls and fixed effects in equation (1) but also add interaction terms with user age, inflow growth in the six months before and after overdraft availability and inflow volatility in the twelve months before the overdraft availability. We cannot reject the null that the coefficients are equal across specifications either economically or statistically.

In the top right panel of Figure 6, we compare the baseline effect in the full sample of users to the results when we restrict the working sample only to users with an active account for at least 12 months before the overdraft availability. This test is relevant, because one might be concerned users who drive our effect were merely opening an account to take advantage of the overdraft facility to make larger purchases and moved money from other accounts into the online account resulting in large savings-to-deposits and large spending responses. As expected, the estimates are substantially more noisy in the restricted sample of long-term users, but we fail to reject the equality of the estimated coefficients either economically or statistically.

In the bottom left panel, we restrict the sample to users who spend at least 60% of their income on average. In this test, we aim to rule out the possibility that the regularity of spending by deposits-to-inflows is driven by users who do not use the account for spending to begin with before the overdraft facility is available because of the availability of other accounts. We rule out this concern directly.

Lastly, in the bottom right panel of Figure 6, we consider the robustness of our finding in terms of the definition of our sorting variable—deposits-over-inflows. Specifically, we consider the average effects based on whether we sort users based on the ratio measured in the month before the overdraft facility was available or in a one-month period starting 3 months before activation. Even in this case, we find no detectable difference in the baseline patterns.

To further assess the robustness of the baseline consumption responses based on deposits-to-inflows, in Figure 7 we compare the estimated coefficients by quintiles across alternative demographic groups to check whether the baseline relationship might be driven by observables. This test is relevant because it could still be the case that individuals in the top quintiles by deposits-to-income might have characteristics that according to the PIH would predict larger consumption response to the availability of credit despite the fact we do not observe these characteristics to matter unconditionally. Whether we compare users who live in European regions (NUTS 1) above and below the median by savings rate (top left panel), regions that were part of a Communist country or not (top right panel), as well as rural against urban users (bottom left panel),[5] or young versus old users (bottom right panel), we fail to detect any systematic differences in the baseline pattern.

The fact that users with higher deposits-to-inflows ratios, and hence higher liquidity at the time the overdraft facility is available, spend more after the overdraft relative to before is a robust feature of the data.

5.3 Evidence of Objective Drivers of Precautionary Saving Motives?

The heterogeneity results so far seem puzzling relative to standard explanations for why users would increase their spending after the overdraft facility is available to them. On the one hand, the increase is unrelated to characteristics that predict different motives for consumption smoothing under the standard life-cycle permanent-income model. On the other hand, the effect is not driven by liquidity constraints either, but in fact the most reactive users are those with the highest liquidity, which is the opposite of what liquidity constraints imply.

In the standard life-cycle model, several other individual characteristics, which are typically unobserved in observational data, could predict a reaction to overdraft availability. For instance, systematic differences in users' risk aversion, time preferences, beliefs about life expectancy, or bequest motives might drive these results. Moreover, expecting imminent large

[5] We define urban those users who live in cities with more than 500,000 inhabitants

expenses due to unobserved health reasons, other unobserved reasons, as well as private information about the probability of becoming unemployed and hence having more volatile income streams in the future might all drive these results (Gomes and Michaelides, 2005; Chetty and Szeidl, 2007; Carroll, 1997).

These dimensions might either predict larger precautionary savings motives due to preference heterogeneity for a given level of objective uncertainty or might translate into differences in precautionary savings due to subjective needs. Once the overdraft facility becomes available to these users, it might act as a form of insurance and trigger higher spending, because these users know they can now tap into negative deposits using the overdraft facility once a shock occurs.

In addition to these precautionary savings motives, one could think about other channels that could explain the willingness to spend liquid assets only after they obtain an overdraft facility, which are not necessarily embedded in the standard life-cycle model. For instance, such agents might have low financial literacy and hence are unable to optimize their allocation of resources over time. Or, they might be distrustful of others and hence display a precautionary saving motive that is not based on their financial conditions.

In Figure 8, we consider three dimensions that might predict differential precautionary savings motives across quintiles by liquidity and which we can measure directly in our data. First, we consider age. Age increases monotonically with the bins by deposits-to-income inflows, ranging from 31.4 to 35.1. Although the difference between the fifth and first bin is statistically different from zero, the magnitude of this difference is less that 10% of the average age in the top bin. Most importantly, though, the typical precautionary savings explanation would suggest that *younger* users have higher precautionary savings motives, because these users are likely to have more uncertain income paths, might expect higher future income growth, might face less employment stability, and might still not be in the workforce at all.

To further test if the standard deviation of income inflows as a proxy for income uncertainty drives our results, we look at this variable directly in Figure 8. Specifically, we average the standard deviation in income inflows over the 12 months before overdraft facility activation across bins. We do not detect any systematic patterns or differences between the bottom and top bin by deposits-to-income. This fact is prima facie evidence that differences in income uncertainty do not justify why users in the top bin behave as if they have stronger precautionary savings motives.

Another potential driver of precautionary savings motives is an increasing path of income over time. We calculate income growth six months after the activation relative to six months before but even in this case, we do not detect any systematic patterns or economically/statistically significant differences across bin by deposits-to-income ratios.

5.4 Eliciting Preferences, Beliefs, and Motivations

Most of the other dimensions we discuss above are typically unobservable in individual-level data sets on borrowing and spending. Standard data sets usually only gather information about choices, but do not include any information on agents' preferences, beliefs, and motivations.

To make progress on this front, we exploited the unique setting of our study, which uses data from a FinTech online-only app-based bank. We were thus able lever the feature that our app allows accessing users directly with surveys and other instruments to elicit in real time a large set of typically unobserved individual preferences, beliefs, and motivations.

In June and July 2019, we fielded a survey intervention we designed ad hoc to elicit users' risk and time preferences, a large set of beliefs, motivations, perceptions, as well as financial literacy and generalized trust. Users could answer the elicitation survey either when using their app on the desktop version or on their mobile phones. We sent 73,000 invitations to the survey, targeting a response rate between 10% to 15%, based on other surveys the FinTech bank with which we cooperate ran on the platform in the past. Overall, we obtained 7,901 responses to the survey, which represents a response rate of 11%, in line with our expectations. Of the 7,901 respondents, we kept the survey outcomes of the users for which we observe the overdraft facility availability and activation in the time period covered by our study. Overall, we obtain 597 unique observations of users that belong to the overdraft facility working sample we used in the analysis so far and for whom we do observe all the elicited preferences and beliefs through the survey responses.[6]

Importantly, when we approached users, we did not disclose that the aim of the intervention was to link their answers to the spending behavior around the introduction of the overdraft facility. Being silent about the overdraft facility was crucial to reduce the concern of experimenter demand effects, i.e., the possibility that subjects guess the aim of the experiment and align their answers and choices to such aim. The issue of experimenter demand effects is one of the strongest concerns faced by experimental economics and survey-based elicitation tools, as discussed recently, for instance, by De Quidt et al. (2018). Because we did not refer to the overdraft facility in any way within our survey, it is implausible that users would understand that the scope of the experiment was to assess the drivers of their spending and borrowing behaviors and hence could manipulate their answers to our questions to not disclose if and how they consume, spend, and borrow. A drawback of the lack of direct reference to the overdraft facility experience is that we could not ask users directly for the motivations they had to activate and use the facility. Because of the issue of demand effects, the answers to such a direct question would have anyway been barely interpretable due to strategic motives in users' answers (see, e.g., D'Acunto, 2018, 2019).

To design the survey, we followed earlier research for the design of questions. We elicited risk aversion by asking users to rank their willingness to take on risks in financial matters on a scale from 1 (very low) to 10 (very high) (see, e.g, Guiso et al., 2008; D'Acunto et al., 2019b,c). For time preferences, we proposed users a hypothetical choice between a certain amount at the time of the survey or increasing amounts one month later (see, e.g., Benjamin et al., 2010; Coibion et al., 2019). For eliciting expectations about upcoming large expenses, we asked users to rank the probability they foresaw any large spending expenses or large medical expenses over the following 12 months (D'Acunto et al., 2019a). We elicited similar rankings for users' expectations about the possibility of losing their job over the following 12 months—which aims to capture the uncertainty in their future income flows (Guiso et al., 1992)—users' satisfaction

[6] We report a translation of the original survey in Appendix Table A3.

with their health conditions, and users' generalized trust towards others (see, e.g., Dominitz and Manski, 2007; Guiso et al., 2004; D'Acunto et al., 2018). To elicit users' financial literacy, we asked them to assess whether the amount that would compound in their checking account at a certain interest rate would be above or below a given value (see, e.g., Lusardi and Mitchell, 2011)). Among potential questions the literature proposed for financial literacy (Lusardi and Mitchell, 2014), we believe that the ability to understand compounding is the most relevant in our setting, in which we study the borrowing and spending behavior of bank users when considering the use of the overdraft facility.

Panel B of Table 3 reports the results for the basic preferences, beliefs, and motivations we elicited. We sort users into five quintiles based on their deposit-to-income ratio before accessing the overdraft facility. We then compute the average quantitative response of these users to the elicitation questions within each bin, which we plot together with the 95% confidence interval for the mean value in each quintile in Figure 9.

Across the dimensions we elicited, we fail to detect any systematic patterns in the cross-section of liquidity—the quintiles based on value of deposits-over-income—either economically or statistically. None of the dimensions we consider, which could have explained the pattern in Figure 4 in a standard life-cycle consumption–savings model, seems able to capture such pattern. Note that not only are the averages within quintiles not different from each other statistically, but they are also similar in terms of economic magnitude, which suggests lack of statistical power or a small sample size in the survey sample do not drive the lack of variation across quintiles.

Overall, our evidence based on elicited preferences, beliefs, and motivations for the users in our sample directly dismisses the most compelling traditional potential channels that would justify a spending increase by liquid users, but not illiquid users, once the overdraft facility was made available to them.

5.5 The Perceived Precautionary Savings Mechanism

The heterogeneity results suggest a pattern whereby users with higher liquidity (cash deposits) over income react more than others to the activation of the overdraft facility in terms of spending. This pattern is intriguing, because we might have expected the most liquid users to be those that had the least need of an overdraft facility if they wanted to spend more before activation. To the extent that the overdraft facility is mainly used to smooth spending and loosen liquidity constraints, we might have expected users in the bottom quintile by deposits-over-income would have reacted the most instead of the pattern we observe in the data.

Users that hold substantial liquidity might change their behavior after they access the overdraft facility due to precautionary savings motives and the need to maintain enough liquidity available in case of potential future negative income shocks.

So far, comparing bins by deposits-to-income ratios does not suggest that users in the top bin have any objective reason to hold stronger precautionary savings motives than users in the lower bins. We move on to assess whether, apart from increasing consumption spending after activating the overdraft facility, users in the top bin also behave in line with precautionary savers in terms of overdraft facility usage. In particular, precautionary savers, contrary to liquidity-constrained individuals, would likely not tap into negative deposits and would not increase their debt levels through the overdraft facility. Instead, they should view the facility as a form of insurance against negative income shocks or unexpected expenses and would thus spend some of the existing liquidity they had accumulated before the overdraft facility was available once they know they can tap into negative deposits if needed.

The results in Figure 4 are broadly consistent with the users in the top bin by deposits-to-income behaving as if they had strong precautionary-savings motives. First, these users are substantially less likely than users in lower bins to tap into negative deposits after activation, despite increasing their consumption spending relative to the pre-period substantially more than these other users. The probability of tapping into negative deposits ranges from 67% for users in the bottom bin to 10% for users in the top bin.

Because the 75^{th} percentile of age in our sample is 38.7, it does not even seem plausible to assume that a large fraction of the individuals in our sample might have objective precautionary savings motives due to potentially unexpected large medical bills or other medical-related expenses. A potential concern with our interpretation is that users decide they want to purchase big ticket items and move cash to the deposit account at our bank before they activate the overdraft facility. But in the data we do not observe heterogeneity in the cumulative inflows at our bank in the three months before activation by deposits-to-income.

Overall, users with a high share of deposits to income ratios and hence high liquidity behave as if they had precautionary savings motives and hence accumulated savings and saved a larger share of their income before the overdraft facility became available to them. Once they have access to the overdraft facility which acts like an insurance for additional future spending needs, possibly due to unexpected spending needs or income shortfalls, they increase consumption spending. These users though do not display any of the characteristics that are typically associated with individuals that have precautionary savings motives, such as high income volatility or higher risk aversion. Based of these considerations, we label the mechanism we document in this paper as *perceived* precautionary savings motive.

5.6 Alternative Explanations and Channels

We discuss a set of possible alternative interpretations for our results. First, it is implausible that the mobile overdraft facility loosens financial constraints on the side of users, because the users with the highest fraction of cash deposits over income react the most to the introduction of the overdraft facility. If anything, the consumption behavior of the most liquidity-constrained users does not change at all.

Second, access to the overdraft facility might help users smooth consumption in case of growing income paths. Our baseline results hold for both young and old users and life-cycle consumption patterns are unlikely to matter for older users.[7] To directly test for this mech-

[7] Note that our sample is younger than the average population, yet we do detect an age range of 25 years between the bottom and top quintiles of the distribution by age.

anism, we also study the income profiles around the overdraft activation and do not find any evidence of different income growth across bins of deposits to income.

Third, the facility might free up liquid resources users were keeping in their bank accounts due to precautionary motives and potential unexpected future income shocks. In this vein, even models of buffer-stock savings that allow for both impatience and precautionary savings motives might explain at least in part our results. Our heterogeneity results do not seem fully consistent with this interpretation for a set of reasons. Income uncertainty decreases with age and the heterogeneity results by age we discuss above are not consistent with this form of precautionary-savings motive. Moreover, we find the pre-activation volatility of income flows does not predict reaction to the availability of credit. Also, as discussed above, users close to the liquidity constraint do not react, whereas those farther away from the constraint react the most, and the buffer-stock interpretation predicts the opposite pattern.

A fourth potential explanation is a buffer-stock model with durable consumption similar to the one Aydin (2015) studies. However, a set of results suggests this interpretation cannot fully explain the results in our setting. In addition to the facts that the least liquidity-constrained users react most and that we do not see any differential reaction based on pre-activation income volatility, we find users that react the most on average do not tap into negative deposits and hence *de facto* never use the facility.

A fifth interpretation we consider is present-biased preferences—the fact individuals discount the distant future by more than they discount the immediate future (Meier and Sprenger, 2010). This interpretation by itself is unlikely to explain all our results, because if the individuals that react the most to overdraft activation were present-biased, they would have consumed out of their higher deposits even *before* activating the overdraft facility, which we do not observe in the data.

Contrary to the alternative explanations we have discussed in this section, the perceived precautionary savings channel is consistent with the baseline facts we document as well as with the fact that users at the top of the distribution by deposits over income flows react the most to the activation of the overdraft facility.

At first, our results might appear inconsistent with a large literature documenting users that are ex-ante most constrained react the most to the extension of credit (see, e.g., Agarwal et al., 2017; Aydin, 2015; Gross and Souleles, 2002). The major difference between these studies and our paper is the variation we exploited so far and the variation this literature uses. Typical papers in this literature study individuals with existing access to credit with lines of credit or credit cards and how an increase in the credit limit (i.e., an increase in the intensive margin of credit) affects spending. A robust finding in this literature is that the ex-ante most constrained users—users that make use of the existing credit the most—react the strongest to the intensive margin extension of credit which is a natural finding. In our case, instead, we study how individuals that previously did not have access to credit adjust their spending to the availability of the overdraft facility, an extensive margin of credit. In our setting, it appears natural that users that previously were most concerned about future unexpected expenses or had higher precautionary savings demands for other reasons which we capture by sorting on deposits-to-income react the most to the provision of a downside insurance.

6 Regression Discontinuity Analysis

A remaining concern with our analysis so far relates to the identification of a causal effect of the overdraft availability on spending choices. As discussed above, the timing at which users open their accounts might coincide with the availability of the overdraft facility, for instance because users plan large future expenses. The test in which we only consider users who had an account with our provider open at least one year before the overdraft facility was made available reduces this concern.

At the same time, other omitted variables might simultaneously impact users' consumption behavior and overdraft activation decision, giving rise to a spurious relation between the two. One example for such a correlated omitted variable might be time-varying, user-specific exposure to television commercials that independently advertise the bank's overdraft and various consumer products, even for users who have been banking with our provider for quite some time and hence do not open new accounts.

To directly address these endogeneity concerns, in this last part of the paper we estimate the causal effects of mobile overdraft on spending in a sharp RDD that exploits variation in users' overdraft limits based on thresholds embedded in the bank's credit allocation algorithm. Our sharp RDD conditions the analysis on users' (possibly endogenous) selection into the mobile overdraft and relies on exogenous variation in the size of the credit line along the intensive margin.

We do not implement this design for the baseline analysis of the paper because we can only exploit a limited number of users in the sample for the RDD setting. By construction, as we discuss in more detail below, the RDD only employes users who lie close to pre-specified thresholds based on the algorithm that assigns the overdraft amount to those activating an overdraft facility. Because of the limited sample, unfortunately any meaningful statistical analysis of heterogeneity and variation across subgroups of users would be impossible.

6.1 Credit Allocation Algorithm

The bank's credit allocation process consists of two steps. First, the bank determines whether users pass all exclusion criteria and are thus eligible for a mobile credit line. Overdraft applicants receive a credit line if they (*i*) are employed, (*ii*) live in countries where the bank offers a mobile overdraft, (*iii*) have a minimum credit score of F, and (*iv*) their checking account did not trigger any direct debit reversals. The bank obtains credit scores from consumer credit bureaus, which collect information on users' credit histories to estimate default probabilities and assign individual credit ratings from A (lowest default risk) to M (highest default risk). A credit score of F implies that the individual has an estimated default probability of less than 10 percent.

Second, the bank determines the maximum overdraft amount for each eligible user based on the applicant's credit score and average account income according to the following formula:

$$\text{Overdraft Amount} = \begin{cases} \text{Max Limit} & \text{if } 2 \times \text{Income} \geq \text{Max Limit} \\ \text{Min Limit} & \text{if } 2 \times \text{Income} \leq \text{Min Limit} \\ 250 \times \lfloor \frac{2\times\cdot\text{Income}}{250} \rceil & \text{otherwise,} \end{cases} \tag{2}$$

where $\lfloor x \rceil$ rounds the number x to the nearest integer.

For each rating notch between A and F, the bank specifies a lower (*Min Limit*) and upper limit (*Max Limit*) for each user's allocated credit amount. Income is a linear function of the user's different inflow types in the months prior to the overdraft application. Our data sharing agreement with the bank does not allow us to report the rating-specific overdraft limits or the precise formula that transforms users' account inflows into income. However, we can disclose that the bank differentiates between regular salary and non-salary related inflows (e.g., pensions, child benefits, study support from parents etc.) and puts a higher weight on the former. The lower and upper overdraft limits monotonically increase in the customer's credit rating and range between 500 and 5,000 Euros.

To determine each user's maximum available overdraft amount, the bank's fully automated credit allocation algorithm multiplies the Income variable by 2. If the resulting value exceeds (falls below) the upper (lower) credit limit, the maximum overdraft amount is bounded from above (below) by the rating-specific limit. If the doubled income falls in between the upper and lower limit, the amount is rounded to the closest 250 Euro multiple at the midpoint. Panel A of Figure 10 illustrates the rounding convention embedded in the credit algorithm. For example, if overdraft applicant A has a salary of 2,100 Euros and no additional account inflows, her implied overdraft amount after multiplying the income by 2 equals 4,200 Euros, which, if rounded to the closest 250 Euro threshold, translates into a maximum available overdraft amount of 4,250 Euros (assuming that the upper and lower credit limits do not bite). The bank's credit allocation process gives rise to 18 unique thresholds in the interval between 500 and 5,000 Euros, at which the maximum overdraft amount jumps discontinuously by 250

Euros. At these thresholds, users with almost identical income that find themselves on opposite sides of the rounding threshold receive different overdraft limits for plausibly exogenous reasons. Crucially, users are not aware of the algorithm and the algorithm is fully automated leaving no room for human intervention.

6.2 Empirical Implementation

We limit our analysis to users whose maximum overdraft amount equals the individual's income multiplied by two and rounded to the nearest multiple of 250. That is, we drop all users whose transformed income exceeds or falls below the upper or lower credit limit (within the given rating notch) such that the rounding thresholds embedded in the bank's credit allocation algorithm do not affect the maximum overdraft amount. For each user in our RDD sample, we compute the forcing variable X_i, which quantifies the individual's distance (in Euros) to the nearest rounding threshold. X_i removes differences in absolute rounding thresholds across individuals and is centered around zero. Users with $X_i \geq 0$ are treated and receive a maximum overdraft amount that is 250 Euros higher than those of control users for whom $X_i < 0$. The probability that a user's overdraft limit gets rounded up by 250 Euros changes discontinuously from 0 to 1 at the rounding threshold. Panel B of Figure 10 illustrates the exact treatment rule of our sharp RDD and plots users' treatment assignment for different values of the forcing variable X_i. In areas close to the rounding threshold (where $X_i = 0$), treated and control users have almost identical income profiles.

To examine the causal effect of mobile credit lines on users' consumption behavior, we implement the following sharp RDD:

$$\tau \equiv \mathbb{E}\left(C_i(1)|X_i = 0\right) - \mathbb{E}\left(C_i(0)|X_i = 0\right). \tag{3}$$

τ is the RD treatment effect and $C_i(1/0)$ is the change in treated (1) or control (0) user's average consumption three months before and after the credit allocation decision, divided by the individual's average inflows in the three months prior to the overdraft application. To estimate this model, we fit a weighted least squares regression of the observed consumption change on a constant and polynomials of X_i on both sides of the rounding threshold. The RD treatment effect is the difference in estimated intercepts from these two local weighted regressions. Formally, each user's consumption change equals:

$$C_i = \begin{cases} C_i(0) & \text{if } X_i \geq 0 \\ C_i(1) & \text{if } X_i < 0. \end{cases} \tag{4}$$

We focus on observations within the interval $[-h, h]$ around the rounding threshold, where $h > 0$ denotes our bandwidth. The kernel function $K(\cdot)$ specifies our regression weights. $\hat{\mu}_{+/-}$ is the estimate of $\mathbb{E}\left(C_i(1/0)|X_i = 0\right)$ for observations above or below the threshold, which we define as:

$$\hat{C}_i = \hat{\mu}_{+/-} + \sum_{j=1}^{p} \hat{\mu}_{+/-,j} X_i^j, \tag{5}$$

where p denotes to the order of our local polynomial. The RD treatment effect then equals:

$$\hat{\tau} = \hat{\mu}_{+} - \hat{\mu}_{-}. \tag{6}$$

To operationalize the RD estimator, we need to specify (i) the order of polynomial p, (ii) the kernel function $K(\cdot)$, and (iii) the bandwidth h. We follow Gelman and Imbens (2018) and only use polynomials of order 1 and 2 to avoid overfitting issues. We apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice for point estimation in our context (Cheng et al., 1997). Finally, we employ the MSE-optimal bandwidth selection procedure recommended by Calonico et al. (2014), which corrects for the non-negligible bias resulting from subjective bandwidth choices. We residualize the outcome variables of our RD analysis with NUTS3×year-month fixed effects to ensure that we compare treated and control users from the same European country at a similar point in time.

6.3 Assessing Identification Assumptions: Treatment Manipulation and Balancing Tests

Our sharp RDD critically relies on the assumption that the forcing variable for individuals just below the threshold is similar to those just above the threshold. If users can manipulate the forcing variable and thereby their assignment to treatment and control groups, this local continuity assumption is violated, which results in biased RD estimates (Roberts and Whited, 2013).

Conceptually, it is unlikely that users can control their treatment assignment in our setting. Most importantly, the bank's credit allocation algorithm is proprietary information and not known by overdraft users. Even if individuals were informed about the precise inner workings of the overdraft allocation formula (in particular its rounding thresholds), it seems implausible that users could precisely manipulate their income, for example, by negotiating a higher wage with their employer (Lee and Lemieux, 2010). Moreover, it appears unlikely that overdraft users would be willing to voluntarily forgo parts of their salary just to obtain access to a higher credit limit.

To formally assess the validity of the local continuity assumption, we test for the presence of a discontinuity in the density of X_i at the rounding threshold. If users systematically inflate their income to receive a higher overdraft limit, we should observe a kink in the distribution of our forcing variable right above the threshold. We use the local polynomial density estimator of Cattaneo et al. (2017) to test whether overdraft users manipulate their assignment into treatment and control group. In Appendix Figure A1, we plot both the frequency distribution (Panel A) and density function based on quadratic local polynomials (Panel B) of our running variable and do not find graphical evidence for bunching above the rounding threshold. In Figure A2 in the Appendix, we report the estimation results of the formal treatment manipulation test by Cattaneo et al. (2017) for different polynomial and bandwidth choices. In all specifications, we fail to reject the null hypothesis that our running variable is locally continuous around the rounding threshold.

The local continuity assumption implies that individuals below and above the cutoff should not only be similar in terms of the forcing variable but also along other characteristics. Since overdraft users lack the ability to precisely manipulate their distance to the rounding threshold, no systematic differences in observable characteristics between the two groups of individuals should exist. Consistent with this argument, we do not find significant differences in the average age, gender, time since account opening, account inflows, and consumption between treated and control users prior to the activation of the mobile overdraft. As an alternative balancing test, we repeat our RD analysis but replace our main outcome variable with each observable user characteristic. In Table A2 of the Appendix, we document the RD treatment effect for all our covariates is economically and statistically indistinguishable from zero.

Overall, the evidence in this subsection indicates that overdraft users do not manipulate their treatment assignment and that individuals above and below the rounding threshold have similar observable characteristics. Both findings suggest the local continuity assumption is satisfied and thereby corroborates the internal validity of our sharp RD design.

6.4 RD Consumption Effect

In Figure 11, we graphically illustrate the RD treatment effect of a 250 Euro higher overdraft limit on users' consumption behavior. We aggregate our data into disjoint bins and make sure each bin contains either treatment or control observations. We then calculate the average value of our outcome variable, plot this value above the midpoint of the bin, and separately fit two linear regressions through all observations on each side of the rounding threshold.

In Panel A of Figure 11, we verify that individuals just above the threshold indeed receive a higher maximum overdraft amount (relative to their income) compared to users just below the threshold. The slope of both fitted regressions lines is negative since, within treatment and control group, individuals with larger values of our forcing variable X_i have a higher income, which we use to normalize users' overdraft limit. In Panel B, we plot the change in average (normalized) consumption three months before and after the user obtained access to the credit line. We find a positive discontinuity in users' consumption growth right at the rounding threshold, indicating treated users consume more relative to control users following the exogenous assignment of a 250 Euro higher overdraft limit. In Table 5, we present the coefficients from estimating the sharp RD design we formalized in equations (3) to (6). We estimate first- and second-order polynomial regressions at the rounding threshold and report both bias-corrected and conventional t-statistics (Cattaneo et al., 2017; Gelman and Imbens, 2018). In columns (1) and (2), we document a positive and highly statistically significant RD treatment effect on users' consumption growth. The coefficient estimates do not attenuate when we add user characteristics as control variables in a linear and additive-separable way. In line with Calonico et al. (2019), we find adding covariates increases the precision of our point estimates, which again suggests the local continuity assumption is satisfied.

We conduct two robustness tests to assess the sensitivity of our RD estimates. First, we examine how sensitive the RD results are with respect to the choice of our bandwidth (Imbens and Lemieux, 2008). Varying the bandwidth is only meaningful over small intervals around the MSE-optimal choice (Cattaneo et al., 2020). Bandwidths much larger than the MSE-optimal bandwidth bias the RD estimator, while substantially smaller bandwidths inflate its variance. Figure A3 in the Appendix shows different bandwidth choices do neither substantially affect the magnitude of the point estimate, nor its significance. Second, we assess how robust our RD point estimates are to excluding data close to the threshold (see, e.g., Barreca et al., 2011, 2016). We drop users located within the radius $r > 0$ of the rounding cutoff, that is, we exclude observations for which $|X_i| \leq r$ (Cattaneo et al., 2020). Appendix Figure A4 plots the coefficient estimates for different choices of r and shows that observations close to the rounding threshold do not drive our results.

7 Conclusion

We study the consumption response to the introduction of an overdraft facility on a FinTech app. The average user increases her consumption spending over income by 4.5 percentage points on impact relative to similar users that have access to the overdraft facility at a later point in time. The increase in consumption is permanent and we observe a reallocation of consumption from discretionary to non-discretionary expenses. For identification, we exploit a sharp regression discontinuity design exploiting different sizes of overdraft based on income and confirm our baseline findings.

When we study heterogeneity in the response by observables, we observe a similar response for young and old users, for users with low and high income volatility, and for users with steep and flat income paths. When we split the sample based on the ratio of deposits over inflows, we find instead a large consumption response for users with high liquid savings, whereas the users with the lowest amount of liquid savings do not react at all to the provision of the overdraft facility. These results are not fully consistent with myopic consumers, models with financial constraints, buffer stock models (with durables) and present bias and the canonical life-cycle permanent income model.

Additional results, instead, suggest a *perceived* precautionary savings channel is at work for users with high deposits over inflow. Before the facility is available, they perceive high income risk or future expenses and consequently save. Once the overdraft facility is available, which acts like an insurance against future shortfalls, they increase their consumption substantially but barely make use the overdraft facility.

Our findings open exciting new avenues for future research. What are the microfoundations of perceived precautionary savings motives? In particular, does this attitude results from biased beliefs about the likelihood of future negative states of the world or is it instead consistent with the neoclassical consumption model in a setting in which consumers have high risk aversion? In terms of policy and real-world applications, do perceived precautionary savings change the effectiveness of conventional fiscal policy such as tax rebates? And could policies be designed to insure perceived precautionary savers in bad times and nudge them to spend their cash in times in which higher aggregate demand is needed?

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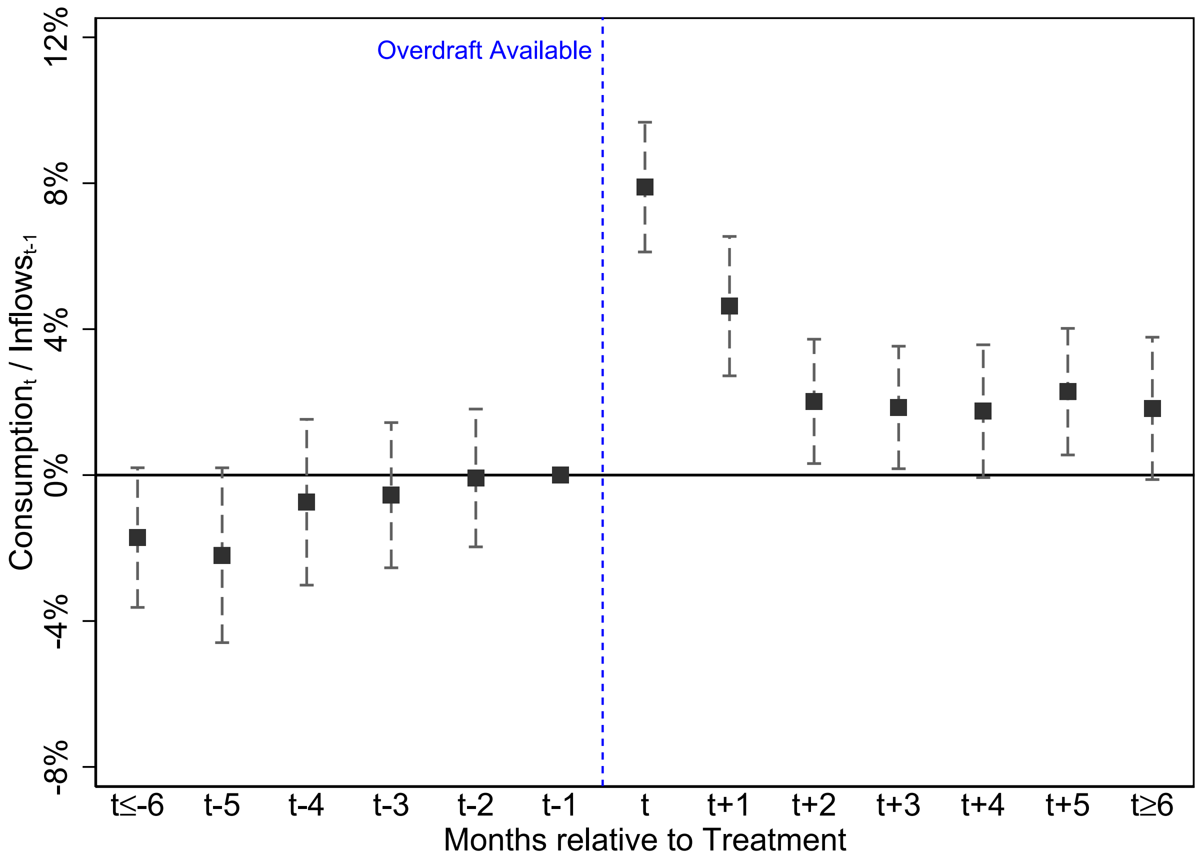
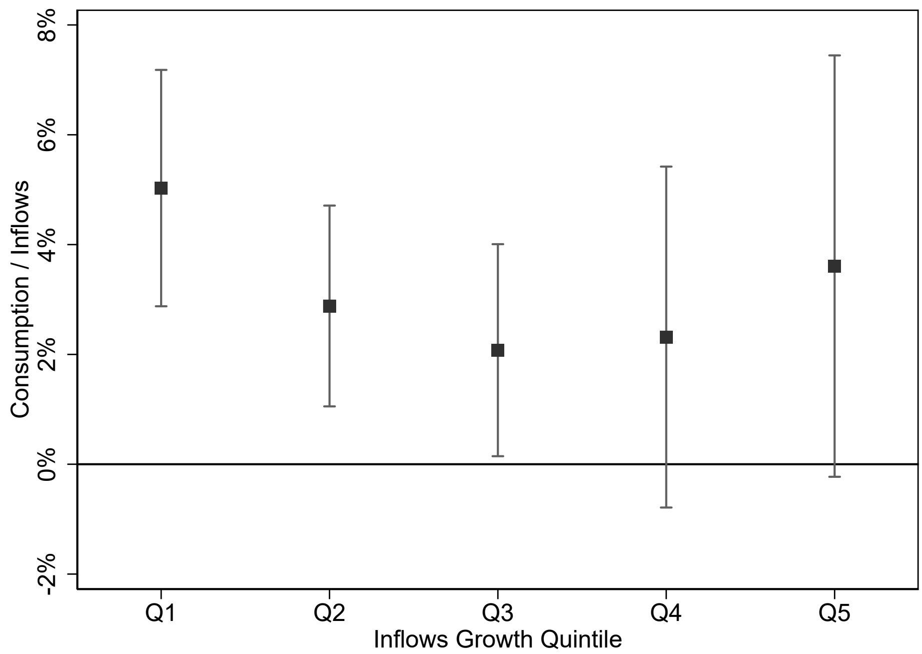
Tables and Figures

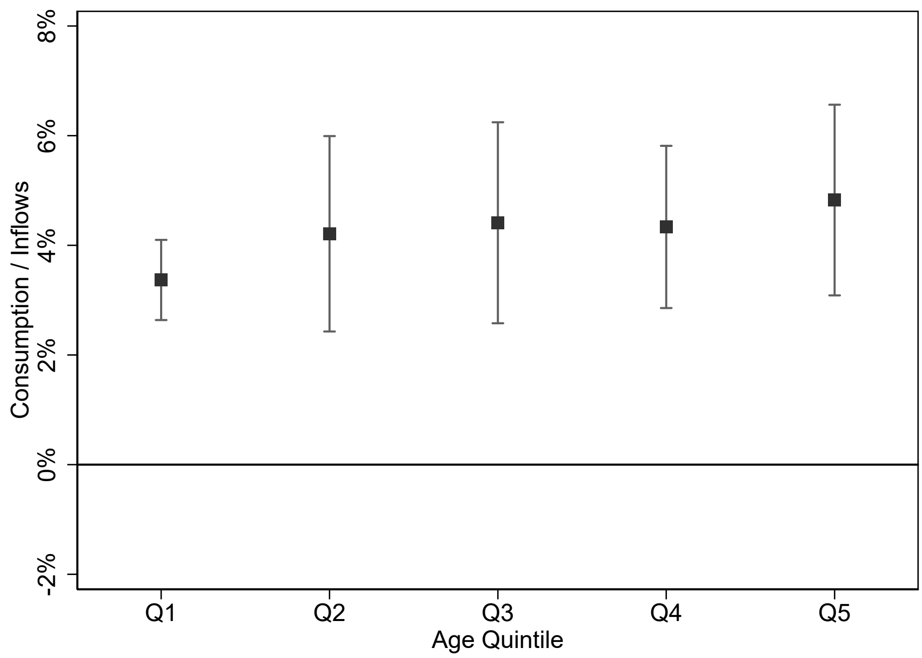
Figure 2: Consumption Pattern around Overdraft Availability



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of mobile overdrafts on users' consumption behavior. We estimate model (1) from Table 2 but replace the *Overdraft Available* indicator with separate time dummies, each marking a one-month period (except for event period $t-1$).

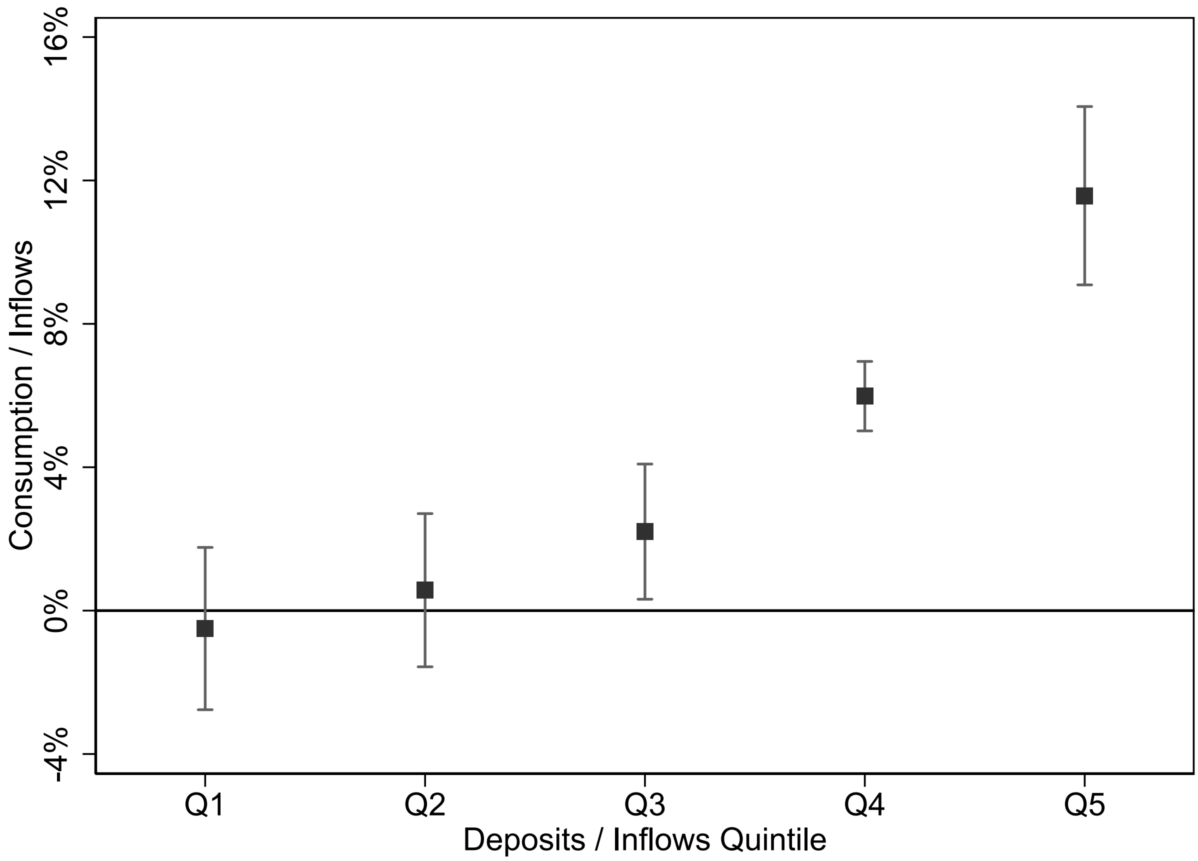
Figure 3: Intertemporal Consumption Smoothing?





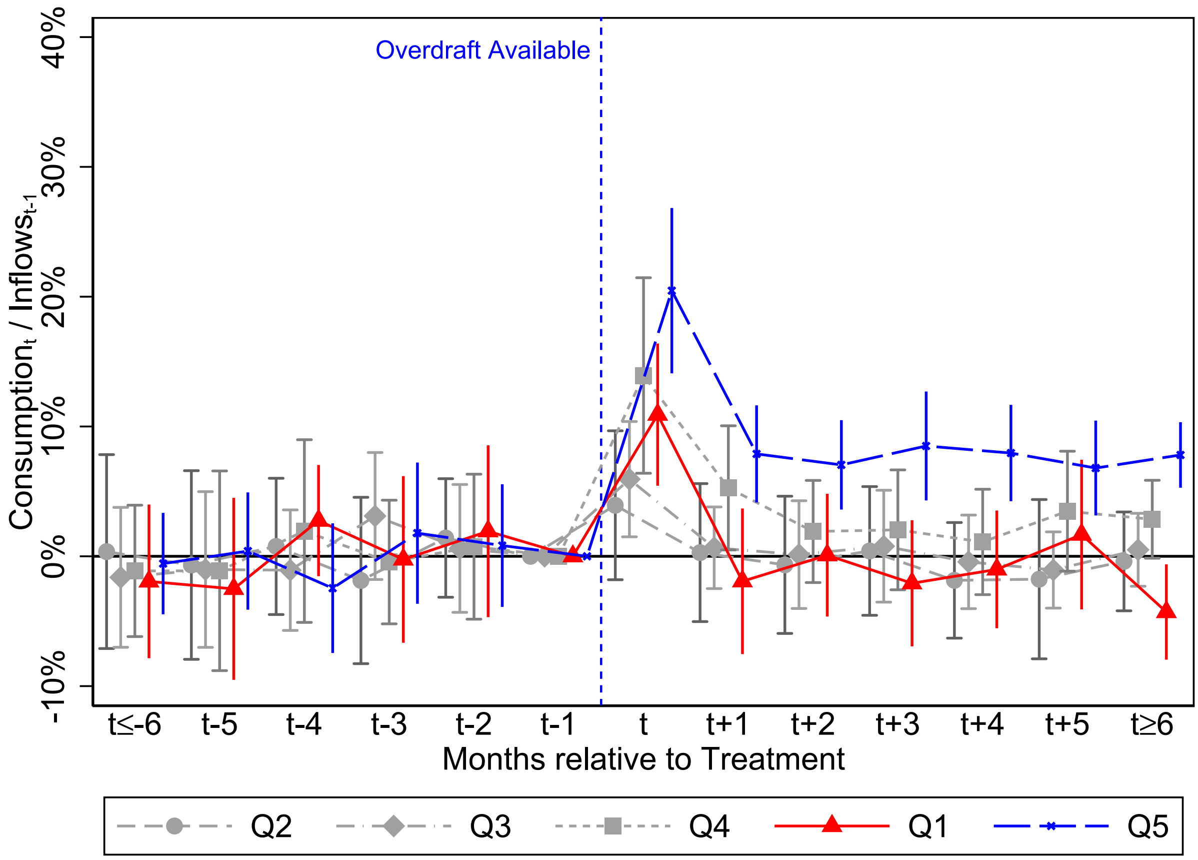
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the underlying user characteristic. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS2 and year-month level.

Figure 4: Consumption Response by Deposit-to-Income Quintile



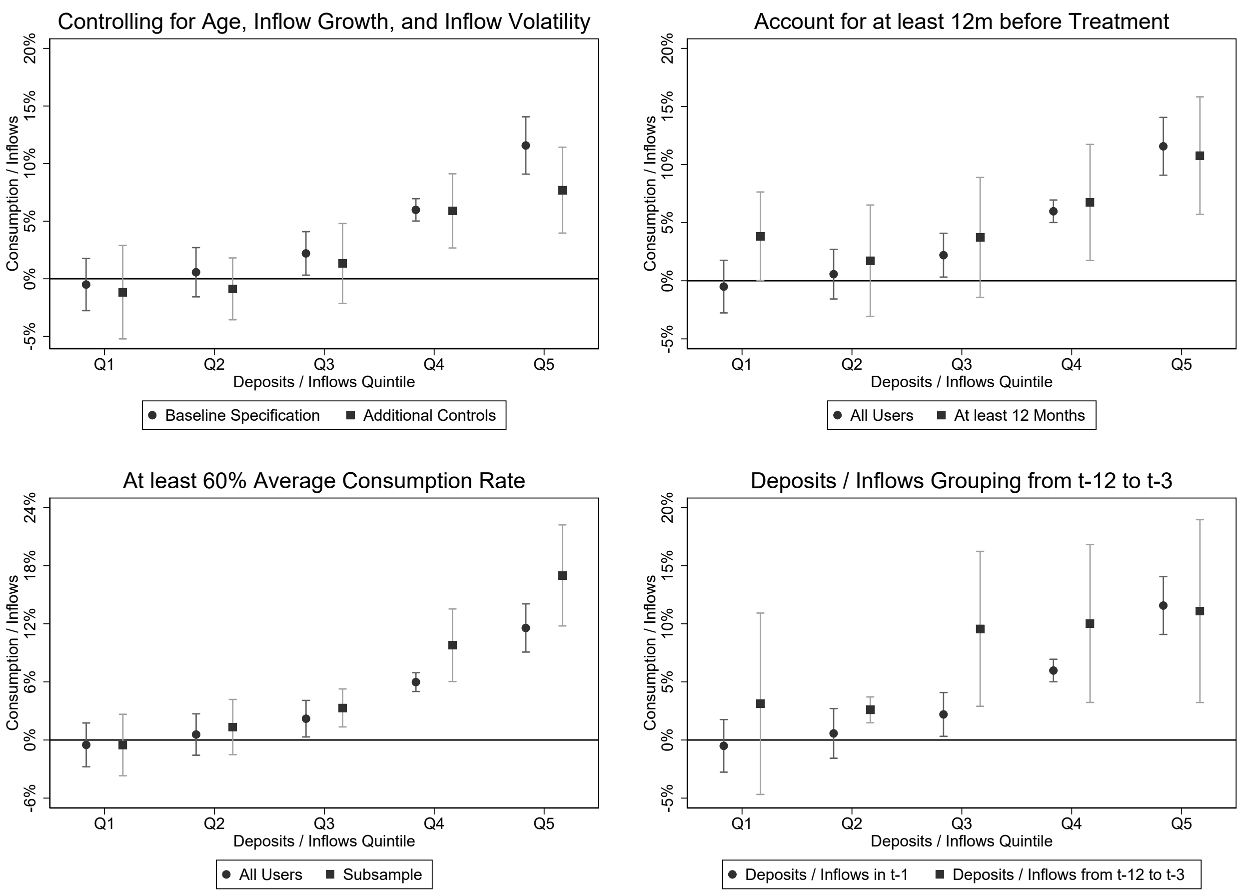
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the underlying user characteristic. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS2 and year-month level.

Figure 5: Consumption Pattern by Deposit-to-Income Quintile



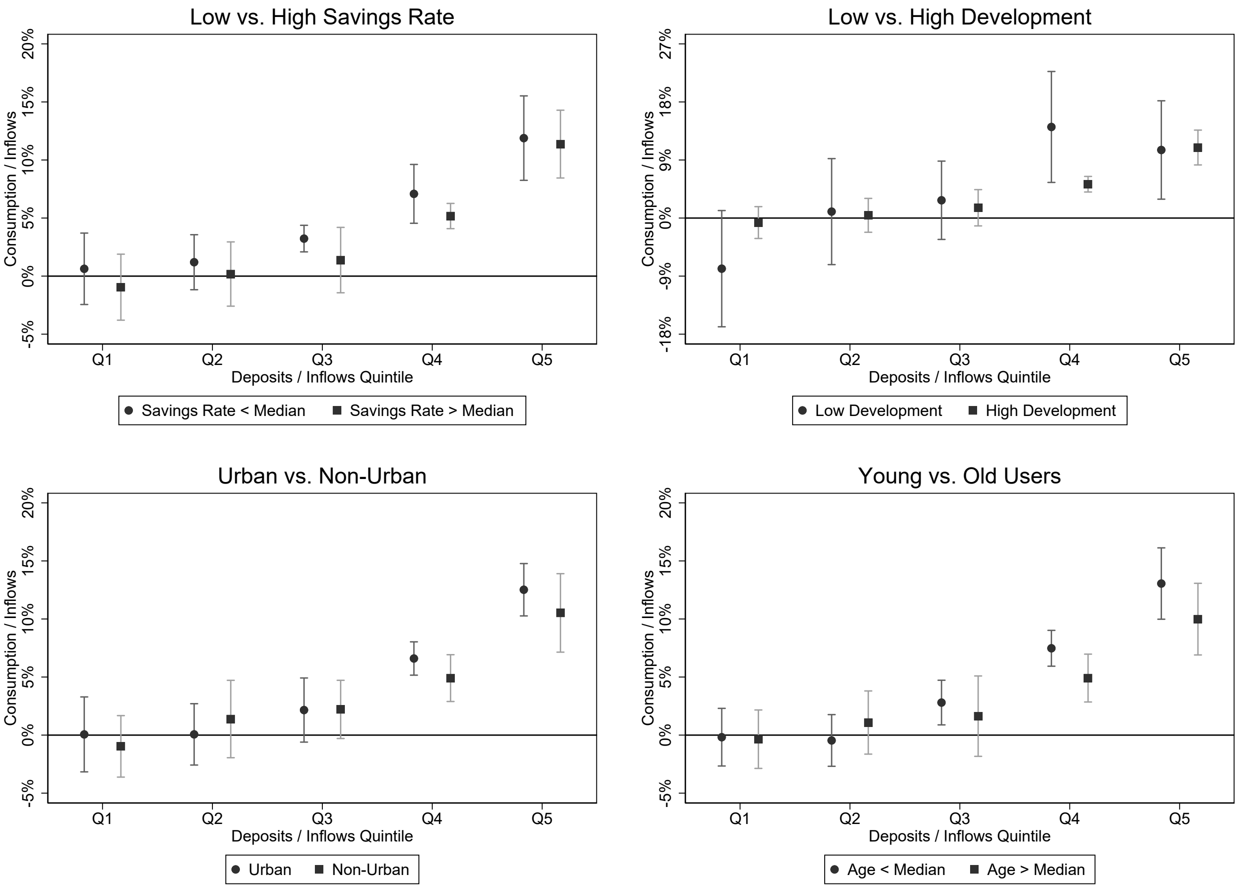
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the heterogeneous effect of mobile overdrafts on the consumption behavior of users with different ex-ante liquidity. To generate this plot, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposit to inflows ratio in the month before treatment. We estimate model (1) from Table 2 but replace the *Overdraft Available* indicator with separate time dummies, which we further interact with our quintile indicators. Each time dummy marks a one-month period (except for event period $t-1$). Coefficients are normalized by subtracting the pre-treatment mean for each quintile. We double cluster standard errors at the NUTS2 and year-month level.

Figure 6: Robustness Tests



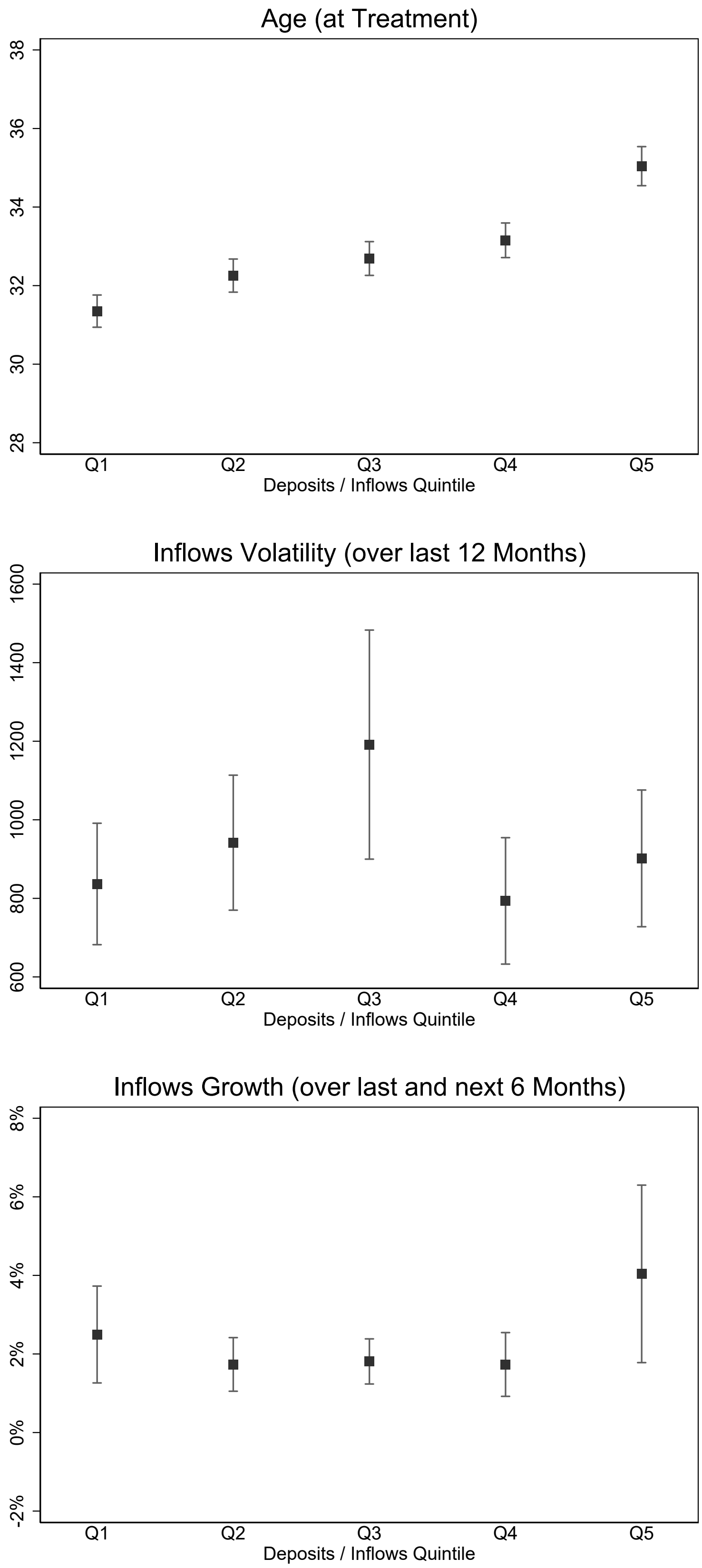
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft for various robustness specifications. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposit to inflows ratio. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. In the top left panel, we additionally control for user characteristics at treatment (overdraft available interacted with user age, inflows growth and inflows volatility at treatment). In the top right panel, we keep only users that had an account with the bank for at least 12 months before they activated the overdraft facility. In the bottom left panel, we focus on users that exhibit an average consumption rate of at least 60% over the sample period. In the bottom right panel, we group users into quintiles based on the average deposit to income ratio from 12 until 3 months before treatment. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS2 and year-month level.

Figure 7: External Validity



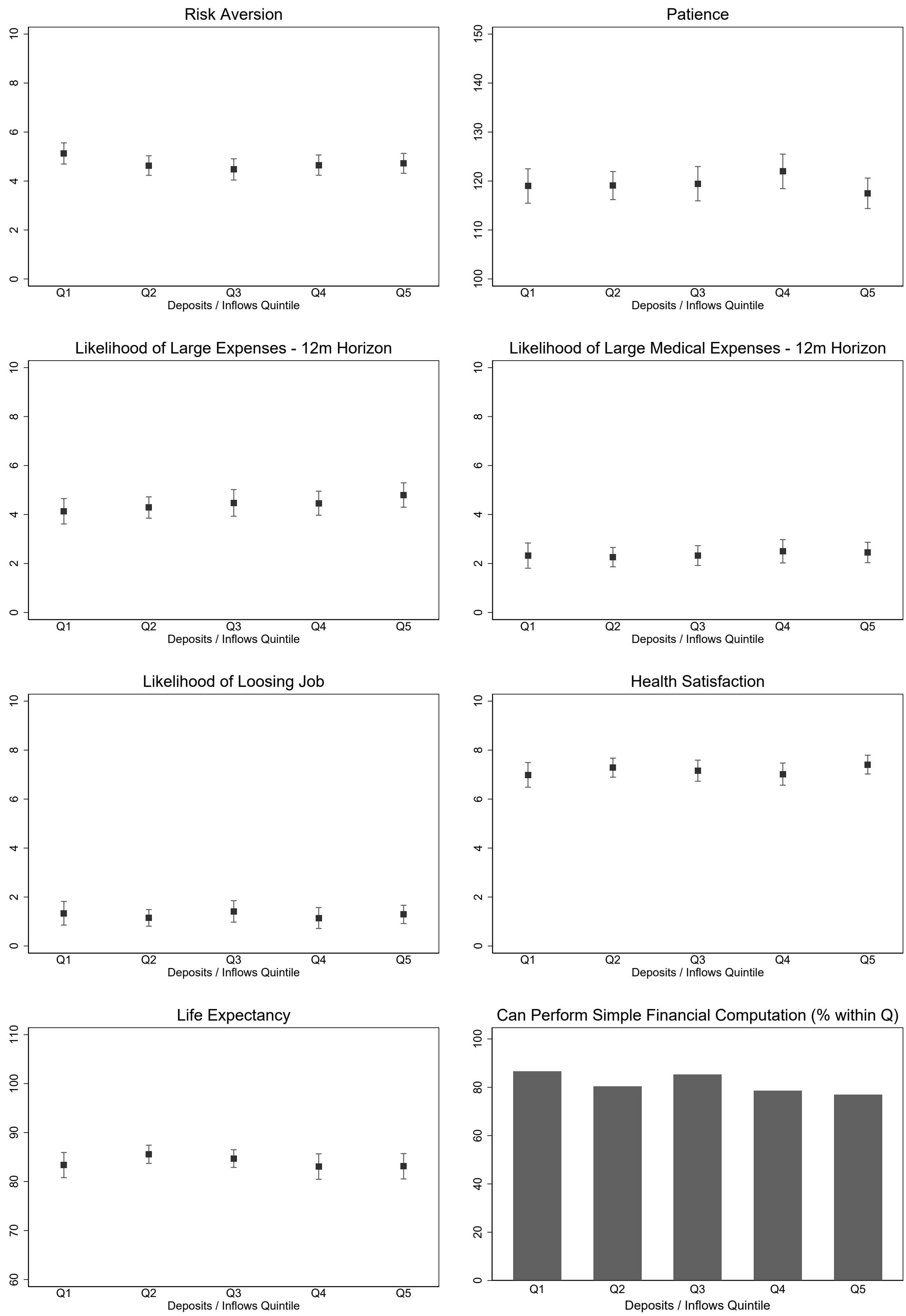
Notes: This figure illustrates the cross-sectional heterogeneity in users' consumption response to the mobile overdraft for various sample splits. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (quintile) based on the deposit to inflows ratio. We then interact each of the 5 quintile indicators with a dummy variable that equals 1 if the user has access to a mobile overdraft in the given month. Vertical bands represent 95% confidence intervals for the point estimates of each quintile. We double cluster standard errors at the NUTS2 and year-month level. Note: savings rate refers to the NUTS1 average savings rate in 2015 from statistisches Bundesamt.

Figure 8: User Characteristics by Deposit-to-Income Quintile



Notes: This figure illustrates the cross-sectional heterogeneity in users' characteristics by deposits to inflows quintile. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the deposit to inflows ratio in the month before treatment. Vertical bands represent 95% confidence intervals for the mean of each quintile.

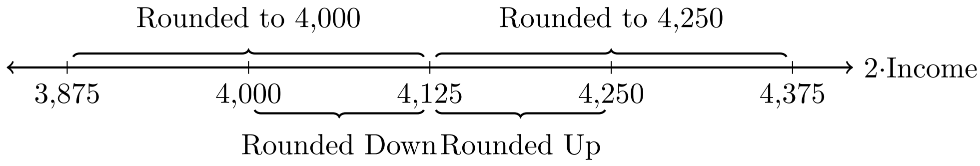
Figure 9: Subjective Beliefs by Deposit-to-Income Quintile



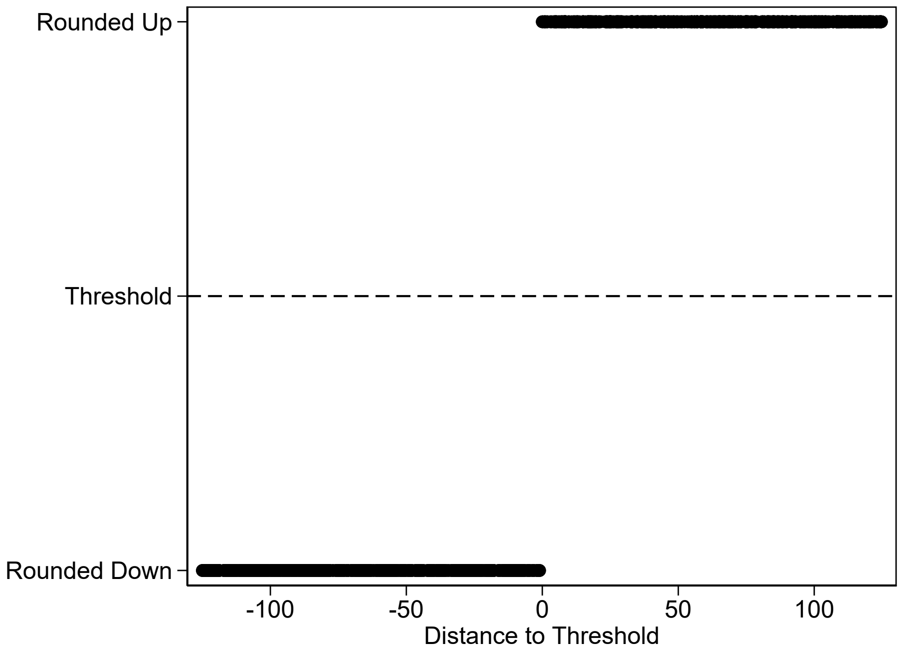
Notes: This figure plots a set of preferences and beliefs dimensions we elicited from users through an ad-hoc survey intervention. To generate these plots, we take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the ratio of deposited amount over income. We limit the sample to users that activate the overdraft facility in our main sample. Vertical bands represent 95% confidence intervals for the point estimates of each quintile.

Figure 10: Treatment Assignment in Regression Discontinuity Analysis

Panel A: Rounding Logic of Overdraft Allocation Algorithm



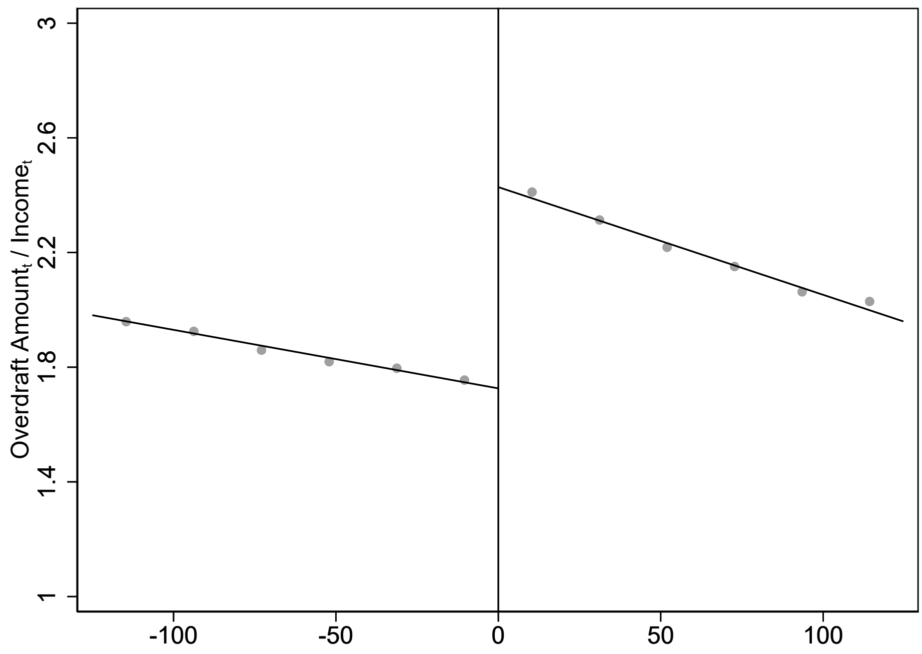
Panel B: Visualization of Sharp Treatment



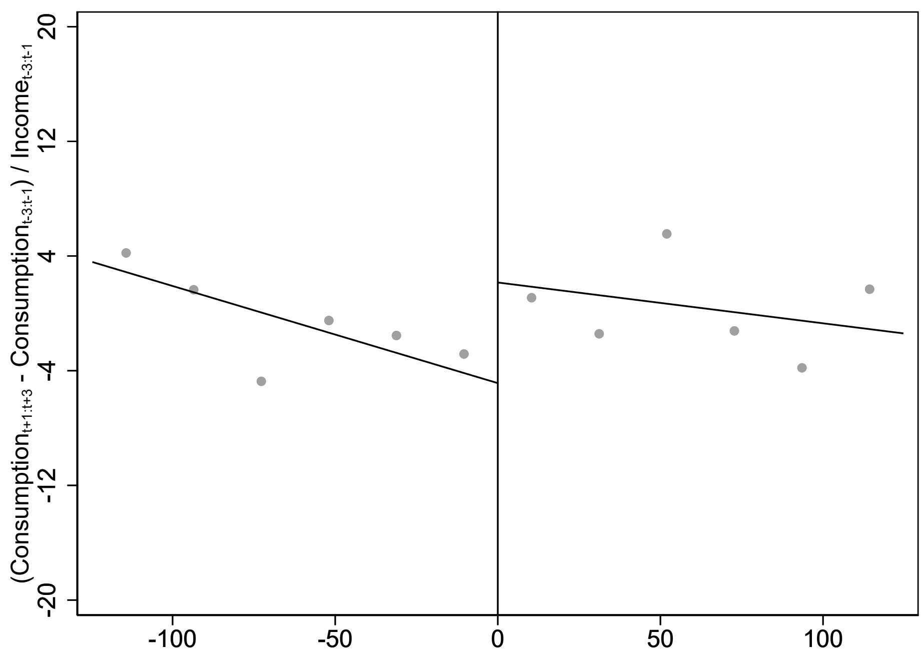
Notes: This figure illustrates how we assign users to treatment and control group in our regression discontinuity analysis based on discrete rounding thresholds embedded in the bank's credit risk model. Panel A visualizes the rounding logic of the overdraft allocation algorithm. Panel B plots users' treatment probability for different values of our forcing variable X_i.

Figure 11: Regression Discontinuity Results

Panel A: Overdraft Amounts



Panel B: Consumption Growth



Notes: This figure provides graphical evidence for the sharp discontinuity in users' overdraft limits and consumption growth rates at the rounding threshold. In Panel A, we plot the income-normalized overdraft limit that users receive at the treatment date. In Panel B, we plot users' consumption growth rate, which we define as the difference in average consumption three months before and after the treatment, normalized by the average account inflows three months prior to the overdraft application. We aggregate our data into 12 disjoint bins, calculate the average value, plot this value above the midpoint of each bin, and separately fit two linear regressions through all observations on each side of the rounding threshold.

Table 1: Descriptive Statistics

	N	Mean	SD	P10	P25	P50	P75	P90
User Age [Years]	603,157	34.07	9.93	23.91	27.00	31.49	38.66	48.91
Female [0/1=Yes]	603,157	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Urban [0/1=Yes]	603,157	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Account Age [Years]	603,157	1.57	0.86	0.47	0.88	1.49	2.18	2.78
Overdraft Available [0/1=Yes]	603,157	0.91	0.29	1.00	1.00	1.00	1.00	1.00
Overdraft Amount [Euro]	574,328	1,561.38	1,602.05	500.00	500.00	1,000.00	2,000.00	3,000.00
Consumption [Euro]	603,157	730.81	949.42	0.00	131.00	465.00	993.00	1,715.00
Inflows [Euro]	603,157	2,219.84	5,948.55	90.00	380.00	1,124.00	2,534.00	4,564.00
Consumption / Inflows [%]	603,157	48.11	44.89	0.00	13.88	37.24	70.08	108.00
Card Consumption [Euro]	603,157	498.58	736.64	0.00	67.00	281.00	646.00	1,206.00
Card Consumption / Inflows [%]	603,157	33.80	37.17	0.00	6.49	22.12	47.85	84.72
Cash Withdrawals [Euro]	603,157	220.92	400.55	0.00	0.00	90.00	300.00	600.00
Cash Withdrawals / Inflows [%]	603,157	13.44	19.56	0.00	0.00	5.33	19.27	40.00
Discretionary [Euro]	603,157	208.36	419.58	0.00	1.00	70.00	242.00	550.00
Non-Discretionary [Euro]	603,157	290.22	469.75	0.00	26.00	159.00	373.00	692.00
Discretionary / Non-Discretionary [%]	484,683	61.03	79.26	0.00	7.66	34.41	82.45	155.17

Notes: This table reports descriptive statistics for our user-month panel. The sample consists of 36,005 users that received an overdraft between February 2015 and September 2017 and covers each individual's complete transaction history from February 2015 to March 2019. For each variable, we report the number of observations (N), mean, standard deviation (SD), 10% quantile (P10), 25% quantile (P25), median (P50), 75% quantile (P75), and 90% quantile (P90). We define all variables in Appendix A1.

Table 2: Effect of Overdraft Availability on Users' Consumption Behavior

Dependent Variable (×100):	$\frac{\text{Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Card Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Cash Withdrawals}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Discretionary}_t}{\text{Non-Discretionary}_t}$
	(1)	(2)	(3)	(4)
Overdraft Available$_t$	4.572***	3.152***	1.345***	2.902***
	(11.11)	(9.71)	(7.73)	(5.38)
Economic Effect Size:	9.503%	9.325%	10.007%	4.755%
Fixed Effects:				
User	Yes	Yes	Yes	Yes
NUTS3 × Year-Month	Yes	Yes	Yes	Yes
Standard Error Clusters:				
NUTS2	48	48	48	48
Year-Month	49	49	49	50
Adjusted R^2	0.301	0.300	0.339	0.185
User-Year-Month Observations	603,157	603,157	603,157	484,683

Notes: This table provides coefficient estimates of OLS regressions estimating the effect of mobile overdraft facilities on users' consumption behavior (equation (1)). *Consumption* is the sum of users' *Card Consumption* and *Cash Withdrawals* in the given month. *Card Consumption* is the user's total amount of electronic card consumption. *Cash Withdrawals* is the user's total amount of cash withdrawals from ATMs in the given month. *Inflows* is the total amount of all incoming transactions a user receives in the given month. *Discretionary* is the sum of users' monthly spending on Entertainment, Shopping, Gastronomy, and Travel. *Non-Discretionary* consumption equals Card Consumption minus Discretionary spending. *Overdraft Available* is a binary indicator that equals 1 if the user has access to a mobile overdraft in the given month. We compute the *Economic Effect Size* as the pre-treatment average of each outcome variable multiplied by the corresponding coefficient estimate. We report t-statistics based on standard errors double-clustered at the NUTS2 and year-month level in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3: User Characteristics by Deposit-to-Income Quintile

Panel A: Financial User Characteristics

	Deposits / Inflows Quintiles					
	Q1	Q2	Q3	Q4	Q5	SD
Flow Characteristics						
Cumulative Inflows$_{t-12:t-1}$	11,491.77	13,381.19	14,930.03	10,580.58	10,753.34	16,980.36
Inflows$_{t-1}$	1,270.25	1,775.88	1,882.12	1,779.34	1,293.43	3,961.29
Inflows$_{t-12:t-1}$	957.65	1,115.10	1,244.17	881.71	896.11	1,415.03
SD(Inflows$_{t-12:t-1}$)	836.63	941.74	1,191.37	793.55	901.77	1,635.70
Cumulative Outflows$_{t-12:t-1}$	11,778.41	13,135.22	13,767.61	9,589.49	7,774.88	15,500.42
Deposit Characteristics						
Deposits$_{t-1}$	39.45	451.87	1,128.83	1,715.09	4,163.05	8,520.52
Deposits$_{t-12}$	283.02	320.74	468.30	434.86	627.48	1,225.21
Deposits$_{t-12:t-1}$	273.90	459.46	729.29	814.87	2,012.25	2,432.76
Negative Deposits$_{t+1:t+3}$	0.65	0.41	0.29	0.19	0.10	0.47
Account Characteristics						
User Age$_t$	31.35	32.25	32.69	33.15	35.05	9.89
Female	0.20	0.20	0.22	0.25	0.23	0.41
Urban	0.50	0.54	0.56	0.54	0.47	0.50
Account Age$_t$	0.67	0.62	0.61	0.55	0.71	0.36
Overdraft Amount	872.87	972.71	1,067.25	1,039.91	1,217.97	824.59
Users	1,909	1,909	1,910	1,908	1,909	9,545

Panel B: Subjective User Beliefs

	Deposits / Inflows Quintiles					
	Q1	Q2	Q3	Q4	Q5	SD
Risk Aversion [0-10]	5.13	4.63	4.47	4.65	4.72	2.31
Trust Level [0-10]	5.29	5.74	5.53	5.31	5.47	2.15
Risk-Return Category [1-4]	2.88	2.85	3.03	2.93	2.86	0.74
Patience [> 100]	118.98	119.07	119.45	121.96	117.48	17.42
Likelihood of Large Expenses [0-10]	4.13	4.29	4.48	4.46	4.80	2.63
Likelihood of Large Medical Expenses [0-10]	2.32	2.26	2.32	2.50	2.45	2.29
Likelihood of Loosing Job [0-10]	1.34	1.15	1.41	1.14	1.29	2.12
Health Satisfaction [0-10]	6.99	7.28	7.16	7.02	7.41	2.21
Reasons for Saving [1-4]	2.20	2.26	2.23	2.35	2.29	0.98
Basic Financial Computation Ability [1-3]	2.85	2.72	2.82	2.70	2.69	0.56
Life Expectancy [number]	83.37	85.57	84.70	83.06	83.13	10.63
Users	96	141	112	114	136	599

Notes: This table provides descriptive statistics of user characteristics and survey responses. Panel A provides descriptive statistics for users at the time of overdraft activation, sorted into quintiles based on the ratio of deposits over inflows in the month before activation of the overdraft facility. Subscript t refers to the activation date, while T denotes the last month of each user in our sample. The last two columns test for differences in means across the two groups of users. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B reports a set of preferences and beliefs dimensions we elicited from users through an ad-hoc survey intervention. We take the cross-section of users at their treatment date and assign them into non-overlapping quintiles from lowest (1^{st} quintile) to highest (5^{th} quintile) based on the ratio of deposited amount over income. We limit the sample to users that activate the overdraft facility in our main sample.

Table 4: Assessing RDD Identification Assumptions

Panel A: Treatment Manipulation Tests

		Bandwidths		Effective N		Test	
		Left	Right	Left	Right	T-Stat.	p-value
$h_- \neq h_+$	$T_2(\hat{h}_1)$	104.17	76.21	373	328	-0.94	0.35
	$T_3(\hat{h}_2)$	75.73	82.98	285	345	-0.85	0.39
	$T_4(\hat{h}_3)$	89.01	55.32	322	221	0.39	0.70
$h_- = h_+$	$T_2(\hat{h}_1)$	111.32	111.32	424	448	-0.05	0.96
	$T_3(\hat{h}_2)$	71.59	71.59	248	289	-0.51	0.61
	$T_4(\hat{h}_3)$	58.32	58.32	201	229	-0.59	0.56

Panel B: User Characteristics around Rounding Thresholds

	Rounded Up			Rounded Down			Difference in Means	
	Mean	SD	Median	Mean	SD	Median	Diff.	t-Stat.
User Age [Years]	32.32	9.34	29.91	33.02	10.12	30.37	0.70	1.13
Female [0/1=Yes]	0.25	0.43	0.00	0.24	0.43	0.00	-0.01	-0.35
Account Age [Years]	0.87	0.38	0.83	0.85	0.41	0.79	-0.01	-0.53
Inflows$_{t-3:t-1}$ [Euro]	1,405.64	1,530.10	1,101.67	1,458.92	1,454.29	1,069.67	53.28	0.56
Consumption$_{t-3:t-1}$ [Euro]	558.89	522.39	427.17	620.04	597.38	482.83	61.14*	1.70
Users	500			474			974	

Notes: This table provides the results of tests assessing our RDD identification assumptions. Panel A reports the results of treatment manipulation tests using the local polynomial density estimator by Cattaneo et al. (2017). $T_q(h_p)$ denotes the q-th order local polynomial test with bandwidth h_p. "Bandwidth" is the mean-squared-error (MSE) optimal bandwidth, "Effective N" is the effective sample size on each side of the threshold, and "T" is the two-sided test statistic with corresponding p-value. The tests in the first three rows allow for different bandwidths on each side of the threshold, while the tests in the last three rows impose a common bandwidth on both sides of the threshold. Panel B provides descriptive user characteristics for individuals above ("Rounded Up") and below ("Rounded Down") the RD rounding threshold. For each variable, we report the mean, standard deviation (SD), and median (P50). In the last two columns, we test for differences in means across both types of users. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 5: Consumption Growth around Rounding Thresholds

Dependent Variable (×100):	$\frac{\text{Consumption}_{t+1:t+3} - \text{Consumption}_{t-3:t-1}}{\text{Inflows}_{t-3:t-1}}$			
	(1)	(2)	(3)	(4)
Conventional	17.63**	23.48**	17.96**	23.70**
	(2.19)	(2.20)	(2.12)	(2.34)
Robust	21.56**	26.52**	21.83**	26.62**
	(2.37)	(2.31)	(2.31)	(2.46)
Covariates	No	No	Yes	Yes
User Observations	876	876	876	876
Order Local Polynomial (p)	1	2	1	2
Order Bias (q)	2	3	2	3
Bandwidth Left	25.47	35.89	23.98	36.86
Bandwidth Right	25.47	35.89	23.98	36.86

Notes: This table presents non-parametric estimates for the RD treatment effect of a 250 Euro higher overdraft amount on users' consumption behavior. The dependent variable is the difference in average consumption three months before and after the treatment, normalized by the average account inflows three months prior to the overdraft application. We residualize users' consumption growth rate with country × year-month fixed effects to ensure that we compare treated and control users from the same European country at a similar point in time. We only use polynomials of order 1 and 2 to avoid overfitting issues (Gelman and Imbens, 2018), apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice (Cheng et al., 1997), and employ the MSE-optimal bandwidth selection procedure recommended by (Calonico et al., 2014). We report both conventional and robust RD estimates (Calonico et al., 2014, 2019). In columns (1) and (2), we do not add any covariates. In columns (3) and (4), we control for *User Age*, gender (*Female*), and *Account Age*. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

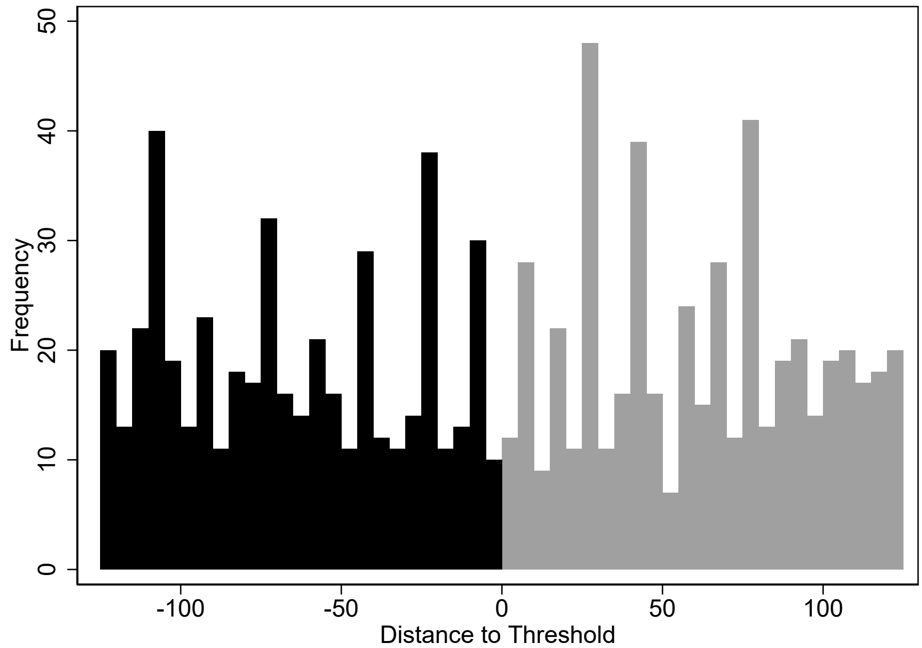
Appendix

Table A1: Variable Definitions

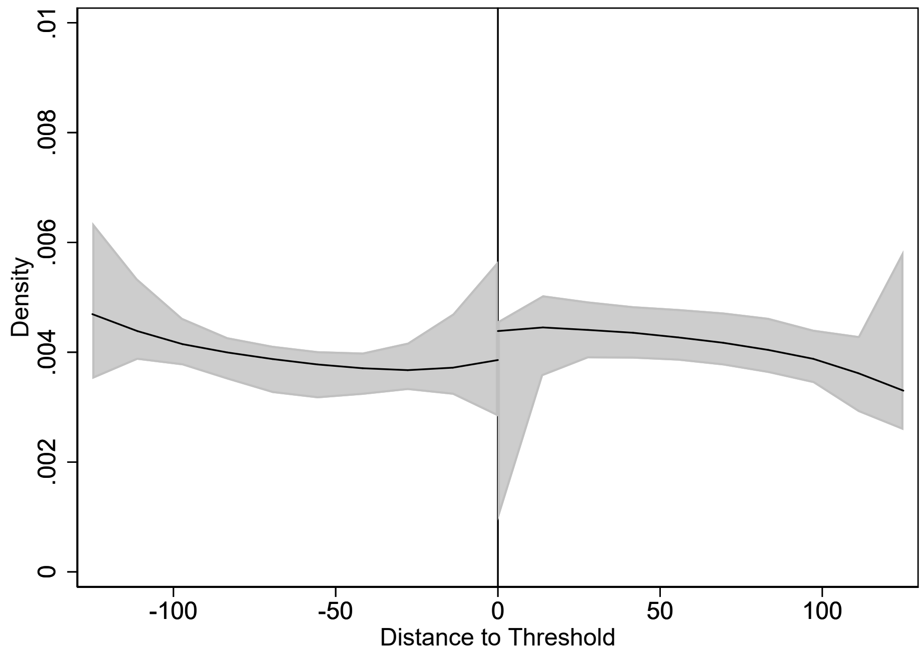
Variable	Definition
Account Age	End of month date minus the date when the user completed the account opening procedure.
Card Consumption	Total amount of electronic card consumption in the given month.
Cash Withdrawals	Total amount of cash withdrawals in the given month.
Consumption	Sum of *Card Consumption* and *Cash Withdrawals*.
Deposits	Total amount of available funds in a user's account at the end of a month.
Discretionary	Sum of users' monthly expenditures on *Entertainment*, *Shopping*, *Gastronomy*, and *Travel*.
Female	Indicator variable equal to one if the user is female.
Inflows	Total amount of all incoming transactions a user receives in the given month.
Urban	Indicator variable equal to one if the user lives in a NUTS3 region with a population of at least 500,000 people.
Negative Deposits	Indicator variable equal to one if the user has a negative account balance in the given month.
Non-Discretionary	*Card Consumption* minus *Discretionary* spending.
Overdraft Available	Indicator variable equal to one if the user has access to a mobile overdraft in the given month.
Overdraft Amount	Maximum overdraft amount granted to the user by the bank in the given month.
User Age	End of month date minus first day of user's birth year.

Figure A1: Distribution of Forcing Variable around Rounding Thresholds

Panel A: Histogram of Forcing Variable

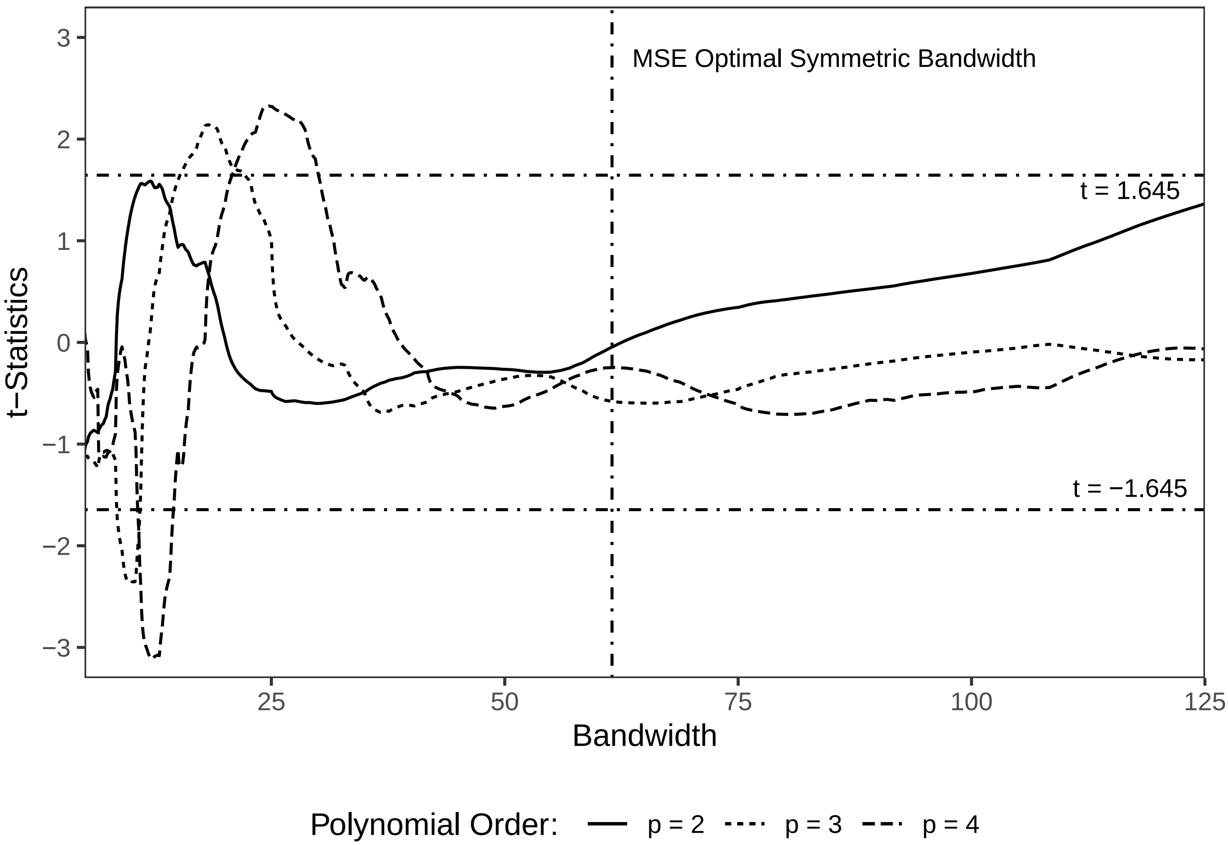


Panel B: Local Polynomial Density Estimate



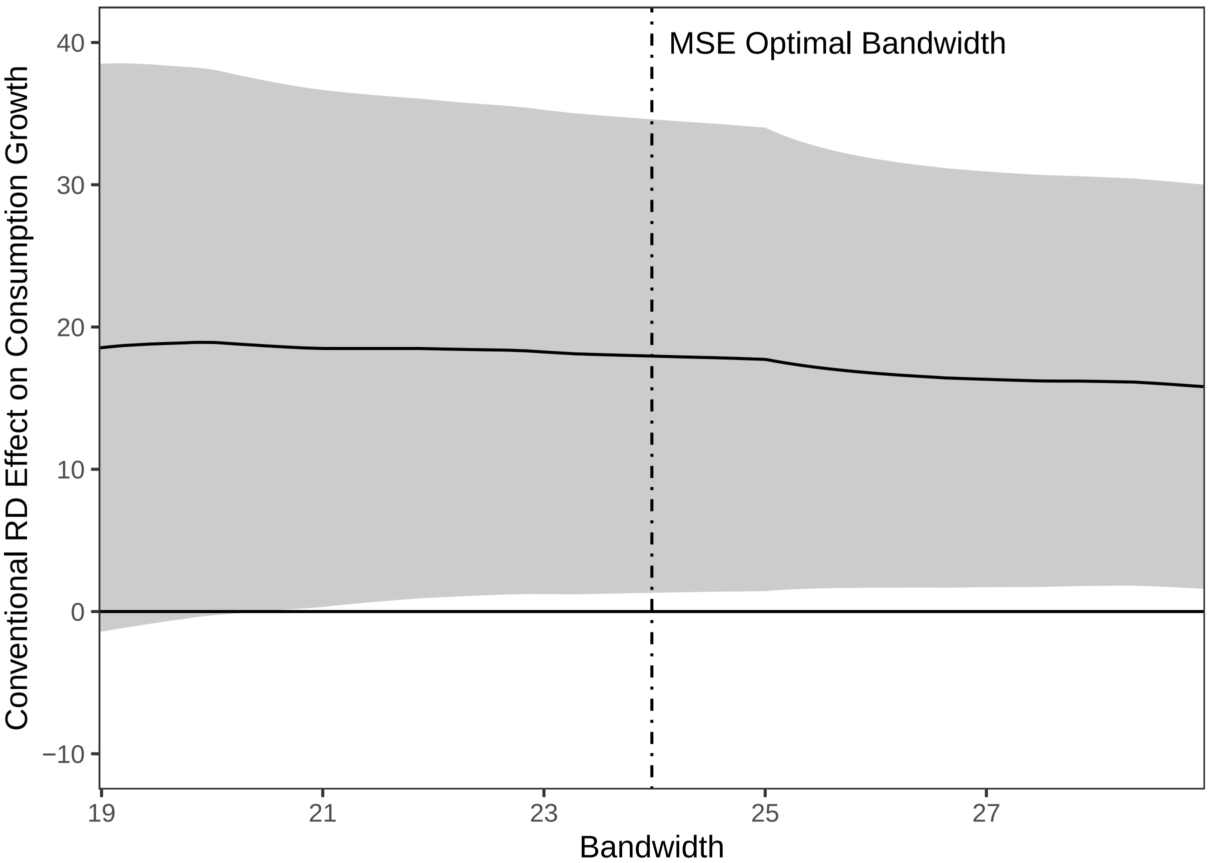
Notes: This figure provides graphical evidence for our treatment manipulation tests in Section 6.3. Panel A plots the number of users and Panel B reports the local polynomial density estimate by Cattaneo et al. (2017) for different values of our forcing variable X_i around the rounding threshold.

Figure A2: Robustness Analyses for Treatment Manipulation Tests



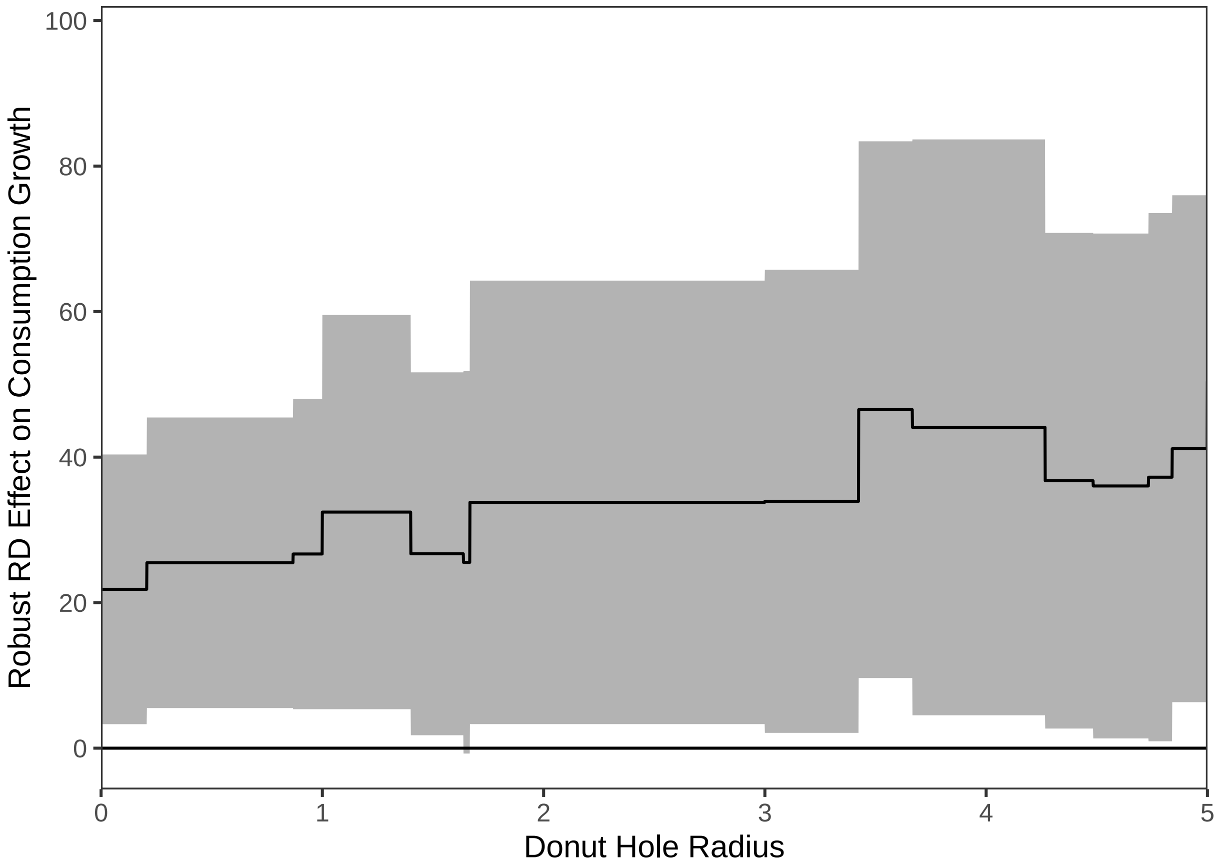
Notes: This figure reports t-statistics for the treatment manipulation test by Cattaneo et al. (2017) for different polynomial orders and bandwidth choices. The vertical horizontal lines indicate the critical 10% significance levels at which the test rejects the null hypothesis that our running variable is locally continuous around the rounding threshold.

Figure A3: Sensitivity of RDD Effects to Bandwidth Choice



Notes: This figure shows convetional regression (RD) discontinuity estimates (solid line) and corresponding 95% confidence intervals (shaded area) for varying bandwidth choices. The figure demonstrates that different bandwidth choices do neither substantially affect the magnitude nor the significance of our main RD consumption effect. Varying the bandwidth is only meaningful over small intervals around the mean-squared-error (MSE) optimal choice (Cattaneo et al., 2020). Bandwidths much larger than the MSE-optimal bandwidth bias the RD estimator, while substantially smaller bandwidths inflate its variance.

Figure A4: Sensitivity of RDD Effects to Observations around Rounding Thresholds



Notes: This figure shows robust regression discontinuity (RD) estimates (solid line) and corresponding 95% confidence intervals (shaded area) for varying donut hole radius choices. This figure demonstrates that our main RD consumption effect is robust to excluding data close to the rounding threshold (e.g., Barreca et al., 2011, 2016). We drop users located within the radius $r > 0$ of the rounding cutoff. Specifically, we exclude observations for which $|X_i| \leq r$ (Cattaneo et al., 2020) and illustrate that observations close to the rounding threshold do not drive our results.

Table A2: User Characteristics around Rounding Thresholds

Dependent Variable:	User Age	Female	Account Age	Consumption	Inflows
	(1)	(2)	(3)	(4)	(5)
Conventional	3.485	-0.00263	0.0568	-347.1*	-535.2*
	(1.28)	(-0.02)	(0.61)	(-1.82)	(-1.84)
Robust	4.192	-0.0407	0.0432	-391.4*	-554.4
	(1.26)	(-0.24)	(0.39)	(-1.72)	(-1.54)
Covariates	No	No	No	No	No
User Observations	972	972	972	972	972
Order Local Polynomial (p)	1	1	1	1	1
Order Bias (q)	2	2	2	2	2
Bandwidth Left	29.77	33.95	41.64	39.81	31.04
Bandwidth Right	29.77	33.95	41.64	39.81	31.04

Notes: This table reports non-parametric estimates for the RD treatment effect of a 250 Euro higher overdraft amount on several user characteristics. The dependent variables are the user's age, gender, and time since account opening at the treatment date as well as the user's level of consumption and inflows in the 3 months prior to the overdraft application. We only use polynomials of order 1 and 2 to avoid overfitting issues (Gelman and Imbens, 2018), apply weights from a triangular kernel because it is the mean squared error (MSE) minimizing choice (Cheng et al., 1997), and employ the MSE-optimal bandwidth selection procedure recommended by Calonico et al. (2014). We report both conventional and robust RD estimates (Calonico et al., 2014, 2019). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table A3: Survey Questions

Question	Possible Answers
Do you rate yourself as a risk-taking person or are you trying to avoid risks?	Scale from 0 (not willing to take risks) to 10 (very willing to take risks)
Would you say that you are a person who trusts others, or not?	Scale from 0 (I do not trust others) to 10 (I trust others fully)
When you make savings or investment decisions for yourself, which of the following statements describes you best?	1 – I take significant risks and want to generate high returns. 2 – I take above-average risks and want to achieve above-average returns. 3 – I take average risks and aim for average returns. 4 – I am not willing to take any financial risk and accept not to generate any returns.
Imagine, you get either 100 Euros immediately or a higher amount of money in a month. What is the lowest amount you would be willing to wait for a month?	1 – 101 Euros 2 – 103 Euros 3 – 108 Euros 4 – 117 Euros 5 – 125 Euros 6 – 133 Euros 7 – 150 Euros 8 – 167 Euros 9 – 183 Euros 10 – 200 Euros 11 – 233 Euros
How likely is it that you will face large, unexpected expenses over the next 12 months?	Scale from 0 (very unlikely) to 10 (very likely)
How likely is it that you will face large medical expenses for yourself or a family member over the next 12 months, including hospitalization and nursing care?	Scale from 0 (very unlikely) to 10 (very likely)
How likely are you to lose your job in the next 12 months?	Scale from 0 (very unlikely) to 10 (very likely)
How satisfied are you with your health at the moment?	Scale from 0 (not satisfied) to 10 (very satisfied)
What do you usually think of when saving?	1 – I usually save for very specific expenses, such as a vacation or a car. 2 – I usually save to have a small amount of money available for unexpected expenses. 3 – I do not save much or cannot save much. Whenever I put money aside, I do it without much thought. 4 – I am saving with the goal of building a small estate that I may pass on to my children, nephews, nieces, or other family members.
Suppose you have 100 Euros in your savings account and earn 10 percent interest per year. How high will be your balance after 2 years?	1 – Lower than 120 Euros 2 – 120 Euros 3 – Higher than 120 Euros
How high do you estimate your life expectancy?	Enter number