Perceived Precautionary Savings Motives: Evidence from FinTech

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Motivation

- High household credit $\rightarrow$ business cycles contraction around the world (Mian, Sufi, and Verner, QJE 2017)
  - Household debt and credit growth predictor of financial crises
  - Financial crises often deep and protracted
- Fiscal and monetary policy operates through household credit, spending (Agarwal et al., QJE 2018; D'Acunto, Hoang, and Weber, 2019)
  - Household spending largest component GDP worldwide
- Understanding the link household credit $\leftrightarrow$ business cycles crucial
- So far, mainly intensive margin results: credit line increase $\rightarrow$ spending
  - Only captures the behavior of those that already borrow (selected)
  - What if give credit to non-borrowers (extensive margin)?

This Paper

Introduction of overdraft facility to customers of online bank

- Unique setting: extensive margin of credit availability
- High-frequency spending data, consumption categories, etc.
- Observe all spending and characteristics before and after overdraft

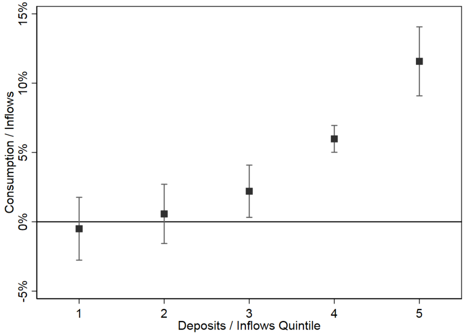
Questions:

- How do non-borrowing agents react to availability of credit?
- Heterogeneous reaction based on characteristics policy can target?

Main Findings

Evidence of *perceived precautionary savings*

- Average spending / income up by 5.3% after overdraft available
- Largest reaction if do not need credit AND do not use it!
  - Users with highest liquidity (deposits / inflows) react the most
  - Bin 5: 80% increase consumption, only 10% negative deposits
- Perceived precautionary savers do not spend, overdraft insures?



Other Findings

Alternative explanations we can rule out directly

- Different demographics
- Liquidity constraints
- Different income paths
- Different income volatility

For already borrowers, patterns as in earlier research

- Consumption reallocation effect: to discretionary from non-discretionary
- Bank fees increase steadily & credit scores worsen

Intriguing policy implications

- Crises often protracted due to excessive savings of liquid households
- Perceived precautionary savers: do not spend even if could
- Credit line to them might increase AD without effects on credit

Institutional Setting

- Data from largest European FinTech Bank
- Digital-only bank
- Bank operates under European banking license
- >1 million customers
- Account setup less than 10 minutes via online chat
- Overdraft facility btw EUR 500 and EUR 5,000 depending on credit risk
- 10% rate on used overdraft
- No credit cards

Our Sample

Observe all financial transactions, time stamp

All users that were granted Overdraft until 2017-09-30

- All transactions until 2019-04-30

Aggregate individual transactions to month level

- 39,477 users
- 718,003 user-months

Average user characteristics

- 34 years old
- Monthly inflows $\sim 2,121$ EUR
- 79% male
- 52% live in large cities ($>$500k inhabitants)
- Average overdraft of 1,143 EUR

Empirical Design 1: Difference-in-Differences Strategy

Compare users *after* overdraft was available to users *before* overdraft was available

- *First difference*: before and after overdraft is available
- *Second difference*: other customers that don't have overdraft yet
- Estimate *treatment effect* of overdraft activation (extensive margin)

$$\text{Outcome Variable}_{i,t} = \beta \times \text{Overdraft Available}_{i,t} + \text{Fixed Effects}_{i,t} + \varepsilon_{i,t}$$

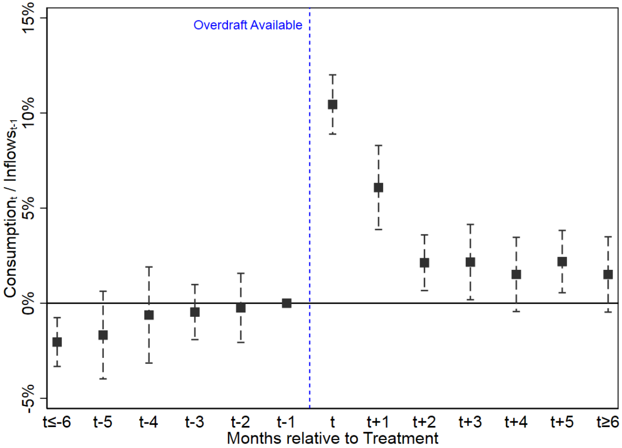
- Overdraft Available$_{i,t} = 1$ if user has access to credit facility
- Fixed Effects$_{i,t}$: user & NUTS3$\times$year-month fixed effects
- Double cluster standard errors at the NUTS2 and year-month level

Overdraft and Spending Behavior

Dependent Variable ($\times 100$):	$\frac{\text{Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Card Consumption}_t}{\text{Inflows}_{t-1}}$	$\frac{\text{Cash Withdrawals}_t}{\text{Inflows}_{t-1}}$
	(1)	(2)	(3)
Overdraft Available$_t$	5.264***	3.456***	1.370***
	(12.26)	(10.96)	(7.87)
Fixed Effects:			
User	Yes	Yes	Yes
NUTS3 $\times$ Year-Month	Yes	Yes	Yes
Standard Error Clusters:			
NUTS2	48	48	48
Year-Month	49	49	49
Adjusted R^2	0.257	0.284	0.328
User-Year-Month Obs.	626,106	626,094	626,318

- Overdraft availability increases consumption by 11% of average
- 2/3 of increase due to card consumption

Spending Pattern around Overdraft Availability

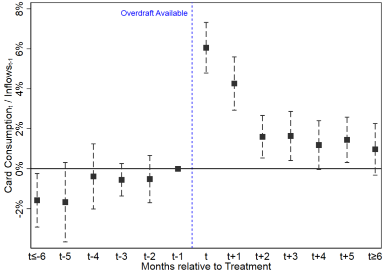


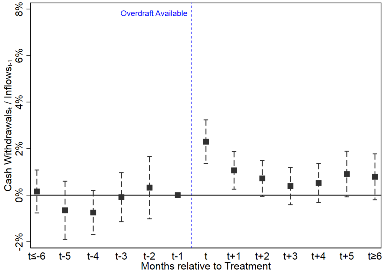
- Largest increase on impact
- Permanent effect in the long run

Card Consumption vs. Cash Withdrawals

How do changes distribute across mobile and cash spending?

- D'Acunto, Rossi, and Weber (2019) find discretionary spending and especially cash withdrawals can be cut quickly and substantially by users
- Consistently, these are the categories that increase with overdraft



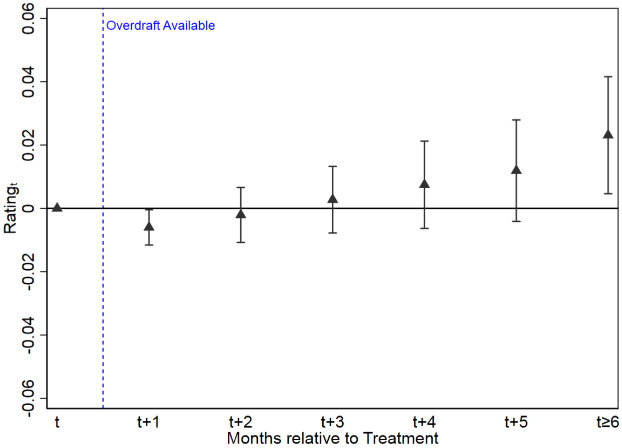


Change in Probability of Big Ticket Expenses

Dependent Variable:	Big Ticket Expense (E. 1000)	Big Ticket Expense (E. 2000)
	(1)	(2)
Overdraft Available$_t$	0.020***	0.012***
	(4.15)	(4.07)
Fixed Effects:		
User	Yes	Yes
NUTS3 × Year-Month	Yes	Yes
Standard Error Clusters:		
NUTS2	48	48
Year-Month	50	50
Adjusted R^2	0.568	0.559
User-Year-Month Obs.	715,137	715,137

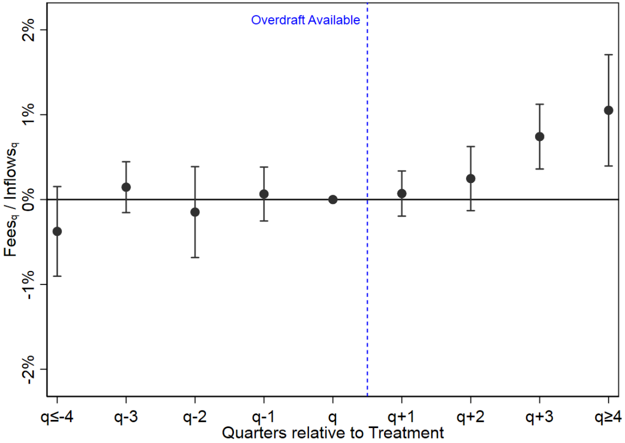
- Increases unconditional probability by 5%

Credit Risk Pattern around Overdraft



- Credit changes rare
- No improved credit due to longer credit history
- Conditional on change, downgrade by 1 notch in long run

Fee Pattern around Mobile Overdraft Availability



- Overdraft fees increase by 1% of inflows in long run

Empirical Design 2: Regression Discontinuity Analysis

- So far correlation between consumption spending and overdraft
- Users might activate in anticipation of future expenses
- Omitted variables affect both activation and spending (advertisement)
- Solution: sharp regression discontinuity design
- Condition on selection & exploit heterogeneity in overdraft amount

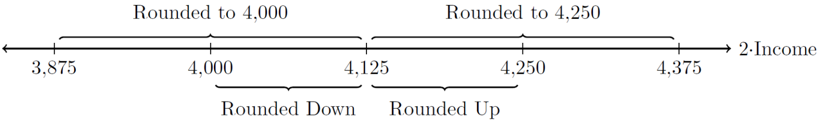
Exploit Discontinuity in Overdraft Allocation Mechanism

Overdraft allocation mechanisms introduces exogenous variation

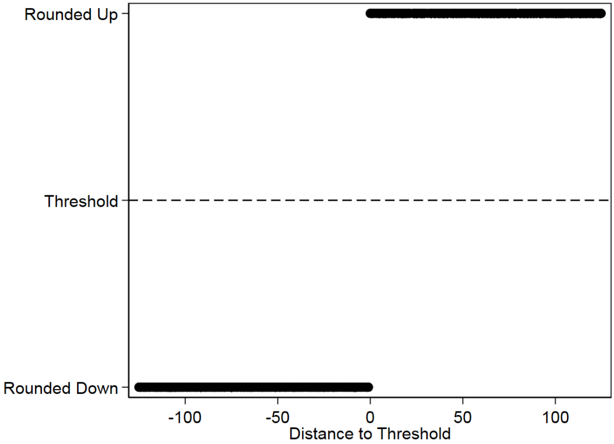
Allocation mechanism unknown to users

App rounds to closest EUR 250 of 2 $\times$ income

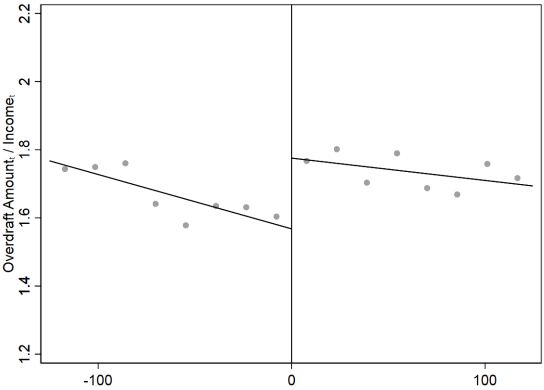
- Do users with higher overdraft amounts increase consumption by more?



Visualization of Sharp Treatment

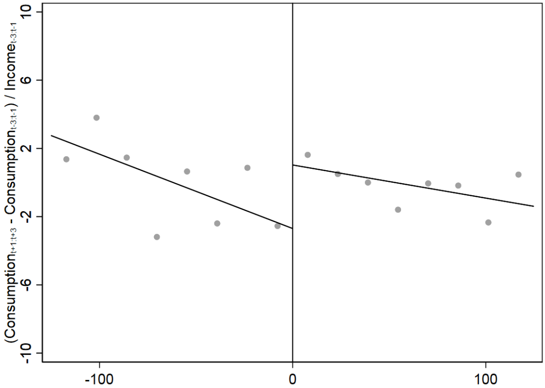


Regression Discontinuity Plots: Overdraft Amount



- Higher overdraft to the right of threshold
- Negative slope due to normalization by income

Regression Discontinuity Plots: Spending Change



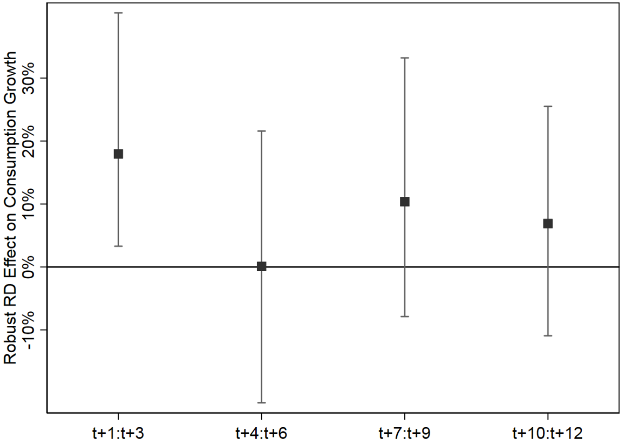
- Users consume more if assigned EUR 250 more

Spending Growth around Rounding Threshold

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
Effective Obs. Left	89	114	62	117
Effective Obs. Right	101	128	71	129

- Coefficients imply MPC of 80% of EUR 250 additional overdraft

RD Spending Effect over Time



- RD effects temporary possibly due to weak treatment of only EUR 250
- Implies substantially heterogeneity in effect of overdraft on consumption

RD Robustness Checks

User characteristics on both sides of the threshold link

Density manipulation tests link

Local continuity of user characteristics around threshold link

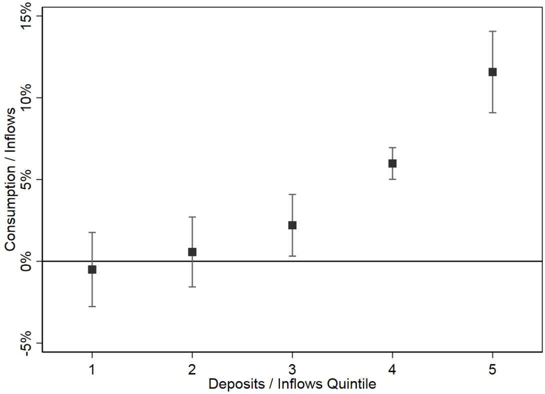
Bandwidth choice robustness link

Donut hole radius test link

Heterogeneity in Spending Response

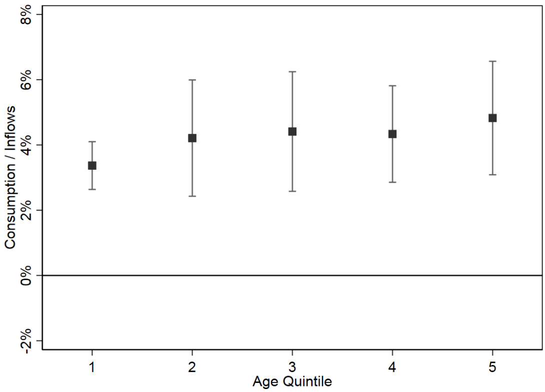
- Lifecycle permanent income hypothesis $\rightarrow$ consumption smoothing
- Implies younger users and users on steeper income paths use facility more
- Liquidity constraints imply low savings users respond more
- Study sample splits by age, income growth, savings-to-income

Largest Effect: High Liquidity



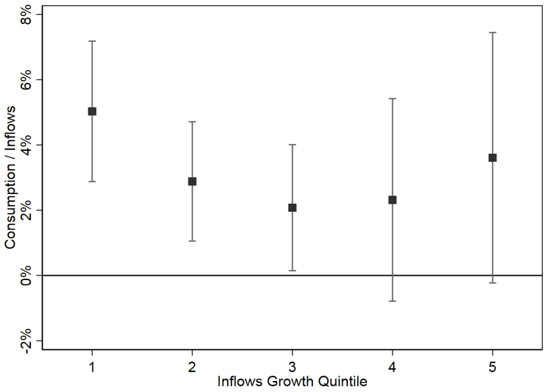
- Largest consumption response for high liquidity individuals
- No differential income volatility pre-activation
- No difference in age across bin
- No difference in income growth, level
- Difference in deposits not due to big inflow in months before activation

Heterogeneity by Age



- No difference by age bin

Heterogeneity by Income Path



- No difference by income growth

Perceived Precautionary Savings

Those who react most did not need credit to spend more

We label this phenomenon **perceived precautionary savings**

- Perceived precautionary savers do not spend despite high liquidity
- They seem to have strong precautionary savings motives
- Not justified by observed income vol, path, age, medical expenses, ...
- Once they have credit, 80% of them spend more ...
- ... BUT only 10% tap into negative deposits (vs. 67% in bottom bin)
- Overall, overdraft makes them spend the resources they could have already spent well before access to the overdraft facility
- Overdraft might act as a form of insurance against potential negative states, reduce the (perceived) precautionary savings motive

Alternative Interpretations

- LCPIH unlikely explanation
- Buffer stock models (with durable assets) cannot explain results in full
- Liquidity constraints predicts opposite results for splits by deposits
- New channel: perceived precautionary savings?
  - Need direct evidence on perceived risks, risk aversion, beliefs
  - At this stage, we cannot disentangle across potential drivers of this phenomenon
  - Currently working with the provider to design ad-hoc survey

Wrapping Up

- Understanding how households react to credit provision important
- We study the *extensive margin* of credit provision
- As expected, households on average increase spending
- But, surprisingly:
  - Largest reaction by households that did not need credit
  - They spend more but still do not use the credit line they receive
  - Need more data to analyse this phenomenon
- Potentially relevant policy implications
  - If anything, would need to provide credit lines to highly liquid households during crises
  - Credit lines might not be tapped, yet make liquid households spend
  - Higher spending by those who can spend could push the economy out of a slump

Appendix

User Characteristics on Both Sides of the Threshold

	Rounded Up		Rounded Down		Difference in Means	
	Mean	SD	Mean	SD	Diff. Mean	t-Stat.
Age [Years]	32.318	9.343	33.023	10.123	0.705	(1.13)
Female [0/1=Yes]	0.248	0.432	0.238	0.427	-0.010	(-0.35)
Time Since Account Opening [Years]	0.866	0.377	0.852	0.405	-0.013	(-0.53)
Rating [1-6]	3.930	1.608	3.584	1.459	-0.346***	(-3.51)
Inflows$_{t-3:t-1}$ [Euro]	1405.639	1530.103	1458.917	1454.291	53.278	(0.56)
Consumption$_{t-3:t-1}$ [Euro]	558.893	522.392	620.036	597.384	61.143*	(1.70)
Observations	500		474		974	

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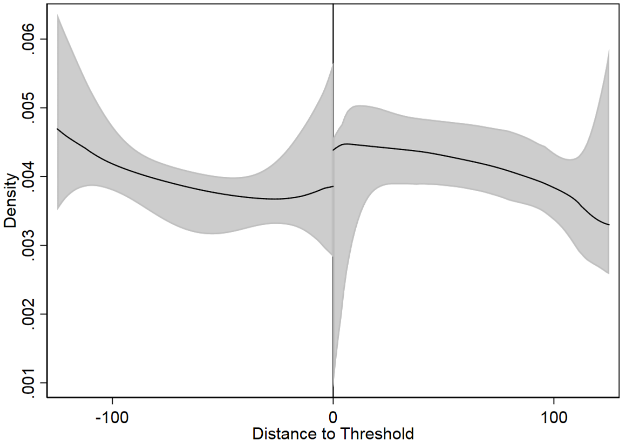
Density Manipulation Tests



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Local Continuity of User Characteristics Around Threshold

Dependent Variable:	Age	Female	Time Since Acc. Opening	Cons. Pre	Inflows Pre
	(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	Yes	Yes	Yes	Yes	Yes
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
Effective Obs. Left	116	126	145	138	118
Effective Obs. Right	129	137	162	156	130

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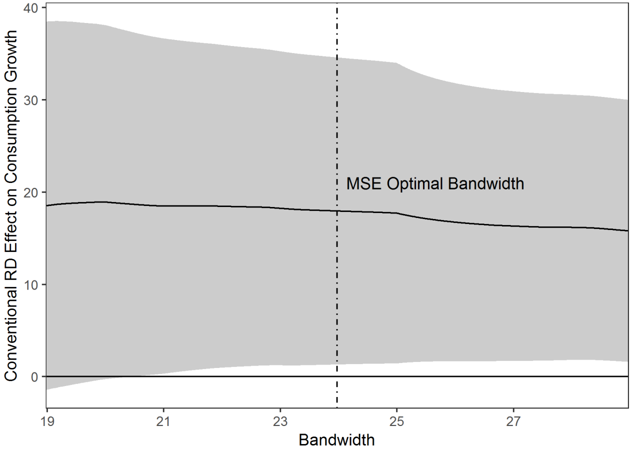
Bandwidth Choice Robustness



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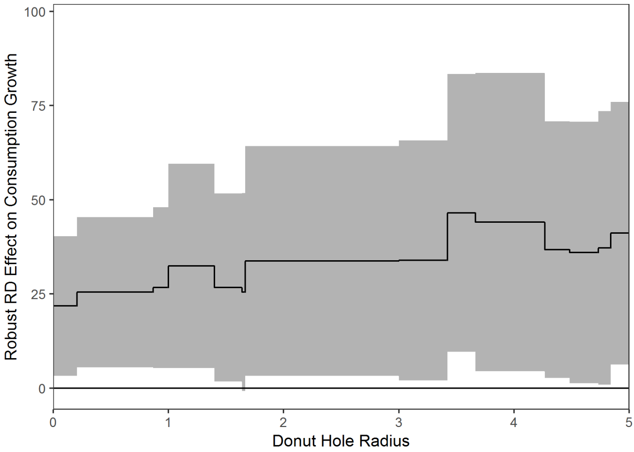
Donut Hole Radius Test



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Consumption Reallocation Effects of Mobile Overdrafts

Dep. Variable (×100):	$\frac{\text{Discretionary}_t}{\text{Non-Discretionary}_t}$	$\frac{\text{Entertainment}_t}{\text{Card Consumption}_t}$	$\frac{\text{Shopping}_t}{\text{Card Consumption}_t}$	$\frac{\text{Gastronomy}_t}{\text{Card Consumption}_t}$	$\frac{\text{Travel}_t}{\text{Card Consumption}_t}$
	(1)	(2)	(3)	(4)	(5)
Overdraft Available$_t$	1.865**	0.069	0.302**	0.141**	0.607***
	(2.54)	(1.50)	(2.55)	(2.12)	(6.21)
Fixed Effects:					
User	Yes	Yes	Yes	Yes	Yes
NUTS3 × Year-Month	Yes	Yes	Yes	Yes	Yes
Standard Error Clusters:					
NUTS2	48	48	48	48	48
Year-Month	50	50	50	50	50
Adjusted R^2	0.159	0.295	0.169	0.293	0.164
User-Year-Month Obs.	544,437	583,469	583,461	583,425	583,419

Credit Risk after Overdraft

Dependent Variable:	Rating$_t$	
	(1)	(2)
	All Users	Users with Rating Changes
Overdraft Available$_t$	0.026**	0.992***
	(2.81)	(3.21)
Fixed Effects:		
User	Yes	Yes
NUTS3 $\times$ Year-Month	Yes	Yes
Standard Error Clusters:		
NUTS2	48	
Year-Month	24	22
Adjusted R^2	0.998	0.698
User-Year-Month Obs.	259,705	622

Mobile Overdraft Availability on Mobile Overdraft Usage

Dependent Variable:	Overdraft Enabled		Negative Deposits	
	(1) Extensive Margin	(2) Intensive Margin	(3) Extensive Margin	(4) Intensive Margin
Overdraft Available$_t$	0.807***		0.526***	
	(67.15)		(42.51)	
Log(Max Amount$_t$)		0.044***		0.035***
		(8.32)		(9.54)
Fixed Effects:				
User	Yes	Yes	Yes	Yes
NUTS3 × Year-Month	Yes	Yes	Yes	Yes
Standard Error Clusters:				
NUTS2	48	48	48	48
Year-Month	41	41	41	41
Adjusted R^2	0.866	0.868	0.540	0.542
User-Year-Month Obs.	668,752	646,657	668,752	646,657

Bank and Late Fees Paid around Overdraft

Dependent Variable ($\times$100):	$\frac{\text{Fees}_q}{\text{Inflows}_q}$	
	(1)	(2)
Overdraft Available$_{q-1}$	0.091	
	(0.44)	
Overdraft Enabled$_{q-1}$		0.391**
		(2.01)
Fixed Effects:		
User	Yes	Yes
NUTS3 $\times$ Year-Quarter	Yes	Yes
Standard Error Clusters:		
NUTS2	48	48
Adjusted R^2	0.131	0.131
User-Year-Quarter Observations	215,799	215,799

Cross-Sectional Heterogeneity in Spending Response

Dependent Variable ($\times$100):	$\frac{\text{Consumption}_t}{\text{Inflows}_{t-1}}$		
	(1)	(2)	(3)
Overdraft Available$_t$	4.017***	3.830***	0.325
	(6.53)	(7.43)	(0.40)
Overdraft Available$_t$ * Inflows Growth $>$ Median	-1.772**		
	(-2.06)		
Overdraft Available$_t$ * Age $>$ Median		0.788***	
		(3.41)	
Overdraft Available$_t$ * Deposits / Inflows $>$ Median			7.433***
			(7.35)
Fixed Effects:			
User	Yes	Yes	Yes
NUTS3 $\times$ Year-Month	Yes	Yes	Yes
Standard Error Clusters:			
NUTS2	41	45	43
Year-Month	49	49	49
Adjusted R^2	0.256	0.253	0.252
User-Year-Month Obs.	74,612	298,145	242,239

Descriptive Statistics

- Steeper income path users and younger users react less
- Highest savings users react most