Consumption Response to Credit Expansions: Evidence from Experimental Assignment of 45,307 Credit Lines

Deniz Aydın

Online Appendix

A Further Details on Experimental Design and Implementation

Automatic limit underwriting. The experimental limit increases are automatic, initiated and pushed by the issuer. Participants are active credit line customers who satisfy the bank's automatic limit underwriting criteria, outlined in Table A.1. First, the sales division focuses on expected value added, factoring in the effects of the limit increase on revenue and risk of default. Second, risky individuals are filtered using in-house risk scores, and credit bureau files are used to filter out individuals who have previously become delinquent. Third, customer relationship management criteria have timing rules built into the credit supply function that filter out cardholders who have recently opened their accounts or have recently experienced credit line increases. Such timing rules render the probability of a line change a function of time since the last limit increase.

A large fraction of the universe of existing cardholding customers have given legal consent in writing (*muvafakatname*) to accept automatic limit increases. These customers, once they pass criteria (1) to (5), are directly pushed for limit increases, after the central bank's clearing system verifies that their preexisting limit is below four times their most recent stated income. It is also common for the customers who have not given consent to automatic limit increases to manually request a limit increase. These customers, if they pass criteria (1) to (5), would be given an increase up to the preapproved limit without requiring a second underwriting process.

Table A.1: Automatic Limit Underwriting: Stylized Decision Rule

#	Division	Criteria	Threshold	Range
(1)	Sales	Expected value added	> 0	$(-\infty, \infty)$
(2)	Risk	Internal score(s)	$> \bar{s}$	$[\underline{s}, \bar{s}]$
(3)	Risk	Delinquent	$= 0$	$[0, \infty)$
(4)	CRM	Months since limit increase	$> \bar{T}^1$	$[0, \infty)$
(5)	CRM	Months since card opening	$> \bar{T}^2$	$[0, \infty)$
$(*)$	*Experiment*	$\mathbb{Z}_i$	$= 1$	$\{0, 1\}$
(6)	Compliance	Consent	$= 1$	$\{0, 1\}$
(7)	Regulatory	Limit-to-income ratio	< 4	$[0, \infty)$

Note. Automated underwriting periodically processes the universe of existing cardholding customers. Customers who pass criteria (1) to (7) are pushed for limit increases. Different divisions within the bank have different decision rules and frequently adjust underwriting parameter thresholds at different times.

Stratification and randomization. Randomization is conducted on two batches of preapproved cardholders who pass the sales, risk, and CRM criteria (1) to (5), but before the limit increases are pushed. Stratification is conducted with respect to the end-of-billing-cycle balances over limits. Selected cardholders are first placed into 11 equal-width bins within each batch. Participants who have paid off their balance more than in full, or have exceeded their limit by a small amount, are placed in the first and last bin, respectively. A random subsample of size n_s is drawn from each stratum s using a STATA random number generator. I obtain a consistent estimator from a standard

Table A.2: Covariate Balance: Pre-trends

	Panel A: Levels					*Panel B: Changes*				
	Limit (Bank)	Inst. (Bank)	Flex. (Bank)	Spent (Bank)	Debt (All banks)	Δ Limit (Bank)	Δ Inst. (Bank)	Δ Flex. (Bank)	Δ Spent (Bank)	Δ Debt (All banks)
ϕ_{-1}	80	33	-7	83	-37	-15	20	-7	72	20
	(106)	(21)	(10)	(52)	(118)	(50)	(15)	(10)	(35)	(65)
ϕ_{-2}	95	13	0	11	-57	-3	-9	-1	18	-66
	(95)	(23)	(9)	(46)	(122)	(99)	(16)	(9)	(33)	(65)
ϕ_{-3}	98	22	1	-7	9	69	-4	12	-34	-24
	(148)	(23)	(9)	(45)	(114)	(63)	(14)	(11)	(32)	(52)
ϕ_{-4}	29	26	-11	27	33	31	0	-4	23	-9
	(168)	(24)	(11)	(46)	(110)	(32)	(16)	(10)	(33)	(64)
p	0.60	0.42	0.78	0.17	0.76	0.65	0.78	0.82	0.14	0.73

Note. Estimates from Equation (3) use data on the 4 quarters prior to the start of the experiment for the N=45,307 participants. The bottom row displays p-values for the null hypothesis that ϕ_j are jointly equal to zero.

Table A.3: Experimental Timeline

Aug. 2014	**Selection** Universe processed by Decision Rule A.1. Customers who pass criteria (1) to (5) are designated as participants.
	Randomization
Sep. 2014	**Implementation** Criteria ($*$) added to Decision Rule A.1. $\mathbb{Z}_i = 0$ fail criteria ($*$), withheld from *lender-initiated* underwriting. $\mathbb{Z}_i = 1$ pass criteria ($*$), continue downstream to criteria (6) to (7). New limits printed on statements, notified.
Oct. 2015	**Start of *Experiment***
Experimental Timeframe	Criteria ($*$) withholds $\mathbb{Z}_i = 0$ from *lender-initiated* underwriting. $\mathbb{Z}_i = 0$ may *request*, and receive, manual limit increases. $\mathbb{Z}_i = 1$ who pass criteria (1) to (7) *may* receive *additional* automatic limit increases.
Jun. 2015	**End of *Experiment*** Criteria ($*$) removed from Decision Rule A.1. Participants may receive automatic limit increases. Participants may request, and receive, manual limit increases.
Dec. 2017	**End of Follow-up**

Table A.4: Empirical Framework

	Panel A: Equation (2) $Y_i = \psi X_i + f_s + \varepsilon_i$, N = 45,307					Panel B: Equation (3) $Y_{it} = \sum_{j=1}^{T} \phi_j X_{ij} + f_t + f_s + \varepsilon_{it}$, $N \times T$ = 45,307 $\times$ T					
	Z_i	X_i	Y_i	Est.	See	Z_{it}	X_{ij}	Y_{it}	Est. In-time	Est. Cumul.	See
First-stage	$\mathbb{Z}_i$	$\mathbb{Z}_i$	$\Delta^\tau L_i$	ψ_τ^{FS}	Table 3	$\mathbb{Z}_i \times f_t$	$\mathbb{Z}_i \times f_{t=j}$	ΔL_{it}	ϕ_j^{FS}	$\Phi_\tau^{\text{FS}} = \sum_{j=1}^{\tau} \phi_j^{\text{FS}}$	Table 3, 4, 5
Intent-to-treat	$\mathbb{Z}_i$	$\mathbb{Z}_i$	$\Delta^\tau D_i$	ψ_τ^{ITT}	Table 3	$\mathbb{Z}_i \times f_t$	$\mathbb{Z}_i \times f_{t=j}$	ΔD_{it}	ϕ_j^{ITT}	$\Phi_\tau^{\text{ITT}} = \sum_{j=1}^{\tau} \phi_j^{\text{ITT}}$	Table 3, 4, 5, 6 Figure 7
Marginal Propensity	$\mathbb{Z}_i$	$\Delta^\tau L_i$	$\Delta^\tau D_i$	ψ_τ^{MP}	Table 3	$\mathbb{Z}_i \times f_t$	ΔL_{it-j+1}	ΔD_{it}	ϕ_j^{MP}	$\Phi_\tau^{\text{MP}} = \sum_{j=1}^{\tau} \phi_j^{\text{MP}}$	Table 3, 4, 5, 6 Figure 7

Note. Y, X, and Z stand for the left-hand-side variable, right-hand-side variable, and the instrument. L stands for credit line limit, and D stands for credit line debt. Δ^τ indicates the change over a period τ. $\mathbb{Z}_i$ denotes the randomized experimental assignment. $t \in \{1, \dots, T\}$ stand for time. Φ_τ^{MP}, the cumulative response of a unit change in credit lines on the left-hand-side variable over a time frame of τ quarters, is the main marginal propensity estimate used throughout the paper.

weighted least-squares problem. The weight is the inverse of the probability of being included in the control group due to the sampling—calculated as N_s/n_s, where N_s is the number of participants in the population and n_s is the number of participants in the sample.

The original list of preapproved customers who pass criteria (1) to (5) contains 54,524 cardholders. I impose two sample restrictions. First, I exclude a third batch of participants, for whom the experimental randomization was ignored due to institutional constraints. Second, I exclude participants associated with a small business to focus exclusively on participants whose cards are their personal liability. There are 6,048 individual participants in the former group and 3,169 small-business participants in the latter group. Small-business cardholders are evenly distributed between treatment and control, and the randomization of the first two batches is independent of the third batch.

Comparison with fiscal stimulus payments. The current experiment has three notable distinctions compared with U.S. fiscal stimulus payments. First, a tax credit, or an advance payment of tax cuts, entails a wealth effect.[1] In contrast, a pure shock to the credit limit is not net wealth, and in the current context also does not entail an indirect wealth effect (e.g., through a revaluation of debt via a change in the interest rate or by signaling permanent income). Second, the timing of stimulus payments is preannounced in writing by the Treasury Department before receipt, and could potentially be anticipated in advance through the legislative process. In contrast, the experimental shock is not preannounced, and is difficult to anticipate.

Finally, commonly cited U.S. stimulus payment studies (e.g., Johnson et al. (2006) and Parker et al. (2013)) use the variation in *timing*, as what is random is not *who* or *how much* but *when*—the order of disbursement is based on the last two digits of the Social Security numbers, which is effectively uncorrelated with expectations and behavior. The current experiment, in the short run, could also be interpreted as randomizing the timing of who gets limit increases over the experimental timeframe. However, it also creates long-run differences in credit limits.

If the transfer is not one time (e.g., a persistent tax cut), the magnitude of the response would

[1] For example, the 2001 Economic Growth and Tax Relief Reconciliation Act lowered the income tax rate in the lowest bracket applied to the first $6,000 ($12,000 for couples) from 15% to 10% as part of a tax cut bill, expected to sunset after 10 years. The stimulus payments represented an advance payment of this tax cut applied retroactively for 2001. In 2008, the Economic Stimulus Act temporarily eliminated income taxes on the first $6,000 ($12,000). The stimulus payments represented a delivery of the reduction in the form of a rebate check. In 2020, the Coronavirus Aid, Relief, and Economic Security Act provided refundable tax credits worth $1,200 ($2,400) in the form of a stimulus payment.

depend on additional assumptions (e.g., the MPC out of permanent/persistent shocks, expectations regarding sunset). However, the $MPC^{\Delta L}$ estimates can still be interpreted as a lower bound. Moreover, Ricardian individuals a la Barro (1974) may take into account the association between borrowing today and the need for taxes tomorrow, in which case the $MPC^{\Delta L}$, which needs to be repaid, should be more similar to the MPC. Finally, in models featuring mental accounting, MPCs may depend on the disbursement channel, and be asymmetric with respect to windfalls/refunds vs. payments; see Shefrin and Thaler (1988) and Baugh et al. (2021).[2]

Relationship between MPC and $MPC^{\Delta L}$. To clarify the relationship between the consumption response to a one-time transfer ΔA and the consumption response to a change in the credit limit ΔL, consider the certainty equivalent version of the permanent income model (linear marginal utility), in which consumption admits an explicit formula and is an affine function of assets and the present value of income,

$$C_0^{\mathrm{PI}} = \frac{R}{1+R}\left[A_0 + \sum_{t=0}^{\infty}\left(\frac{1}{1+R}\right)^t \mathbb{E}_0\left[Y_t\right]\right]$$

In this model, consumption is a martingale, and debt is a unit root process. New borrowing presages income growth, as it equals the present value of expected future increases in permanent income. Consumption depends only on the first moment of the present value of permanent income, and precautionary motives are absent. Consumers respond to shocks to permanent income one-for-one and annuitize asset windfalls. Although credit shocks could affect consumption behavior through a change in the interest rate R that entails intertemporal substitution and debt revaluation effects, a change to the credit limit that does not entail wealth effects does not affect consumption behavior

The assumption of prudence (convex marginal utility) and an ad-hoc credit constraint leads to a lower average propensity to consume (APC) and heterogeneous marginal propensity to consume (MPC) that are higher near the credit limit. When the consumer is relatively impatient, buffer-stock behavior emerges. In this model, when the credit limit increases, consumption becomes less responsive to income shocks, decreasing consumption volatility and leading to lower expected marginal utility and increased current consumption at all distance-to-limit levels.

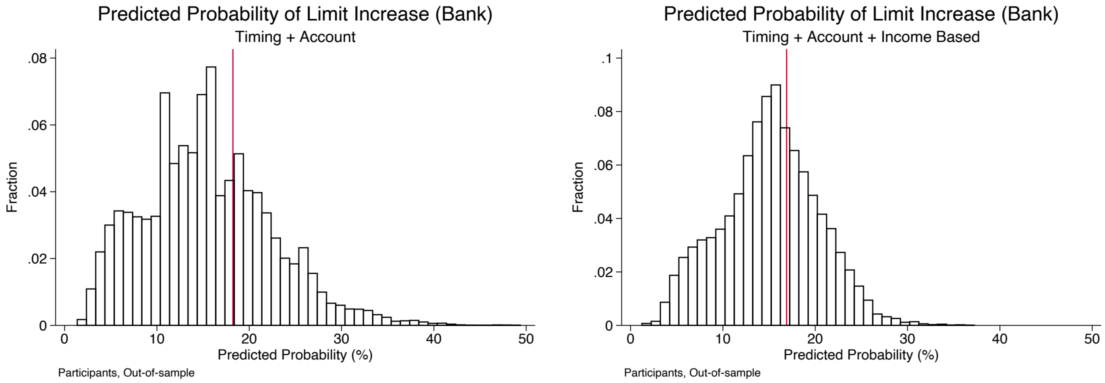
Let $Y_t = Y^{\mathrm{P}} + y_t$ consist of a predictable permanent level $Y^{\mathrm{P}} > 0$ and an unpredictable shock y_t. Notice that the consumer can feasibly—in a manner that leaves the budget constraint and the credit constraint unchanged—borrow out of the increased credit limits to increase assets and vice versa. However, this will come at a periodic cost (or conversely, foregone benefit) proportional to the annuity factor: $C + \frac{A'}{1+R} = A + Y$ if and only if $C + \frac{A'+\varepsilon}{1+R} = (A+\varepsilon) + (Y - \frac{R}{1+R}\varepsilon)$; and $A_0 > -L$ if and only if $A_0 + \varepsilon > -(L-\varepsilon)$. Hence, optimal consumption C^* satisfies

$$C_0^*(\, A_0,\, Y^{\mathrm{P}},\, y;\, L) = C_0^*(\, A_0 + \varepsilon,\, Y^{\mathrm{P}} - \varepsilon\frac{R}{1+R},\, y;\, L - \varepsilon) \tag{5}$$

Equation (1) then follows from implicitly differentiating (5). See Guerrieri and Lorenzoni (2017) for a similar proof.

[2] Also see Kaplan and Violante (2014) for a discussion of the relationship between the MPC out of the receipt of the transfer and the estimated *rebate coefficient*; Blinder (1981), Poterba (1988), Souleles (1999), and Parker (1999) on the effect of tax and fiscal policy on consumption behavior.

Figure A.1: Predictability of Limit Increases



Note. The out-of-sample prediction is for the limit increases the treatment group receives in the first quarter of the experiment. The Figure on the right is based on the subset of participants with labor income information. Vertical lines indicate the cutoff above which the logistic regression predicts a limit increase.

B Additional Analyses

B.1 Predictability and Anticipation

I study the predictability of the limit increases using kitchen-sink logit regressions. I use data on the 8 quarters prior to the start of the experiment, and three sets of right-hand-side variables: (i) timing rules: 10 indicators for quarters since the last limit increase, visually displayed in Figure 4; (ii) account usage characteristics: levels, changes, quadratic terms, and dummy variables for revolving and installment debt utilization at the bank; and (iii) income-based variables for customers for whom this information is available—change in log labor income and a quadratic in the total limit-to-income ratio.

I use the kitchen-sink regressions to obtain a predicted probability for a limit increase $\hat{p} \in [0,1]$, both in-sample and out-of-sample. The out-of-sample prediction is for the limit increases the treatment group receive in the first quarter of the experiment. The histogram of these out-of-sample predicted probabilities is displayed in Figure A.1.

I measure predictive performance in two ways. First, I obtain a binary classification using the predicted probabilities and measure the accuracy of this classification. I assume the logistic regression predicts a limit increase if the predicted probability $\hat{p}$ is above a particular threshold $\bar{p}$. I choose $\bar{p}$ to equal the empirical frequency with which limits are increased over the period the logistic model is estimated, which equals 0.18. I then calculate the sensitivity (i.e., true positive rate), which is the ratio of correctly predicted limit increases to actual limit increases, and the precision, which is the ratio of correctly predicted limit increases to predicted limit increases. Second, I report the commonly used area under the receiver operating characteristic curve. This threshold-invariant measure quantifies the discriminatory ability of the binary classifier as its discrimination threshold is varied.

The results are reported in Table 2. Panel A studies this predictive relationship from the perspective of the participants. Panel B studies the relationship from the perspective of typical cardholder, using data on a random subsample of all credit line customers excluding participants (N=10,000). I focus on the out-of-sample performance of the predictive model from the perspective of participants. This model predicts a limit increase when the predicted probability is higher than the empirical frequency with which limits are increased over the period the logistic model is estimated, which occurs in-sample about half of the time. Out-of-sample, the model predicts a limit increase for 33% of the actual limit increases (sensitivity). Moreover, 80% of those predicted to see their limits increase actually see their limits increase (precision). The threshold-invariant area under the curve (AUC) is 0.55 (where 0.50 would correspond to random classification), pointing to a very low discriminatory power of the econometric specification to predict limit increases out-of-sample.

Comparing the responses for the one-in-three participants for whom the model predicts a limit increase versus those for whom it does not using estimates Φ_τ^{MP} from the nested specification Equation (4) yields 12.9 (3.6) and 17.8 (3.0) cents, respectively, with no statistically significant differences across the two groups (p=0.30).

B.2 Informational Content of the Limit Increases

One explanation for across-the-board increases in spending may be due to participants' viewing the credit line extension as an informational cue and an endorsement by the bank and evidence that their economic future is possibly rosier than previously thought. For example, if the individual is uncertain about the true level of permanent income, she may form a Bayesian posterior conditional on the limit increase. Therefore, borrowing and spending may respond to a change in credit limits because these changes signal changes in the present value of earnings, in line with the permanent income model.

One important advantage of the environment is that credit limit increases at the bank are not associated with higher future income growth, either in percentage changes, or *unpredictable shocks*, over the course of 1, 2, or 3 years subsequent to a limit increase. Figure A.2 shows that the conditional distribution of future earnings growth for customers who receive a limit increase in a given quarter is virtually indistinguishable from those who do not. Similarly, Table A.5 estimates simple regressions to test for differences in group averages and finds no economically meaningful association.

This lack of a positive relationship between the limit increases and future income growth has a number of implications for the *rational* individual. For example, 97% of the participants had previously experienced limit increases in the 18 quarters before the experiment. These participants should be calibrated regarding the lack of an association between limit increases and income prospects. Moreover, for those who initially erroneously make the association, the long-run response should be hump-shaped. Therefore, unlike a once-in-a-lifetime event in which rational expectations are more likely to fail, in our context, repeated experience potentially creates an opportunity for learning and the informational-cue effects are perhaps more likely to be attenuated.

Note that behavioral variants of the aforementioned mechanism also merit consideration. For example, individuals who care about expected future utility flows and have a systematic bias toward an overoptimistic reading may act as if the limit increases are informative. Decisions based on distorted beliefs might then lead to consumption that is higher than would be implied by rational updating, even if there exists no positive relationship between the limit increases and future growth; see Brunnermeier and Parker (2005). Relatedly, a cue like the limit increase could directly change the marginal utility derived from consumption, leading to a mechanical and spontaneous increase in spending. For example, repeated past pairings of consumption with the credit limit increases could raise the value of a cue-stock and create cue-based complementarities, as in Laibson (2001) and Bernheim and Rangel (2004).

To understand the effects of repeated experience, I compare the responses Φ_τ^{MP} from the nested specification Equation (4) for participants who had previously not experienced a limit increase (3%), who had seen their limits increased once or twice (56%), or had seen their limits increased at least three times (41%), over the 18 quarters prior to the experiment. The estimated responses are 24.5 (10.5), 16.4 (2.4) and 14.7 (4.0) cents, respectively, but with no statistically significant differences across the groups. Higher responses observed for the participants who had previously not experienced a limit increase is compatible with the former behavioral hypothesis, that a tendency towards over-optimism has a more pronounced effect for participants who had limited opportunities for calibration.

B.3 Lumpiness and Feasibility

Could the response be explained by transactions that are lumpy or were not feasible under the old limit? First, 2.4% of the participants in the treatment group spend in installment form in a single category a sum that is larger than the old limit L_0 during the experimental timeframe, accompanied by installment debt growth larger than the old limit. I denote this group with the dummy variable, Lumpy_i.[3] Second, 72% of the participants had the additional limits they receive as available credit. I denote the 28% of the participants who did not have the additional limits with the dummy variable, Infeasible_i.

Table A.7 then compares the 3-quarter debt growth of these participants over the experimental timeframe to the treatment and control groups. Across all of the sample splits, the effects are statistically significant when participants Lumpy_i and Infeasible_i are considered separately. Hence, lumpiness and infeasibility cannot explain the borrowing response.

B.4 What Explains the Buffers?

In incomplete markets models, uninsurable uncertainty leads to a desire to build up precautionary savings as a buffer to self-insure and avoid fluctuations in the path of consumption. As income risk is a crucial source of uninsurable uncertainty, a first-order model implication is that those facing greater income risk will desire larger buffers.[4]

To test this key prediction, I isolate *unpredictable shocks* to income by purging quarterly log-real-income of individual and calendar quarter fixed effects and a quadratic in age, and calculating changes. I focus on the N=1,981 participants with a strongly balanced panel of income data running from quarters -12 to 12 relative to the onset. I then calculate the variance of these changes at the individual level, Risk_i, separately for *Past*—12 quarters prior to the onset—and *Future*—the 12 quarters following the onset. [5] For *Past*, the mean, standard deviation, and $p90$-$p10$ range of Risk_i are 0.050, 0.066, and 0.123, respectively. For *Future*, the mean, standard deviation, and $p90$-$p10$ range are 0.051, 0.072, and 0.137, respectively.

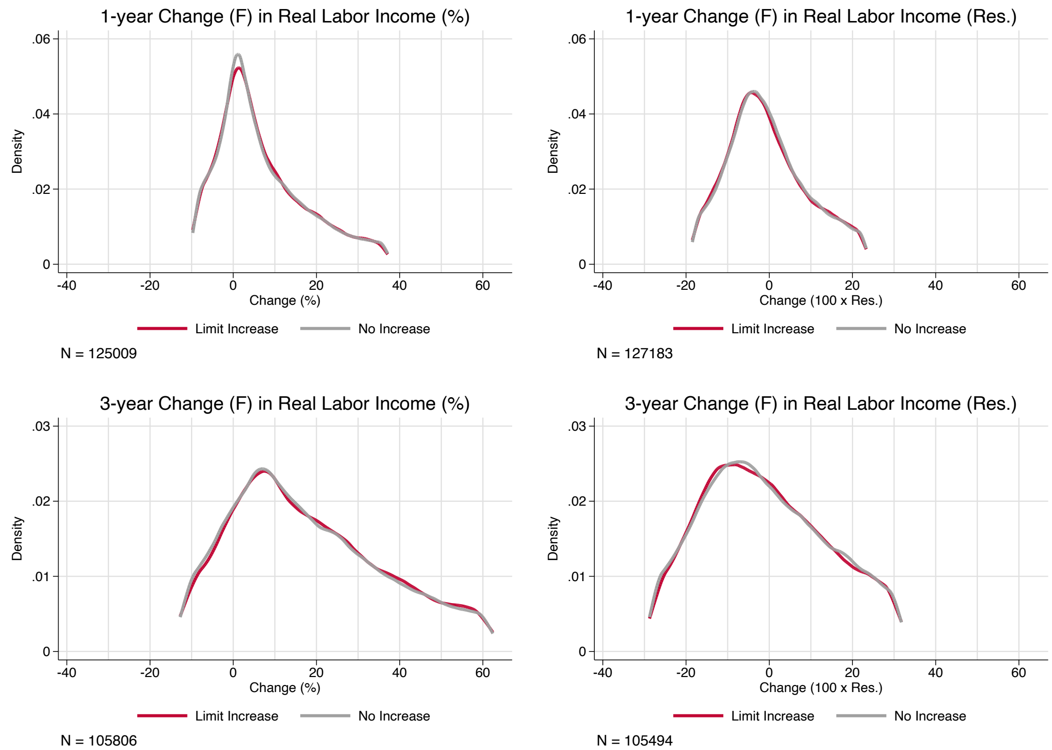
I use four measures to proxy for the size of the buffers: the complement to 1 of credit line utilization, log credit limit, log available credit (unused limit), and the ratio of available credit to monthly income. Table 8 then examines regressions in which the left-hand-side variable is the buffer, and the right-hand-side variable is income risk.

[3] Note that this pattern by itself does not imply that the debt is accumulated via a purchase that is indivisible; it is also possible for an individual to purchase many items in the same category in a given month. I use this methodology only to place an upper bound on the increase in debt due to lumpy installment purchases. Figure A.4 plots the histograms of these ratios, in which each observation represents a customer-month. The figures provide visual confirmation that installment debt growth and the expenditure in the largest installment spending category are below L_0 for for the majority of individual-month observations during the experimental timeframe.

[4] Theory predicts that consumers engage in precautionary savings either due to prudence (i.e. convex marginal utility, Carroll (1997)), or due to the possibility that credit constraints might bind in the future (e.g., Deaton (1991)). Risk aversion, the discount factor, and family composition—variables for which I do not have a proxy—are also likely to be key determinants of the size of the buffer.

[5] Note that there are many caveats with using naturally occurring data to investigate uninsurable income risk. First, naturally occurring income risk is endogenous, and invariably correlated with other attributes—e.g., riskier occupations may attract less risk-averse individuals. Second, the uninsurable component of labor-income risk may not necessarily be what is measured by the econometrician, if individuals have private information about their income prospects. Third, the existence of other types of buffers (e.g., family, friends, firm) may affect uninsurable risk. Finally, this approach purges economy-wide fluctuations, whose incidence may not be evenly distributed. See Carroll (1994), Lusardi (1998), Gourinchas and Parker (2002), and Jappelli et al. (2008) for a discussion of these issues.

Figure A.2: Limit Increases and Income Growth



Note. Kernel densities compare income growth for individuals who receive a limit increase versus those who do not. Each observation represents income growth starting from a baseline quarter in the 18 quarters before the experiment. Figures on the left plot the real change in simple percentage terms. Figures on the right plot *unpredictable shocks*—the change in the residuals after log real quarterly income is purged of calendar date and a quadratic in age. Densities use an unbalanced panel of pooled data on participants and the random subsample of the universe of existing cardholding customers for whom income growth can be calculated. Figures are winsorized at each tail.

Table A.5: Limit Increases and Income Growth

	Panel A: Percent Changes			*Panel B: Unpredictable Shocks*		
	1y	2y	3y	1y	2y	3y
β	0.003	0.299	0.428	- 0.120	- 0.142	- 0.035
	(0.08)	(0.12)	(0.14)	(0.07)	(0.09)	(0.12)
α	6.9	14.9	18.0	- 0.3	- 1.4	- 0.9
	(0.03)	(0.05)	(0.06)	(0.03)	(0.04)	(0.05)
p	0.97	0.01	<0.01	0.08	0.12	0.77

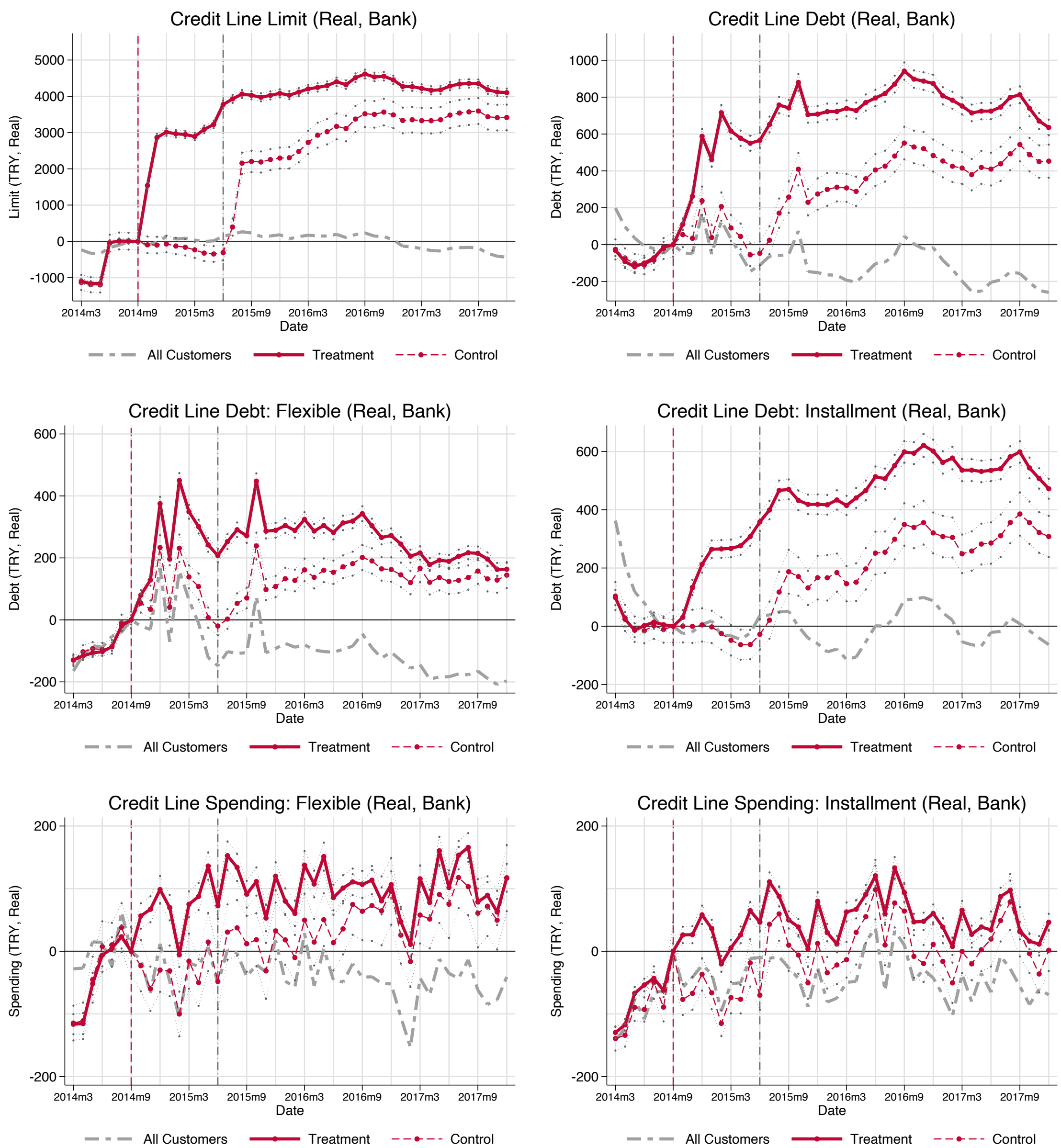
Note. Estimated coefficients from regression $Y_{it} = \alpha + \beta\, \mathbb{1}\{\Delta L_{it} > 0\} + \epsilon_{it}$. The left-hand-side variable is income growth over a period of 1, 2, or 3 years; either in simple percentage terms (Panel A) or *unpredictable shocks*—the change in the residuals after quarterly log-real-income is purged of calendar date and a quadratic in age—(Panel B) both displayed in Figure A.2. The right-hand-side variables are a dummy for limit increase at the bank and a constant. Each observation represents income growth starting from a baseline quarter in the 18 quarters before the experiment. p-values for $H_0 : \beta = 0$.

Table A.6: Balance Sheet Effects

			Baseline Level	Short-run				Long-run		*p*-value	
				1*m*	2*m*	1*q*	3*q*	8*q*	12*q*	3*q*	12*q*
Total Balance (All banks)	Δ Debt Credit Line + Overdraft	(TRY)	3,721			283 (49)	502 (72)	410 (87)	317 (104)	<0.001	0.002
	Δ Debt Total	(TRY)	18,463			499 (262)	538 (471)	723 (708)	1,611 (748)	0.253	0.031
	Δ Has Big Ticket Debt		0.60			.010 (.004)	.017 (.007)	.010 (.009)	.016 (.009)	0.009	0.076
Credit Line (Other banks)	Limits Increased		0			-.010 (.005)	-.035 (.007)	-.041 (.008)	-.035 (.008)	<0.001	<0.001
	Δ Limit	(TRY)	5,350			-148 (46)	-241 (66)	-275 (106)	-151 (122)	<0.001	0.216
	Δ Debt Credit Line	(TRY)	2,181			-32 (38)	-52 (59)	-19 (62)	-14 (72)	0.379	0.843
Real Terms (Bank)	Δ Limit	(TRY)	5,898	1,636 (22)	2,965 (27)	3,085 (27)	4,080 (37)	1,097 (118)	755 (119)	<0.001	<0.001
	Δ Debt Flexible	(TRY)	413	26 (13)	94 (14)	142 (20)	227 (19)	141 (25)	57 (25)	<0.001	0.022
	Δ Debt Installment	(TRY)	1,046	31 (16)	133 (22)	208 (26)	386 (34)	249 (40)	213 (45)	<.001	<0.001
Income	Δ Wage Base	(TRY)	2,465	-2 (55)	55 (34)	26 (52)	-69 (54)	10 (62)	11 (101)	0.196	0.914
	Δ Wage Overtime + Bonus	(TRY)	2,500	-8 (60)	69 (35)	30 (52)	-58 (54)	4 (63)	3 (102)	0.280	0.974
Delinquencies (Bank)	Δ NPL 90+ (%)		0	-0.006 (0.010)	0.017 (0.029)	-0.013 (0.040)	0.009 (0.141)	0.057 (0.273)	0.111 (0.321)	0.951	0.729
	Δ NPL Rest. (%)		0	0.006 (0.011)	0.026 (0.019)	-0.031 (0.037)	-0.130 (0.087)	-0.139 (0.183)	0.115 (0.265)	0.134	0.664
Assets (Bank)	Δ Assets Checking	(TRY)	1,011	8 (63)	-2 (55)	-46 (57)	-24 (78)	0 (94)	-104 (93)	0.762	0.267

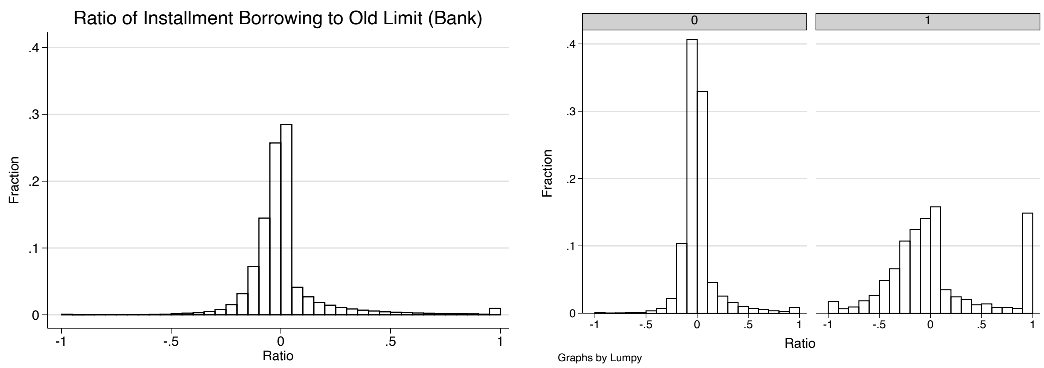
Note. Intent-to-treat estimates from Equation (2) use data on N = 45,307 participants. Real levels calculated using the implicit price deflator for personal consumption expenditures. Labor income and checking asset responses for the subset of customers with this information. p-values for the null hypothesis that the estimated coefficients are equal to zero.

Figure A.3: Event Study: Contract Choice and Spending Patterns—Real Terms



Note. Figures plot the levels of covariates for treatment ($\mathbb{Z}_i = 1$) and control ($\mathbb{Z}_i = 0$) groups by calendar month. The y-axis is normalized to have levels equal to zero at the onset of the experiment. Real levels calculated using the implicit price deflator for personal consumption expenditures.

Figure A.4: Lumpiness



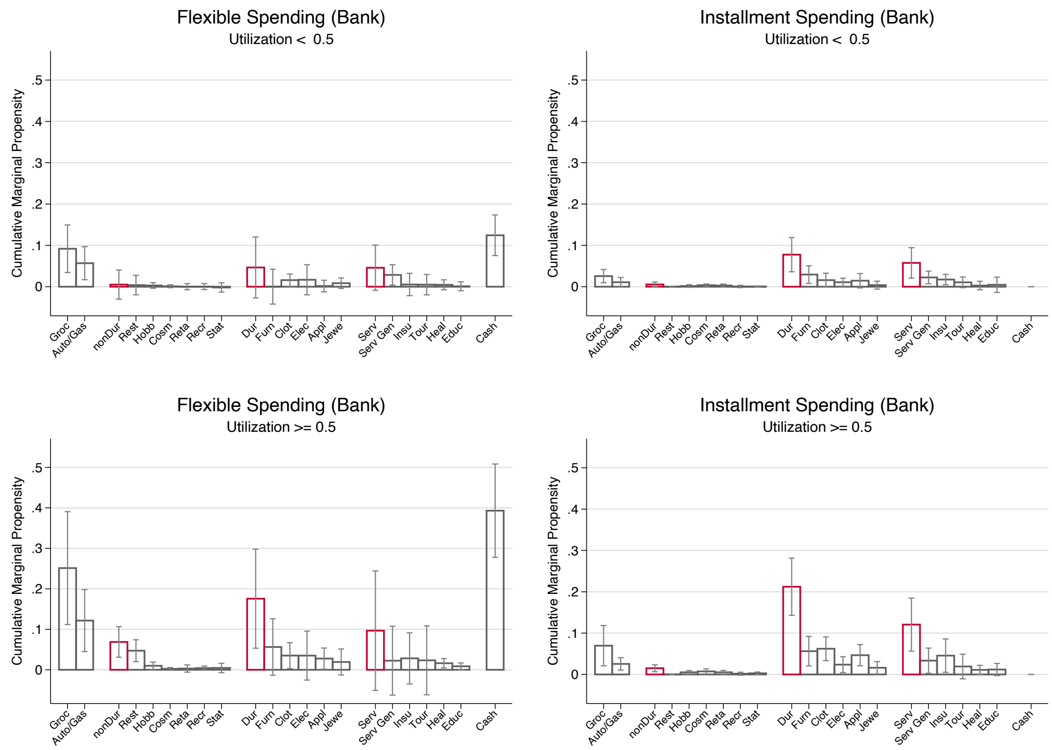
Note. Figures plot the ratio of the change in installment debt at the bank to the old limit L_0. Each observation represents an individual-month, using data on 45,307 participants for the experimental timeframe of T=9 months. For display purposes, observations larger than 1 and smaller than -1 are replaced by 1 and -1, respectively. The panel on the right plots the same ratio separately by variable Lumpy$_i$, which is a dummy variable that is positive for the participants who make at least one categorical installment purchase larger than their old limit L_0.

Table A.7: Lumpiness and Feasibility

	Panel A: All Participants			*Panel B: Utilization < .25*			*Panel C: Available Credit > 2,500*		
$\mathbb{Z}$	519 (69)	460 (69)	194 (80)	250 (89)	219 (90)	189 (95)	411 (110)	376 (110)	244 (116)
$\mathbb{Z}\cdot$ Lumpy		2,221 (215)			1,931 (232)			2,768 (631)	
$\mathbb{Z}\cdot$ Infeasible			765 (56)			180 (51)			636 (89)
Fraction									
Lumpy		1.5%			0.9%			0.7%	
Infeasible			27.5%			20.2%			16.0%

Note. In each panel, the first column reports simple intent-to-treat estimates from Equation (2) using data on N = 45,307 participants, as reported in Table 3, where the left-hand-side variable is the 3-quarter change in total credit line debt. The second column reports estimates from a specification that also includes $\mathbb{Z}_i \cdot \text{Lumpy}_i$ as a right-hand-side variable. Similarly, the third column reports estimates from a specification that includes $\mathbb{Z}_i \cdot \text{Infeasible}_i$ as a right-hand-side variable.

Figure A.5: Spending Patterns by Distance-to-limit



Note. Figure reports the categorical 3-quarter cumulative marginal propensity to spend on bank cards. Top (bottom) Figures focus on participants with a baseline utilization rate of less than (greater than or equal to) 0.5. Estimates obtained using Equation (3) on a sample of $N = 45{,}307$ participants, focusing on the experimental timeframe of $T = 3$ quarters, using as the right-hand-side variable the change in credit limits at bank. Red bars correspond to the total increase in spending on three main subcategories—nondurables, durables, and services. The upper and lower shadows indicate 99.8% confidence intervals for the estimate of the mean, to account for Bonferroni correction to handle many outcomes, and clustering at the individual level.

Table A.8: Utilization Transition Matrix

τ = -4q	= 0	(0, 0.25)	[0.25, 0.50)	[0.50, 0.75)	[0.75, 1]
∅	319 0.08	1,165 0.29	1,071 0.26	879 0.22	653 0.16
= 0	764 0.23	1,434 0.43	570 0.17	341 0.10	191 0.06
(0, 0.25)	960 0.06	9,370 0.60	3,393 0.22	1,433 0.09	551 0.04
[0.25, 0.50)	345 0.03	4,040 0.38	3,248 0.31	1,957 0.19	954 0.09
[0.50, 0.75)	166 0.02	1,758 0.26	1,959 0.29	1,787 0.26	1,115 0.16
[0.75, 1]	107 0.02	899 0.18	1,186 0.24	1,370 0.28	1,322 0.27
	2,661 0.06	18,666 0.41	11,427 0.25	7,767 0.17	4,786 0.11

τ = -12q	= 0	(0, 0.25)	[0.25, 0.50)	[0.50, 0.75)	[0.75, 1]
∅	1,201 0.07	6,118 0.35	4,412 0.26	3,299 0.19	2,263 0.13
= 0	558 0.10	2,445 0.45	1,235 0.23	778 0.14	436 0.08
(0, 0.25)	544 0.05	6,121 0.57	2,450 0.23	1,127 0.11	438 0.04
[0.25, 0.50)	193 0.03	2,333 0.41	1,627 0.28	1,039 0.18	541 0.09
[0.50, 0.75)	94 0.03	1,028 0.31	961 0.29	779 0.23	464 0.14
[0.75, 1]	71 0.03	621 0.22	742 0.26	745 0.26	644 0.23
	2,661 0.06	18,666 0.41	11,427 0.25	7,767 0.17	4,786 0.11

Note. Participants are allocated to 6×5 = 30 categories based on their utilization across all banks. Columns stand for utilization in the quarter before the experiment, the histogram of which is displayed in Figure 8. Rows stand for utilization τ quarters prior to that. In each box, the first entry displays the number of participants, and the second row stands for the transition probabilities. Due to rounding, summed probabilities may not add up to 1.

C Further Details on Institutional Features

This section provides details on institutional features relevant for the interpretation of the findings.

C.1 Spending and Borrowing on Credit Lines

The credit lines studied here are very similar to the typical credit card in the United States. There is a limit L_t assigned to a customer, potentially across many cards. This limit caps the total liabilities on the credit line, including flexible and installment components of debt carried across pay periods, denoted D_t^{Flex} and D_t^{Inst}; as well as new flexible spending and installment spending incurred in a given month, denoted C_t^{Flex} and C_t^{Inst}.

First, consider a customer who only engages in flexible spending. The end-of-billing-cycle balance printed on the statement capitalizes the flexible debt carried over from the previous period, interest on this debt, and new flexible spending—i.e., $\text{Bal}_t = C_t^{\text{Flex}} + D_{t-1}^{\text{Flex}}\,(1+R)$. Many customers choose to pay the statement balance off in full, $\text{Pay}_t = \text{Bal}_t$, and hence do not revolve balances. Cardholders who choose not to pay off their end-of-billing-cycle balances carry interest-bearing flexible debt equivalent to the unpaid component of these balances, i.e., $D_t^{\text{Flex}} = \text{Bal}_t - \text{Pay}_t$. The customer deaccumulates flexible debt when $\text{Pay}_t > R\, D_{t-1}^{\text{Flex}} + C_t^{\text{Flex}}$.

Table A.9: Installment Calculations

				t -1	0	1	2	3	4	5
Spending	Flexible	C_t^{Flex}		0	50	100	0	0	0	0
	Installment	C_t^{Inst}	$=\sum_{k\geq t} C_{j=t,k}^{\text{Inst}}$	0	0	0	80	0	0	0
End-of-billing-cycle statement	Flexible debt ($t-1$) + interest	$D_{t-1}^{\text{Flex}}(1+R)$	(1)	0	0	0	51	0	20.4	0
	Flexible spent	C_t^{Flex}	(2)	0	50	100	0	0	0	0
	Installments due	$\sum_{j\leq t} C_{j,k=t}^{\text{Inst}}$	(3)	0	0	0	20	20	20	20
	Balance	Bal_t	(1)+(2)+(3)	0	50	100	71	20	40.4	20
	Payments	Pay_t	(4)	0	50	50	71	0	40.4	20
Debt	Flexible	D_t^{Flex}	(1)+(2)+(3)-(4)	0	0	50	0	20	0	0
	Installment	D_t^{Inst}	$=\sum_{j\leq t}\sum_{k>t} C_{j,k}^{\text{Inst}}$	0	0	0	60	40	20	0

Note. C_t^{Flex} and C_t^{Inst} indicate flexible and installment spending, with $C_{j,k}^{\text{Inst}}$ indicating installment purchases made at time j with payments due time k. D_t^{Flex} and D_t^{Inst} indicate flexible and installment debt, and Bal_t indicates end-of-billing-cycle balances, and Pay_t the payments made towards these balances.

Table A.9 illustrates these calculations. At $t = 0$, the customer with no debt spends 50 in flexible form, which is reflected in her end-of-billing-cycle balance, Bal_t. She chooses to pay these balances off in full, and does not carry flexible debt across pay periods. At $t = 1$, the customer spends 100 in flexible form, but only pays off 50, hence carries over the remaining 50 in flexible debt D_t^{Flex} across pay periods. This flexible debt is capitalized to end-of-billing-cycle balances at $t = 2$ along with interest, 2% per month, totaling to 51.

Second, consider a customer who makes a single installment purchase at time t amounting to C, to be paid over N installments. In the data, the total whole amount of this purchase (including interest) will show up as an installment spending in period t. In the statement, the first installment amounting to $\frac{1}{N}C$ is due in the month of purchase, and is capitalized to the end-of-billing-cycle balance, Bal_t. The remaining $N-1$ installments, amounting to $\frac{N-1}{N}C$, are capitalized to installment debt. In the next period, $t+1$, the second installment amounting to $\frac{1}{N}C$ is capitalized to Bal_{t+1} and the stock of installment debt decreases by $\frac{1}{N}C$, and so on. The customer may choose to pay off the due installments that are capitalized to the end-of-billing-cycle balances, or carry these balances across pay periods in flexible form.

Table A.9 illustrates these calculations. At $t=2$, the customer spends 80, including interest, to be paid over 4 installments. The first installment payment of 20, alongside the flexible debt carried over and interest totaling to 51, is capitalized to the end-of-billing-cycle balances. The remaining installments, totaling to 60, are reflected in installment debt, D_t^{Inst}. After seeing her end-of-billing-cycle balances at $t=2$ she chooses to pay these balances off in full, and does not carry flexible debt across pay periods. At $t=3$, the second installment amounting to 20 is capitalized to the end-of-billing-cycle balances. She does not make any payments towards the end-of-billing-cycle balances and carries over 20 in flexible debt across pay periods, and so on.

To generalize this intuition, let $C_{j,k}^{\text{Inst}}$ denote the installments due at time k for purchases made in time j. The installment spending incurred during a month, by definition, equals $C_t^{\text{Inst}} = \sum_{k\geq t} C_{j=t,k}^{\text{Inst}}$. End-of-billing-cycle balances, flexible debt, and installment debt are then given by

$$
\begin{aligned}
\text{Bal}_t &= D_{t-1}^{\text{Flex}}\,(1+R) + C_t^{\text{Flex}} + \sum_{j\leq t} C_{j,k=t}^{\text{Inst}} \\
D_t^{\text{Flex}} &= D_{t-1}^{\text{Flex}}\,(1+R) + C_t^{\text{Flex}} + \sum_{j\leq t} C_{j,k=t}^{\text{Inst}} - \text{Pay}_t \\
\Delta D_t^{\text{Flex}} &= R\; D_{t-1}^{\text{Flex}} + C_t^{\text{Flex}} + \sum_{j\leq t} C_{j,k=t}^{\text{Inst}} - \text{Pay}_t \\
D_t^{\text{Inst}} &= \sum_{j\leq t}\sum_{k>t} C_{j,k}^{\text{Inst}} \\
\Delta D_t^{\text{Inst}} &= \sum_{k>t} C_{j=t,k}^{\text{Inst}} - \sum_{j\leq t} C_{j,k=t}^{\text{Inst}}
\end{aligned}
$$

C.2 Delinquencies

In the case of a late payment of end-of-billing-cycle balances, the bank will follow up with the customer via text messages and phone calls, and send a preliminary notice. A 91-days-late account is forwarded to collections, and non-performing status is reported to the credit bureau. The contract is kept in collections for about an additional 90 days, during which recovery is attempted by the bank through customer contact. Missing due payment on end-of-billing-cycle balances is reported to credit bureaus. However, missing due installment payment do not impose severe penalties, but are capitalized to end-of-billing-cycles.

C.3 Macroprudential Environment

Figure A.6 displays the household debt to GDP ratio, which rose from about 3% in 2000 to a peak of 19.6% in 2013. Similar growth patterns were also observed in narrow and broad monetary aggregates, and the rise in household debt was associated with a large current account deficit. The experiment takes places around a period where a set of macroprudential policies, including caps on limit-to-income ratios, attempted to contain this household debt growth; and coupled with tighter monetary policy, led to a reversal of the trend in household indebtedness in 2014. See Kara (2016). The credit lines of individuals are capped by the banking regulatory authority to a maximum of four times the monthly post-tax income, including rental and interest income. The limit cap applies to the total of credit lines across all banks, and is coordinated through a credit registry managed by the central bank. Although this cap is not binding for the majority of cardholders, it does bind for a small fraction of participants, who does bounce back from the central bank's clearing system.

C.4 Installment Loans in the U.S. in the 1920s

Persons (1930): *The expansion of credit involved in installment selling has been hotly and voluminously debated. This sales method has been variously hailed as the foundation of our prosperity and as the most dangerous credit development of this decade. ... Recent studies estimate that 70 to 80 per cent of furniture is now sold on installments. ... It has been estimated that 140 million dollars worth of clothing is sold on installments annually. ... Without further elaboration we may accept the current estimates that annual installment sales are now about 6 billions and that the total debt outstanding at a given time is about half that sum, or 3 billions. Of this debt about half results from the sale of automobiles and trucks, both new and in the used car market.*

Olney (1999): *The collapse of consumption in 1930 came on the heels of a decade of virtual explosion in household use of installment debt. ... Outstanding nonmortgage consumer debt more than doubled in the 1920s, reaching a 1929 peak of -9.3 percent of income- that was not surpassed until 1939. ... Installment buying accounted for much of the 1920s expansion in household credit use. ... Finance charges on installment plans were considered a charge for the convenience of paying later and were therefore not subject to usury laws. Available evidence indicates that the effective rate of interest-which reflects the finance charge, assorted fees, and the difference between cash and time prices- was generally in the neighborhood of 30 to 40 percent 'but sometimes ranged as high as 100 percent for installment contract. ... Durable goods had contract maturities of twelve to eighteen months and down payments of 10 to 25 percent. ... Over 41 percent of the 506 families of federal employees whom the BLS surveyed in 1928 bought a good on installments, purchasing furniture, clothing, radios, automobiles, pianos, and appliances.*

D Data Appendix

D.1 Variable Definitions

The analysis uses anonymized administrative data from a large European retail bank in Turkey, as well as credit bureau files from the local credit registry. The unit of observation for variables at the bank is individual-by-month, and for variables based on credit bureau records is individual-by-quarter. Both run from January 2010. Variables at bank run through December 2017, and credit bureau variables run through September 2017.

If an individual has multiple accounts at the bank, these accounts are matched and variables are aggregated using a unique citizenship number and verified using a customer identification number, which ensures perfect match quality. Information regarding credit line variables are end-of-billing-cycle calculations. Information on asset and liability balances at the bank are end-of-calendar-month values; credit bureau variables are from the date of the query. The data on checking balances, credit line spending (total and sectoral), and wages are winsorized at 25,000 TRY.

Income. Labor income information, including base pay, overtime, and bonuses, is only available for a subset of customers whose employers have a direct deposit relationship with the bank. Monthly earnings information contains only post-tax labor income, and does not include financial income (e.g., interest, dividend, or other capital income) or government transfers (e.g., benefits and social security income). This information is reported directly by employers, and is available for 17,690 participants in the quarter before the experiment. For N=1,981 participants, the panel is strongly balanced running from quarters -12 to 12 relative to the onset.

Spending. The analysis of spending in Section 3.3 uses data on credit line transactions. This information is taken from credit line statements, and is consolidated for all credit lines a customer has at the bank. Transaction volume is the sum of consumption expenditures within the month. Transaction data contain information on categorical spending (e.g., groceries, appliances, health), mapped using a unique retailer point-of-sale machine identifier. Every transaction is categorized. A full list of categories is given in Table A.11.

Credit bureau. Credit bureau variables are obtained from the local credit registry (*Kredi Kayıt Bürosu*). For credit lines, credit bureau data reports total unpaid liabilities, including installment and flexible debt balances carried across pay periods, as well as within-month expenditures that are *not* carried across pay periods. For other types of debt, information is available on the face value of the amount outstanding.

Assets. About two-thirds of participants (30,796) have an active checking account in local currency at the bank at the onset. This type of account is a conventional and liquid demand deposit account that can easily be accessed at a branch or by ATM, but also allows for in-store debit purchases. This type of account does not bear interest, and allows unlimited withdrawals or transactions without notice or penalty. Subject to underwriting approval, it is possible to link an overdraft account to the typical checking account, whereby an interest is charged if the balances are negative.

Section 3.2 studies the heterogeneity of the response by coarse groupings based on the 6-month average of the end-of-month balances of all liquid assets the participant has at the bank and the in-house brokerage. These liquid assets include checking and savings accounts, as well as investments in funds, stocks and bonds. Consistent with what is commonly used in the literature, they excludes housing, illiquid retirement accounts, and life insurance policies. Savings accounts are interest-bearing time deposits with a predetermined term, usually up to 6 months.

D.2 Institutional Details

Here I provide details on calculations in Section 1 which are derived from other sources.

As of 2014, 39% of adults aged 25+ own credit cards (compared with 44% and 67% in the E.U. and U.S), and an annual volume equivalent to 21% of GDP flows through credit lines as in-store expenditures (compared with 17% for the E.U. in 2014 and U.S. in 2015). Notably, credit lines are the predominant method for non-cash payments, with debit cards accounting for only 6% of in-store payments made using a debit or credit card.

- See Demirgüç-Kunt et al. (2018) for data on credit card ownership of adults aged 25+ in Turkey, the E.U. and the U.S.
- For Turkey, the aggregate transaction volume on credit and debit cards is taken from the Interbank Card Center (BKM). Credit line in-store transaction volume for year 2014 (measuring only domestic cards, spent domestically) is 420,974 million TRY. Similarly, debit card transaction volume for year 2014 (measuring domestic cards, spent domestically) is 417,195 million TRY, of which only 29,141 million TRY is accounted by in-store purchases, with the rest accounted by ATM withdrawals. For retail sales, I cite PricewaterhouseCoopers.
  - The ratio of annual in-store purchases using credit lines to nominal GDP is 421 billion TRY divided by 2,044 billion TRY, which gives 21%.
  - The ratio of annual in-store purchases using credit lines to total retail sales is 421 billion TRY divided by 608 billion TRY, which gives 69%.
  - The ratio of debit card in-store purchases to total in-store transactions is 29 billion TRY divided by (29 + 421) billion TRY, which gives 6.4%.
- For the E.U., the aggregate transaction volume on credit cards for year 2014, € 2.4 trillion, is taken from the European Central Bank Payment Statistics for 2014; and nominal GDP for year 2014, € 14.1 trillion, is taken from Eurostat.
  - The ratio of aggregate transaction volume on credit cards to nominal GDP is € 2.4 trillion divided by € 14.1 trillion, which gives 17%.
- For the U.S., the aggregate transaction volume on credit cards for year 2015, $ 3.16 trillion, is taken from the The Federal Reserve Payments Study 2016; and nominal GDP for year 2015, $ 18.23 trillion, is taken from FRED.
  - The ratio of aggregate transaction volume on credit cards to nominal GDP is $ 3.16 trillion divided by $ 18.23 trillion, which gives 17.3%.

The maximum interest rate that can be charged on any credit card and checking linked overdraft account is capped by the regulatory authority at 24% APR.

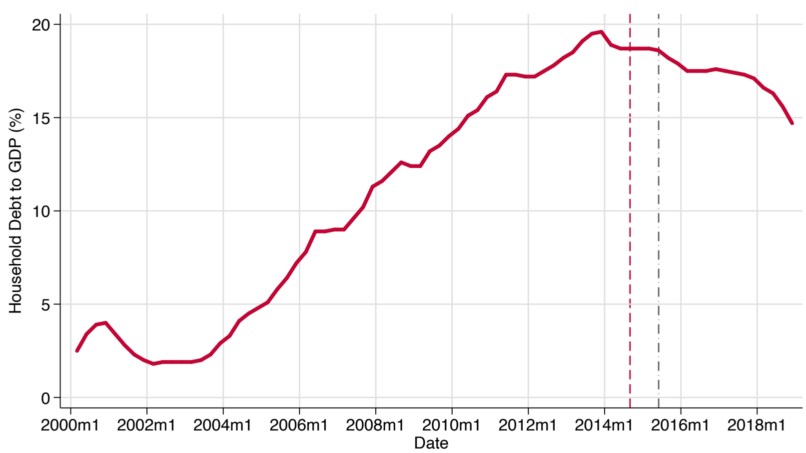
- See CBRT.

Table A.10: Macroeconomic Variables

Nominal GDP (TL, billions)	2,044
Nominal GDP (USD, billions)	939
Nominal GDP Per Capita (USD)	12,079
GDP Per Capita Based on PPP (2021 USD)	23,946
GDP Per Capita Based on PPP (EU28=1)	0.64
Population (millions)	77
Unemployment rate (%)	10.5
Inflation (CPI,%)	8.9
Exchange Rate (TL/$)	2.28
2-Year Benchmark Rate (%)	9.95
10-Year Benchmark Rate (%)	9.97
5-Year CDS Rate (bps)	208
NPL Ratio (gross,%)	2.9

Note. GDP and population variables based on 2014 values. The remaining variables based on September 2014 values. Source: Turkey Data Monitor, IMF, Bloomberg, Turkstat, and Worldbank.

Figure A.6: Macroeconomic Aggregates: Household Debt



Note. Figure displays quarterly household debt to GDP for the local economy. The dashed and dash-dot lines denote the start and end dates of the experiment.

Table A.11: Transaction Categories and Aggregation

Group	Category	Subcategory	Group	Category	Subcategory
Groceries		Butchers, Greengrocers, Charcuterie	Durables	Appliances	Major Appliances
Groceries		Supermarkets	Durables	Clothing	Shoes, Bags, Accessories
Groceries		Alcohol, Cigarettes	Durables	Clothing	Clothing
			Durables	Electronics	Computer
Auto & Gas		Gas	Durables	Electronics	Cellular Phones
Auto & Gas		Car Wash, Protection	Durables	Furniture	Garden Plants, Equipment
Auto & Gas		Tires, Service, Spare Parts	Durables	Furniture	Home Textile, Interior Decoration
			Durables	Furniture	Carpet
non-Durables	Cosmetics	Hairdresser, Beauty Centre	Durables	Furniture	Furniture
non-Durables	Cosmetics	Perfumery, Cosmetics	Durables	Furniture	Glassware
non-Durables	Hobbies	Associations, Club Memberships	Durables	Furniture	Construction, Building Materials
non-Durables	Hobbies	Photo	Durables	Jewelery	Optics
non-Durables	Hobbies	Souvenir	Durables	Jewelery	Clock, Jewelery
non-Durables	Hobbies	Bookstores			
non-Durables	Hobbies	Musical instruments	Services	Education	Courses
non-Durables	Hobbies	Toys	Services	Education	Schools
non-Durables	Recreation	Sports Activities	Services	Health	Physician/Dental
non-Durables	Recreation	Museum, Art Gallery	Services	Health	Pharmacies, Health supplies
non-Durables	Recreation	Cinema, Theater, Concert	Services	Health	Hospitals
non-Durables	Restaurants	Cafes, Bars, Bakeries, Fast Food	Services	Health	Laboratories
non-Durables	Restaurants	Restaurant	Services	Insurance	Other Financial Services
non-Durables	Retail	Department Stores	Services	Insurance	Insurance
non-Durables	Stationary	Photocopying, Printing	Services	Services	Natural Gas, Electricity, Water
non-Durables	Stationary	Office Supplies, Stationery	Services	Services	Other Services
			Services	Services	Advertising, Consultancy
			Services	Tourism	Hotels, Resorts
			Services	Tourism	Car Rental
			Services	Tourism	Transportation