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Managing Risk in Cards Portfolios: Risk Appetite and Limits

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Abstract

We describe an important risk management tool at financial institutions, risk appetite frameworks. We observe those frameworks for credit cards portfolios at four large banks and analyze when and why banks adjust them. The risk appetite frameworks for these banks monitor 40 to 150 metrics. We focus on metrics related to outstanding balances of which we identified 79. Overall, we find that these frameworks are sticky. Most adjustments occur during scheduled annual reviews and are relatively limited. Limit breaches are rare. Thresholds are often changed the month after a breach or after the utilization rate crossed 90 percent, but most breaches imply risk mitigating measures such as tightening credit standards. Notably, managers' reactions were even stickier in the pandemic period.

Keywords: Banking supervision, Risk management, Risk Limits, Risk Appetite Frameworks, Credit Cards
JEL Classification: G32, G21, G28

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1 Introduction

Banks are subject to regulation and supervision that impact their credit supply (BCBS, 2016) and risk-taking (Hirtle and Kovner, 2022). Regulation sets the rules they must follow, such as capital and liquidity requirements, and consumer protection rules. Supervision uses softer information to assess banks' ability to manage risk (Federal Reserve Board, 2023). Managing risk involves risk identification, risk assessment, and risk remediation.

In this paper, we describe and analyze an important risk management tool, risk appetite frameworks. Banks develop risk appetite frameworks (RAFs) around a collection of risk metrics and limits. These limits serve as thresholds that risk mangement teams monitor to ensure key risk metrics do not breach pre-established levels. The framework cascades the banks' risk appetite level set by the firms' board of directors down to each business line. Regular reporting of those metrics by the business line to risk functions enables firms to capture drifts in risk levels, anticipate breaches of risk appetite, and remediate them. We describe how banks set and formalize those frameworks for credit card portfolios. We assess when and why banks adjust their risk limits.

To do so, we leverage reports banks generate monthly for internal risk management purposes. Those reports are shared with supervisors in the routine baseline monitoring process. We extract limits data from the reports using an optical character recognition algorithm. We observe risk appetite frameworks for the credit cards portfolios of four large consumer banks. For each bank, we observe this risk appetite data monthly from 2014 to 2021.

We find that risk appetite frameworks for credit risk in credit card portfolios monitor between 40 to 150 portfolio-level metrics. Those frameworks are sticky as most adjustments occur during scheduled annual reviews. Typically, a handful of metrics might be added or removed and a few thresholds adjusted. Banks often target a risk limit utilization rate between 70 and 80% and use two thresholds, soft (amber) and hard (red) to manage potential mitigating actions. In this analysis, we find that risk limit metrics rarely breached the higher, red thresholds. In fact, thresholds are often adjusted to accommodate or anticipate a breach. And firms are more likely to change these thresholds within a month after a breach or after the utilization rate of the hard threshold reaches 90%. Threshold changes are not the only way to manage a breach. Most breaches also motivate risk mitigating measures such as tighter credit standards.

Risk appetite frameworks do provide information on credit standards as thresholds are loosened or tightened. But they crystallize long-term through-the-cycle risk appetite rather than business cycle adjustments. We do not observe significant adjustments to risk limits in the pandemic period (post April 2020). In fact, shifts in risk appetite frameworks during this period were below average relative to previous months, likely reflective of the heightened uncertainty. But risk appetite frameworks are tools to define maximum risk appetite, not credit policies. Hard risk appetite thresholds can accommodate a variety of different credit policy that can vary over the cycle. Credit policy measures (tighter underwriting, credit line actions...) might have been taken in the pandemic to make sure portfolios remained within risk appetite but appetites themselves remained steady and there were generally fewer threshold changes in that period (Fig. 2a).

Those results contribute to the literature on the impact of banking supervision. Research often focuses on the impact of capital requirements (BCBS (2016), Favara et al. (2021), Haughwout et al. (2022)) and stress testing (Cortés et al. (2020), Berrospide and Edge (2019), Bräuning and Fillat (2020)). Balla et al. (2022) shows financial institutions reduce risk taking in mortgage lending when under heightened regulatory scrutiny. Thanks to original data, we can shed light on risk management practices, a key focus of supervision (as laid out in letter SR 12-17 / CA 12-14 (2012)). Baldan et al. (2016) propose a quantitative model to cascade bank level capital consumption into business line level risk appetite metrics. Ellul and Yerramili (2013) shows a strong and independent risk management function can curtail tail risk exposures at banks. Gontarek and Bender (2019), using semi-structured interviews with risk governance actors, show firms appear to improve monitoring and take into account aggregate risk levels following the adoption of risk appetite frameworks. There are also signs that the cascading of bank level capital consumption into business line level risk appetite metrics may contribute to improved risk management. We can directly observe risk appetite frameworks and measure when and why banks adjust them. We show they are long-term strategic documents that banks use to guide their practices.

The remainder of the paper is organized as follows. Section 2 reviews risk management supervision, risk appetite framework guidelines, and the data collection strategy. Section 3 describes risk appetite frameworks. Section 4 analyzes the determinants of breaches and threshold changes. Section 5 concludes.

2 Data

2.1 Supervising Risk Management

Banking supervision is distinct from regulation. Regulation is the set of rules banks must follow, such as requirements for capital, liquidity, or fair lending. Bank supervision is government oversight of banks. Examiners (from the Federal Reserve, the OCC, etc.) monitor, inspect, and examine financial institutions to ensure they comply with regulations and operate in a safe-and-sound manner. Safety-and-soundness supervision focuses on banks' ability to manage risk. The post Dodd-Frank supervision framework for large financial institutions (with assets of $50bn or more) emphasizes two areas of focus (SR 12-17 / CA 12-14, 2012): (1) enhancing banks' resiliency to lower the probability of their failure or inability to serve as a financial intermediary; and (2) reducing the impact on the financial system and the broader economy in the event of a firm's failure. The supervision of risk management practices is a key component of enhancing resiliency through capital and liquidity planning. Supervisory letter (SR 12-17 / CA 12-14, 2012) sets forth the need for the banks' board to maintain a clearly articulated corporate strategy and institutional risk appetite. At the business line level, incentives have to be consistent with the institutional risk appetite. Supervision expects each business line to have an independent and strong risk management framework that supports identification, measurement, assessment, and control of the full spectrum of risks.

Risk appetite statements are a crucial component of large banks' risk governance frameworks. According to Office of the Comptroller of the Currency (OCC) guidelines (Office of the Comptroller of the Currency, 2014), they ought to have qualitative components and quantitative limits:

> *The covered bank should set limits at levels that take into account appropriate capital and liquidity buffers and prompt management and the board of directors to reduce risk before the covered bank's risk profile jeopardizes the adequacy of its earnings, liquidity, and capital.*

Risk appetite for the upcoming year is validated at the board level using a few high level metrics. The credit committee then cascades those limits down to each line of business, defining an array of metrics to monitor. The banks' risk committee reviews and approves those limits. But limits are not meant to be hard constraints or adjusted only once a year during the annual review exercise. As stated in the OCC handbook (Office of the Comptroller of the Currency, 2018), firms could adjust limits on an ad-hoc basis:

> *The limits should be tools that management can adjust when conditions or risk appetites change. Management also should have a process to authorize and document exceptions to*

risk limits when warranted.

Note that OCC guidelines are high-level ones. Banks have to set up statements but are free to decide what risk measures to use at each level of the firm and set limits internally. At the business line level, a risk appetite framework usually takes the form of a set of risk metrics, each managed against a limiting threshold. Some firms choose to define a single threshold, often referred to as a red threshold, which represents the limit or ceiling the firm sets to capture its risk appetite in a specific metric. Others define two thresholds, adding a second, or amber, threshold below the red one. Breaching the amber threshold generally warrants heightened monitoring of the limit and functions as a signal of material change in the risk metric. As a result, firms can plan more meaningful risk mitigating actions ahead of a breach of the red threshold.

We show an illustrative example in Figure 1. Here, the firm would be tracking a performance metric, setting both an amber and red threshold at 1.2% and 1.4% respectively. Actuals breached the amber threshold twice and the red threshold once.

2.2 Data Collection

We extract risk appetite frameworks data from Management Information System (MIS) reports of four large banks. Those reports are prepared on a monthly basis for internal bank purposes and shared with lines of business' management and risk officers. They detail limits' breaches (if any) and utilization rates (ratio of metric monitored to its limiting threshold). In the event of a breach, those reports lay out explanations and remediation plans, to be validated by risk management functions. Those reports are routinely shared with the firms' regulators for baseline monitoring purposes.

We focus on risk appetite frameworks reporting for credit cards portfolios. Each firm has its own reporting format but those formats are generally stable from month to month. We calibrate optical character recognition algorithms for each firm and extract the time series of their risk metrics, values, and limiting thresholds from 2014 to 2021. The database has a panel structure with monthly frequency and statistical individuals being the metrics monitored.

To make sure the breaches we capture are real events and not mistakes of our optical character recognition algorithms, we verify each breach manually. We also control data points where utilization rates are growing abnormally over a given month.

Descriptive statistics for the pre- and post-April 2020 period are in Table 1 and Table 2, respectively. We observe that firms rarely adjust thresholds and breaches are a relatively rare occurrence. For the pre-April 2020 period, average utilization was between 70 and 80 percent. Around 6% of the entire sample saw a limit change. Comparatively, for the post-April 2020 period, average metric utilization was less than 70 percent. For a balanced panel, we observe at most two breaches and five thresholds changes in a given month.

3 Risk Appetite Frameworks

The business line risk appetite frameworks we observe include 40 to 150 metrics. Firms review limits frameworks annually. Those reviews offer the opportunity to add new metrics and retire old ones. But adding and retiring metrics are rare events, and the number of limits is very stable. Another option is retaining the same metrics and changing the thresholds against which they are managed. Again, firms rarely adjust thresholds and we observe at most five adjustments any given month if we exclude the few automatically adjusting thresholds. There are months where we do not observe any threshold adjustments (Fig. 2a).

Threshold changes can be informative about lenders' risk positioning. For example, if the firm decides to be more restrictive on the net credit loss metric, underwriting might have to get more conservative to avoid a breach. In that sense, the risk limit framework reflects a firm's changing appetite. To summarize risk positioning, we compute a net limit increase (NLI) indicator as the difference between the number of thresholds that are loosened and those that are tightened, divided by the total number of metrics monitored. Credit card risk appetite frameworks measure risks throughout the lifecycle of the line of credit, including at origination, customer services, delinquency, collections, etc. This paper focuses on metrics related to outstanding balances where we identified 79 such metrics.

Firms have progressively tightened their risk appetite for those metrics between 2018 and 2021 (Fig 2b). We can compare this risk stance with information on credit standards from the Senior Loan Officer Opinion Survey (SLOOS), which surveys a larger group of lenders than the four universal firms we are focusing on. Consistently, the number of banks that have reduced credit limits has been increasing over the same period. The SLOOS series however displays a significant break at the start of the pandemic.

RAFs can however only provide limited information on the credit supply stance. Firms also leverage Recession Readiness Playbooks, or similar plans, as additional risk-management tools to prepare for economic stress. Similar to RAFs, most playbooks are developed at the portfolio level, or line of business. These plans define a set of early warning indicators that, if breached, trigger credit tightening and risk-mitigating actions appropriate to the severity of the downturn. Unlike risk appetite frameworks, playbooks often track a broader list of metrics, including macroeconomic and internal portfolio variables, such as the 4-week moving average of unemployment claims, share of minimum due payers, or 30+ days past due rates. In comparison, firms develop RAFs for card risk-limit metrics independent of the business cycle. As a result, it is likely that many firms' playbooks were activated during COVID, and therefore, many were already engaged in risk-mitigating strategies, such as forebearance programs and credit line decreases, likely managing away from established RAF red and amber thresholds.

Firms generally target a limits utilization rate, and manage risk metrics as a share of the threshold. For example, they set up a maximum share of subprime borrowers, and are comfortable with the actual share reaching 70% of that appetite in business as usual environments. The rate is chosen overall and applies to all metrics in the framework. The median usage of the red thresholds across these four firms is 73% (Fig 3a), with a significant concentration between the median and 100%. The density sharply drops after 100% usage, as most metrics are usually not breached any given month. The distribution shows a mass around 0% usage, corresponding to compliance metrics. Firms use those to keep track of adverse events. Since those rarely happen, the observed value of the metric is 0, hence a 0% usage. We observe at most a couple of breaches in a month in our sample (Fig 3b). The median breach amounts to 16% of the threshold.

When actual values exceed the threshold, firms must take mitigating actions. But actions are often taken *before* the breach even happens, as continuous monitoring enables firms to anticipate them. Thresholds can be adjusted to accommodate or anticipate a breach. We often see thresholds being changed the month after a breach (Fig 4a) or after the utilization rate crossed 90% for the metric (Fig 4b). But in most instances, there are no threshold adjustments after either event, as the majority of the distribution suggests more than three years between observed threshold changes. This is consistent with other risk-mitigating measures bringing the metric back to acceptable levels.

4 Breaches and Threshold Changes

We turn to analyzing the determinants of thresholds changes in a regression setting, to control for seasonality in credit cards portfolios and bank specific policies. We exclude compliance metrics from the analysis.

4.1 Accommodating Breaches

We start by testing whether breaches can lead to threshold changes. An accommodating threshold change would turn off the additional risk taking signal. The business line cannot make this decision on its own and needs to work with risk management teams on any adjustments to ensure the additional risk taking is acknowledged and managed. Such exceptions can be temporary or permanent. The firm might also decide to keep the original threshold and design a remediation plan instead.

To examine how often a breach leads to a threshold change, we estimate several specifications using lagged breaches on the event of a threshold change. We estimate α in

$$\text{Threshold Change}_{i,t} = \alpha * \text{Breach}_{i,t-1} + \rho_t + \psi_b + \sigma_{i,t}, \tag{1}$$

ρ_t are time fixed effects (monthly) and ψ_b are bank fixed effects.

Results are presented in Table 7. Across specifications, a breach in the month immediately before has a positive and significant impact on the occurrence of a threshold change. This suggests that managers react relatively quickly to adjust in the event of a breach. The impact of a breach is bigger in the post pandemic period (post April 2020, columns 3 and 4). Managers might have paid closer attention to limits behavior in this highly uncertain period and be more reactive.

We add one more lag in Table 8. A two-month old breach also increases the probability of a threshold change, but the impact is smaller than that of a one-month old breach (column 1). We confirm the impact of a breach on a threshold change is higher in the pandemic period (columns 2 and 3) and is mostly driven by recent breaches. There does not seem to be additional reactivity to older breaches (column 4).

Importantly, across all specifications, breaches and threshold changes are positively but not perfectly correlated. While some breaches are accommodated with threshold changes, most actually trigger remediation plans, consistent with binding and forceful risk appetite frameworks.

4.2 Anticipating Breaches

We now test for preemptive threshold changes. Business leaders can adjust thresholds when they notice a growing utilization rate. But they could not adjust the framework on their own, they would have to get approval from risk management teams. Moving the goalpost indeed requires approval from that second line of defense, to ensure the limits remain meaningful. This process requires management to acknowledge shifting risks and to come up with a strategy to handle them.

We start by verifying higher utilization rates are predictive of future breaches. We estimate the relationship between the utilization rate level at date $t-1$ and a breach at date t by estimating the vector δ in

$$\text{Breach}_{i,t} = \sum_{k=2}^{5} \mathbb{1}[\text{Utilization Rate}_{i,t-1} = k] * \delta_k + \tau_t + \eta_b + \text{e}_{i,t}, \tag{2}$$

where $\text{Breach}_{i,t}$ is a dummy for a breach of limit i at date t. Utilization $\text{Rate}_{i,t-1}$ is the utilization rate for limit i at date $t-1$. As it is unlikely management reacts to a one point change in utilization rate while being indifferent to its initial level, we discretize utilization. This can be written as:

$$\text{Utilization Rate}_{i,t-1} = \begin{cases} 1 & \text{if utilization}_{i,t-1} < 70\%, \\ 2 & \text{if } 70-80\%, \\ 3 & \text{if } 80-90\%, \\ 4 & \text{if } 90-100\%, \text{and} \\ 5 & \text{if } > 100\%. \end{cases} \tag{3}$$

Category 5 is equivalent to a breach dummy. τ_t are time fixed effects (monthly) and η_b are bank fixed effects.

In column 1 of Table 6, we see that a breach next period becomes more likely as utilization rates reach 80%. The likelihood is 6 times higher if the utilization rate is between 90 and 100% than if it is between 80 and 90%. As credit portfolios are adjusting slowly, the impact of a higher than 100% utilization (a breach) at date $t-1$ on a breach at date t is an order of magnitude bigger. The increased likelihood of a breach next period when utilization reaches 80% is driven by the post April 2020 period (columns 3 and 4).

As growing utilization rates do predict breaches, we can test whether management anticipates those and adjust thresholds preemptively. To test for those proactive threshold adjustments, we estimate the vector β in

$$\text{Threshold Change}_{i,t} = \text{Utilization Rate}_{i,t-1} * \beta + \lambda_t + \mu_b + \epsilon_{i,t} \tag{4}$$

Threshold $\text{Change}_{i,t}$ is an indicator variable for the threshold for limit i at date t being different from the one at date $t-1$. Those changes are either automated, if the threshold is defined by a rule with time-varying parameters, or the result of ad-hoc management decisions. Utilization $\text{Rate}_{i,t-1}$ is the utilization rate for limit i at date $t-1$ and defined as before. As retail credit is seasonal, we add monthly time fixed effects, λ_t. We also control for bank specific policies with fixed effects, μ_b. We expect that as the previous month's utilization increases, the likelihood of a threshold change occurring for a given month also increases.[1]

In Table 3, we present the results from the regressions for threshold change and utilization rate. Overall, we find that the utilization rate is an important driver of threshold changes. In column 1, we see that the impact of a higher than 100% rate is not statistically different from that of a rate between 90 and 100%, suggesting threshold changes can anticipate breaches. Results are similar when focusing on pre-pandemic data only (column 2).

If we rather focus on post-April 2020 data, we find management reacting exclusively to higher than 100% rate. This can be because of the unexpected and unusual nature of the pandemic shock, making management cautious about moving the goalpost. Even if unemployment, a primary driver of default in cards portfolios (Banerjee and Canals-Cerdá (2012); Canals-Cerdá and Kerr (2015)), reached 13%, an increase in unemployment benefits lead to *increases* in disposable income (Figure 5) as many borrowers had income replacement rates over 100% (Ganong et al., 2020). As the usual relationship between income and unemployment broke down, management had to rely more heavily on information outside of usual models (Ho, 2022).

It could also be that our dataset does not allow us to observe an annual review in the post-pandemic period. It is likely non-urgent threshold adjustments will happen then. In column 4, there is a positive sign on the interaction with the post-April 2020 dummy and higher than 100% rate, while the other interaction terms have negative signs. This implies that the likelihood of management reacting to a threshold change is greater for highest utilization groups during the pandemic.

Adjusting thresholds can mean tightening or loosening risk taking, depending on the direction of the change. To examine the effect of increased utilization on *unidirectional* threshold changes, we modify the dependent variable in equation 4 to account for two situations: an increase in the threshold (e.g., limit loosening) and decrease (e.g., limit tightening). Table 4 and Table 5 present the results for each of the respective specifications. Results are more robust for the case of a limit threshold increase. For the post-April 2020 period (column 3), only an increase in utilization over 100% is associated with increased likelihood in a threshold increase – this effect is muted when estimated over the entire sample (column 4).

[1] We also estimate 4 using a continuous measure of utilization; results can be found in the appendix.

5 Conclusion

We describe risk appetite frameworks, an important risk management tool for banks. Firms monitor about 100 metrics and track how close these get to soft and hard thresholds. We find those frameworks to be sticky and most adjustments take place during scheduled annual reviews. Even those adjustments are limited, with a handful of metrics added or removed. Breaches are rare but require threshold adjustments and risk mitigating measures. Thresholds are more often changed more often changed the month after a breach or after the utilization rate crossed 90% (of the hard threshold) than any other month.

Risk appetite frameworks were not significantly amended during the pandemic. We find some evidence of slightly faster risk management but overall little change in reaction to an unprecedented event. Those frameworks served as guidelines in an environment with limited information where managers had to make decisions mostly based on expectations.

References

Baldan, Cinzia, Geretto Enrico, and Francesco Zen, "A quantitative model to articulate the banking risk appetite framework," *Journal of Risk Management in Financial Institutions*, 02 2016, *9*, 175–196.

Balla, E., R. Brastow, D. Edgel, and M. Rose, "The Effect of Regulatory Oversight on Nonbank Mortgage Subsidiaries," *J Real Estate Finan Econ*, 2022.

Banerjee, Piu and José J Canals-Cerdá, "Credit risk analysis of credit card portfolios under economic stress conditions," 2012.

BCBS, "Literature review on integration of regulatory capital and liquidity instruments," *Basel Committee on Banking Supervision Working Paper*, 2016, *30.*

Berrospide, Jose and Rochelle Edge, "The Effects of Bank Capital Buffers on Bank Lending and Firm Activity: What Can We Learn from Five Years of Stress-Test Results?," *Finance and Economics Discussion Series*, 07 2019, *2019.*

Bräuning, Falk and José Fillat, "The Impact of Regulatory Stress Tests on Bank Lending and Its Macroeconomic Consequences," Working Papers 20-12, Federal Reserve Bank of Boston October 2020.

Canals-Cerdá, José J and Sougata Kerr, "Forecasting credit card portfolio losses in the Great Recession: a study in model risk," *Journal of Credit Risk*, 2015, pp. 14–10.

Cortés, Kristle R., Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E. Strahan, "Stress tests and small business lending," *Journal of Financial Economics*, 2020, *136* (1), 260–279.

Ellul, Andrew and Vijay Yerramili, "Stronger Risk Controls, Lower Risk: Evidence from U.S. Bank Holding Companies," *The Journal of Finance*, 2013, *68* (5), 1757–1803.

Favara, Giovanni, Ivan Ivanov, and Marcelo Rezende, "GSIB surcharges and bank lending: Evidence from US corporate loan data," *Journal of Financial Economics*, 2021, *142* (3), 1426–1443.

Federal Reserve Board, "Understanding Federal Reserve Supervision," 2023.

Ganong, Peter, Pascal Noel, and Joseph Vavra, "US unemployment insurance replacement rates during the pandemic," *Journal of public economics*, 2020, *191*, 104273.

Gontarek, Walter and Ruth Bender, "Examining risk governance practices in global financial institutions: the adoption of risk appetite statements," *Journal of Banking Regulation*, March 2019, *20* (1), 74–85.

Haughwout, A, D. Morgan, M. Neubauer, M. Pinkovskiy, and W. van der Klaauw, "Non-conforming Preferences: Jumbo Mortgage Lending and Large Bank Stress Tests," Working Paper 1029, Federal Reserve Bank of New York September 2022.

Hirtle, Beverly and Anna Kovner, "Bank Supervision," *Annual Review of Financial Economics*, 2022, *14* (1), 39–56.

Ho, Paul, "Forecasting in the absence of precedent," *Journal of Economic Surveys*, 2022.

Office of the Comptroller of the Currency, *OCC Guidelines Establishing Heightened Standards for Certain Large Insured National Banks, Insured Federal Savings Associations, and Insured Federal Branches* 12 CFR Appendix D to Part 30 2014.

—, *Comptroller's Handbook - Safety and Soundness Management Corporate and Risk Governance version 2.0* Office of the Comptroller of the Currency 2018.

SR 12-17 / CA 12-14, *Consolidated Supervision Framework for Large Financial Institutions* SR 12-17 / CA 12-14 2012.

Figures and Tables

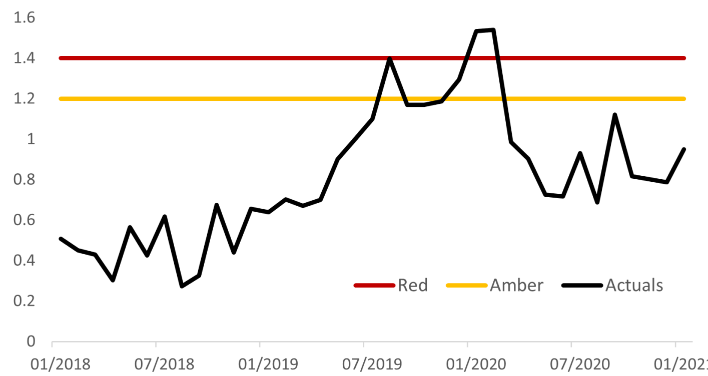
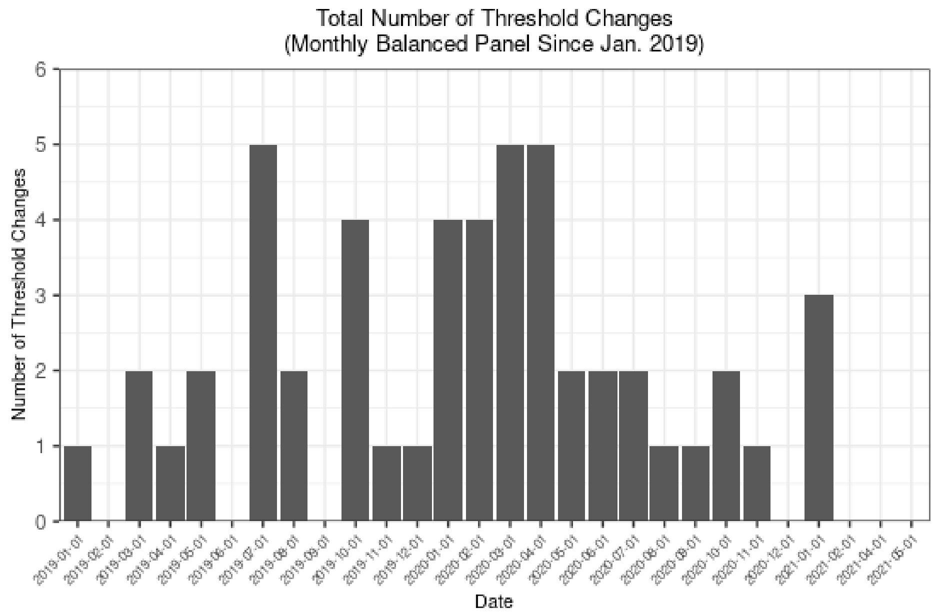
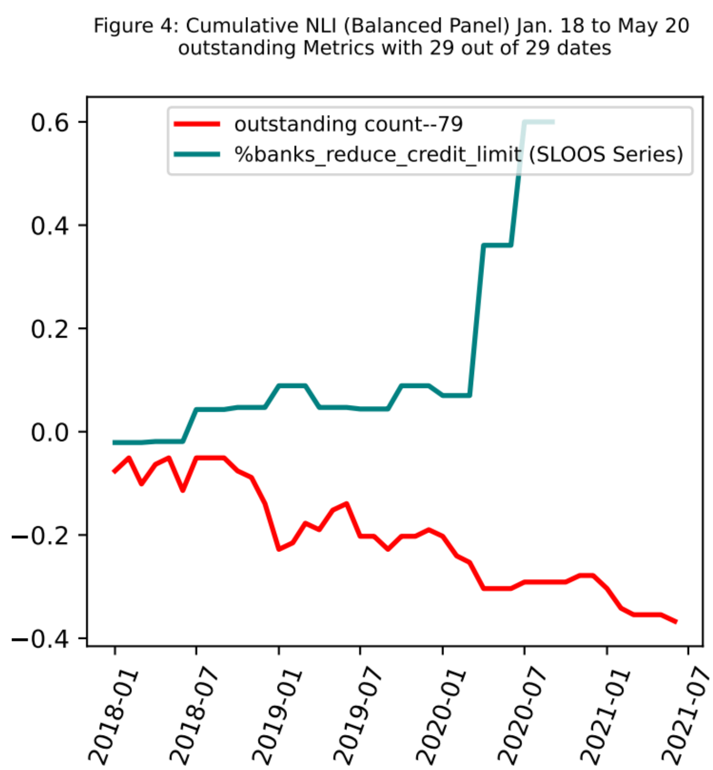


Figure 1: Illustrative Example of Amber/Red Threshold Limits. Data shown here as an example do not correspond to any actual risk metric or any threshold values for any firm in our sample.

Figure 2: Thresholds Changes

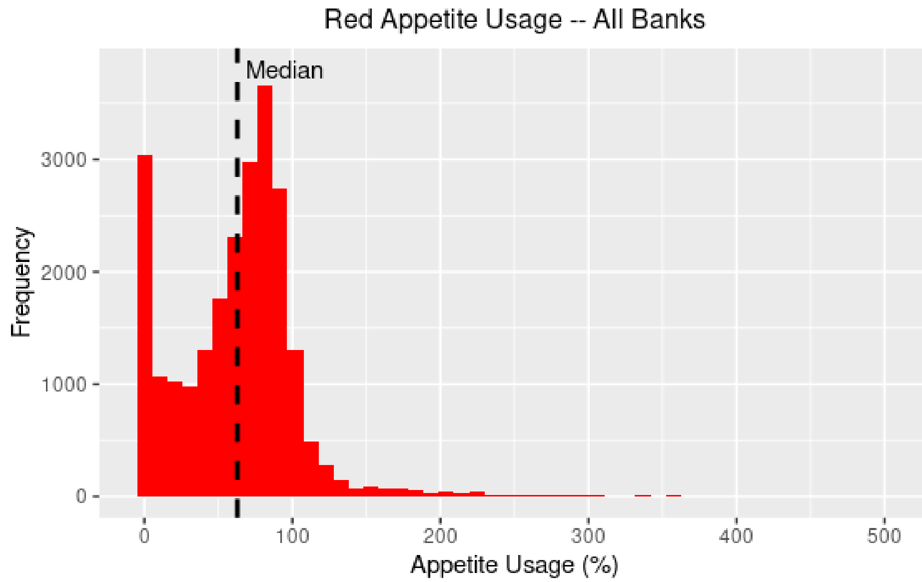


(a) Number of thresholds changes

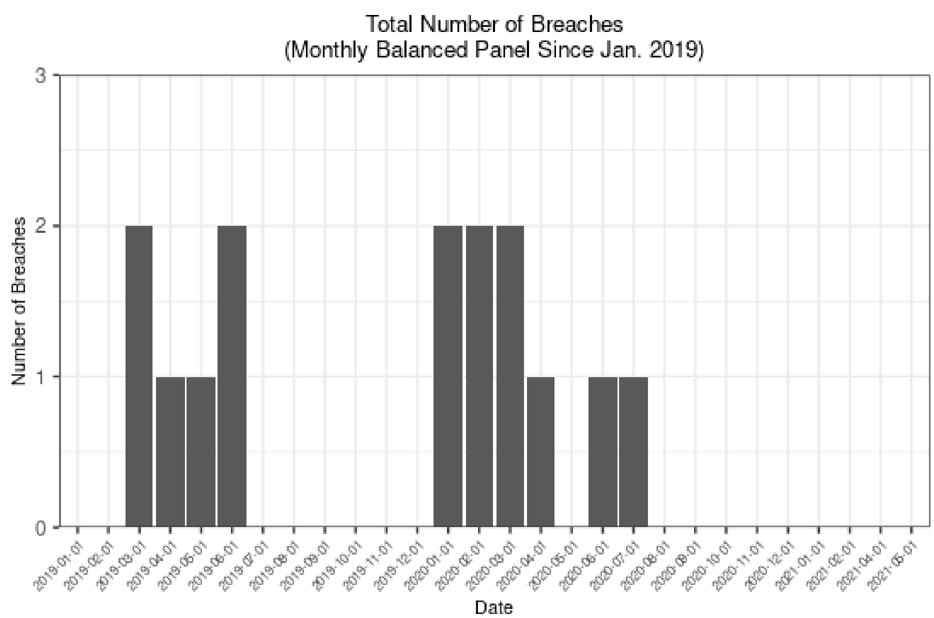


(b) Net Limit Indicator

Figure 3: Appetite and Breaches

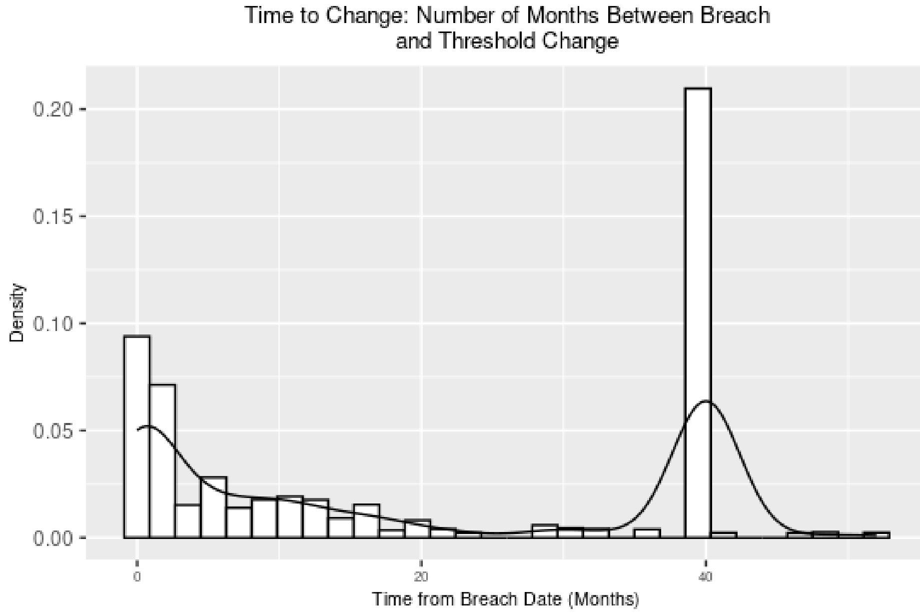


(a) Distribution of appetite usage

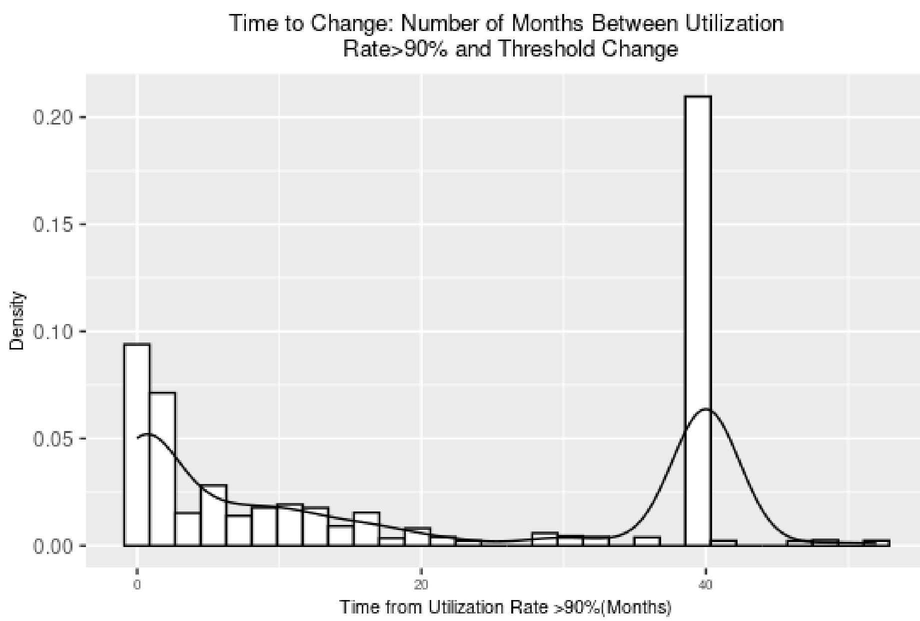


(b) Number of breaches

Figure 4: Time to Change



(a) After breaches



(b) When utilization reaches 90%

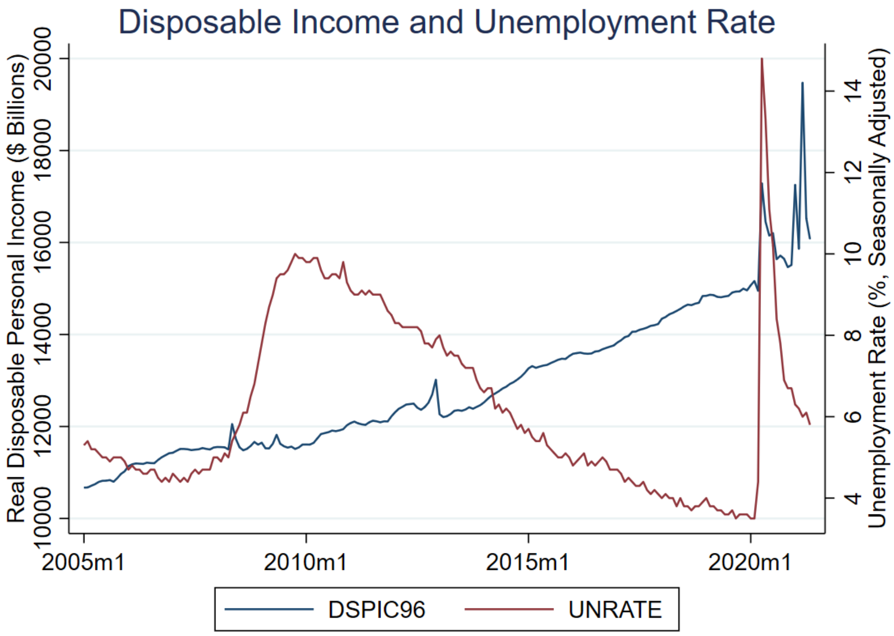


Figure 5: Disposable income and Unemployment Rate

Table 1: Descriptive Statistics – Pre-April 2020 Period

	Mean	Standard Deviation	5th percentile	95th percentile
Red Breach Indicator	0.071	0.258	0.000	1.000
Utilization Rate (Discretized)	2.076	1.339	1.000	5.000
Utilization Rate (Log)	4.047	0.971	2.303	4.739
Limit Increase Indicator	0.033	0.179	0.000	0.000
Limit Decrease Indicator	0.029	0.166	0.000	0.000
Sample size	21445			

Table 2: Descriptive Statistics – Post-April 2020 Period

	Mean	Standard Deviation	5th percentile	95th percentile
Red Breach Indicator	0.096	0.294	0.000	1.000
Utilization Rate (Discretized)	1.814	1.327	1.000	5.000
Utilization Rate (Log)	3.808	1.067	1.897	4.777
Limit Increase Indicator	0.050	0.218	0.000	0.000
Limit Decrease Indicator	0.051	0.220	0.000	1.000
Sample size	5829			

Table 3: The Effect of Limit Utilization on Threshold Changes

Dependent Variable: *Threshold Change (Indicator)*

	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_bucket = 2	0.0391***	0.0467***	-0.00897	0.0429***
	(0.00518)	(0.00547)	(0.0157)	(0.00550)
utilization_bucket = 3	0.0643***	0.0705***	0.0238	0.0665***
	(0.00514)	(0.00546)	(0.0150)	(0.00548)
utilization_bucket = 4	0.0949***	0.106***	0.0263	0.101***
	(0.00594)	(0.00627)	(0.0181)	(0.00629)
utilization_bucket = 5	0.0815***	0.0802***	0.0895***	0.0758***
	(0.00646)	(0.00707)	(0.0157)	(0.00710)
2.utilization_bucket#1.post_april				-0.0330**
				(0.0159)
3.utilization_bucket#1.post_april				-0.0171
				(0.0152)
4.utilization_bucket#1.post_april				-0.0514***
				(0.0183)
5.utilization_bucket#1.post_april				0.0325**
				(0.0165)
Constant	0.0318***	0.0253***	0.0606***	0.0316***
	(0.00233)	(0.00258)	(0.00529)	(0.00234)
Observations	19,325	16,180	3,145	19,325
R-squared	0.095	0.085	0.164	0.096
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 4: The Effect of Limit Utilization on Threshold Increases

	Dependent Variable: *Threshold Increase Indicator*			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_bucket = 2	0.0230***	0.0292***	-0.0139	0.0260***
	(0.00387)	(0.00408)	(0.0118)	(0.00410)
utilization_bucket = 3	0.0352***	0.0436***	-0.0252**	0.0403***
	(0.00387)	(0.00409)	(0.0116)	(0.00411)
utilization_bucket = 4	0.0674***	0.0782***	-0.00468	0.0738***
	(0.00449)	(0.00473)	(0.0138)	(0.00475)
utilization_bucket = 5	0.0643***	0.0651***	0.0612***	0.0615***
	(0.00484)	(0.00527)	(0.0119)	(0.00530)
2.utilization_bucket#1.post_april				-0.0224*
				(0.0118)
3.utilization_bucket#1.post_april				-0.0413***
				(0.0116)
4.utilization_bucket#1.post_april				-0.0562***
				(0.0138)
5.utilization_bucket#1.post_april				0.0169
				(0.0124)
Constant	0.0116***	0.00658***	0.0340***	0.0114***
	(0.00173)	(0.00191)	(0.00396)	(0.00173)
Observations	18,683	15,657	3,026	18,683
R-squared	0.063	0.058	0.117	0.064
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 5: The Effect of Limit Utilization on Threshold Decreases

Dependent Variable: *Threshold Decrease Indicator*

VARIABLES	(1) Whole Sample	(2) Pre-April 2020 Only	(3) Post-April 2020 Only	(4) Interaction with Post-April 2020
utilization_bucket = 2	0.0185***	0.0207***	5.02e-05	0.0196***
	(0.00398)	(0.00418)	(0.0125)	(0.00422)
utilization_bucket = 3	0.0348***	0.0337***	0.0400***	0.0325***
	(0.00397)	(0.00419)	(0.0119)	(0.00423)
utilization_bucket = 4	0.0368***	0.0390***	0.0286**	0.0367***
	(0.00466)	(0.00491)	(0.0145)	(0.00495)
utilization_bucket = 5	0.0272***	0.0244***	0.0394***	0.0235***
	(0.00504)	(0.00547)	(0.0128)	(0.00553)
2.utilization_bucket#1.post_april				-0.0137
				(0.0122)
3.utilization_bucket#1.post_april				0.0183
				(0.0117)
4.utilization_bucket#1.post_april				-0.00116
				(0.0142)
5.utilization_bucket#1.post_april				0.0209
				(0.0130)
Constant	0.0201***	0.0181***	0.0300***	0.0202***
	(0.00177)	(0.00195)	(0.00418)	(0.00178)
Observations	18,744	15,706	3,038	18,744
R-squared	0.055	0.049	0.094	0.056
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 6: The Effect of Limit Utilization on Red Breaches

		Dependent Variable: *Red Breach Indicator*		
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_bucket = 2	-0.00453	-0.00751	0.00579	-0.00683
	(0.00457)	(0.00486)	(0.0135)	(0.00484)
utilization_bucket = 3	0.0114**	0.00671	0.0345***	0.00737
	(0.00453)	(0.00484)	(0.0129)	(0.00482)
utilization_bucket = 4	0.0669***	0.0587***	0.125***	0.0592***
	(0.00524)	(0.00556)	(0.0156)	(0.00554)
utilization_bucket = 5	0.544***	0.530***	0.610***	0.530***
	(0.00569)	(0.00627)	(0.0135)	(0.00626)
2.utilization_bucket#1.post_april				0.00846
				(0.0140)
3.utilization_bucket#1.post_april				0.0246*
				(0.0134)
4.utilization_bucket#1.post_april				0.0616***
				(0.0161)
5.utilization_bucket#1.post_april				0.0753***
				(0.0145)
Constant	0.0165***	0.0180***	0.0127***	0.0171***
	(0.00206)	(0.00229)	(0.00457)	(0.00206)
Observations	19,322	16,177	3,145	19,322
R-squared	0.352	0.339	0.419	0.354
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 7: The Effect of Lagged Breaches on Threshold Changes

Dependent Variable: *Threshold Change Indicator*

	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
breach_l1 = 1	0.0690***	0.0588***	0.104***	0.0571***
	(0.00627)	(0.00690)	(0.0147)	(0.00697)
1.breach_l1#1.post_april				0.0610***
				(0.0157)
Constant	0.0539***	0.0524***	0.0618***	0.0538***
	(0.00159)	(0.00172)	(0.00406)	(0.00159)
Observations	21,841	18,199	3,642	21,841
R-squared	0.063	0.049	0.159	0.064
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 8: The Effect of Lagged Breaches on Threshold Changes – *continued*

	Dependent Variable: *Threshold Change Indicator*			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
breach_l1 = 1	0.0420***	0.0321***	0.104***	0.0305***
	(0.00968)	(0.0103)	(0.0280)	(0.0103)
1.breach_l1#1.post_april				0.0892***
				(0.0291)
breach_l2 = 1	0.0201**	0.0233**	-0.00849	0.0227**
	(0.00972)	(0.0103)	(0.0285)	(0.0104)
1.breach_l2#1.post_april				-0.0222
				(0.0296)
Constant	0.0553***	0.0537***	0.0664***	0.0552***
	(0.00172)	(0.00183)	(0.00487)	(0.00172)
Observations	18,963	16,484	2,479	18,963
R-squared	0.069	0.053	0.191	0.069
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Appendix

Table 9: Threshold Changes and Utilization Rate

Regressions for Threshold Changes and Utilization Rate (1-Month Lag and Log of Value)

	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_level	0.0237***	0.0215***	0.0343***	0.0206***
	(0.00198)	(0.00215)	(0.00504)	(0.00216)
1.post_april#c.utilization_level				0.0179***
				(0.00494)
Constant	-0.0264***	-0.0208**	-0.0479**	-0.0244***
	(0.00814)	(0.00893)	(0.0198)	(0.00815)
Observations	17,378	14,664	2,714	17,378
R-squared	0.086	0.072	0.164	0.087
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 10: Threshold Changes and Utilization Rate (Discretized) - Probit Model with FE

	Regressions for Threshold Changes (Probit Model)			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Red Threshold Change	Interaction with Post-April 2020
utilization_bucket = 2	0.195**	0.193**	0.0498	0.176*
	(0.0872)	(0.0936)	(0.418)	(0.0907)
utilization_bucket = 3	0.278***	0.213**	0.487	0.182*
	(0.0893)	(0.0988)	(0.406)	(0.0949)
utilization_bucket = 4	0.484***	0.434***	0.223	0.453***
	(0.0986)	(0.107)	(0.481)	(0.103)
utilization_bucket = 5	0.365***	0.307**	0.453	0.343***
	(0.109)	(0.123)	(0.384)	(0.119)
post_april = 1				0.0935
				(0.599)
2.utilization_bucket#1.post_april				0.0482
				(0.273)
3.utilization_bucket#1.post_april				0.676***
				(0.215)
4.utilization_bucket#1.post_april				0.126
				(0.245)
5.utilization_bucket#1.post_april				0.0436
				(0.271)
Observations	7,926	6,986	337	7,926
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 11: Breaches and Utilization Rate (Discretized) - Probit Model with FE

	Regressions for Breaches (Probit Model)			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Red Breach	Interaction with Post-April 2020
utilization_bucket = 2	-0.0129	-0.0671	0.0256	-0.0906
	(0.123)	(0.135)	(0.485)	(0.129)
utilization_bucket = 3	0.249**	0.171	0.351	0.144
	(0.101)	(0.112)	(0.375)	(0.107)
utilization_bucket = 4	0.558***	0.439***	0.744**	0.473***
	(0.0951)	(0.105)	(0.369)	(0.100)
utilization_bucket = 5	1.370***	1.226***	1.286***	1.320***
	(0.0806)	(0.0895)	(0.292)	(0.0867)
post_april = 1				-0.291
				(0.707)
2.utilization_bucket#1.post_april				0.294
				(0.359)
3.utilization_bucket#1.post_april				0.429
				(0.265)
4.utilization_bucket#1.post_april				0.496*
				(0.256)
5.utilization_bucket#1.post_april				-0.0491
				(0.234)
Observations	6,145	4,925	418	6,145
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 12: Threshold Changes and Utilization Rate (Discretized) - Logit Model with FE

Regressions for Threshold Changes (Logit Model)

	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_bucket = 2	0.374**	0.382**	0.0828	0.343**
	(0.167)	(0.180)	(0.728)	(0.175)
utilization_bucket = 3	0.571***	0.455**	0.747	0.397**
	(0.168)	(0.188)	(0.721)	(0.180)
utilization_bucket = 4	0.922***	0.840***	0.302	0.879***
	(0.185)	(0.203)	(0.856)	(0.194)
utilization_bucket = 5	0.669***	0.544**	0.715	0.647***
	(0.210)	(0.239)	(0.684)	(0.231)
post_april = 1				0.249
				(1.176)
2.utilization_bucket#1.post_april				0.0844
				(0.494)
3.utilization_bucket#1.post_april				1.117***
				(0.389)
4.utilization_bucket#1.post_april				0.101
				(0.445)
5.utilization_bucket#1.post_april				-0.0342
				(0.497)
Observations	7,926	6,986	337	7,926
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 13: Threshold Changes and Utilization Rate (Discretized) - Marginal Effects for FE Logit

Regression for Threshold Change (Logit FE) - Marginal Effects

	(1)	(2)
VARIABLES	0b.post_april	1.post_april
1bn.utilization_bucket		0.249
		(1.176)
2.utilization_bucket		0.334
		(1.236)
3.utilization_bucket		1.366
		(1.195)
4.utilization_bucket		0.350
		(1.207)
5.utilization_bucket		0.215
		(1.236)
Observations	7,926	7,926

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Breaches and Utilization Rate (Discretized) - Logit Model with FE

	Regressions for Breaches (Probit Model)			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Red Breach	Interaction with Post-April 2020
utilization_bucket = 2	-0.0129	-0.0671	0.0256	-0.0906
	(0.123)	(0.135)	(0.485)	(0.129)
utilization_bucket = 3	0.249**	0.171	0.351	0.144
	(0.101)	(0.112)	(0.375)	(0.107)
utilization_bucket = 4	0.558***	0.439***	0.744**	0.473***
	(0.0951)	(0.105)	(0.369)	(0.100)
utilization_bucket = 5	1.370***	1.226***	1.286***	1.320***
	(0.0806)	(0.0895)	(0.292)	(0.0867)
post_april = 1				-0.291
				(0.707)
2.utilization_bucket#1.post_april				0.294
				(0.359)
3.utilization_bucket#1.post_april				0.429
				(0.265)
4.utilization_bucket#1.post_april				0.496*
				(0.256)
5.utilization_bucket#1.post_april				-0.0491
				(0.234)
Observations	6,145	4,925	418	6,145
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table 15: Breach and Utilization Rate (Discretized) - Marginal Effects for FE Logit

Regression for Red Breach (Logit FE) - Marginal Effects		
	(1)	(2)
VARIABLES	0b.post_april	1.post_april
1bn.utilization_bucket		-0.651
		(1.341)
2.utilization_bucket		-0.460
		(1.418)
3.utilization_bucket		-0.0986
		(1.348)
4.utilization_bucket		0.274
		(1.342)
5.utilization_bucket		-1.271
		(1.315)
Observations	6,145	6,145

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Red Breaches and Utilization Rates (Level)

	Regressions for Breaches (LPM)			
	(1)	(2)	(3)	(4)
VARIABLES	Whole Sample	Pre-April 2020 Only	Post-April 2020 Only	Interaction with Post-April 2020
utilization_level	0.0636***	0.0612***	0.0787***	0.0616***
	(0.00210)	(0.00227)	(0.00548)	(0.00229)
1.post_april#c.utilization_level				0.0116**
				(0.00523)
Constant	-0.179***	-0.174***	-0.209***	-0.178***
	(0.00862)	(0.00943)	(0.0215)	(0.00864)
Observations	17,375	14,661	2,714	17,375
R-squared	0.068	0.063	0.094	0.068
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y