flex

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Financial health and liquidity smoothing

Evidence from a regression discontinuity design

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Summary of findings

This report studies whether gaining access to Flex's rent-splitting product improves or worsens downstream financial health for applicants near the underwriting margin. The central empirical advantage of the paper is that it does not rely on broad comparisons between very different renters. Instead, it compares applicants who are just above and just below Flex's approval thresholds, then traces how their credit bureau outcomes evolve over time. This study design makes the main results interpretable as causal effects of Flex for borderline applicants, while the broader full-distribution analyses help place those local effects in the context of the customer base.

At a high level, the findings are more consistent with modest benefit than with harm. The report does not show evidence that access to Flex systematically worsens financial outcomes for near-cutoff applicants on any measure. At the same time, the estimated benefits are generally modest. The right take-away is therefore a restrained one: access to Flex appears not to create broad downstream harm*, and it may produce modest but meaningful improvements on some of the margins most closely tied to short-run financial strain.

The main causal result is that approval for rent splitting does not appear harmful on average for borderline applicants. Across a large set of bureau outcomes, most intent-to-treat (ITT) estimates are close to zero, and the outcomes that do move tend to move in a favorable rather than unfavorable direction. The clearest causal improvements are in credit-seeking behavior and later-stage distress. Approved applicants have fewer inquiries, more days since last inquiry, lower 90+ DPD balances by later horizons, slightly less payday-like or nontraditional-credit use, and fewer total tradelines by the end of the post-application window. Those ITT results are substantively important even when the magnitudes are not large. In a setting where one might reasonably worry that added liquidity could worsen borrowing behavior or deepen financial fragility, the absence of broad harmful effects is itself informative. (See: ITT Estimation Approach: The effect of being approved for rent-splitting)

In addition to looking at a set of large outcomes, we also created composite outcomes that combine multiple outcomes into a single measure. The composite results reinforce the same message. The overall benefit index is modest, but later-horizon gains appear in payment-stress relief and costly-coping reduction, which is consistent with a small harm-reduction story rather than a large transformation in household balance sheets. The composite findings suggest that Flex's value is more likely to accumulate over the medium-run by easing short-run payment pressure rather than through large, immediate improvements in broad credit standing. That is conceptually consistent with the product's intended role as a liquidity-smoothing tool. (See: Composite Benefit Outcomes)

The usage-based instrumental variable (IV) results point in the same direction as the ITT estimates, but they do not overturn the magnitude story. Treatment-on-the-treated estimates suggest that actual early usage may produce somewhat larger gains on some margins, especially in payment-stress relief at later horizons, yet the overall pattern

remains modest rather than dramatic. That consistency between ITT and TOT matters. It suggests that the main findings are an artifact of diluted treatment assignment, while also clarifying that even among users the product does not appear to generate very large downstream effects across the full outcome set. (See: Usage, Early Usage IV: Extensive Margin, and Early Usage IV: Intensive Margin)

All of the analyses mentioned thus far have compared everyone with access to everyone without access, but we know there is a wide variety of situations present in Flex's customer base. To address this, we conducted a formal heterogeneity analysis. The formal heterogeneity analysis is cautious rather than decisive. The group averaged treatment effects (GATES) framework can successfully rank applicants by predicted gains using only pre-treatment information, but the realized effects do not line up cleanly across our data-driven group assignments. Thus we cannot yet claim to have identified a sharply defined "highest-benefit" segment using that method alone. Even so, the heterogeneity analysis is still useful because it shows that the average effect is not obviously hiding a simple, strong ordering of winners and losers. The evidence leaves open the possibility of meaningful heterogeneity, but it does not support a confident operational segmentation rule on its own. (See: Who Benefits Most?)

In addition to our GATES analysis, we also looked for applicant types using a segmentation approach. The pre-treatment credit-state segmentation shows that the borderline sample is financially fragile and internally diverse. Most applicants fall into either Severe derogatory history or Collections history, while smaller groups are Current but constrained or More stable borderline. These groups differ sharply in baseline utilization, credit scores, and prior distress. As one might expect, we also see the mix of segments change dramatically across risk profiles. (See: Pre-Treatment Credit States and A4.3 Pre-treatment Credit States Across the Risk Distribution)

Those credit states are more useful for interpretation than for changing the headline treatment story. They help clarify what kinds of households are applying to Flex and what forms of baseline strain they bring into the sample, but they do not overturn the main conclusion of modest average benefits and no clear evidence of broad harm. (See: Pre-Treatment Credit States and Dynamics Across Financial Health Categories)

The crowd-out results suggest that Flex is more likely to substitute for outside credit search than for large blocks of other debt. The clearest overall substitution signals are fewer credit inquiries and some reduction in nontraditional-credit trade use. By contrast, revolving balances, available revolving credit, and utilization are mostly inconclusive in the aggregate. That pattern is substantively plausible. A product designed to smooth rent timing would be expected to reduce the need to search for additional short-run credit or rely on certain costly alternatives before it would be expected to generate large immediate changes in broader debt stocks. (See: Is Flex Crowding Out Other Credit?)

The full-distribution analyses add important scope and context, but they are descriptive rather than causal. Across the risk distribution, the broader applicant pool is strongly stratified by financial health: higher-risk deciles have materially worse baseline profiles, and those differences are large even before any treatment enters the picture. (See: The Full Distribution and Descriptive Trajectories by Risk Decile)

The decile segmentation helps show where the near-cutoff RDD sample sits inside the broader credit-risk landscape. The appendix heatmaps make clear that severe derogatory history is concentrated in the higher-risk deciles, while the lower-risk deciles look substantially more stable. That matters because it reinforces that the main causal estimates are local effects for borderline applicants, not universal effects for the entire applicant pool. (See: The Full Distribution and Appendix A4.3 Pre-treatment credit states across the risk distribution)

The change-from-baseline tables by risk tier provide additional descriptive context. Higher-risk segments show larger post-application movement on many outcomes, but those movements should not be given a causal

interpretation because mean reversion, secular change, and selection into application are all likely at work. (See: Change from Baseline by Risk Tier)

The portfolio mix tells two complementary stories. Near the cutoff, approved and denied applicants have very similar baseline credit portfolios, which supports the credibility of the RDD comparison. Across the full risk distribution, however, portfolio composition varies substantially by Flex risk decile, indicating that different risk segments are not just more or less distressed versions of the same borrower type, but often have meaningfully different underlying credit profiles. That portfolio result is important for interpretation. The local identification works precisely because near-cutoff approved and denied applicants are so similar, but the broader descriptive analyses show that Flex is operating in a heterogeneous applicant population with systematic differences in credit composition across the risk distribution. (See: Baseline Credit Portfolio Mix, Appendix A4.1 Baseline portfolio mix by Flex risk decile, and Appendix A4.2 Change in portfolio mix by Flex risk decile)

An exploratory heterogeneity result in the appendix is also worth noting. A simple baseline strain split (segmenting by financial strain) produces a clearer pattern than the formal GATES exercise: applicants with higher pre-application strain show more positive composite effects than those with lower strain, especially for the overall index, credit standing, and credit slack. This pattern is potentially important because it suggests that the households under the greatest short-run pressure may benefit more from access to rent splitting. At the same time, it should be interpreted cautiously. Unlike the main RDD estimates, this split is best understood as exploratory evidence about where benefits may be concentrated, not as the paper's primary heterogeneity result. (See: Appendix A6.2 Strain-split benchmark)

A final point worth noting is on the validity of the study design itself. The approved and denied groups near the cutoff appear well balanced on observed pre-treatment outcomes and baseline portfolio composition. That does not prove the design, but it is a key reason the main causal interpretation is credible and why the null and near-null results should be taken seriously. (See: Was approval as-good-as-random? and Baseline Credit Portfolio Mix)

Taken together, these findings support a fairly disciplined conclusion. For financially precarious applicants near Flex's approval margin, access to rent splitting does not appear to generate broad downstream harm, and it may modestly reduce some of the most salient markers of short-run financial strain. The evidence is strongest for a small-benefit, no-obvious-harm interpretation, not for a large-treatment-effect interpretation.

Just as importantly, the broader descriptive sections show that these local causal estimates are being estimated inside a highly segmented applicant population. Risk deciles, credit states, and portfolio mix all point to meaningful baseline heterogeneity in the kinds of households who apply for Flex. That broader segmentation context should help readers understand both the practical importance and the natural limits of the paper's causal claims.

New questions raised by these results

This study was designed to help us get a lay of the land when it comes to Flex's customers and the effect of rent splitting on financial well-being. With these results in hand, we can start asking more targeted follow-up questions that may be worth pursuing as we build our knowledge base.

- Are the households with the largest potential gains the most distressed, or the ones that are constrained but still have enough slack to use the product effectively?
- Is the main value of rent splitting insurance rather than financing?
- What outcomes are missing from bureau data? If rent splitting mainly helps with overdrafts, utility shutoffs, late fees, missed essentials, or stress, then the current outcome set may understate the product's real value?
- Does rent-splitting need to be paired with other tools to generate more material effects? For example: bill smoothing beyond rent, behavioral interventions that incentivize saving, automated liquidity smoothing, etc.
- Are there meaningful dynamic effects beyond the current window?
- Should product expansion target adjacent frictions rather than more of the same? If rent splitting reduces search for outside credit but does not move debt stocks much, maybe the next step is solving paycheck timing, emergency expenses, or irregular bill spikes

1. Introduction

For many renters, the high cost of housing is compounded by the impact such a large expense has on liquidity. Almost one in four renters in the US (23.9%, as of 2023 U.S. Census Bureau (2025)) are severely rent burdened, meaning 50% or more of their income goes towards covering rent. Nearly half of renting households (46.3%) dedicate at least 30% of their income to rent. For many of these households, paying rent in full on the first of the month leaves little to no breathing room for other expenses that accrue before their next paycheck. Here, we use the term liquidity smoothing to refer to closing that timing gap: spreading expenses across time so they better align with income timing (Stephens Jr. 2002; Olafsson and Pagel 2018).

That timing mismatch matters because many households operate with very little cash buffer. Household finance research has shown that a large share of families are financially fragile, meaning they do not have enough readily available cash to absorb modest shocks or random fluctuations in expenses, even when they have income or assets on paper (Lusardi, Schneider, and Tufano 2011; Kaplan, Violante, and Weidner 2014). Administrative account data tell a similar story: many households do not maintain cash buffers large enough to comfortably cover ordinary swings in expenses and income (JPMorgan Chase Institute 2019).

When households cannot smooth rent payments, they still have to cope somehow. They may delay other bills, revolve credit card balances, overdraw a checking account, borrow from friends or family, or turn to higher-cost short-term products. In that sense, rent splitting sits in the same broad landscape as other products that households reach for when liquidity smoothing is a priority. These products include overdrafts, payday credit, buy now pay later (BNPL), and earned wage access, but the comparison between these products and Flex should not be pushed too far. Flex's rent splitting product is tied to a single high-salience fixed obligation, rent, and is better understood as a targeted liquidity tool than as a general-purpose way to finance discretionary spending (Consumer Financial Protection Bureau 2022, 2024).

This narrower use case is important for interpreting the use of rent splitting. Access to short-term liquidity can help households bridge a temporary mismatch and avoid more harmful forms of financial strain, but it can also make outcomes worse when the product is expensive, repeatedly rolled over, or used under sustained distress (Gross and Souleles 2002; Melzer 2011, 2018; Dobridge 2016). Related evidence from mortgage relief points in the same direction: easing pressure around a large recurring payment can improve balance sheets and reduce downstream distress (Keys et al. 2014; Lee and Maghzian 2023). For that reason, the right question is not whether short-term liquidity is always good or always bad. The right question is whether a particular product helps households manage timing risk without pushing them into a more precarious position later. Some of that value may come from the fit of the product to a particular household's situation, while other value might come from safeguards built into the product—e.g., not allowing customers to carry interest-accruing balances.

While Flex conceptually overlaps with other short term credit products, it also has an insurance-like dimension. Part of the value of gaining access to rent splitting through Flex may come from knowing that a buffer is available when rent and paycheck timing do not line up, even if the customer does not need to use it in every month. That feature matters for how we think about financial health effects. A product like this may improve outcomes not only by directly changing cash flow in the month it is used, but also by reducing the need to rely on costlier or less safe fallback strategies.

This paper studies those questions using a regression discontinuity design (RDD) centered on the approval rule for rent splitting. The design allows us to compare applicants who were just approved with applicants who were just denied, creating quasi-random variation in access near the approval cutoff. We use that variation to estimate how access to rent splitting affects a set of downstream measures of financial health, including credit scores, utilization, available revolving credit, delinquencies, collections, and other markers of payment stress. We also examine whether the effects of access are strongest for applicants who appear most liquidity constrained at baseline, since those are the households for whom a timing buffer should matter most as compared to those experiencing more persistent income shortages.

1.1 Benefits & Harm

When evaluating a credit product used by households living close to the margin, we first want to establish that the product isn't causing harm as measured by the objective financial state of households. Flex is most relevant when a household is already under pressure—rent is due, cash is tight, and the alternatives may include late payment fees, overdraft fees, carry credit card balances, or other expensive coping strategies with fewer safeguards than Flex. The hope is that access to formal credit with safeguards in place is a viable alternative to informal or riskier credit.

That perspective also matters for how to think about the research design. The RDD compares applicants who are all near the approval cutoff, which means the analysis is centered on people who are already close to the margin of eligibility, all of whom have signaled a need for liquidity smoothing by applying for access to Flex. In practical terms, our sample consisting of those at the margin of eligibility makes this an especially conservative test. If access to rent splitting helps avoid harm even in that narrow and financially precarious slice of the applicant pool, the result is meaningful. If it appears to worsen outcomes, that is equally important from a policy and consumer-protection standpoint. Either way, the core question is whether households in need of liquidity smoothing find themselves in a more or less stable financial position when they can split their rent across paychecks.

2. Data

2.1 Study population and decision environment

This study begins from Flex applications rather than from the renter population at large. The core analytic sample is restricted to renters who applied for access to Flex for the first time between February and October 2024 and were evaluated under a single underwriting policy. That policy assigns each applicant a continuous proprietary risk score between 0 and 1, then applies sharp approval cutoffs. Those approval rules create the local comparison that anchors our causal design, where applicants who are just barely below the cutoff are rejected, while those just above are approved.

Operationally, the main RDD sample is defined by a narrow bandwidth of 0.005 on either side of the underwriting cutoffs, leaving us with a total range of risk scores of 0.01 (1% of the range of risk scores). This bandwidth is quite narrow compared to typical data driven bandwidth selection, but we can afford to restrict variation in creditworthiness at the time of application because of the application volume. Even with these strict criteria, we identified 5,187 approvals and 4,432 rejections.[1] Together, treatment and control make up 1.7% of all applications during the study period.

2.2 Panel construction

We combine Flex application and decision data with de-identified credit bureau data and organize the result as an event-time panel. We are able to construct a balanced person-quarter panel starting in December 2023 and ending in September 2025. Because the bureau data are collapsed to quarter-end observation months, the event-time coding treats the application quarter itself as the time of treatment. That gives us a common application-quarter baseline and a common post-application window for tracing short- and medium-run effects.

Those observations matter for two reasons. First, the application-quarter baseline and earlier pre-application quarters, where available, let us test whether marginally approved and marginally rejected applicants were already moving along similar financial trajectories before outcomes could respond to access. Second, they give us baseline levels that can be differenced out when we estimate changes after application, which further increases estimation precision. Post-application observations then let us study how access to rent splitting changes financial outcomes over time rather than only at a single endpoint.

Finally, because Flex records data on a monthly rent payment calendar, we collapse our internal usage data to fit the person-quarter panel provided by the credit bureau. This will be relevant when we move beyond our intent to treat (ITT) framework to a treatment on the treated (TOT) framework that includes usage patterns. That said, our sampling was specifically targeting the ITT, which means mere approval is enough to place an applicant in the treatment condition. To understand why that matters, we can walk through the critical steps in the application process. New applicants go through a soft credit check in which a risk score is assigned, an underwriting decision is made based on that risk score, applicants are presented with an offer that includes a description of fees and credit line size, and finally the applicant can accept the offer or not. An applicants does not have to accept the offer or split their rent in order to be in treatment; what matters is whether they could get access, not whether they finished onboarding, used the product, and so on.

1. In our RDD sample, we see a 54% approval rate, as compared to an 87.5% approval rate among all applicants.

2.3 What the data measure

The current report studies several domains of financial health that correspond to face valid outcomes rent splitting could plausibly affect for households living close to the margin. Some domains capture broad financial position, such as credit score and available credit. Others capture specific coping strategies and signs of distress, such as delinquency, collections, credit-inquiries, and payday-like borrowing. The table below outlines the domains and variables we rely upon when modeling outcomes in our balanced panel.Who are Flex residents in affordable housing?

Table 1. Outcome domains in the analysis
Domains and variables drawn from the same outcome list used in the balance checks and primary models

Domain	What This Domain Captures	# Outcomes	Key Variables
Auto & durable goods	Exposure to auto credit, which can reflect both durable-goods access and debt burden	2	Open auto trades; Any open auto
Collections & charge-off	Deeper downstream distress after payment problems have already occurred	3	Collections count; Charge-off count; Charge-off balance
Core baseline health	Broad measures of credit standing and economic capacity	4	VantageScore 4.0; Clarity Early Risk; Net income (3m); Net income (6m)
Credit access & capacity	How much formal borrowing room a household has when cash is tight	2	Revolving limit; Revolving available credit
Credit seeking & new credit	Signals that households are searching for or opening outside credit	4	Credit inquiries in past 3 months; Days since inquiry; Trades reported in past 3 months; Months since newest trade opened
Credit usage & utilization	How intensively existing credit is being used and how heavy monthly obligations look	4	Revolving utilization %; Overall utilization %; Total monthly payment; Utilization (derived)
Debt & balances	Outstanding debt stocks across major product categories	5	Total balance (open); Revolving balance; Installment balance; Auto balance; Collections balance
Delinquency & payment distress	Missed-payment flows and the buildup of payment stress	6	Trades 60+ DPD; Trades 90+ DPD; 60+ day delinquencies (3m); 90+ day delinquencies (3m); Balance 60+ DPD; Balance 90+ DPD
Identity & stability	Residential and employment stability proxies	2	Months at address; Months at employer
Payday-like / alternative finance	Use of nontraditional short-term credit and distress within those products	5	Storefront installment trades (3m); Storefront installment past due ($); Storefront single-pay trades (3m); Single-pay past due ($); Any payday-like nontraditional trade
Portfolio structure	The size, maturity, and shape of the credit file	3	Total trades (excl collections); Open trades; File age (months)
Public records	Rare but severe forms of legal or catastrophic financial distress	3	Bankruptcies (count); Judgments (count); Tax liens (count)

2.4 Core and auxiliary samples

The causal analyses reported here focus on applicants inside the local bandwidth around the approval cutoff. That is the sample for which the identifying assumptions are strongest, and it is why the design should be read as a conservative test centered on financially precarious applicants near the margin of approval. However, we also retain broader descriptive samples that span the full range of risk scores because they help place the local estimates in context. Those auxiliary samples are useful for description and follow-on analysis, but they do not carry the same identification strength as the near-cutoff RDD sample.

Table 2. Analytic sample profile
Counts are measured in the application quarter

Sample	Use in Analyses	Applicants	Approved	Rejected	Approval Rate	Cohort Window
Quarterly event-time sample	All applicants retained in the event-time panel	15,205	10,046	5,159	66.1%	Feb 2024–Oct 2024
RDD local bandwidth sample	Near-cutoff sample used for the main causal estimates	9,613	5,456	4,157	56.8%	Feb 2024–Oct 2024
Full-distribution sample	Broader applicant sample used for descriptive risk-distribution analyses	4,997	4,004	993	80.1%	Feb 2024–Oct 2024

2.4.1 Was approval as-good-as-random?

The credibility of the RDD rests on a simple idea: applicants just above and just below the approval cutoff should look very similar before the underwriting decision. Because we observe applicants in the application quarter itself and, for most cohorts, in earlier quarters as well, we can check that directly on the financial outcomes we care about rather than relying only on generic background covariates.

The balance table shows broad similarity across nearly all metrics: a few scattered differences clear conventional significance thresholds, but none do so at the 1 percent level and there is no coherent pattern of imbalance across domains. The accompanying plot focuses on the largest standardized differences within each domain, and even those are generally well inside the usual 0.1 SD benchmark. Taken together, these diagnostics are what we would hope to see if approval near the cutoff was effectively as-good-as-random.

Table 3. Pre-treatment balance: Nominated outcomes
Approved vs Rejected • 43 outcomes across 12 domains

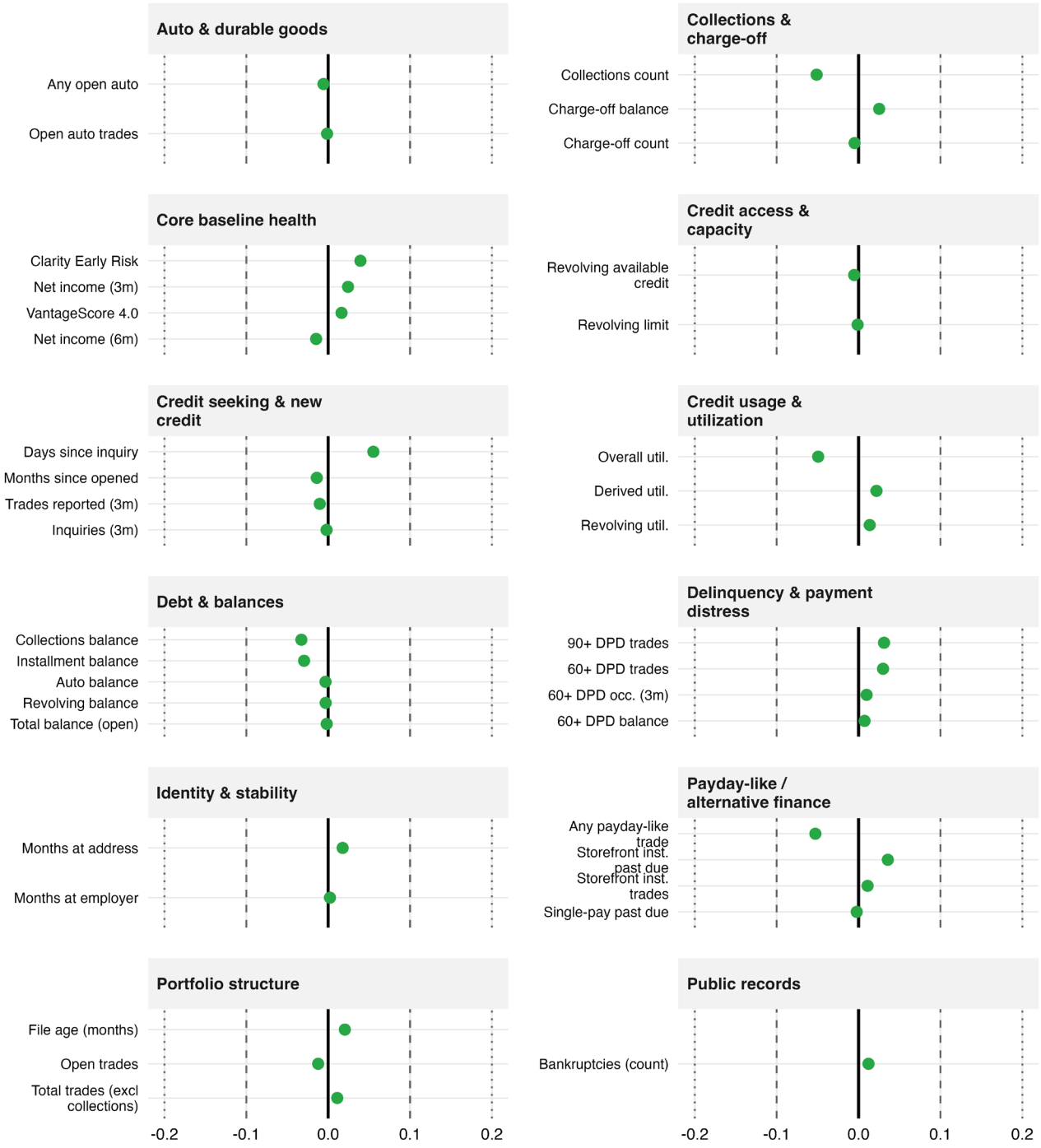
Outcome	Control[1]	Treatment	Difference[2]	p-value[3]
Auto & durable goods				
Any open auto	0.31 (0.46)	0.31 (0.46)	-0.00 (0.01)	0.805
Open auto trades	0.22 (0.43)	0.22 (0.44)	-0.00 (0.01)	0.949
Collections & charge-off				
Collections count	2.26 (2.26)	2.14 (2.29)	-0.12 (0.05)**	0.015
Charge-off balance	3438.69 (7235.32)	3625.57 (7613.14)	186.88 (156.63)	0.233
Charge-off count	1.53 (1.77)	1.52 (1.81)	-0.01 (0.04)	0.819
Core baseline health				
Clarity Early Risk	528.70 (43.62)	530.42 (43.92)	1.72 (0.98)*	0.078
Net income (3m)	3722.29 (2542.88)	3788.71 (2926.25)	66.42 (95.05)	0.485
VantageScore 4.0	546.40 (55.29)	547.31 (56.03)	0.91 (1.18)	0.442
Net income (6m)	3787.55 (3167.01)	3744.37 (2682.04)	-43.18 (89.80)	0.631
Credit access & capacity				
Revolving available credit	553.97 (2998.46)	536.92 (3314.25)	-17.05 (66.43)	0.797
Revolving limit	922.42 (3791.21)	917.73 (4414.61)	-4.69 (86.19)	0.957

Outcome	Control[1]	Treatment	Difference[2]	p-value[3]
Credit seeking & new credit				
Days since inquiry	201.75 (241.84)	215.54 (257.51)	13.79 (5.66)**	0.015
Months since opened	15.02 (18.92)	14.76 (18.38)	-0.26 (0.40)	0.520
Trades reported (3m)	4.27 (4.24)	4.22 (4.03)	-0.04 (0.09)	0.628
Inquiries (3m)	3.56 (8.32)	3.54 (7.98)	-0.02 (0.18)	0.930
Credit usage & utilization				
Overall utilization %	76.29 (39.83)	74.26 (42.67)	-2.04 (1.01)**	0.044
Utilization (derived)	89.72 (43.87)	90.76 (51.21)	1.04 (2.05)	0.611
Revolving utilization %	66.41 (50.74)	67.14 (56.18)	0.73 (1.90)	0.701
Total monthly payment	334.24 (644.88)	335.95 (783.52)	1.71 (14.99)	0.909
Debt & balances				
Collections balance	2733.09 (4194.83)	2596.48 (4159.19)	-136.61 (88.45)	0.122
Installment balance	11403.93 (20905.00)	10805.18 (19779.04)	-598.75 (432.26)	0.166
Auto balance	5806.28 (10595.63)	5771.22 (10906.60)	-35.05 (227.10)	0.877
Revolving balance	395.04 (1777.75)	388.90 (2229.61)	-6.14 (42.03)	0.884
Total balance (open)	13139.72 (26800.66)	13086.97 (32875.83)	-52.74 (626.03)	0.933
Delinquency & payment distress				
No. trades 90+ DPD	0.54 (1.09)	0.58 (1.16)	0.03 (0.02)	0.160
No. trades 60+ DPD	0.55 (1.10)	0.58 (1.17)	0.03 (0.03)	0.177
60+ DPD occurrences (3m)	0.12 (0.94)	0.13 (0.89)	0.01 (0.02)	0.659
60+ DPD balance	2770.75 (10055.01)	2855.00 (12601.53)	84.25 (237.61)	0.723
90+ DPD occurrences (3m)	0.10 (0.92)	0.11 (0.82)	0.00 (0.02)	0.863
90+ DPD balance	2182.08 (9350.00)	2194.58 (10689.50)	12.51 (210.60)	0.953
Identity & stability				
Months at address	36.80 (45.60)	37.64 (48.70)	0.83 (1.12)	0.458
Months at employer	33.66 (43.02)	33.75 (40.48)	0.09 (1.01)	0.927
Payday-like / alternative finance				
Any payday-like/nontraditional trade	0.85 (0.36)	0.83 (0.37)	-0.02 (0.01)**	0.012
Storefront installment past due ($)	15.59 (132.15)	21.68 (201.67)	6.09 (3.69)*	0.099
Storefront installment trades (3m)	0.01 (0.09)	0.01 (0.09)	0.00 (0.00)	0.620
Single-pay past due ($)	1.97 (29.88)	1.90 (33.09)	-0.07 (0.70)	0.920
Storefront single-pay trades (3m)	0.01 (0.21)	0.01 (0.23)	-0.00 (0.00)	0.962
Portfolio structure				
File age (months)	84.95 (60.59)	86.21 (63.20)	1.26 (1.33)	0.343
Open trades	2.93 (3.67)	2.88 (3.51)	-0.04 (0.08)	0.565
Total trades (excl collections)	9.02 (8.34)	9.12 (8.35)	0.09 (0.18)	0.601
Public records				
Bankruptcies (count)	0.06 (0.28)	0.06 (0.29)	0.00 (0.01)	0.565
Judgments (count)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	NA
Tax liens (count)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	NA

[1]Mean shown with SD in parentheses. [2]Difference = Treatment mean − Control mean, with SE in parentheses. *** p<0.01, ** p<0.05, * p<0.10. [3]p-values: two-sided t-test (continuous) or chi-squared test (binary).

Largest pre-treatment imbalances by domain

Within each domain, the figure shows the most imbalanced outcomes, up to six per domain.



Dashed lines mark +/-0.1 SD and dotted lines mark +/-0.2 SD. Balance is evaluated on raw, untransformed variables.

2.4.2 Baseline credit portfolio mix

Outcome-level balance is reassuring (and expected given how we generate our treatment and control groups), but examining the state of applicants' credit portfolios when they apply for Flex provides additional insight. Here again the pattern is one of close overlap: marginally approved and marginally rejected applicants enter the application process with very similar mixes of revolving, installment, mortgage, and nontraditional credit exposure. Of course, we should expect these two groups to have very similar credit portfolios, but we'll see later that as we move across the applicant risk distribution, credit mixes and balances differ dramatically across applicant risk levels.

Table 4. Baseline Portfolio Mix by Treatment Group

Approved vs Rejected in the application quarter • 'All trades' denominator

Group	N	Balance Share	[1]SD	Count Share	SD	Mean Balance	Mean Count
Auto							
Rejected	3,771	36.7%	0.443	17.5%	0.222	6,106	1.1
Approved	4,950	36.1%	0.444	17.4%	0.216	6,067	1.2
Collections							
Rejected	3,771	13.2%	0.305	40.3%	0.293	401	3.6
Approved	4,950	14.5%	0.318	39.8%	0.292	376	3.5
HELOC							
Rejected	3,771	0.0%	0.000	0.3%	0.024	0	0.0
Approved	4,950	0.0%	0.006	0.4%	0.034	27	0.0
Installment/Personal							
Rejected	3,771	4.3%	0.174	10.5%	0.186	197	1.1
Approved	4,950	5.0%	0.192	11.0%	0.191	216	1.2
Mortgage							
Rejected	3,771	0.9%	0.087	0.5%	0.034	1,211	0.0
Approved	4,950	1.0%	0.095	0.6%	0.039	1,816	0.1
Payday-like (Clarity)							
Rejected	3,771	3.6%	0.163	1.2%	0.055	94	0.1
Approved	4,950	3.2%	0.153	1.1%	0.049	90	0.1
Revolving							
Rejected	3,771	17.2%	0.342	29.7%	0.271	373	1.9
Approved	4,950	18.1%	0.350	29.6%	0.269	349	1.9
Student							
Rejected	3,771	24.4%	0.394	0.2%	0.021	5,424	0.0
Approved	4,950	22.2%	0.386	0.2%	0.028	4,822	0.0

[1]Shares = product family balance/count ÷ combined total (Premier all trades + payday-like). Payday-like uses Clarity total balance on open non-traditional trades (clntr5020) and open non-traditional trades (satisfactory + delinquent) reported in last 3 months (clntr2005 + clntr2105).

3. Results

This section focuses on the primary empirics in this study. We begin with the ITT estimates identified by the RDD and event-study design, then turn to usage-based TOT analyses and the full distribution to place those local effects in broader context. More exploratory and supporting analyses are collected in the extensive appendix.

3.1 ITT estimation approach: the effect of being approved for rent-splitting

This study was designed with a specific estimand—where an estimand is the causal quantity of interest—in mind: the effect of gaining access to rent splitting. We estimate this ITT effect by combining the strengths of RDDs and staggered difference-in-differences (henceforth DiD). Specifically, the RDD creates our as-if random assignment using Flex's underwriting policy cutoffs at the time of application. Because we are looking at marginally approved/rejected applicants across nine months, we effectively have a staggered roll-out with monthly cohorts, which is how the DiD framework enters the picture. We want our estimation approach to use the quasi-random assignment afforded by the RDD to create groups of treated and untreated individuals such that we can recover the effect of access to Flex within-cohorts across time.

The main wrinkle in this setup is that we have quarterly outcome data and monthly cohorts. Thus, we use the Sun-Abraham estimator to get event study dynamics and include application month fixed effects to ensure we are comparing applicants from the same month. In the event-time coding used here, the baseline is the application quarter and the first post-treatment period is the first full quarter after application, so the omitted reference period is the application-quarter baseline.[2]

Table 5. Intent-to-Treat Estimates by Horizon
Event study coefficients from sunab() specification

Outcome	h=0	h=1	h=2	h=3	h=4
Auto & durable goods					
Any open auto	0.00 (0.00)	0.00 (0.01)	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
Open auto trades	-0.00 (0.00)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.02 (0.01)
Collections & charge-off					
Charge-off balance	3.2% (2.8%)	1.9% (4.2%)	3.7% (5.2%)	3.2% (6.2%)	-10.1% (8.1%)
Charge-off count	0.00 (0.01)	-0.01 (0.01)	0.00 (0.02)	0.01 (0.02)	-0.02 (0.03)
Collections count	0.00 (0.01)	0.03 (0.02)	0.05* (0.03)	0.04 (0.03)	0.08* (0.04)
Core baseline health					
Clarity Early Risk	-0.67 (0.57)	-0.18 (0.78)	0.82 (0.92)	0.64 (1.04)	0.76 (1.33)
Net income (3m)	4.86 (49.56)	8.36 (59.30)	32.00 (62.86)	68.55 (69.42)	32.16 (94.02)
Net income (6m)	47.48 (29.72)	16.69 (45.93)	24.76 (51.69)	23.66 (58.17)	1.10 (76.35)
VantageScore 4.0	-0.43 (0.62)	-0.18 (0.86)	0.53 (1.02)	0.47 (1.16)	0.98 (1.48)
Credit access & capacity					
Revolving available credit	-19.20* (11.09)	-34.01** (15.46)	-22.65 (20.37)	-18.18 (24.02)	5.89 (32.20)
Revolving limit	-31.86** (15.35)	-43.17* (22.50)	-43.47 (29.56)	-37.26 (35.06)	1.51 (46.46)

2. We estimate intent-to-treat effects with a Sun-Abraham event-study specification, Yit=i+t+ci+l≠-1lSAitl+it, where Yit is the outcome for applicant i in quarter t, i are applicant fixed effects, t are calendar-quarter fixed effects, ci are application-month fixed effects, and SAitl denotes the Sun-Abraham event-time indicators. Coefficients are interpreted relative to the omitted reference period, which in the main specification is the application-quarter bureau snapshot. Standard errors are clustered at the applicant level.

Outcome	h=0	h=1	h=2	h=3	h=4
Credit seeking & new credit					
Days since inquiry	9.94*** (2.68)	14.00*** (3.99)	11.80** (4.92)	15.33*** (5.82)	22.22*** (7.77)
Inquiries (3m)	-0.27*** (0.10)	-0.43*** (0.12)	-0.51*** (0.13)	-0.29** (0.14)	-0.41** (0.18)
Months since opened	-0.23 (0.16)	-0.21 (0.21)	-0.15 (0.26)	-0.33 (0.30)	-0.17 (0.40)
Trades reported (3m)	-0.07** (0.04)	-0.04 (0.05)	-0.03 (0.05)	-0.03 (0.06)	-0.13 (0.08)
Credit usage & utilization					
Overall utilization (pp)	0.59 (0.57)	0.30 (0.73)	0.70 (0.83)	0.55 (0.95)	0.78 (1.26)
Revolving utilization (pp)	1.69* (1.02)	0.78 (1.37)	-1.61 (1.58)	-0.76 (1.80)	-1.24 (2.36)
Total monthly payment	0.51 (4.67)	5.74 (6.14)	3.16 (7.02)	6.69 (8.08)	2.39 (10.63)
Utilization, derived (pp)	2.18* (1.32)	-0.54 (1.67)	-3.03 (1.93)	-4.33** (2.18)	-2.71 (2.88)
Debt & balances					
Auto balance	3.2% (3.5%)	3.3% (5.3%)	1.0% (6.6%)	-5.2% (7.9%)	3.2% (10.6%)
Collections balance	1.2% (3.1%)	9.6%** (4.4%)	9.8%* (5.2%)	10.0% (6.2%)	9.6% (8.0%)
Installment balance	-4.0% (4.7%)	-5.1% (6.5%)	-4.6% (7.7%)	-4.0% (8.8%)	-0.6% (11.7%)
Revolving balance	-0.0% (3.0%)	2.0% (4.3%)	-1.5% (5.2%)	2.9% (6.1%)	2.0% (7.9%)
Total balance (open)	-1.8% (4.4%)	-0.0% (5.9%)	-1.2% (7.1%)	-3.6% (8.1%)	-9.5% (10.7%)
Delinquency & payment distress					
60+ DPD balance	0.9% (5.2%)	1.7% (7.3%)	-3.6% (8.7%)	-8.8% (9.8%)	-22.2%* (12.4%)
60+ DPD occurrences (3m)	0.01 (0.01)	0.01 (0.01)	-0.00 (0.01)	-0.02 (0.01)	-0.02 (0.02)
90+ DPD balance	-4.1% (5.0%)	0.2% (7.2%)	-5.4% (8.6%)	-9.8% (9.6%)	-25.0%** (12.1%)
90+ DPD occurrences (3m)	0.00 (0.00)	0.00 (0.01)	-0.00 (0.01)	-0.02* (0.01)	-0.02** (0.01)
No. trades 60+ DPD	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	-0.00 (0.02)
No. trades 90+ DPD	0.00 (0.00)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	-0.01 (0.02)
Identity & stability					
Months at address	0.28 (0.46)	0.61 (0.59)	0.97 (0.68)	0.80 (0.79)	0.70 (1.02)
Months at employer	0.42 (0.44)	0.91 (0.57)	1.23* (0.65)	1.55** (0.75)	0.22 (0.96)
Payday-like / alternative finance					
Any payday-like/nontraditional trade	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.01* (0.01)
Storefront installment past due ($)	-0.2% (0.6%)	-0.9% (0.8%)	-0.6% (1.1%)	-1.1% (1.2%)	-1.2% (1.6%)
Portfolio structure					
File age (months)	0.10 (0.15)	0.07 (0.25)	0.00 (0.34)	-0.22 (0.43)	-0.42 (0.58)
Open trades	-0.07* (0.03)	-0.04 (0.05)	-0.04 (0.05)	-0.02 (0.06)	-0.12 (0.08)
Total trades (excl collections)	0.00 (0.02)	-0.01 (0.03)	-0.03 (0.04)	-0.07 (0.05)	-0.17** (0.07)
Public records					
Bankruptcies (count)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)

Percent changes (%) shown for log-transformed outcomes (balances); percentage point changes (pp) for utilization measures; coefficients in original units otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Above we show how outcomes (each row; grouped by domain) across our domains evolve over time (each column is one quarter) beginning with the first full quarter after application (h=0) and extending to four quarters post application (h=4). The values are the difference between treatment and control, such that positive values mean treatment had a larger value than control. The first thing to notice is that most outcomes show no material difference between treatment and control over any of the five quarters. Second, all of these estimates are very precise as a result of our large sample and fixed effects estimation approach. By partially out idiosyncratic person-level differences, we are able to get extremely precise estimates of differences between treatment and control over time. Similarly, our precise estimates make null results quite informative, as we're often powered to detect effects that are small enough that any meaningful effect would have been picked up if it was there.

Finally, there is a clear pattern to the outcomes that do show significant effects over time. Those who gained access to Flex had more days since their last inquiry, fewer inquiries overall, fewer trades 90 days past due (DPD) and smaller balances 60/90 DPD, fewer total tradelines, and marginally less usage of payday loans. These effects

paint a picture of financially distressed households who are able to rely on splitting their rent through Flex and see the benefits of access accumulate over the subsequent quarters. Critically, we don't see any evidence that having access to Flex is deleterious on any outcome we measured.[3]

4. Composite benefit outcomes

The table we just examined is a granular view of outcomes that revealed access to rent splitting through Flex doesn't create harm and has a handful of small benefits over time. The next set of analyses builds a small group of composite measures that pool related outcomes into intuitive categories. The composites are oriented so that higher values always mean better financial health or less harm. This makes them easier to read as summary measures of whether access to Flex leaves borderline applicants in a more stable position.

The overall summary index is intentionally narrow. It averages three core families: payment stress, credit slack, and credit standing, and leaves nontraditional-credit outcomes as a separate secondary family. That choice is deliberate as the first three families map directly to the main harm-reduction question, while costly coping is better read as a substitution channel that may behave differently from the core bureau-based outcomes.

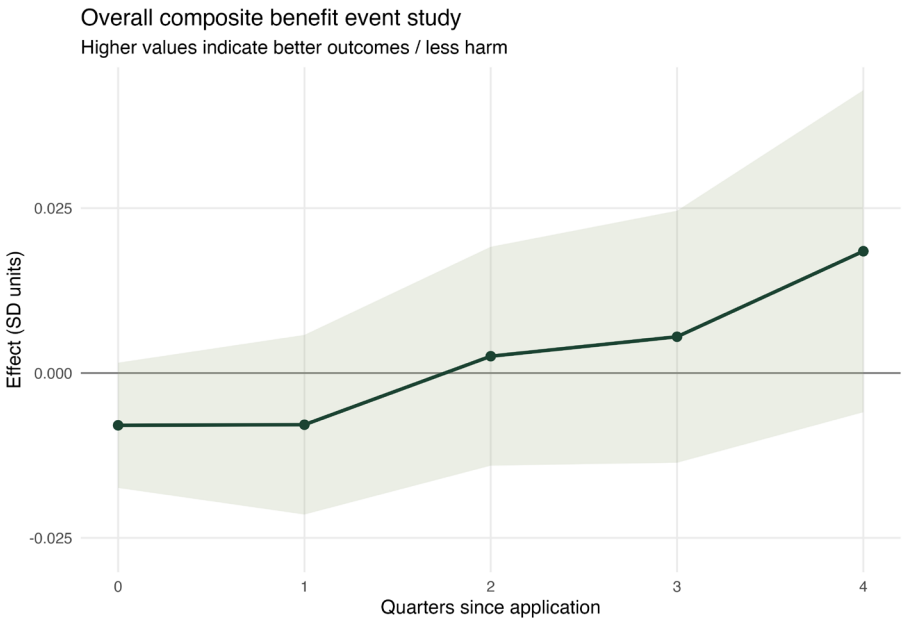
Again, we see no evidence of harm to those who gained access to Flex, some small benefits that manifest by the end of our study period, and positive trends across the board.

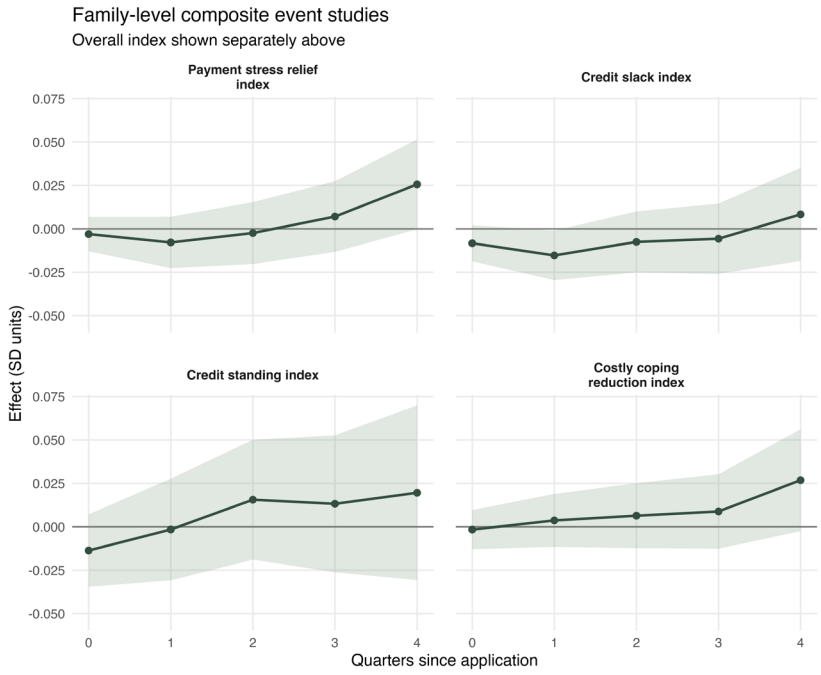
Table 6. Composite benefit outcomes by horizon
Higher values indicate better financial health / less harm

Composite	h=0	h=1	h=2	h=3	h=4
Overall financial health benefit index	-0.008 (0.005)	-0.008 (0.007)	0.003 (0.008)	0.005 (0.010)	0.018 (0.012)
Payment stress relief index	-0.003 (0.005)	-0.008 (0.008)	-0.002 (0.009)	0.007 (0.010)	0.026* (0.013)
Credit slack index	-0.008 (0.005)	-0.015** (0.007)	-0.008 (0.009)	-0.006 (0.010)	0.008 (0.014)
Credit standing index	-0.014 (0.011)	-0.002 (0.015)	0.016 (0.018)	0.013 (0.020)	0.020 (0.026)
Costly coping reduction index	-0.002 (0.006)	0.004 (0.008)	0.006 (0.010)	0.009 (0.011)	0.027* (0.015)

Indices are standardized to the application-quarter baseline. Estimates are in SD units; standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

3. Evidence statement based on this study's sample and methods. The study did not detect statistically significant adverse average effects on the measured outcomes during the observation period. Results are estimated for applicants near the underwriting cutoff and may not generalize beyond this group. Individual experiences may vary.





4.1 Who benefits most?

The RDD estimates tell us the average effect of approval for applicants near the underwriting cutoff. The next question is whether that local average masks meaningfully different treatment responses across otherwise similar borderline applicants.

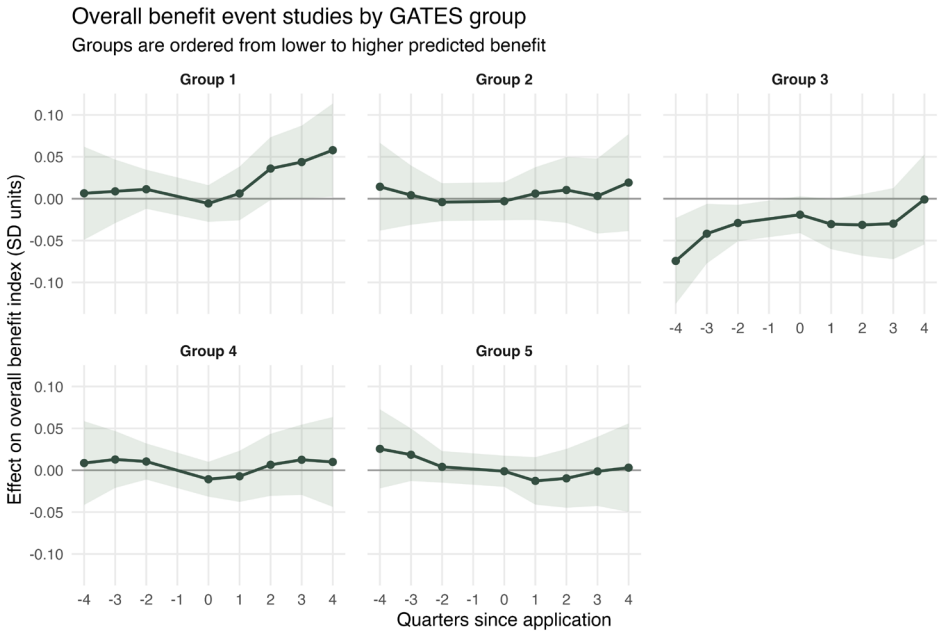
We study that question with a principled group average treatment effects (GATES) approach. In plain terms, we use

only information observed by the time of application to sort applicants into groups with lower and higher predicted benefit, then estimate the treatment effect within those ranked groups. The ranking combines local design variables with credit measures observed in the quarter of application and older trended credit histories from earlier quarters. Appendix A6.1 describes that setup and its diagnostics in more detail.

Table 9. Overall benefit effects by GATES group
Estimated effects within five groups ranked from lower to higher predicted benefit

Predicted-benefit group	Applicants	Approval rate	Mean predicted gain	Overall benefit ATT
Group 1	1,819	56.5%	-0.015	0.025 (0.016)
Group 2	1,819	56.8%	-0.007	0.007 (0.016)
Group 3	1,819	56.8%	-0.003	-0.022 (0.016)
Group 4	1,819	57.7%	0.000	0.000 (0.015)
Group 5	1,819	55.9%	0.009	-0.005 (0.015)

Entries are average post-application effects in SD units, with standard errors in parentheses.



The GATES results are cautious. The ranking does separate applicants by predicted gains, but the estimated treatment effects do not line up in a clear monotone ladder across groups. The safest reading is therefore limited: there may be some heterogeneity in who benefits from access, but the data do not support a strong, stable ordering of beneficiaries. Appendix A6.1 reports the method and diagnostics in more detail, while Appendix A6.2 and Appendix A6.3 report more exploratory subgroup analyses.

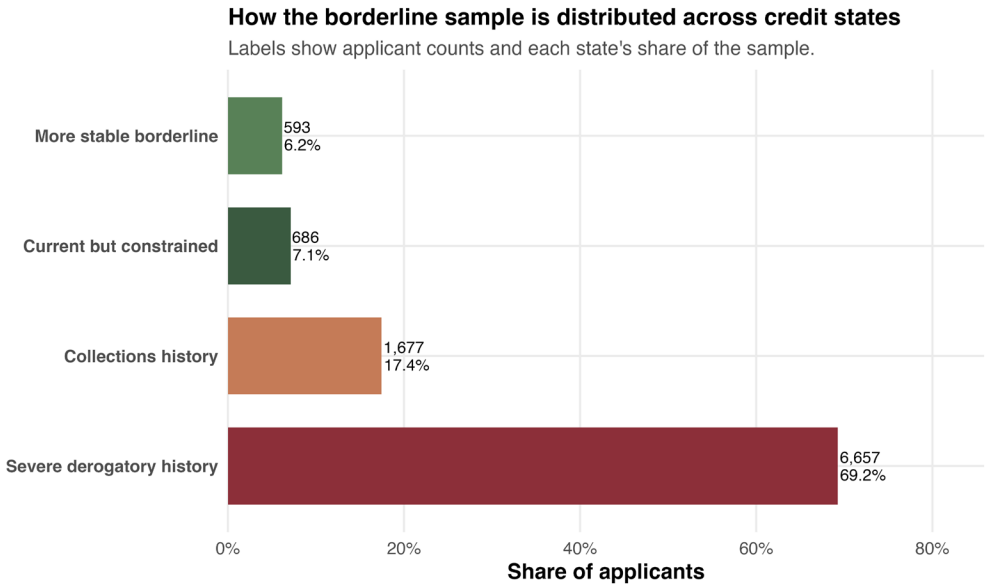
4.2 Pre-treatment credit states

The baseline strain split is useful, but it collapses many different kinds of financial fragility into a single dimension. The next step uses up to four quarters leading into and including the application quarter to assign each applicant to a more interpretable credit state. The goal is to distinguish people who already show severe derogatory history from those who are current but tight, or those who have collections history without yet showing the most severe forms of distress.

For the nontraditional-credit fields, we treat missing values as no observed use. That matters for interpretation. Once those fields are handled that way, direct nontraditional-credit exposure is informative but still too sparse to carry the full segmentation on its own. It works better here as a substitution channel and as part of the descriptive profile of each credit state than as the main state definition.

Table 10. Pre-treatment credit states
Rule-based segments built from the four quarters before application

Credit state	Applicants	Approval rate	Any NT exposure pre	Mean rev. util. pre	Mean Vantage pre
Severe derogatory history	6,657	56.4%	4.6%	73.0	536.1
Collections history	1,677	56.5%	0.5%	67.9	564.4
Current but constrained	686	59.9%	0.3%	86.9	575.4
More stable borderline	593	58.0%	0.0%	48.1	617.3



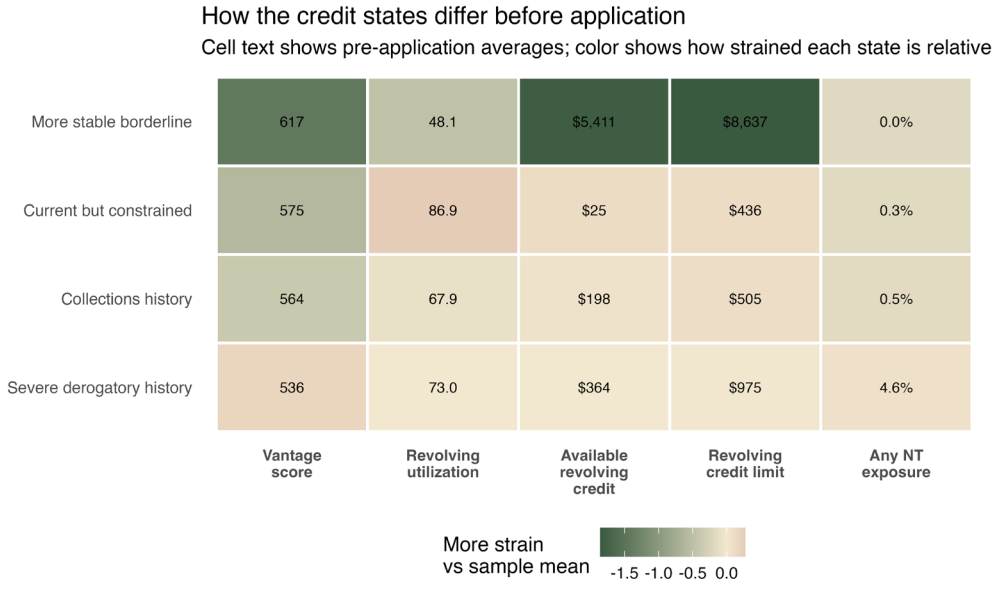


Table 11. Composite benefit effects by pre-treatment credit state
These states sharpen mechanism more than they change the top-line benefit story

Credit state	Credit standing	Credit slack	Overall benefit index	Payment stress relief
Severe derogatory history	-0.00 (0.02)	-0.01 (0.01)	0.00 (0.01)	0.02 (0.01)
Collections history	0.04 (0.04)	-0.00 (0.02)	0.01 (0.02)	-0.01 (0.01)
Current but constrained	0.02 (0.07)	0.01 (0.02)	0.00 (0.03)	-0.03 (0.02)
More stable borderline	0.04 (0.18)	-0.08 (0.09)	-0.05 (0.08)	-0.12 (0.07)

Entries are ATT estimates in SD units with standard errors in parentheses.

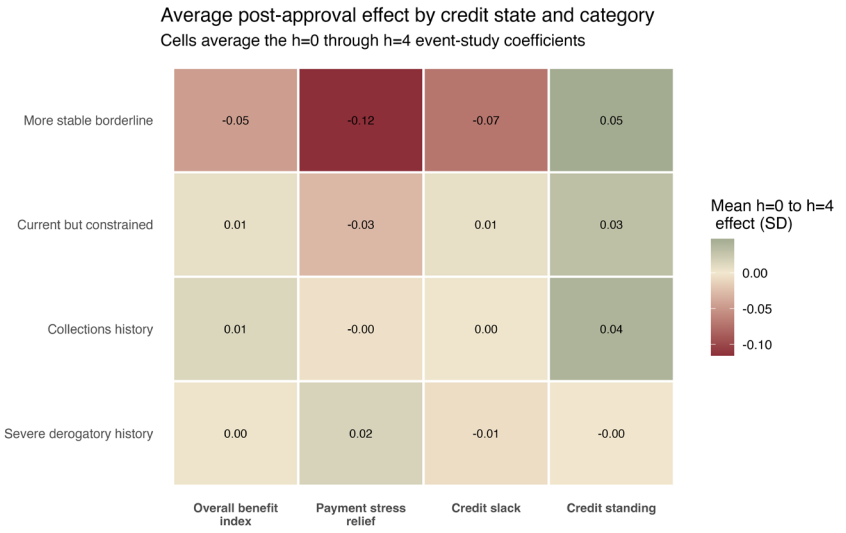
4.3 Dynamics across financial health categories

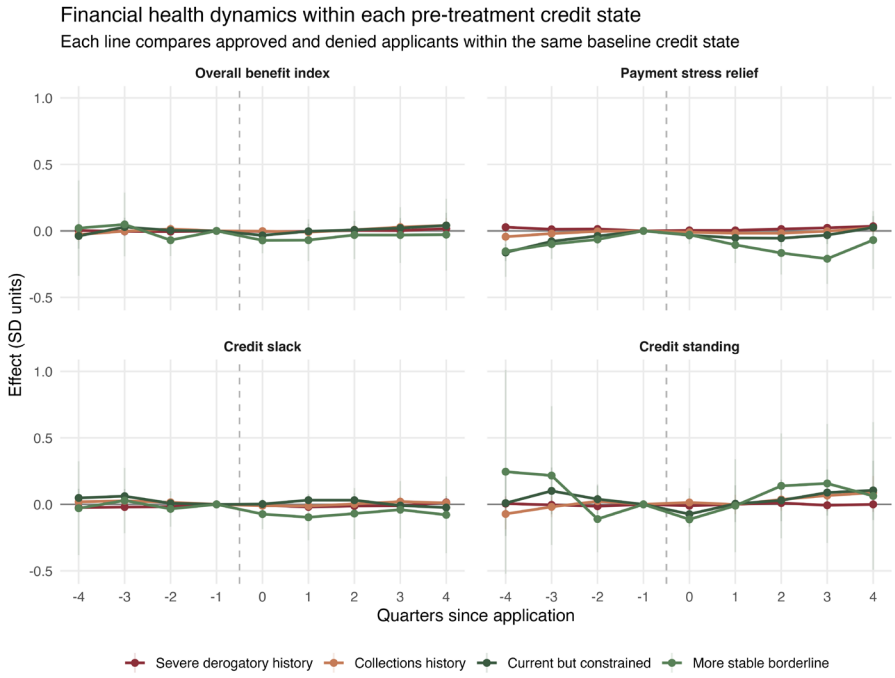
The ATT table is useful as a compact summary, but it hides the timing of the treatment-control gap within each credit state. The next section traces the event-study path for each core financial health category so we can see whether gains show up quickly, build over time, or remain concentrated in particular segments.

Table 12. Quarter-by-quarter dynamics by pre-treatment credit state
Each entry is the treatment-control gap within a credit state

Financial health category	h=0	h=1	h=2	h=3	h=4
Severe derogatory history					
Overall benefit index	-0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.02 (0.01)
Payment stress relief	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.02* (0.01)	0.04** (0.02)
Credit slack	-0.01 (0.01)	-0.02** (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.02)
Credit standing	-0.01 (0.01)	0.00 (0.02)	0.01 (0.02)	-0.01 (0.02)	0.00 (0.03)
Collections history					
Overall benefit index	-0.00 (0.01)	-0.01 (0.02)	0.01 (0.02)	0.03 (0.02)	0.04 (0.03)
Payment stress relief	-0.01 (0.01)	-0.02 (0.01)	-0.02 (0.02)	-0.00 (0.02)	0.02 (0.03)
Credit slack	-0.01 (0.01)	-0.01 (0.02)	0.00 (0.02)	0.02 (0.02)	0.01 (0.03)
Credit standing	0.01 (0.03)	-0.00 (0.04)	0.04 (0.04)	0.07 (0.05)	0.09 (0.06)
Current but constrained					
Overall benefit index	-0.03* (0.02)	-0.00 (0.03)	0.01 (0.03)	0.02 (0.04)	0.04 (0.05)
Payment stress relief	-0.03* (0.02)	-0.05** (0.03)	-0.05* (0.03)	-0.03 (0.03)	0.03 (0.04)
Credit slack	0.00 (0.02)	0.03 (0.02)	0.03 (0.03)	-0.01 (0.03)	-0.02 (0.04)
Credit standing	-0.07 (0.05)	0.00 (0.07)	0.03 (0.08)	0.09 (0.09)	0.11 (0.11)
More stable borderline					
Overall benefit index	-0.07 (0.05)	-0.07 (0.08)	-0.03 (0.09)	-0.03 (0.11)	-0.03 (0.14)
Payment stress relief	-0.03 (0.03)	-0.11 (0.07)	-0.17** (0.08)	-0.21** (0.10)	-0.07 (0.11)
Credit slack	-0.07 (0.06)	-0.10 (0.09)	-0.07 (0.10)	-0.04 (0.11)	-0.08 (0.15)
Credit standing	-0.11 (0.12)	-0.01 (0.18)	0.14 (0.20)	0.16 (0.23)	0.06 (0.28)

Entries are event-study coefficients in SD units with standard errors in parentheses. Higher values indicate better outcomes / less harm.





4.4 Is Flex crowding out other credit?

We cannot directly observe a one-for-one substitution decision between Flex and another credit product. What we can observe is whether access to rent splitting changes the later use of other credit margins. In this section, lower revolving pressure, fewer inquiries, fewer new tradelines, or less nontraditional credit exposure are read as evidence consistent with crowd-out. For available revolving credit, the sign flips: a positive estimate is consistent with crowd-out because it means more unused credit remains available.

The table now focuses on the most interpretable short-run margins: revolving credit pressure, credit-seeking, and nontraditional credit. That is a better fit for the mechanism we care about than broader debt categories such as auto or installment balances.

Table 13. Overall substitution vs complementarity signals
Classification is based on the sign and strength of the estimated ATT

Non-Flex credit margin	Effect	Interpretation
Revolving pressure		
Revolving balance	0.8% (4.4%)	Unrelated / inconclusive
Available revolving credit	$-22 ($17)	Unrelated / inconclusive
Revolving utilization	-0.08 pp (1.34)	Unrelated / inconclusive
Credit seeking		
Credit inquiries	-0.39 (0.11)	Likely substitute / crowd-out
New tradelines	-0.06 (0.05)	Unrelated / inconclusive
Nontraditional credit		
NT trade count (0-imputed)	-0.01 (0.00)	Likely substitute / crowd-out
Any NT trade (0-imputed)	-0.20 pp (0.16)	Unrelated / inconclusive

Negative effects imply crowd-out for debt, inquiries, tradelines, and NT exposure. Positive effects imply crowd-out for available revolving credit.

Table 14. Where substitution signals appear by credit state
Only non-inconclusive results shown

Category	Non-Flex credit margin	Effect	Interpretation
Severe derogatory history			
Credit seeking	Credit inquiries	-0.45 (0.13)	Likely substitute / crowd-out
Credit seeking	New tradelines	-0.10 (0.06)	Likely substitute / crowd-out
Collections history			
Revolving pressure	Revolving utilization	-7.04 pp (3.93)	Likely substitute / crowd-out
Current but constrained			
Credit seeking	Credit inquiries	-0.68 (0.35)	Likely substitute / crowd-out
More stable borderline			
Credit seeking	Credit inquiries	-1.97 (1.13)	Likely substitute / crowd-out

5. Endogenous variables

One consequence of our ITT design is that we do not take into account whether or not an approved applicant uses the product and, if so, how often. In these section, we'll examine the effects of using Flex to split rent on our outcome set.

We have two kinds of usage measures we'll use, both of which look at usage early in the customer lifecycle (i.e., the quarter of application and the following quarter). Our first analysis looks at whether an approved applicant used the product at all in those quarters; that's the extensive margin, or the proportion of the population that used the product. Our second analysis deals with how intense usage was among those who split their rent; that's the intensive margin, or frequency of usage among users.

These reports include all survey questions, response options, and aggregated results. Results can also be made available to policymakers and researchers upon request for verification.

5.0.1 Early usage IV: extensive margin

Below we see the results from our 'any usage' models, which look very similar to the results from our ITT. This suggests that our ITT results were not a function of low usage rates diluting the overall effect of Flex.

Table 15. Treatment on Treated: Extensive Margin
IV estimates using any split-payment usage in the first post-application quarter

Outcome	h=0	h=1	h=2	h=3	h=4
Auto & durable goods					
Any open auto	0.01 (0.01)	0.02 (0.02)	-0.00 (0.02)	-0.02 (0.02)	0.00 (0.03)
Open auto trades	0.01 (0.02)	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)	0.02 (0.03)
Collections & charge-off					
Charge-off balance	6.1% (9.9%)	0.0% (12.9%)	-5.0% (14.8%)	-5.2% (16.5%)	-31.2% (21.6%)
Charge-off count	-0.02 (0.03)	-0.03 (0.04)	-0.04 (0.05)	-0.01 (0.06)	-0.09 (0.08)
Collections count	0.02 (0.05)	0.01 (0.07)	0.04 (0.08)	-0.04 (0.09)	-0.02 (0.13)
Composite benefit outcomes					
Overall financial health benefit index	-0.02 (0.02)	-0.03 (0.02)	0.01 (0.02)	0.04 (0.03)	0.01 (0.03)
Payment stress relief index	-0.00 (0.02)	-0.00 (0.02)	0.02 (0.03)	0.05* (0.03)	0.06* (0.03)
Credit slack index	-0.03 (0.02)	-0.05** (0.02)	-0.02 (0.03)	-0.01 (0.03)	-0.02 (0.04)
Credit standing index	-0.02 (0.04)	-0.03 (0.05)	0.03 (0.05)	0.07 (0.05)	0.00 (0.07)
Costly coping reduction index	0.01 (0.02)	-0.00 (0.02)	0.01 (0.03)	0.03 (0.03)	0.03 (0.04)
Core baseline health					
Clarity Early Risk	-0.90 (1.97)	-1.75 (2.38)	2.49 (2.58)	1.56 (2.75)	0.72 (3.44)
Net income (3m)	126.60 (173.05)	94.17 (190.28)	32.34 (212.63)	285.82 (233.39)	-368.33 (303.19)
Net income (6m)	127.04 (95.58)	126.98 (145.30)	51.08 (159.05)	126.53 (167.46)	-356.13 (220.94)
VantageScore 4.0	-0.90 (2.15)	-1.00 (2.60)	-0.09 (2.86)	4.00 (3.05)	-0.83 (3.85)
Credit access & capacity					
Revolving available credit	-24.51 (37.38)	-78.42 (47.86)	-52.40 (61.33)	-24.27 (68.24)	-30.24 (93.82)
Revolving limit	-20.63 (50.06)	-73.64 (66.68)	-110.20 (86.87)	-54.29 (96.45)	-55.79 (131.93)
Credit seeking & new credit					
Days since inquiry	12.25 (8.89)	21.33* (11.83)	19.75 (13.56)	19.96 (15.06)	22.99 (19.81)
Inquiries (3m)	0.39 (0.33)	0.02 (0.32)	-0.43 (0.32)	0.26 (0.33)	0.02 (0.39)
Months since opened	-0.48 (0.52)	-0.24 (0.64)	-0.23 (0.71)	-1.01 (0.77)	0.29 (0.99)
Trades reported (3m)	-0.19 (0.13)	-0.21 (0.14)	-0.16 (0.16)	-0.05 (0.17)	-0.13 (0.23)
Credit usage & utilization					
Overall utilization (pp)	1.74 (1.95)	1.23 (2.26)	2.70 (2.43)	1.65 (2.57)	2.36 (3.42)
Revolving utilization (pp)	6.53* (3.34)	6.86 (4.35)	-3.09 (4.58)	2.55 (5.00)	-2.18 (6.42)
Total monthly payment	21.03 (16.68)	24.22 (19.81)	-2.54 (21.27)	8.70 (22.75)	18.56 (28.75)
Utilization, derived (pp)	8.73* (4.49)	1.64 (5.64)	-7.17 (6.23)	-4.91 (6.73)	-4.43 (8.74)
Debt & balances					
Auto balance	12.0% (12.4%)	12.7% (16.1%)	-3.4% (18.7%)	-20.2% (20.8%)	5.4% (27.8%)
Collections balance	6.6% (10.6%)	10.0% (13.2%)	0.2% (14.2%)	-13.6% (15.1%)	-15.0% (19.4%)
Installment balance	-18.8% (16.9%)	-22.7% (19.9%)	-25.4% (21.8%)	-6.8% (23.2%)	29.0% (30.3%)
Revolving balance	5.0% (10.0%)	8.3% (12.6%)	-11.7% (14.0%)	6.4% (15.3%)	-1.7% (19.6%)
Total balance (open)	-5.4% (15.5%)	7.6% (18.3%)	-12.0% (20.0%)	0.7% (21.4%)	10.9% (27.5%)
Delinquency & payment distress					
60+ DPD balance	-3.6% (17.2%)	20.0% (20.7%)	-2.7% (22.4%)	-20.8% (23.5%)	-6.9% (29.3%)
60+ DPD occurrences (3m)	0.02 (0.02)	0.01 (0.03)	-0.01 (0.03)	-0.02 (0.02)	0.00 (0.03)
90+ DPD balance	-4.7% (16.5%)	9.5% (20.4%)	2.3% (22.0%)	-22.7% (23.0%)	-18.2% (28.5%)
90+ DPD occurrences (3m)	0.01 (0.02)	0.01 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)
No. trades 60+ DPD	0.00 (0.02)	0.02 (0.03)	0.01 (0.03)	0.00 (0.03)	0.02 (0.05)
No. trades 90+ DPD	-0.01 (0.02)	0.01 (0.03)	0.00 (0.03)	-0.01 (0.03)	-0.01 (0.05)

Outcome	h=0	h=1	h=2	h=3	h=4
Identity & stability					
Months at address	1.81 (1.58)	3.00* (1.79)	2.65 (1.94)	2.13 (2.08)	-0.43 (2.57)
Months at employer	0.42 (1.55)	2.10 (1.82)	2.29 (1.91)	3.47* (2.03)	-0.10 (2.59)
Payday-like / alternative finance					
Any payday-like/nontraditional trade	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.02)
Storefront installment past due ($)	-0.8% (1.9%)	0.0% (2.4%)	-0.9% (3.0%)	-2.8% (3.5%)	-1.0% (4.4%)
Portfolio structure					
File age (months)	0.65 (0.51)	0.20 (0.73)	-0.51 (0.94)	-1.05 (1.17)	-1.20 (1.70)
Open trades	-0.17 (0.12)	-0.20 (0.14)	-0.11 (0.15)	0.02 (0.16)	-0.10 (0.21)
Total trades (excl collections)	-0.03 (0.07)	-0.14 (0.10)	-0.23* (0.13)	-0.25 (0.15)	-0.29 (0.22)
Public records					
Bankruptcies (count)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.01)	-0.00 (0.01)

Percent changes (%) shown for log-transformed outcomes (balances); percentage point changes (pp) for utilization measures; coefficients in original units otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

5.0.2 Early Usage IV: Intensive Margin

Here we examine the effect of Flex as a function of usage frequency among users. Again, we see the same pattern of results. It's worth noting that the estimates in this table are in units of bills paid, so we're see how much an outcome changes for each additional bill paid in the quarter.

Table 16. Treatment on Treated: Intensive Margin
IV estimates using the number of split-paid bills in the first post-application quarter

Outcome	h=0	h=1	h=2	h=3	h=4
Auto & durable goods					
Any open auto	0.00 (0.00)	0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
Open auto trades	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
Collections & charge-off					
Charge-off balance	2.1% (3.4%)	0.0% (4.4%)	-1.7% (5.1%)	-1.8% (5.7%)	-11.0% (7.6%)
Charge-off count	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.02)	-0.00 (0.02)	-0.03 (0.03)
Collections count	0.01 (0.02)	0.00 (0.02)	0.01 (0.03)	-0.01 (0.03)	-0.01 (0.04)
Composite benefit outcomes					
Overall financial health benefit index	-0.01 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)
Payment stress relief index	-0.00 (0.01)	-0.00 (0.01)	0.01 (0.01)	0.02* (0.01)	0.02* (0.01)
Credit slack index	-0.01 (0.01)	-0.02** (0.01)	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Credit standing index	-0.01 (0.01)	-0.01 (0.02)	0.01 (0.02)	0.02 (0.02)	0.00 (0.02)
Costly coping reduction index	0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Core baseline health					
Clarity Early Risk	-0.31 (0.68)	-0.60 (0.82)	0.86 (0.89)	0.54 (0.95)	0.25 (1.21)
Net income (3m)	43.92 (60.09)	32.80 (66.32)	11.11 (73.06)	92.76 (75.84)	-123.81 (101.99)
Net income (6m)	44.20 (33.28)	44.30 (50.72)	17.61 (54.84)	41.85 (55.40)	-117.81 (73.18)
VantageScore 4.0	-0.31 (0.74)	-0.34 (0.89)	-0.03 (0.98)	1.38 (1.05)	-0.29 (1.35)
Credit access & capacity					
Revolving available credit	-8.38 (12.78)	-26.83 (16.38)	-17.93 (20.99)	-8.39 (23.59)	-10.64 (33.01)
Revolving limit	-7.05 (17.12)	-25.19 (22.82)	-37.71 (29.74)	-18.77 (33.35)	-19.63 (46.44)
Credit seeking & new credit					
Days since inquiry	4.22 (3.06)	7.35* (4.07)	6.81 (4.68)	6.94 (5.24)	8.11 (6.99)
Inquiries (3m)	0.14 (0.11)	0.01 (0.11)	-0.15 (0.11)	0.09 (0.11)	0.01 (0.14)
Months since opened	-0.16 (0.18)	-0.08 (0.22)	-0.08 (0.24)	-0.35 (0.27)	0.10 (0.35)
Trades reported (3m)	-0.06 (0.04)	-0.07 (0.05)	-0.05 (0.05)	-0.02 (0.06)	-0.05 (0.08)

Outcome	h=0	h=1	h=2	h=3	h=4
Credit usage & utilization					
Overall utilization (pp)	0.58 (0.65)	0.41 (0.75)	0.90 (0.81)	0.55 (0.86)	0.79 (1.15)
Revolving utilization (pp)	2.18* (1.12)	2.24 (1.42)	-1.00 (1.49)	0.84 (1.65)	-0.72 (2.12)
Total monthly payment	7.19 (5.71)	8.28 (6.78)	-0.87 (7.28)	3.01 (7.86)	6.52 (10.10)
Utilization, derived (pp)	2.79* (1.44)	0.51 (1.74)	-2.14 (1.86)	-1.48 (2.03)	-1.31 (2.59)
Debt & balances					
Auto balance	4.1% (4.2%)	4.3% (5.5%)	-1.2% (6.4%)	-7.0% (7.2%)	1.9% (9.8%)
Collections balance	2.3% (3.6%)	3.4% (4.5%)	0.1% (4.9%)	-4.7% (5.2%)	-5.3% (6.8%)
Installment balance	-6.4% (5.8%)	-7.8% (6.8%)	-8.7% (7.4%)	-2.3% (8.0%)	10.2% (10.6%)
Revolving balance	1.7% (3.4%)	2.8% (4.3%)	-4.0% (4.8%)	2.2% (5.3%)	-0.6% (6.9%)
Total balance (open)	-1.8% (5.3%)	2.6% (6.3%)	-4.1% (6.9%)	0.2% (7.4%)	3.8% (9.7%)
Delinquency & payment distress					
60+ DPD balance	-1.2% (5.9%)	6.8% (7.1%)	-0.9% (7.7%)	-7.2% (8.1%)	-2.4% (10.3%)
60+ DPD occurrences (3m)	0.01 (0.01)	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
90+ DPD balance	-1.6% (5.6%)	3.2% (7.0%)	0.8% (7.5%)	-7.9% (7.9%)	-6.4% (10.0%)
90+ DPD occurrences (3m)	0.00 (0.01)	0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.01)
No. trades 60+ DPD	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.02)
No. trades 90+ DPD	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	-0.00 (0.01)	-0.00 (0.02)
Identity & stability					
Months at address	0.62 (0.54)	1.03* (0.62)	0.91 (0.67)	0.73 (0.71)	-0.15 (0.88)
Months at employer	0.14 (0.54)	0.72 (0.63)	0.79 (0.66)	1.19* (0.70)	-0.04 (0.89)
Payday-like / alternative finance					
Any payday-like/nontraditional trade	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.01 (0.01)
Storefront installment past due ($)	-0.3% (0.6%)	0.0% (0.8%)	-0.3% (1.0%)	-1.0% (1.2%)	-0.3% (1.5%)
Portfolio structure					
File age (months)	0.22 (0.18)	0.07 (0.25)	-0.17 (0.32)	-0.36 (0.40)	-0.42 (0.59)
Open trades	-0.06 (0.04)	-0.07 (0.05)	-0.04 (0.05)	0.01 (0.05)	-0.04 (0.07)
Total trades (excl collections)	-0.01 (0.02)	-0.05 (0.03)	-0.08* (0.04)	-0.09 (0.05)	-0.10 (0.08)
Public records					
Bankruptcies (count)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)

Percent changes (%) shown for log-transformed outcomes (balances); percentage point changes (pp) for utilization measures; coefficients in original units otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

6. The full distribution

The RDD estimates are intentionally local: they tell us about applicants near the approval cutoff, not about the full applicant pool. This section uses the broader bubble-plus sample to answer a different, descriptive question: how do financial outcomes evolve across the wider applicant risk distribution among people who appear in Flex's orbit?

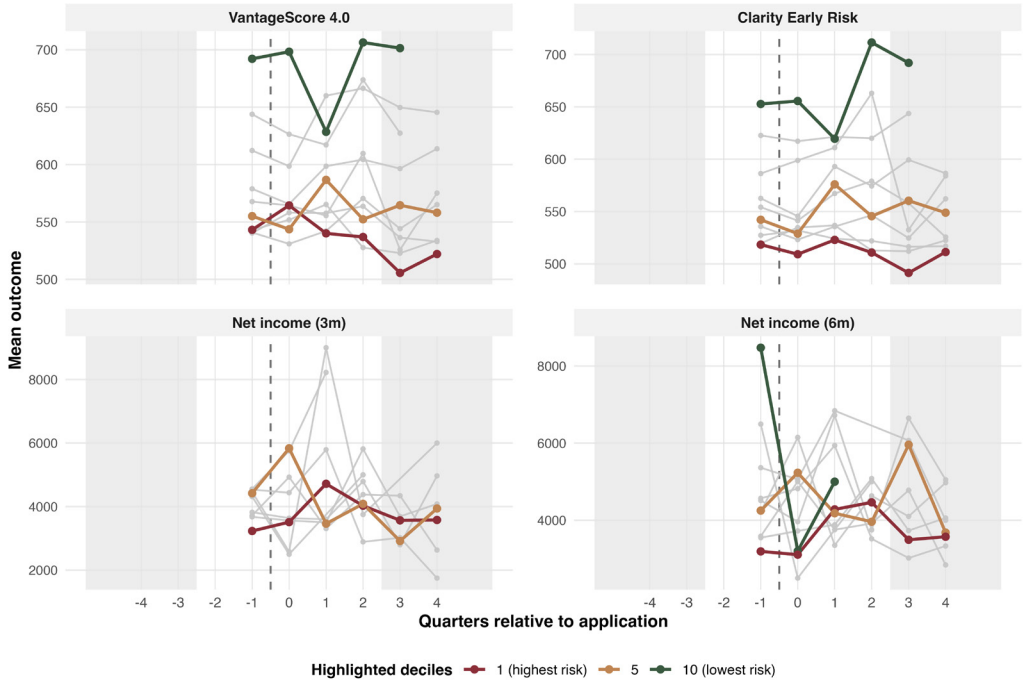
That broader view is useful for scope and context, but it is not a second causal design. The figures and tables below should be read as descriptive patterns that help situate the local RDD results, not as treatment effects. Additional portfolio-mix descriptives for the full-distribution sample are reported in the appendix.

6.1 Descriptive trajectories by risk decile

The first set of figures stays close to raw levels. For each domain, it traces mean outcomes quarter by quarter across FlexScore deciles so we can see how baseline gaps and post-application trajectories vary across the distribution.

Core baseline health

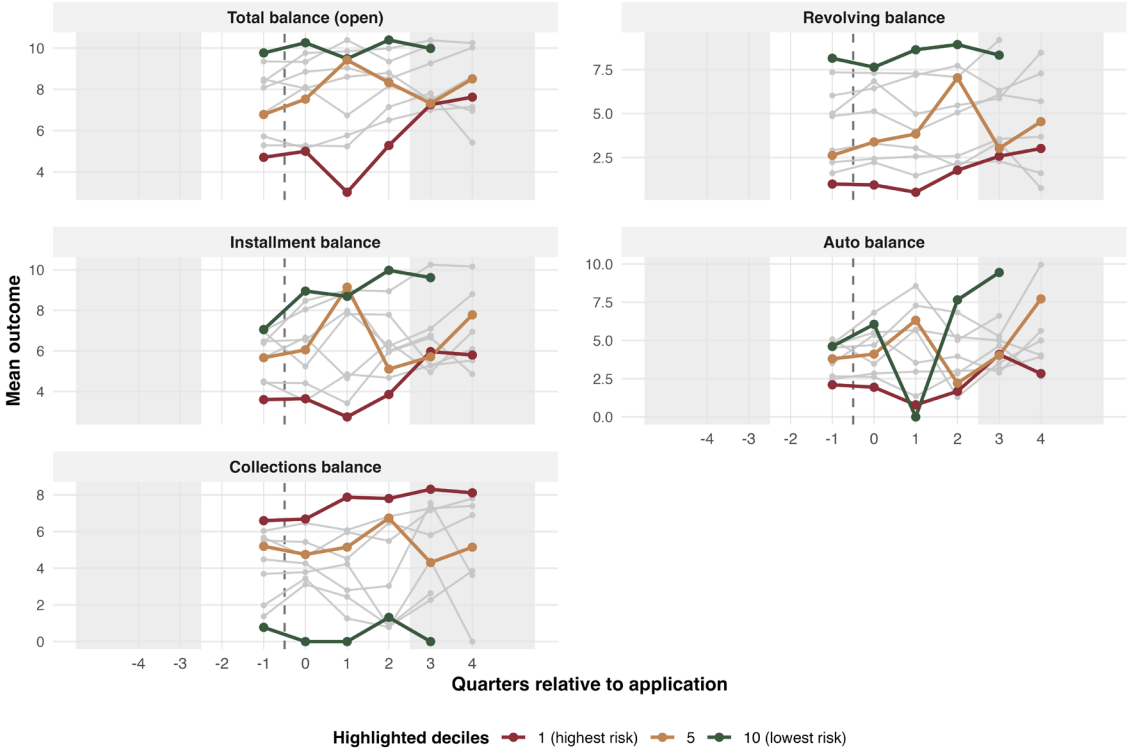
Colored lines highlight the highest-, middle-, and lowest-risk deciles. Thin gray lines show the remaining deciles. Shaded quarters have partial coverage.



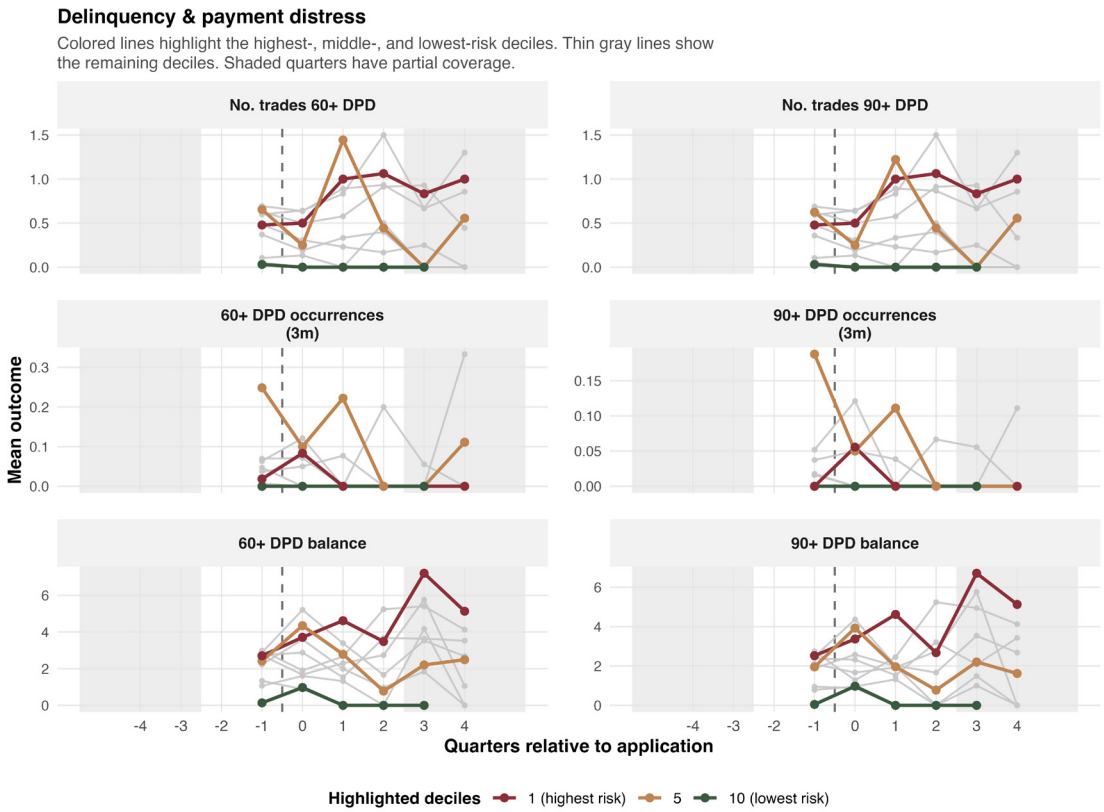
Descriptive only; no causal identification.

Debt & balances

Colored lines highlight the highest-, middle-, and lowest-risk deciles. Thin gray lines show the remaining deciles. Shaded quarters have partial coverage.



Descriptive only; no causal identification.



Descriptive only; no causal identification.

6.2 Change from baseline by risk tier

The next set of tables switches from levels to within-tier changes relative to the application-quarter baseline. This makes the direction and magnitude of movement easier to compare across broad parts of the risk distribution. For readability, the deciles are pooled into three tiers:

- **High risk** (deciles 2–3): the riskiest retained portion of the descriptive sample
- **Mid risk** (deciles 4–7): the broad middle of the applicant distribution
- **Low risk** (deciles 8–10): applicants with the strongest baseline credit profiles

Important caveats:

- **No causal identification.** Unlike the RDD sections above, there is no experimental or quasi-experimental source of variation here. Changes from baseline reflect the combined influence of secular trends, mean reversion, economic conditions, and any behavioral response to application or underwriting exposure; they cannot be attributed to any single cause.
- **Mean reversion is expected.** Applicants who seek access to Flex disproportionately do so during a period of financial stress. Even absent any intervention, we would expect credit scores to rise and delinquency indicators to fall as transitory shocks dissipate (to the extent that application is induced by transitory shocks). This is especially relevant for the high-risk tier.
- **Starred estimates indicate statistical precision, not causation.** An asterisk (*) denotes that the 95% confidence interval for the change excludes zero — i.e., the change is distinguishable from no change. This is a statement about the data, not about the program.

Table 17. Full Distribution: Change from Baseline — High (2-3) Risk
Change in mean from the application-quarter baseline | * = 95% CI excludes zero

Outcome	Baseline	0	1	2	3	4
Core baseline health						
Clarity Early Risk	523.59	9.393	6.597	-7.167	-9.169	-4.062
Net income (3m)	3696.18	482.985	-271.917	1211.455	266.574	-156.801
Net income (6m)	3565.63	740.793*	265.024	724.568	606.579	-47.187
VantageScore 4.0	541.71	14.108	19.716*	-0.167	-11.463	-8.314
Debt & balances						
Auto balance	2.56	0.200	-0.387	0.340	1.274	0.755
Collections balance	5.85	-0.527	0.178	0.463	1.365*	1.763*
Installment balance	4.48	-0.607	-0.325	0.988	1.437	0.738
Revolving balance	1.93	0.423	0.093	0.412	1.047	0.756
Total balance (open)	5.51	-0.315	-0.004	1.388*	1.854*	0.810
Delinquency & payment distress						
60+ DPD balance	2.86	-0.347	-0.774	1.774*	1.578*	0.951
60+ DPD occurrences (3m)	NA	0.043	-0.014	0.028	-0.020	0.107
90+ DPD balance	2.56	-0.630	-0.578	1.897*	0.821	1.200
90+ DPD occurrences (3m)	NA	0.049	-0.026	-0.019	-0.014	0.008
No. trades 60+ DPD	0.66	-0.077	0.079	0.259	0.120	0.233
No. trades 90+ DPD	0.66	-0.074	0.082	0.236	0.123	0.183

Baseline = mean in the application quarter. Horizons 0–4 are the first five quarters after application. Decile 1 excluded.

Table 18. Full Distribution: Change from Baseline — Mid (4-7) Risk
Change in mean from the application-quarter baseline | * = 95% CI excludes zero

Outcome	Baseline	0	1	2	3	4
Core baseline health						
Clarity Early Risk	548.14	-13.156*	15.434	8.546	7.144	8.293
Net income (3m)	4292.51	-38.056	443.716	-228.605	-1380.181*	-24.737
Net income (6m)	4369.70	833.088	323.064	-250.623	696.925	-126.791
VantageScore 4.0	560.66	-8.681	5.910	22.652*	0.054	11.191
Debt & balances						
Auto balance	4.24	0.451	0.981	-0.856	-0.411	1.789
Collections balance	4.71	-0.230	-0.715	-0.256	0.036	0.413
Installment balance	6.16	0.020	1.068	0.302	-0.347	1.226
Revolving balance	3.83	0.961*	0.062	0.837	0.597	0.521
Total balance (open)	7.52	0.633	0.805	0.925*	0.376	0.820

Outcome	Baseline	0	1	2	3	4
Delinquency & payment distress						
60+ DPD balance	2.55	1.240*	0.083	-0.929	0.548	-0.668
60+ DPD occurrences (3m)	NA	-0.051	-0.045	-0.095*	-0.095*	-0.051
90+ DPD balance	2.10	1.072*	-0.130	-0.675	0.780	-0.757
90+ DPD occurrences (3m)	NA	-0.041	-0.031	-0.056*	-0.056*	-0.056*
No. trades 60+ DPD	0.53	-0.206*	0.171	0.252	-0.302*	-0.051
No. trades 90+ DPD	0.52	-0.192	0.134	0.265	-0.289*	-0.038

Baseline = mean in the application quarter. Horizons 0–4 are the first five quarters after application.

Table 19. Full Distribution: Change from Baseline — Low (8-10) Risk
Change in mean from the application-quarter baseline | * = 95% CI excludes zero

Outcome	Baseline	0	1	2	3	4
Core baseline health						
Clarity Early Risk	612.35	3.183	3.980	44.397*	13.361	-28.353 NA
Net income (3m)	4479.44	187.231	3742.564	520.564 NA	NaN NA	NaN NA
Net income (6m)	5983.27	-1808.074	489.526	-983.274 NA	84.726 NA	-1983.274 NA
VantageScore 4.0	647.59	-21.100*	-7.588	31.372*	18.079	-2.088
Debt & balances						
Auto balance	4.64	1.121	2.216	1.668	2.707*	5.319*
Collections balance	1.40	1.328*	0.146	-0.448	0.728	-1.401*
Installment balance	6.80	1.585*	2.106*	1.212	2.313*	3.358*
Revolving balance	7.13	-0.149	0.275	0.624	0.739	0.147
Total balance (open)	9.14	0.538	0.866	0.686*	1.012*	1.104*
Delinquency & payment distress						
60+ DPD balance	0.88	0.304	-0.380	-0.875*	0.514	-0.875*
60+ DPD occurrences (3m)	NA	0.000	0.000	0.000	0.000	0.000 NA
90+ DPD balance	0.62	0.310	-0.120	-0.615*	-0.120	-0.615*
90+ DPD occurrences (3m)	NA	0.000	0.000	0.000	0.000	0.000 NA
No. trades 60+ DPD	0.07	-0.008	-0.068*	0.085	-0.068*	-0.068 NA
No. trades 90+ DPD	0.07	-0.008	-0.068*	0.085	-0.068*	-0.068 NA

Baseline = mean in the application quarter. Horizons 0–4 are the first five quarters after application. NA indicates partial coverage.

7. Discussion

This report provides an answer to a narrow but important question: what happens to downstream financial health when borderline applicants gain access to Flex's rent-splitting product? Across the main regression discontinuity analyses, the evidence does not suggest that access to Flex worsens financial outcomes for applicants near the underwriting margin. If anything, the pattern of results is more consistent with modest benefit than with harm. The clearest improvements appear in measures related to credit seeking, payment stress, and some forms of costly coping, while most other outcomes remain close to zero. That combination of findings is substantively important. In a setting where one might reasonably worry that added liquidity could aggravate financial fragility, the absence of broad harmful effects is itself informative.

At the same time, the results do not support the presence of large effects, at least in this sub-population. The estimated gains are generally small, and the composite results suggest a product that may ease short-run strain more than it transforms broader household balance sheets. That distinction matters for how the product should be understood. The evidence here is more consistent with liquidity smoothing than with debt reduction or rapid credit repair. In that sense, Flex appears to help at the margin by reducing some of the frictions associated with rent timing, but rent splitting alone does not appear sufficient to generate large improvements across the full set of bureau-based outcomes we study.

The broader descriptive analyses also make clear that these local causal estimates sit inside a highly heterogeneous applicant population. Risk deciles, pre-treatment credit states, and baseline portfolio mix all show meaningful variation in financial condition and credit structure across the customer base. That heterogeneity is useful for interpretation, but it also places natural limits on extrapolation; it's just not obvious how results among those approved/rejected at the margin apply to the broader customer base. The regression discontinuity results identify effects for applicants near the approval cutoff, not for all prospective users. The descriptive sections help show how those borderline applicants fit within the broader population, but they should not be read as extending the causal conclusions to lower-risk segments without further evidence.

These findings raise several natural next questions. One is where benefits are most concentrated: among the most distressed households, among more moderate but still constrained households, or somewhere in between. Another is whether the modest average effects reflect the narrow scope of the product rather than the absence of genuine demand for liquidity smoothing. If rent splitting mainly reduces acute short-run pressure without addressing adjacent frictions such as emergency expenses, paycheck timing, or savings shortfalls, then a broader product suite may be needed to generate more material downstream effects. Relatedly, some of the most relevant benefits may fall outside the credit bureau data used here, including avoided late fees**, overdrafts, utility disruptions, consumption shortfalls, or reductions in financial stress. Those are plausible channels of value that this report cannot fully assess, but future work should.

Disclosures

Flexible Finance, Inc. ("Flex") is a financial technology company, not a bank. All lines of credit (including "Flex Rent"), banking services, and payment transmissions are offered by Lead Bank or Column N.A., Member FDIC. An application and credit assessment are required for approval. Credit line amounts vary based on eligibility (graphics are illustrative only); to access a credit line, you are required to make timely payments each month. Unsecured lines of credit are provided for a recurring monthly membership fee of $14.99 at 0% APR. A bill payment fee of 1% of your total rent is also charged when you pay your rent using the Flex app (additional card processing fee applies when using a credit card). Memberships automatically renew until canceled. See your offer for more details. Positive rent payment history and information about your line of credit may be reported to one or more national credit bureaus. Terms and conditions apply. Brokering activities are performed by Flexible Finance Brokering, Inc. www.getflex.com

Column N.A. only supports Flex Rent at this time.

*Evidence statement based on this study's sample and methods. The study did not detect statistically significant adverse average effects on the measured outcomes during the observation period. Results are estimated for applicants near the underwriting cutoff and may not generalize beyond this group. Individual experiences may vary.

**Experience and results may vary. Be sure to check your property's policies to avoid late fees, as fees may still be assessed at your property's discretion.

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Appendix

The appendix collects supporting analyses that are useful for robustness, interpretation, or follow-on work but are not essential to the main RDD and full-distribution narrative.

A1. Composite construction and sensitivity

These appendix materials ask two follow-up questions about the composite outcomes. First, do the composite families have enough support and overlap to behave like meaningful summary measures? Second, does the "who benefits most?" pattern survive if the overall index is defined in other reasonable ways?

A1.1 Component support and family diagnostics

Table 20. Composite family support
Coverage and surviving components after zero-variance filtering

Family	Components used	Coverage in the application quarter	Coverage one quarter after application	Coverage five quarters after application	Components
Payment stress relief index	8	94.6%	94.8%	94.9%	60+ DPD occurrences (3m), 90+ DPD occurrences (3m), 60+ DPD balance, 90+ DPD balance, Collections count, Collections balance, Charge-off count, Charge-off balance
Credit slack index	4	94.6%	94.8%	94.9%	Revolving available credit, Revolving limit, Revolving utilization %, Total monthly payment
Credit standing index	2	94.4%	94.6%	94.8%	VantageScore 4.0, Clarity Early Risk
Costly coping reduction index	2	100.0%	100.0%	100.0%	Storefront installment past due ($), Any payday-like/nontraditional trade

Table 21. Costly coping diagnostics
The surviving components in this family are limited and highly asymmetric

Component	Baseline mean	Share > 0 at baseline
Storefront installment past due ($)	0.129	2.1%
Any payday-like/nontraditional trade	0.841	84.1%

Table 22. Baseline correlation across composite families
Pairwise correlations among family-level indices in the application quarter

Composite family	Payment stress	Credit slack	Credit standing	Costly coping
Payment stress	1.000	0.032	0.276	0.111
Credit slack	0.032	1.000	0.219	0.017
Credit standing	0.276	0.219	1.000	0.076
Costly coping	0.111	0.017	0.076	1.000

A1.2 Alternative overall-index definitions

Table 23. Sensitivity of the overall index definition

The main high-constraint vs low-constraint pattern is strongest for the core 3-family definitions

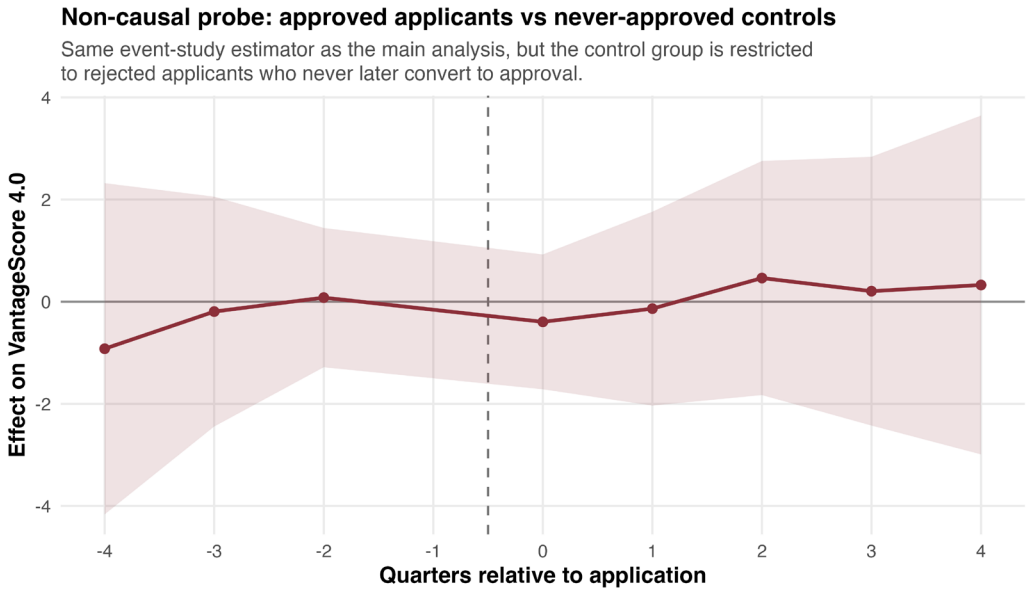
Specification	Coverage in the application quarter	Overall ATT	High constraint	Low constraint	High - Low	p-value
Primary overall (3 families, >=2 present)	94.6%	0.001 (0.007)	0.064 (0.009)	-0.059 (0.010)	0.123*** (0.013)	<0.001
Full overall (+ costly coping, >=2 present)	94.6%	0.003 (0.006)	0.053 (0.007)	-0.046 (0.008)	0.099*** (0.011)	<0.001
Distress-focused (payment stress + costly coping)	100.0%	0.006 (0.006)	0.028 (0.008)	-0.007 (0.009)	0.035*** (0.012)	0.003
Primary overall, strict (all 3 present)	94.4%	0.000 (0.007)	0.064 (0.009)	-0.061 (0.010)	0.124*** (0.013)	<0.001
Costly coping only	100.0%	0.008 (0.008)	0.024 (0.010)	-0.001 (0.014)	0.025 (0.017)	0.149

Entries are SD-unit effects with standard errors in parentheses. Stars reflect the High-Low difference.

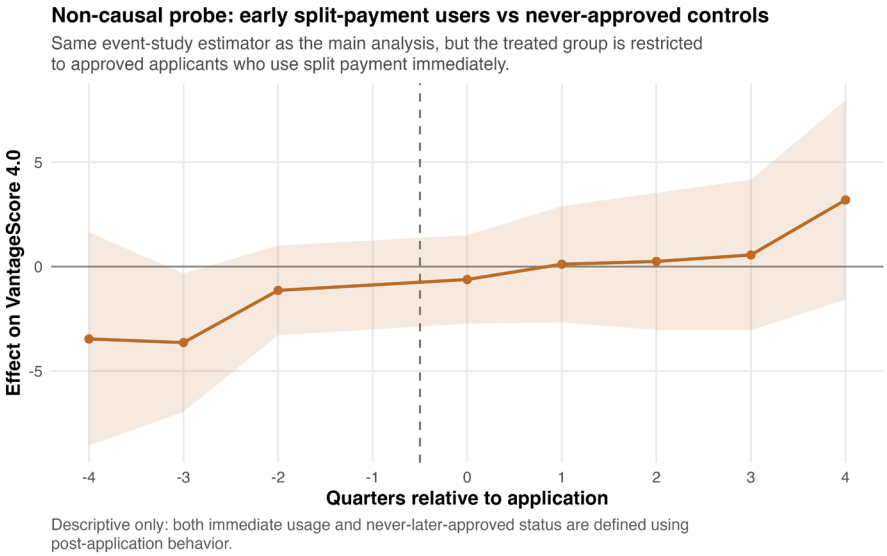
A2. Additional Non-Causal Probes

We do see some rejected applicants from our RDD setup that apply again and are approved. The analyses in this section remove those cases from our data, not because it makes for better estimates, but to diagnose whether that matters for our primary estimates (ITT). It does not.

A2.1 Controls that never get approved



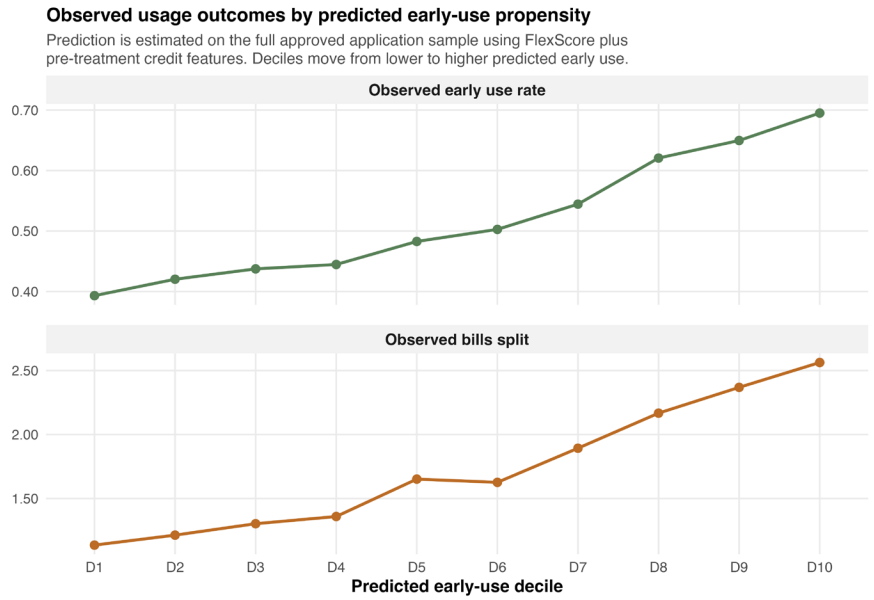
A2.2 Early compliers only and controls that never get approved



A2.3 Predicting take-up and usage

This analysis asks which pre-treatment credit characteristics predict heavier early Flex usage among approved borderline applicants. It is descriptive rather than causal: we use baseline bureau features such as utilization, available credit, credit limits, score, and credit-state indicators to see whether they help distinguish which approved applicants go on to use Flex more intensively in the first two post-application quarters.

The strongest predictor is baseline revolving utilization: approved applicants who enter with tighter revolving credit usage tend to use Flex more in the early post-application window. Baseline VantageScore and revolving credit limits also have weaker positive associations with early usage intensity, while the coarse credit-state indicators like severe derogatory history or collections history add comparatively little once those underlying credit features are included.



A3. Control crossover and switching

Table 25. Control crossover summary
How often rejected applicants are later approved

Rejected applicants	Later approved	Share later approved
4,157	1,625	39.1%

Table 26. When control crossover happens
Event time of the first later approval among rejected applicants who eventually cross over

First later approval quarter	Applicants	Share of crossovers
-1	145	8.9%
0	629	38.7%
1	392	24.1%
2	212	13.0%
3	148	9.1%
4	70	4.3%
5	29	1.8%

Table 27. Control crossover by distance to the cutoff
Later approval rates remain similar on either side of the original decision boundary

Distance bin	Rejected applicants	Share later approved
(-0.0025,0]	15	46.7%
(0,0.0025]	1,780	38.9%
(0.0025,0.005]	1,702	39.4%
NA	660	38.5%

A4. Full-distribution descriptives

These appendix materials collect supplementary descriptive views of the broader applicant distribution, including portfolio composition and pre-treatment credit-state mix across risk levels.

A4.1 Baseline portfolio mix by Flex risk decile

Table 28. Baseline Portfolio Mix by FlexScore Decile
Bubble-plus sample in the application quarter | balance-share summary

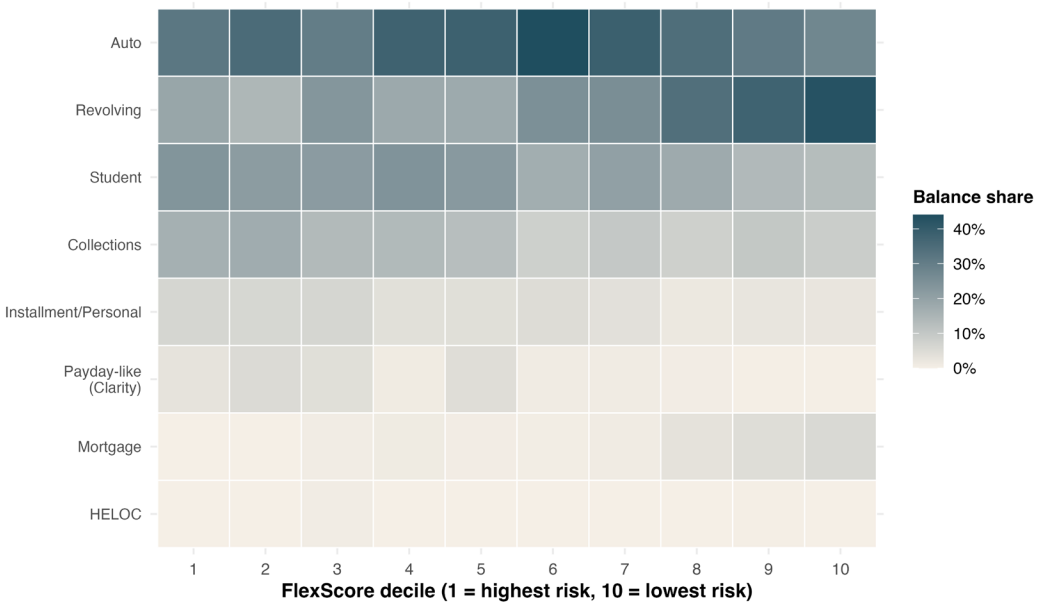
FlexScore Decile	N	Balance Share [1]	SD	Count Share	SD	Mean Balance	Mean Count
Auto							
1	187	32.0%	—	—	—	5K	—
2	170	35.5%	—	—	—	6K	—
3	183	30.3%	—	—	—	5K	—
4	201	38.0%	—	—	—	9K	—
5	193	38.4%	—	—	—	9K	—
6	171	44.0%	—	—	—	13K	—
7	217	38.7%	—	—	—	11K	—
8	199	34.6%	—	—	—	10K	—
9	196	31.0%	—	—	—	12K	—
10	177	27.4%	—	—	—	13K	—
Collections							
1	187	16.3%	—	—	—	686	—
2	170	17.3%	—	—	—	355	—
3	183	13.7%	—	—	—	367	—
4	201	13.7%	—	—	—	520	—
5	193	12.5%	—	—	—	565	—
6	171	8.0%	—	—	—	945	—
7	217	9.9%	—	—	—	1K	—
8	199	7.9%	—	—	—	1K	—
9	196	10.1%	—	—	—	3K	—
10	177	8.7%	—	—	—	2K	—
HELOC							
1	187	0.0%	—	—	—	0	—
2	170	0.0%	—	—	—	0	—
3	183	0.7%	—	—	—	0	—
4	201	0.0%	—	—	—	0	—
5	193	0.0%	—	—	—	0	—
6	171	0.0%	—	—	—	0	—
7	217	0.0%	—	—	—	0	—
8	199	0.0%	—	—	—	0	—
9	196	0.3%	—	—	—	128	—
10	177	0.1%	—	—	—	847	—
Installment/Personal							
1	187	6.4%	—	—	—	117	—
2	170	6.2%	—	—	—	114	—
3	183	6.4%	—	—	—	130	—
4	201	3.9%	—	—	—	297	—
5	193	4.1%	—	—	—	520	—
6	171	4.8%	—	—	—	1K	—
7	217	3.7%	—	—	—	750	—
8	199	1.8%	—	—	—	670	—
9	196	2.6%	—	—	—	694	—
10	177	2.4%	—	—	—	2K	—

FlexScore Decile	N	Balance Share [1]	SD	Count Share	SD	Mean Balance	Mean Count
Mortgage							
1	187	0.0%	—	—	—	0	—
2	170	0.0%	—	—	—	0	—
3	183	0.7%	—	—	—	0	—
4	201	1.1%	—	—	—	1K	—
5	193	0.6%	—	—	—	1K	—
6	171	0.5%	—	—	—	2K	—
7	217	0.9%	—	—	—	2K	—
8	199	3.2%	—	—	—	8K	—
9	196	4.6%	—	—	—	13K	—
10	177	5.7%	—	—	—	22K	—
Payday-like (Clarity)							
1	187	3.1%	—	—	—	66	—
2	170	5.2%	—	—	—	73	—
3	183	4.2%	—	—	—	77	—
4	201	1.1%	—	—	—	86	—
5	193	4.5%	—	—	—	183	—
6	171	1.0%	—	—	—	142	—
7	217	0.9%	—	—	—	291	—
8	199	0.6%	—	—	—	126	—
9	196	0.2%	—	—	—	24	—
10	177	0.2%	—	—	—	51	—
Revolving							
1	187	19.0%	—	—	—	103	—
2	170	14.5%	—	—	—	155	—
3	183	23.2%	—	—	—	514	—
4	201	18.1%	—	—	—	832	—
5	193	17.9%	—	—	—	611	—
6	171	24.9%	—	—	—	2K	—
7	217	25.5%	—	—	—	2K	—
8	199	34.2%	—	—	—	4K	—
9	196	37.9%	—	—	—	6K	—
10	177	42.8%	—	—	—	10K	—
Student							
1	187	23.7%	—	—	—	4K	—
2	170	21.6%	—	—	—	5K	—
3	183	21.9%	—	—	—	7K	—
4	201	24.1%	—	—	—	5K	—
5	193	22.5%	—	—	—	7K	—
6	171	16.8%	—	—	—	9K	—
7	217	20.5%	—	—	—	9K	—
8	199	17.9%	—	—	—	11K	—
9	196	13.8%	—	—	—	9K	—
10	177	12.9%	—	—	—	12K	—

[1]Shares = product family balance/count ÷ combined total (Premier all trades + payday-like). Payday-like uses Clarity total balance on open non-traditional trades (clntr5020) and open non-traditional trades (satisfactory + delinquent) reported in last 3 months (clntr2005 + clntr2105). SD, Count Share, and Mean Count cells marked "—" as these columns are not printed per-decile in the PDF appendix.

Baseline portfolio composition by risk decile

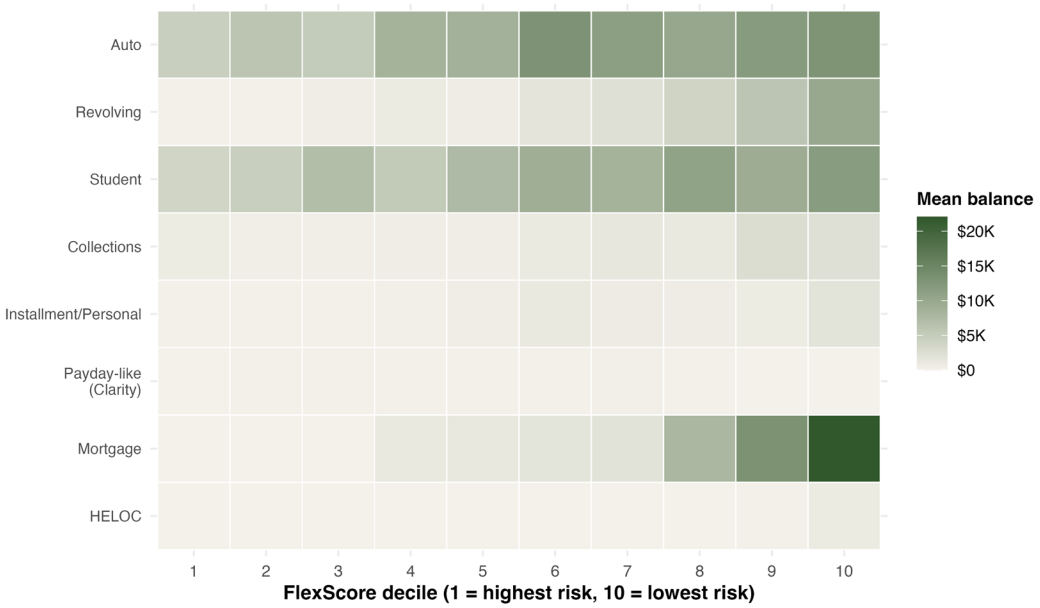
Darker cells mark product families that take up a larger share of the average baseline balance within each decile.



Bubble-plus sample in the application quarter.

Average baseline balances by product family and risk decile

This view separates debt levels from portfolio shares so large product families no longer dominate the figure.



Bubble-plus sample in the application quarter.

A4.2 Change in portfolio mix by Flex risk decile

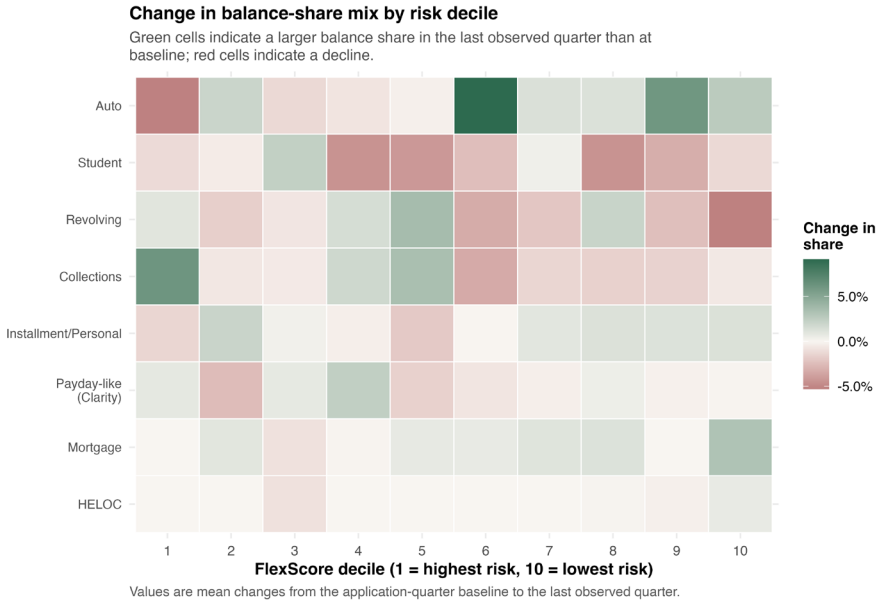
Table 29. Change in Portfolio Mix by FlexScore Decile
Application-quarter baseline vs last observed quarter | balance-share change

FlexScore Decile	N	Δ Balance Share	SE
Auto			
1	183	-5.3%	3.2%
2	170	2.0%	3.6%
3	183	-1.3%	3.8%
4	199	-0.7%	3.1%
5	191	-0.3%	3.2%
6	171	9.1%	2.9%
7	215	1.3%	2.3%
8	198	1.3%	2.3%
9	196	6.1%	2.4%
10	177	2.7%	2.1%
Collections			
1	183	6.2%	2.2%
2	170	-0.6%	3.2%
3	183	-0.5%	2.7%
4	199	1.8%	2.1%
5	191	3.5%	2.2%
6	171	-3.4%	1.6%
7	215	-1.4%	1.5%
8	198	-1.6%	1.3%
9	196	-1.6%	1.5%
10	177	-0.6%	1.3%
HELOC			
1	183	0.0%	0.0%
2	170	0.0%	0.0%
3	183	-0.9%	0.7%
4	199	0.0%	0.0%
5	191	0.0%	0.0%
6	171	0.0%	0.0%
7	215	-0.0%	0.0%
8	198	0.1%	0.1%
9	196	-0.3%	0.3%
10	177	0.7%	0.5%
Installment/Personal			
1	183	-1.4%	2.0%
2	170	2.1%	1.6%
3	183	0.3%	1.6%
4	199	-0.3%	1.4%
5	191	-2.0%	1.1%
6	171	-0.0%	1.3%

FlexScore Decile	N	Δ Balance Share	SE
7	215	1.0%	1.1%
8	198	1.2%	0.8%
9	196	1.2%	0.8%
10	177	1.3%	0.7%
Mortgage			
1	183	0.0%	0.0%
2	170	1.0%	0.7%
3	183	-0.9%	0.7%
4	199	-0.1%	0.1%
5	191	0.7%	0.6%
6	171	0.7%	0.6%
7	215	1.1%	0.7%
8	198	1.2%	0.9%
9	196	0.0%	1.3%
10	177	3.2%	1.3%
Payday-like (Clarity)			
1	183	0.8%	1.4%
2	170	-2.5%	1.5%
3	183	0.8%	1.3%
4	199	2.4%	1.1%
5	191	-1.6%	1.3%
6	171	-0.7%	0.5%
7	215	-0.3%	0.3%
8	198	0.5%	0.6%
9	196	-0.2%	0.1%
10	177	-0.1%	0.1%
Revolving			
1	183	1.0%	3.3%
2	170	-1.7%	2.9%
3	183	-0.7%	2.7%
4	199	1.5%	2.5%
5	191	3.6%	2.4%
6	171	-3.3%	2.5%
7	215	-2.1%	2.2%
8	198	2.1%	2.5%
9	196	-2.4%	2.2%
10	177	-5.3%	2.6%
Student			
1	183	-1.2%	2.9%
2	170	-0.4%	3.4%
3	183	2.4%	3.0%
4	199	-4.5%	2.1%
5	191	-4.2%	2.6%
6	171	-2.5%	2.2%
7	215	0.4%	2.1%
8	198	-4.5%	2.0%

FlexScore Decile	N	Δ Balance Share	SE
7	215	0.4%	2.1%
8	198	-4.5%	2.0%
9	196	-3.2%	1.8%
10	177	-1.3%	1.8%

Values are mean changes from the application-quarter baseline to the last observed quarter.



Values are mean changes from the application-quarter baseline to the last observed quarter.

A4.3 Pre-treatment credit states across the risk distribution

Using the same rule-based thresholds as the borderline-sample credit-state segmentation in the main text, we can classify the broader bubble-plus sample and ask how those states vary with baseline risk. This is descriptive only, but it is a useful way to see whether the higher-risk end of the applicant pool is disproportionately made up of people with severe derogatory history or collections exposure.

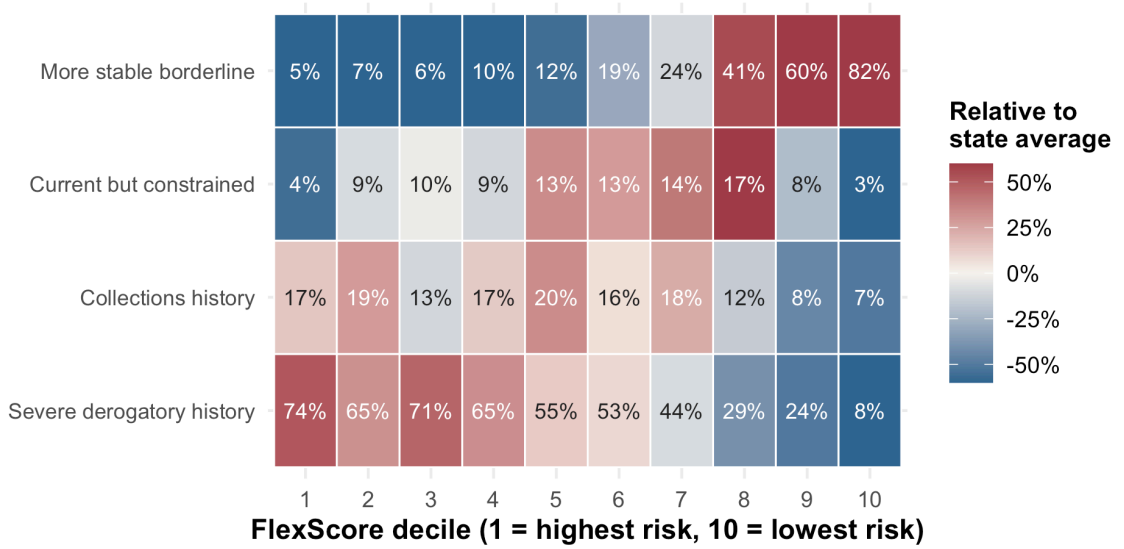
Table 30. Credit-state composition by broad risk category
Same state rules as the borderline-sample segmentation; decile 1 is shown separately

Risk category [1]	Applicants	Severe derogatory	Collections	Current but constrained	More stable
Highest risk (1)	201	73.6%	16.9%	4.5%	5.0%
High (2-3)	387	68.0%	16.0%	9.3%	6.7%
Mid (4-7)	879	54.2%	17.6%	12.2%	16.0%
Low (8-10)	624	21.0%	9.5%	9.5%	60.1%

[1]Shares sum to 100% within each risk category. Decile 1 overlaps most with the narrow approval-margin region used in the main RDD.

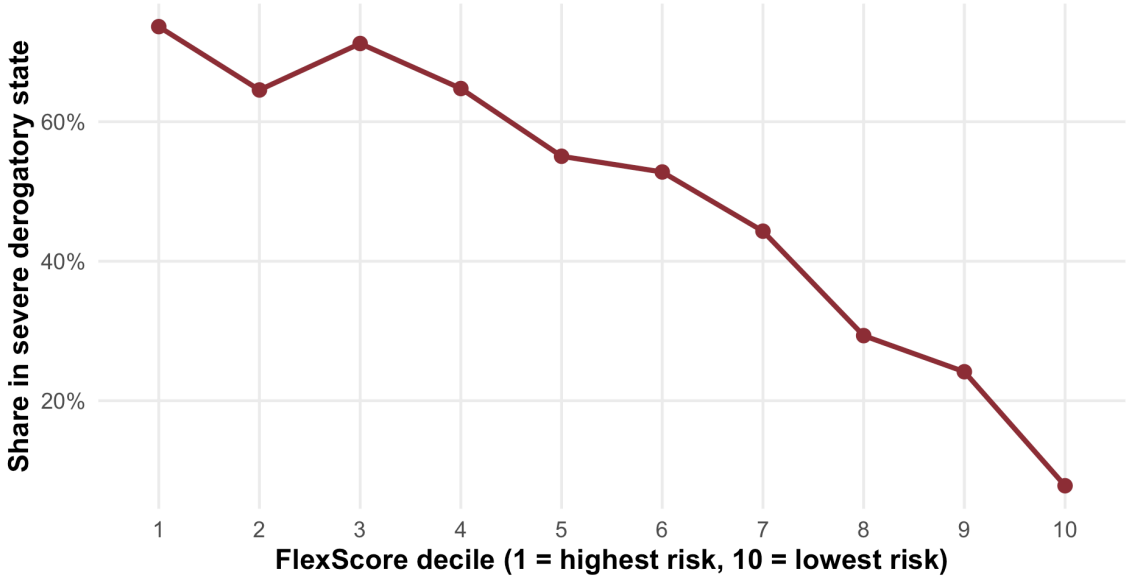
Credit-state composition shifts across the full risk distribution

Cell labels show the actual within-decile share. Fill colors show how over- or under-represented each state is relative to its own average share across deciles, which makes differences in the middle of the risk distribution easier to see.



Severe derogatory history is concentrated in the higher-risk deciles

Descriptive only: the state definition uses the same thresholds as the main-text borderline segmentation.



A5. Timing-alignment robustness

These appendix analyses ask whether the main composite results are sensitive to when, within a calendar quarter, an applicant applies. The cleanest subset is the set of quarter-end application months, March, June, and September 2024, because those cohorts line up most closely with the bureau snapshot used as the application-quarter baseline.

A5.1 Sample definition and balance

Table 31. Timing buckets in the baseline RDD sample
Application month relative to the quarter-end bureau snapshot used as the application-quarter baseline

Timing bucket	Applicants	Approved	Rejected	Approval rate
0 months: quarter-end application	3,537	2,074	1,463	58.6%
1 month before quarter-end	3,055	1,653	1,402	54.1%
2 months before quarter-end	3,021	1,729	1,292	57.2%

Table 32. Support for the perfectly timed subset
Distinct applicants observed at each quarter in the analysis window

Horizon	Applicants observed
Application-quarter baseline	3,537
First post-application quarter	3,537
Second post-application quarter	3,537
Third post-application quarter	3,537
Fourth post-application quarter	3,537
Fifth post-application quarter	2,085

Table 33. Balance diagnostic summary: full sample vs perfectly timed subset
The quarter-end application subset remains well balanced near the cutoff

Sample	Applicants	Approved	Rejected	Median |SMD|	90th pct. |SMD|	Share |SMD| > 0.10
Full RDD sample	9,613	5,456	4,157	0.012	0.039	0.0%
Perfectly timed subset	3,537	2,074	1,463	0.024	0.071	0.0%

Table 34. Largest baseline imbalances in the perfectly timed subset
Top 15 variables by absolute standardized mean difference

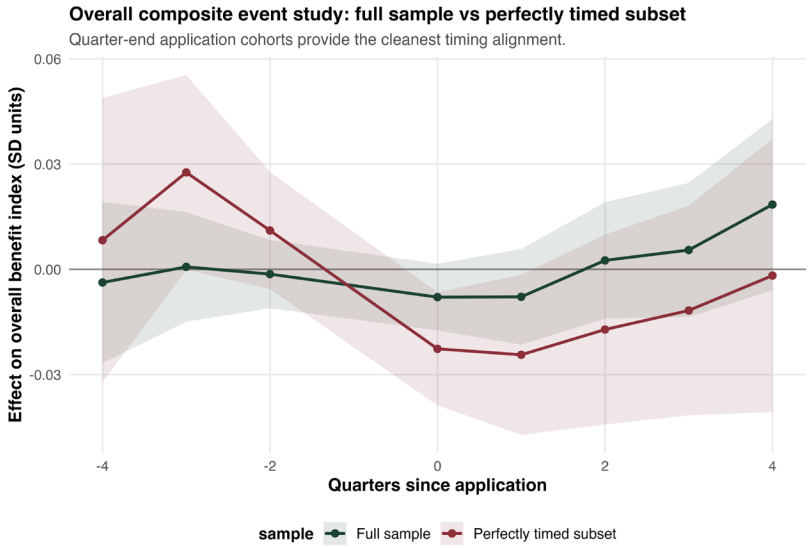
Outcome	Control mean	Treatment mean	Difference	p-value	SMD
Months at address	34.262	38.645	4.383	0.019	0.092
Overall utilization %	78.049	74.471	-3.578	0.031	-0.088
Collections count	2.222	2.039	-0.183	0.018	-0.083
Charge-off balance	3,694.609	3,314.832	-379.776	0.167	-0.049
No. trades 90+ DPD	0.516	0.602	0.086	0.038	0.075
No. trades 60+ DPD	0.530	0.612	0.082	0.050	0.071
Any payday-like/nontraditional trade	0.856	0.830	-0.026	0.042	-0.071
Storefront installment past due ($)	10.494	21.347	10.852	0.060	0.066
Days since inquiry	201.860	217.773	15.913	0.095	0.063
Months since opened	16.001	15.134	-0.867	0.242	-0.042
Any open auto	0.292	0.320	0.028	0.095	0.060
Open auto trades	0.214	0.232	0.018	0.240	0.041
Auto balance	5,437.857	6,064.626	626.769	0.090	0.059
Revolving balance	356.854	459.395	102.540	0.190	0.043
Clarity Early Risk	527.931	529.743	1.812	0.267	0.041

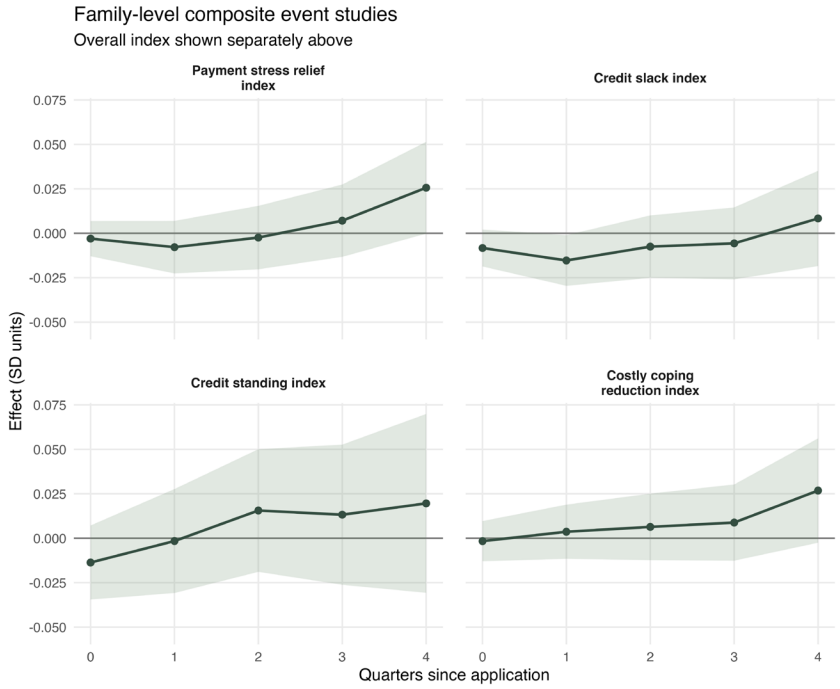
A5.2 Composite outcomes in the perfectly timed subset

Table 35. Composite ATT estimates in the perfectly timed subset
Event-study aggregate effects for quarter-end application cohorts only

Composite	ATT
Overall financial health benefit index	-0.017 (0.011)
Payment stress relief index	-0.024 (0.012)
Credit slack index	-0.003 (0.012)
Credit standing index	-0.027 (0.024)
Costly coping reduction index	0.018 (0.015)

Entries are SD-unit effects with standard errors in parentheses.


Overall composite event study: full sample vs perfectly timed subset
Quarter-end application cohorts provide the cleanest timing alignment.
Effect on overall benefit index (SD units)
0.06
0.03
0.00
-0.03
-4
-2
0
2
4
Quarters since application
sample
Full sample
Perfectly timed subset


Family-level composite event studies
Overall index shown separately above
Payment stress relief index
Credit slack index
Credit standing index
Costly coping reduction index
Effect (SD units)
0.075
0.050
0.025
0.000
-0.025
-0.050
0
1
2
3
4
Quarters since application

A5.3 Full sample vs perfectly timed comparison

Table 36. Composite ATT comparison: full sample vs perfectly timed subset
The subset is nested inside the full sample, so this table is descriptive rather than a formal difference test

Composite	Full sample	Perfectly timed subset
Overall financial health benefit index	0.001 (0.007)	-0.017 (0.011)
Payment stress relief index	0.003 (0.007)	-0.024 (0.012)
Credit slack index	-0.007 (0.007)	-0.003 (0.012)
Credit standing index	0.006 (0.014)	-0.027 (0.024)
Costly coping reduction index	0.008 (0.008)	0.018 (0.015)

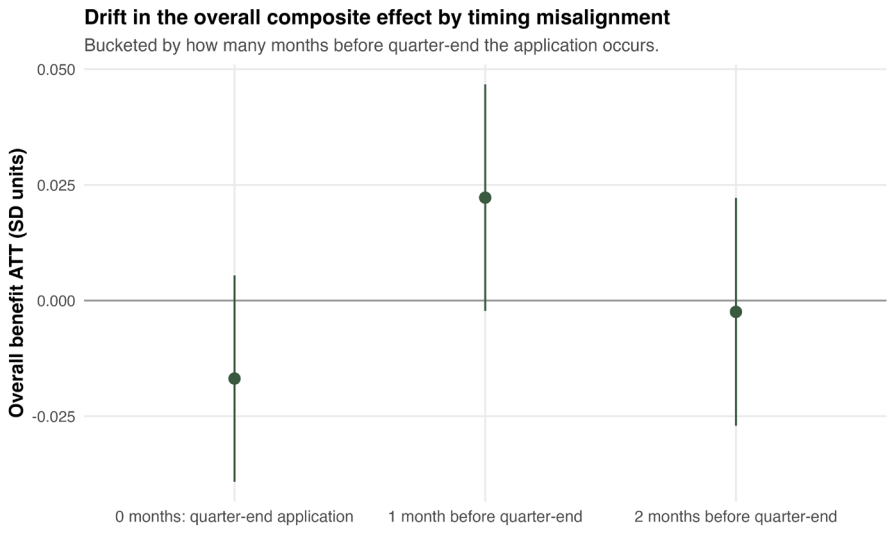
Entries are SD-unit ATT estimates with standard errors in parentheses.

A5.4 Drift by months-to-quarter-end

Table 37. Overall composite ATT by timing bucket
Comparing quarter-end application cohorts to cohorts observed 1 or 2 months before quarter-end

Timing bucket	Applicants	Approval rate	Overall benefit ATT
0 months: quarter-end application	3,537	58.6%	-0.017 (0.011)
1 month before quarter-end	3,055	54.1%	0.022 (0.012)
2 months before quarter-end	3,021	57.2%	-0.002 (0.013)

Entries are SD-unit ATT estimates with standard errors in parentheses.



A5.5 Fully pre-application baseline (one quarter earlier)

The main text normalizes event studies to the application-quarter bureau snapshot, which keeps the reference period as close as possible to the underwriting decision. As a stricter timing robustness check, this subsection re-estimates the ITT event studies using the fully pre-application quarter as the omitted baseline and re-standardizes the composite indices at that earlier point. This choice is cleaner in the narrow sense that it is fully pre-application, but it also moves the reference period farther from the decision month for every cohort.

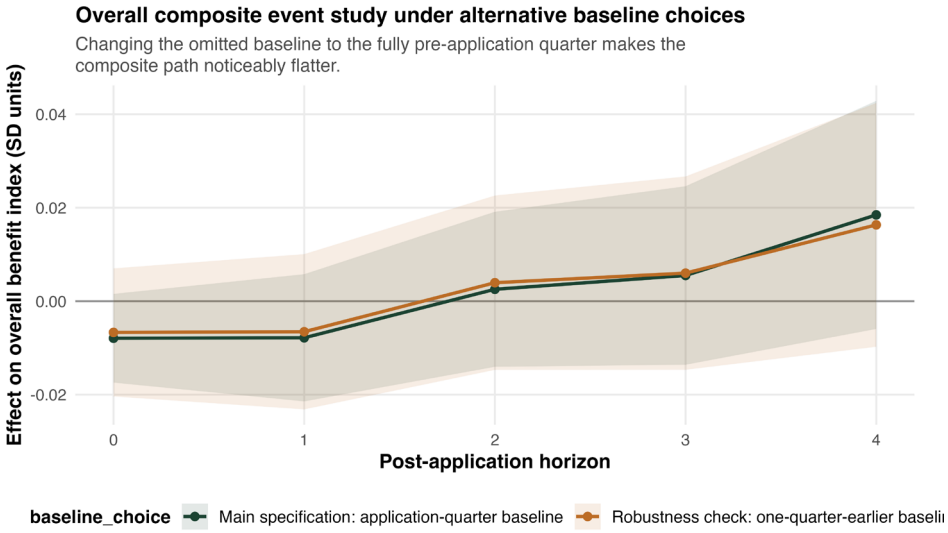


Table 38. Composite ITT estimates under the fully pre-application baseline
Composite indices are also re-standardized one quarter before application for this robustness check

Composite	First post-application quarter	Second post-application quarter	Third post-application quarter	Fourth post-application quarter	Fifth post-application quarter
Overall financial health benefit index	-0.007 (0.007)	-0.007 (0.008)	0.004 (0.010)	0.006 (0.011)	0.016 (0.013)
Payment stress relief index	-0.010 (0.007)	-0.014 (0.009)	-0.009 (0.010)	-0.000 (0.011)	0.012 (0.014)
Credit slack index	0.001 (0.007)	-0.006 (0.009)	0.002 (0.010)	0.003 (0.011)	0.013 (0.015)
Credit standing index	-0.011 (0.015)	0.001 (0.018)	0.018 (0.020)	0.015 (0.022)	0.023 (0.028)
Costly coping reduction index	-0.010 (0.009)	-0.005 (0.011)	-0.002 (0.012)	-0.001 (0.013)	0.025 (0.018)

Entries are SD-unit event-study coefficients with standard errors in parentheses. Stars reflect two-sided p-values.

Table 39. Selected raw outcomes under the fully pre-application baseline check
Comparing the main fourth-post-application-quarter estimate to the earlier-baseline robustness rerun

Outcome	Application-quarter snapshot under earlier-baseline spec	Fourth post-application quarter main spec	Fourth post-application quarter earlier-baseline spec
60+ DPD occurrences (3m)	0.007 (0.006)	-0.022 (0.015)	-0.014 (0.015)
90+ DPD occurrences (3m)	0.005 (0.005)	-0.023 (0.011)	-0.017 (0.010)
60+ DPD balance	0.041 (0.050)	-0.222 (0.124)	-0.193 (0.125)
90+ DPD balance	0.014 (0.049)	-0.250 (0.121)	-0.263 (0.122)
Days since inquiry	-5.779 (3.045)	22.215 (7.766)	25.213 (8.297)
Total trades (excl collections)	0.011 (0.019)	-0.173 (0.073)	-0.186 (0.080)
Any payday-like/nontraditional trade	0.005 (0.003)	-0.009 (0.005)	-0.007 (0.007)

Entries are event-study coefficients with standard errors in parentheses. The application-quarter column under the earlier-baseline specification shows how far that snapshot sits from the fully pre-application reference quarter.

A6. Heterogeneity methods and exploratory benchmarks

These appendix materials collect the technical details for the main-text GATES analysis and two more exploratory heterogeneity exercises. The first subsection documents the GATES setup and simple diagnostics for the ranked groups. The remaining two subsections report descriptive subgroup exercises that are useful for interpretation but weaker than the main GATES analysis.

A6.1 GATES method and diagnostics

The main-text GATES analysis uses only information available by the time of application to rank borderline applicants into five groups from lower to higher predicted benefit. The ranking model combines local design variables, application-quarter credit measures, and older trended credit summaries from earlier quarters, and it is estimated using repeated sample splitting so that each applicant's predicted benefit is generated out of sample. The tables below document the covariate library that feeds that ranking and the broad properties of the resulting groups.

Table 7. Pre-treatment covariate library for GATES
Applicant-level features measured in the quarter of application or earlier

Baseline signal	Feature form	Applicant coverage
RDD design		
Distance to cutoff	RDD design measure	100.0%
Absolute distance to cutoff	RDD design measure	100.0%
Absolute FlexScore	RDD design measure	100.0%
Credit standing		
VantageScore 4.0	Application-quarter baseline value	93.7%
Clarity early risk score	Application-quarter baseline value	84.4%
Credit slack		
Revolving available credit	Application-quarter baseline value	94.6%
Revolving credit limit	Application-quarter baseline value	94.6%
Overall utilization	Application-quarter baseline value	70.0%
Total monthly payment burden	Application-quarter baseline value	94.6%
Payment distress		
60+ DPD occurrences	Application-quarter baseline value	85.7%
90+ DPD occurrences	Application-quarter baseline value	85.7%
60+ DPD balance	Application-quarter baseline value	94.6%
90+ DPD balance	Application-quarter baseline value	94.6%
Any 60+ DPD tradeline	Application-quarter baseline flag	94.6%
Any 90+ DPD tradeline	Application-quarter baseline flag	94.6%
Collections & charge-off		
Collections count	Application-quarter baseline value	94.6%
Collections balance	Application-quarter baseline value	94.6%
Charge-off count	Application-quarter baseline value	94.6%
Charge-off balance	Application-quarter baseline value	94.6%
Any collections	Application-quarter baseline flag	85.7%

Baseline signal	Feature form	Applicant coverage
Costly coping		
Nontraditional-credit trade count	Application-quarter baseline value	100.0%
Nontraditional-credit balance	Application-quarter baseline value	100.0%
Any nontraditional-credit trade	Application-quarter baseline flag	100.0%
Credit seeking		
Inquiries in the past 3 months	Application-quarter baseline value	85.7%
Days since last inquiry	Application-quarter baseline value	81.5%
Trades reported in the past 3 months	Application-quarter baseline value	94.6%
Months since newest trade opened	Application-quarter baseline value	91.5%
Portfolio structure		
Total tradelines	Application-quarter baseline value	94.6%
Open tradelines	Application-quarter baseline value	94.6%
File age	Application-quarter baseline value	91.5%
Stability		
Months at residence	Application-quarter baseline value	73.8%
Months at employment	Application-quarter baseline value	73.0%
Public records		
Any bankruptcy record	Application-quarter baseline flag	94.6%
Any judgment record	Application-quarter baseline flag	94.6%
Any tax-lien record	Application-quarter baseline flag	94.6%
Trended payment history		
All-trade payment ratio	Older pre-application trended summary (three earlier quarters: average + trend)	81.0%
Bankcard payment ratio	Older pre-application trended summary (three earlier quarters: average + trend)	75.6%
Revolving payment ratio	Older pre-application trended summary (three earlier quarters: average + trend)	92.4%
Trended utilization history		
Bankcard balance-to-credit ratio	Older pre-application trended summary (three earlier quarters: average + trend)	94.6%
Revolving balance-to-credit ratio	Older pre-application trended summary (three earlier quarters: average + trend)	94.6%
Trended balance history		
All-trade average balance	Older pre-application trended summary (three earlier quarters: average + trend)	94.6%
Bankcard average balance	Older pre-application trended summary (three earlier quarters: average + trend)	94.6%
Revolving average balance	Older pre-application trended summary (three earlier quarters: average + trend)	94.6%

Coverage is the share of borderline applicants with an observed value for the underlying signal when it enters the GATES ranking model.

Table 8. GATES ranking groups
Applicants are sorted into five groups by predicted benefit using repeated sample splitting

Predicted-benefit group	Applicants	Approval rate	Mean predicted gain	Mean realized post-baseline change
Group 1	1,819	56.5%	-0.015	0.002
Group 2	1,819	56.8%	-0.007	0.007
Group 3	1,819	56.8%	-0.003	-0.012
Group 4	1,819	57.7%	0.000	0.014
Group 5	1,819	55.9%	0.009	0.009

Predicted gain is the out-of-sample treatment-effect score from the ranking model. Realized change is the applicant-level change in the overall benefit index after application relative to the quarter of application.

A6.2 Strain-split benchmark

The original high-versus-low strain split remains useful as a transparent benchmark, but it conditions directly on a hand-built baseline score and is therefore more vulnerable to mechanical patterning and mean reversion than the main GATES exercise.

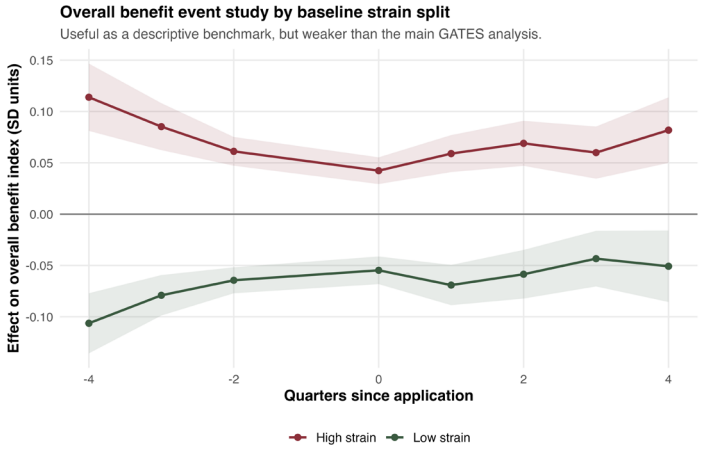
Table 40. Interim strain-split benchmark groups
The benchmark split divides borderline applicants into higher- and lower-constraint groups at the application-quarter baseline

Constraint group	Applicants	Mean strain score	Approval rate
High constraint	4,549	0.358	56.4%
Low constraint	4,548	-0.353	57.1%

Table 41. Composite heterogeneity by baseline strain
ATT estimates within the borderline approval sample

Composite	High strain	Low strain	High - Low
Overall financial health benefit index	0.06 (0.01)	-0.06 (0.01)	0.12*** (0.01)
Credit standing index	0.13 (0.02)	-0.11 (0.02)	0.23*** (0.03)
Credit slack index	0.04 (0.01)	-0.05 (0.01)	0.09*** (0.01)
Payment stress relief index	0.03 (0.01)	-0.02 (0.01)	0.05*** (0.01)
Costly coping reduction index	0.02 (0.01)	-0.00 (0.01)	0.02 (0.02)

Higher values indicate better outcomes / less harm. Entries are average post-treatment effects in SD units with standard errors in parentheses. Stars reflect the High-Low difference.



A6.3 Baseline domain clustering

This clustering exercise is descriptive rather than causal. It does not learn segments from treatment effects. Instead, it groups borderline applicants by baseline domain composites from the broader financial-health outcome set and a small aligned trended-history block, then asks whether the estimated RDD effect differs across those pre-treatment profiles. The trended features are built only from the older pre-application quarters in the trended panel, rather than from the most recent quarter that overlaps the application period.

Table 42. Cluster-choice diagnostics
Average silhouette width over candidate numbers of segments

Number of clusters	Average silhouette width
2	0.201
3	0.175
4	0.195
5	0.203
6	0.151

Table 43. Baseline domain composite support for clustering
Coverage is measured before median imputation for clustering

Domain composite	Components	Baseline coverage
Collections and charge-off	4	94.6%
Costly coping	3	100.0%
Credit seeking	3	94.6%
Credit slack	4	94.6%
Credit standing	2	94.4%
Payment distress	4	94.6%
Public records	1	94.6%
Stability	2	75.7%
Trended balance history	6	94.6%
Trended payment history	6	94.2%
Trended utilization pressure	4	94.6%

Table 44. Cluster summary (chosen k = 5)
Segments are ordered from more strained to more stable average baseline profiles

Segment	Applicants	Approval rate	Most below-average domains	Most above-average domains
Segment 1	462	58.2%	Public records, Credit seeking	Trended utilization pressure, Trended balance history
Segment 2	4,083	56.2%	Trended utilization pressure, Trended balance history	Payment distress, Credit seeking
Segment 3	912	54.9%	Collections and charge-off, Credit seeking	Stability, Public records
Segment 4	2,824	57.2%	Payment distress, Credit seeking	Trended utilization pressure, Trended balance history
Segment 5	1,332	58.5%	Trended utilization pressure, Stability	Costly coping, Payment distress

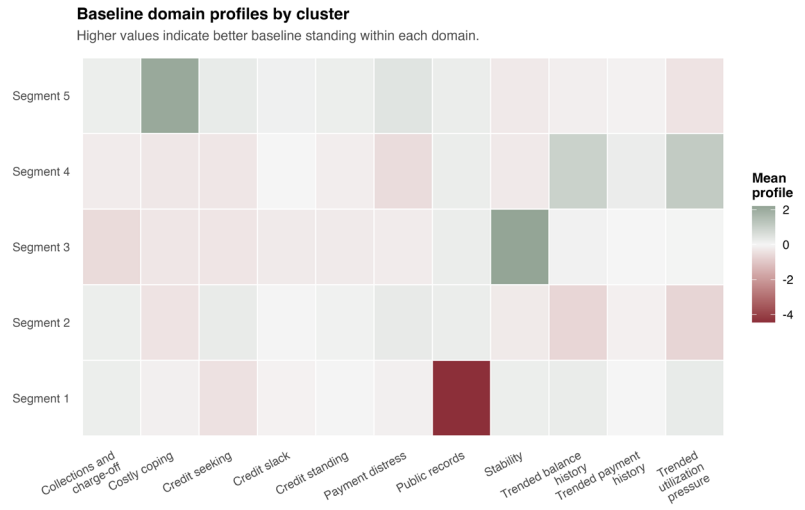


Table 45. Overall composite ATT by baseline cluster

Descriptive segment heterogeneity using the same RDD/event-study estimator within cluster

Segment	Applicants	Approval rate	Overall benefit ATT	Most below-average domains	Most above-average domains
Segment 1	462	58.2%	-0.013 (0.036)	Public records, Credit seeking	Trended utilization pressure, Trended balance history
Segment 2	4,083	56.2%	-0.005 (0.010)	Trended utilization pressure, Trended balance history	Payment distress, Credit seeking
Segment 3	912	54.9%	0.008 (0.020)	Collections and charge-off, Credit seeking	Stability, Public records
Segment 4	2,824	57.2%	0.018 (0.013)	Payment distress, Credit seeking	Trended utilization pressure, Trended balance history
Segment 5	1,332	58.5%	-0.029 (0.024)	Trended utilization pressure, Stability	Costly coping, Payment distress

Entries are SD-unit ATT estimates with standard errors in parentheses.

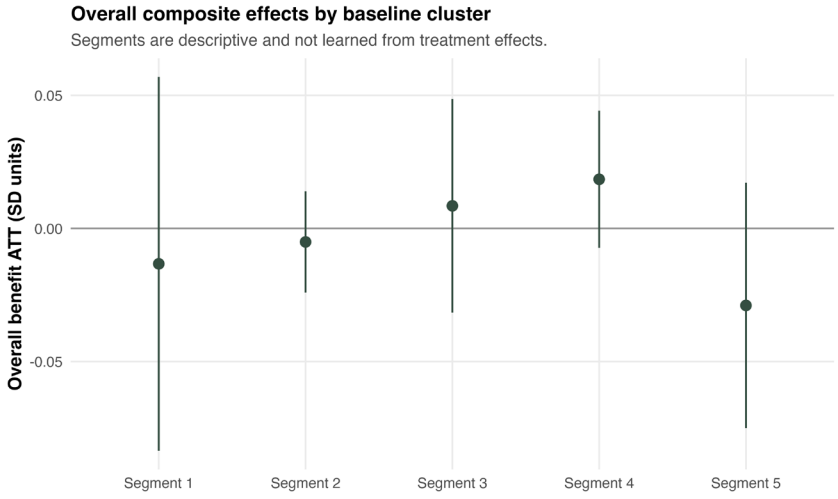


Table 46. Composite ATT table by baseline cluster
A descriptive complement to the main-text GATES analysis

Composite	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
Costly coping reduction index	0.028 (0.033)	0.042 (0.010)	0.062 (0.025)	0.012 (0.013)	-0.131 (0.037)
Credit standing index	-0.040 (0.070)	0.000 (0.021)	0.015 (0.041)	0.029 (0.026)	-0.037 (0.053)
Credit slack index	0.043 (0.039)	0.002 (0.009)	0.003 (0.023)	-0.028 (0.017)	-0.023 (0.021)
Overall financial health benefit index	-0.013 (0.036)	-0.005 (0.010)	0.008 (0.020)	0.018 (0.013)	-0.029 (0.024)
Payment stress relief index	-0.042 (0.039)	-0.019 (0.009)	0.008 (0.023)	0.053 (0.015)	-0.039 (0.024)

Entries are SD-unit ATT estimates with standard errors in parentheses.