Debt Aversion and Household Borrowing: Evidence from Mortgage Repayment

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Abstract

A large share of households partially prepay their mortgage each month even when they would earn a higher return investing at the risk-free rate, causing losses in net present value terms and contradicting basic portfolio theory. Interest rate increases from 2022–2024 raised investment returns and lowered the present value of mortgage prepayment. Yet prepayment rates did not decline, resulting in $4.6 billion in losses. Prepayment is persistent, widespread, and not explained by inattention or inertia. Instead, evidence points to debt aversion: Prepayment is higher near mortgage completion and among high-credit-score, low-debt borrowers. Exogenous cash flow shocks also increase prepayment.

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1 Introduction

Evidence from lab experiments and surveys has shown that many households are averse to holding debt, even when borrowing is financially advantageous (Martínez-Marquina and Shi, 2024; Meissner and Altmann, 2022; Loewenstein and Prelec, 1992). Thaler (1990) argues that such preferences can explain systematic deviations from benchmark lifecycle and portfolio choice models: if households treat debt as psychologically costly, they will save too much, borrow too little, and hold portfolios that appear suboptimally safe. Recent work has found patterns consistent with debt aversion in student loan take-up (Eckel et al., 2007; Gopalan et al., 2021; Caetano et al., 2019) and investment decisions in low-income countries (Berkouwer and Dean, 2022). However, there is little systematic evidence on how prevalent debt aversion is among the broad population of households, or how much it costs. This paper provides such evidence, using one of the largest and most consequential components of household balance sheets in the United States: mortgage debt.

Measuring debt aversion in the wild has been challenging because it requires a setting where the cost of holding debt is unambiguously lower than the return on a safe alternative. The monetary tightening of 2022 provides such a setting for the mortgage market. For most of the past two decades, risk-free interest rates were below the rates on outstanding mortgages, so a household paying down its mortgage was earning a positive return relative to its outside investment opportunities. Beginning in 2022, risk-free yields rose above the interest rate on roughly half of outstanding conforming mortgages. A household prepaying such a mortgage now forgoes a higher return available at the risk-free rate, making prepayment a strictly dominated investment. This new environment allows us to observe, at scale, how much households are willing to pay to avoid having debt.

We show that debt aversion is pervasive. More than one in five borrowers with a negative rate spread—meaning their mortgage rate is below the risk-free rate, after accounting for taxes—continue to make voluntary extra payments each month. The likelihood of prepaying a given fixed-rate mortgage did not change even as risk-free yields rose, and the behavior is

persistent within borrowers over time. We estimate that from January 2022 through November 2024, the present value of losses from negative-spread prepayment amounted to $4.6 billion in the conforming fixed-rate single-family mortgage market. The average monthly prepayment among these borrowers was $556, with an average NPV loss of about $87 per payment. Even though prepayment is pervasive, most borrowers make small prepayments of a few hundred dollars, and the large average losses come from the minority that make large extra prepayments without paying off their mortgage in full.

Several features of the data point to debt aversion rather than inattention, inertia, financial illiteracy, or mechanical auto-payment. First, prepayment is virtually unresponsive to interest rate changes within borrower and is unrelated to lagged interest rates or interest rates at the time of origination, ruling out sluggish adjustment as the primary explanation. Second, prepayment is highly persistent over time—even after excluding borrowers who make identical payments each month—and borrowers who prepay their mortgages also prepay their auto loans and carry less credit card debt, suggesting a stable cross-product preference against holding debt. Third, borrowers with higher credit scores are *more* likely to engage in negative-NPV prepayment than other borrowers. Households who refinanced when rates were low—a proxy for financial attentiveness—are equally likely to prepay as others, and Survey of Consumer Finances data show that prepayers are more likely to hold stocks and retirement accounts. These patterns rule out financial illiteracy or lack of access to higher-return alternatives as primary explanations.

Perhaps the most striking evidence comes from the end of the mortgage. The probability of prepayment nearly doubles as borrowers approach their final payment, to nearly 50%. This pattern is a sharp prediction of debt aversion with concave disutility: experimental evidence shows that the psychological benefit of eliminating debt entirely exceeds the benefit of a marginal reduction, so borrowers should be most willing to sacrifice returns when full repayment is within reach (Martínez-Marquina and Shi, 2024; Meissner and Altmann, 2022). The spike in prepayment near completion is difficult to reconcile with alternative explanations. It

is not driven by retirement timing or lifecycle savings motives: payments on credit cards and other financial products do not change when mortgage prepayment rises, and controlling for borrower fixed effects and calendar time does not attenuate the result. Credit score incentives also cannot explain it, as credit scores do not discretely improve upon mortgage completion. Standard portfolio theory predicts no change in prepayment near completion, since the return to prepaying does not change as the balance falls. The end-of-mortgage result does not imply that *all* negative-spread prepayment reflects debt aversion, but it provides direct evidence that debt aversion is operative for a substantial share of borrowers.

We emphasize that many commonly proposed explanations for prepayment, such as a desire to be debt-free before retirement, or a preference for the psychological "peace of mind" of owning one's home outright, are not alternatives to debt aversion but rather *instances* of it. Debt aversion, as we define it, is any disutility from holding debt that is not captured by the financial cost of that debt. A household that sacrifices investment returns to eliminate its mortgage before retirement is exhibiting precisely the preference our model captures. The question our paper answers is not whether such preferences exist—survey and experimental evidence already suggests they do—but how prevalent they are in practice and how much they cost.

While prepayment is not related to the NPV of prepaying, it is related to short-term cash flows, similar to Ganong and Noel (2020). We show that exogenous cash flow shocks, coming from COVID stimulus checks and Alaska Permanent Fund dividends, increase prepayment propensity. We also compare adjustable-rate (ARM) to fixed-rate (FRM) mortgages. In contrast to FRMs, interest rate increases reduce ARM borrowers' monthly cash flows but have little effect on the net present value of prepaying. Rate increases reduce ARM borrowers' propensity to prepay, suggesting that cash flows rather than present value calculations drive changes in prepayment behavior. Because many debt-averse households may lack the liquidity to prepay, our estimate that 22% of negative-spread borrowers prepay each month should be interpreted as a lower bound on the prevalence of debt aversion. We exploit variation in ARM borrowers'

rate resets to estimate the share of households that would prepay absent cash flow constraints. Under our preferred assumptions, we estimate that XX% of borrowers are debt-averse—that is, they would prepay their mortgage even at a financial loss if they had sufficient liquidity. We also provide a lower bound on the intensity of debt aversion: using the framework of our model, the median prepaying household behaves as if $1 of mortgage debt costs at least $XX more than $1 of forgone savings, implying a debt-aversion premium of at least XX basis points.

What do our results mean for economic theory? We highlight two implications of debt aversion, beyond the obvious modifications to models of portfolio choice. First, dispersion in debt aversion can generate sluggish aggregate responses to interest rate changes — not because households fail to observe rate movements (Sims, 2003; Reis, 2006), but because many are inframarginal with respect to prepayment. This mechanism can account for the muted pass-through of monetary policy to household balance sheets without requiring inattention. Second, if households are averse to borrowing per se, they may behave as if liquidity-constrained even when they have unused borrowing capacity (Thaler, 1990). Mortgages are the largest component of household debt, and roughly one in three mortgage borrowers prepays at least once per year, so these preference-driven distortions operate at a scale that matters for aggregate consumption and wealth accumulation.

Our findings are robust to a range of assumptions about interest rates and investment alternatives. We measure prepayment using publicly available Fannie Mae loan performance data and replicate key results using a credit registry. The central finding—that prepayment rates do not respond to changes in interest rate spreads—does not depend on specific assumptions about tax rates or outside investment options, since it is identified from within-borrower variation over time. The *level* of losses does depend on assumptions about households' marginal tax rates, which determine the after-tax mortgage rate and the after-tax return on alternative investments. Using NBER TAXSIM and data from the Survey of Consumer Finances, we estimate that the share of borrowers with negative rate spreads ranges from 39% to 69%, and aggregate losses from $2.2 billion to over $8.4 billion, depending on assumptions about the

best available alternative.

Our findings contribute to several literatures. In the same spirit as Genesove and Mayer (2001), who provide the first large-scale evidence of loss aversion in the housing market, we provide the first such evidence for debt aversion. While debt aversion has been documented in lab experiments and student loan markets (Gopalan et al., 2021; Eckel et al., 2007; Prelec and Loewenstein, 1998), ours is the highest-stakes and most widespread setting in which it has been studied.[1] Our results also speak to the "co-holding puzzle"—that many households simultaneously hold high-interest debt and low-interest assets (Gross and Souleles, 2002). Existing explanations emphasize the lack of fungibility between debt and credit (Telyukova and Wright, 2008) or insurance against credit limit volatility (Fulford, 2015), but these do not explain why households would pay down *low*-interest debt while earning *higher*-interest savings. Finally, unlike most documented financial "mistakes"—such as failure to refinance (Keys et al., 2016) or failure to shop for mortgages (Woodward and Hall, 2012)—mortgage prepayment is an *active* choice requiring deliberate action, making it more informative about household preferences and harder to address through nudges alone (Bhutta et al., 2020).

The remainder of the paper is organized as follows. Section 2 derives the NPV of mortgage prepayment and establishes the frictionless benchmark prediction that no household should prepay when the risk-free rate exceeds its mortgage rate. Section 3 describes our data sources. Section 4 documents four empirical patterns: the prevalence and cost of negative-spread prepayment, its insensitivity to interest rate changes, its sensitivity to cash flow shocks,

[1] Several earlier papers have documented mortgage curtailment (prepayment without refinancing) as a descriptive phenomenon. Amromin et al. (2007) estimate $1.5 billion in losses from prepayment in the 1990s, when the losses arose primarily from the tax arbitrage between mortgage interest deductions and tax-deferred retirement accounts—a channel reduced by the Tax Cuts and Jobs Act of 2017 (McClelland et al., 2022). Adelman et al. (2010) link prepayment to saving propensity and liquidity risk. McCollum et al. (2015) document continued curtailment using loan-level records for 2001–2011, and Xu (2023) provides additional descriptive evidence using Fannie Mae data. Choi (2022) reviews personal finance advice on curtailment, noting that such advice may have been reasonable when mortgage rates were high but is harder to justify in the current environment. None of these studies quantify curtailment in the post-2022 regime in which risk-free yields exceed fixed-rate mortgage coupons, making curtailment a strictly dominated strategy. Relative to this prior work, our contribution is threefold: we identify a setting where prepayment is unambiguously costly, we connect prepayment to debt aversion as a mechanism rather than treating it as a descriptive puzzle, and we exploit credit registry data to link mortgage curtailment to broader household financial behavior.

and the spike in prepayment near mortgage completion. Section 5 develops three candidate explanations—attention costs, debt aversion, and cash flow constraints—and presents evidence that debt aversion best accounts for the data. Section 6 concludes.

2 Mortgage Valuation and the Cost of Prepayment

A conventional fixed-rate mortgage with a monthly interest rate r_m and a term of N months can be viewed as a stream of N fixed payments. Let c denote the equal monthly payment. The principal value P of this mortgage is then the present value of all future payments:

$$P = \sum_{t=1}^{N} \frac{c}{(1+r_m)^t}. \tag{1}$$

Households, however, have the option to *curtail* the loan—that is, make a payment larger than c in a given month. Unlike a standard extra payment on credit card debt, prepayment via curtailment reduces only the *final* month's payment (rather than all future payments). As we will show, this feature has important implications for the net present value (NPV) of the decision to curtail.

Consider a prepayment of amount Δ made when N payments remain. The principal balance of the loan falls by Δ, thereby reducing the terminal payment by an amount γ that can be derived from the mortgage amortization formula. Specifically, letting P denote the remaining principal balance,

$$P - \Delta = \sum_{t=1}^{N-1} \frac{c}{(1+r_m)^t} + \frac{c-\gamma}{(1+r_m)^N}. \tag{2}$$

Solving for γ yields

$$\gamma = \Delta(1+r_m)^N.$$

Thus, a partial prepayment now lowers the terminal payment by γ, but the earlier monthly payments c remain unchanged.

To evaluate the financial cost or benefit of such a prepayment, denote by r the household's

opportunity cost of capital (e.g., the after-tax yield on an alternative investment). The net present value of a curtailment of size Δ is then

$$\text{NPV} = \Delta \frac{(1+r_m)^N}{(1+r)^N} - \Delta. \tag{3}$$

Whenever $r_m < r$, this expression is negative because the present value of the reduced final payment, discounted at rate r, is below the return that could be earned at rate r. In other words, if $r_m - r < 0$, a household strictly prefers to invest Δ at the higher outside rate r rather than to pay down its mortgage. Conversely, if $r_m > r$, prepaying (or refinancing) produces a positive NPV because the mortgage's effective rate of return exceeds r. Prepaying will always have zero NPV for an adjustable-rate mortgage having $r \equiv r_m$.

Naturally, r_m may exceed r if, for example, long-term market rates have fallen below the contractual mortgage rate since origination. In that case, prepayment has a positive NPV, but refinancing may be even more beneficial than prepayment. Our analysis focuses on the case $r_m < r$, in which case both refinancing and prepayment are unambiguously suboptimal from a purely financial perspective. We thus abstract from the option-like nature of refinancing.[2]

Prepayment is also a relatively illiquid investment compared with risk-free assets, since extracting equity from a house requires fees, a higher interest rate, and time costs. One caveat is that borrowers can *recast* their mortgage—re-amortize the remaining balance to obtain a lower monthly payment. However, industry evidence suggests that recasting is extremely rare due to stringent lender requirements (Lerner, 2021; Brown, 2023).

A frictionless benchmark

The NPV formula above implicitly defines a frictionless portfolio problem. A household receives a liquid cash flow F and allocates it between (i) an outside asset earning an after-tax, risk-free return r, and (ii) an extra principal payment on a fixed-rate mortgage earning an after-tax

[2]See, for instance, Agarwal et al. (2013) for a derivation of optimal refinancing rules and Keys et al. (2016) for empirical evidence on refinancing decisions.

return r_m. Let $x \in [0,1]$ be the share of F allocated to prepayment. Expected wealth next period is:

$$W(x) = xF(1+r_m) + (1-x)F(1+r). \tag{4}$$

Maximizing $W(x)$ implies $x = 1$ when $r_m > r$ and $x = 0$ otherwise. The benchmark therefore predicts (i) no dominated prepayment, and (ii) an aggregate prepayment share that jumps discontinuously when the spread $r_m - r$ crosses zero.

The frictionless benchmark predicts that no household should prepay its mortgage when a higher after-tax return is available at the risk-free rate. The next sections show that this prediction is violated. We first describe our data (Section 3), then document four empirical patterns that characterize prepayment behavior (Section 4): its prevalence and cost, its insensitivity to interest rate changes, its sensitivity to cash flow shocks, and an increase near mortgage completion. Section 5 then develops three candidate explanations—attention costs, debt aversion, and cash flow constraints—and assesses which best fits the evidence.

3 Data and Measurement

Mortgage data. Our main source of data is the Fannie Mae Single-Family Loan Performance dataset, which includes monthly loan-level performance history for fully amortizing, single-family fixed-rate conforming mortgages with terms of 30 years or less. We include both purchase and refinance loans originated on or after January 1, 1999, exclude loans that were ever delinquent, and limit the sample to January 2011–November 2024. We take a 1% random sample for computational convenience.

The dataset includes variables measuring the principal balance, interest rate, maturity at origination, and a recalculated maturity that accounts for past prepayment. We use the mortgage amortization formula to calculate payments in excess of the required monthly payment. Because principal balances are rounded to the nearest $1,000, the formula sometimes predicts prepayment due to rounding error; we therefore ignore prepayment amounts less than $20,

which exceeds the maximum measurement error. We verify the calculation by confirming that changes in remaining maturity match expected values and by recovering known prepayment in a simulated dataset. Because we identify prepayment from changes in the outstanding principal balance rather than from total payment amounts, escrow payments for property taxes and homeowner's insurance—which do not reduce principal—cannot be misclassified as prepayment in our data.

We study adjustable-rate mortgages using the Freddie Mac Single-Family Non-Standard Dataset, which has a similar structure but includes ARMs.

Tax rates. We use the 2010–2019 Surveys of Consumer Finances (SCF) and the NBER TAXSIM program to calculate marginal tax rates. We subset SCF respondents to those with fixed-rate mortgages, calculate their federal and state marginal tax rates, and match these rates to loans in the Fannie Mae data by year, origination principal, and state.[3] For our baseline analysis, we assume that households with a tax-deferred retirement plan available face an effective marginal tax rate of zero on investment returns.[4] We then calculate the after-tax mortgage interest rate (r_m in Equation 3) and after-tax maturity-matched Treasury yield (r in Equation 3). We also present results under alternative tax assumptions.

Discount rates. Our baseline results use maturity-matched Treasury rates as the risk-free rate: the 10-year Treasury note yield for mortgages with five or more years remaining, the 5-year note for two to five years, the 2-year note for one to two years, and the 1-year Treasury bill for less than one year. We also show results using alternative discount rates.

Consumer credit records. Other credit variables come from the University of California Consumer Credit Panel (UC–CCP), which consists of loan-level credit records for a 2% sample of

[3] Since the mortgage data do not include the state of residence, we randomly assign mortgages to states proportional to state population. See Appendix A for details.

[4] As of 2024, about 14% of households contribute the maximum amount to their tax-deferred retirement accounts each year (Vanguard, 2024).

the U.S. population, observed quarterly from 2004 to 2023. We restrict our sample to mortgage borrowers with information on actual and scheduled payment amounts, so we do not need the amortization formula to identify prepayment. The UC–CCP also provides borrowers' credit scores and balances on other financial products each quarter, allowing us to link mortgage prepayment to broader financial behavior.[5]

The main limitation of the UC–CCP is that it does not include interest rates, so we cannot calculate the NPV of prepayment in these data. A secondary limitation is the inability to distinguish true prepayment (which reduces remaining maturity) from "clerical" early payments (e.g., making next month's payment before its due date). The Fannie Mae data allow us to remove clerical prepayment (see Appendix A), but this is not possible in the UC–CCP, so the credit-registry series indicates a somewhat higher level of prepayment. Figure A2 illustrates the discrepancy: the benchmark Fannie Mae prepayment flag and the UC–CCP flag differ, but when we add back clerical prepayers in the Fannie Mae data, the two series converge.

4 Empirical Patterns

The frictionless benchmark in Section 2 predicts that no household should prepay when $r_m < r$, and that aggregate prepayment should respond to changes in the interest rate spread. We now examine the data along four dimensions that bear on this prediction and help distinguish between candidate explanations. First, we document the prevalence and cost of negative-spread prepayment. Second, we test whether prepayment responds to interest rate changes. Third, we ask whether prepayment responds instead to cash flow shocks. Fourth, we examine prepayment near mortgage completion. Section 5 then develops candidate explanations formally and assesses which best fits the evidence.

[5] Similar to Amromin et al. (2020) and Adelman et al. (2010), we use credit card ownership and balances to predict mortgage prepayment, but we rely on administrative data rather than self-reported values.

4.1 Prevalence and Cost of Negative-Spread Prepayment

We begin by documenting the scale of prepayment when it is financially costly. Panel A of Figure 3 shows the distribution of after-tax interest rate spreads ($r_m - r$) in the Fannie Mae data. During 2011–2021 (blue), the mass is almost entirely positive, as outstanding mortgage rates were well above risk-free yields. After 2022 (red), more than half of observations are negative. As an illustrative exercise, Panel B shows the hypothetical NPV of a \$1 prepayment for a mortgage with an interest rate of 4% and 100 months remaining. Holding r_m and Δ fixed, we vary r from 0.01% to 8%, corresponding to spreads of about -4 to $+4$ percentage points. Mechanically, for negative interest rate spreads, the net present value is negative. The slope of the line of best fit is approximately 0.08, indicating that for every percentage-point decrease in the spread, households lose nearly 10 cents per dollar prepaid—or about 10% of their excess payment.

Despite this shift in the interest rate environment, prepayment behavior barely changed. Figure 1 plots the distribution of outstanding mortgage rates against the 10-year Treasury yield (Panel A) and total prepayment volume by spread sign (Panel B). The volume of negative-spread prepayment (red bars) grows rapidly after early 2022, but positive-spread prepayment does not decline commensurately—total prepayment volume is roughly stable. Among borrowers with a negative spread, about 22% prepay in any given month.

The upper panels of Figure 4 show histograms of excess payment amounts for 2011–2021 and 2022–2024, right-truncated at \$600. The distribution has a very long right tail, so the average payment (\$556) is substantially larger than the median. Most prepayments are small, with pronounced bunching at round numbers—especially \$100 and \$200—which reflects deliberate payment choices rather than data rounding, since the excess amount is calculated relative to the expected amortization payment. Aggregate losses are therefore driven disproportionately by the minority making large payments. Panels C and D scale prepayment by the loan's monthly payment, right-truncated at 1 (capturing about 90–95% of payments). The pattern is similar in both time periods: the mean and median prepayment as a share of the

monthly payment are about 23% and 14%, respectively. Panels E and F show the NPV of these payments. From 2011–2021, nearly all excess payments carried a positive NPV, since most mortgages had a positive rate spread.[6] From 2022–2024, the distribution shifts inward, with over half of observed payments carrying a negative NPV.

Table 1 provides summary statistics from the Fannie Mae dataset at the loan-month level, comparing prepayers and non-prepayers. Panel A covers the full sample period (January 2011–November 2024); Panel B restricts to January 2022–November 2024; Panel C further restricts to negative-spread mortgages in the later period. Across the full sample, prepayers and non-prepayers look remarkably similar on most dimensions: origination balances of roughly $220,000, remaining balances near $180,000, and comparable marginal tax rates on both income and mortgage interest (about 12% each). Prepayers have slightly lower mortgage interest rates (3.93% vs. 4.10%) and shorter origination terms, on average. Naturally, prepaying households have shorter effective remaining terms: 219 months vs. 259 months across all years, and 228 vs. 265 months in the 2022–2024 subsample. Among negative-spread loans in Panel C, the differences are larger: prepayers have origination balances of about $268,000 and remaining balances of $222,000, compared to $281,000 and $246,000 for non-prepayers. The key observable distinction throughout is that prepayers tend to have higher credit scores, a pattern we return to in Section 5.

How large are the aggregate losses? Figure 5 shows the time series. There was almost no negative-NPV prepayment prior to February 2022. By the fourth quarter of 2023, total losses reached about $250 million per month, implying an average cost of roughly $115 per prepaying borrower. The cumulative total from January 2022 to November 2024 is approximately $4.6 billion for GSE-backed mortgages, with an average NPV of nearly −$87 per payment.

Another way to gauge the cost is in terms of forgone return. Figure 6 shows the average rate spread for negative-spread prepayers, weighted by dollar volume: this increased in absolute value from about −0.2 to nearly −1.25 percentage points over the period. On average, these

[6] Of course, during 2011–2021, the NPV from refinancing could have been even higher.

borrowers forgo nearly a full percentage point of return.

4.2 Assumptions

Our calculations rely on assumptions about tax benefits of mortgage interest and the appropriate opportunity cost of capital. Table 3 shows how different assumptions affect the results.

The first row reports our benchmark: investment returns are taxed at the marginal income tax rate, except for households with an eligible tax-deferred retirement account (for whom the effective tax rate is zero); mortgage interest is tax-deductible for itemizers; and the maturity-matched Treasury rate is the opportunity cost. Under these assumptions, 52% of mortgages carry a negative spread from January 2022–November 2024, and total losses are $4.6 billion.

The availability of tax-free retirement accounts matters substantially. The second row assumes all investment returns are taxed at τ, removing the tax-free channel. Because the average marginal tax rate for prepayers is about 12%, this reduces the effective 10-year Treasury return from roughly 4% to about 3.5%. Since this yield is close to the median mortgage rate, even a half-percentage-point shift substantially changes the share of mortgages with a negative spread: it falls from 52% to 39%, and total losses fall by more than half, to $2.2 billion. In the third row, we ignore taxes entirely, which raises losses to $6.3 billion.

Finally, although the maturity-matched Treasury rate is a reasonable benchmark, mortgage payments should arguably be discounted at a somewhat higher rate due to refinancing and default risk. When we use the yield on maturity-matched mortgage-backed securities instead, the negative-spread share rises to 69% and the average loss per payment nearly doubles to $120. These estimates suggest that our benchmark may be a lower bound on the true magnitude of losses. Under all assumptions, the aggregate cost is substantial.

4.3 Insensitivity to Interest Rates

The frictionless benchmark predicts a strong link between interest rate movements and prepayment. Figure 1 already suggests little aggregate correlation. We now test this formally.

We estimate the linear probability model:

$$Prepay_{it} = \beta \text{ Spread}_{it} + \Omega X_{it} + \varepsilon_{it}, \tag{5}$$

where Spread_{it} is the difference between the mortgage rate and a comparable risk-free rate. Table 7 reports results. In the cross-section (Column 1), each percentage-point higher spread is associated with a 1 pp *lower* probability of prepayment—the wrong sign. Adding loan fixed effects (Column 2), so that time-series variation in r identifies the effect, the coefficient falls to about 0.3 pp and is economically negligible. Column 3 confirms the cross-sectional pattern: households with lower mortgage rates prepay more.

Two robustness exercises reinforce the null. First, we add annual lags of the spread up to four years (Table A2); all lagged coefficients are precisely estimated zeros. Second, a binscatter (Figure A5) reveals a flat relationship across the entire range of spreads, in both the full sample and the 2022–2024 subsample. There is no evidence of a threshold or nonlinearity that might indicate switching costs or inaction bands.

4.4 Sensitivity to Cash Flows

If prepayment does not respond to interest rates, what explains its time-series variation? We examine whether disposable cash flow—rather than the present value of future payments—drives extra mortgage payments.

Income shocks. Figure 7 plots total monthly prepayment alongside real disposable income growth for high-income (top 10%) and middle-income (middle 40%) households, using data from Blanchet et al. (2022).[7] Among the top 10%, prepayment closely tracks income gains and shows abrupt jumps following COVID-19 relief payments (dashed vertical lines). Additional corroboration comes from the Alaska Permanent Fund Dividend: each October, Alaskan households receive a lump-sum payment, followed by a noticeable uptick in mortgage prepayment

[7] Data are downloaded from https://realtimeinequality.org/.

(see Appendix B and Table A1).

ARM vs. FRM comparison. Adjustable-rate mortgages provide a more direct test. When market rates rise, ARM borrowers face both a higher discount rate *and* a higher monthly payment. FRM borrowers face only the former. If households respond to current cash flow rather than NPV, ARM prepayment should decline more.

We estimate:

$$\text{Prepay}_{it} = \beta \cdot ARM_i \times \text{LIBOR}_t + \delta_i + \gamma_t + \varepsilon_{it}, \tag{6}$$

using a sample of FRMs and ARMs past their introductory fixed-rate period. Table 8 reports the results. Column 1 confirms that a 1 pp LIBOR increase raises ARM rates by about 0.644 pp, corresponding to a roughly $52 increase in monthly payments. Column 2 shows that this reduces ARM prepayment by 1.9 pp, while FRM borrowers—whose payments are unchanged—show no effect. Columns 3–5 decompose by payment size: small-dollar prepayments ($20–$500) decline most, consistent with a liquidity mechanism.

Comparing ARMs still in their introductory period ("locked in") with those already floating reinforces this pattern. Table 9 shows that after the lock-in period, LIBOR fluctuations pass through fully to payments and generate a stronger negative effect on prepayment.

We confirm the timing using a local projection around ARM rate resets:

$$\text{Prepay}_{i,t+k} - \text{Prepay}_{i,t-1} = \beta_k(\text{Rate}_{i,t} - \text{Rate}_{i,t-1}) + \gamma X_{it} + \varepsilon_{it}, \quad k = -2, 0, 1, 2. \tag{7}$$

Figure 8 plots the estimated β_k coefficients. A 1 pp rate increase reduces prepayment probabilities by 0.5–1.1 pp over the following two months, relative to a baseline of 18%.

4.5 Prepayment Near Mortgage Completion

We next examine how prepayment varies with the remaining mortgage balance. Figure 9 plots the probability of prepaying against remaining principal using UC–CCP data.[8] For large balances, prepayment occurs at a roughly constant rate of about 26%. As the balance falls below roughly $5,000, the probability rises sharply: at $500 remaining, it reaches nearly 50%. Even between $500 and $2,000, the probability at the lower balance is 58% higher.[9]

Is this spike driven by other factors that change near mortgage completion, such as shifts in consumption opportunities or credit behavior? Figure 10 plots four placebo outcomes—originating a new auto loan, opening a new credit card, becoming delinquent on any trade line, and revolving credit utilization—against remaining mortgage balance. None show a similar spike. We formalize this in a within-borrower regression:

$$y_{it} = \sum_{j=1}^{7} \beta_j \mathbb{1}(\text{bal}_{it} \in B_j) + \delta_i + \gamma_t + \varepsilon_{it}, \tag{8}$$

where $\text{bal} \in [0, 1]$ is the share of remaining principal and the B_j are bins from 0–1% through 40–50%, with balances above 50% as the omitted category. Table A3 confirms: even controlling for borrower and time fixed effects, prepayment rises near completion while the placebo outcomes do not.

5 Mechanisms and Interpretation

The patterns in Section 4 present a puzzle. A substantial share of borrowers make prepayments that are financially costly (Section 4.1), do not adjust when the cost increases (Section 4.3), do respond to cash flow shocks (Section 4.4), and are far more likely to prepay when full repayment is within reach (Section 4.5). We now develop three candidate explanations—

[8] The baseline probability is higher in this dataset than in Fannie Mae because we cannot remove "clerical" prepayers. See Section 3 and Appendix A.

[9] Fu (1998) finds a similar pattern using data from the 1960s–1990s.

attention costs, debt aversion, and cash flow constraints—and assess which can account for these facts.

5.1 Candidate Explanations

We consider three mechanisms, not mutually exclusive, that can rationalize prepayment even when it is not NPV-maximizing.

Attention and search costs. Households may face costs of monitoring interest rates or finding alternative uses of funds. A tractable representation is a fixed adjustment cost $\kappa > 0$: the household prepays only if the perceived gain exceeds that cost,

$$(r_m - r)\, F \;\geq\; \kappa. \tag{9}$$

This creates an inaction band: small rate changes leave behavior unchanged, while sufficiently large changes trigger adjustment (Andersen et al., 2020). A closely related microfoundation is rational inattention, in which households choose information precision at a cost (Reis, 2006; Berger et al., 2024). The key predictions are: (i) eventual sensitivity to sufficiently large rate changes, (ii) response to lagged as well as current rates, and (iii) more attentive or sophisticated borrowers should be *more* responsive to rate changes. Additionally, when a household receives an increase in available cash, it should be *less* likely to prepay under this theory, since the benefits of finding higher-return uses of funds increase.

The insensitivity of prepayment to interest rate changes mirrors a related finding in the mortgage origination literature: Anenberg et al. (2023) show that household borrowing amounts also respond little to changes in interest rates. Our setting is particularly well-suited to study this insensitivity. Changes in bond yields or CD rates alter the opportunity cost of paying down a fixed-rate mortgage without changing the mortgage's own characteristics, allowing us to isolate household sensitivity to economic incentives while holding mortgage terms constant.

Since mortgages constitute the largest component of household debt and excess repayments affect roughly one-third of mortgages each year, understanding this insensitivity is important for both household finance and monetary policy transmission.

Debt aversion. Attention-based stories imply that households *would* change behavior if they knew about outside opportunities. Debt aversion offers a different explanation, rooted in preferences. Experimental evidence shows that consumers overvalue debt reduction per se, even at the cost of higher-yielding opportunities (Loewenstein and Prelec, 1992; Prelec and Loewenstein, 1998; Meissner, 2016; Duffy and Orland, 2020; Meissner and Albrecht, 2022; Martínez-Marquina and Shi, 2024). Beyond the lab, evidence has come from field experiments (Field, 2009; Caetano et al., 2019) and observational studies of student loans (Gopalan et al., 2021; Eckel et al., 2007), where results have been mixed. No previous research has documented the costs of debt aversion in a setting as widespread as ours.

We model a psychological cost of carrying mortgage debt D. Let x be the share of cash flow F devoted to prepayment. The household maximizes next-period wealth net of this cost:

$$V(x) = W(x) - u(D - xF), \tag{10}$$

where $W(x)$ is defined in Equation (4) and the cost function satisfies $u' > 0$, $u'' < 0$. The first-order condition is

$$r_m - r = -u'(D - x^\star F), \tag{11}$$

so prepayment can occur with a negative return spread whenever the spread is compensated by the marginal utility of reducing debt. An additively separable debt-utility term of this sort arises naturally from the mental-accounting framework of Thaler (1990) and Prelec and Loewenstein (1998).

The concavity of u implies that the marginal benefit of debt reduction is higher when the balance is low. Martínez-Marquina and Shi (2024) provide experimental evidence for exactly

this pattern: households are more willing to sacrifice returns to pay off debt when balances are smaller. This generates a distinctive prediction: prepayment should spike near mortgage completion, when the psychological benefit of full elimination is largest. Standard portfolio theory predicts no such change, since the financial return to prepaying does not vary with the remaining balance.

Two additional predictions follow. First, if debt aversion is a stable preference, households that prepay their mortgage should also exhibit similar behavior on other debts. Second, although debt aversion does not directly predict sluggish responses, it can generate low *aggregate* sensitivity to rate changes if many households are inframarginal—that is, if heterogeneity in debt aversion means few households are near the margin between prepayment and investment.

Cash flow constraints. In mortgage modification settings, Ganong and Noel (2020) show that changes in NPV have little effect on behavior, whereas changes in short-run cash flow have large effects.[10] By analogy, households that ignore NPV may still respond to cash flow shocks. The prediction is straightforward: prepayment should track liquidity shocks regardless of NPV. An important implication is that the observed prepayment rate is a *lower bound* on the prevalence of debt aversion, since cash-constrained households may be unable to act on their preference even if they hold it.

5.2 Evidence for Debt Aversion

We now bring together evidence from Section 4 and additional cross-sectional tests to assess which explanation best fits the data.

Stable household-level preferences. A natural starting point is whether prepayment reflects stable individual characteristics or transitory shocks. Table 6, Panel A, decomposes the varia-

[10] Cookson et al. (2022) provide related evidence that household responses to cash flows cannot be explained by standard forward-looking models.

tion in prepayment using UC–CCP data. Individual fixed effects alone explain about 25% of the variation ($R^2 = 0.255$); adding time fixed effects raises this to 0.376. Prepayment is highly persistent: conditional on prepaying in month t, the probability of prepaying in $t+1$ exceeds 80%. Conditional on *not* prepaying, the probability in $t+1$ is below 5%.

Within-borrower variation reinforces the pattern. Adding credit covariates (Column 3), higher credit scores are associated with more prepayment: a 100-point increase raises the probability by 4.8 pp. Credit card ownership and larger credit card balances predict *less* prepayment. Including individual fixed effects (Column 4), these coefficients strengthen: the credit score coefficient rises to 0.114, and the credit card indicator increases in magnitude from −5.2 to −8.7. When a household's credit score improves, it becomes more likely to prepay; when it acquires a credit card, it becomes less likely. These within-borrower patterns point to a stable relationship between aversion to debt across products.

Cross-product consistency. If debt aversion is a preference rather than a product-specific mistake, it should manifest across debt types. Panel B of Table 6 tests this using auto loans. Households that prepay their mortgage are 8.5 pp more likely to also prepay an auto loan in the same quarter, a roughly 50% increase relative to the 17% base rate. These households also choose shorter auto loan terms—about 2–3 months shorter on both average and maximum term length. The cross-product correlation holds conditional on age, credit score, gender, and state fixed effects, indicating that it does not simply reflect higher income or better financial position.

Prepayment near completion and concave disutility. Section 4.5 documented that the probability of prepaying rises from about 26% to nearly 50% as the remaining balance approaches zero (Figure 9), while four placebo credit outcomes show no such spike (Figure 10). This pattern matches the prediction of concave $u(D)$: the psychological benefit of eliminating debt entirely exceeds the benefit of marginal reduction (Martínez-Marquina and Shi, 2024; Meissner and Albrecht, 2022).

Standard portfolio theory predicts no change near completion, since the financial return to prepaying does not vary with the balance. Several alternative explanations can also be ruled out. Retirement timing is also unlikely to explain the completion spike. Panel B of Figure 2 shows prepayment probabilities by borrower age, calculated from UC–CCP data. The profile follows an inverse-U shape: the likelihood of prepayment rises steadily from the early 30s through the mid-50s and then declines through the mid-70s. This hump-shaped pattern closely mirrors the lifecycle profile of household income, which peaks in the late 40s to mid-50s before declining into retirement. Crucially, there is no discontinuity at age 65, when the probability of retirement increases sharply. If mortgage prepayment were driven by a desire to eliminate debt at retirement, we would expect a discrete jump in prepayment at or around this age; no such jump exists. Rather, the age profile is consistent with prepayment tracking available cash flow over the lifecycle: households prepay more when income is high and less when it falls, regardless of proximity to retirement.

More importantly, the completion spike survives borrower and time fixed effects (Table A3), which absorb any age-related or cohort-related confounders. Credit score incentives also cannot explain the pattern, since credit scores do not discretely improve upon mortgage completion.

Financial literacy If negative-NPV prepayment reflected financial ignorance, we would expect it to be concentrated among less sophisticated borrowers. The data show the opposite. Table 5 breaks out prepayment behavior by borrower characteristics. Borrowers with above-median credit scores are *more* likely to have a negative spread (in part because they secured lower rates at origination) *and* are more likely to prepay conditional on having one. They also make larger extra payments. Figure 2, Panel A, shows the gradient directly: prepayment rises from about 10% per month for borrowers in the 600s to above 20% for those near 800.

First-time home buyers are *less* likely to engage in negative-spread prepayment, not more. Perhaps most strikingly, borrowers who originated in 2020–2021—a group enriched for atten-

tive households who refinanced when rates were low—are no less likely to prepay a negative-spread mortgage (Table 5). These borrowers demonstrated sophistication in one domain (refinancing) while exhibiting the same "costly" behavior in another (prepayment), consistent with a deliberate preference rather than a financial mistake.

Stock market participation. If negative-NPV prepayment reflected a lack of access to higher-return alternatives, we would expect prepayers to be *less* likely to participate in equities. Data from the 2022 Survey of Consumer Finances show the opposite. We classify a household as a prepayer if it reports being "ahead" on its mortgage payment schedule relative to "on track" or "behind."[11] Households that prepay their mortgage are 27.5% more likely to hold any stock (defined as a positive total market value of directly and indirectly held equities) than non-prepayers. Unconditional on stock ownership, prepayers' equity holdings are about 36% larger than those of non-prepayers (excluding the top 5% of the stock value distribution, which is dominated by extreme right-tail observations). Even conditional on owning stocks, prepayers hold about 6% more in equities. Prepayers are also 11% more likely to hold an IRA or Keogh retirement account. These patterns indicate that households who engage in costly mortgage prepayment are not simply unaware of or unable to access higher-return investments—they actively participate in equity markets while simultaneously choosing to pay down low-interest debt.

Inattention and inertia. Inattention predicts that sufficiently large rate changes, or sufficiently attentive borrowers, should eventually respond. Neither pattern appears in the data.

We construct two proxies for attentiveness. First, we identify 2020–2021 refinancers, who demonstrated active rate-monitoring. Second, we classify borrowers by the residuals from an auxiliary regression of mortgage rates on credit scores, LTV, and origination-quarter fixed

[11] This categorical variable is available in the SCF and captures households that have made payments in excess of the amortization schedule.

effects:

$$\text{Rate}_i = \alpha + \beta_1 \text{CreditScore}_i + \beta_2 \text{LTV}_i + \gamma_{q(i)} + \varepsilon_i, \tag{12}$$

with the lowest-residual quartile representing those who secured especially favorable rates. For both groups, we re-estimate the spread-sensitivity regressions from Section 4.3. Figure 11, Panel A, shows that even among the most attentive borrowers, the estimated sensitivity of prepayment to interest rate spreads is economically negligible—close to zero in all subsamples.

Inertia is also an unlikely explanation. If borrowers began prepaying when it was financially beneficial and simply failed to stop, we would expect those who started in a low-rate environment to show higher continuation rates than those who started in a high-rate environment. Figure 11, Panel B, shows the opposite: borrowers who first prepaid after March 2022 (when rates were high and prepayment was costly) converge to the same ∼90% continuation probability within two months as those who began in a low-rate environment. Persistence is high but unrelated to the interest rate environment at origination.

Finally, dropping borrowers who make exactly the same payment each month—a group for whom autopay or habit could explain persistence—does not change the results. Table A4 replicates the rate-sensitivity regressions from Table 7 excluding these borrowers; the coefficients are nearly identical.

One additional question is whether some borrowers may follow biweekly or 13th-month payment strategies—making half a payment every two weeks or one extra full payment per year—that mechanically generate "excess" payments without reflecting a deliberate monthly decision. In the distribution of payments as a fraction of the expected monthly payment (Figure 4, Panels C–D), such strategies would appear as a mass at approximately 1.5 times the expected payment (corresponding to an extra half-payment in a given month). We do observe some bunching at this ratio, but it is quantitatively small relative to the overall prepayment volume. The vast majority of excess payments do not correspond to round multiples of the scheduled payment, indicating that biweekly plans account for at most a minor share of the behavior we document.

More broadly, the high month-to-month continuation probability (above 80%) might suggest that prepayment is set-and-forget rather than an active monthly decision. However, the fact that prepayment responds to contemporaneous cash flow shocks—rising after stimulus payments and falling when ARM payments increase—indicates that households do revisit this decision, at least in response to material changes in disposable income. As we have shown, dropping borrowers who make exactly the same dollar payment each month, the group most likely on autopay, also does not change the results.

Several commonly cited motives for prepayment—a desire to be debt-free before retirement, "peace of mind," or eliminating the monthly payment—are sometimes presented as alternatives to debt aversion. We argue that they are better understood as *instances* of it. Debt aversion, as modeled in Equation (10), encompasses any disutility from holding debt not captured by its financial cost. A household that sacrifices investment returns to eliminate its mortgage before retirement is exhibiting exactly this preference. The question is not whether such households exist—they clearly do—but whether the preference is large enough to generate the patterns we document, and whether it is better described as a stable preference than as a mistake. The evidence in this section suggests the answer to both questions is yes.

5.3 Cash Flows and the Prevalence of Debt Aversion

Section 4.4 showed that prepayment responds strongly to cash flow shocks: aggregate prepayment tracks income growth for high-income households, spikes after the Alaska Permanent Fund dividend, and declines for ARM borrowers whose monthly payments increase. This cash flow sensitivity has an important implication for interpreting the 22% prepayment rate documented in Section 4.1.

If some debt-averse households lack the liquidity to act on their preference, then the observed prepayment rate understates the true prevalence of debt aversion. The ARM results provide a way to gauge the magnitude of this understatement. A 1 pp increase in LIBOR raises ARM payments by roughly $52 per month and reduces prepayment by 1.9 pp (Table 8, Col-

umn 2). This elasticity provides a way to estimate the share of households that would prepay absent cash flow constraints. Specifically, we use the ARM coefficient to predict how much prepayment would increase if all borrowers had sufficient liquidity—that is, if the cash flow margin were relaxed. Under the assumption that the ARM elasticity captures the causal effect of cash flow on prepayment, and extrapolating to the distribution of cash flow shortfalls in the FRM population, we estimate that approximately XX% of all negative-spread borrowers would prepay if they were not cash constrained. This implies that the observed 22% prepayment rate substantially understates the true prevalence of debt aversion among mortgage borrowers.[12]

We can also provide a lower bound on the *intensity* of debt aversion. The first-order condition in Equation (11) implies that any household prepaying at a negative spread reveals a marginal debt-aversion premium of at least $|u'(D - x^\star F)| \geq |r_m - r|$: the household is willing to forgo at least $|r_m - r|$ in annual return per dollar of debt reduced. Under our benchmark assumptions, we calculate the after-tax spread for each prepaying borrower with a negative spread and take the median. The median negative spread among prepayers is approximately −XX basis points, implying that the median prepaying household behaves as if each dollar of mortgage debt generates at least XX basis points of annual psychological cost above and beyond its financial carrying cost. This is a lower bound, since inframarginal households—those whose debt aversion well exceeds the threshold for prepayment—may have considerably stronger preferences.

6 Conclusion

Consider a mortgage borrower who has extra money each month. She could invest in a 401(k) or other retirement plan; or she could put the extra cash towards her mortgage, helping pay it off faster. Personal finance writer Dave Ramsey's best-selling *Total Money Makeover* counsels the latter: one of his seven "financial baby steps" is to *pay off your home early*. For Ramsey,

[12] We describe this calculation in detail in Appendix [X]. The key identifying assumption is that the cash flow elasticity estimated from ARM rate resets generalizes to the broader population of mortgage holders.

ridding oneself of debt is not merely a sound investment—it is a moral imperative.[13] This view is at odds with standard portfolio theory, which holds that no special consideration should be given to whether cash is spent on a new investment or used to pay off debt, so long as the risk-adjusted return is maximized.[14] Our findings suggest that Dave Ramsey's audience is large—and that they are willing to pay for the privilege of following his advice.

Between one-fifth and one-quarter of U.S. conforming mortgage borrowers voluntarily prepay each month, and this share does not respond to changes in interest rates. Monetary policy tightening in 2022 raised risk-free yields above the rate on roughly half of outstanding mortgages, yet borrowers did not reduce prepayment, resulting in $4.6 billion in losses from GSE mortgages alone—a pure transfer from households to mortgage investors. Prepayment is persistent within borrowers, correlated across debt products, and spikes as the remaining balance approaches zero. Households respond to cash flow shocks but not to changes in the present value of repayment. Taken together, these patterns point to debt aversion—a preference for reducing debt that goes beyond its financial cost—as a primary driver of prepayment behavior.

Strikingly, negative-NPV prepayment is not concentrated among unsophisticated borrowers. Households with higher credit scores are *more* likely to prepay at a loss, and those who refinanced optimally when rates were low are equally prone to costly prepayment afterward. Survey data confirm that prepayers are more likely to hold stocks and retirement accounts. These patterns rule out financial illiteracy as the primary explanation and instead point to a deliberate, if costly, preference.

Our findings have several implications for economic theory. First, debt aversion can generate aggregate unresponsiveness to interest rate changes even without inattention or adjustment costs. If many households are inframarginal with respect to repayment, marginal changes in rates will be insufficient to alter portfolio allocations, producing a "sluggish" aggregate response of the sort often attributed to sticky information or rational inattention (Sims, 2003;

[13] On the *Dave Ramsey Show*, he states that "the borrower is slave to the lender, voluntarily signing up to give our lives away. Well, this show is about breaking free." See: https://www.youtube.com/watch?app=desktop&v=3qZ9CMbtDQA&t=7m30s.

[14] This holds the liquidity and risk of different options the same.

Reis, 2006). Second, households that are averse to borrowing may act liquidity-constrained despite having unused borrowing capacity, reluctant to smooth consumption through additional debt (Thaler, 1990). This could help explain why household portfolios appear suboptimally "safe" from the perspective of traditional lifecycle theory (Cocco et al., 2005). Third, the scale of prepayment—roughly one-third of mortgages each year—means that portfolio distortions from debt aversion are not confined to a small set of unsophisticated households but represent a first-order feature of household balance sheets.

An important open question is why debt-averse households borrow in the first place. If carrying debt generates disutility, one might expect such households to avoid mortgages altogether or to borrow less at origination. One possibility is that debt aversion operates more strongly on existing balances than on the decision to take on new debt, consistent with the concave disutility function in our model: the psychological cost of holding a specific debt balance may be more salient than the ex ante prospect of future indebtedness. Another is that housing market constraints leave even debt-averse households with little alternative to mortgage financing. Studying how debt aversion shapes borrowing *entry* decisions is a natural direction for future work.

Our results also connect to work on tax salience (Chetty et al., 2009). Just as consumers respond to posted prices rather than after-tax prices, mortgage borrowers appear to respond to their monthly payment obligations rather than to the opportunity cost of prepayment. The lack of salience of investment returns has direct implications for how monetary policy transmits to household borrowing decisions: even large changes in the risk-free rate may fail to alter mortgage repayment behavior if households do not attend to the spread between their mortgage rate and available returns.

Finally, unlike most documented financial "mistakes," prepayment is an *active* choice. Failure to refinance, failure to shop for a mortgage, and failure to rebalance a portfolio all involve inaction, and can in principle be addressed through default options, reminders, or other nudges. Prepayment requires the opposite: households must deliberately send extra money

each month. Changing this behavior would require not a nudge but a more direct intervention—one that addresses the underlying preference for debt reduction rather than simply making the optimal choice easier to find.

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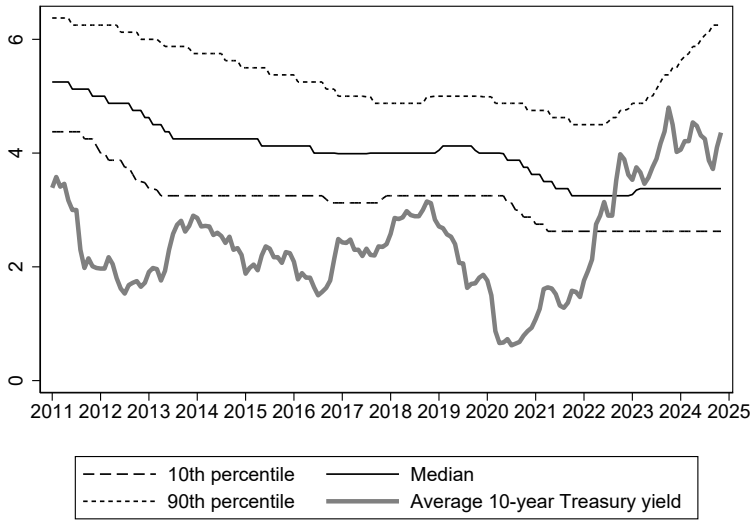
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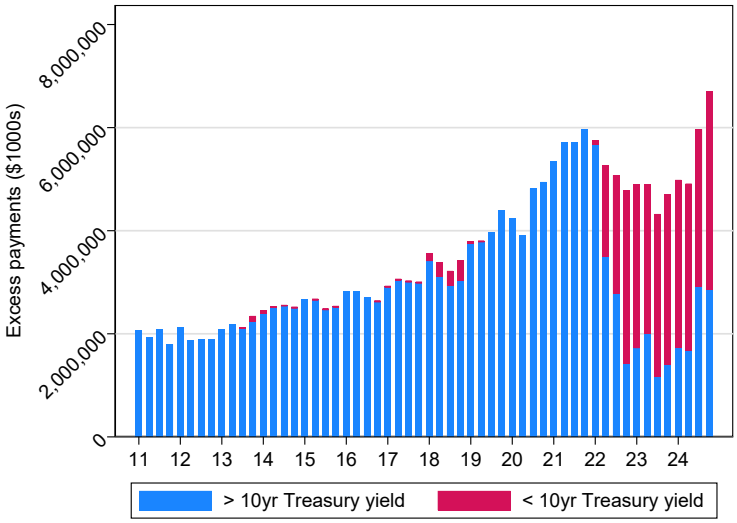
7 Figures and Tables

Figure 1

(a) Rates on outstanding mortgages and average 10-year Treasury yield



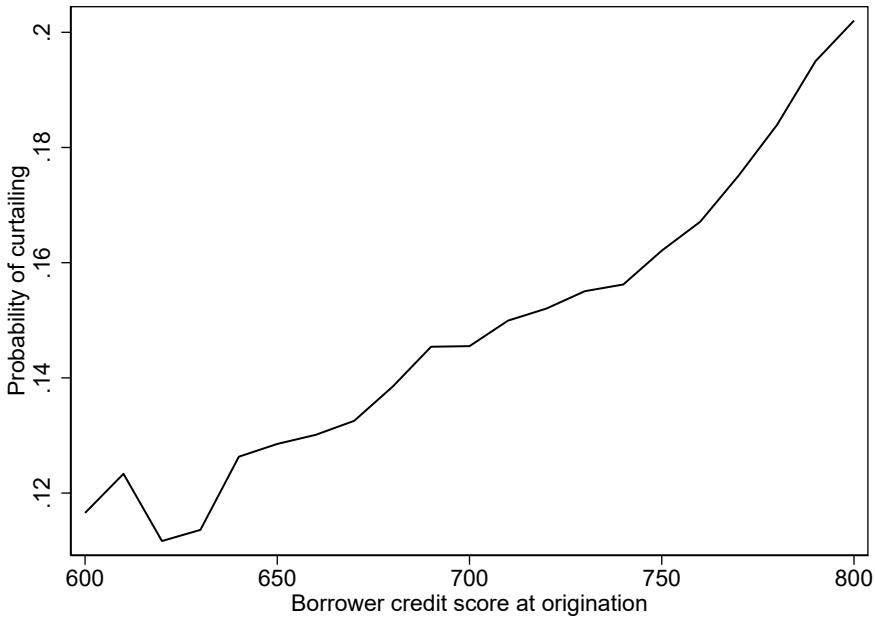
(b) Total excess payments by loans with above/below 10yr Treasury yields



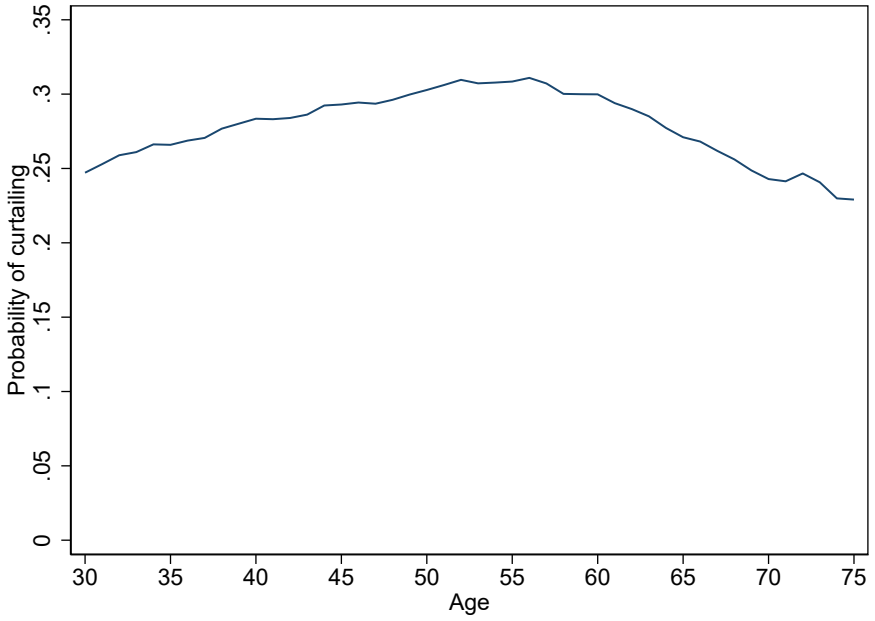
Note: Panel (a) shows the 10th, 50th, and 90th percentile for outstanding mortgage interest rates in black/dashed lines and average 10-year Treasury yield in gray, by month. Panel (b) shows total volume of prepayment amounts each quarter. The blue represents the share of prepayment volume from loans with mortgage interest rates above the prevailing 10-year Treasury yield, and the red shows the share from loans with below the 10-year Treasury yield. Interest rate data come from Fannie Mae and Treasury data come from FRED.

Figure 2: Probability of prepayment by borrower characteristics

(a) Probability of prepayment by borrower credit score



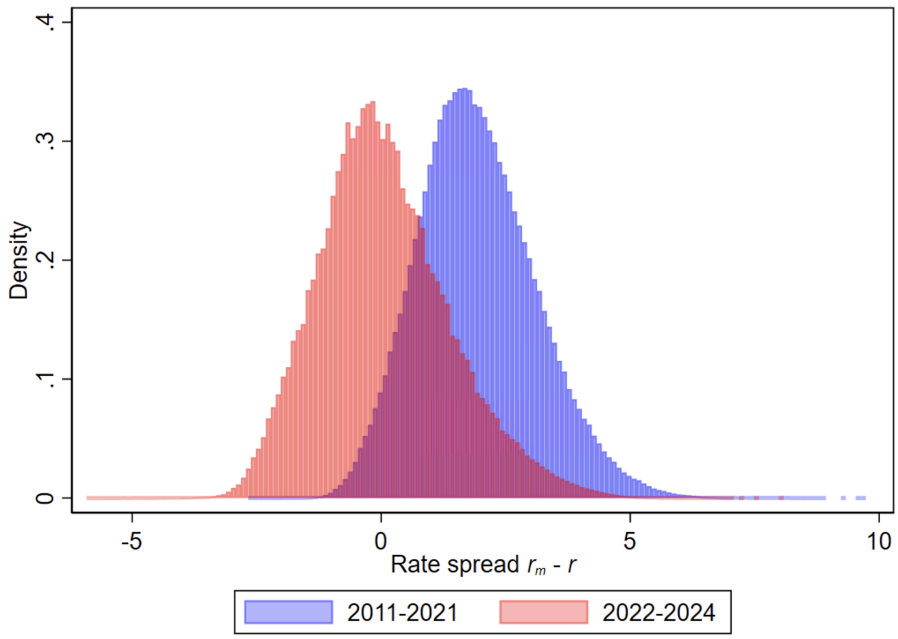
(b) Probability of prepayment by borrower age



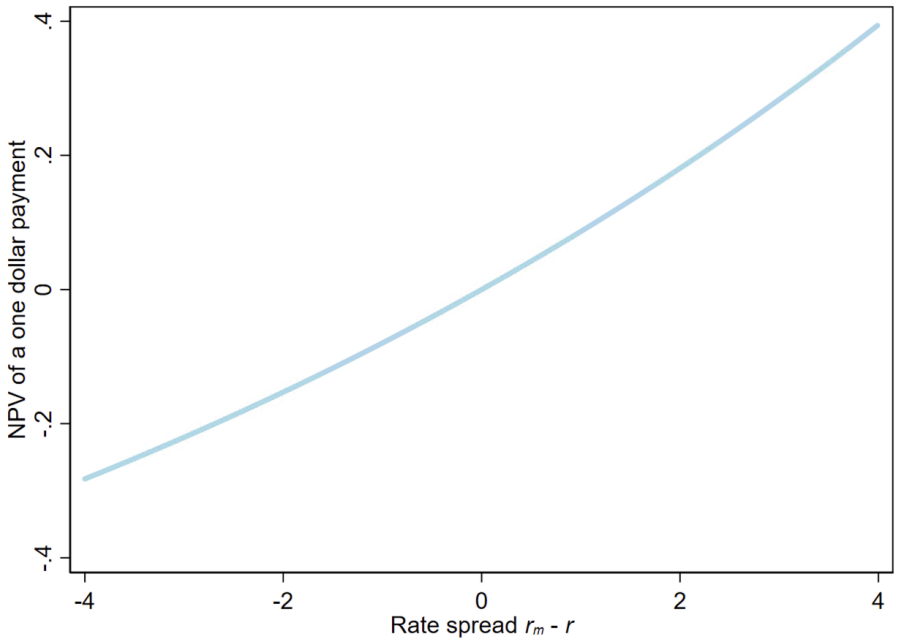
Note: Panel (a) shows the likelihood a household prepays its mortgage by credit score of borrower at origination. Credit scores are rounded to the nearest 10. Panel (b) shows the likelihood a household prepays its mortgage by age of borrower. Authors' calculations based on Fannie Mae Single-Family Loan Performance dataset and the UC–CCP.

Figure 3: Interest rate spreads and net present value of prepayments

(a) Distribution of interest rate spreads



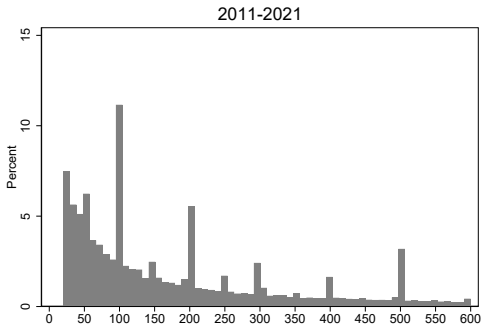
(b) Hypothetical NPV of a $1 prepayment



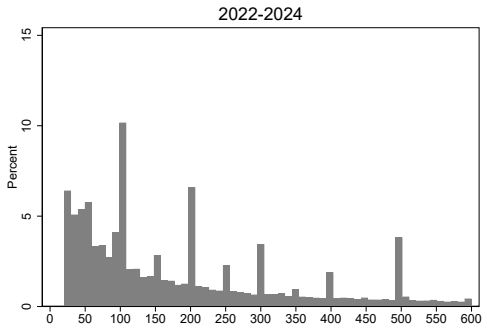
Note: Panel (a) shows the distribution of interest rate spreads for 2011-2021 (blue) and 2022-2024 (red). Panel (b) shows the hypothetical NPV of a $1 prepayment with 100 months remaining against different values of r. Authors' calculations based on Fannie Mae Single-Family Loan Performance dataset.

Figure 4: Distribution of excess payments

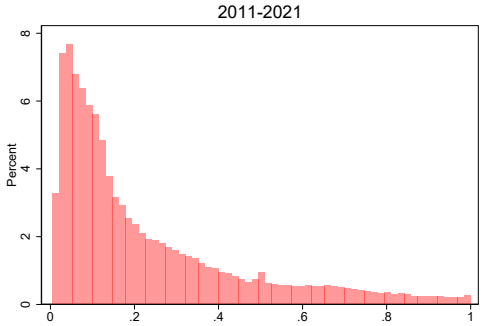
(a) Notional value 2011-2021



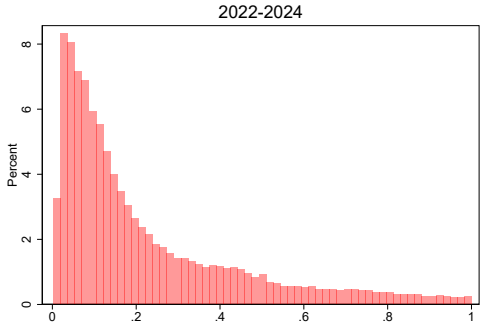
(b) Notional value 2022-2024



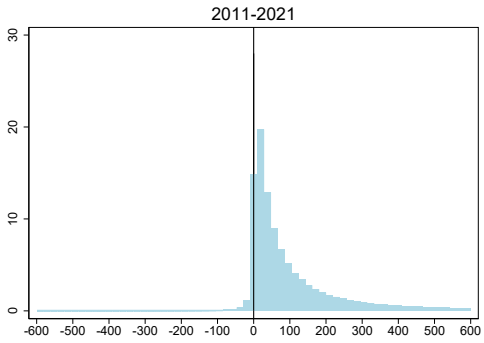
(c) Notional value scaled by monthly payment 2011-2021



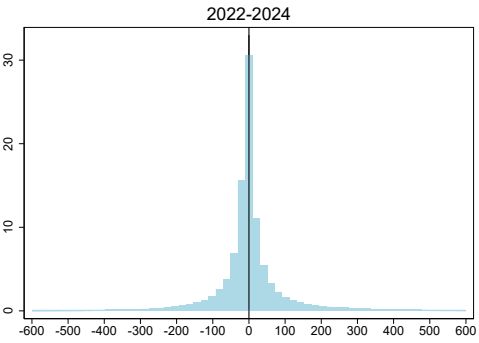
(d) Notional value scaled by monthly payment 2012-2024



(e) NPV 2011-2021



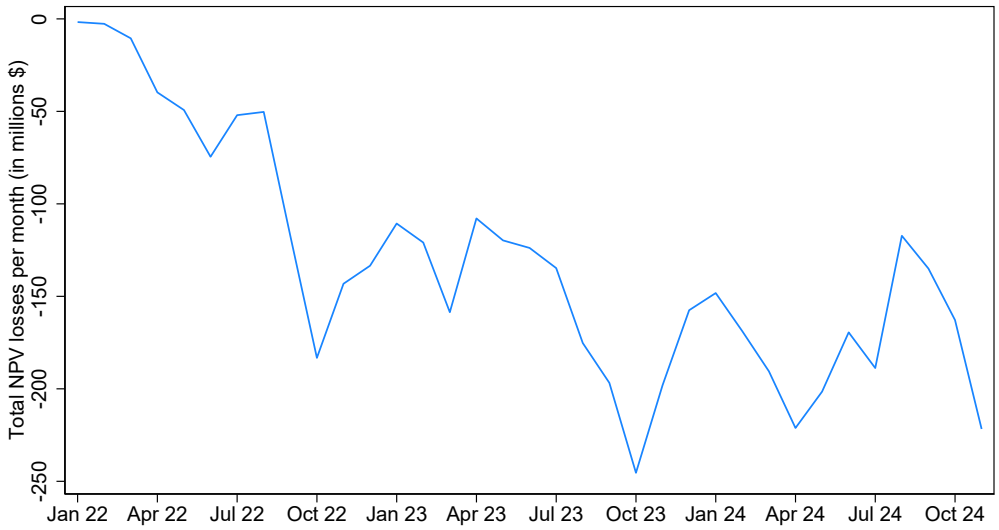
(f) NPV 2022-2024



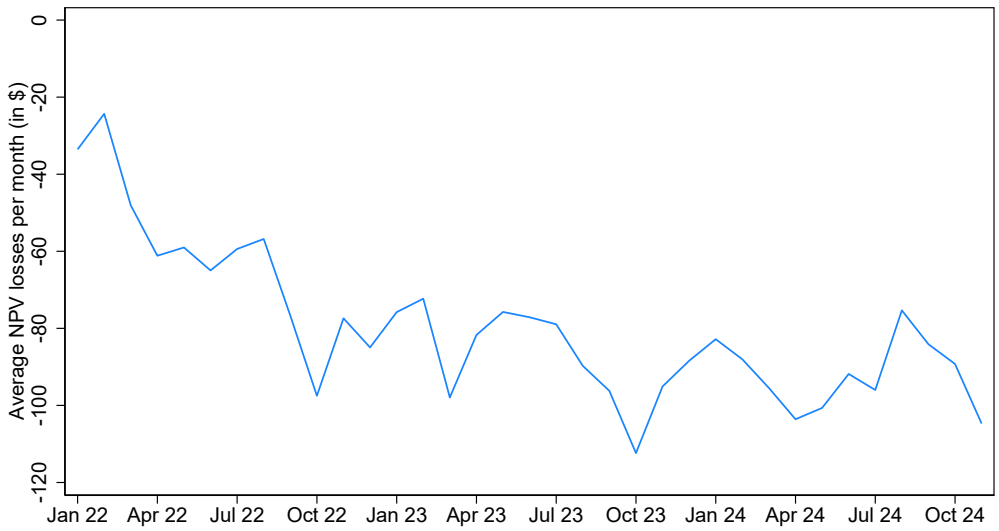
Note: The top row shows the distribution of prepayment amounts in dollar values. The middle row shows the distribution of prepayment amounts but scaled by the monthly payment. The bottom row shows the NPV of these payments. The left column is 2011-2021, and the right column is 2022-2024. NPV is calculated using tax-adjusted mortgage interest rates and tax-adjusted maturity-matched Treasury yields.

Figure 5: NPV of excess payments for negative interest rate spread mortgages

(a) Total NPV losses



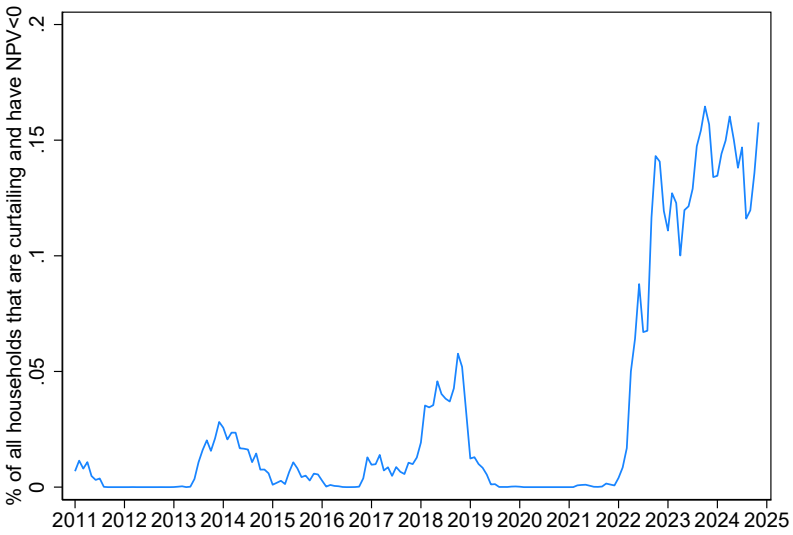
(b) Average NPV losses



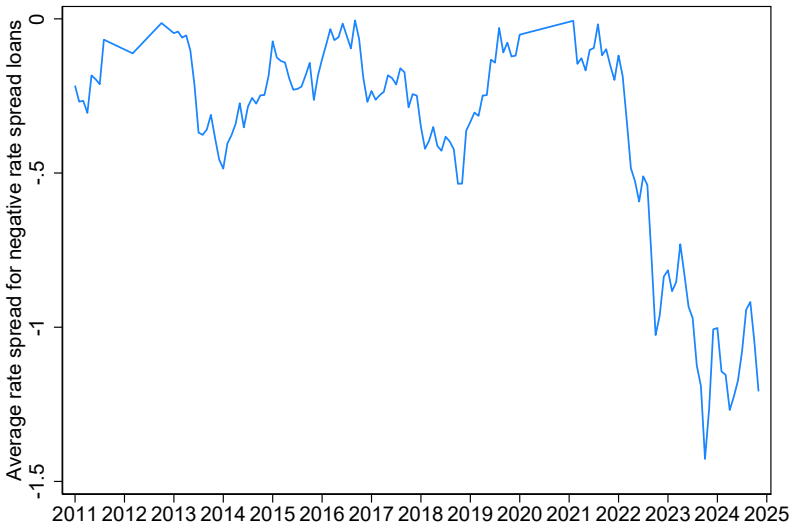
Note: Panel (a) shows the total NPV losses by per month for loans with negative interest rate spreads. Panel (b) shows the average NPV of these payments. NPV is calculated using tax-adjusted mortgage interest rates and tax-adjusted maturity-matched Treasury yields

Figure 6

(a) Share of negative rate spread households prepaying



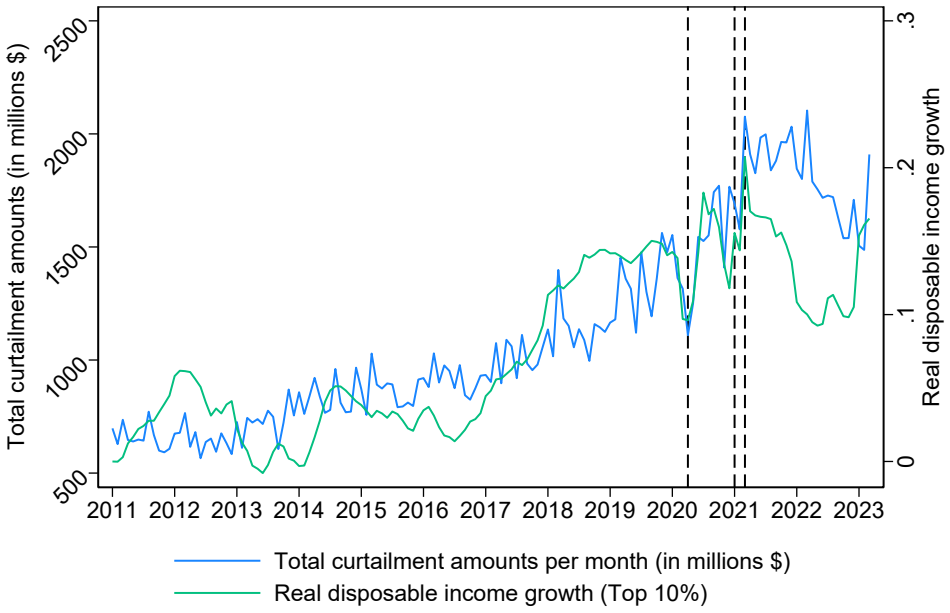
(b) Average negative rate spread (weighted by prepayment amount)



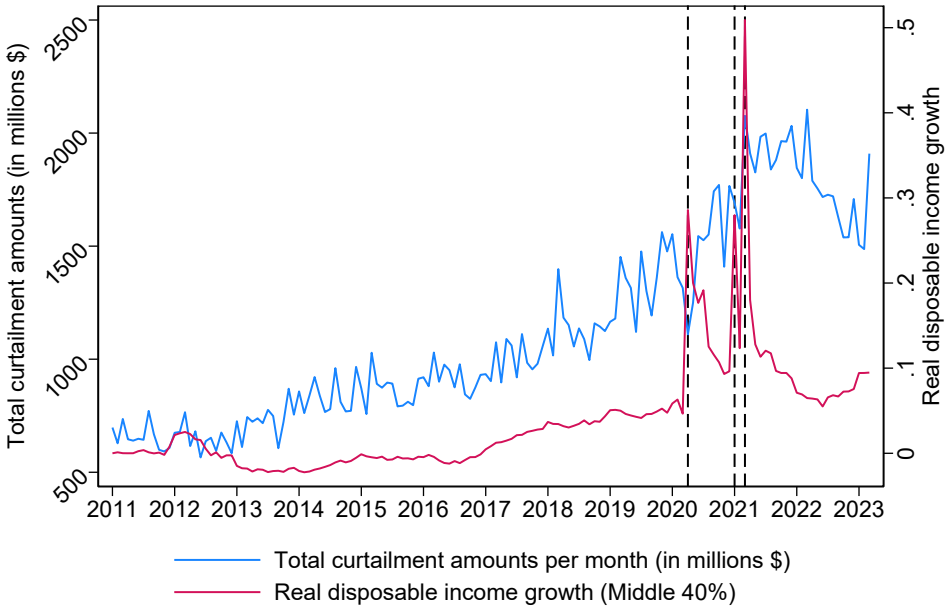
Note: Panel (a) shows share of all households that have a negative interest rate and who prepay by month. Panel (b) shows the average interest rate spread for negative rate spread loans, weighted by the dollar value of prepayment.

Figure 7: Total prepayment amounts and real disposable income growth

(a) Top 10%

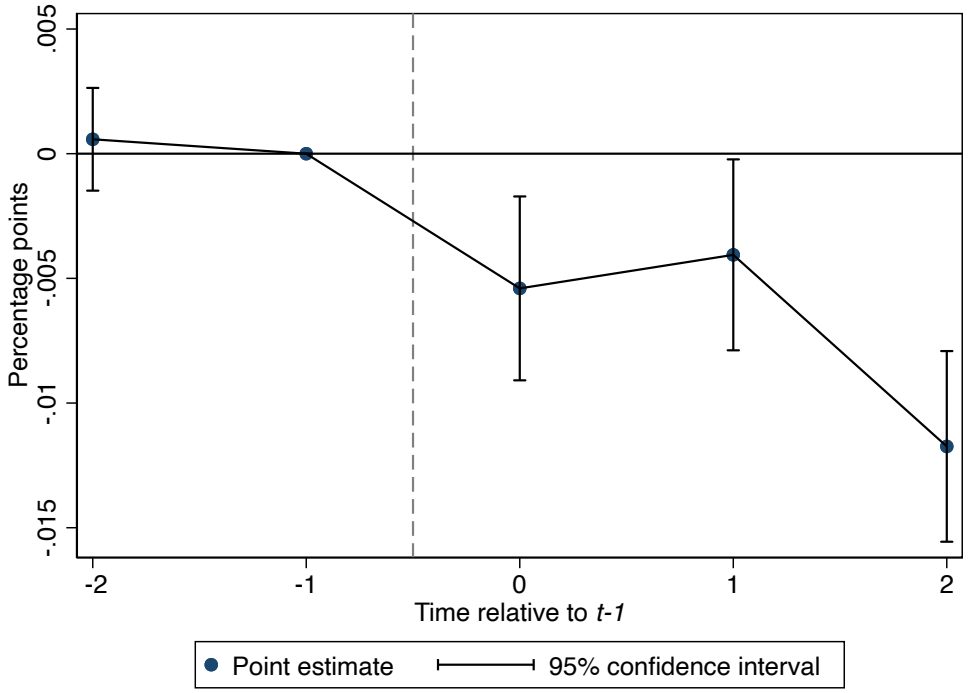


(b) Middle 40%



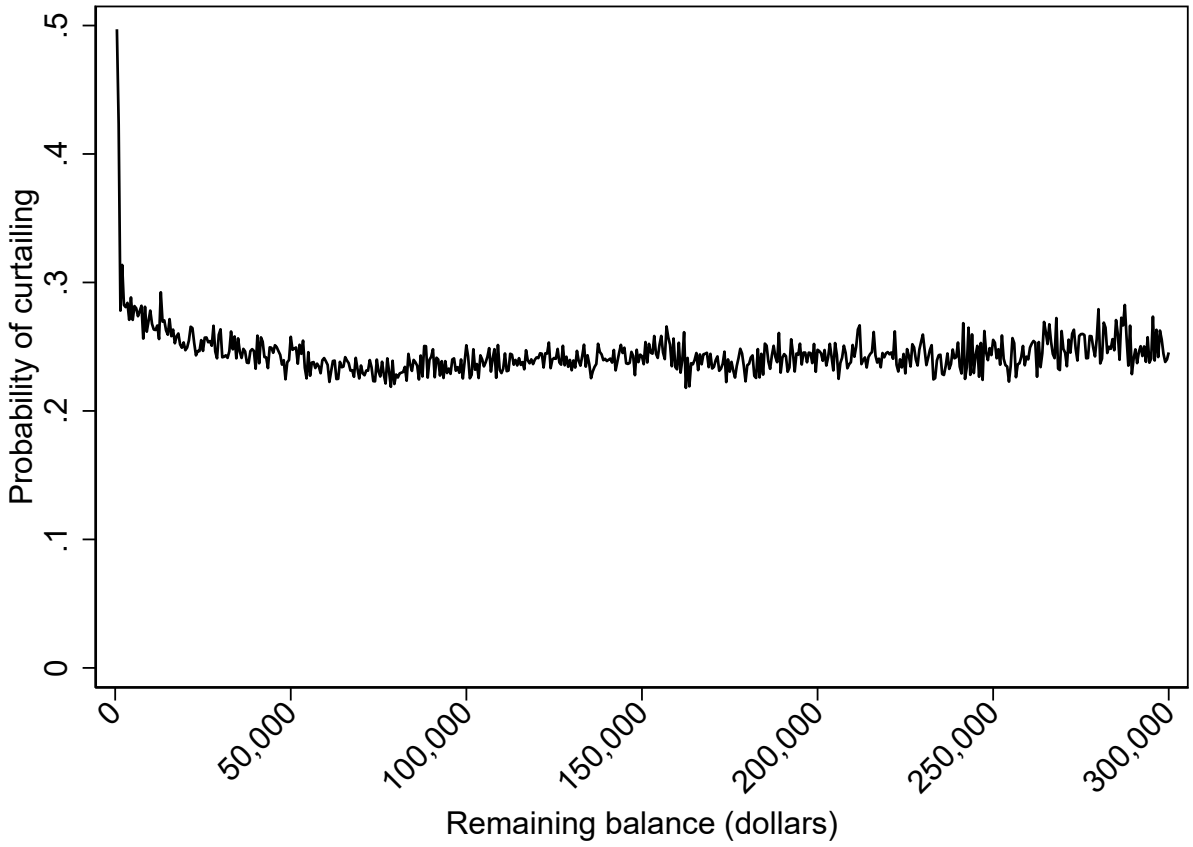
Note: Green and red lines are real disposable income growth for the top 10% and middle 40% of the income distribution, respectively. Blue line is total prepayment amounts per month in millions of dollars. Dashed lines represent months when COVID-19 stimulus checks were sent (April 2020, January 2021, March 2021). Income data come from Realtime Inequality.

Figure 8: Probability of prepayment around interest rate changes



Note: Figure plots estimates of β_k's from the local projection in Equation (7). Specifically, we estimate $Prepayment_{i,t+k} - Prepayment_{i,t-1} = \beta_k(Rate_{i,t} - Rate_{i,t-1}) + \gamma X_{it} + \varepsilon_{it}$ for $k = -2, 0, 1, 2$. Authors' calculations based on Freddie Mac Single-Family Non-Standard dataset.

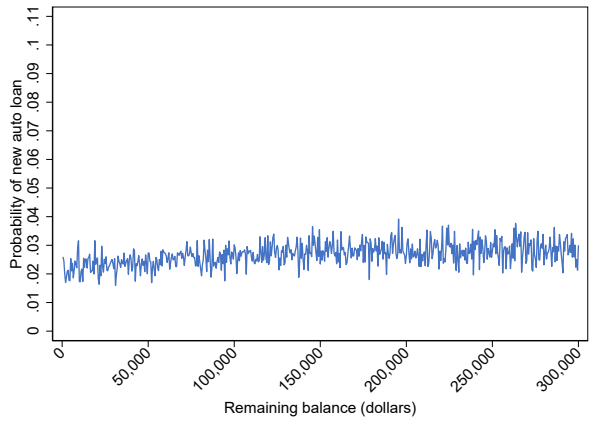
Figure 9: Probability of prepaying by remaining principal balance



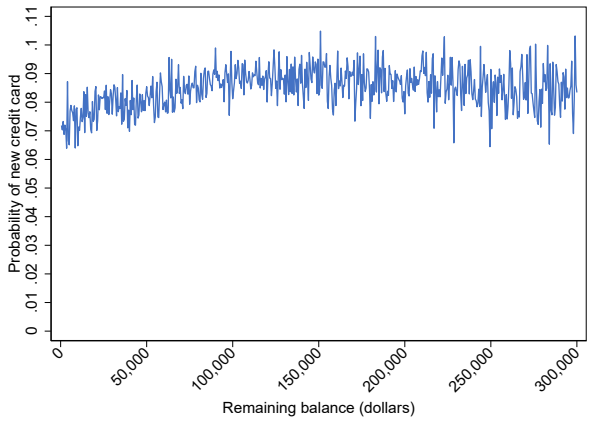
Note: Figure shows the likelihood of a loan prepaying by remaining principal balance. Balances are rounded to the nearest $500 and capped at $300,000. Authors' calculations based on the University of California Consumer Credit Panel (UC–CCP).

Figure 10: Placebo credit outcomes by remaining mortgage principal balance

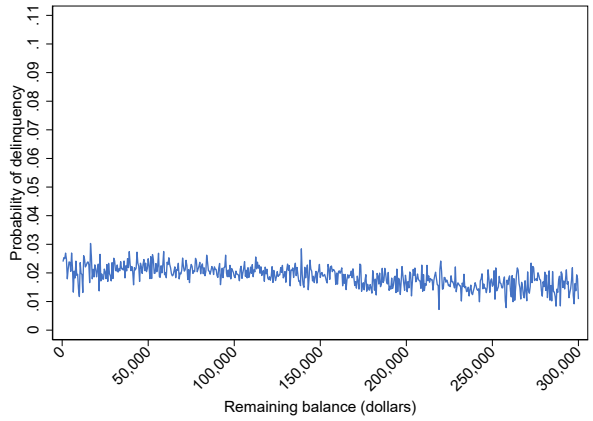
(a) New auto loan



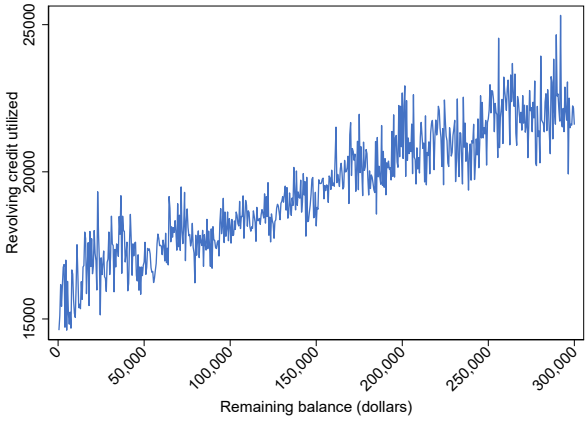
(b) New credit card



(c) New delinquency



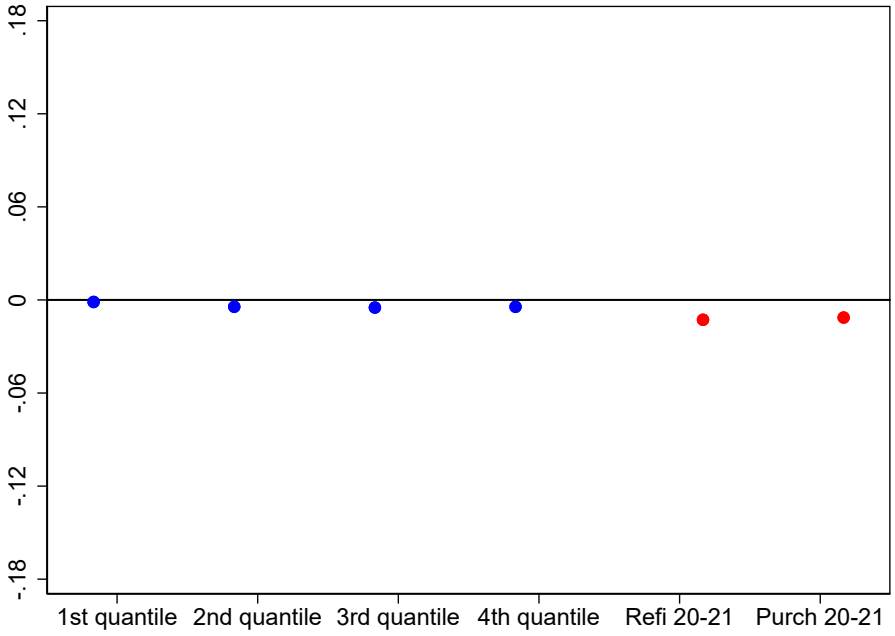
(d) Revolving credit utilized



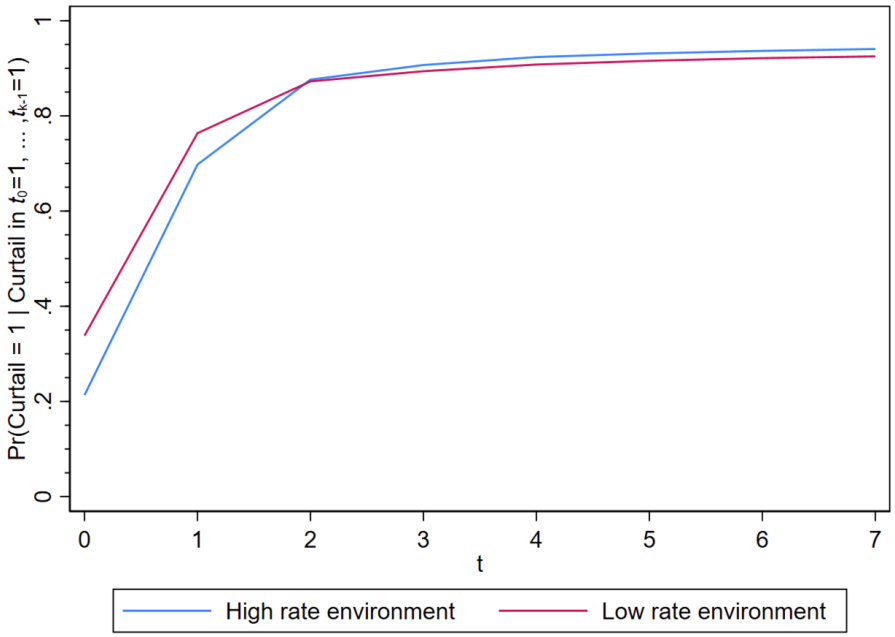
Note: All figures show mean outcome against remaining principal balance. Balances are rounded to the nearest $500 and capped at $300,000. Panel (a) plots the probability of originating a new auto loan. Panel (b) plots the probability of opening a new credit card. Panel (c) plots the probability of current delinquency on any trade line. Panel (d) plots total credit utilization. Authors' calculations based on the University of California Consumer Credit Panel (UC–CCP).

Figure 11: Sophistication, attentiveness and inertia

(a) Effects of interest rate spreads on prepayment by measures of attentiveness



(b) Conditional continuation probabilities by timing of first prepayment



Note: In Panel A, each dot represents the coefficient on $Spread$ from Equation (5) using different samples. The blue dots correspond to samples by quartiles of residuals from Equation (12). The red dots correspond to the 2020-2021 purchase and refinance samples. Panel B shows the probability of prepaying at time $t+k$ month conditional on prepaying in the k previous months. The blue line represents loans that first prepaid in a high-rate environment (March 2022-November 2024). The red line represents loans that first prepaid in a low-rate environment (Jan 2011-February 2022).Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset.

Table 1: Summary statistics

Panel A: All loans (Jan 2011 -Nov 2024)						
	All		Curtailers		Non-Curtailers	
	Mean	SD	Mean	SD	Mean	SD
Origination balance	220,101	127,033	217,338	124,026	220,740	127,710
Current balance	178,191	130,929	178,730	123,144	178,067	132,665
Term (in months)	306	83	293	88	309	95
Months to legal maturity	260	95	243	97	264	95
Effective months to maturity	251	100	219	103	259	98
Mortgage interest rate	4.07	1.01	3.93	0.99	4.10	1.02
Marginal tax rate (federal + state)	11.70	14.17	11.74	14.10	11.69	14.18
Marginal tax rate (mortgage interest)	11.21	12.49	10.79	12.42	11.30	12.51
Loan-month obs.	17,166,690		3,227,051		13,939,639	
Panel B: All loans (Jan 2022 - Nov 2024)						
	All		Curtailers		Non-Curtailers	
	Mean	SD	Mean	SD	Mean	SD
Origination balance	254,261	141,381	248,120	136,828	255,907	142,532
Current balance	220,539	142,181	205,486	137,893	224,572	143,039
Term (in months)	314	77	301	83	318	75
Months to legal maturity	266	91	251	94	271	90
Effective months to maturity	257	96	228	101	265	94
Mortgage interest rate	3.62	1.08	3.49	0.99	3.66	1.10
Marginal tax rate (federal + state)	11.99	13.65	12.01	13.62	11.98	13.65
Marginal tax rate (mortgage interest)	8.62	12.19	8.39	12.06	8.68	12.23
Loan-month obs.	4,621,147		976,476		3,644,671	
Panel C: Negative rate spread loans (Jan 2022 - Nov 2024)						
	All		Curtailers		Non-Curtailers	
	Mean	SD	Mean	SD	Mean	SD
Origination balance	278,811	145,307	268,048	139,589	281,903	146,762
Current balance	241,020	145,572	222,232	139,814	246,416	146,740
Term (in months)	301	83	287	88	305	82
Months to legal maturity	258	94	242	96	263	92
Effective months to maturity	251	98	224	101	258	95
Mortgage interest rate	3.09	0.60	3.04	0.59	3.10	0.60
Marginal tax rate (federal + state)	7.91	12.85	8.11	12.84	7.85	12.85
Marginal tax rate (mortgage interest)	11.89	13.27	11.33	13.09	12.06	13.31
Loan-month obs.	2,391,713		533,679		1,858,034	

Note: Authors' calculations based Fannie Mae Single-Family Loan Performance, 2010-2019 Surveys of Consumer Finances, and NBER Taxsim. Each cell is a loan-month observation. Marginal tax rate with respect to taxpayer earnings are set to 0 for households with an available retirement account.

Table 3: NPV losses under different assumptions

	Share with spread<0	Total NPV (in millions $)	Average NPV (in $)
Benchmark results	.52	-4,632.35	-86.80
No available retirement account	.39	-2,217.65	-53.60
No tax adjustments	.59	-6,263.63	-102.25
MBS	.69	-8,411.53	-119.55

Note: Column (1) reports the share of loans with a negative interest rate spread for a given set of assumptions about taxes and opportunity costs. Column (2) reports the aggregate NPV losses in millions of dollars for these loans. Column (3) reports the average NPV loss per payment for these loans, conditional on paying in excess of the monthly minimum. The first row is the benchmark results. In the second row, we assume households do not have a tax-deferred retirement account available. Row three shows results when we do no tax adjustments. Fourth row uses post-tax mortgage interest rates but mortgage-backed securities as the discount rate. Estimates from Jan 2022 - Nov 2024. Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset, FRED, 2010-2019 Surveys of Consumer Finances and NBER Taxsim. See Section 4.2 for more details.

Table 5: Prepayment heterogeneity

	$\mathbb{P}$(Spread<0)	$\mathbb{P}$(Curtail|Spread<0)	Notional value	NPV
All	0.52	0.22	$555.98	-$86.80
Subgroup				
High Credit Score	0.56	0.24	$617.70	-$95.59
Low Credit Score	0.47	0.20	$464.53	-$73.78
First-time Home-buyer	0.42	0.19	$581.59	-$103.26
Not First-time Home-buyer	0.54	0.23	$552.36	-$84.48
Urban	0.52	0.22	$565.54	-$88.77
Rural	0.47	0.23	$457.12	-$66.43
Originated 2020-2021	0.70	0.22	$519.26	-$92.57

Note: Column (1) reports the likelihood of having a negative interest rate spread. Column (2) reports the probability of prepaying conditional on having a negative interest rate spread. Column (3) reports the average notional value of prepayment for negative rate spread loans. Column (4) represents the NPV of these payments. Each row reports estimates for a specific subgroup. “High" and “low" credit score loans are those with above- and below- median credit scores (773), respectively. Urban is defined by residing in an MSA. Estimates from Jan 2022 - Nov 2024. Authors’ calculations based on the Fannie Mae Single-Family Loan Performance dataset, FRED, 2010-2019 Surveys of Consumer Finances and NBER Taxsim.

Table 6: Predicting prepayment from credit behavior

Panel A: Predicting mortgage curtailment

	(1)	(2)	(3)	(4)
Credit score			0.0477***	0.114***
			(0.000468)	(0.000776)
Total mortgage balance (thousands)			0.00308***	0.00406***
			(0.000162)	(0.000264)
Has a credit card			-5.187***	-8.665***
			(0.122)	(0.146)
Total credit card balance (thousands)			-0.0785***	-0.0971***
			(0.00350)	(0.00468)
Observations	1,158,679	1,158,679	1,158,679	1,158,679
Individual FEs	✓	✓		✓
Quarter FEs		✓		
Mean of outcome	22.15	22.15	22.15	22.15
R^2	0.255	0.376	0.0107	0.272

Panel B: Predicting auto loan curtailment

	$\mathbb{1}(Auto_Curtail)$	Average auto loan term	Longest auto loan term
$\mathbb{1}(Mort_Curtail)$	8.521***	-	-
	(0.200)	-	-
$Mort_Curtail$	-	-2.337***	-3.539***
	-	(0.231)	(0.247)
Observations	890,917	102,449	102,449
Borrower controls	✓	✓	✓
Quarter FEs	✓		
Mort. orig. quarter FEs		✓	✓
Mean of outcome	16.97	66.06	68.89

Data and inference. Authors' calculations using the University of California Consumer Credit Panel (UC–CCP). Standard errors in parentheses. For binary outcomes scaled to 0/100, coefficients are percentage-point effects. In Panel B, Column (1) reports borrower-clustered SEs; Columns (2)-(3) report heteroskedasticity-robust SEs. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel A (mortgage prepayment). Linear probability models at the household-quarter level; the dependent variable equals 100 if the household prepaid its mortgage in that quarter. Columns (1)-(2) include no covariates (Column (2) adds quarter fixed effects). Columns (3)-(4) add credit covariates: credit score, total mortgage balance (thousands), credit-card indicator, and total credit-card balance (thousands). Individual fixed effects are included in Columns (1), (2), and (4) as indicated in the table.

Panel B (auto loans). Linear regressions. Column (1): outcome is an indicator equal to 100 if any auto loan is prepaid (household-quarter level) with borrower controls and quarter fixed effects. Columns (2)-(3): outcomes are the household's average and longest auto-loan terms (months), estimated at the mortgage-origination (loan) level; controls are fixed at mortgage origination with origination-quarter fixed effects. Borrower controls are age, age squared, credit score, gender, and state fixed effects.

Table 7: Effects of interest rate spread on the probability of prepaying

	All			High Credit Score			Low Credit Score		
Spread	-0.01***	-0.00***	-0.01***	-0.01***	-0.00***	-0.01***	-0.01***	0.00***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Loan FEs		✓			✓			✓	
Month FEs			✓			✓			✓
Mean of outcome	0.19	0.19	0.19	0.21	0.21	0.21	0.17	0.17	0.17

Note: Table reports estimates from the linear probability model in Equation (5). "High" and "low" credit score loans are those with above- and below- median credit scores (773), respectively. Interest rate spread is calculated using post-tax mortgage interest rate and post-tax maturity-matched Treasury yields. $N = 17,166,690$ in Columns (1) and (3). $N = 17,164,564$ in Column (2). $N = 8,571,442$ in Columns (4) and (6). $N = 8,570,528$ in Column (5). $N = 8,595,248$ in Columns (7) and (9). $N = 8,549,036$ in Column (8). Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset, FRED, 2010-2019 Surveys of Consumer Finances and NBER Taxsim. Estimates are from Jan 2011 - Nov 2024. Standard errors (in parentheses) are clustered at the loan-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: ARMs vs FRMs

	(1) Mortgage Rate	(2) $\mathbb{P}$(Curtail)	(3) 20-100	(4) 100-500	(5) >=500
$\mathbb{1}(ARM)\times$ LIBOR	0.644***	-0.019***	-0.009***	-0.009***	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	12,439,344	12,439,344	12,439,344	12,439,344	12,439,344
Loan FEs	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓
Mean of outcome	4.26	0.18	0.07	0.08	0.04
R^2	0.97	0.52	0.45	0.46	0.38

Note: LIBOR is the twelve-month LIBOR rate. $\mathbb{1}$(ARM) is an indicator equal to 1 if the loan is an adjustable-rate mortgage and 0 if it is a fixed-rate mortgage. The dependent variable in Column 1 is the loan's interest rate. The dependent variable in Column 2 is an indicator equal to 1 if the loan prepays in that month. Columns 3-5 are indicators equal to 1 if the prepayment amount is in $(20, 100)$, $[100, 500)$, or ≥ 500 dollars, respectively. Standard errors (in parentheses) are clustered at the loan-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Effects of interest rate variation: Flexible rate vs “locked-in" loans

	(1) Mortgage Rate	(2) $\mathbb{P}$(Curtail)	(3) 20-100	(4) 100-500	(5) $\geq$500
$\mathbb{1}$(Flexible rate)	-2.064***	0.058***	0.019***	0.031***	0.007***
	(0.015)	(0.004)	(0.003)	(0.003)	(0.002)
LIBOR $\times\mathbb{1}$(Flexible rate)	0.759***	-0.031***	-0.015***	-0.012***	-0.003**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	3,079,361	3,079,361	3,079,361	3,079,361	3,079,361
Loan FEs	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓
Mean of outcome	3.51	0.18	0.06	0.07	0.06
R^2	0.84	0.57	0.42	0.48	0.50

Note: LIBOR is the twelve-month LIBOR rate. $\mathbb{1}$(Flexible rate) is an indicator equal to 1 if the loan is not in its introductory rate period. The dependent variable in Column 1 is the loan's interest rate. The dependent variable in Column 2 is an indicator equal to 1 if the loan prepays in that month. Columns 3-5 are indicators equal to 1 if the prepayment amount is in $(20, 100)$, $[100, 500)$, or ≥ 500 dollars, respectively. Standard errors (in parentheses) are clustered at the loan level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix

A Detailed Data Construction

A.1 Identifying early payments

Our main sample is the Fannie Mae Single-Family Loan Performance dataset, a monthly panel of conventional loans purchased by Fannie Mae. We observe the mortgage's interest rate, term, balance at origination (rounded to the nearest thousand) and current unpaid principal balance (the exact dollar amount). We do not observe a loan's monthly minimum payment in the data, but we are able to calculate an estimated payment using the monthly interest rate, the original loan principal, and the term of the loan. Specifically, for a given principal P, term (in months) N, and monthly interest rate r_m, we calculate monthly payment MP as

$$MP = \frac{P \times r_m}{1-(1+r_m)^{-N}} \tag{13}$$

The share of each monthly payment that goes toward interest in a given month is equal to the monthly interest rate r_m times the remaining unpaid principal; the share that is applied toward principal is simply the monthly payment minus that share.

We observe the outstanding principal balance each month for a given mortgage. Using the outstanding balance in month t, we calculate the *expected* outstanding balance in month $t+1$ by subtracting the principal share of the monthly payment from the outstanding balance in month t, i.e. $\mathbb{E}[B_{t+1}] = B_t - (1-r_m) \cdot MP$. If the difference between the observed balance and the expected balance is negative, the household has paid in excess of its monthly minimum. We define prepayment to be excess payments greater than \$20 to account for measurement error.

It is not always the case that a household paying in excess of its monthly minimum is prepayment. Some households pay extra, but do not specify that the excess cash should be put

toward the remaining principal. Instead, the excess payment is used a future payment. This behavior does not reduce the overall interest burden nor does it shorten the effective maturity date; we do not consider this prepayment, and so we remove the flag for these observations. To do so, we start by flagging all households who pay in excess of $20 or more in a given month. Then, we remove the flag if we observe that the household "underpaid" by a near-symmetric amount in the next three months. Consider a month in which we observe a household with a $500 monthly payment, $450 of which goes toward principal. Suppose this household is flagged as paying an excess of $50. In the following month, we observe that the household has underpaid by $50, meaning the difference between expected and actual remaining principal is -50. This means the household did not originally prepay, but rather earmarked the extra cash to go to a future payment.

Lastly, we do not consider any excess payment in the final month of a loan's term to be a prepayment. This is because we are unable to distinguish if the loan has matured or has been refinanced. Because of this, the estimated probability of prepaying for very small (less than $2,000 or so) remaining balances is mechanically attenuated. This is not because households are less likely to prepay with small remaining balances – the exact opposite is true (see Figure 9). Figure A3 shows the probability of prepaying against remaining balance using the Fannie Mae data. We see the exact pattern as in the credit registry data, but for very small balances, the estimated probabilities are artificially low.

A.2 Tax data

We use the 2010-2019 Surveys of Consumer Finances (SCF) and the NBER TAXSIM program to calculate marginal tax rates, using the approach established by Gale et al. (2022). Our approach is as follows.

First, since the public use SCF does not include respondents' geographic information, we randomly assign households to states. Specifically, we make the probability of being assigned to a state proportional to each state's population; for example, since California's population is

about 1/9 of the U.S. population as a whole, each household has a 1/9 probability of being assigned to California.

Second, we restrict the set of SCF respondents to closely resemble the households we observe in the Fannie Mae dataset. That is, we remove ARMs, mortgages originated before 1999, etc. Using this subset, we calculate the federal, state, and mortgage interest marginal tax rates for each respondent in the SCF. Using TAXSIM, we then calculate the effective federal and state marginal tax rates with respect to taxpayer earnings for each respondent in the SCF. We also calculate the implicit marginal tax rate with respect to mortgage interest by adding $100 to each household's mortgage interest expense; the difference between the baseline tax liability and the new tax liability after adding the $100 is the implicit marginal tax rate on mortgage interest.

Lastly, since the SCF is a triennial survey, we apply the results for each year to the next two subsequent years. That is, the rates calculated for 2010 will be the same in 2011 and 2012. Tax rates calculated using the 2019 SCF are used for 2019-2023. Within each state-year-origination balance bin[15], we randomly match SCF respondents' tax rates to loans in the Fannie Mae dataset.

For our benchmark assumptions, we assign federal and state marginal tax rates to 0 for respondents that indicate they have some sort of retirement account.

B Alaska Permanent Dividend Fund

To empirically test if curtailment is driven by positive income shocks, we leverage eligibility and timing in dividend payouts from the Alaska Permanent Fund. Established in 1976, the fund pays yearly dividends to eligible Alaska residents. The dividend's nominal value reached a low of $331 in 1984, but has consistently surpassed $1,000 since 1996, reaching its highest point of $3,284 in 2022 (Jones and Marinescu, 2022).[16] All Alaska residents that have lived in

[15]Mortgage origination balances are rounded to the nearest $250,000 and capped at $1 million.

[16]https://pfd.alaska.gov/Division-Info/summary-of-dividend-applications-payments

the state for at least a full calendar year who intend to remain residents indefinitely are eligible for the dividend. We cannot observe if the loans in Alaska are held by eligible residents, but we use the state identifier as a proxy for eligibility. In other words, if a loan is coded as being in Alaska, we consider this household to be eligible, and households in all other states are ineligible. Dividends are distributed in October of each year. If prepayment is linked to income shocks, then we should see an increase in prepayment for Alaska households in October. To test this, we estimate the following linear probability model:

$$Y_{it} = \beta AK_i \times OCT_t + \alpha_i + \gamma_t + \varepsilon_{it} \tag{14}$$

where AK_i is an indicator equal to 1 if loan i is in Alaska, and OCT_t is an indicator equal to 1 if the calendar month is October. We include loan and month fixed effects (α_i and γ_t, respectively). Depending on the specification, Y is either a prepayment indicator or an indicator for prepayment amounts.

Estimates are reported in Table A1. The dependent variable in Column 1 is a prepayment indicator. The estimates imply that Alaska residents are nearly a full percentage point more likely to prepay in October on average. Relative to the sample mean, this is a roughly 5% increased likelihood. In Columns 2-4, we use indicators for prepayment amount as the dependent variable ($20-100, $100-500, and $\geq$ $500). While the coefficients are not statistically different from 0 at the 5% level of significance, the positive sign on each coefficient suggests that Alaska residents are using the excess income to repay their mortgages.

As a placebo test, we simulate eligibility and re-estimate (14) 50 times using indicators for all other states (including D.C.). We plot the distribution of the 51 $\widehat{\beta}$'s in Figure A4, Panel A and the associated t-statistics in Panel B. In Panel A, the blue dot is the coefficient from the regression using the Alaska indicator, and the red dots are the coefficients from all other states. The coefficient on the interaction using the Alaska indicator is by far the largest, nearly a full percentage point. The coefficients from the simulations are largely centered around 0. In Panel

B, we see that the estimated coefficient for Alaska is also the most statistically different from 0. Again, the blue dot depicts Alaska, and the red dots depict all other states. The dashed vertical lines represent -1.96 and 1.96, the critical values for 5% significance. With a 95% confidence level and 51 simulations, we expect to see about 3 false positives; we find 5 other states with statistically significant $\widehat{\beta}$'s. Alaska's t-statistic is also the largest. We also simulate eligibility timing and re-estimate (14) 11 times, using all other calendar month indicators, and plot the distribution of the 12 $\widehat{\beta}$'s in Panel C. The figure shows that October is associated with the largest increase in the likelihood of prepayment, with November being the second. These are the only two statistically significant coefficients, as well. In sum, both the main analysis and placebo tests show that the dividend does indeed induce prepayment, suggesting that households prepay based on available cash flows.

C Inertia

One possibility is that households begin prepaying in a low interest rate environment when prepayment was beneficial; when rates rise, they fail to reoptimize because prepaying was a sound investment previously, so inattention leads them to believe prepaying remains financially wise. This theory is motivated by the fact that the probability of a household prepaying in month t given prepaying in month $t-1$ is about 80%. To study this, we identify households whose first prepayment occurred in a low-rate environment (January 2011 - February 2022) and those whose first prepayment occurred in a high-rate environment (March 2022 - November 2024). We remove likely "autopayers" – loans that pay the exact same amount each month for 12 consecutive months – to capture *active* decisions to prepay. We then calculate the conditional probability of prepaying at month $t+k$ given the household has prepaid in the previous k periods for each household type. In other words, we first calculate the unconditional probability of prepaying, then the probability of prepaying conditional on doing so last month, then the probability of prepaying conditional on doing so the last two months, and so on.

Results are shown in Figure 11b. The blue line represents loans that first prepaid in a high rate environment, and the red line represents loans that first prepaid in a low rate environment. While the unconditional probabilities differ substantially ($\sim$ 20% vs $\sim$35%) across the two groups, by just two consecutive months later, both groups' conditional probabilities hover asymptotically at about 90%. These results show that households do exhibit persistence in their decisions to partially prepay, but this persistence does not correlate with the interest rate environment when they first began prepaying.

Additional Figures and Tables

Figure A1: Data dictionary

Fannie Mae variables

Name	Description
Mortgage interest rate (r_m)	Pre-tax mortgage interest rate
Origination principal balance	Principal balance of the loan at origination (rounded to the nearest $1000)
Current principal balance	Remaining principal balance in month *t*
Term	Length (in months) of the loan
Months to legal maturity	Number of months remaining until the loan is due to be paid in full as defined by the contract
Months to maturity	Number of months remaining until the outstanding principal balance of the mortgage amortizes to a zero balance after considering early payments

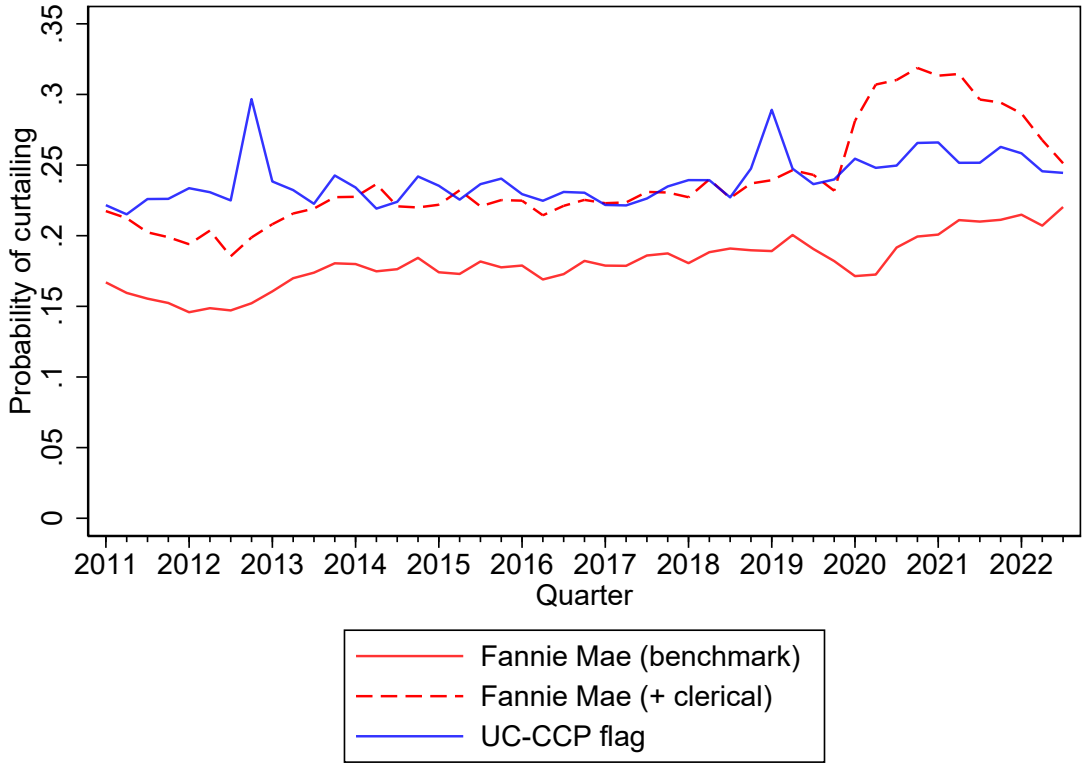
TAXSIM variables

Name	Description
Federal marginal tax rate	The estimated federal marginal tax rate on taxpayer earnings
State marginal tax rate	The estimated state marginal tax rate on taxpayer earnings

Constructed variables

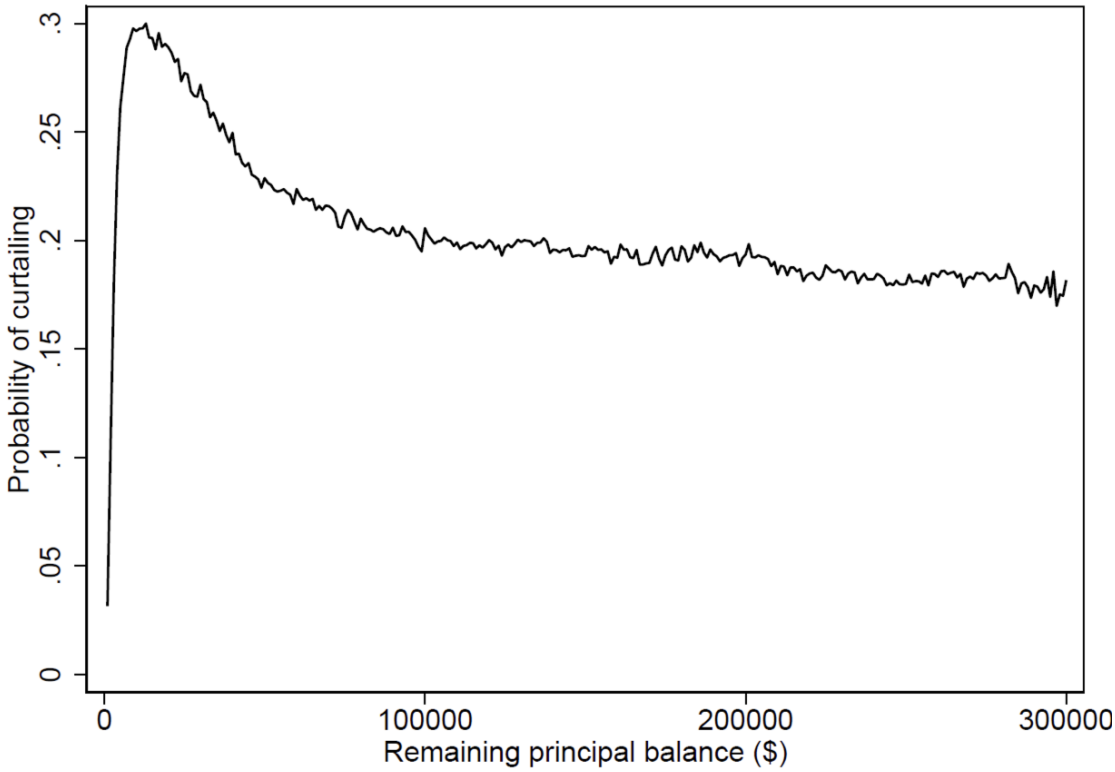
Name	Description
Monthly payment (*MP*)	The estimated monthly payment of the mortgage
Principal share of MP	The amount of the estimated monthly payment that is applied toward remaining principal each month
Expected principal balance	How much of the outstanding principal balance should remain in month *t* if the household pays exactly the monthly payment in month *t-1*
Curtailment amount	Expected principal balance - current (observed) principal balance
Curtailment flag	Indicator equal to 1 if the curtailment amount > $20

Figure A2: Credit Registry vs. Loan Performance Data



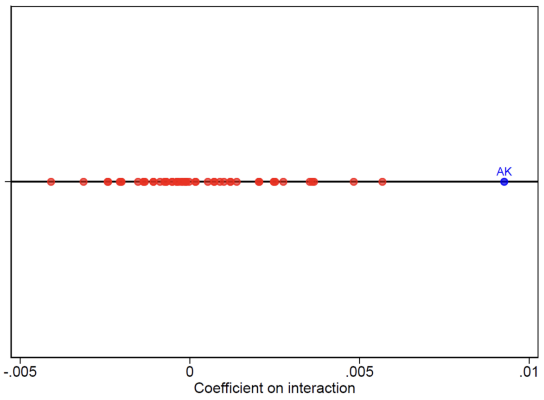
Note: Figure plots the probability of prepaying by quarter from 2011Q3 - 2023Q1. The red lines represent Fannie Mae Single-Family Loan Performance data. The solid red line uses the benchmark prepayment flag and the dashed red line uses the benchmark flag + clerical prepayment. The blue line represents the UC–CCP data.

Figure A3: Probability of prepaying by remaining balance

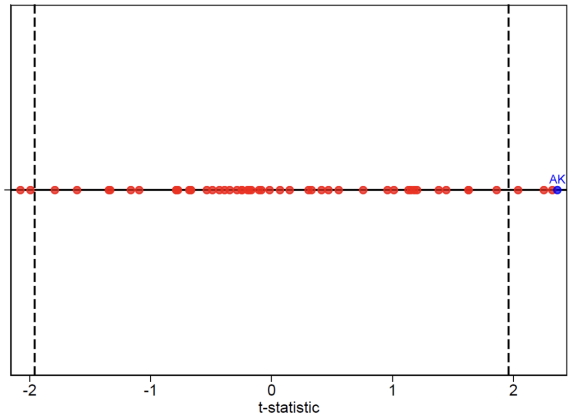


Note: Figure plots the probability of prepaying by remaining principal balance rounded to the nearest $1,000. Authors' calculations based on the Fannie Mae Single Family Loan Performance dataset.

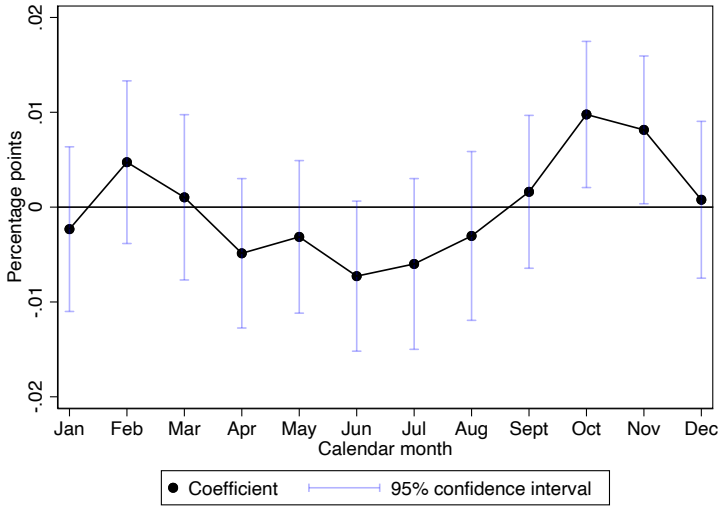
Figure A4: Effects of Alaska Permanent Fund Dividend on Prepayment



(a) Distribution of estimated coefficients on interaction term for all states



(b) Distribution of t-statistics

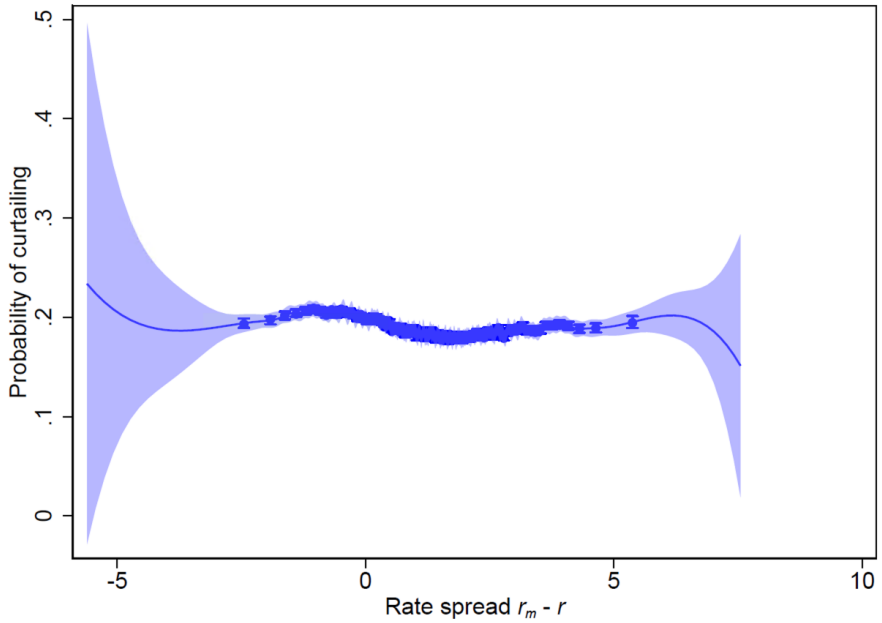


(c) Coefficients on interaction term by calendar month

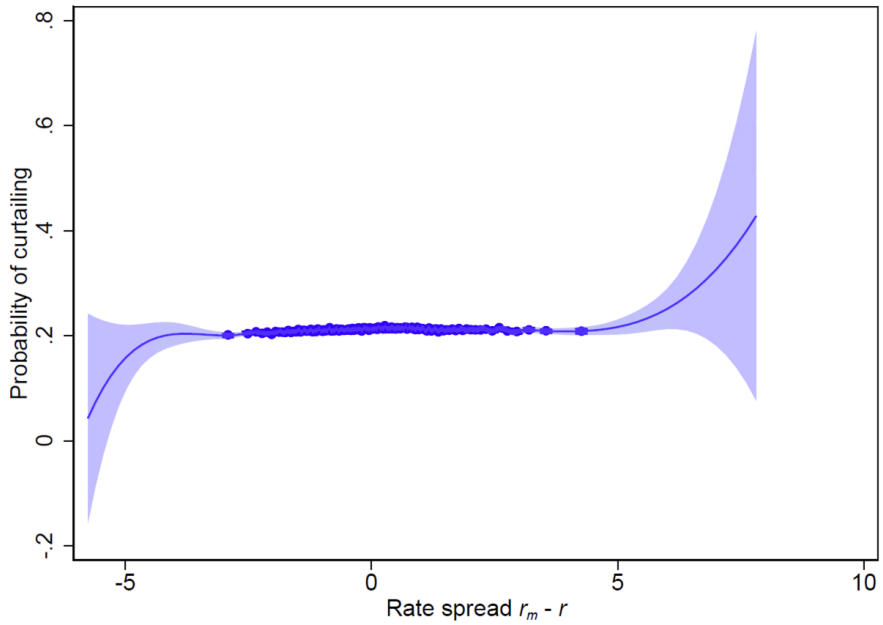
Note: Panel (a) plots the point estimates from (14) from all 51 regressions. Panel (b) plots the associated t-statistics. Panel (c) again plots the point estimates from (14) but for all 12 calendar months; coefficients are black and 95% confidence intervals are light blue. Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset.

Figure A5: Effects of interest rate spreads on prepayment: binscatter approach

(a) 2011-2024



(b) 2022-2024



Note: Both panels show binscatter estimates of Equation 5 controlling for loan fixed effects using Cattaneo et al. (2024) estimator. Panel A uses observations from 2011-2024, and Panel B only uses observations from 2022-2024. In both specifications, we estimate a third-degree polynomial with three smoothness constraints. Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset.

Table A1: Effects of the Alaska Permanent Fund Dividends on Prepayment

	$\mathbb{1}(Curtail)$	20-100	100-500	≥ 500
$AK_i \times OCT_t$	.009*	0.001	0.006	0.003
	(0.004)	(0.003)	(0.003)	(0.002)
Observations	22,002,642	22,002,642	22,002,642	22,002,642
Loan FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Mean of outcome	.17	0.061	0.08	0.03
R^2	.47	.41	.41	.34

Note: This table reports estimates from equation (14). The dependent variable in Column 1 is a prepayment indicator. The dependent variables in Columns 3-5 are indicators for prepayment amount in $(20, 100)$, $[100, 500)$, or ≥ 500 dollars, respectively. Standard errors (reported in parentheses) are clustered at the loan level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Effects of interest rate spread on the probability of prepaying

	(1)	(2)	(3)	(4)	(5)
Spread	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1-year lag		-0.00***	-0.00***	-0.00***	-0.00***
		(0.00)	(0.00)	(0.00)	(0.00)
2-year lag			0.00***	0.00***	0.00***
			(0.00)	(0.00)	(0.00)
3-year lag				0.00***	0.00***
				(0.00)	(0.00)
4-year lag					0.00***
					(0.00)
Loan FEs	✓	✓	✓	✓	✓
Number of lags	0	1	2	3	4
Loan-month obs	17,614,564	13,044,558	9,637,158	6,914,454	4,889,247

Note: Table reports estimates from the linear probability model in Equation (5). Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset, FRED, 2010-2019 Surveys of Consumer Finances and NBER Taxsim. Estimates are from Jan 2011 - Nov 2024. Standard errors (in parentheses) are clustered at the loan-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Credit outcomes by remaining mortgage principal balance

	(1) 𝟙(Curtail)	(2) 𝟙(New auto)	(3) 𝟙(New CC)	(4) 𝟙(Current delinq.)	(5) Revolving credit utilized
≤ 1 %	0.165***	-0.002	0.000	0.003	-1545.091
	(0.028)	(0.002)	(0.002)	(0.004)	(826.099)
$(1,5]$ %	0.070***	-0.001	0.003	0.001	157.683
	(0.007)	(0.002)	(0.002)	(0.004)	(442.151)
$(5,10]$ %	0.006***	-0.001	0.000	0.001	0.268
	(0.006)	(0.002)	(0.001)	(0.003)	(353.887)
$(10,20]$ %	0.060***	-0.001	0.001	-0.001	-125.820
	(0.005)	(0.001)	(0.001)	(0.002)	(288.919)
$(20,30]$ %	0.056***	-0.000	0.000	0.002	-331.914
	(0.004)	(0.001)	(0.001)	(0.002)	(263.811)
$(30,40]$ %	0.043***	-0.001	0.001	-0.001	-170.921
	(0.004)	(0.001)	(0.001)	(0.002)	(235.557)
$(40,50]$ %	0.026***	-0.001	0.001	-0.000	-308.483
	(0.003)	(0.001)	(0.001)	(0.001)	(190.570)
Observations	1,943,845	1,943,845	1,943,845	1,943,845	1,757,625
Loan FEs	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓
R^2	0.38	0.06	0.12	0.10	0.71

Note: Table plots estimates from Equation (8). Column (1) uses a mortgage curtailment indicator for the dependent variable. Column (2) is a new auto loan indicator. Column (3) is a new credit card indicator. Column (4) is a new delinquency indicator. Column (5) is revolving credit utilized. Authors' calculations based on the University of California Consumer Credit Panel (UC–CCP). Standard errors (in parentheses) are clustered at the borrower-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Effects of interest rate spread on the probability of prepaying: No autopayers

	All			High Credit Score			Low Credit Score		
Spread	-0.01***	-0.01***	-0.02***	-0.01***	-0.01***	-0.02***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Loan FEs		✓			✓			✓	
Month FEs			✓			✓			✓
$\bar{Y}$	0.28	0.28	0.28	0.30	0.30	0.21	0.26	0.26	0.26

Note: Table reports estimates from the linear probability model in Equation (5). "High" and "low" credit score loans are those with above- and below- median credit scores (773), respectively. $\bar{Y}$ represents the baseline probability of prepaying for each group. Interest rate spread is calculated using post-tax mortgage interest rate and post-tax maturity-matched Treasury yields. $N = 8,567,137$ in Columns (1) and (3). $N = 8,497,184$ in Column (2). $N = 4,309,527$ in Columns (4) and (6). $N = 4,278,426$ in Column (5). $N = 4,257,610$ in Columns (7) and (9). $N = 4,218,698$ in Column (8). Authors' calculations based on the Fannie Mae Single-Family Loan Performance dataset, FRED, 2010-2019 Surveys of Consumer Finances and NBER Taxsim. Estimates are from Jan 2011 - Nov 2024. Standard errors (in parentheses) are clustered at the loan-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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