

# Rates Up, Balances Up: Uneven Monetary Transmission in Consumer Credit Markets \*

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April 2026

## Abstract

What happens to consumer borrowing when interest rates rise? We revisit this question and find that consumers tend to borrow more when rates increase. Using a representative sample of consumer credit records, we estimate dynamic responses of consumer debt with individual-level local projections and an IV design that instruments the 1-year Treasury rate with high-frequency monetary policy shocks. A 25 basis point increase in the 1-year Treasury rate raises total debt by about 2% of mean debt over three years (\$1,539). On the extensive margin, the total number of credit accounts also increases. Heterogeneity analyses reveal persistently stronger responses among more financially constrained consumers. Additional evidence points to an indirect transmission channel: tighter policy weakens local labor markets and income, increasing credit reliance among more financially constrained borrowers. Our findings suggest that contractionary monetary policy can increase indebtedness among vulnerable consumers, highlighting an important distributional dimension of monetary transmission.

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\*First Draft: March 2026. We thank Andrés Sarto, Shihan Xie, Julia Fonseca, Yuchen Chen, Greg Howard, Avantika Pal, and seminar participants at the University of Illinois Urbana-Champaign for helpful comments.

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# 1 Introduction

What happens to consumer borrowing when interest rates rise? This is a central question for monetary transmission, household finance, and the distributional effects of monetary policy. A large empirical literature suggests that higher rates should reduce borrowing: they raise borrowing costs, increase debt-service burdens, and tighten cash flow, especially on interest-sensitive liabilities and at short horizons. But monetary tightening also weakens aggregate demand and labor-market conditions. If income falls or becomes more uncertain, some households may instead rely more on credit to smooth consumption or meet existing obligations. Therefore, *ex-ante*, the effect of monetary tightening on consumer debt is ambiguous.

Most of the existing empirical evidence looks at the direct effects of monetary policy on household borrowing. Studies on mortgage pass-through show that changes in policy rates affect households' cash flow through monthly payments (Di Maggio et al., 2017). While the work on refinancing, emphasizes how higher rates reduce the attractiveness of borrowing against housing wealth (Anenberg et al., 2025). These settings are especially well suited to measure the immediate effect of tighter monetary policy on borrowing costs and debt-service burdens, and much of the evidence is concentrated at relatively short horizons. However, monetary policy also works through the indirect channel. A growing literature emphasizes that tighter policy weakens labor income and aggregate demand, and that these effects can be quantitatively important for household behavior (Kaplan et al., 2018; Cloyne et al., 2018; Holm et al., 2021). Once both channels are allowed to operate, the response of consumer debt is no longer obvious.

In this paper, we study the response of consumer debt to monetary tightening over a long horizon, where direct borrowing-cost effects and slower-moving income effects can both come into play. Our study uses a large panel dataset of anonymized credit records for consumers and high-frequency monetary policy shocks. Our data comes from the Gies Consumer and Small Business Credit Panel (GCCP), a one-percent random sample of individuals with a credit report at a major U.S. credit bureau. The data allow us to observe a broad set of liabilities in one place, including mortgage debt, revolving debt, credit card debt, auto debt, personal finance debt, installment debt, and HELOC debt. We use annual aggregation of high-frequency monetary policy shocks to estimate dynamic responses using local projections following Jordà (2005).

Our main finding is that contractionary monetary policy increases total consumer debt. A 25 basis point increase in the 1-year Treasury rate increases total debt by about 0.33%

of mean debt on impact (about \$256) and by about 1.99% after three years (about \$1,539). The response builds gradually and remains positive through year five. Number of credit lines and monthly payments also increase, indicating that the increase in debt does not reflect only a narrow accounting margin or the slow evolution of a single product. Product-level estimates show increases in revolving debt, credit card debt, personal finance debt, personal installment debt, auto debt, and HELOC debt.

The increase in debt is highly uneven across households. The effect is stronger among more financially constrained borrowers. By year three, total debt rises by about 19% of mean debt for below-median-income consumers, compared with about 5% for the middle-income group and 4% for the top 5%. Across credit-score groups, the corresponding responses are about 20% for consumers with scores 350–660, 5% for the middle group, and essentially zero for the highest-score group. The same ranking appears in flexible borrowing products such as revolving and personal finance debt. These patterns indicate that the aggregate increase in debt is stronger among borrowers who appear more exposed to cash-flow and income risk.

The mechanism evidence points to indirect transmission through labor-market conditions. Income falls more at lower points of the income distribution after contractionary shocks. Debt responses are also larger in high-unemployment MSAs. In addition, when we add realized income changes to the debt specification, the estimated total-debt response becomes small and statistically weak. These exercises do not identify a clean mediation share, and we do not interpret them as formal decompositions. Taken together, however, they are consistent with a simple interpretation: tighter monetary policy weakens labor-market income, and more exposed households respond by relying more on credit.

The remainder of the paper is structured as follows. Section 2 discusses the literature. Section 3 provides a discussion on the theoretical framework. Section 4 describes the data used in our analysis. Section 5 presents the empirical strategy and results. Section 6 investigates the indirect channel mechanism. Section 7 concludes.

## 2 Related Literature

This paper contributes to three strands of the literature: monetary policy and household borrowing, indirect channels of monetary transmission, and the distributional effects of monetary policy.

First, we contribute to the literature on monetary policy and household borrowing. A large empirical literature studies how monetary policy affects household balance sheets through direct credit-market channels, emphasizing borrowing costs, cash-flow changes, refinancing, and credit supply constraints.

Seminal work shows that lower interest rates reduce mortgage payments, raise disposable income, support house prices, and stimulate consumption (Di Maggio et al., 2017; Beraja et al., 2019). The strength of this pass-through depends on institutional features such as mortgage contract structure and refinancing frictions, and may exhibit path dependence driven by past rate environments (Berger et al., 2021; ?).

A related literature emphasizes credit supply. Tighter policy reduces mortgage originations by pushing borrowers against debt-to-income (DTI) constraints (Bosshardt et al., 2024) or by tightening bank balance sheets through deposit outflows (Drechsler et al., 2024). Non-bank lenders may partially offset these effects by acting as a “spare tire” for credit supply (Cucic and Gorea, 2025). Evidence from credit card markets is consistent with these patterns: higher rates reduce credit card spending and revolving balances, particularly for constrained households (Bräuning and Stavins, 2025; Grigoli and Sandri, 2026). Some papers also document substitution across credit products in response to rate changes (Anenberg et al., 2025).

By contrast, in the United States, household liabilities are largely fixed-rate and deposit rates are relatively sticky, muting both the cash-flow channel and the offsetting increase in interest income. At the same time, more flexible labor markets imply stronger employment and income responses to monetary tightening. These differences make it more likely that indirect income effects dominate over time, increasing households’ reliance on credit and leading to rising debt.

Our findings stand in contrast to this view. We show that, at medium horizons, contractionary monetary policy can increase total household debt. This difference arises because the existing literature primarily isolates direct channels, while our framework allows indirect income effects to operate fully over time. A closely related paper by Fagereng et al. (2025) studies the response of household indebtedness using Norwegian administrative data. They find that contractionary monetary policy reduces debt-to-income ra-

tios, as households decrease borrowing and nominal debt changes dominate opposing income effects. A key difference lies in the institutional setting. In countries such as Norway, Denmark, Canada, and other settings household debt is predominantly composed of adjustable-rate mortgages. Mortgage payments adjust quickly with policy rates, making the direct cash-flow channel quantitatively dominant. In addition, deposit rates in several of these economies adjust more elastically to policy rates, increasing interest income for savers following tightening and partially offsetting adverse balance-sheet effects. By contrast, in the United States, household liabilities are more heavily fixed-rate and deposit rates are comparatively sticky, muting both the pass-through to mortgage cash flows and the offsetting increase in interest income. Labor-market institutions may also matter. Relative to many European settings, the U.S. labor market is characterized by weaker employment protection and faster employment adjustment (OECD, 2016), implying that contractionary shocks may translate more strongly into labor-income losses. These institutional differences make it more likely that the indirect income channel dominates in the U.S. and raises households' reliance on credit.

Second, this paper contributes to the literature on the indirect channel of monetary policy. A central implication of heterogeneous-agent New Keynesian (HANK) models is that monetary policy affects household behavior not primarily through intertemporal substitution, but through general-equilibrium effects on labor income and disposable resources (Kaplan et al., 2018). In these models, indirect effects can dominate direct interest-rate effects because households differ sharply in marginal propensities to consume and in their exposure to labor-income risk. Empirical work has increasingly provided support for this view. (Cloyne et al., 2018) show that the consumption response to monetary policy is concentrated among households whose balance sheets make them more sensitive to income fluctuations, while (Holm et al., 2021) find that indirect income effects gradually build and eventually outweigh direct effects. Recent work further documents substantial heterogeneity in labor-income responses to monetary shocks across the distribution and across extensive and intensive margins of adjustment (Hubert and Savignac, 2024; Cantore et al., 2022; Coglianesse et al., 2025).

Our contribution to this strand is to provide empirical evidence that the indirect channel matters not only for consumption and labor income, but also for borrowing behavior. Much of the existing literature motivates the indirect channel theoretically, or studies its effects on income and expenditure. We show that once the income consequences of monetary tightening are allowed to operate over longer horizons, some households respond by increasing debt. In this sense, our paper links the HANK view of monetary transmission

to the evolution of household balance sheets.

Third, this paper contributes to the literature on the distributional effects of monetary policy. A growing body of work emphasizes that monetary policy has heterogeneous effects across households and that these heterogeneous effects matter for aggregate transmission. (Auclert, 2019) formalizes this idea by showing that monetary policy redistributes through several channels—including earnings heterogeneity and interest-rate exposure—and that these redistributions affect aggregate demand when households differ in MPCs. On the empirical side, (Coibion et al., 2017) show that contractionary monetary policy increases income and consumption inequality in the United States. Using administrative microdata, subsequent work documents rich heterogeneity in the income effects of monetary shocks across the distribution, with important roles for labor income and balance-sheet composition (Hubert and Savignac, 2024; Cantore et al., 2022). Related research also highlights that monetary contractions can have regressive labor-market effects even when studied through large quasi-experimental episodes (Coglianese et al., 2025).

Our paper adds a new dimension to this literature by focusing on the distributional consequences of monetary policy for household indebtedness. Rather than studying inequality in income, wealth, or consumption directly, we show that contractionary shocks raise debt disproportionately among lower-income and lower-credit-score households. This evidence suggests that monetary tightening can amplify financial fragility among more exposed borrowers, even as aggregate demand weakens. In this sense, our paper identifies household debt accumulation as a novel distributional margin of monetary transmission.

### 3 Theoretical Framework

The effect of a higher interest rate on household borrowing is theoretically ambiguous. In standard (frictionless) representative benchmark economy, higher interest rate tends to be associated with less borrowing due to intertemporal substitution effect. Once households differ in aspects such as wealth, labor market shock exposure, and access to credit, however, monetary policy also redistributes across consumers. This is the central insight of the HANK literature: monetary policy operates not only through intertemporal substitution, but also through general equilibrium (GE) effects (Kaplan et al., 2018; Auclert, 2019).

This perspective leaves the relation between our outcome of interest, household borrowing, to monetary policy rate even less clear. Households at distinct wealth distribution may behave differently in the credit market to finance their consumption. A contractionary

monetary policy shock can lower borrowing through the substitution effect, but it can also raise households' demand for liquidity when the economy deteriorates. At the same time, tighter monetary policy may weaken collateral values and compress credit supply. As a result, the sign of the response of household borrowing is not obvious *ex ante*.

For indebted households, especially those with adjustable-rate debt, a contractionary policy shock can raise debt-service payments and depress disposable income. The implication for borrowing is subtle. If a household has sufficient access to flexible credit, a deterioration in current cash flow may increase its demand for short-term liquidity, revolving debt, or other consumer credit to smooth expenditure. In that case, contractionary monetary policy can raise borrowing for these households.

HANK models also emphasize that monetary policy affects household labor income and unemployment risk unevenly. A contractionary shock weakens labor demand and expected income for some households more than others. For low-liquidity households, this may increase near-term borrowing needs as these consumers attempt to smooth consumption in the face of income shortfalls. The sign of the response is therefore heterogeneous. Meanwhile, for borrowers, higher rates worsen net worth and may tighten borrowing constraints. In housing markets, contractionary policy can also lower house prices, reduce home equity, and make refinancing less attractive or less feasible. These forces push borrowing downward, especially for collateral-dependent credit.

The theoretical framework above guides our empirical analysis, which is designed to investigate the effect of contractionary monetary policy on household borrowing. It yields the following two empirical hypotheses.

**Hypothesis 1.** *The average effect of contractionary monetary policy on household borrowing is ambiguous ex ante.*

**Hypothesis 2.** *Households with vulnerable financial positions borrow more when monetary policy tightens.*

## 4 Data

### 4.1 Consumer Credit Panel

Our study uses the Gies Consumer and Small Business Credit Panel (GCCP), a panel dataset of anonymized credit records for consumers and small businesses obtained from a major credit bureau. The GCCP features a one-percent random sample of individuals with a credit report, linked to alternative credit records and business credit records for individuals who own a business.<sup>1</sup> The dataset spans 2005–2023 and contains annual snapshots measured at the close of the first quarter of each year. Sampling is based on the last two digits of Social Security numbers. This sampling method accounts for natural flows into the panel as new Social Security numbers are issued, as well as outflows due to death or prolonged inactivity, ensuring that the sample remains representative of the broader population over time.

Each GCCP record includes all reported debt obligations, or “tradelines,” with information on credit type (mortgage, auto, student, or credit card), balances and limits, and payment history. The data also include VantageScores, public records such as bankruptcies and judgments, debts in collections, and demographic variables such as age, sex, income, and 5-digit zip code. Demographic variables are administrative or modeled: age is computed from date of birth, sex is a bureau-provided name-based classification, and income is a bureau-provided estimate based on credit-report variables.

Our primary outcome is total debt, which includes both housing and non-housing liabilities recorded in the credit file. We complement this with number of tradelines and monthly payments, which aims to proxy for the extensive margin of credit reliance. We also examine major debt categories, including revolving debt, credit card debt, auto debt, personal finance debt, personal installment debt, and HELOC debt. All dollar variables are winsorized at the 99th percentile and converted to 2018 dollars using March CPI.

The final sample includes 36,683,885 consumer-year observations, summarized in Table 2. The average consumer is 49 years old, and about half of the sample is female. The mean credit score is 689, while average annual income is \$84,864. Consumers in the sample hold an average total balance of \$77,330 across all credit products, have about 5 open trade lines, and make average monthly payments of \$857.

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<sup>1</sup>Alternative credit records include information not reported to the major credit bureaus, such as payday loans and title loans. See also Kohli et al. (2024) and Duarte et al. (2025) for other papers using the GCCP.

ities recorded in the credit file. The measure of total debt allows us to capture the net balance-sheet response once households adjust across products and over time. We also observe monthly payments. We complement these outcomes with the number of trade lines and monthly payments, which aims to proxy for the extensive margin of credit reliance. We also examine major debt categories, including revolving debt, credit card debt, auto debt, personal finance debt, personal installment debt, and HELOC debt.

All dollar variables are winsorized at the 99th percentile and converted to 2018 dollars using March CPI. Table 1 provides the summary statistics for the debt balances. Monthly payments are measured as the total monthly payment due on open accounts, and trade lines count currently open accounts. Mean total debt in the sample is \$77,330, of which \$15,456 is non-mortgage debt and \$7,339 is revolving debt. Mortgage-related balances account for a large share of the household balance sheet in levels, which is one reason total debt is a more informative outcome than any single non-mortgage product in isolation.

For heterogeneity analyses we split the borrowers based on income and credit score. We use three income groups—below median, P50–P95, and top 5%—and three credit-score groups—350–660, 661–820, and 821–850. These groupings are chosen for interpretability.

## 4.2 Monetary Policy Shocks

We rely on the high-frequency identification of monetary policy surprises ([Gürkaynak et al., 2005](#)). The surprise component is constructed by price changes of Federal funds rate futures contracts in the 30-minute window around FOMC announcements. The identifying assumption is that all public information is already incorporated into the prices at the beginning of the narrow window and therefore contains no other news that affect interest rate expectations.

However, as recent studies have shown, this methodology might capture the “information effect” of monetary policy, which could bring biases in the estimation of monetary policy transmission ([Nakamura and Steinsson, 2018](#)). The idea is, for example, an unexpected monetary easing might lead to pessimism among the market participants about economic fundamentals. Therefore, central banks could potentially convey information of their perception of the economic state to the investors, through various communication tools. Arguably, the “information effect” could be an important factor for understanding how consumer credit respond to monetary policy, especially when the financial constraint is also at play.

We use monetary policy shocks from the work of [Nakamura and Steinsson \(2018\)](#), which

separates the “pure” monetary policy effect and “information effect”. We follow the literature to construct annual aggregation of high-frequency monetary policy shocks around FOMC announcements. We also consider alternative shock measures, including [Gürkaynak et al. \(2005\)](#) and [Jarociński and Karadi \(2020\)](#) shocks.

The timing of the shock is aligned to the annual structure of the credit data. Because the debt data are measured at annual March snapshots, we aggregate announcement-level shocks within the corresponding March-year. This timing is not merely a data convenience. Our question is explicitly about medium-run debt adjustment, not only the immediate response of one contract margin over a quarter or two. Debt accumulation, repayment behavior, account opening, and income deterioration all unfold over time, so an annual design is well suited to studying whether indebtedness ultimately rises or falls after tightening. At the same time, annual aggregation can smooth short-run dynamics, so the estimates should be interpreted as medium-run reduced-form responses rather than high-frequency borrowing elasticities.

## 5 Empirical Framework and Results

### 5.1 Baseline Local Projections

We use IV local projections to trace out the dynamic impact of monetary policy on consumer credit borrowing decisions. Following [?](#) , for each horizon  $h \in \{0, 1, \dots, 5\}$  year, we estimate a horizon-specific two-stage system:

$$i_t = \pi \text{MPS}_t + \rho' X_{t-1} + \text{FE} + u_t, \quad (1)$$

$$\Delta_h Y_{i,t+h} = Y_{i,t+h} - Y_{i,t-1} = \beta_h \hat{i}_t + \Gamma_h' X_{t-1} + \text{FE} + \varepsilon_{i,t+h}. \quad (2)$$

Here,  $i_t$  is the 1-year Treasury rate,  $\text{MPS}_t$  is the high-frequency monetary policy shock used as an instrument, and  $X_{t-1}$  contains lagged macro controls. We include person, income-bin, credit-score-bin, and ZIP-code fixed effects, and we two-way cluster standard errors by person and year. Coefficients are scaled so that estimates correspond to a 25 basis point increase in the 1-year Treasury rate.

Two features of this specification are worth emphasizing. First, the dependent variable is a long difference,  $Y_{i,t+h} - Y_{i,t-1}$ , so  $\beta_h$  measures the cumulative change in debt through

horizon  $h$  relative to the pre-shock year. This makes the coefficients easy to interpret and matches the economic object of interest: the medium-run response of household indebtedness, not only the next-year increment. Second, the identifying variation comes from high-frequency monetary policy surprises rather than endogenous movements in policy rates tied to the state of the economy. For that reason, we interpret the baseline total-debt estimates as reduced-form causal responses of household debt to contractionary monetary policy shocks in the observed sample.

### 5.1.1 Heterogeneity

To study how the response varies across borrowers, we estimate an interacted IV local projection:

$$\Delta_h Y_{i,t+h} = \sum_k \beta_{h,k} \left( \hat{i}_t \times \mathbf{1}\{i \in k\} \right) + \sum_k \Gamma'_{h,k} (X_{t-1} \times \mathbf{1}\{i \in k\}) + \text{FE} + \varepsilon_{i,t+h}. \quad (3)$$

$k$  denotes either income groups or credit-score groups. In the first stage, we instrument  $i_t$  with  $\text{MPS}_t$  and instrument each interaction  $i_t \times \mathbf{1}\{i \in k\}$  with  $\text{MPS}_t \times \mathbf{1}\{i \in k\}$ . The resulting  $\beta_{h,k}$  coefficients trace group-specific impulse responses. Because baseline debt levels differ substantially across borrowers, we focus primarily on responses scaled by group means when interpreting heterogeneity; raw dollar estimates are informative about levels, while scaled responses are more informative about distributional incidence.

These heterogeneous responses should not be given the same causal interpretation as the baseline average effect. Income, credit score, and local conditions are endogenous states that summarize many deeper dimensions of exposure and balance-sheet strength. We therefore treat the heterogeneity estimates as evidence on where the aggregate response comes from, not as treatment effects of borrower type.

## 5.2 Results

### 5.2.1 Monetary Tightening Increases Total Debt

The central result of the paper is that contractionary monetary policy raises total consumer debt. The response is positive on impact, builds gradually for several years, and remains positive through the end of the five-year horizon. In economic terms, the effect is sizable: by year three, a 25 basis point increase in the 1-year Treasury rate raises total debt by about 1.99% of mean debt (about \$1,539). Figure 1 plots the baseline impulse responses for total debt, trade lines, and monthly payments.

The dynamic profile is economically informative. The response does not appear as a short-lived spike that quickly reverses. Instead, debt accumulates gradually and remains elevated well after the shock. That pattern is harder to reconcile with a story centered only on a narrow, contemporaneous interest-rate margin. It fits more naturally with a broader process in which tighter policy affects household balance sheets through slower-moving channels such as repayment pressure, product substitution, and weaker income growth. The paper's emphasis on total debt over several years is precisely intended to capture that net medium-run adjustment.

### 5.2.2 Increase is Observed Across Several Dimensions

The increase in total debt is accompanied by movement along other margins of household credit use. The number of trade lines rises after contractionary shocks, and monthly payments rise as well. These facts matter because they help discipline interpretation. A rise in debt without any change in account counts could reflect only slower repayment or revaluation within a fixed set of liabilities. A rise in payments without broader balance growth could reflect repricing alone. Instead, the joint movement of balances, trade lines, and payments points to a broader increase in household credit reliance after tightening.

The product-level estimates reinforce that interpretation. We find positive responses in revolving debt, credit card debt, personal finance debt, personal installment debt, auto debt, and HELOC debt. The timing differs across products in a sensible way. Flexible borrowing products respond earlier, while other liabilities build more gradually. We do not interpret each product as mapping one-for-one into a separate mechanism, but the overall pattern argues against reading the total-debt response as an artifact of one isolated debt category. Instead, the evidence suggests that tighter policy changes household borrowing behavior across several margins at once (Figure 2).

### 5.2.3 Financially Constrained Borrowers Show Stronger Response

The aggregate increase in debt is not evenly distributed across households. Once responses are scaled by group means, the effect is clearly concentrated among lower-income and lower-credit-score borrowers. Figures 4 and 3 show that the year-three response of total debt is roughly 19% of mean debt for below-median-income borrowers, compared with about 5% for the middle-income group and 4% for the top 5%. Across credit-score groups, the corresponding pattern is even sharper: the increase is largest for borrowers with scores 350–660, much smaller for the middle group, and essentially absent for the highest-score group.

This is the most meaningful way to read the heterogeneity results. In levels, higher-income borrowers may still show large dollar changes because they begin with larger balance sheets. But incidence is not about who has the biggest level response; it is about where the aggregate effect is economically strongest relative to baseline exposure. On that margin, the debt increase is concentrated much more heavily at the lower end of the income and credit-score distributions.

The same ranking appears in flexible borrowing products such as revolving debt and personal finance debt, and in some cases higher-income borrowers reduce these balances on impact. This product-level heterogeneity is informative because these are precisely the margins most likely to respond when households face cash-flow stress or a deterioration in near-term income prospects. Taken together, the heterogeneous responses suggest that the average increase in debt is driven primarily by borrowers with fewer buffers and greater exposure to income risk.

These results do not imply that the direct effect of tighter policy disappears. The direct channel still points toward lower borrowing by making credit more expensive and by tightening cash flow on existing liabilities. Our evidence instead suggests that, once one allows for adjustment across products and over time, this direct force does not dominate the net debt response for all households. In the data, total indebtedness rises, and it rises most strongly among borrowers who appear more exposed to income and liquidity stress.

## 6 Mechanism: Indirect Transmission

Our mechanism analysis is designed as triangulation rather than formal decomposition. We use three complementary exercises. First, we examine how income responds to contractionary shocks across the income distribution. Second, we test whether debt responses are stronger in weaker local labor markets by interacting the shock with MSA unemployment categories. Third, we estimate an income-controlled specification that adds realized income changes to the debt regression. This last exercise follows the spirit of [Holm et al. \(2021\)](#), but we use it only as an attenuation test: because income is itself a post-treatment variable, the resulting coefficients should be interpreted as the debt response holding realized income fixed, not as a structural mediation estimate.

This distinction is important for interpretation. No single mechanism exercise identifies a clean channel on its own. Our goal is narrower: to assess whether the pattern of debt responses is more consistent with indirect transmission through labor-market and income conditions than with a purely direct borrowing-cost story.

### 6.1 Income Responses Across the Distribution

Our first mechanism exercise asks whether contractionary shocks reduce income more strongly at lower points of the distribution. The answer is yes. [Figure 5](#) shows larger declines for lower-income households, a pattern consistent with tighter policy increasing income inequality and placing greater pressure on the borrowers most likely to rely on credit. This does not by itself establish that lower income causes the debt response at the individual level, but it helps discipline interpretation. A purely direct borrowing-cost story would have less reason to generate such a clear income gradient at the same time as the strongest debt accumulation appears among lower-income borrowers.

This reading is also consistent with the broader indirect-effects literature. In [Holm et al. \(2021\)](#), direct effects dominate initially, but indirect effects build over time and become increasingly important after roughly two to three years, especially for more exposed households. That timing is strikingly similar to the gradual build-up we observe in debt.

## 6.2 Labor Market Channel

Our second exercise exploits local labor-market variation. We estimate MSA-level IV local projections and interact the policy-rate regressor with local unemployment categories:

$$\begin{aligned} \Delta_h Y_{m,t+h} = & \beta_{\text{Low}}^h \hat{i}_t + \delta_{\text{Mid}}^h \left( \hat{i}_t \times \mathbf{1}\{\text{Middle MSA}_{m,t}\} \right) \\ & + \delta_{\text{High}}^h \left( \hat{i}_t \times \mathbf{1}\{\text{High MSA}_{m,t}\} \right) + \Gamma_h' X_{t-1} + \alpha_m + \varepsilon_{m,t+h}. \end{aligned} \quad (4)$$

The low-unemployment group is the omitted category. In the first stage, we instrument  $i_t$  with  $\text{MPS}_t$ , and instrument each interaction term  $i_t \times \mathbf{1}\{\cdot\}$  with  $\text{MPS}_t \times \mathbf{1}\{\cdot\}$ . Our coefficient of interest is  $\delta_{\text{High}}^h$ : under the labor-market amplification hypothesis, we expect  $\delta_{\text{High}}^h > 0$ .

That is what we find. Figure 6 shows that the response of local debt is strongest in high-unemployment areas and weakest in low-unemployment areas, with the middle group generally lying in between.

This evidence is not quasi-experimental across locations. High-unemployment MSAs differ from low-unemployment MSAs along many dimensions, and we do not interpret the interaction coefficients as clean causal estimates of labor-market exposure. But the sign pattern is informative. It is more consistent with an indirect income-and-employment channel than with a story in which tighter policy affects borrowing only through common mechanical repricing of debt contracts.

## 7 Conclusion

Using a large panel of consumer credit records and high-frequency monetary policy shocks, we show that contractionary monetary policy increases consumer debt over longer horizons. The total number of credit lines and monthly payments also increase. This effect is observed in several borrowing margins rather than in one narrow category.

This response is uneven; with more financially constrained borrowers showing a stronger response. This suggests that tighter monetary policy does not affect all households through a common representative-agent margin. Instead, it generates a much more uneven adjustment in which the households most exposed to cash-flow and income stress account for a disproportionate share of the increase in indebtedness.

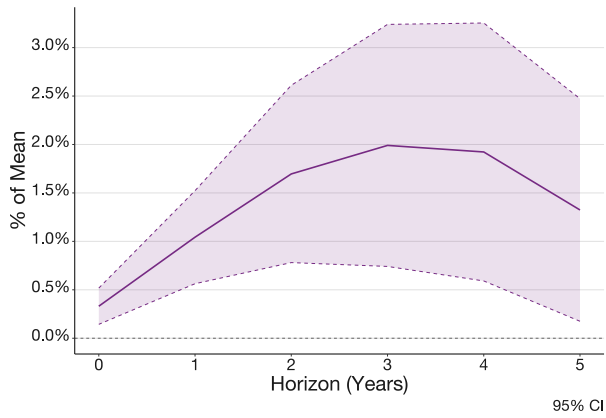
Our suggestive evidence points towards income channel as the mechanism. Income fall more at the lower end of the distribution, debt responses are stronger in weaker local labor markets, and the estimated debt response becomes much smaller once realized income changes are held fixed. Taken together, these results are consistent with an important role for indirect transmission through labor-market and income channels.

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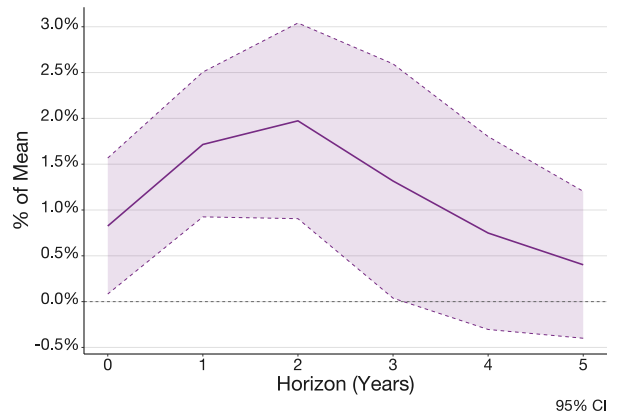
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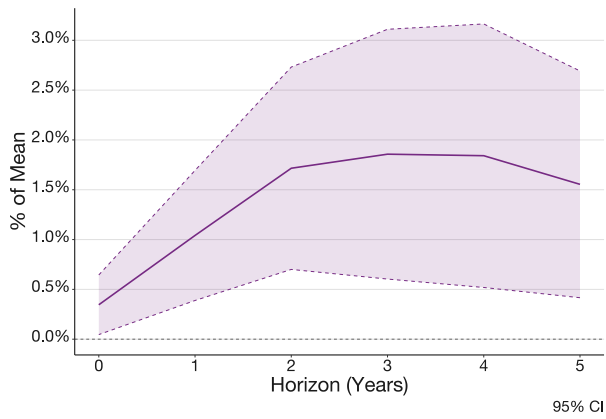
**Figure 1: Baseline debt responses.**



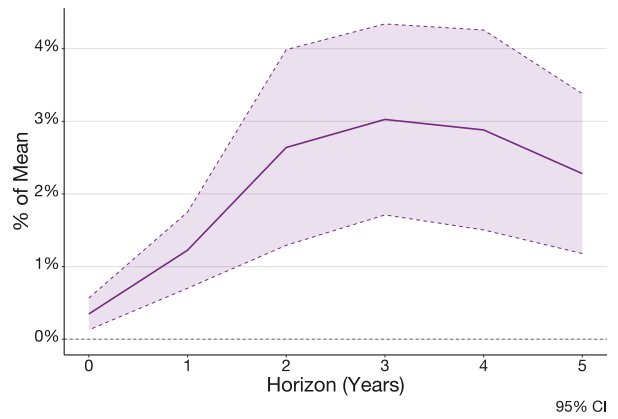
**(a) Total debt**



**(b) Trade lines**

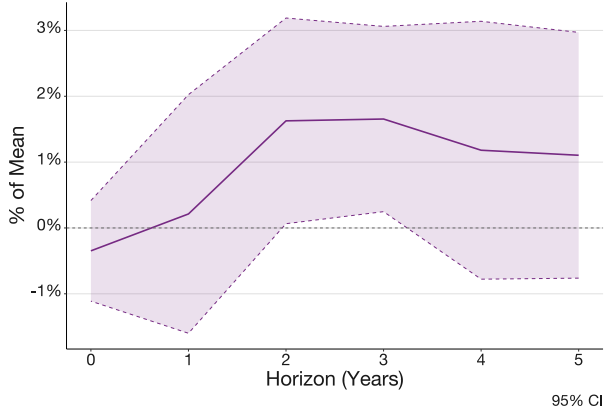


**(c) Monthly payments**

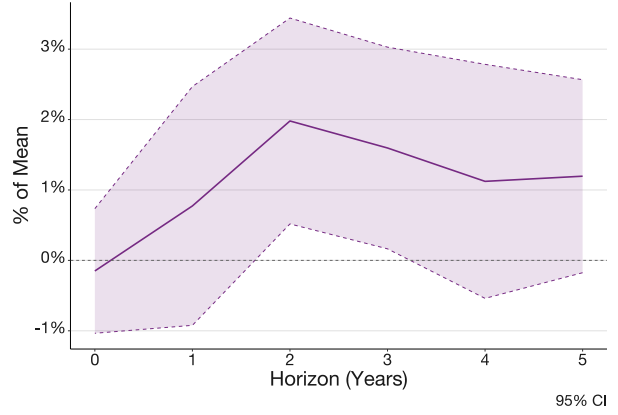


**(d) Total debt, JK shock**

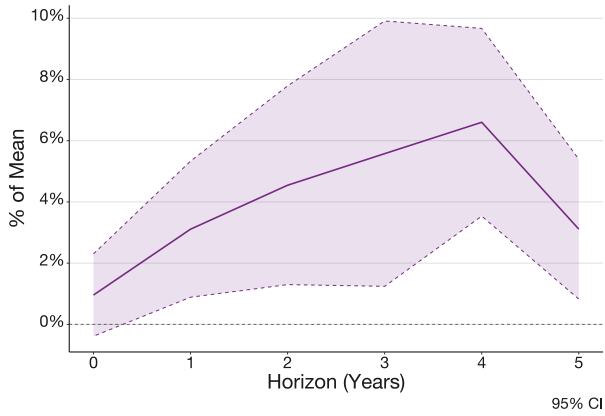
**Figure 2: Product-level debt responses.**



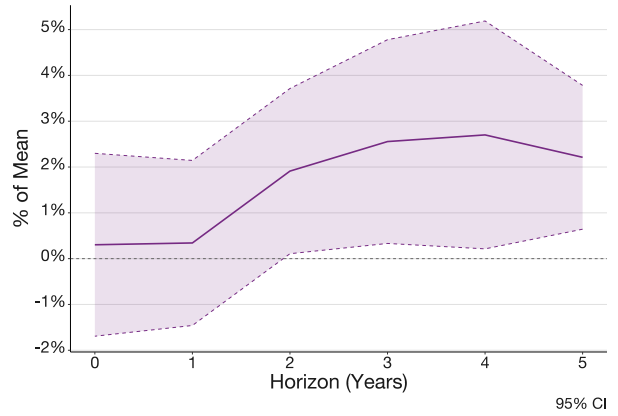
**(a) Revolving debt**



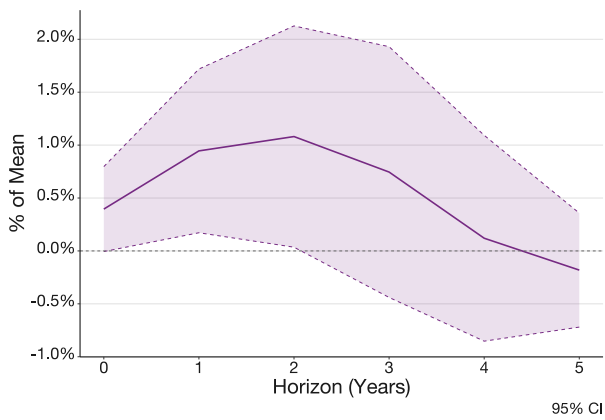
**(b) Credit card debt**



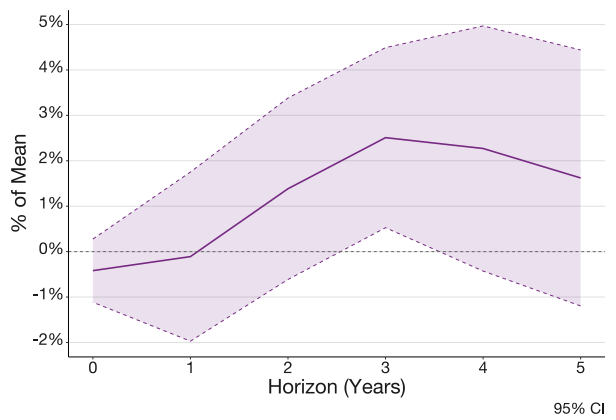
**(c) Personal finance debt**



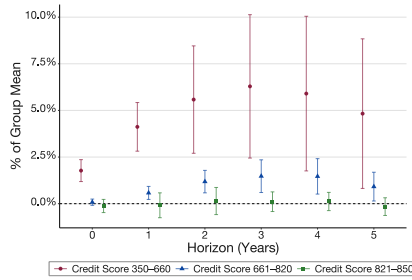
**(d) Personal installment debt**



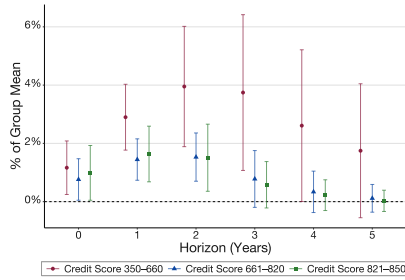
**(e) Auto debt**



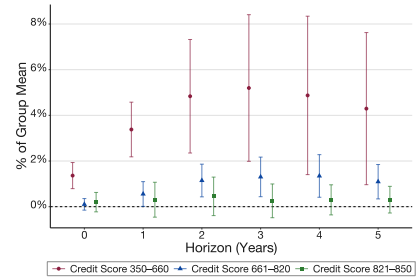
**(f) HELOC debt**



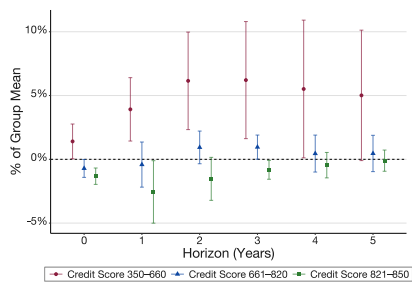
(a) Total debt



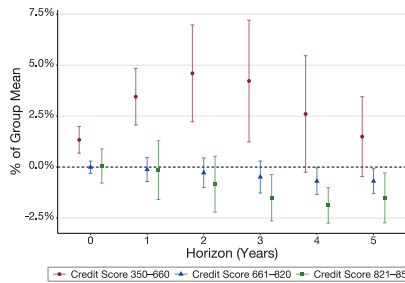
(b) Trade lines



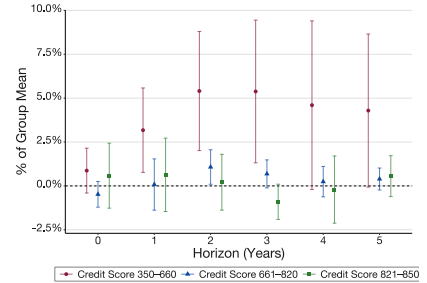
(c) Monthly payments



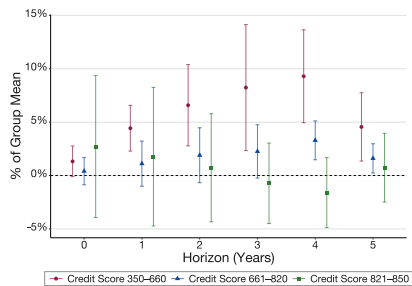
(d) Revolving debt



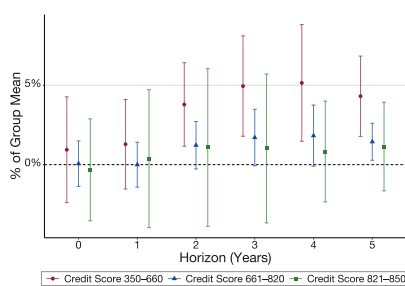
(e) Auto debt



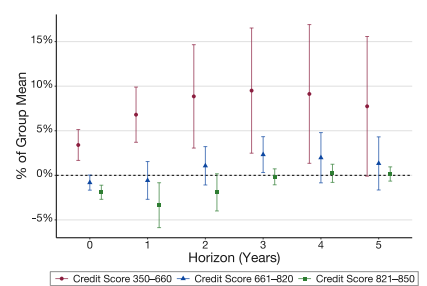
(f) Credit card debt



(g) Personal finance debt

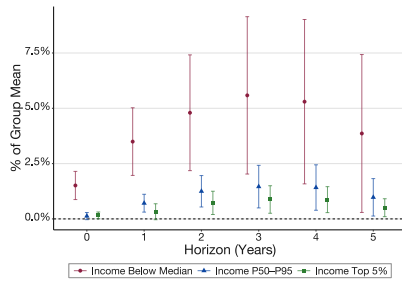


(h) Personal installment debt

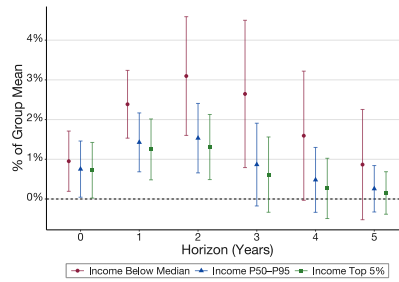


(i) HELOC debt

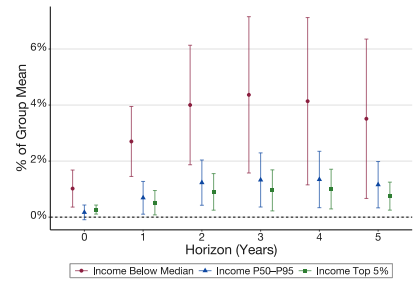
Figure 3: Heterogeneity by credit score, scaled by group means.



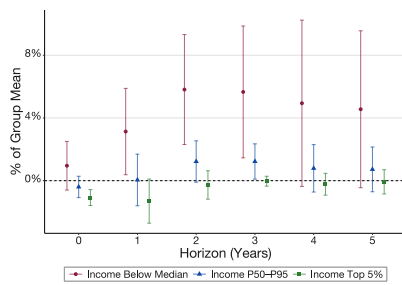
**(a) Total debt**



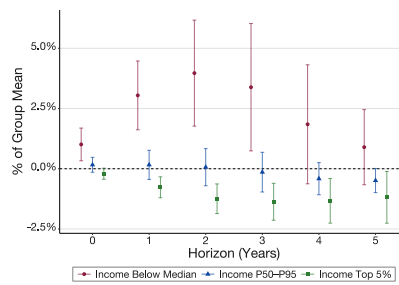
**(b) Trade lines**



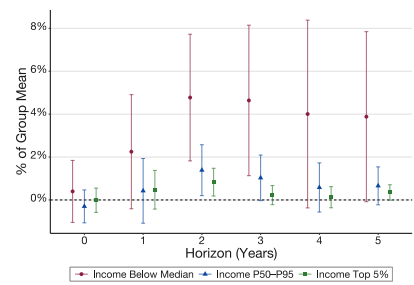
**(c) Monthly payments**



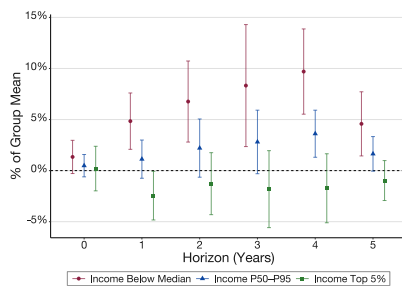
**(d) Revolving debt**



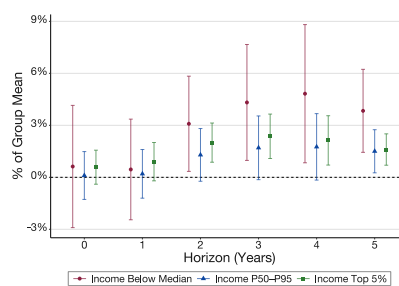
**(e) Auto debt**



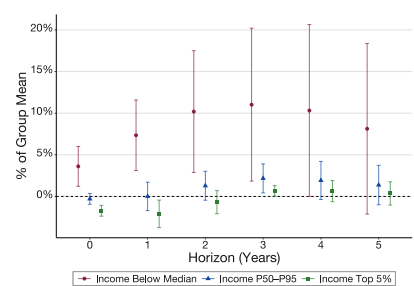
**(f) Credit card debt**



**(g) Personal finance debt**

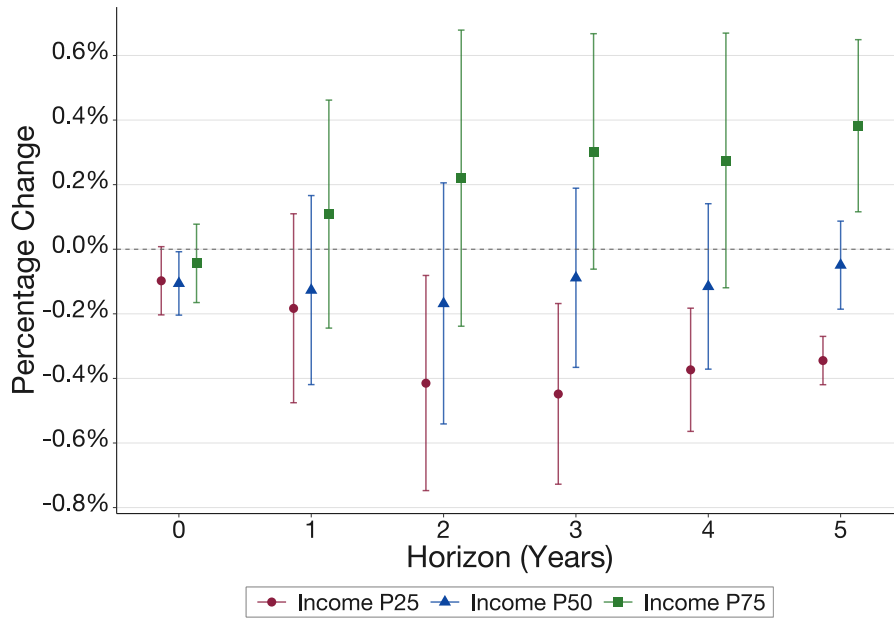


**(h) Personal installment debt**

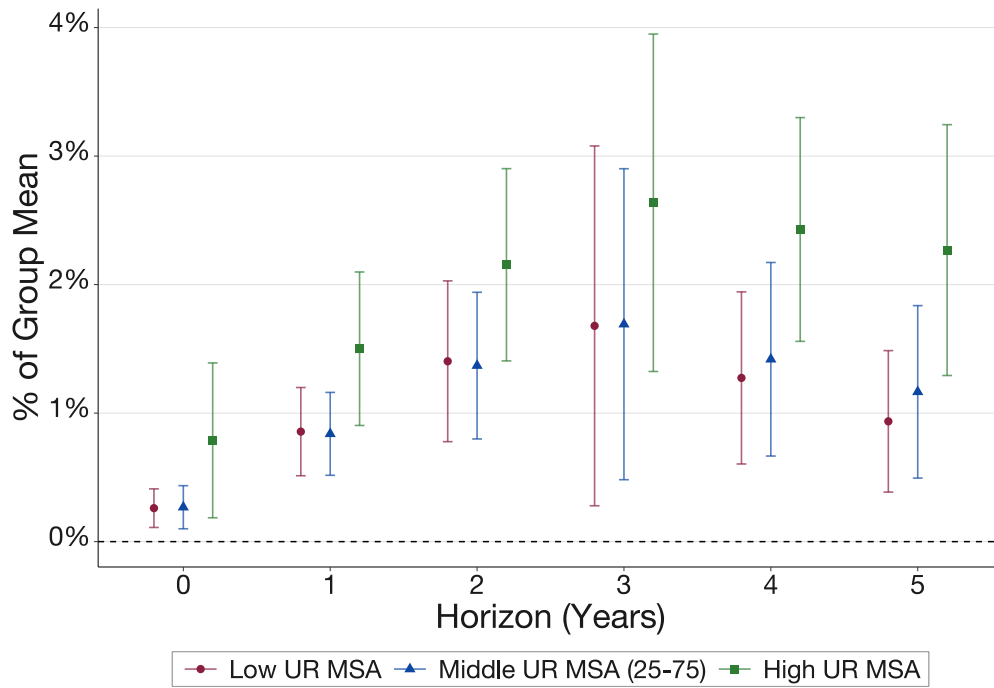


**(i) HELOC debt**

**Figure 4: Heterogeneity by income, scaled by group means.**



**Figure 5: Income response by percentile**



**Figure 6: Total debt by local unemployment**

**Table 1: Summary statistics for debt levels**

|                      | Balance    |       |        | Balance   Balance > 0 |        |        |
|----------------------|------------|-------|--------|-----------------------|--------|--------|
|                      | Median     | Mean  | SD     | Median                | Mean   | SD     |
| Total balance        | 9.85       | 77.33 | 139.59 | 30.31                 | 103.91 | 153.04 |
| Non-mortgage         | 3.30       | 14.49 | 24.06  | 10.27                 | 20.02  | 26.24  |
| Mortgage             | 0.00       | 62.12 | 129.59 | 151.54                | 196.72 | 163.40 |
| First mortgage       | 0.00       | 57.00 | 121.58 | 155.48                | 197.82 | 153.10 |
| Second mortgage      | 0.00       | 0.95  | 6.25   | 35.67                 | 33.18  | 17.13  |
| HELOC                | 0.00       | 2.81  | 13.94  | 37.06                 | 46.41  | 34.42  |
| Cash-out refi        | 0.00       | 0.80  | 13.63  | 37.76                 | 66.01  | 104.26 |
| Revolving            | 0.68       | 7.07  | 17.94  | 3.07                  | 11.08  | 21.45  |
| Credit card          | 0.63       | 4.15  | 8.22   | 2.73                  | 6.53   | 9.52   |
| Auto                 | 0.00       | 5.03  | 10.67  | 15.47                 | 18.40  | 13.08  |
| Personal finance     | 0.00       | 0.13  | 0.91   | 4.00                  | 4.27   | 3.07   |
| Personal installment | 0.00       | 1.36  | 5.99   | 6.98                  | 12.53  | 13.77  |
| Observations         | 36,683,885 |       |        |                       |        |        |

|                         | Mean       | Median | SD     |
|-------------------------|------------|--------|--------|
| Age                     | 49         | 48     | 18     |
| % Female                | 52         | 100    | 50     |
| Credit score            | 689        | 700    | 107    |
| Income (\$)             | 84,864     | 68,000 | 67,088 |
| Number of debt accounts | 5          | 4      | 5      |
| Monthly payment (\$)    | 857        | 290    | 1,251  |
| Observations            | 36,683,885 |        |        |

**Table 2:** Summary statistics for all variables

**Table 3: Baseline total-debt response**

|                | H = 0          | H = 1           | H = 2            | H = 3            | H = 4            | H = 5           |
|----------------|----------------|-----------------|------------------|------------------|------------------|-----------------|
| MPS            | 256***<br>(74) | 807***<br>(189) | 1312***<br>(361) | 1539***<br>(493) | 1487***<br>(525) | 1024**<br>(453) |
| N              | 35,365,529     | 34,470,275      | 31,888,359       | 29,457,450       | 27,156,694       | 24,980,613      |
| R <sup>2</sup> | 0.03           | 0.06            | 0.11             | 0.15             | 0.20             | 0.26            |
| FE             | ✓              | ✓               | ✓                | ✓                | ✓                | ✓               |

**Table 4: Total debt by income**

|                     | H = 0          | H = 1           | H = 2            | H = 3            | H = 4            | H = 5           |
|---------------------|----------------|-----------------|------------------|------------------|------------------|-----------------|
| Income Below Median | 346***<br>(74) | 801***<br>(179) | 1099***<br>(306) | 1280***<br>(416) | 1214***<br>(434) | 885**<br>(417)  |
| Income P50–P95      | 142<br>(91)    | 789***<br>(228) | 1388***<br>(402) | 1621***<br>(545) | 1575***<br>(582) | 1084**<br>(480) |
| Income Top 5%       | 494**<br>(236) | 991*<br>(562)   | 2214***<br>(820) | 2680***<br>(969) | 2661***<br>(915) | 1548**<br>(631) |
| N                   | 35,365,529     | 34,470,275      | 31,888,359       | 29,457,450       | 27,156,694       | 24,980,613      |
| R <sup>2</sup>      | 0.03           | 0.07            | 0.11             | 0.16             | 0.21             | 0.26            |
| FE                  | ✓              | ✓               | ✓                | ✓                | ✓                | ✓               |

**Table 5: Total debt by credit score**

|                      | H = 0          | H = 1            | H = 2            | H = 3            | H = 4            | H = 5           |
|----------------------|----------------|------------------|------------------|------------------|------------------|-----------------|
| Credit Score 350–660 | 563***<br>(95) | 1307***<br>(211) | 1772***<br>(466) | 1996***<br>(622) | 1873***<br>(671) | 1532**<br>(649) |
| Credit Score 661–820 | 78<br>(83)     | 560***<br>(172)  | 1147***<br>(298) | 1430***<br>(433) | 1420***<br>(469) | 886**<br>(381)  |
| Credit Score 821–850 | -219<br>(320)  | -152<br>(605)    | 255<br>(660)     | 189<br>(478)     | 209<br>(443)     | -279<br>(430)   |
| N                    | 35,365,529     | 34,470,275       | 31,888,359       | 29,457,450       | 27,156,694       | 24,980,613      |
| R <sup>2</sup>       | 0.03           | 0.07             | 0.11             | 0.15             | 0.21             | 0.26            |
| FE                   | ✓              | ✓                | ✓                | ✓                | ✓                | ✓               |

**Table 6: Trade lines by income**

|                     | H = 0            | H = 1             | H = 2             | H = 3             | H = 4           | H = 5          |
|---------------------|------------------|-------------------|-------------------|-------------------|-----------------|----------------|
| Income Below Median | 0.03**<br>(0.01) | 0.07***<br>(0.01) | 0.09***<br>(0.02) | 0.08***<br>(0.03) | 0.05*<br>(0.02) | 0.03<br>(0.02) |
| Income P50–P95      | 0.05**<br>(0.03) | 0.10***<br>(0.03) | 0.11***<br>(0.03) | 0.06<br>(0.04)    | 0.04<br>(0.03)  | 0.02<br>(0.02) |
| Income Top 5%       | 0.06**<br>(0.03) | 0.10***<br>(0.03) | 0.10***<br>(0.03) | 0.05<br>(0.04)    | 0.02<br>(0.03)  | 0.01<br>(0.02) |
| N                   | 35,365,529       | 34,470,275        | 31,888,359        | 29,457,450        | 27,156,694      | 24,980,613     |
| R <sup>2</sup>      | 0.06             | 0.12              | 0.17              | 0.24              | 0.30            | 0.36           |
| FE                  | ✓                | ✓                 | ✓                 | ✓                 | ✓               | ✓              |

**Table 7: Trade lines by credit score**

|                      | H = 0            | H = 1             | H = 2             | H = 3             | H = 4            | H = 5          |
|----------------------|------------------|-------------------|-------------------|-------------------|------------------|----------------|
| Credit Score 350–660 | 0.03**<br>(0.01) | 0.08***<br>(0.01) | 0.10***<br>(0.03) | 0.10***<br>(0.04) | 0.07**<br>(0.04) | 0.05<br>(0.03) |
| Credit Score 661–820 | 0.05**<br>(0.02) | 0.10***<br>(0.02) | 0.10***<br>(0.03) | 0.05<br>(0.03)    | 0.02<br>(0.02)   | 0.01<br>(0.02) |
| Credit Score 821–850 | 0.08**<br>(0.04) | 0.13***<br>(0.04) | 0.12**<br>(0.05)  | 0.05<br>(0.03)    | 0.02<br>(0.02)   | 0.00<br>(0.01) |
| N                    | 35,365,529       | 34,470,275        | 31,888,359        | 29,457,450        | 27,156,694       | 24,980,613     |
| R <sup>2</sup>       | 0.06             | 0.12              | 0.18              | 0.24              | 0.30             | 0.36           |
| FE                   | ✓                | ✓                 | ✓                 | ✓                 | ✓                | ✓              |

**Table 8: Monthly payments by income**

|                     | H = 0       | H = 1       | H = 2        | H = 3        | H = 4         | H = 5        |
|---------------------|-------------|-------------|--------------|--------------|---------------|--------------|
| Income Below Median | 3***<br>(1) | 9***<br>(2) | 13***<br>(4) | 14***<br>(5) | 13***<br>(5)  | 11**<br>(5)  |
| Income P50–P95      | 2<br>(2)    | 8**<br>(4)  | 15***<br>(5) | 16***<br>(6) | 16***<br>(6)  | 14***<br>(5) |
| Income Top 5%       | 8***<br>(2) | 14**<br>(6) | 25***<br>(9) | 27**<br>(10) | 28***<br>(10) | 21***<br>(7) |
| N                   | 35,365,529  | 34,470,275  | 31,888,359   | 29,457,450   | 27,156,694    | 24,980,613   |
| R <sup>2</sup>      | 0.03        | 0.07        | 0.11         | 0.16         | 0.21          | 0.27         |
| FE                  | ✓           | ✓           | ✓            | ✓            | ✓             | ✓            |

**Table 9: Monthly payments by credit score**

|                      | H = 0       | H = 1        | H = 2        | H = 3        | H = 4        | H = 5        |
|----------------------|-------------|--------------|--------------|--------------|--------------|--------------|
| Credit Score 350–660 | 6***<br>(1) | 14***<br>(3) | 21***<br>(5) | 22***<br>(7) | 21***<br>(8) | 18**<br>(7)  |
| Credit Score 661–820 | 1<br>(1)    | 6**<br>(3)   | 12***<br>(4) | 13***<br>(5) | 14***<br>(5) | 11***<br>(4) |
| Credit Score 821–850 | 4<br>(4)    | 6<br>(7)     | 8<br>(8)     | 5<br>(7)     | 6<br>(6)     | 6<br>(6)     |
| N                    | 35,365,529  | 34,470,275   | 31,888,359   | 29,457,450   | 27,156,694   | 24,980,613   |
| R <sup>2</sup>       | 0.03        | 0.07         | 0.11         | 0.16         | 0.21         | 0.27         |
| FE                   | ✓           | ✓            | ✓            | ✓            | ✓            | ✓            |

**Table 10: Revolving debt by income**

|                     | H = 0           | H = 1          | H = 2          | H = 3          | H = 4       | H = 5       |
|---------------------|-----------------|----------------|----------------|----------------|-------------|-------------|
| Income Below Median | 19<br>(16)      | 63**<br>(28)   | 116***<br>(36) | 113***<br>(43) | 99*<br>(54) | 91*<br>(51) |
| Income P50–P95      | -44<br>(38)     | 5<br>(92)      | 134*<br>(74)   | 134**<br>(63)  | 86<br>(85)  | 79<br>(80)  |
| Income Top 5%       | -231***<br>(56) | -280*<br>(154) | -59<br>(99)    | -7<br>(35)     | -49<br>(76) | -17<br>(85) |
| N                   | 35,161,434      | 34,316,522     | 31,755,552     | 29,330,414     | 27,010,971  | 24,884,821  |
| R <sup>2</sup>      | 0.02            | 0.04           | 0.06           | 0.09           | 0.12        | 0.16        |
| FE                  | ✓               | ✓              | ✓              | ✓              | ✓           | ✓           |

**Table 11: Revolving debt by credit score**

|                      | H = 0           | H = 1           | H = 2          | H = 3          | H = 4         | H = 5        |
|----------------------|-----------------|-----------------|----------------|----------------|---------------|--------------|
| Credit Score 350–660 | 45**<br>(22)    | 125***<br>(41)  | 197***<br>(62) | 199***<br>(75) | 176**<br>(88) | 160*<br>(83) |
| Credit Score 661–820 | -66**<br>(33)   | -38<br>(83)     | 86<br>(60)     | 89**<br>(45)   | 42<br>(68)    | 42<br>(67)   |
| Credit Score 821–850 | -162***<br>(40) | -312**<br>(153) | -187*<br>(105) | -100**<br>(46) | -56<br>(62)   | -13<br>(52)  |
| N                    | 35,161,434      | 34,316,522      | 31,755,552     | 29,330,414     | 27,010,971    | 24,884,821   |
| R <sup>2</sup>       | 0.02            | 0.04            | 0.06           | 0.09           | 0.12          | 0.16         |
| FE                   | ✓               | ✓               | ✓              | ✓              | ✓             | ✓            |

**Table 12: Credit card debt by income**

|                     | H = 0       | H = 1       | H = 2         | H = 3         | H = 4       | H = 5       |
|---------------------|-------------|-------------|---------------|---------------|-------------|-------------|
| Income Below Median | 7<br>(12)   | 37*<br>(22) | 78***<br>(25) | 76***<br>(29) | 66*<br>(37) | 64*<br>(33) |
| Income P50–P95      | -19<br>(24) | 26<br>(48)  | 86**<br>(38)  | 64*<br>(34)   | 36<br>(36)  | 41<br>(28)  |
| Income Top 5%       | -1<br>(29)  | 48<br>(47)  | 84**<br>(33)  | 23<br>(23)    | 13<br>(25)  | 35*<br>(19) |
| N                   | 35,161,434  | 34,316,522  | 31,755,552    | 29,330,414    | 27,010,971  | 24,884,821  |
| R <sup>2</sup>      | 0.02        | 0.04        | 0.07          | 0.10          | 0.14        | 0.19        |
| FE                  | ✓           | ✓           | ✓             | ✓             | ✓           | ✓           |

**Table 13: Credit card debt by credit score**

|                      | H = 0       | H = 1         | H = 2          | H = 3          | H = 4        | H = 5       |
|----------------------|-------------|---------------|----------------|----------------|--------------|-------------|
| Credit Score 350–660 | 20<br>(15)  | 73***<br>(28) | 124***<br>(40) | 123***<br>(48) | 105*<br>(56) | 98*<br>(51) |
| Credit Score 661–820 | -27<br>(21) | 5<br>(42)     | 61**<br>(28)   | 39*<br>(23)    | 14<br>(25)   | 22<br>(18)  |
| Credit Score 821–850 | 20<br>(32)  | 22<br>(36)    | 7<br>(28)      | -31*<br>(18)   | -7<br>(33)   | 19<br>(20)  |
| N                    | 35,161,434  | 34,316,522    | 31,755,552     | 29,330,414     | 27,010,971   | 24,884,821  |
| R <sup>2</sup>       | 0.02        | 0.05          | 0.07           | 0.11           | 0.14         | 0.19        |
| FE                   | ✓           | ✓             | ✓              | ✓              | ✓            | ✓           |

**Table 14: Personal finance debt by income**

|                     | H = 0      | H = 1       | H = 2        | H = 3        | H = 4        | H = 5       |
|---------------------|------------|-------------|--------------|--------------|--------------|-------------|
| Income Below Median | 2<br>(1)   | 8***<br>(2) | 11***<br>(3) | 14***<br>(5) | 16***<br>(4) | 8***<br>(3) |
| Income P50–P95      | 0<br>(1)   | 1<br>(1)    | 2<br>(1)     | 3*<br>(2)    | 4***<br>(1)  | 2*<br>(1)   |
| Income Top 5%       | 0<br>(1)   | -1**<br>(1) | -1<br>(1)    | -1<br>(1)    | -1<br>(1)    | -0<br>(0)   |
| N                   | 35,161,434 | 34,316,522  | 31,755,552   | 29,330,414   | 27,010,971   | 24,884,821  |
| R <sup>2</sup>      | 0.02       | 0.03        | 0.06         | 0.08         | 0.12         | 0.16        |
| FE                  | ✓          | ✓           | ✓            | ✓            | ✓            | ✓           |

**Table 15: Personal finance debt by credit score**

|                      | H = 0      | H = 1       | H = 2        | H = 3        | H = 4        | H = 5       |
|----------------------|------------|-------------|--------------|--------------|--------------|-------------|
| Credit Score 350–660 | 3*<br>(2)  | 9***<br>(2) | 14***<br>(4) | 17***<br>(6) | 19***<br>(5) | 9***<br>(3) |
| Credit Score 661–820 | 0<br>(1)   | 1<br>(1)    | 2<br>(1)     | 2*<br>(1)    | 3***<br>(1)  | 1**<br>(1)  |
| Credit Score 821–850 | 1<br>(1)   | 0<br>(1)    | 0<br>(0)     | -0<br>(0)    | -0<br>(0)    | 0<br>(0)    |
| N                    | 35,161,434 | 34,316,522  | 31,755,552   | 29,330,414   | 27,010,971   | 24,884,821  |
| R <sup>2</sup>       | 0.02       | 0.03        | 0.06         | 0.08         | 0.12         | 0.17        |
| FE                   | ✓          | ✓           | ✓            | ✓            | ✓            | ✓           |

**Table 16: Personal installment debt by income**

|                     | H = 0      | H = 1      | H = 2         | H = 3         | H = 4         | H = 5         |
|---------------------|------------|------------|---------------|---------------|---------------|---------------|
| Income Below Median | 6<br>(16)  | 4<br>(13)  | 27**<br>(12)  | 38**<br>(15)  | 43**<br>(18)  | 34***<br>(11) |
| Income P50–P95      | 2<br>(13)  | 4<br>(13)  | 23*<br>(14)   | 31*<br>(17)   | 32*<br>(18)   | 27**<br>(11)  |
| Income Top 5%       | 12<br>(10) | 18<br>(11) | 41***<br>(12) | 48***<br>(13) | 43***<br>(15) | 33***<br>(9)  |
| N                   | 35,161,434 | 34,316,522 | 31,755,552    | 29,330,414    | 27,010,971    | 24,884,821    |
| R <sup>2</sup>      | 0.02       | 0.04       | 0.06          | 0.08          | 0.12          | 0.16          |
| FE                  | ✓          | ✓          | ✓             | ✓             | ✓             | ✓             |

**Table 17: Personal installment debt by credit score**

|                      | H = 0      | H = 1      | H = 2         | H = 3         | H = 4         | H = 5         |
|----------------------|------------|------------|---------------|---------------|---------------|---------------|
| Credit Score 350–660 | 10<br>(18) | 13<br>(15) | 39***<br>(14) | 52***<br>(17) | 54***<br>(20) | 45***<br>(13) |
| Credit Score 661–820 | 1<br>(12)  | -0<br>(12) | 21<br>(13)    | 29*<br>(15)   | 31*<br>(17)   | 25**<br>(10)  |
| Credit Score 821–850 | -3<br>(13) | 3<br>(17)  | 8<br>(20)     | 8<br>(19)     | 6<br>(13)     | 9<br>(11)     |
| N                    | 35,161,434 | 34,316,522 | 31,755,552    | 29,330,414    | 27,010,971    | 24,884,821    |
| R <sup>2</sup>       | 0.02       | 0.04       | 0.06          | 0.08          | 0.12          | 0.16          |
| FE                   | ✓          | ✓          | ✓             | ✓             | ✓             | ✓             |

**Table 18: Auto debt by income**

|                     | H = 0         | H = 1          | H = 2          | H = 3          | H = 4          | H = 5         |
|---------------------|---------------|----------------|----------------|----------------|----------------|---------------|
| Income Below Median | 34***<br>(12) | 104***<br>(25) | 135***<br>(38) | 115**<br>(46)  | 63<br>(43)     | 30<br>(27)    |
| Income P50–P95      | 11<br>(10)    | 11<br>(20)     | 4<br>(26)      | -9<br>(28)     | -27<br>(22)    | -32*<br>(17)  |
| Income Top 5%       | -15*<br>(8)   | -54***<br>(16) | -88***<br>(22) | -97***<br>(28) | -94***<br>(33) | -84**<br>(39) |
| N                   | 35,161,434    | 34,316,522     | 31,755,552     | 29,330,414     | 27,010,971     | 24,884,821    |
| R <sup>2</sup>      | 0.02          | 0.03           | 0.05           | 0.07           | 0.10           | 0.13          |
| FE                  | ✓             | ✓              | ✓              | ✓              | ✓              | ✓             |

**Table 19: Auto debt by credit score**

|                      | H = 0         | H = 1          | H = 2          | H = 3          | H = 4           | H = 5         |
|----------------------|---------------|----------------|----------------|----------------|-----------------|---------------|
| Credit Score 350–660 | 51***<br>(13) | 133***<br>(27) | 177***<br>(46) | 162***<br>(59) | 100*<br>(56)    | 57<br>(38)    |
| Credit Score 661–820 | -0<br>(9)     | -7<br>(17)     | -16<br>(22)    | -29<br>(23)    | -40**<br>(20)   | -40**<br>(18) |
| Credit Score 821–850 | 3<br>(24)     | -8<br>(41)     | -47<br>(39)    | -84***<br>(33) | -106***<br>(25) | -85**<br>(35) |
| N                    | 35,161,434    | 34,316,522     | 31,755,552     | 29,330,414     | 27,010,971      | 24,884,821    |
| R <sup>2</sup>       | 0.02          | 0.03           | 0.05           | 0.07           | 0.10            | 0.13          |
| FE                   | ✓             | ✓              | ✓              | ✓              | ✓               | ✓             |

**Table 20: HELOC debt by income**

|                     | H = 0           | H = 1           | H = 2         | H = 3        | H = 4       | H = 5      |
|---------------------|-----------------|-----------------|---------------|--------------|-------------|------------|
| Income Below Median | 11***<br>(4)    | 23***<br>(7)    | 32***<br>(12) | 35**<br>(15) | 32*<br>(17) | 26<br>(16) |
| Income P50–P95      | -13<br>(15)     | 0<br>(39)       | 58<br>(40)    | 97**<br>(40) | 86*<br>(52) | 61<br>(54) |
| Income Top 5%       | -209***<br>(40) | -254**<br>(103) | -83<br>(86)   | 81**<br>(39) | 78<br>(79)  | 44<br>(87) |
| N                   | 35,161,434      | 34,316,522      | 31,755,552    | 29,330,414   | 27,010,971  | 24,884,821 |
| R <sup>2</sup>      | 0.01            | 0.03            | 0.04          | 0.07         | 0.10        | 0.14       |
| FE                  | ✓               | ✓               | ✓             | ✓            | ✓           | ✓          |

**Table 21: HELOC debt by credit score**

|                      | H = 0           | H = 1            | H = 2         | H = 3         | H = 4        | H = 5       |
|----------------------|-----------------|------------------|---------------|---------------|--------------|-------------|
| Credit Score 350–660 | 25***<br>(7)    | 51***<br>(12)    | 66***<br>(22) | 71***<br>(27) | 68**<br>(30) | 58*<br>(30) |
| Credit Score 661–820 | -29*<br>(15)    | -20<br>(38)      | 37<br>(38)    | 81**<br>(36)  | 69<br>(50)   | 47<br>(53)  |
| Credit Score 821–850 | -165***<br>(35) | -291***<br>(111) | -166*<br>(92) | -15<br>(40)   | 19<br>(45)   | 13<br>(35)  |
| N                    | 35,161,434      | 34,316,522       | 31,755,552    | 29,330,414    | 27,010,971   | 24,884,821  |
| R <sup>2</sup>       | 0.01            | 0.03             | 0.04          | 0.07          | 0.10         | 0.14        |
| FE                   | ✓               | ✓                | ✓             | ✓             | ✓            | ✓           |

**Table 22: Total debt by local unemployment**

|                         | H = 0               | H = 1               | H = 2               | H = 3               | H = 4               | H = 5               |
|-------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Rate (IV)               | 0.011***<br>(0.003) | 0.034***<br>(0.007) | 0.055***<br>(0.012) | 0.068**<br>(0.025)  | 0.057***<br>(0.015) | 0.047***<br>(0.014) |
| Rate (IV) x Low UR MSA  | 0.000<br>(0.001)    | 0.001<br>(0.002)    | 0.001<br>(0.003)    | -0.001<br>(0.007)   | -0.006<br>(0.004)   | -0.009*<br>(0.005)  |
| Rate (IV) x High UR MSA | 0.021**<br>(0.009)  | 0.026**<br>(0.010)  | 0.031***<br>(0.009) | 0.038***<br>(0.009) | 0.040***<br>(0.007) | 0.044***<br>(0.009) |
| N                       | 6942                | 6549                | 6156                | 5763                | 5370                | 4977                |
| R <sup>2</sup>          | 0.26                | 0.34                | 0.40                | 0.38                | 0.43                | 0.47                |
| FE                      | ✓                   | ✓                   | ✓                   | ✓                   | ✓                   | ✓                   |