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

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Abstract

What happens to consumer borrowing when interest rates rise? Using a representative panel of consumer credit records and individual-level local projections, we show that contractionary monetary policy increases rather than reduces household debt. A 1 s.d. contractionary shock raises total debt by $3,967, or 7%, over three years. On the extensive margin, the number of credit accounts also increases in response to a contractionary shock. The effect is stronger and more persistent for financially constrained consumers. Mechanism evidence is consistent with an indirect channel: tighter policy weakens labor markets and household income, increasing reliance on credit among exposed borrowers. Our findings highlight an important distributional dimension of monetary transmission, as tightening raises indebtedness among vulnerable households.

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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 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., 2020; 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 come 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 Jorda (2005).

Our main finding is that contractionary monetary policy increases total consumer debt. A 1 s.d. contractionary shock increases total debt by \$718 on impact and by \$3,967 after three years (7% of the mean). The response builds gradually and remains positive through year five. The number of credit accounts and monthly payments also rise, 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 rely more on credit.

Our paper contributes to two literatures. First, we add to work on the transmission of monetary policy to household credit and balance sheets by showing that contractionary shocks can increase, rather than reduce, total consumer debt over medium horizons. Existing studies have identified powerful direct channels through mortgage contracts, refinancing, and debt composition. Di Maggio et al. (2017) show that mortgage-rate pass-through can have large effects on household cash flow, consumption, and deleveraging. Anenberg et al. (2025) show that higher mortgage rates sharply reduce cash-out refinancing, but much of that response reflects substitution into other borrowing products, implying a much smaller response of total new household borrowing than product-level estimates would suggest. Our paper is closely related to this work in spirit, but asks a different question. Rather than focusing on one contract margin or one borrowing product, we study the medium-run response of total bureau-observed debt. This allows us to measure the net effect of monetary tightening on household indebtedness once adjustment across products and over time is taken into account. Our contribution is to measure the net response of total debt once these margins and slower-moving indirect effects are allowed to operate jointly.

Second, we contribute to the literature on indirect and heterogeneous effects of monetary policy. In Heterogeneous Agent New Keynesian (HANK) models, indirect general-equilibrium effects operating through labor income can be quantitatively more important than direct intertemporal-substitution effects for many households (Kaplan et al., 2018). Recent empirical work also points in this direction. Cloyne et al. (2020) show that household responses to monetary policy depend strongly on balance-sheet position and argue that general-equilibrium income effects play a key role in transmission. Using administrative data from Norway, Holm et al. (2021) find that direct effects dominate initially, but indirect effects build over time and eventually outweigh direct effects in household consumption responses. Our contribution is to bring this perspective to consumer credit data. We provide empirical evidence that contractionary monetary policy can raise total debt, especially for lower-income and lower-credit-score households, and that the pattern of responses is consistent with indirect transmission through labor-market and income channels.

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

2 Theoretical Framework

The effect of a higher interest rate on household borrowing is theoretically ambiguous. In a standard frictionless representative-agent economy, a higher interest rate tends to be associated with less borrowing because of the 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 makes the relationship between household borrowing and the policy rate even less clear. Households at different points in the 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.*

3 Data

3.1 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.[1] 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 58,050,890 consumer-year observations, summarized in Table 1. The average consumer is 49 years old, and about half of the sample is female. The mean credit score is 654, while average annual income is $78,000. Consumers in the sample hold an average total balance of $57,055 across all credit products, have about 4 open credit accounts, and make average monthly payments of $643.

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[1] Alternative credit records include information not reported to the major credit bureaus, such as payday loans and title loans. Kohli and Mohr (2024), and Duarte et al. (2025) for other papers using the GCCP.

ties recorded in the credit file. We complement these outcomes with the number of credit accounts 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 2 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 $57,055, of which $11,039 is non-mortgage debt and $5,242 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.

3.2 Monetary Policy Shocks

We rely on the high-frequency identification of monetary policy surprises (Kuttner, 2001; Bernanke and Kuttner, 2005; 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 contain 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 bias 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 responds 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.

4 Empirical Framework and Results

4.1 Baseline Local Projections

We use local projections to trace out the dynamic impact of monetary policy on consumer credit borrowing decisions. Following Jorda (2005), for each horizon $h \in \{0, 1, \ldots, 5\}$, we estimate:

$$\Delta_h Y_{i,t+h} := Y_{i,t+h} - Y_{i,t-1} = \beta_h \, \mathrm{MPS}_t + \Gamma_h' X_{t-1} + \mathrm{FE} + \varepsilon_{i,t+h}, \tag{1}$$

where $Y_{i,t+h}$ is the outcome for individual i at horizon h, MPS_t is the standardized contractionary monetary policy shock in year t, and X_{t-1} contains lagged macro controls. We have person, income bins, credit-score bins, and ZIP code fixed effects to account for time-invariant heterogeneity. We double cluster standard errors by person and year.

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 β_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.

4.1.1 Heterogeneity

To study how the response varies across borrowers, we interact the monetary policy shock with borrower-group indicators:

$$\Delta_h Y_{i,t+h} = \sum_k \beta_{h,k} \left(\mathrm{MPS}_t \times \mathbf{1}\{i \in k\} \right) + \sum_k \Gamma'_{h,k} \left(X_{t-1} \times \mathbf{1}\{i \in k\} \right) + \mathrm{FE} + \varepsilon_{i,t+h}. \qquad (2)$$

k denotes either income groups or credit-score groups. The resulting coefficients trace impulse responses for each group. Because baseline debt levels differ substantially across borrowers, we focus primarily on responses scaled by group means when interpreting heterogeneity. The raw dollar estimates are informative about levels, but the scaled responses are more useful for understanding the distributional incidence of the effect.

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.

4.2 Results

4.2.1 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 one-standard-deviation contractionary shock raises total debt by about \$3,967, or roughly 7% of mean debt. 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.

4.2.2 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).

4.2.3 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 to 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.

5 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.

5.1 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.

5.2 Labor Market Channel

Our second exercise exploits local labor-market variation. We estimate MSA-level local projections and interact monetary policy shocks with local unemployment categories. The idea is straightforward: if weaker labor markets amplify the indirect effects of tightening, then the debt response should be larger in high-unemployment MSAs.

Formally, we estimate:

$$\begin{aligned}\Delta_h \log(\text{Debt})_{m,t+h} = \beta^h_{\text{Low}}\,\text{MPS}_t + \delta^h_{\text{Mid}}\left(\text{MPS}_t \times \mathbb{1}\{\text{Middle MSA}_{m,t}\}\right) \\ + \delta^h_{\text{High}}\left(\text{MPS}_t \times \mathbb{1}\{\text{High MSA}_{m,t}\}\right) + X_t'\gamma^h + \alpha_m + \varepsilon_{m,t+h},\end{aligned}$$

where MSAs are grouped into low-, middle-, and high-unemployment categories based on the cross-sectional distribution of unemployment rates (below the 25th percentile, between the 25th and 75th percentiles, and above the 75th percentile, respectively). The coefficient β^h_{Low} captures the response in low-unemployment MSAs, while δ^h_{Mid} and δ^h_{High} measure differential responses relative to this baseline.

The key prediction is that $\delta^h_{\text{High}} > 0$: if tightening disproportionately weakens income and employment in already fragile labor markets, then households in high-unemployment MSAs should exhibit larger increases in debt.

That is what we find. Figure 7 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 causal. 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. Rather, the sign pattern is informative. It is more consistent with an indirect income-and-employment channel than with a mechanism in which tighter policy affects borrowing only through common mechanical repricing of debt contracts.

5.3 Controlling for Income

Our third exercise compares the unconditional debt response with a specification that adds realized income changes to the right-hand side. In the slides, this is framed as the debt response "holding income fixed," following the spirit of Holm et al. (2021). Figure 6 shows that once realized income changes are included, the debt response becomes much smaller and loses precision relative to the unconditional specification.

This attenuation is suggestive but should not be overinterpreted. Because realized income is itself affected by the shock, the exercise does not identify the structural share of the debt response caused by income. Holm et al. (2021) are explicit about related identification concerns in their own decomposition, and the same caution applies here. What the specification does show is that a large part of the debt response is tightly linked to the post-shock income path. Once that path is held fixed, little of the original response remains.

6 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 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 to the income channel as the main 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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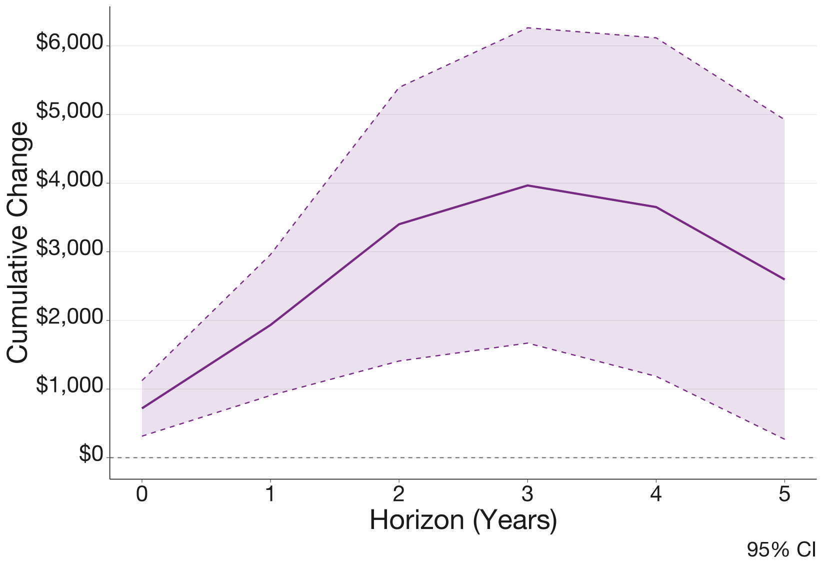
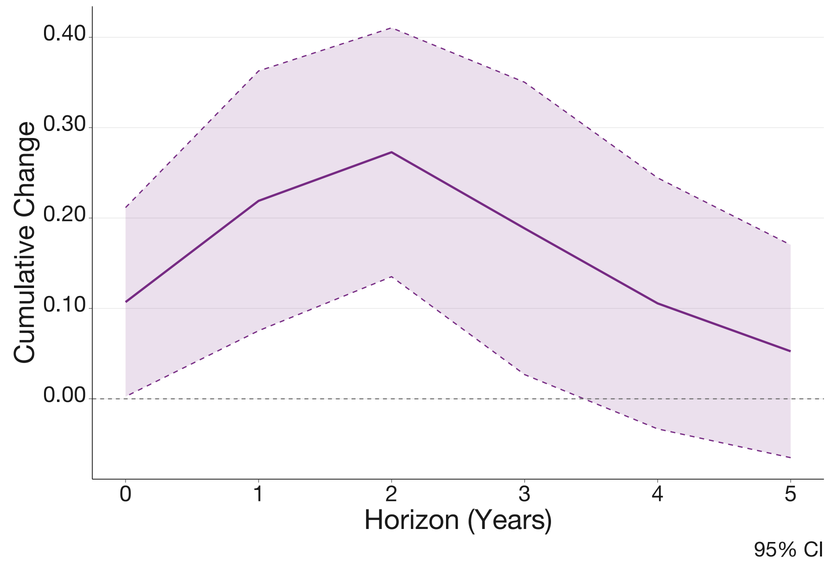
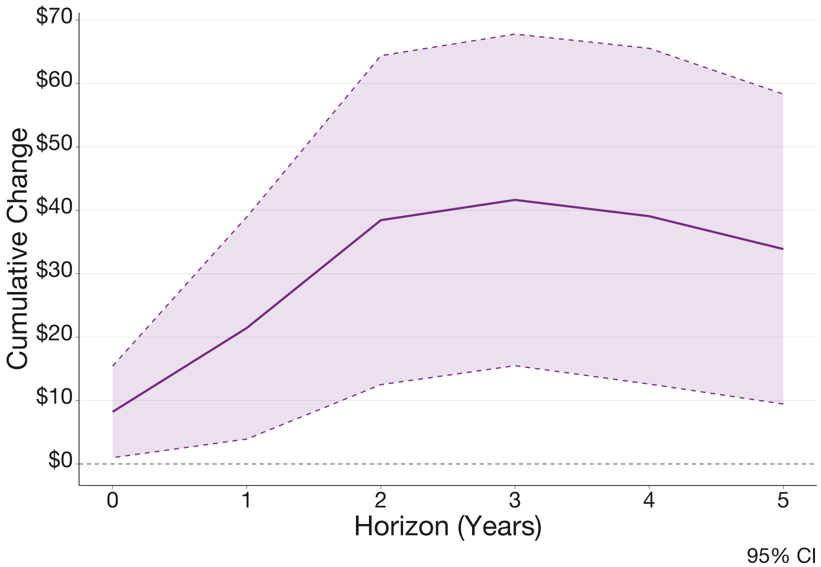
Figure 1: Baseline Debt Response



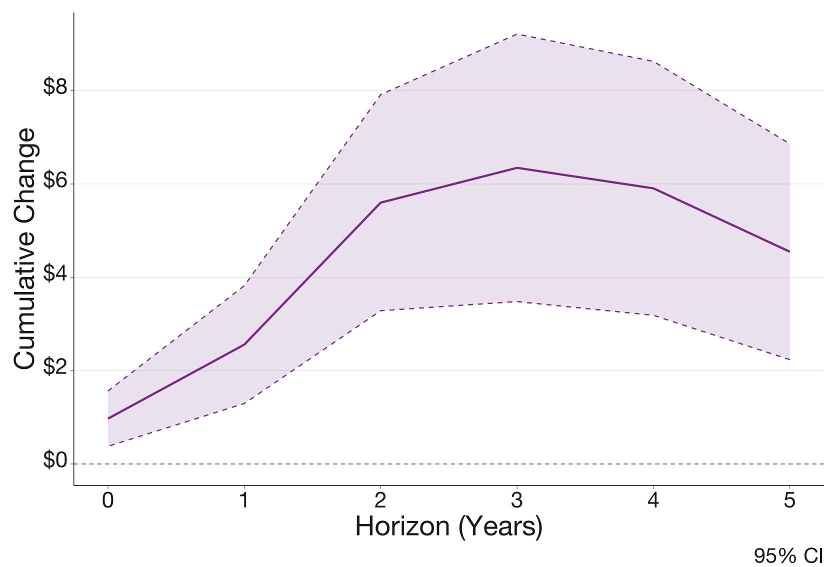
(a) Total Debt



(b) Tradelines

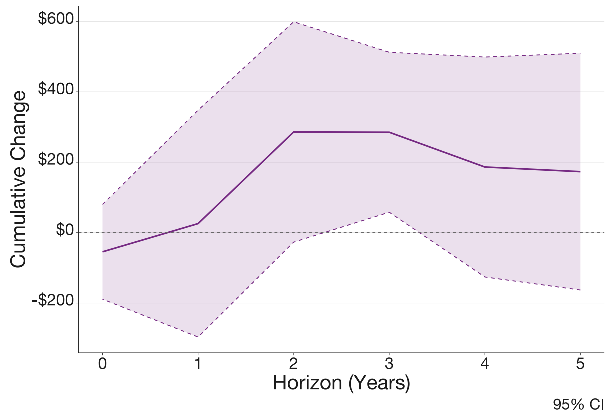


(c) Monthly Payments

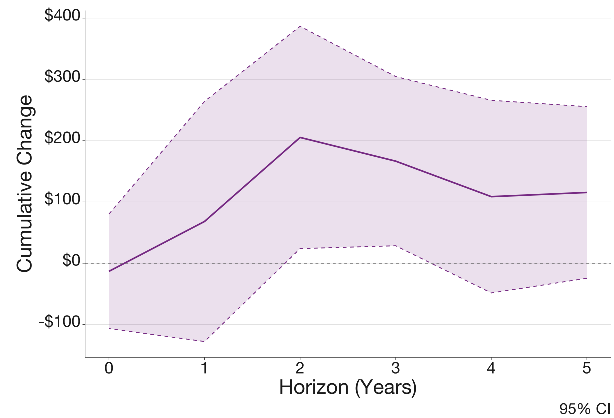


(d) Total Debt (JK shock)

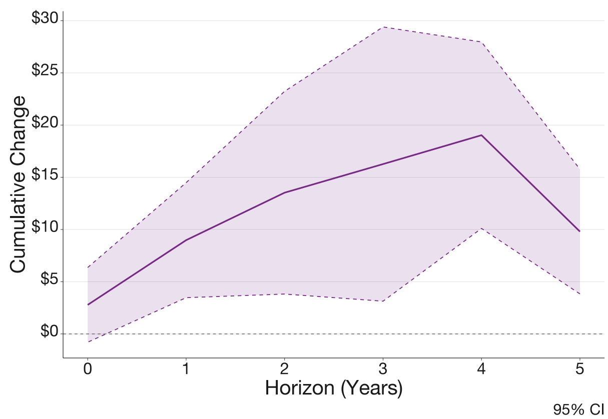
Figure 2: Product-level Debt Response



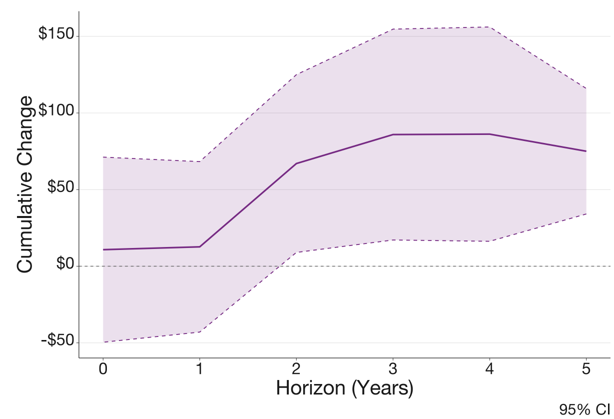
(a) Revolving Debt



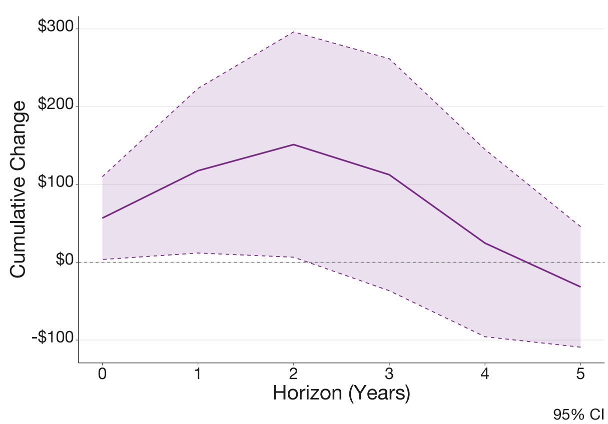
(b) Credit Card Debt



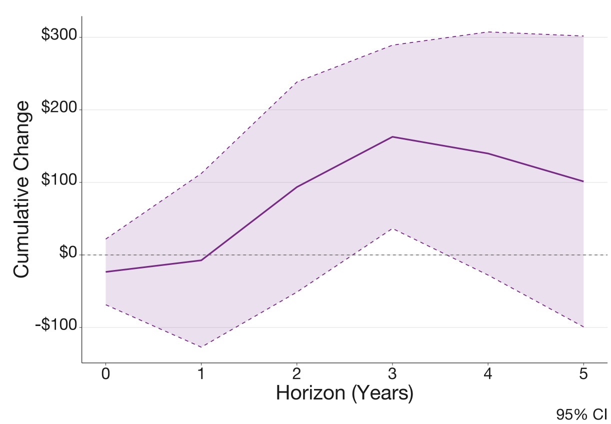
(c) Personal Finance Debt



(d) Personal Installment Debt

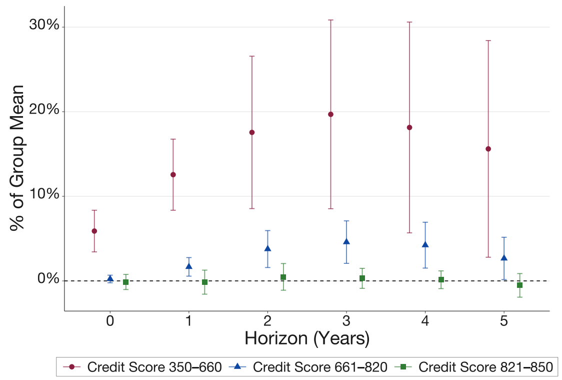


(e) Auto Debt

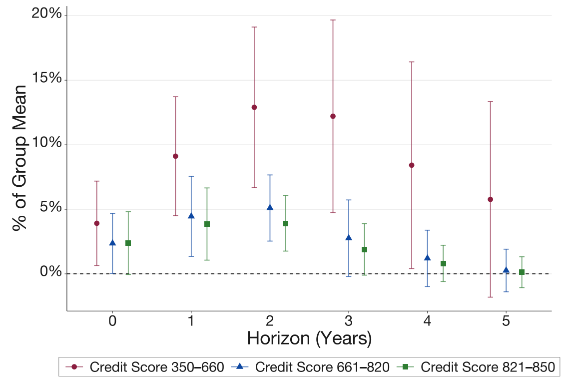


(f) HELOC Debt

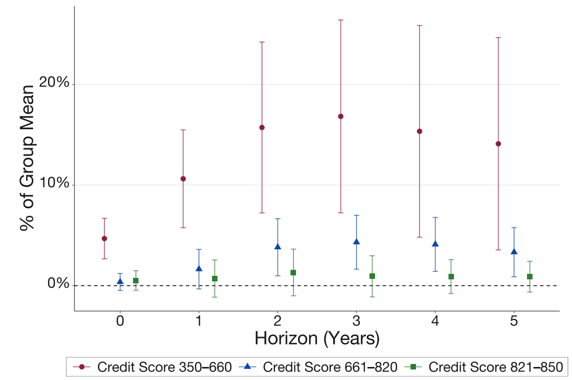
Figure 3: Debt Response by Credit Score Bin
Response scaled by group mean



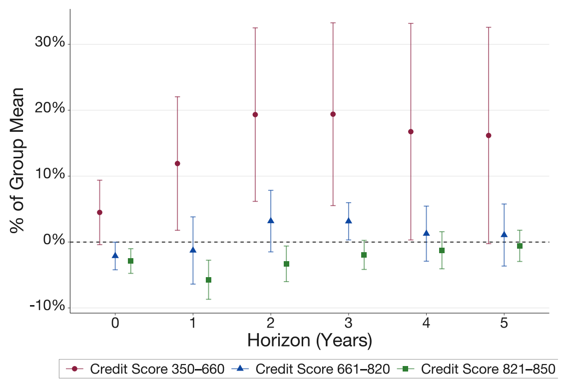
(a) Total Debt



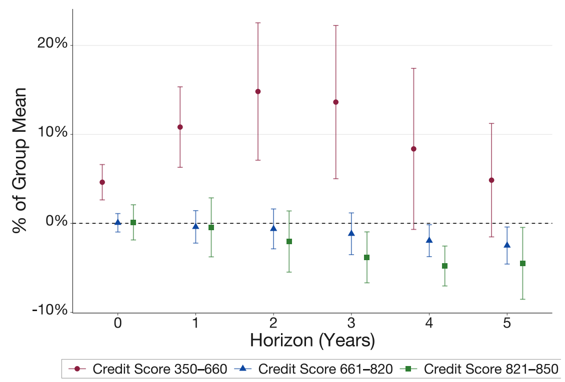
(b) Tradelines



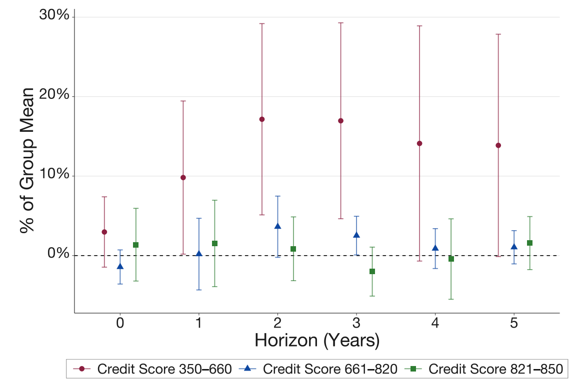
(c) Monthly Payments



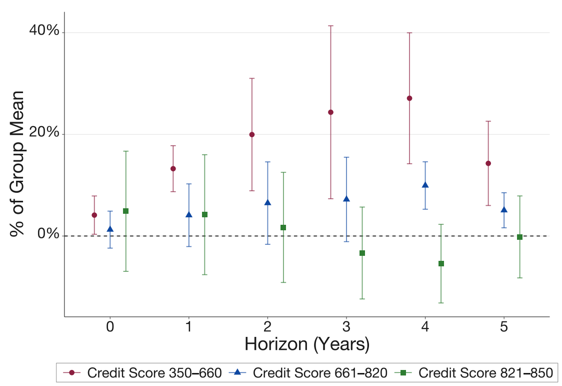
(d) Revolving Debt



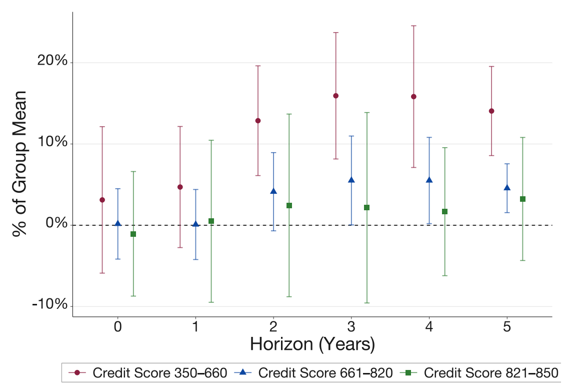
(e) Auto Debt



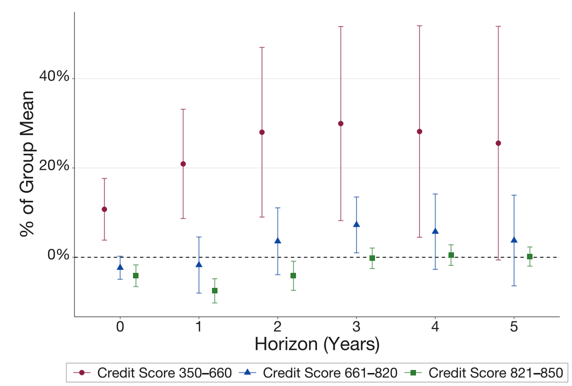
(f) Credit Card Debt



(g) Personal Finance Debt



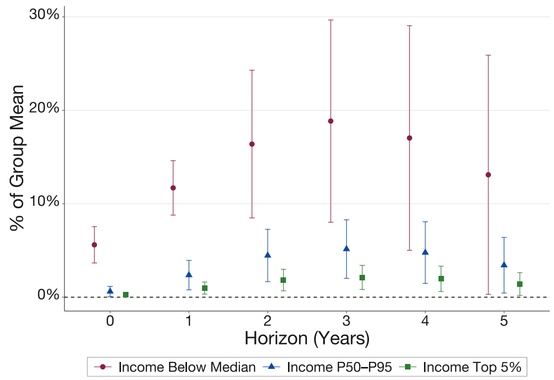
(h) Personal Installment Debt



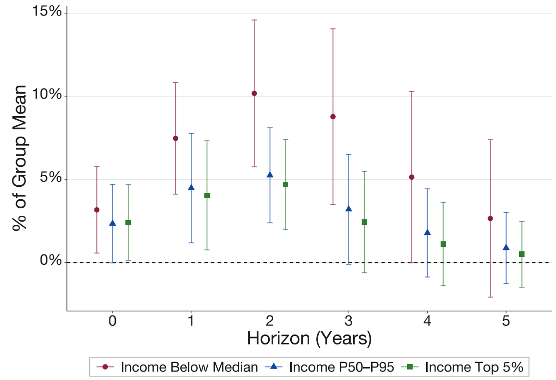
(i) HELOC Debt

Figure 4: Debt Response by Income Bin

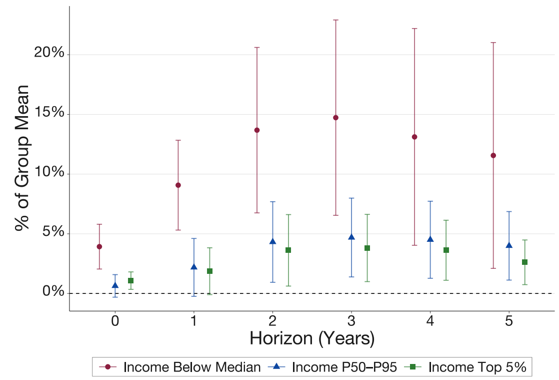
Response scaled by group mean



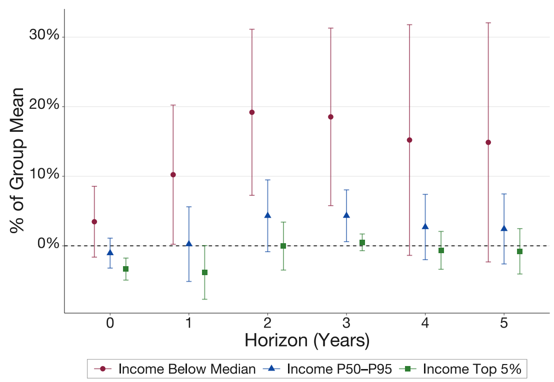
(a) Total Debt



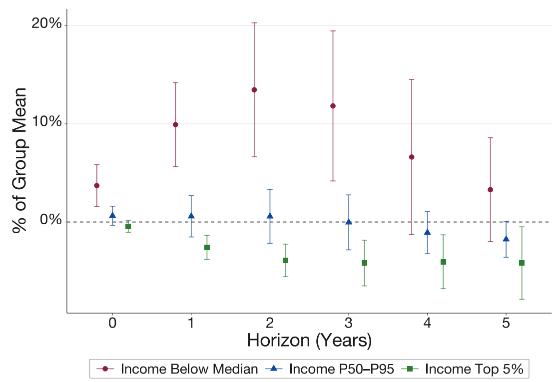
(b) Tradelines



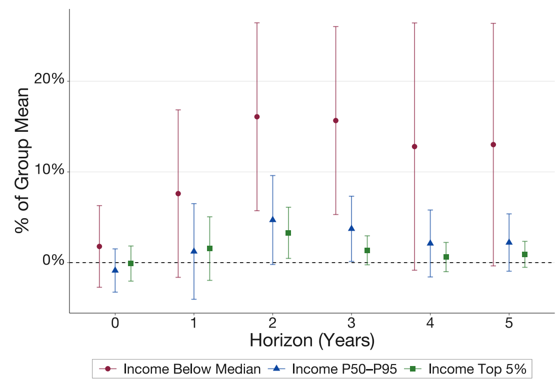
(c) Monthly Payments



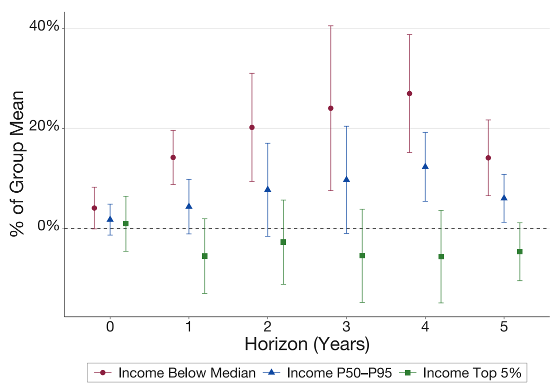
(d) Revolving Debt



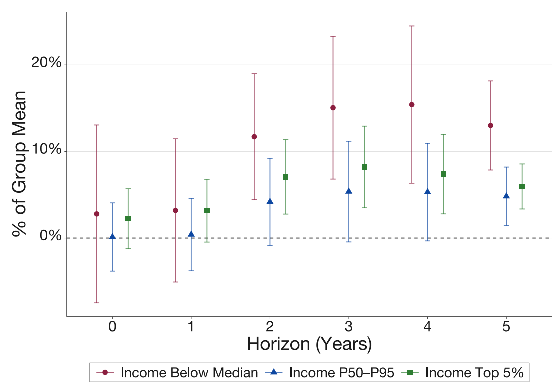
(e) Auto Debt



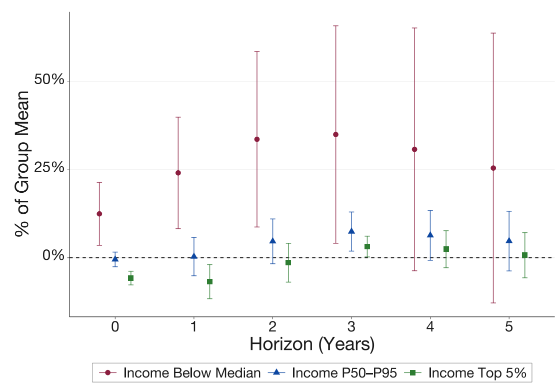
(f) Credit Card Debt



(g) Personal Finance Debt



(h) Personal Installment Debt



(i) HELOC Debt

Figure 5: Income Response by Income Bin

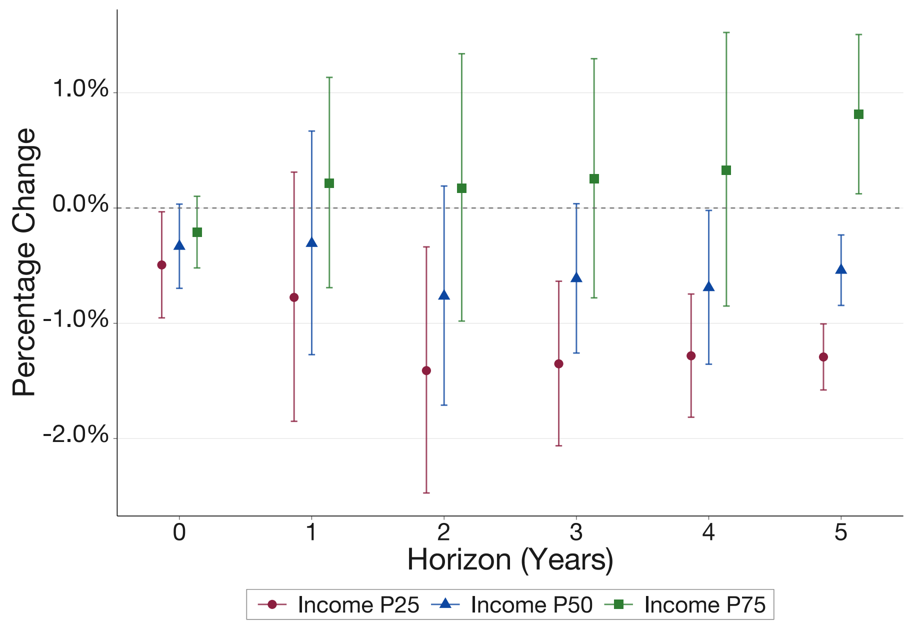


Figure 6: Debt Response with and without Income Controls

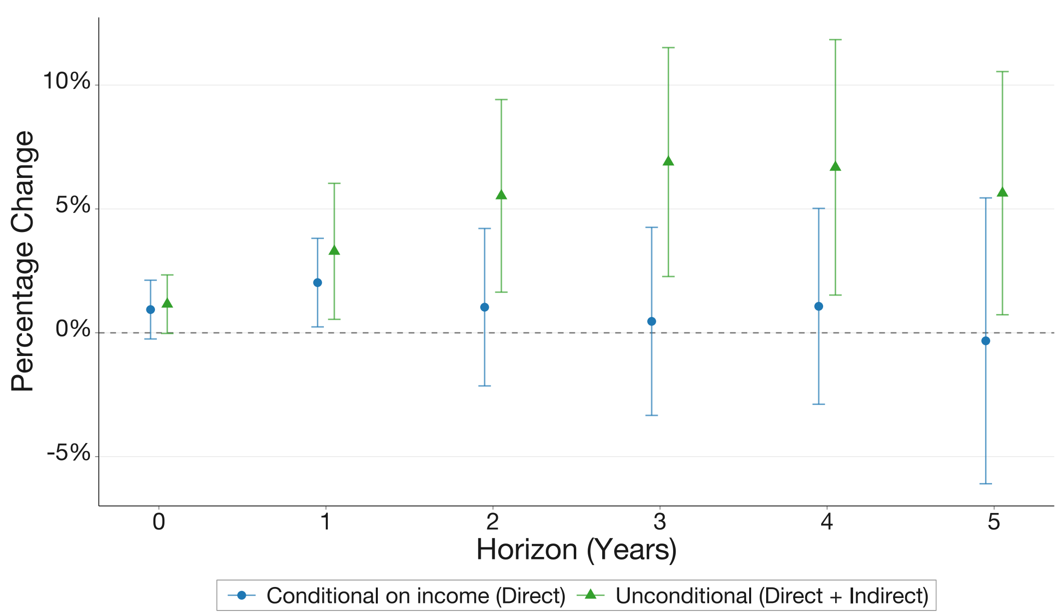


Figure 7: Total Debt Response by MSA-level Unemployment

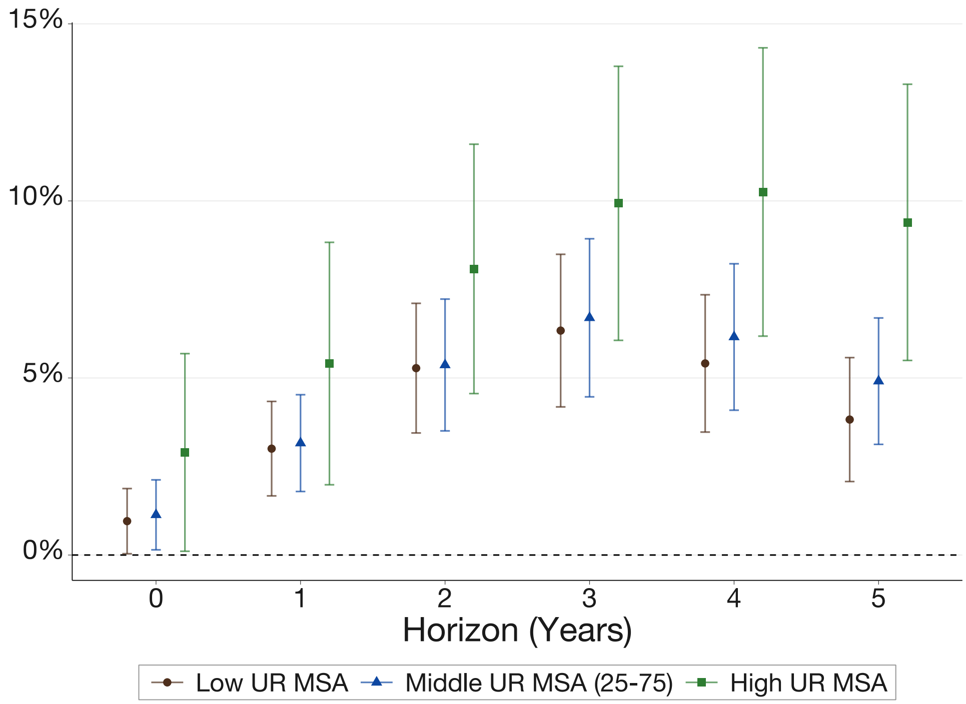


Table 1: Summary Statistics

	Mean	Median	SD
Age	49	48	19
Credit Score	654	667	155
Income ($ K)	78	64	63
Total Debt ($ K)	57	1.5	120
Number of Credit Accounts	4	2	5
Monthly Payment ($)	643	57	1,112
Observations	58,050,890		

Table 2: Debt-level Summary Statistics

	Balance		Balance $\mid$ Balance > 0	
	Mean	SD	Mean	SD
Total Debt	57,055	120,555	93,585	142,898
Non-mortgage	11,039	21,108	18,661	24,717
Mortgage	45,382	110,718	190,886	154,231
First Mortgage	41,590	103,829	192,577	144,365
Second Mortgage	609	4,497	28,172	12,584
HELOC	1,936	10,757	42,586	28,543
Cash-out Refi	2,374	16,788	80,820	57,036
Revolving	5,242	14,762	10,181	19,311
Credit card	3,170	7,163	6,182	9,024
Auto	3,872	9,449	18,148	12,626
Student Loan	1,746	8,088	22,371	19,414
Personal Finance	93	696	3,639	2,452
Personal Installment	993	4,760	11,309	11,889

Table 3: Total Debt Response

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
MPS	718***	1933***	3402***	3967***	3652***	2596**
	(207)	(524)	(1017)	(1172)	(1258)	(1188)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.04	0.07	0.11	0.16	0.22	0.27
FE	✓	✓	✓	✓	✓	✓

Table 4: Total Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	933***	1934***	2708***	3114***	2815***	2164**
	(164)	(247)	(668)	(912)	(1013)	(1079)
Income P50–P95	492**	2050***	3902***	4520***	4201***	3017**
	(249)	(719)	(1274)	(1433)	(1513)	(1370)
Income Top 5%	1391**	2477	6459**	7704***	6950***	3812**
	(643)	(1781)	(2851)	(2693)	(2405)	(1837)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.03	0.07	0.11	0.16	0.21	0.27
FE	✓	✓	✓	✓	✓	✓

Table 5: Total Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	1379***	2963***	4155***	4657***	4287***	3683**
	(295)	(516)	(1094)	(1349)	(1506)	(1546)
Credit Score 661–820	272	1463***	3342***	4093***	3775***	2365**
	(200)	(519)	(1020)	(1154)	(1239)	(1139)
Credit Score 821–850	-446	-404	937	871	707	-773
	(858)	(1399)	(1620)	(1214)	(1069)	(1310)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.04	0.07	0.11	0.16	0.21	0.27
FE	✓	✓	✓	✓	✓	✓

Table 6: Tradelines Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	0.07**	0.17***	0.23***	0.20***	0.11*	0.06
	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)
Income P50–P95	0.14*	0.27***	0.32***	0.20*	0.11	0.05
	(0.07)	(0.10)	(0.09)	(0.10)	(0.08)	(0.07)
Income Top 5%	0.17**	0.29**	0.34***	0.18	0.08	0.04
	(0.08)	(0.12)	(0.10)	(0.11)	(0.09)	(0.07)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.07	0.12	0.18	0.24	0.31	0.37
FE	✓	✓	✓	✓	✓	✓

Table 7: Tradelines Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	0.08**	0.18***	0.25***	0.24***	0.17**	0.11
	(0.03)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)
Credit Score 661–820	0.14**	0.27***	0.31***	0.17*	0.07	0.02
	(0.07)	(0.10)	(0.08)	(0.09)	(0.07)	(0.05)
Credit Score 821–850	0.19*	0.31***	0.32***	0.15*	0.07	0.01
	(0.10)	(0.12)	(0.09)	(0.08)	(0.06)	(0.05)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.07	0.12	0.19	0.25	0.31	0.37
FE	✓	✓	✓	✓	✓	✓

Table 8: Monthly Payments Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	10***	22***	33***	36***	32***	28**
	(2)	(5)	(9)	(10)	(11)	(12)
Income P50–P95	6	21*	42**	46***	44***	39***
	(5)	(12)	(17)	(16)	(16)	(14)
Income Top 5%	22***	38*	74**	78***	74***	54***
	(8)	(21)	(31)	(29)	(26)	(20)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.04	0.07	0.11	0.16	0.22	0.27
FE	✓	✓	✓	✓	✓	✓

Table 9: Monthly Payments Reponse by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	15***	33***	50***	53***	48***	44***
	(3)	(8)	(14)	(15)	(17)	(17)
Credit Score 661–820	3	15	35***	39***	37***	30***
	(4)	(9)	(13)	(12)	(12)	(11)
Credit Score 821–850	9	13	24	17	16	16
	(9)	(17)	(22)	(19)	(16)	(14)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.04	0.07	0.11	0.16	0.22	0.28
FE	✓	✓	✓	✓	✓	✓

Table 10: Revolving Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	50	146**	274***	265***	217*	213*
	(37)	(73)	(87)	(93)	(121)	(125)
Income P50–P95	-90	21	373	373**	234	210
	(95)	(236)	(227)	(164)	(207)	(222)
Income Top 5%	-548***	-627*	-5	83	-107	-129
	(132)	(323)	(289)	(101)	(228)	(273)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.06	0.09	0.13	0.17
FE	✓	✓	✓	✓	✓	✓

Table 11: Revolving Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	103*	273**	443***	444***	384**	370*
	(57)	(118)	(154)	(162)	(192)	(192)
Credit Score 661–820	-171**	-103	257	254**	103	86
	(86)	(210)	(192)	(116)	(172)	(194)
Credit Score 821–850	-339***	-673***	-389**	-229*	-146	-68
	(112)	(178)	(162)	(132)	(169)	(142)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.07	0.10	0.13	0.18
FE	✓	✓	✓	✓	✓	✓

Table 12: Credit Card Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	21	91	193***	188***	154*	156*
	(28)	(57)	(63)	(63)	(83)	(82)
Income P50–P95	-44	62	239*	189**	107	112
	(62)	(137)	(127)	(93)	(96)	(82)
Income Top 5%	-9	131	278**	114*	52	77
	(84)	(151)	(122)	(69)	(70)	(62)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.03	0.05	0.08	0.11	0.15	0.20
FE	✓	✓	✓	✓	✓	✓

Table 13: Credit Card Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	49	163**	284***	281***	234*	230*
	(37)	(81)	(102)	(104)	(125)	(118)
Credit Score 661–820	-73	9	185*	128**	45	53
	(56)	(117)	(100)	(63)	(65)	(54)
Credit Score 821–850	46	52	29	-68	-15	53
	(79)	(94)	(69)	(53)	(87)	(58)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.03	0.05	0.08	0.11	0.15	0.20
FE	✓	✓	✓	✓	✓	✓

Table 14: Personal Finance Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	5*	18***	25***	30***	33***	17***
	(3)	(3)	(7)	(10)	(7)	(5)
Income P50–P95	1	3	6	8*	10***	5**
	(1)	(2)	(4)	(4)	(3)	(2)
Income Top 5%	0	-2	-1	-2	-2	-2
	(1)	(1)	(2)	(2)	(2)	(1)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.06	0.09	0.13	0.17
FE	✓	✓	✓	✓	✓	✓

Table 15: Personal Finance Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	6**	18***	27***	34***	37***	20***
	(3)	(3)	(8)	(12)	(9)	(6)
Credit Score 661–820	1	3	5	5*	7***	4***
	(1)	(2)	(3)	(3)	(2)	(1)
Credit Score 821–850	1	1	0	-1	-1	-0
	(1)	(1)	(1)	(1)	(1)	(1)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.06	0.09	0.13	0.17
FE	✓	✓	✓	✓	✓	✓

Table 16: Personal Installment Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	19	21	78***	100***	103***	87***
	(35)	(28)	(25)	(28)	(31)	(18)
Income P50–P95	2	6	59	76*	75*	68***
	(29)	(30)	(36)	(42)	(41)	(24)
Income Top 5%	34	48*	107***	124***	111***	90***
	(27)	(28)	(33)	(36)	(35)	(20)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.06	0.09	0.12	0.17
FE	✓	✓	✓	✓	✓	✓

Table 17: Personal Installment Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	23	35	95***	118***	117***	104***
	(34)	(28)	(25)	(29)	(33)	(21)
Credit Score 661–820	2	1	59*	78**	78**	65***
	(31)	(31)	(35)	(40)	(39)	(22)
Credit Score 821–850	-8	3	18	15	12	23
	(28)	(36)	(41)	(43)	(29)	(28)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.04	0.06	0.09	0.12	0.17
FE	✓	✓	✓	✓	✓	✓

Table 18: Auto Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	99***	266***	361***	317***	178	88
	(29)	(59)	(94)	(105)	(108)	(72)
Income P50–P95	35	32	31	-2	-59	-96*
	(27)	(59)	(77)	(78)	(60)	(51)
Income Top 5%	-26	-152***	-230***	-246***	-238***	-246**
	(18)	(37)	(50)	(70)	(82)	(111)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.03	0.06	0.08	0.11	0.14
FE	✓	✓	✓	✓	✓	✓

Table 19: Auto Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	133***	312***	427***	393***	241*	140
	(29)	(66)	(113)	(127)	(133)	(94)
Credit Score 661–820	3	-21	-33	-61	-102**	-130**
	(28)	(49)	(60)	(62)	(48)	(55)
Credit Score 821–850	6	-25	-113	-211***	-265***	-249**
	(56)	(93)	(97)	(81)	(63)	(114)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.02	0.03	0.06	0.08	0.11	0.14
FE	✓	✓	✓	✓	✓	✓

Table 20: HELOC Debt Response by Income Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Income Below Median	25***	47***	66***	69**	61*	50
	(9)	(16)	(25)	(31)	(35)	(38)
Income P50–P95	-15	11	152	242***	207*	154
	(34)	(90)	(105)	(92)	(117)	(141)
Income Top 5%	-465***	-545***	-113	257**	196	59
	(80)	(200)	(227)	(121)	(216)	(264)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.01	0.03	0.05	0.07	0.11	0.15
FE	✓	✓	✓	✓	✓	✓

Table 21: HELOC Debt Response by Credit Score Bin

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
Credit Score 350–660	53***	103***	138***	148***	139**	126*
	(17)	(31)	(48)	(55)	(60)	(66)
Credit Score 661–820	-67*	-50	102	206**	163	107
	(37)	(91)	(108)	(91)	(122)	(147)
Credit Score 821–850	-336***	-609***	-336**	-19	39	13
	(100)	(112)	(135)	(95)	(96)	(89)
N	51,377,912	49,516,272	45,416,597	41,670,579	38,161,990	34,879,776
R^2	0.01	0.03	0.05	0.07	0.11	0.15
FE	✓	✓	✓	✓	✓	✓

Table 22: Income-controlled Total Debt Response

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
MPS	-327	-344	32	520	179	93
	(299)	(351)	(582)	(508)	(438)	(305)
N	50,496,484	48,016,635	43,656,078	39,761,552	36,167,280	32,841,758
R^2	0.04	0.08	0.13	0.19	0.26	0.32
FE	✓	✓	✓	✓	✓	✓

Table 23: Total Debt Response by MSA Unemployment

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5
MPS	0.011**	0.032***	0.054***	0.067***	0.062***	0.049***
	(0.005)	(0.007)	(0.009)	(0.011)	(0.011)	(0.009)
MPS x Low UR MSA	-0.002	-0.002	-0.001	-0.004	-0.007**	-0.011**
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
MPS x High UR MSA	0.018*	0.022*	0.027**	0.032**	0.041***	0.045***
	(0.010)	(0.012)	(0.011)	(0.011)	(0.013)	(0.014)
Low UR MSA	0.637***	1.424***	1.955***	2.127***	2.318***	3.174***
	(0.183)	(0.167)	(0.218)	(0.356)	(0.425)	(0.516)
High UR MSA	0.261	0.282	0.377	-0.070	-0.919	-0.901
	(0.560)	(0.654)	(0.707)	(0.747)	(0.921)	(1.681)
N	6942	6549	6156	5763	5370	4977
R^2	0.26	0.37	0.44	0.49	0.51	0.56
FE	✓	✓	✓	✓	✓	✓