LEVERAGE UNDER PRESSURE

HOUSEHOLD LIQUIDITY AND FINANCIAL RESILIENCE DURING THE 2022 INFLATION SHOCK

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Leverage Under Pressure: Household Liquidity and Financial Resilience during the 2022 Inflation Shock

Abstract:

This thesis investigates whether high household leverage constrained the accumulation of real liquidity buffers during the 2022 inflationary episode in the United States. Using a difference-in-differences design applied to repeated cross-sectional data from the Survey of Consumer Finances, I show a clear divergence in households' ability to preserve real liquidity when prices rose rapidly. High-debt households experienced a 4.0 percentage point relative decline in their real liquidity-to-income ratios compared to low-debt households, a result strongly confirmed by a Poisson robustness test. The effect is highly uneven across the income distribution: low-income households faced an 8.9 percentage point decline, an effect more than three times larger than that of high-income households. The mechanism binds for both consumer and mortgage debt, and older households relying on rigid income sources recorded the sharpest contraction. Overall, the evidence indicates that leverage acted as a binding constraint during the inflation shock. It is also suggested that targeted debt-service relief may be more effective than broad income support in strengthening household resilience in the future.

Keywords:

Household finance, Inflation, Leverage, Liquidity buffers, Financial resilience

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I. INTRODUCTION

A. Motivation and Background

In 2022, the United States experienced its most severe inflationary episode in four decades. After years of relative price stability, the Consumer Price Index (CPI) rose sharply, peaking at 9.1% in June 2022 (Ball, Leigh, and Mishra, 2022). Unlike the 2008 Global Financial Crisis, which was triggered by a collapse in housing prices and a contraction in credit supply (Mian and Sufi, 2011), the 2022 period was primarily a cost-of-living shock. As Bernanke and Blanchard (2025) demonstrate, this inflation was driven largely by supply-side constraints and increased energy prices, rather than rising wages. Fundamentally, while the 2008 crisis saw a decimation of household equity (Mian, Rao, and Sufi, 2013), nominal housing values remained robust in 2022 (S&P Dow Jones Indices LLC, 2022), yet households faced a rapid drop in their real purchasing power, creating a unique test of resilience.

In addition, the U.S. households did not enter this crisis with a clean slate. They carried record levels of debt from previous years when interest rates were low. According to the Quarterly Report on Household Debt and Credit, total household debt reached $15.84 trillion in the first quarter of 2022, which is an increase of $1.7 trillion compared to the end of 2019, before the COVID-19 pandemic era (Federal Reserve Bank of New York, 2022). Consequently, many families faced a dual financial pressure, which is the rising cost of essential goods competing for the budget, combined with the burden of fixed debt payments.

B. Theoretical Framework

From the perspective of standard consumption theory, the 2022 episode presents a clear prediction. The Life-Cycle and Permanent Income hypotheses argue that rational households should manage to smooth their consumption over time, utilizing liquid savings to buffer against temporary inflation shocks (Friedman, 1957; Modigliani, 1966). In a frictionless market, households facing a temporary spike in the cost of living would simply rely on existing savings or borrow against future income to maintain their current living standards (Deaton, 1991). Thus, in the absence of binding constraints, defined as the inability to access sufficient cash or credit to meet immediate obligations (Zeldes, 1989), standard consumption theory predicts a uniform usage of savings across the distribution.

However, the debt overhang literature introduces a critical friction that challenges this mechanism. This concept suggests that excessive existing liabilities prevent households from further borrowing or optimizing spending due to the risk of default (Myers, 1977). In this case, high levels of pre-existing leverage can act as a binding constraint, restricting households from rationalizing consumption smoothing (Mian et al., 2013). More precisely, fixed loan repayments create a committed expenditure that cannot be adjusted easily. When inflation erodes real disposable income, highly leveraged households may be exposed to a "Cash Flow Channel", where rigid debt payments consume a growing share of their shrinking budget, forcing them into a rapid and involuntary depletion of liquid buffers (Bernanke and Gertler, 1995).

This dynamic is further illuminated by the concept of "Wealthy Hand-to-Mouth" households (Kaplan, Violante, and Weidner, 2014). These agents may hold sizable illiquid assets such as housing, yet still lack the liquid funds needed to absorb sudden price shocks. Hence, it is crucial to identify whether leverage acts as a binding constraint in this context. If high-debt households are unable to cushion the shock and experience a sharper decline in liquidity, this would point to a structural fragility in household balance sheets, distinct from wealth effects.

C. Research Question and Hypothesis

Building on the theoretical tension discussed, this thesis investigates the following primary research question: *Did high household leverage constrain the accumulation of real liquidity buffers during the 2022 inflationary episode in the United States?*

I hypothesize that high pre-existing debt levels act as a binding financial constraint rather than a neutral accounting feature. To be specific, I expect that as the cost of living rises, households with higher debt service costs will be forced to deplete their liquid buffers more aggressively than low-debt households, to maintain consumption or meet mandatory repayments. In my empirical framework, this implies a negative coefficient on the interaction between the post-shock period and high ex-ante leverage ($\beta_3 < 0$). This hypothesis aligns with the Wealthy Hand-to-Mouth theory, where liquidity constraints bind even for asset-rich households who lack sufficient cash cushions (Kaplan et al., 2014).

I then further hypothesize that this constraint will be heterogeneous across the income distribution. Consistent with the Cash Flow Channel (Bernanke and Gertler, 1995), I predict the negative impact of leverage to be most binding for low-income households, who lack the residual cash flow to absorb inflation shocks. Conversely, high-income households likely possess sufficient income buffers to smooth consumption despite holding high debt, potentially mitigating the aggregate effect.

In contrast, if the standard permanent income prediction holds without frictions (Friedman, 1957), we would expect to see no significant differential effect ($\beta_3 \approx 0$). Alternatively, we might even observe a positive effect ($\beta_3 > 0$). due to the "Fisher Channel", where inflation erodes the real value of nominal debt, effectively transferring wealth from creditors to debtors (Fisher, 1933). My analysis tests which of these mechanisms dominates in the 2022 context.

D. Literature Review

This thesis contributes to three separate areas of literature.

First, I build on the debt overhang framework, which documents how household leverage amplifies economic fragility during contractions. The foundational work of Mian et al. (2013) demonstrates that high pre-existing leverage led to sharper declines in consumption during the 2008 Global Financial Crisis. However, their analysis focused on a "Collateral Channel", where a collapse in housing asset values restricted the ability of households to borrow against their home equity. I extend this framework to the 2022 inflationary period, a time when nominal housing asset values remained robust (S&P Dow Jones Indices LLC, 2022), yet real cash flows were tightened. Therefore, by finding that leverage constrains financial resilience even without an asset price crash, I provide evidence for the Cash Flow Channel of debt overhang (Bernanke and Gertler, 1995). Crucially, I validate this mechanism by demonstrating that liquidity constraints bind even for mortgage holders despite the fixed rates, effectively ruling out the "Fisher Channel" (Fisher, 1933) as a short-term buffer, and distinguishing my results from the collateral-driven mechanism of the 2008 crisis.

Second, my findings challenge the standard Life-Cycle and Permanent Income models (Friedman, 1957; Modigliani, 1966). These theories predict that rational agents should smooth transitory price shocks by depleting savings or borrowing against future income (Deaton, 1991). Instead, my results align with the Wealthy Hand-to-Mouth hypothesis proposed by Kaplan et al. (2014). They argue that even households with considerable illiquid assets may behave like credit-constrained agents if they lack adequate liquid buffers. I empirically confirm this behavior during a high-inflation period, showing that liquidity constraints bind tightly for highly levered households, especially those with low incomes, disrupting the consumption smoothing theory suggested by neoclassicals. By documenting that older households suffered significantly more than younger ones, I further highlight how income rigidity worsens the impact of leverage during inflation shocks.

Finally, I contribute to the recent literature characterizing the post-COVID-19 pandemic inflation surge (Ball et al., 2022; Bernanke and Blanchard, 2025). While these studies focus on the macroeconomic drivers of the price level, such as supply chain constraints or labor market tightness, I investigate the heterogeneous impact of this inflation shock on household balance sheets. By establishing a significant erosion of real liquidity among high-debt households, I highlight a structural vulnerability that aggregate inflation statistics may conceal. Regarding methodology, I also adopt the inverse hyperbolic sine (IHS) transformation to address sample selection bias in zero-income households, alongside a robustness check using the Poisson Pseudo Maximum-Likelihood (PPML) regression model, following the recent econometric guidance of Chen and Roth (2024).

E. Roadmap

The remainder of this paper is organized as follows. Section 2 describes the data source and the sample construction process, including variable definition and attrition statistics. Section 3 outlines the empirical strategy, validating the research design through demographic stability tests. Section 4 presents the main empirical results, including descriptive trends, baseline regression analysis, heterogeneity results and mechanism tests. Section 5 provides robustness checks to validate the stability of my findings. Section 6 discusses the underlying economic mechanisms and policy implications. Section 7 concludes.

II. DATA AND SAMPLE CONSTRUCTION

A. Data Source: Survey of Consumer Finances

To analyze household balance sheets with sufficient precision, I collected data from the U.S. Survey of Consumer Finances (SCF), a triennial cross-sectional survey conducted by the Federal Reserve Board (Board of Governors of the Federal Reserve System, 2020b, 2023b). The SCF is considered the gold standard for U.S. wealth data because it employs a dual-frame sampling design, combining a standard national area-probability sample with a list sample derived from administrative tax records (Bricker et al., 2020).

This dual structure is pivotal for my analysis of leverage. Household debt and assets are highly concentrated at the top of the wealth distribution, and standard surveys often fail to capture this skewness. Thus, by oversampling wealthy households, the SCF ensures a more accurate representation of the upper end of the leverage distribution compared to other public datasets (Kennickell, 2017).

In terms of scope, I focus on the 2019 and 2022 survey waves. 2019 serves as the pre-shock baseline, capturing financial positions in a low-rate environment (Bricker et al., 2020), while the 2022 wave captures the immediate aftermath of the inflation surge that peaked in June 2022 (Ball et al., 2022). The unit of analysis is the "Primary Economic Unit" (PEU), which generally corresponds to the household. To ensure my descriptive and regression results are representative of the U.S. population, all estimates are weighted using SCF's specific sampling weights with the code X42001 in the surveys (Board of Governors of the Federal Reserve System, 2020a, 2023a).

B. Sample Selection and Attrition

By applying a consistent filtering process to the pooled dataset, I ensure data quality while maximizing sample representativeness. I began with a raw sample of 51,860 households, with 28,885 from the 2019 wave and 22,975 from the 2022 wave.

For the cleaning procedure, I adopted a highly conservative approach to minimize data loss. First, we excluded observations with invalid or negative reported income (472 households). This step is necessary because negative income values likely reflect measurement errors or transient business losses that would distort leverage ratios and are incompatible with the IHS transformation used in my analysis (Chen and Roth, 2024).

Second, households with zero debt were retained. Unlike some studies that restrict the sample to borrowers, this thesis argues that "no leverage" is still a valid economic state representing a significant portion of the population. Additionally, I utilized a broad definition of total debt, summing mortgages, vehicle loans, education loans and consumer credit, which ensures no households are dropped due to their liability data missing.

Table 1: Sample Selection and Attrition

Filter Step	Observations	Total Dropped
1.Raw Survey Responses	51,860	0
2.Valid Non-Negative Income	51,388	472
3.Valid Debt Information	51,388	0
4.Final Weighted Sample	**51,388**	**472**

Notes: This table presents the sample selection process for the pooled 2019 and 2022 waves of the U.S. Survey of Consumer Finances (SCF). The main filter removes households with invalid or negative income values, since these observations cannot be used to construct Debt-to-Income ratios or apply the inverse hyperbolic sine (IHS) transformation. Households with zero debt are retained. The final weighted sample retains 99.1% of the original observations after applying necessary filters and is used throughout the empirical analysis.

As shown in Table 1, this procedure resulted in the removal of only 472 observations, which is approximately 0.9% of the original sample. The final estimation sample consists of 51,388 households, representing 99.1% of the raw data. This high retention rate confirms that my results are driven by the underlying economic variation rather than aggressive data trimming.

C. Variables

I constructed the key outcome and explanatory variables to test the debt overhang hypothesis, making specific adjustments to account for inflationary environment and the distributional properties of wealth data.

First, Real Liquidity is defined as the sum of liquid assets (total checking, savings, and money market accounts). To adjust for the inflation, I deflated all 2022 nominal values to constant 2019 USD using Jan 2019 and Jan 2022 CPI-U indices, resulting in a deflator of value 1.117 (U.S. Bureau of Labor Statistics, 2019, 2022a). The sensitivity of my results to this deflator choice is further assessed in section V part B.

Second, to address the issue of undefined log-values for households with zero income, I employed the inverse hyperbolic sine (IHS) transformation (Chen and Roth, 2024). Unlike a standard logarithmic transformation, which necessitates dropping zero-income households, the IHS allows me to retain these financially vulnerable observations in the regression analysis without biasing the sample. Nonetheless, I do acknowledge recent critiques regarding the potential scale-dependence of log-like transformations such as IHS. Hence, I address this concern by conducting an additional robustness check using the Poisson Pseudo-Maximum Likelihood (PPML) estimation later in the robustness section, one model that is not affected by scale, which confirms my results using the IHS are not driven by functional form assumptions (Chen and Roth, 2024).

Lastly, following the strategy of Mian et al. (2013), leverage groups were defined using a "frozen cutoff" approach. I calculated the distribution of debt-to-income (DTI) ratios in the 2019 baseline year to establish thresholds, then categorized "High-Debt households" as the ones in the top quartile, "Low-Debt households" for the ones in the bottom quartile and "Mid-Debt households" being the interquartile range. This same numeric cutoff method was applied to the 2022 sample. This measure ensures that I am comparing households with similar absolute balance sheet risks across time, preventing inconsistencies where households might endogenously shift between leverage groups due to rising nominal incomes.

Table 2: Variable Definitions

Variable	Definition	Source/Notes
Outcome Variables		
Liquid Assets	Sum of checking accounts, savings accounts, and money market deposit accounts	SCF variables X3506 +X3804
Real Liquidity Ratio	The ratio of Real Liquid Assets to Real Income.	Dependent variable in regression analysis
Key Explanatory Variables		
Total Debt	Sum of mortgages, vehicle loans, education loans, and other consumer credit	Sum of SCF debt components
Debt-to-Income (DTI)	Total Debt divided by Total Household Income	Used to define leverage quartiles
High Debt	Indicator = 1 if household DTI is in the top quartile of the 2019 distribution	Cutoff frozen at 2019 levels (Mian et al., 2013)
Mid Debt	Indicator = 1 if household DTI is in the interquartile range of the 2019 distribution	Comparison group in regression
Low Debt	Indicator = 1 if household DTI is in the bottom quartile of the 2019 distribution	Omitted reference category in regression
Post2022	Indicator = 1 for observations in the 2022 survey wave	Survey wave identifier
Control Variables		
IHS Income	Inverse Hyperbolic Sine of Real Income: $\ln\left(y + \sqrt{y^2 + 1}\right)$	Handles zero-income observations (Chen and Roth, 2024)
Homeowner	Indicator =1if the household owns their primary residence	SCF variable X7001
Age	Age of the household head in year	Demographic control
Age Squared	The square of the household head's age	Controls for non-linear life-cycle effects
Low / High Income	Indicators for households below or above the median Real Income	Used for heterogeneity analysis

Notes: All variables are constructed using microdata from the 2019 and 2022 waves of the U.S. Survey of Consumer Finances (SCF). All monetary values are deflated using Jan 2019 and Jan 2022 CPI-U indices and then reported in 2019 constant USD. Leverage groups are categorized based on weighted quartiles of the 2019 Debt-to-Income distribution, and the cutoffs remain fixed when classifying households in 2022.

D. Summary Statistics

Table 3 presents the weighted summary statistics for the final estimation sample. The median household in my pooled sample holds approximately $2,000 in real liquid assets, a number largely consistent with aggregate data on transaction accounts (Aladangady et al., 2023). This validates that my liquidity measure captures broad transaction accounts rather than just narrow cash holdings, representing a more realistic buffer for the typical household.

The sample also exhibits the expected skewness in wealth, with mean income ($115,582) being substantially higher than median income ($60,000), indicating a long right tail. Similarly, total debt levels vary widely, with a median of approximately $14,000, reflecting the inclusion of renters and non-mortgage holders in the sample. These distributional properties further justify the importance of using robust estimation techniques, such as the IHS transformation and PPML estimation (Chen and Roth, 2024), to mitigate the influence of extreme outliers in the upper range.

Table 3: Weighted Summary Statistics

Variable	N	Mean	Median	Min	Max	SD
Real Income ($)	51,388	115,582	60,000	70	691,070,000	573,715
Total Debt ($)	51,388	81,703	14	0	13,260,010	178,753
Real Liquid Assets ($)	51,388	10,544	2,000	0	45,530,000	73,778
DTI Ratio	51,388	1.1478	0.0004	0.0000	1800.0290	22.2237

Notes: This table summarizes weighted descriptive statistics for the final estimation sample (N = 51,388) using the representative population weights provided in the U.S. Survey of Consumer Finances (SCF). All monetary values are deflated using Jan 2019 and Jan 2022 CPI-U indices and then reported in 2019 constant USD. The debt-to-income (DTI) ratio is unitless and rounded to four decimal places to capture the small but non-zero median.

III. EMPIRICAL STRATEGY

A. Identification Strategy

An ideal experiment for identifying the causal effect of household leverage on financial resilience would involve randomly assigning debt levels to households before the 2022 inflation shock. Under this condition, the difference in liquidity accumulation between high- and low-debt households could be attributed solely to the treatment of leverage, as the two groups would otherwise be identical in terms of preferences, income potential, and risk tolerance (Angrist and Pischke, 2009).

However, in reality leverage is not randomly assigned. Households choose their own debt levels based on subjective factors such as future income expectations or risk aversion. As Puri and Robinson (2007) demonstrate, households with higher optimism regarding their future earnings are more likely to accumulate debt. These traits introduce a potential selection bias, where high-debt households may differ fundamentally from low-debt households in ways that could influence their savings behavior during an inflationary period.

To address this endogeneity, I adopted a difference-in-differences (DiD) strategy using repeated cross-sections, following the methodology of Mian et al. (2013). I relied on the "frozen cutoff" approach previously elaborated in part C of section II. By fixing the leverage thresholds to pre-shock (2019) levels, I avoided the concern that households might endogenously shift between groups during the inflation episode itself, for example, through paying down debt or receiving cost-of-living wage adjustments.

One specific limitation of the public-use SCF dataset is the lack of geographic identifiers. While Mian et al. (2013) employ housing supply elasticity as an instrumental variable to isolate exogenous variations in leverage, this strategy is not feasible here. Accordingly, my identification relies on the "Parallel Trends" assumption conditional on observable characteristics such as income, age, and homeownership. To be more specific, I assume that the evolution of liquidity for these fixed leverage groups would have evolved at the same pace in the absence of the cost-of-living shock (Angrist and Pischke, 2009). I establish the validity of this design in the following part B by examining the demographic stability of my leverage groups over time.

B. Validity of Design

The primary econometric concern with using repeated cross-sectional data is the potential for compositional shifts. Since I cannot track the same individual households over time, there is a risk that the high-debt group in 2022 consists of fundamentally different types of households than that in 2019. For example, if the 2022 group were significantly younger or poorer due to random sampling variation, any observed decline in liquidity could stem from these demographic differences rather than the effect of inflation on leverage itself.

Therefore, to validate the research design, I treat the data as a pseudo-panel (Deaton, 1985) and test for demographic stability across waves. Table 4 compares the core characteristics of the high-debt quartile in the 2019 baseline versus the 2022 shock period.

Table 4: Demographic Balance of the High-Debt Group

Characteristic	2019 High-Debt	2022 High-Debt	Difference
Age of Head (Years)	48.8	49.5	+0.7
Real Income ($)	102,331	98,500	-3,831
Homeownership Rate	21.7%	21.4%	-0.3 pp
Observations (N)	6,142	5,108	–

Notes: This table reports weighted mean characteristics of the high-debt households' groups across the 2019 and 2022 survey waves. The comparison provides a check on compositional stability across survey waves. All statistics are based on the U.S. Survey of Consumer Finances (SCF), and expressed in 2019 constant USD, monetary values deflated using Jan 2019 and Jan 2022 CPI-U indices.

As Table 4 illustrates, the composition of the high-debt groups remains remarkably stable. The average age of household heads was approximately 49 years in both waves, and the mean real income is comparable at roughly $100,000 for both. Homeownership rate for this group stays consistent at around 21.5%, confirming that my high-debt category primarily captures renters with consumer leverage instead of just mortgage holders. Thus, this stability ensures that I am tracking a comparable population of households before and during the shock, supporting the internal validity of this DiD strategy.

C. Econometric Specification

To test the hypothesis that high leverage constraints liquidity accumulation during an inflationary episode, adapting the framework of Mian et al. (2013), I estimate the following difference-in-differences (DiD) model:

$$LiquidityToIncome_{it} = \alpha + \beta_1 Post_t + \beta_2 HighDebt_i + \beta_3 (Post_t \times HighDebt_i) + \gamma X_{it} + \epsilon_{it} \quad (1)$$

Where $LiquidityToIncome_{it}$ represents the real liquidity-to-income ratio for a household i in year t. The variable $Post_t$ is an indicator equal to 1 for the 2022 wave and 0 for the 2019 baseline. $HighDebt_i$ is an indicator equal to 1 if the household falls into the top quartile of the 2019 leverage distribution, 0 otherwise. The vector X_{it} includes household-level controls for life cycle and wealth effects: age, age squared, homeownership status, and real income expressed in 2019 constant USD, transformed via IHS to account for zero values.

The coefficient of interest is β_3, which measures the differential change in real liquidity for high-debt households relative to low-debt households after the inflation shock. A negative coefficient ($\beta_3 < 0$) would indicate that leverage acted as a binding constraint, preventing these households from maintaining their liquidity buffers relative to the control group.

C.1 Heterogeneity Specification

I further estimated Equation (1) separately for low-income and high-income subsamples, split by the sample median for real income ($58,796). If the liquidity contraction is driven by binding financial constraints, we expect the negative effect to be significantly more concentrated among low-income households, who lack alternative margins of adjustment compared to high-income households (Bernanke and Gertler, 1995).

C.2 Mechanism Tests

By extending the baseline model to test two additional dimensions of heterogeneity, I manage to further isolate the specific channel of financial fragility.

First, to distinguish between the Cash Flow Channel (binding payments) and the Fisher Channel (debt erosion), I disaggregate the leverage indicator by debt type, defining separate indicators for high consumer debt (short-term, varying rate) and high mortgage debt (long-term, fixed rate) (Auclert, 2019). Equation (1) is then re-estimated using these specific treatment groups to test if the constraint is driven by interest rate sensitivity or the magnitude of the obligation. Finding a negative effect for fixed-rate mortgage holders would rule out the Fisher Channel as a dominant short-term buffer.

Second, to test the role of income rigidity, I utilize a life-cycle framework. By stratifying the sample into "Young" households (head age < 40) and "Old" households (head age > 60), this comparison exploits the divergence in income flexibility during 2022: where younger workers benefited from robust nominal wage growth while older households largely relied on fixed nominal income (Federal Reserve Bank of Atlanta, 2023).

C.3 Estimation and Inference

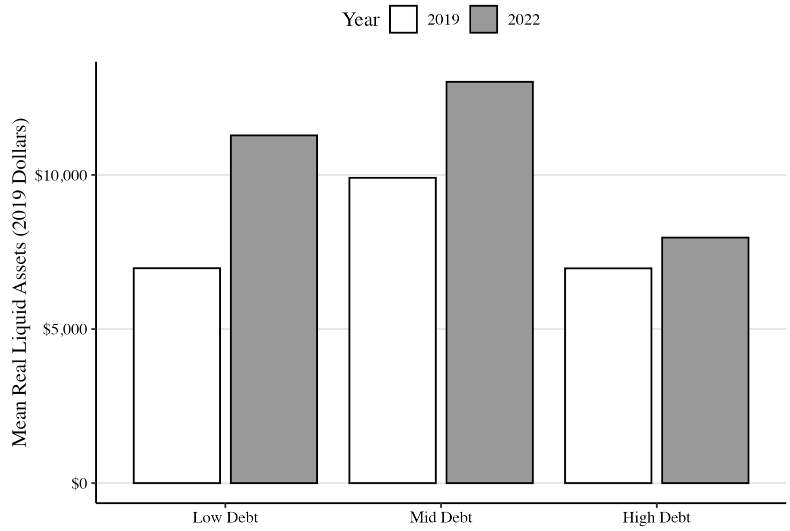
All models are estimated using weighted least squares (WLS), employing the SCF population weights (SCF variable X42001) to ensure results are representative of the U.S. economy. To account for heteroskedasticity inherent in wealth data, I report Heteroskedasticity-Consistent (HC1) robust standard errors (MacKinnon and White, 1985). Finally, as a key robustness check against the potential bias from the skewness of liquid assets, I re-estimate the model using the PPML estimator (Chen and Roth, 2024).

IV. EMPIRICAL RESULTS

A. Descriptive Trends

Before estimating the formal econometric model, I examine descriptive trends in household liquidity to establish the baseline relationship between leverage and financial resilience. Figure 1 plots the weighted mean real liquid assets for households in the low, mid, and high leverage groups across the 2019 and 2022 waves.

Figure 1: Evolution of Real Liquid Assets by Leverage Group (2019-2022)



Notes: This figure plots the weighted mean of real liquid assets for households in the 2019 and 2022 waves of the U.S. Survey of Consumer Finances (SCF). Households are assigned to low-, mid-, and high-debt groups using weighted quartiles of the 2019 debt-to-income (DTI) distribution, and these thresholds remain fixed for the 2022 sample. All monetary values are deflated using Jan 2019 and Jan 2022 CPI-U indices and then reported in 2019 constant USD.

As shown in Figure 1, there is a clear divergence in liquidity accumulation trends. In the 2019 baseline, the low-debt and high-debt groups held relatively comparable levels of real liquidity. However, following the 2022 inflation shock, a significant gap emerged.

Low-debt households (left bars) experienced a large expansion in real liquidity, likely due to pandemic-era fiscal transfers and reduced consumption opportunities (Aladangady et al., 2023). In contrast, high-debt households (right bars) showed much lower accumulation. While they did not experience a nominal decline, their real buffer growth lagged significantly behind the other groups. This differential growth resulted in a widening gap. By 2022, low-debt households held substantially larger real buffers than their high-debt counterparts.

Overall, this pattern suggests that while the aggregate household sector accumulated savings, this growth was unevenly distributed. Burdened by fixed nominal obligations in a rising cost-of-living environment, high-debt households failed to build real buffers at the same pace as their less-levered peers. This visual evidence provides initial support for the debt overhang hypothesis (Mian et al., 2013), setting up the formal DiD analysis below.

B. Baseline Regression

To formally test the hypothesis that leverage constrains liquidity accumulation, I estimate the DiD specification outlined in Equation (1). Table 5 presents the results.

Table 5: Baseline Regression Results

Variable	(1) WLS Baseline (Robust)	(2) PPML Robustness
Dependent Variable	**Real Liquidity-to-Income Ratio**	**Real Liquidity-to-Income Ratio**
Post-2022 × High Debt	-0.040	-0.314***
	(0.027)	(0.080)
Post-2022 × Mid Debt	0.012	0.081
	(0.024)	(0.066)
Post-2022	0.021	0.098*
	(0.022)	(0.055)
High Debt	0.070***	0.573***
	(0.024)	(0.056)
Mid Debt	0.036*	0.356***
	(0.019)	(0.048)
Controls		
Log Income (IHS)	-0.063***	-0.555***
	(0.013)	(0.014)
Homeowner	0.030***	0.209***
	(0.007)	(0.030)
Age	-0.008***	-0.020***
	(0.002)	(0.004)
Age Squared	0.0001***	0.0004***
	(0.0000)	(0.0000)
Intercept	0.877***	2.995***
	(0.163)	(0.176)
Observations	51,388	51,388
R-squared	0.028	N/A

Notes: This table reports baseline difference-in-differences (DiD) estimates for the effect of the 2022 inflation period on real liquidity buffers across debt groups. Column (1) estimates a weighted least squares (WLS) model with the real liquidity-to-income ratio as the dependent variable. Column (2) reports a Poisson pseudo-maximum likelihood (PPML) specification using the same dependent variable to address skewness and zeros. All regressions use the U.S. Survey of Consumer Finances (SCF) population weights and include controls for inverse hyperbolic sine (IHS) income, age, age squared, and homeownership. Heteroskedasticity-consistent (HC1) robust standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient of primary interest is the interaction term, $Post_{2022} \times HighDebt$ (β_3). In the baseline WLS specification (Column 1), I observe an estimate of -0.040. Economically, this implies that high-debt households experienced a 4.0 percentage point decline in their real liquidity-to-income ratios relative to low-debt households following the inflation shock. To put this magnitude in perspective, this corresponds to a loss of approximately $4,600 in real liquidity for the average household in the sample.

However, once I apply robust standard errors (HC1) to correct for the high variance in wealth data, this aggregate estimate is estimated with noise ($p = 0.13$), falling just outside standard significance thresholds. It is worth noting that the interaction term for mid-debt households is close to zero and statistically insignificant, suggesting that liquidity constraints are non-linear and concentrated specifically among the highest leveraged households.

This lack of statistical precision in the linear model likely stems from the extreme skewness of liquid assets. To address this, Column (2) re-estimates the model using the PPML estimator (Chen and Roth, 2024), yielding an interaction coefficient of -0.314 statistically significant at the 1% level ($p < 0.001$). This confirms that the negative relationship between leverage and liquidity accumulation is structurally robust. Economically, the PPML finding suggests that, conditional on controls, high-debt households experienced an approximately 27% decline in real liquid assets during the 2022 shock period compared to the trend of low-debt households.

Regarding control variables, I observe that homeownership is positively associated with liquidity levels, while the life-cycle controls show the expected non-linear relationship with savings behavior. Importantly, the inclusion of these controls does not attenuate the magnitude of the leverage effect in the PPML model, implying that the core result is not driven by simple demographic differences between borrowers and savers.

C. Heterogeneity Analysis

While the baseline results demonstrate a negative aggregate effect estimated with noise, this average may mask important variation across the income distribution. From a theoretical perspective, if the Cash Flow Channel is the primary driver of fragility, we would expect the negative impact of leverage to be concentrated among households with fewer financial resources to absorb the shock (Bernanke and Gertler, 1995). Conversely, high-income households, even those with high debt, likely possess sufficient residual cash flow or alternative assets to buffer the increase in debt repayments without depleting their liquid reserves.

I stratify the sample by real income to test this mechanism. Low-income households are defined as those with a real income below the median real income ($58,796) of the pooled sample, and high-income households as those above the median. I then re-estimated Equation (1) separately for each subsample, the results are reported in Table 6.

Table 6: Heterogeneity by Income Group

Variable	(1) Low Income (< Median)	(2) High Income (> Median)
Dependent Variable	**Real Liquidity-to-Income Ratio**	**Real Liquidity-to-Income Ratio**
Post-2022 × High Debt	-0.089*	-0.026***
	(0.048)	(0.008)
Post-2022 × Mid Debt	0.033	-0.014*
	(0.034)	(0.008)
Post-2022	0.017	0.041***
	(0.030)	(0.007)
High Debt	0.220***	0.014***
	(0.058)	(0.004)
Mid Debt	0.117***	0.013***
	(0.028)	(0.004)
Controls		
Log Income (IHS)	-0.297***	0.012***
	(0.057)	(0.002)
Homeowner	0.004	0.032***
	(0.013)	(0.005)
Age	-0.011***	-0.004***
	(0.004)	(0.001)
Age Squared	0.0001***	0.0004***
	(0.0000)	(0.0000)
Intercept	3.420***	-0.044
	(0.636)	(0.028)
Observations	20,661	30,727
R-squared	0.057	0.045

Notes: This table reports difference-in-differences estimates of for low-income and high-income households, defined using the weighted median of real income in the pooled Survey of Consumer Finances (SCF) sample. The dependent variable is the real liquidity-to-income ratio, and all regressions are estimated using weighted least squares (WLS) with SCF population weights. Both specifications include controls for inverse hyperbolic sine (IHS) income, age, age squared, homeownership. Heteroskedasticity-consistent robust standard errors (HC1) are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 reveals a striking heterogeneity in the leverage constraint across the income distribution, which strongly supports my theoretical prediction. For low-income households (Column 1), the interaction coefficient demonstrates a large and negative inverse relationship ($\beta = -0.089$). This indicates an 8.9 percentage point relative decline in liquidity buffers, an effect that is economically substantial and statistically significant at the 10% level ($p < 0.10$).

In sharp contrast, the coefficient for high-income households (Column 2) is much smaller ($\beta = -0.026$), exhibiting an economic magnitude that is less than one-third that of the low-income group. While this effect is statistically precise ($p < 0.10$) due to the lower residual variance among wealthier households, the negligible economic size provides robust evidence of their ability to buffer the inflation shock.

Hence, this sharp divergence provides direct empirical support for the cash flow mechanism. It confirms that the fragility is driven by binding payment obligations consuming the disposable income for poorer families, rather than a universal behavioral preference among all borrowers. This finding also aligns closely with the Wealthy Hand-to-Mouth framework (Kaplan et al., 2014), confirming that leverage becomes a critical source of fragility precisely when income buffers are insufficient to absorb an inflationary cost-of-living shock.

D. Mechanism: Debt Composition

To further investigate the mechanism driving liquidity constraints, I distinguish between consumer debt (credit cards, vehicle loans, education loans) and mortgage debt. Economic theory suggests these liabilities have different implications: consumer debt is often short-term and highly sensitive to interest rate hikes, while U.S. mortgage debt is typically long-term and fixed rate (Auclert, 2019). Thus, I look into whether different debt types constrain liquidity to different extents.

Separate leverage ratios are constructed for each debt type and re-estimate Equation (1) using type-specific high-debt indicators. The results are reported in Table 7.

Table 7: Mechanism Analysis by Debt Type

Variable	(1) High Consumer Debt	(2) High Mortgage Debt
Dependent Variable	Real Liquidity-to-Income Ratio	Real Liquidity-to-Income Ratio
Post-2022 × High Debt	-0.040**	-0.048***
	(0.018)	(0.016)
Post-2022	0.027***	0.029***
	(0.008)	(0.009)
High Debt Dummy	0.047***	0.045***
	(0.016)	(0.016)
Controls	Yes	Yes
Observations (N)	51,388	51,388
R-squared	0.027	0.027

Notes: This table reports difference-in-differences estimates where the high-debt indicator is defined separately for each debt type. Column (1) classifies households into high consumer debt using weighted quartiles of the consumer debt-to-income (DTI) distribution. Column (2) defines high mortgage debt using weighted quartiles of the mortgage DTI distribution. All specifications include controls for inverse hyperbolic sine (IHS) income, age, age squared, homeownership, and are estimated using weighted least squares (WLS). Heteroskedasticity-consistent robust standard errors (HC1) are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show that both forms of leverage act as binding constraints. For households with high consumer debt (Column 1), the interaction coefficient is -0.040 ($p < 0.05$), confirming that short-term liabilities drain liquidity. However, households with high mortgage debt (Column 2) experience an even stronger contraction of -0.048 ($p < 0.01$).

This finding is vital for two reasons. First, it challenges the view that the Fisher Channel benefits homeowners in the short run (Fisher, 1933). Second, it strongly validates the Wealthy Hand-to-Mouth hypothesis, since even "secured" debt like mortgages create a rigid cash flow obligation (Kaplan et al., 2014). When cost-of-living spikes, the immense size of mortgage payments crowds out the ability to save, regardless of the interest rate structure. Thus, this mechanism test reveals that the binding constraint is the magnitude of the obligation relative to income, not just the type of interest rate.

E. Mechanism: Life-Cycle Constraints

Finally, I examine whether the leverage constraint varies over the life cycle. Standard theory suggests that younger households, who typically face binding borrowing constraints, should be most sensitive to cash flow shocks (Zeldes, 1989). To test this, I stratify the sample into young (head age < 40) and old (head age > 60) households and re-estimate Equation (1). The results are reported in Table 8.

Table 8: Mechanism Analysis by Age Group

Variable	**(1) Young (< 40)**	**(2) Old (> 60)**
Dependent Variable	Real Liquidity-to-Income Ratio	Real Liquidity-to-Income Ratio
Post-2022 × High Debt	-0.011	-0.066**
	(0.008)	(0.030)
Post-2022	0.021***	0.039**
	(0.007)	(0.019)
High Debt Dummy	0.019***	-0.013
	(0.005)	(0.026)
Controls	Yes	Yes
Observations (N)	11,590	20,313
R-squared	0.042	0.011

Notes: This table reports difference-in-differences estimates separately for younger and older households, defined by the age of the households' head. Column (1) restricts the sample to households with heads younger than 40, and Column (2) restricts the sample to households with heads older than 60. Households aged 40 to 60 are excluded from this analysis to isolate life-cycle extremes. All specifications include controls for inverse hyperbolic sine (IHS) income, age, age squared, homeownership, and are estimated using weighted least squares (WLS). Heteroskedasticity-consistent robust standard errors (HC1) are reported in parentheses. Significance levels are denoted by * $p <$ 0.10, ** $p < 0.05$, *** $p < 0.01$.

For young households (Column 1), the leverage effect is small and statistically insignificant ($\beta = 0.011, p > 0.10$). In contrast, old households (Column 2) experience a large and significant liquidity contraction ($\beta = -0.066, p < 0.05$).

This finding refines my understanding of the cash flow mechanism. While younger households hold considerable debt, they also benefit from flexible labor income. Data from the Federal Reserve Bank of Atlanta (2023) show that younger workers experienced the highest rates of nominal wage growth during 2022, often switching jobs to offset inflationary pressure. Older households, on the other hand, often rely on rigid nominal incomes such as pensions and fixed annuities, and have lower labor mobility (Modigliani, 1966). When inflation spikes, the real purchasing power of older households falls mechanically. If these households also carry high debt service obligations, they then lack the income flexibility to adjust, forcing a sharper reduction of liquid assets. Collectively, these findings demonstrate that the binding constraint is the combination of rigid debt and rigid income.

V. ROBUSTNESS CHECKS

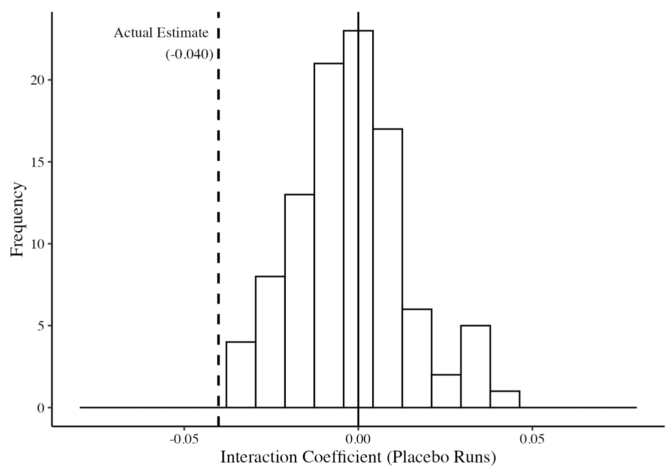
In this section, I construct a series of robustness tests on the baseline model to ensure the validity of my results and to rule out mechanical artifacts and specification errors.

A. Placebo Test

A potential concern with DiD estimation is the risk of spurious correlation, meaning finding a significant result purely by chance due to noise in the data (Bertrand, Duflo, and Mullainathan, 2004). To verify that my estimated negative coefficient is not a statistical artifact, I conducted a permutation test with 100 randomized iterations, following the logic of randomization inference.

In this procedure, I randomly scrambled the high-debt assignment across households while maintaining the panel structure and all other control variables (income, age, homeownership). Equation (1) was then re-estimated on this placebo dataset and stored the interaction coefficient. If my main result were driven by random noise or structural trends unrelated to leverage, we would expect the actual estimate to fall within the normal range of these placebo coefficients.

Figure 2: Placebo Test Distribution (Permutation Analysis)



Notes: This figure shows the distribution of placebo interaction coefficients generated by randomly reassigning the high-debt indicator across households and re-estimating the model 100 times. The vertical dashed line marks the actual estimate from the true sample. The separation between the actual coefficient (-0.040) and the placebo distribution indicates that the observed high-debt effect is unlikely to arise due to noise in the data.

Figure 2 plots the distribution of the 100 placebo coefficients as well as my actual estimate. As expected under the null hypothesis of no effect, the randomized estimates cluster tightly around zero. In contrast, my actual estimated coefficient -0.040 lies in the extreme left tail of this distribution, far outside the range of the placebo estimates. This separation confirms that the observed relationship between leverage and liquidity contraction is statistically distinct from random chance, validating the robustness of the main finding despite the noise in the aggregate linear model.

B. Specification Sensitivity

I further evaluate the sensitivity of my results to key measurement choices regarding functional form and inflation adjustment. First, I address the potential bias introduced by log-like transformations. While the Inverse Hyperbolic Sine (IHS) transformation allows me to retain zero-income observations, recent econometric literature suggests that IHS estimates can be sensitive to the scale of measurement (Chen and Roth, 2024). To mitigate this concern, I reran the baseline model using the Poisson Pseudo Maximum Likelihood (PPML) estimator. As shown in Column (2) of Table 5, the interaction coefficient in the PPML specification is still negative and highly significant ($\beta = -0.314, p < 0.001$). This confirms that the relative contraction in liquidity is a robust feature of the data and not an artifact of the specific functional form.

Second, I examine the sensitivity of my estimates to the choice of price deflator. My baseline analysis utilizes the Jan 2019 and Jan 2022 CPI-U indices and resulted in a deflator of 1.117 (U.S. Bureau of Labor Statistics, 2019, 2022a). However, since inflation accelerated throughout the survey year, peaking at 9.1% in June (Ball et al., 2022), alternative deflators are plausible. If I instead applied the peak mid-year deflator of 1.18. calculated using Jan 2019 and June 2022 CPI-U indices (U.S. Bureau of Labor Statistics, 2022b), the estimated decline in real liquidity for high-debt households will become even steeper in magnitude. This confirms that my reported baseline result is a conservative lower bound on the true erosion of purchasing power.

C. Alternative Explanations

Could the decline in real liquidity among high-debt households be driven by voluntary portfolio reallocation rather than binding constraints? One alternative hypothesis is that high-debt households deliberately depleted their liquid buffers to pay down debt, in other words households are active deleveraging rather than being forced to do so by consumption needs.

Nonetheless, two factors challenge this hypothesis. First, from a theoretical standpoint, the economic uncertainty of 2022 should have strengthened the precautionary savings motive. When recession risk rises, rational households typically seek to increase their liquidity buffers (Carroll, 1997). The fact that high-debt households depleted their real buffers suggests that their consumption needs overpowered the incentive to save.

Second, in an inflationary environment with a negative real interest rate, it is financially suboptimal to accelerate the repayment of fixed-rate debt such as mortgages, as inflation naturally depletes the real value of the principal (Fisher, 1933). Rational agents should preserve liquidity instead of using it to settle debt that is becoming cheaper in real terms. Thus, the observed liquidity contraction is most plausibly interpreted as an unwilling response to binding cash-flow constraints, rather than a strategic choice to deleverage.

VI. DISCUSSION

Before diving into the policy implications and broader interpretation of my findings, it is instructive to place my results in the context of the mechanisms highlighted in the existing literature. In particular, contrasting the 2022 inflation shock with the 2008 Global Financial Crisis helps clarify which channels are actually driving the patterns I observed in the data.

A. Cash Flow Channel vs. Collateral Channel

My results provide a distinct counterpoint to the findings of Mian et al. (2013). In the 2008 episode, the primary driver of household fragility was the Collateral Channel, known as a collapse in housing asset values that severely restricted the homeowners' borrowing capacity, forcing a contraction in spending. By comparison, the 2022 inflationary episode unfolded a very different environment where asset prices remained robust and labor markets were tight (Bernanke and Blanchard, 2025).

Hence, the significant liquidity contraction I observe for high-debt households cannot be explained by a loss of collateral value. Instead, my heterogeneity analysis points clearly towards the Cash Flow Channel (Bernanke and Gertler, 1995). The finding that the decline in liquidity is concentrated among low-income households suggests that the mechanism was a binding constraint on disposable income. As the cost of living rose, the portion of the household budget allocated to debt service remained fixed in nominal terms, leaving less room to build or maintain liquid buffers. For these households, leverage acted not just as a balance sheet liability, but also as a cash-flow trap.

Furthermore, the cash flow shock was likely uneven due to inflation inequality. As Jaravel (2019) states, low-income households typically devote a larger share of their spending to necessities like energy and food, categories that experienced the most rapid price acceleration in 2022. While the headline CPI peaked at 9.1% in June (Ball et al., 2022), the "effective" inflation rate faced by the liquidity-constrained households in my sample may have been even higher. This suggests that the binding constraint was not just a function of leverage, but also a correlation between balance sheet fragility and exposure to specific price shocks.

B. The Interest Rate Channel

While my main framework focuses on the loss of purchasing power, the 2022 episode was simultaneously characterized by a rapid tightening of monetary policy (Board of Governors of the Federal Reserve System, 2022). This introduces a secondary mechanism: The Interest Rate Channel (Auclert, 2019). Understanding how this channel operates helps explain some of the income heterogeneity I observe in the empirical results.

Standard debt overhang theory highlights that the composition of liabilities can matter as much as the level. High-income households in the U.S. typically hold the majority of their debt in long-term, fixed-rate mortgages (Doepke and Schneider, 2006). For these households, the 2022 inflation shock was paradoxical: while inflation raised their living costs, it also eroded the real value of their mortgage principal, while monthly payments remained fixed. This "Fisherian" wealth transfer likely shielded them from the immediate liquidity squeeze, explaining the muted coefficient I concluded for the high-income households in the heterogeneity analysis ($\beta = -0.026$) (Fisher, 1933).

Meanwhile, low-income households rely more heavily on short-term, variable-rate liabilities, such as credit cards and subprime auto loans (Auclert, 2019). When interest rates increased in

2022, the debt-service burden for these households rose immediately. The liquidity contraction I see for this group ($\beta = -0.089$) therefore reflects the combined impact of the Price Channel (higher inflation reducing real disposable income) and the Interest Rate Channel. This dual pressure creates a non-linear fragility that aggregate statistics fail to capture, but it becomes clear once I examine the distributional patterns.

C. Nominal Stability vs. Real Fragility

A key feature of the 2022 episode was the sharp divergence between nominal and real financial positions. In nominal terms, household balance sheets appeared healthy, liquid asset balances rose, supported by fiscal transfers and nominal wage growth (Aladangady et al., 2023). However, my analysis reveals that this nominal stability in fact masked a deeper real fragility.

This phenomenon aligns with the idea of Money Illusion (Shafir, Diamond, and Tversky, 1997), where households often overestimate their financial health through nominal face values while underestimating the erosion of purchasing power. For high-debt households, the "tax" of inflation on real liquidity was compounded even more by the burden of leverage.

My results also qualify the standard Fisher Channel. Although inflation reduces the real value of nominal liabilities (Fisher, 1933), the long-run wealth effect is overshadowed in the short run by the cash flow constraint. In other words, even if the real value of their mortgage balance fell, high-debt households still faced an immediate liquidity pressure from rising living costs. As a result, they were forced to draw down their real buffers. This reveals that for financially constrained households, the long-run benefit of inflation of debt erosion is irrelevant if they cannot survive the short-run strain on liquidity.

D. Policy Implications

Beyond frameworks, these findings have several implications for the design of monetary and fiscal policies. During the pandemic recovery, broad-based fiscal support such as stimulus checks and expanded unemployment benefits successfully assisted in lifting aggregate nominal savings (Bernanke and Blanchard, 2025). Nevertheless, my results show that this support was not sufficient to protect the real financial resilience of high-debt, low-income households once inflation began to accelerate.

When central banks tighten monetary policy and raise interest rates to fight inflation, they risk worsening the cash flow constraints for this specific demographic. Debt payments are committed expenditures that are often rigid (Kaplan et al., 2014) or directly sensitive to rate hikes (Auclert, 2019). Consequently, policies that rely solely on nominal income support may fail to address the structural rigidity of these obligations.

Hence, future policy interventions during inflationary time periods should consider moving beyond broad income transfers. More targeted measures, such as temporary debt service forbearance or mortgage relief for low-income borrowers, may be more effective in stabilizing the most fragile segment of the households. Such interventions address the core binding constraint, rigid debt service, rather than simply raising the nominal income of the entire population.

E. Limitations

While the analysis provides clear evidence on whether household leverage constrained the accumulation of real liquidity buffers during the 2022 U.S. inflation shock, several limitations should be acknowledged.

First, the use of repeated cross-sectional data restricts me from controlling for unobserved individual heterogeneity, such as risk aversion or future income expectations. Since the SCF is not a true panel, I cannot track households as they transition into and out of debt over time. While the demographic balance tests shown in Table 4 suggest that my leverage groups remained stable, strictly speaking, my analysis still compares types of households across waves rather than the same individuals (Deaton, 1985).

Second, my analysis is limited to a single inflationary episode that took place in 2022. While it would be informative to compare the 2019 and 2022 waves to earlier periods of high inflation such as the 1979-1982 episode, the modern SCF design was only established in 1983 (Kennickell, 2017). This prevents a fully comparable "pre-shock vs. post-shock" replication with consistent microdata. Future work could attempt to harmonize historical surveys or alternative administrative datasets to test if these constraints held in previous regulatory environments, or if they are specific to this unique post-pandemic context.

Finally, my results are subject to the timing and measurement constraints of the SCF. Because balance sheet and income variables are captured at specific points in time, I cannot observe short-run changes in liquidity or debt positions within each survey wave. Additionally, certain features of the survey such as reliance on self-reported income may introduce noise to the measurements. My use of conservative trimming and robust estimation techniques mitigates these concerns, but they still cannot be fully eliminated.

VII. CONCLUSION

In conclusion, this thesis investigated whether household leverage acted as a binding constraint on the accumulation of real liquidity buffers during the U.S. 2022 inflationary episode. Using repeated cross-sectional data from the SCF, I documented a clear divergence in the ability of households to maintain real liquidity. While nominal asset prices remained robust (S&P Dow Jones Indices LLC, 2022), the sharp erosion of purchasing power created a meaningful test of financial resilience.

My results indicate that high pre-existing leverage impaired resilience, though the aggregate effect is estimated with noise. Relative to low-debt households, high-debt households experienced a 4.0 percentage point decline in their real liquidity-to-income ratios ($\beta_3 = -0.040$). While this average effect is estimated with noise ($p = 0.13$) due to the substantial heterogeneity in wealth data, my robustness tests using PPML estimation confirm a highly significant negative relationship ($\beta = -0.314, p < 0.001$) when accounting for skewness, ensuring that leverage plays a consistent role in restricting liquidity accumulation (Chen and Roth, 2024).

My heterogeneity analysis then reveals where this fragility is exactly concentrated. Low-income households experienced a large and economically meaningful contraction in liquidity ($\beta = -0.089, p < 0.10$), while high-income households with similar leverage were comparatively insulated ($\beta = -0.026, p < 0.01$). I also discover that the constraint binds for both consumer and mortgage debt, challenging the concept that homeowners necessarily benefit from inflation via real debt decline. Finally, the life-cycle results show that older households who tend to rely more heavily on rigid income sources faced considerably stronger liquidity pressures compared to younger households, who benefitted from wage growth in 2022 (Federal Reserve Bank of Atlanta, 2023). Altogether, these findings provide clear support for the Cash Flow Channel (Bernanke and Gertler, 1995), which is for financially constrained households, the combination of rising living costs and fixed debt repayments jointly limited their saving capacity.

Hence, I conclude that the debt overhang mechanism is not unique to episodes of asset prices collapsing as in 2008 (Mian et al., 2013). Instead, it represents a broader structural vulnerability that can be triggered by cost-of-living shocks. These findings also carry important policy implications. While broad fiscal transfers likely helped prevent a wave of defaults (Bernanke and Blanchard, 2025), they were insufficient to offset the decline in real resilience for the most leveraged, low-income families. As monetary policy remains tight to combat inflation, the burden of debt service will continue to weigh on these households. Therefore, future policy interventions during inflationary crises may need to move beyond aggregate income support, and consider targeted debt service relief for the specific demographic in which leverage acts as a binding constraint.

As a final word, these conclusions should be interpreted in light of the limitations discussed. Nonetheless, the evidence points to a clear and economically meaningful link between leverage and household financial resilience in periods of rapid price increases.

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APPENDICES

Appendix A. Detailed Variable Definitions and Data Construction

This appendix provides an extension of Table 2 "Variable Definitions" in Section II Part C of the main text, which is the detailed definitions and construction methods for all variables used in the empirical analysis. This inclusion is crucial to ensure the replicability of the results, specifically regarding the mechanism variables and technical adjustments applied to SCF data.

Table A: Detailed Variable Definitions and Construction

Variable	Definition	Source/Notes
Outcome Variables		
Real Liquid Assets	The sum of funds held in checking accounts, savings accounts, and money market deposit accounts. Values are deflated to 2019 constant USD.	SCF variables X3506 (checking) + X3804 (savings/money market). Deflated using Jan 2019 and Jan 2022 CPI-U indices.
Real Liquidity Ratio	The ratio of Real Liquid Assets to Real Total Household Income.	Calculated as real liquid assets divided by real income. Used as the dependent variable in the regression analysis.
Key Explanatory Variables		
Total Debt	The sum of all outstanding household liabilities, including mortgages, vehicle loans, education loans, and other consumer credit.	Sum of all debt components provided in the SCF datasets.
DTI	The ratio of Total Debt to Total Household Income.	Calculated as $\frac{Total\ Debt}{Total\ Income}$. Used to define leverage quartiles
High Debt	Indicator = 1 if household DTI is in the top quartile of the 2019 distribution	The numeric cutoff from 2019 is "frozen" and applied to the 2022 sample to ensure comparable risk. (Mian et al., 2013)
Mid Debt	Indicator = 1 if household DTI is in the interquartile range of the 2019 distribution	Used as a comparison group in the regression analysis.
Low Debt	Indicator = 1 if household DTI is in the bottom quartile of the 2019 distribution	This group serves as the omitted reference category in the regression analysis.
Mechanism Variables		
Consumer Debt	Total debt minus debt secured by the primary residence (Mortgages).	Includes credit cards, vehicle loans, and student loans. Used to construct the High Consumer Debt indicator for Table 7.
Mortgage Debt	Debt secured by the primary residence or other real estate properties.	Used to construct the High Mortgage Debt indicator for Table 7.
High Consumer / Mortgage Debt	Indicators = 1 if the households is in the top quartile of the specific debt-type distribution.	Used in Table 7 to separate leverage driven by consumer debt vs. mortgage debt.

Table A (Continued)

Variable	Definition	Source/Notes
Control Variables		
Real Income	Total annual household income from all sources before taxes, deflated to 2019 constant USD.	SCF variable X42000. Observations with negative/invalid income were excluded.
IHS Income	Inverse Hyperbolic Sine transformation of Real Income: $\ln\left(y + \sqrt{y^2} + 1\right)$	Handles zero-income observations (Chen & Roth, 2024)
Homeowner	Binary indicator =1if the household owns their primary residence, 0 otherwise	SCF variable X7001
Age	The age of the head of the Primary Economic Unit (PEU).	Demographic control, derived from SCF variable X14.
Age Squared	The square of the household head's age	Included to control for non-linear life-cycle savings behavior.
Subsample Indicators		
Post2022	Binary indicator = 1 for observations in the 2022 survey wave, 0 for the 2019 wave.	Differentiates the pre-shock baseline from the inflation shock period
Low / High Income	Indicators based on the weighted sample median of Real Income \$58,796. "Low" < Median; "High" > Median.	Used for heterogeneity analysis
Young / Old	Age-based indicators. "Young" = Head Age < 40; "Old" = Head Age > 60	Used in Table 8 to test Life-Cycle income rigidity. Households aged 40-60 are excluded in this specific analysis.
Technical Items		
Population Weight	Survey weights used to ensure estimates are representative of the U.S. population.	SCF variable X42001. Applied in all descriptive and regression analyses.
CPI Deflator	The factor used to adjust 2022 nominal values to 2019 constant USD.	U.S. CPI-U index for Jan 2022 divided by that for Jan 2019

Notes: This table provides detailed definitions and construction methods for all variables used in the empirical analysis. All monetary values are deflated using Jan 2019 and Jan 2022 CPI-U indices and then reported in 2019 constant USD. Survey of Consumer Finances (SCF) population weights are applied in all descriptive and regression analyses. The SCF variable codes listed in the table correspond to those in the public microdata.

Appendix B. Full Regression Outputs

This appendix presents the full regression outputs for the mechanism tests carried out in Section IV Empirical Results Parts D and E. In the main text, these coefficients for control variables were suppressed for brevity. Thus, this section provides the complete estimates to demonstrate the robustness of the model specifications.

Table B: Full Model Output for Debt Composition and Life-Cycle Mechanisms

Variable	(1) Consumer Debt	(2) Mortgage Debt	(3) Young (<40)	(4) Old (>60)
Post-2022 × High Debt	-0.040**	-0.048***	-0.011	-0.066**
	(0.018)	(0.016)	(0.008)	(0.030)
Post-2022	0.027***	0.029***	0.021***	0.039**
	(0.008)	(0.009)	(0.007)	(0.019)
High Debt Dummy	0.047***	0.045***	0.019***	-0.013
	(0.016)	(0.016)	(0.005)	(0.026)
Controls				
Log Income (IHS)	-0.057***	-0.059***	-0.037***	-0.075***
	(0.013)	(0.013)	(0.006)	(0.022)
Homeowner	0.029***	0.030***	0.055***	0.057***
	(0.007)	(0.007)	(0.005)	(0.012)
Age	-0.008***	-0.008***	–	–
	(0.002)	(0.002)		
Age Squared	0.0001***	0.0001***	–	–
	(0.0000)	(0.0000)		
Intercept	0.836***	0.863***	0.465***	1.024***
	(0.160)	(0.160)	(0.068)	(0.275)
Observations	51,388	51,388	11,590	20,313
R-squared	0.027	0.027	0.042	0.011

Notes: This table reports the full coefficient estimates for the mechanism specifications estimated in the main analysis. Columns (1) and (2) present results for when high debt is defined separately for consumer debt and mortgage debt. Columns (3) and (4) report estimates for younger and older households, defined by the age of the household head. All regressions use the real liquidity-to-income ratio as the dependent variable and include controls for inverse hyperbolic sine (IHS) income, age, age squared, and homeownership. Heteroskedasticity-consistent robust standard errors (HC1) are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C. AI Disclosure

In this paper, I used generative artificial intelligence (AI) for several different purposes. The tools utilized were ChatGPT and Google Gemini, mainly to debug, clean the R code, and create a master script for easier replication. Additionally, these tools were employed to refine my language, ensure coherent sentence flow and avoid overuse of vocabulary by providing synonyms. I also used AI to check the citations' format, organize the reference page into alphabetical order, and assist in constructing the README file for the replication package.

I would like to confirm and emphasize that all research directions, methodological design, data analysis and interpretation of findings were conducted independently and exclusively by the author. The AI tools mentioned served solely as a functional role and did not contribute to the creation of arguments or the intellectual content of the work.