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Mark Robinson, Pedro Silos, Diego Vilan

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Household Debt, the Labor Share, and Earnings Inequality *

Mark Robinson† Pedro Silos ‡ Diego Vilán §

Abstract

We show that the secular decline in real interest rates in the United States, which began in the early 1980s and persisted for nearly four decades, reduced the labor's share of output and the unemployment rate, and increased earnings inequality. We establish this link using a model of frictional labor markets, estimated from household-level data, in which unemployment risk is only partially insurable. Rising debt resulting from lower interest rates reduces the value of unemployment, leading to lower equilibrium wages relative to productivity and a lower unemployment rate. Wage dispersion also rises. The model is consistent with panel-data reduced-form evidence linking unemployment duration, assets, debt, and post-unemployment wages. In the model, a decline in the real interest rate of the magnitude observed in the data generates a decline in the labor's share of 6 percentage points and in the unemployment rate of 0.3 percentage points. The variance of log earnings rises from 0.66 to 0.75.

Keywords: Labor Share, Household Indebtedness, Reservation Wage

JEL Classification Numbers: J30, E24, E27

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†Email: markrobinson6@gmail.com

‡**Corresponding author.** Department of Economics, Temple University, 2nd Floor, Gladfelter Hall, 1115 Polett Walk, Philadelphia, PA 19122 USA. Email: pedro.silos@temple.edu.

§Board of Governors of the Federal Reserve and Georgetown University. Email: diego.vilan@frb.gov.

1 Introduction

Starting in the early 1980s and continuing through the 2010s, real interest rates dropped in the United States and much of the developed world. Researchers have pointed to various reasons for this decline, including rising savings rates from East Asia, lower investment demand, and demographic changes. Regardless of the exact causes, this drop in real interest rates caused a rise in household debt, both in unsecured forms like credit cards and in secured forms like mortgages. This paper explores how the secular rise in debt has impacted labor markets, showing that falling real interest rates contributed to a decline in labor's share of output, a lower unemployment rate, and greater earnings inequality.

The key premise is that higher debt (or fewer savings) makes being unemployed less sustainable. This occurs because unemployment risk is only partially insurable: unemployment benefits run out after a certain period, and savings or borrowing can only cover expenses for so long. As households took on more debt in response to falling real interest rates, their financial situations weakened, leaving them more financially vulnerable, and forcing them to accept lower wages to exit unemployment. We formalize this idea using a standard job search model with a financial market, where households can save or borrow (up to a point) at a fixed real interest rate. Workers can become unemployed with some exogenous separation probability, but their job-finding probability depends on households' balance sheets. Unemployment benefits act as a form of insurance but expire after a set period, requiring unemployed workers to rely on their savings — or to borrow further if they are already in debt — to cover expenses. The rise in debt as a result of the decline in real interest rates, lowers the value of unemployment relative to employment. As a result, the rise in debt causes a decline in the unemployment rate and lowers the labor's share because workers must accept lower wages relative to their productivity. Finally, the rise in debt also increases earnings (wage) inequality. The intuition is that as the marginal utility of consumption rises (low assets) the value of workers' alternative to employment drops proportionately more at low wages. In other words, the reservation wage policy is concave in assets. In the model, the labor market is segmented by skill to be consistent with the evidence that the labor market experiences are different for different groups of workers (see Gregory et al. (2024)): some workers face higher separation rates with short employment spells and other workers are virtually shielded from labor market shocks. We map this heterogeneity to observed levels of education. Workers of different education levels face disparate labor market experiences affecting their wealth accumulation. For instance, asset-to-income ratios are significantly higher for higher-skilled workers.

To motivate the structural model we use the Survey of Income and Program Participation (SIPP) in 2017 through 2019 to estimate reduced-form relationships between labor market variables and households' balance sheets. Taking advantage of the high-frequency panel dimension, we link unemployment duration and wages post-unemployment-spells to different types of debt and financial assets. This analysis uncovers a strong negative relationship between unemployment duration and credit card debt, and a weaker but still significant relationship with mortgage debt. When regressing unemployment on different types of assets, the coefficients have the anticipated (positive sign) but the relationship appears modest. Finally, we find a strong positive relationship between unemployment duration and first wages (or earnings) post-unemployment. We complement this evidence with data from the 2019 Survey of Consumer Finances (SCF). Despite not being a panel, the SCF allows us to show how robust the relationship between assets/debt and earnings is, as the assets/debt information in the SCF is quite detailed. Conditional on several controls, the positive relationship between earnings and net worth is robust. These reduced-form results, especially those from the SIPP — a high-frequency panel particularly well suited to study unemployment — are a contribution in themselves. They complement recent evidence by Herkenhoff et al. (2023) who relate access to credit to unemployment dynamics. Focusing only on displaced workers, and not on all unemployed workers, that paper finds more access to credit during unemployment increases unemployment duration. While this result appears to be at odds with our premise, it is actually consistent. Available credit acts as an asset that allows workers better consumption smoothing while unemployed. We show that being in debt is correlated with lower unemployment duration, and this is particularly true for credit card debt, and to some extent with mortgage debt. However, we are silent about how that debt level affects the availability of credit while unemployed. Our empirical results also complement evidence shown in Bloemen and Stancanelli (2001) who employing a Dutch survey on reservation wages and wealth, find that financial wealth increases reservation wages.[1]

We calibrate the model to the US economy as described by the SIPP during the years 2017 through 2019. These years were characterized by low real interest rates, a low labor's share, high household indebtedness, and high earnings inequality. Taking the real interest rate observed in the data as exogenous (set at 0.18% monthly), we set the model's parameters so that the model describes the US economy in 2018 accurately in regards to debt to income ratios, earnings inequality, and unemployment insurance policies. With the model's structural parameters in hand we validate the model using reduced form relationships between unemployment duration, households' balance sheets, and post-unemployment wages. As in the data, the model predicts a negative relationship between unemployment duration and debt, as well as a positive relationship between duration and post employment wages. Our counterfactual exercise is to set the real interest rate to the level to the year 1982 (about 0.5% monthly). We compare this economy with the one in the years 2017-2019: relative to the low interest rate economy the unemployment rate rises slightly (about 0.3 percentage points), wages relative to productivity (the labor's share) rises about 6 percentage points. The higher interest rate economy features substantially less earnings inequality; the variance of log earnings drops from 0.75 to 0.66. In the model, the skill premium — the average wages of workers with a college degree relative to workers with only a high school diploma — rises from 1.39 in 1982 to 1.55 in 2018. These

[1] The effect of homeownership, but not on mortgage debt, on post-employment wages has been examined empirically by Yang (2019).

results suggest that both the rise in the skill premium and the fall in labor's share, apart from origins that are technological in nature, have been caused in part by the interplay of frictional labor markets, the rise in debt, and the partial insurance of unemployment risk.

The downward trend in labor's share — the fraction of economic output that accrues to workers — represents an important structural shift in the economy with potentially broad economic implications for labor productivity, income growth, and household inequality. As such, the decline of the labor share has attracted significant attention and has been written about extensively. Some possible reasons for the drop range from the effects of globalization and technological changes to debilitated worker unions. In this paper, we argue that the rise in U.S. household debt over that period has also been a factor contributing to the decline in the labor share. Similarly, there is a vast literature that examines the rise in earnings inequality and its relationship to job polarization or capital-skill complementarity, for example. This paper proposes an alternative channel, in which earnings dispersion grew over time due to increasing household indebtedness. The dispersion in financial wealth, and in particular the increase in the number of households with rising levels of debt, generates dispersion in reservation wages, and hence in actual wages.

Our work highlights the critical role that the decline in real interest rates has played in shaping several well-documented trends over the past four decades: the decrease in household saving rates and the corresponding rise in debt, the increase in earnings inequality, and the decline in labor's share of income. These developments have been central to three major areas of research at the intersection of wealth and labor market dynamics—areas to which our work contributes.

The first area concerns the relationship between wealth and labor market behavior. A growing body of research examines how the ability to save—and the constraints imposed by limited borrowing capacity—affects employment outcomes, wage dynamics, and inequality. These models often emphasize how labor market risks and frictions interact with wealth accumulation, showing that factors such as on-the-job search, unemployment spells, and restricted access to credit can lead to substantial disparities in individual outcomes. While we build on many of the mechanisms developed in this literature, our focus shifts toward understanding broader macroeconomic trends—specifically, how changes in the real interest rate alone can influence labor market inequality and the distribution of income.

A second relevant area of research explores the causes behind the long-run decline in labor's share of income. Much of this literature emphasizes shifts in the balance of power between firms and workers, driven by structural changes such as globalization, automation, the erosion of unions, and increasing market concentration. However, the precise mechanisms remain contested. We contribute to this literature by proposing a novel explanation that emphasizes the interplay between labor market search frictions and household wealth.

Finally, our work contributes to a third strand of literature focused on the rise in earnings inequality. One prominent explanation points to the shifting demand for skills, particularly the increasing complementarity between capital and high-skilled labor relative to other workers. The weakening of unions, the decline in the real value of the minimum wage, and broader deregulation have all contributed to slower wage growth for many. Global economic integration has further amplified these effects by exposing some jobs to international competition, while disproportionately benefiting others that are either shielded or in high global demand.

We bring together these areas of research to explore the following question: how might a standard search model of the labor market, embedded with uninsurable risk and allowing for precautionary savings, account for changes in both labor's income share and wage inequality in response to a decline in real interest rates?[2]

The remainder of the paper is organized as follows. First, we present empirical evidence showing that between 1982 and 2019, the labor share decreased while household debt increased. The third section introduces a mechanism that offers a plausible explanation for

[2]We include a more comprehensive literature review in Appendix A.

this decline and proposes a model capable of capturing the relevant dynamics. Section four outlines the model's calibration, followed by Section five, which conducts an extensive set of validation tests. Section six presents the results of our main counterfactual analysis, comparing two economies within our framework: one with high interest rates and another with relatively lower rates. Finally, Section seven concludes with key findings and implications.

2 Data

The study's principal focus lies with the interaction of the dynamics of the labor share, earnings inequality and household debt. Figure 1 plots the labor share as calculated by the U.S. Bureau of Labor Statistics suggesting this downward trend was relatively mild and steady until the early 2000s and has become significantly more pronounced since then. The steepest part of the decline -from 63 percent in 2000 to approximately 57 percent in 2018- followed a moderate downward drift in the 1980s and early 1990s, and a slight recovery in the late 1990s.

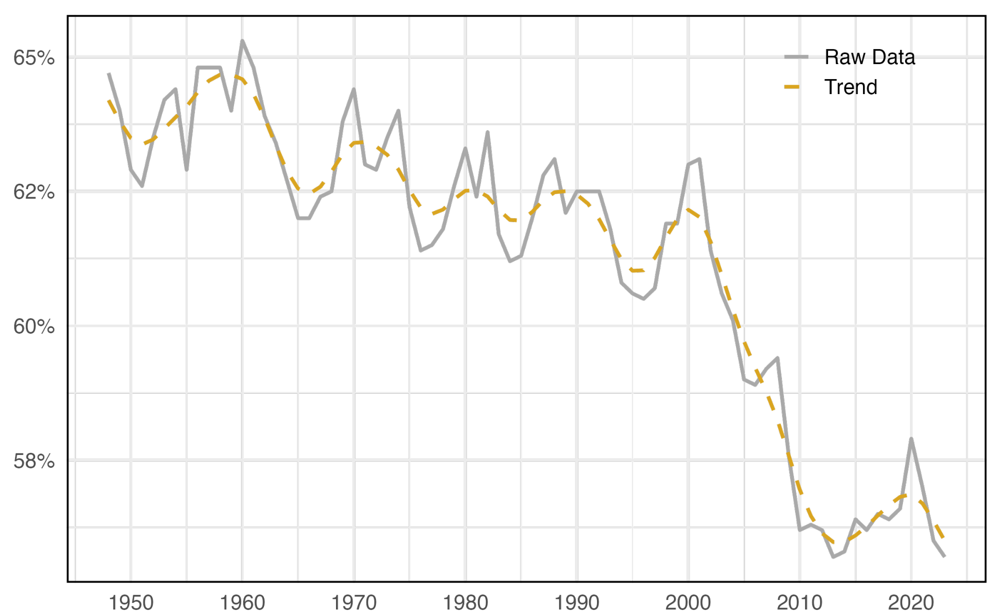

Figure 1: U.S. Labor Share 1947-2023

Figure 2 presents various measures of U.S. household indebtedness in the postwar period. Driven by periods of low interest rates and financial innovations—such as credit cards and home equity loans—U.S. households have steadily increased their leverage since the end of World War II[3]. While overall household debt as a share of GDP has risen consistently, mortgage and nonmortgage debt have followed distinct trajectories. Mortgage debt has shown a steady increase since the 1980s, with rapid acceleration in the early 2000s, culminating in a sharp peak around the 2008 financial crisis. This was followed by a marked decline, reflecting deleveraging in the housing market, before stabilizing and experiencing minor fluctuations in the 2010s and early 2020s. In contrast, nonmortgage debt has followed a more gradual upward trend, characterized by periods of steady, moderate growth. While it has not exhibited the extreme volatility of mortgage debt, it has grown consistently, peaking in the early 2020s before declining slightly. Overall, considering that household indebtedness increased while the labor share declined over the same period, this trend raises important questions about how household net worth influences the distribution of economic output between workers and other economic agents.

Finally, Figure 3 presents a measure of the skill premium, defined as the relative wage of skilled versus unskilled workers from 1963 to 2019. We use data from the U.S. Census Current Population Survey (CPS) and follow the methodology outlined by Ohanian et al. (2023). The figure shows that after an initial decline in the late 1970s to early 1980s, the skill premium has followed a strong and sustained upward trajectory, particularly from the mid-1980s onward, with some fluctuations around the early 2000s. By the end of the period, the ratio reaches its highest level, indicating a persistent and widening wage gap between skilled and unskilled workers and an overall increase in earnings inequality over time.

[3] Further empirical details and disaggregated series can be found in Appendix E.

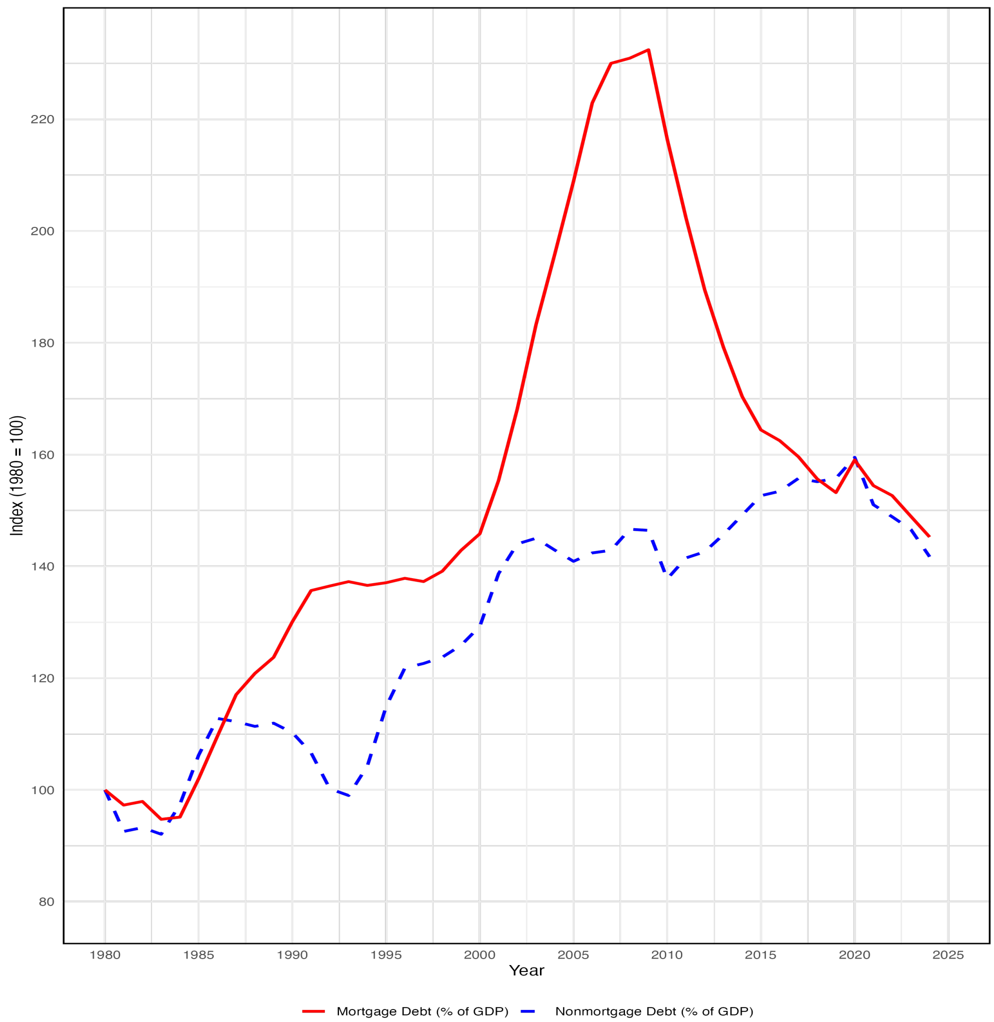

Figure 2: Household Debt (1980-2024)

2.1 Financial Wealth and Wages: Measurement

Our hypothesis about these macroeconomic aggregates centers on three key household- or individual-level variables: net worth (debt), unemployment duration, and earnings. To explain the decline in the labor share, we posit that lower asset levels (or higher debt) resulting from reduced interest rates influence reservation wages, leading to shorter periods of unemployment. We analyze individual and household-level data from two major surveys: the Survey of Consumer Finances (SCF) and the Survey of Income and Program Participation (SIPP) to investigate the behavior of these variables.

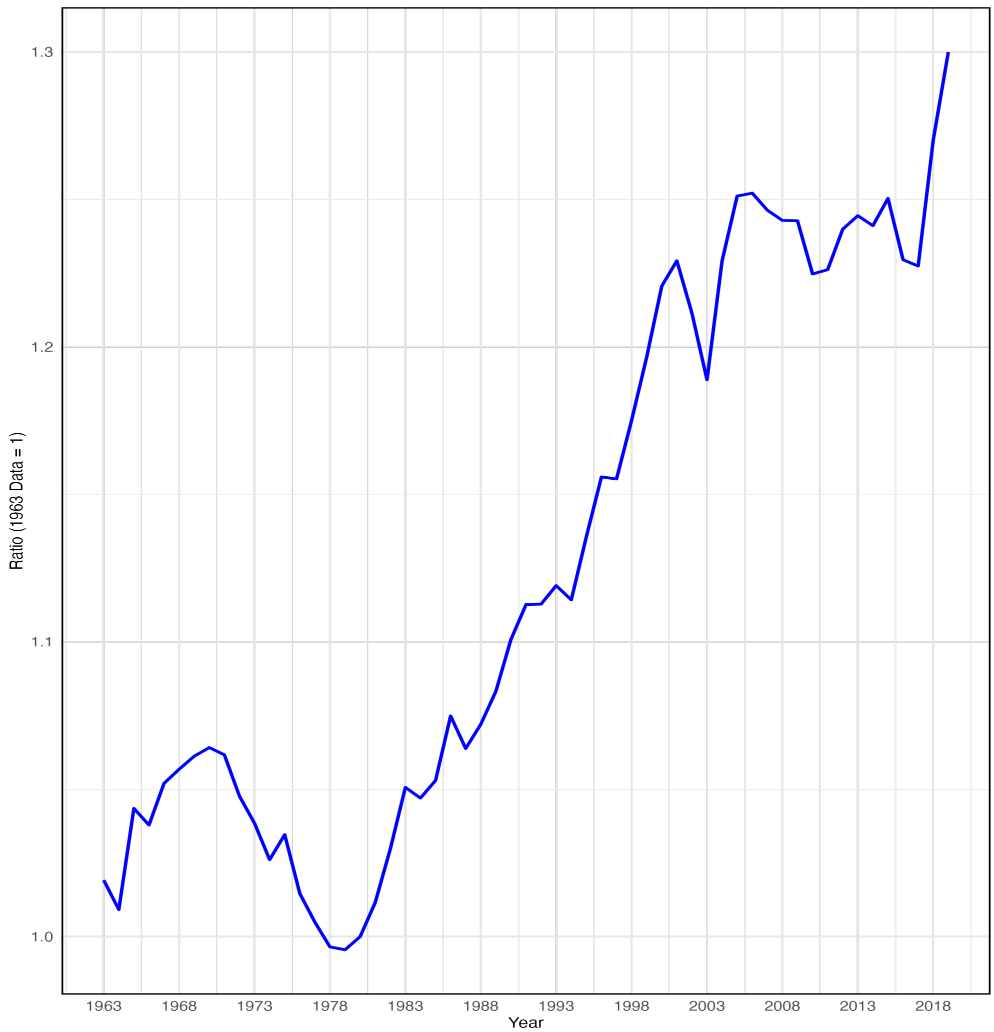

Figure 3: Skill Premium (Skilled vs. Unskilled)

Each survey offers distinct advantages. The SCF provides high-quality asset data but lacks information on unemployment duration. We therefore use the SCF to explore the relationship between earnings (or wages) and measures of net worth, debt, or asset-to-income ratios. The SIPP, while less detailed in its asset data, offers panel-based, high-frequency data that includes information on unemployment duration. This allows us to examine the connections between asset positions, earnings, and unemployment dynamics. Our analysis employs a reduced-form approach, acknowledging that no causality can be inferred from the estimated regressions.

We employ the 2019 Survey of Consumer Finances public release to study the relationship between a household's net worth and wages. We utilize a sample of 128,600 represented households who were employed that year and made at least $30,160 in yearly wages; that number is the amount a household earning a full-time minimum wage would receive[4].

Table 1 highlights the 2019 SCF public release's mean and median net worth across various household characteristics. Cross-sectional differences in net worth across groups abound. For instance, families where the reference person held a college degree had more than twice the median net worth compared to the overall sample. Additionally, disparities in net worth across different groups generally reflect similar patterns seen in income, with those in the highest income percentiles possessing a net worth more than ten times greater than the median. Finally, as individuals save for retirement throughout their working years, a life-cycle pattern in net worth becomes evident in the data.

Table 2 compares the mean net worth across different family characteristics for the 2019 SCF public release with those families that the study focuses on: those that were employed and earned at least the minimum income. While the general patterns seen in the full sample appears to carry on, the net worth of the older age groups seems to be substantially higher. This could reflect a higher concentration of high earners that have postponed retirement in our sample, given that our survey design requires the reference person to be employed at the time of the survey.

[4]This is meant to represent a household of two people, working 2,080 hours a year, making at least $7.25 per hour. To avoid risk-sharing considerations one could also focus exclusively on single workers and/or unmarried couples. Although results are robust to this survey design, the number of observations drops significantly and we chose to perform our analysis with the full original sample. See appendix Appendix B for the relevant sample comparison.

Table 1: 2019 SCF: Households' Median and Mean Net Worth by Selected Characteristics (Values in Thousands of Dollars)

Characteristic	Median Net Worth	Mean Net Worth
All Households	141	866
Income Percentile		
$\leq$ 20	11	131
20 - 39.9	53	159
40 - 59.9	106	253
60 - 79.9	232	489
80 - 89.9	437	996
90 - 100	1,849	5,596
Education of Reference Person		
No High School Diploma	24	160
High School Diploma	86	353
Some College	104	434
College Degree	358	1,758
Race/Ethnicity of Reference Person		
White Non-Hispanic	210	1,103
African American Non-Hispanic	24	162
Hispanic or Latino	42	223
Asian	—	—
Age of Reference Person (Years)		
$\leq$ 35	16	89
35 - 44	106	508
45 - 54	196	967
55 - 64	246	1,364
65 - 74	309	1,410
$\geq$ 75	294	1,110

Table 2: 2019 SCF Sample: Households' Mean Net Worth by Selected Characteristics (Values in Thousands of Dollars)

Characteristic	Sample	SCF
All Households	891	866
Education of Reference Person		
No High School Diploma	207	160
High School Diploma	353	353
Some College	384	434
College Degree	1,608	1,758
Race/Ethnicity of Reference Person		
White Non-Hispanic	1,112	1,103
African American Non-Hispanic	193	162
Hispanic or Latino	270	223
Asian	—	—
Age of Reference Person (Years)		
≤ 35	116	89
35 - 44	591	508
45 - 54	1,039	967
55 - 64	1,518	1,364
65 - 74	2,898	1,410
≥ 75	3,917	1,110

To better understand the relationship between reservation wages and net worth, wages were regressed on net worth and a series of co-variates: race, education level, sex, age, and number of children. Regression results are shown in Table 3. In the top row, wages are regressed on net worth (and the other co-variates.). The number shown is the coefficient on net worth, with the standard error in parenthesis. The data suggests that raising the net worth of an individual by $1,000 is associated with raising their annual wages by $6. For people with negative net worth, having a lower (more negative) net worth is actually associated with lower wages. In the bottom row, log wages are regressed on the log of positive net worth and debt (and other co-variates). Again, the number shown is the coefficient on (log) net worth, with the standard error in parenthesis. Our findings suggest that a 1% increase in an individual's net worth is associated with a 0.17% increase in their annual wages.

Table 3: Coefficient on Net Worth (NW)

Variable	**All Data**	**Non-Neg NW**	**Neg. NW**
Levels	0.0062*** (0.002)	0.0063*** (0.0022)	-0.029 (0.022)
Logs	n.a.	0.173*** (0.010)	-0.032** (0.015)
Sample Size (N)	3,208	2,918	288
Significance: *** at 1%, ** at 5%, * at 10%			

Note: The table shows results when wages are regressed on net worth, using data from the 2019 Survey of Consumer Finances. Other covariates include race, education level, sex, age, and the number of children. Net worth is defined as assets (including nonliquid assets) minus liabilities. The Appendix C reports coefficients for all the other independent variables.

We further assess the robustness of these findings by employing an alternative definition of net worth, focusing exclusively on liquid assets and debts. Operating under the assumption that access to liquid resources may be crucial for labor market outcomes, we exclude housing components from our original net worth measure and re-run the regressions. The results appear to reaffirm the baseline specification in terms of signs and significance. Specifically, under a liquid net worth specification, a 1 percent rise in households' net worth continues to be associated with an approximate 0.17 percent rise in annual wages.

Table 4: Coefficient on Liquid Net Worth (NWL)

Variable	All Data	Non-Neg NW	Neg. NW
Levels	0.0063*** (0.002)	0.0061*** (0.002)	-0.0015 (0.017)
Logs	n.a.	0.171*** (0.009)	-0.020* (0.012)
Sample Size (N)	3,208	2,884	382
Significance: *** at 1%, ** at 5%, * at 10%			

Note: The table shows results when wages are regressed on liquid net worth, using data from the 2019 Survey of Consumer Finances. Other covariates include race, education level, sex, age, and the number of children. Liquid net worth is defined as assets minus liabilities and the total equity value in a household's primary residence. The Appendix C reports coefficients for all the other independent variables.

2.2 Net Worth and Unemployment: Evidence from SIPP

The Survey of Income and Program Participation (SIPP) is a longitudinal survey conducted by the U.S. Census Bureau to collect data on the income, employment, and program participation of individuals and households in the United States. The SIPP has recently changed, providing a continuous panel in which households are interviewed for four years. We use the 2017-2019 data, providing information on sources of income, including wages, business income, and government assistance programs. Wealth data is collected once per year. Employment data includes information on job transitions, offering a picture of the labor market dynamics during this period. We employ information collected in the surveys of 2018, 2019, and 2020, so the maximum we observe individuals is for 36 months.[5]

We begin by restricting workers to those older than 20 and younger than 60. We also calculate an average level of earnings over each workers' entire history. If that average is zero or missing, we eliminate that worker from the sample. For each worker, we

[5]We do not use the 2021 survey because it collects information about 2020 outcomes. The recession associated with the COVID-19 pandemic was so extreme and extraordinary that we discarded the 2021 survey.

calculate the duration of each unemployment spell (most workers only experience one unemployment spell over the entire three-year period). The empirical analysis will be based on a sample of 4,150 unemployment spells. For each unemployment spell we record the worker's age at that time, financial variables, marital status, etc. Table 5 summarizes the variables employed in the analysis, showing the average, standard deviation, minimum, and maximum. The average unemployment duration is almost four months long, and there are long-term unemployed in the sample with a maximum observed duration of 30 months. The average age of workers is about 36 and 60% of them are older than 30. About 40% are college-educated and 20% are black. About half are never married, and they are earning, on average, roughly $3,600 dollars per month.

We report six variables describing workers' balance sheets. These variables are all at the individual level and not at the household level. As is well known, the distribution of wealth is disperse but less so in the SIPP since it oversamples low income households. The highest net worth is only $7.6 million and the lowest level is a negative wealth of -$750,000. The average net worth is close to $70,000, and of that amount, roughly $3,000 are in checking accounts and about $5,500 in savings accounts. The average amount of unsecured debt is $13,500 of which $1,800 is credit card debt. The average mortgage debt is close to $25,000.

We link unemployment duration with earnings (or wages) and financial variables through linear regressions. We measure financial variables (e.g., debt) with either a dummy variable for positive levels or the ratio of the financial variable to a worker's average earnings. All regressions we show below have duration as the dependent variable. In addition to variables representing debt, assets, or labor market compensation, regressions control for a year dummy, a dummy for race, marital status, and gender, a dummy for receiving unemployment compensation, and a college dummy.

Table 6 shows the coefficients of regressions where the financial variable is some level of debt. We focus on all unsecured debt, credit card debt, and mortgage debt. We measure

Table 5: Summary Statistics

Variable	Mean	SD	Max	Min
Age	36.2	11.0	59.0	21.0
Fraction >30 y.o.	0.6	0.5	1.0	0.0
Race	0.2	0.4	1.0	0.0
College	0.4	0.5	1.0	0.0
Marital	0.5	0.5	1.0	0.0
Net Worth	69,396	322,234	7,611,900	-746,350
Unsec. Debt	13,538	44,567	746,750	0.0
Credit Card Debt	1,814	5,537	59,900	0.0
Mortgage Debt	24,618	76,915	1,210,000	0.0
Checking Acc.	3,028	12,298	202,000	0.0
Savings Acc.	5,516	23,387	327,000	0.0
Unemp. Duration	3.9	3.4	30.0	1.0
Earnings	3,664	3,963	70,150	1,001

each variable by either an indicator variable that takes the value of one when the worker holds any positive level of debt or the ratio of the debt balance relative to the worker's average earnings.[6] The coefficients are negative for all six debt variables, implying that a higher level of debt relative to earnings (or a positive level of debt relative to no debt) is associated to a shorter unemployment duration. The mortgage-to-earnings ratio is not significant, although the unsecured debt dummy is very close to significant at the 10% level. Overall, it appears that credit card debt is strongly and negatively associated with unemployment duration. From the perspective of the theoretical model we describe below, the ability to borrow to finance consumption while unemployed is an important determinant of the duration of unemployment.

Table 7 presents the corresponding coefficients when we replace the variable for debt with a variable for assets. We focus on three measures of wealth: net worth (total assets minus total debts), checking account balances, and savings account balances. Similar to our approach with debt, we measure assets or wealth using either an indicator variable for

[6]The reason to examine the debt to earnings ratio, as opposed to the debt level, is to dampen the potential effect that unobserved characteristics have on duration. These unobserved characteristics can affect duration beyond the effect captured by the measure of formal education or marital status.

Table 6: Regression: Unemployment Duration on Debt

Variable	Ind. Unsecured > 0	Unsecured Ratio	Ind. Credit Card > 0	Credit Card Ratio	Ind. Mort. > 0	Mort. Ratio
Coefficient	-0.25	-0.01**	-0.43***	-0.09***	-0.39**	-0.01
P-value	*(0.11)*	*(0.03)*	*(0.01)*	*(0.01)*	*(0.03)*	*(0.33)*
R-squared	0.03	0.03	0.03	0.03	0.03	0.03

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All models regress unemployment duration on the same set of explanatory variables except for one variable, which represents a type of debt. We consider all unsecured debt, credit card, and mortgage debt. For each type of debt, we represent it as either an indicator variable for positive debt level (e.g., Ind. CC > 0 takes the value 1 if the individual has credit card debt, and zero otherwise) or as the ratio between debt and the individual's average earnings over her entire sample. The Appendix D reports coefficients for all the other independent variables (see main text for the list of variables).

positive balances or the ratio of asset/wealth levels to earnings.

Most coefficients related to assets or wealth are close to zero, with some being positive and others negative. However, the estimates exhibit a high degree of uncertainty, as reflected in the large p-values. The only exception is the indicator for having a positive savings account balance, which is associated with a longer unemployment duration (a coefficient of 0.57, significant at the 5% level). Overall, these results suggest that the level of debt has a much stronger relationship with unemployment duration than the level of assets.

Table 8 shows the relationship between unemployment duration and subsequent earnings or wages post-unemployment spells. We use both wages and earnings as our model below does not distinguish between the two. For these regressions, we use the same set of controls as for the regressions linking duration and financial assets/debt. The coefficient is significant for both earnings and earnings per hour, showing that longer duration is associated with higher earnings post-unemployment.

In summary, the empirical results shown in this section are suggestive of a close link between households' financial assets/debts, their unemployment duration and the wages they obtain post-unemployment. Clearly, these are suggestive associations and selection

Table 7: Regression: Unemployment Duration on Assets

Variable	Ind. Net Worth > 0	Net Worth Ratio	Ind. Checking > 0	Checking Ratio	Ind Saving > 0	Saving Ratio
Coefficient	0.12	-0.00	0.05	-0.03	0.57*	-0.02
P-value	*(0.50)*	*(0.19)*	*(0.89)*	*(0.31)*	*(0.05)*	*(0.37)*
R-squared	0.03	0.03	0.04	0.04	0.18	0.17

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All models regress unemployment duration on the same set of explanatory variables except for one variable, which represents net worth or assets. We consider all net worth, checking and savings accounts. For each asset we represent it as either as an indicator variable for positive asset balance or net worth (e.g. Ind. CC > 0 takes the value 1 if the individual has a positive checking account balance, and zero otherwise) or as the ratio between net worth or assets and the individual's average earnings over her entire sample. The Appendix D reports coefficients for all the other independent variables (see main text for the list of variables).

Table 8: Regression: Unemployment Duration on Earnings

Variable	Earnings	Earnings Per Hour
Coefficient	0.36**	2.83***
P-value	*(0.04)*	*(0.00)*
R-squared	0.18	0.84

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The table reports two regressions of unemployment duration on earnings (first column) and earnings per hour (second column) in addition to all other variables also used in the debt and asset regressions. Earnings or wages are measured as the first earnings (or wage) level observed after an unemployment spell. The Appendix D reports coefficients for all the other independent variables (see main text for the list of variables).

and other issues prevent any causal analysis from an increase in debt to unemployment duration and earnings. The goal of the structural model presented below is precisely to quantify a causal channel from a drop in interest rates to higher debt to lower wages and higher earnings inequality.

3 Model

Our quantitative analysis is based on a model in which risk-averse workers receive wage offers drawn from a distribution and decide whether to accept or reject them. These decisions depend on their financial position, causing acceptance rates—and consequently, job-finding rates—to vary with asset holdings. Workers can save or borrow in a risk-free asset, and the labor market is assumed to be frictional rather than perfectly competitive, where workers would otherwise be paid their marginal product. These frictions naturally give rise to heterogeneity in unemployment durations and labor market outcomes.

We do not explicitly model the origin of the wage-offer distribution that workers face. In other words, we do not specify why firms set the wages they do. Instead, our focus is on how accepted offers—and consequently, observed wages—respond to changes in interest rates through their impact on asset holdings. We posit that the level of wage offers is linked to the output of a firm employing a worker. Consequently, if aggregate productivity in the economy changes, we would expect the wage offer distribution to adjust accordingly. One possible interpretation of our exogenous wage distribution is that it arises from a Burdett and Mortensen (1998) or Postel-Vinay and Robin (2002) framework, in which firms balance offering lower wages with lower acceptance probabilities against higher wages with higher acceptance probabilities.

The labor share is defined as the ratio of average wages to a given productivity level, A.[7] To isolate the effects of interest rate changes on the distribution of actual wages, we hold A constant across the two periods we compare. Specifically, after calibrating the model for 2019, we exogenously reset the interest rate to its 1982 level while allowing all other model variables to adjust endogenously. This approach enables us to identify the impact of higher leverage on the model's endogenous variables. Since productivity is exogenous and we abstract from capital, assuming that productivity does not change between 1982

[7] In the calibration below, we set A so that average wages relative to productivity match the labor share observed in 1982.

and 2019 is without loss of generality[8].

A few potentially important dimensions are abstracted from. First, we exclude capital to focus on the labor market; a lower labor share here simply means a lower wage relative to labor productivity. In a setting with capital, higher capital demand would increase labor productivity. Second, we do not model how firm entry responds to changes in interest rates. Incorporating entry would require modeling the firm's decision on the optimal posted wage. Here, our emphasis is on workers' behavior and the way asset holdings affect their compensation. Third, the model does not account for on-the-job search; in other words, agents in the model do not seek alternative opportunities once they become employed. The model's setup and timing are discussed next.

3.1 Setup and timing

Time is discrete, and there is a unit mass of infinitely-lived agents indexed from zero to one. There is a single consumption good whose price is always 1. During time period s, agent i has the following utility function:

$$V_{iT} = \mathbb{E}_s \sum_{t=s}^{\infty} \beta^t u(c_{it})$$

where:

$$u(c) = \begin{cases} \frac{c^{1-\gamma}-1}{1-\gamma} & \gamma \neq 1 \\ \log(c) & \gamma = 1 \end{cases}$$

and γ is exogenous.

In the model, agents are heterogeneous along several dimensions. Crucial to our

[8]We are interested in measuring wages relative to productivity (the labor share), and if we allow productivity to change exogenously, the firm offer distribution and the distribution of accepted wages will change as well. However, the distribution of accepted wages relative to productivity will not. This exercise allows us to isolate changes in the endogenous variables that arise solely from changes in interest rates.

analysis are those aspects that might influence the labor supply decision. Because agents' unemployment experiences and savings rates vary significantly, we posit that there are ex-ante factors (not modeled in our framework) that lead them to have different employment-to-unemployment separation probabilities, discount factor, access to debt, and other key parameters discussed below. To keep this ex-ante heterogeneity manageable, we classify agents into three distinct groups based on education levels.

Agents are initially differentiated by their employment status: they can either be employed or searching for a job. Employed agents are further differentiated by their wage level w_{it}. Agents begin each period with a wealth a_{it} and receive interest income equal to $a_{it}r$, where $r > 0$ is the exogenous interest rate (if a_{it} is negative, then the agent instead makes an interest payment; that is, wealth is decreased by $a_{it}r$). Agents also receive an earnings payment e_{it}, which includes both wages and unemployment payments. If employed, the earnings payment is wage w_{it}; if unemployed the payment is exogenous $b_j(n)$, where j denotes an agent's skill level, and n denotes unemployment duration. That is to say, in the model, unemployment insurance increases with the agent's productivity, but benefits are only provided for a fixed number of periods. All resources gathered by agents, whether from wages or unemployment payments, can then be used for consumption or wealth accumulation purposes and will influence labor outcomes as described in section 3.2.

Due to the risk of unemployment that agents face every period, they will seek to self-insure against this eventuality. They can do so by accumulating assets via savings, or by borrowing against their future earnings. An agent's wealth level can become negative but can never fall below the exogenous limit, $\underline{a}_j < 0$. During any particular period, an agent simultaneously chooses an amount to consume c_{it} and next-period wealth $a_{i,t+1}$, such that, for an agent of skill level j the budget constraint is:

$$\begin{aligned} c_{it} + a_{i,t+1} &\leq a_{it}(1+r) + e_{it} \\ a_{i,t+1} &\geq \underline{a}_j \\ c_{it} &\geq 0 \end{aligned}$$

Once the consumption-savings decision is made, the agent's employment status for the next period is determined. From an agent's point of view, both the job-separation probability δ_j, and the wage-offer distribution $f_j(w^o)$ are exogenous. At this point, there are two possibilities for employed agents: with probability δ_j the agent will be unemployed next period, and with probability $1 - \delta_j$ the agent will continue to be employed at the same wage, $w_{it} = w_{i,t+1}$. An employed agent never experiences a raise or salary cut, although agents who go from employment to unemployment and are subsequently rehired may experience a change in their wage.

Unemployed agents, on the other hand, receive a new wage offer, w^o_{it}, every period they are unemployed. Each offer is drawn from an exogenous wage distribution specific to the agent's type. With probability $1 - \rho$ each period the agent is able to choose whether to accept or reject the offer. If the offer is accepted, the agent will be employed at a wage $w_{i,t+1} = w^o_{it}$ next period. If rejected, the agents keep searching and will continue to be unemployed in period $t+1$. Finally, with probability ρ the agent has to exogenously accept the job offered. This feature of the model is designed to capture, in a reduced form, the stigma that can be associated with long unemployment spells and why some workers might prefer to accept a less-than-ideal job offer. Furthermore, consistent with the data we assume that this reputation concern is more relevant for medium and high-skilled workers[9]. Table 9 below summarizes the model's timing.

[9]Research on the stigma associated with unemployment duration highlights its significant impact on labor market outcomes. Kroft et al. (2013) found that the likelihood of receiving job callbacks declines substantially with longer periods of unemployment, emphasizing the stigma effect. Similarly, Eriksson and Rooth (2014) demonstrated that employers often perceive long-term unemployed individuals as less motivated, even

Summary of Timing

State in Period t	Unemployed with wealth a_{it} and duration n	Employed with wealth a_{it} and wage w_{it}
First Action	Choose c_{it} and $a_{i,t+1}$ s.t. $c_{it} + a_{i,t+1} \leq a_{it}(1+r) + b(n)$ and $a_{i,t+1} \geq \underline{a}$ and $c_{it} \geq 0$	Choose c_{it} and $a_{i,t+1}$ s.t. $c_{it} + a_{i,t+1} \leq a_{it}(1+r) + w_{it}$ and $a_{i,t+1} \geq \underline{a}$ and $c_{it} \geq 0$
Transition Probabilities	Job offer. Probability ρ that agent is forced to accept.	Probability δ that agent is separated from job
Second Action	If not forced, accept or reject job offer	N.A.
State in Period $t+1$	Wealth is $a_{i,t+1}$. If offer accepted, employed with wage $w_{i,t+1} = w^o_{i,t}$. If rejected, unemployed.	Wealth is $a_{i,t+1}$. If separated from job, unemployed. Otherwise, employed at wage $w_{i,t+1} = w_{it}$

Table 9: This table summarizes the timing of actions taken by employed and unemployed workers. The right column shows actions for the employed and the resulting changes in the relevant variables. The left column shows the same for the unemployed workers.

3.2 The Household Problem

An employed agent with wealth a and wage w solves the following recursive problem[10]:

when their qualifications are identical to other candidates. Blanchard and Diamond (1994) linked long-term unemployment to hysteresis in labor markets, showing how it perpetuates stigma and creates persistent joblessness. Supporting these findings, Ghayad (2014) used field experiments to reveal that unemployment duration is a more critical factor for employers than gaps in experience, further illustrating how prolonged unemployment can disadvantage job seekers.

[10]For easier readability, time and skill subscripts have been eliminated in this section. In turn, if a variable carries a $t+1$ subscript, this has been replaced by an apostrophe (thus, $a_{i,t+1}$ has been replaced with a').

$$
\begin{aligned}
E(a, w) &= \max_{c,a'}\{u(c) + \beta(\delta U(a', 0) + (1 - \delta)E(a', w))\} \qquad (3.1)\\
\text{s.t.:} \quad a(1 + r) + w &\geq c + a'\\
a' &\geq \underline{a}\\
c &\geq 0
\end{aligned}
$$

When deciding how much to consume and how much to save, an unemployed agent with wealth a, and who has been unemployed for n periods, faces the following optimization:

$$
\begin{aligned}
U(a, n) &= \max_{c,a'}\{u(c) + \beta((1 - \rho)\mathbb{E}_{w^o} V(a', w^o, n + 1) + \rho\mathbb{E}_{w^o}(a', w^o))\} \qquad (3.2)\\
\text{s.t.:} \quad a(1 + r) + b &\geq c + a'\\
a' &\geq \underline{a}\\
c &\geq 0
\end{aligned}
$$

When deciding whether to accept or reject a job offer w^o, an unemployed agent with wealth a solves this problem:

$$V(a, w^o, n) = \max(E(a, w^o), U(a, n)) \qquad (3.3)$$

It follows that for each level of wealth a, a wage offer w will be accepted if and only if $E(a, w) \geq U(a)$. Since E is increasing in w and U is not dependent on w, it follows that for each a there is some value $w^*(a)$ at which $E(a, w) \geq U(a)$ if and only if $w \geq w^*(a)$. This value is the reservation wage and can be defined as:

$$w^*(a) = \{w : V(a, w) = E(a, w) = U(a, n)\} \qquad (3.4)$$

As a function of assets a the reservation wage function $w(a, n)$ for general duration n is concave, as shown in Figure 4

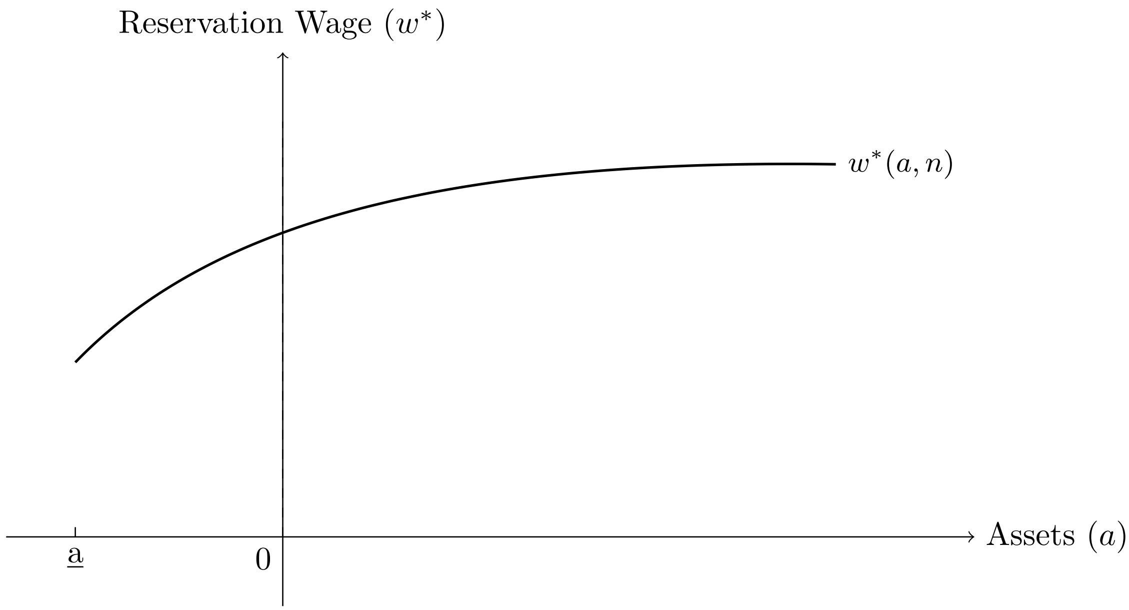

Figure 4: The figure shows the reservation wage as a function of wealth a for a general level of duration n. For large enough unemployment benefits the reservation wage is positive even at the borrowing constraint.

3.3 Steady-State Equilibrium

The model's stationary equilibrium is determined by individuals' optimal decisions over job acceptance and asset accumulation when facing an exogenous interest rate and a distribution of wage offers. Each unemployed agent weighs the value of remaining unemployed (with its associated benefits and savings possibilities) against the value of accepting a particular wage offer, which depends on current assets. Once employed at a given wage, agents choose consumption and savings in response to the wage income and an exogenously given borrowing limit, potentially accumulating assets over time.

Given these policy rules, the economy's distribution of assets and wages evolves each period according to a transition function that accounts for stochastic job offers, employment transitions (including job separation), and individual savings decisions. A stationary equilibrium emerges when the cross-sectional distribution of agents over employment status, wages, and asset holdings no longer change. In partial equilibrium, the interest rate and the wage offer distribution are fixed, so the resulting invariant distribution characterizes how many agents hold different levels of assets and accept different wages in the long run.

4 Calibration

The model is calibrated to match moments corresponding to the United States economy during the years 2017-2019.[11] The model period is set equal to one month, and we assume that the per-period utility function is of the constant relative risk aversion class. We set the coefficient of relative risk aversion, γ, at 2.5, in line with the literature. Since in the data, there are large differences in employment outcomes by education levels (as well as differences in savings behavior), we map the ex-ante skill level in the model to educational attainment in the data. We group workers into three categories defined by their education. The first group (low-skill) consists of individuals with a high school diploma or less. The second group (medium skill) includes those who have earned a bachelor's degree or who have some college (e.g. an associate's degree). The highest-skilled group, (labeled high skill), comprises individuals with a master's degree, doctorate, or other forms of postgraduate education.

The annual nominal interest rate in 2018 was about 4.4%, and the year-over-year inflation rate was roughly 2.2%, so we set the real interest rate to 2.2% annually, which implies a 0.18% monthly.[12]. The employment separation rate δ is taken directly from SIPP data, as the likelihood of transitioning from employment to unemployment. The employment separation rates at the monthly frequency for the low-skill, medium-skill, and high-skilled workers are 1.22%, 0.85%, and 0.469%, respectively. Finally, we set the probabilities of a mandatory acceptance of an offer to small numbers: 1% for the low-skill group, and 3% for

[11] The reason to calibrate the model economy to the recent past (as opposed to calibrating it to the early eighties) is due to the quality of the microdata. The SIPP in 2017—2019 is of higher quality than that of the early eighties.

[12] Specifically as $(1 + 0.022)^{1/12} - 1 = 0.0018$

the middle and high-skill groups.

The remaining parameters are calibrated so that the model replicates certain features of the US economy in 2018. To calibrate the unemployment benefits b as a function of duration, we look at different state-level policies. These set a maximum duration of unemployment benefits. A benefit that expires after an unemployment duration of 4 months appears to be a good approximation to actual unemployment benefits policies. We therefore set the following policy:

$$b_j(n) = \begin{cases} b_j(n) = b_j & if \quad n \leq 4 \\ b_j(n) = 0 & if \quad n > 4 \end{cases} \tag{4.1}$$

To calibrate the baseline benefits b_j we target the average unemployment payment relative to average earnings by skill level. In other words, 24%, 19%, and 15% for low, middle, and high skill respectively. Note that in the data the unemployment benefit can be zero if there is no take-up or if the unemployment spell is long enough and benefits have been exhausted. Therefore, in the data, during periods in which workers receive unemployment benefits the replacement rate is larger than the calibrated shares.

The exogenous wage offer distribution $f(w)$ is assumed to be log-normal, with normalized mean in levels equal to 1 (for the low-skill group) and standard deviation σ_j. The mean μ_j for the medium and high-skill groups are calibrated so that the average wages for these two groups relative to the average wage of the first group match the analogous relative averages in the data. The standard deviation was set to match Gini index of workers' earnings by skill level: 0.39 (low-skill), 0.435 (medium-skill), and 0.423 (high-skill). The average earnings of low-skilled workers is normalized to 1. In the SIPP data, the average earnings of the two higher-skill groups relative to the low-skilled group are 1.49 (for the middle-skill) and 2.37 (for the high-skill).

To calibrate the debt limit $\underline{a}$ and the discount factor β we target moments in the SIPP data that relate to financial assets and debt. Because the purpose of assets in the model is to smooth unemployment risk, we constrain the types of assets we consider when mapping the data and the model moments. In particular, instead of a measure of net worth that includes all possible assets (real estate, art, etc) and all possible debt (mortgage, student loans, etc) we calculate a measure of liquid net worth that includes purely financial assets: checking and savings accounts, stocks, bonds, CDs, and vehicles.[13] We consider credit card and vehicle debt as our measure of debt. The skill-specific debt limit $\underline{a}_j$ is calibrated to match the ratio of the mean liquid net worth of those in debt (that is, the mean liquid net worth for those with negative liquid net worth). The ratio in our three-year SIPP panel is -1.78, -1.44, and -1.15% for low, middle, and high-skilled workers respectively. The discount factor β_j is set to match mean liquid net worth divided by mean earnings. These ratios in the data are 2.43, 4.33, and 6.00 for low-, middle- and high-skill workers. Table 10 reports the parameters along with the moments in the data used to estimate the parameters' values.

Parameter	Definition	Target	Target Value
σ	Earnings Gini by skill level (low, mid, high)	Earnings Gini SIPP 2017–2019	0.390 0.435 0.423
$\underline{a}$	Debt limit by skill level (low, mid, high)	Mean Negative Net Worth to Earnings	-1.78 -1.44 -1.15
β	Discount rate by skill level (low, mid, high)	Mean Net Worth to mean earnings	2.43 4.33 6.00
b	Unemployment Benefit by skill level (low, mid, high)	Mean Unemployment Benefit to Mean Earnings	23.7% 19.0% 15.0%
μ	Mean of Wage Offer Distribution by skill level (low, mid, high)	Average Earnings (low skill normalized to 1)	1.00 1.49 2.37

Table 10: Calibrated parameters, their definitions, and corresponding target moments for the three skill levels (low, medium, high).

The calibrated parameter values (including those calibrated externally) are shown on

[13]Including vehicles does not change moments by a large amount. Despite not being a financial asset, vehicles are fairly liquid as they can be sold in little time.

Table 11.

Parameter	Low Skill	Mid Skill	High Skill
γ	2.500	2.500	2.500
ρ	0.010	0.030	0.030
δ	0.012	0.008	0.005
$\underline{a}$	-2.323	-3.769	-5.065
β	0.951	0.968	0.975
σ	1.295	1.204	1.639
b	0.230	0.285	0.376
μ	-0.694	-1.079	-2.505

Table 11: Calibration parameters and their values.

To obtain moments from the model we simulate a large number of agents (one million for each skill level), large enough so that their choices represent draws from the model's stationary distribution. Table 12 compares the targeted data moments with the values generated by the model. The model fit is overall satisfactory especially in the two sets of wealth/debt-related moments. The model slightly overestimates the negative liquid net worth to earnings ratio for the low skilled (-1.63 vs 1.78) but the same moment for the medium and high skilled workers are on target. The model also fits well the overall liquid net worth to earnings only slightly underestimating this ratio for the low and high skilled workers. The model slightly overestimates it for the medium skill. The Gini earnings in the data for the medium skill is larger than in the model (0.44 vs. 0.38) but the model's earnings inequality for the other two skill groups is roughly equal to the data's.

Moment	Data	Model
Negative Net Worth to Earnings (L)	-1.78	-1.63
Negative Net Worth to Earnings (M)	-1.44	-1.44
Negative Net Worth to Earnings (H)	-1.15	-1.16
Liquid Net Worth to Earnings (L)	2.43	2.33
Liquid Net Worth to Earnings (M)	4.33	4.44
Liquid Net Worth to Earnings (H)	6.00	5.94
Replacement Ratio (L)	23.7%	23.8%
Replacement Ratio (M)	19.0%	19.0%
Replacement Ratio (H)	15.0%	15.2%
Gini Earnings (L)	0.39	0.42
Gini Earnings (M)	0.44	0.38
Gini Earnings (H)	0.42	0.41
Average Earnings (L)	1.00	1.00
Average Earnings (M)	1.49	1.50
Average Earnings (H)	2.37	2.46

Table 12: Moments generated by the model and their counterparts in SIPP 2017—2019 data. The labels L, M, and H refer to the skill level of workers.

5 Model Validation

We aim to validate the model by assessing how well it replicates moments in the data that were not targeted in the calibration. In particular, we are interested in the model's ability to replicate relationships between unemployment, assets, and wages at the individual level that are in line with the SIPP data. We begin by judging the model in terms of the asset distribution (how large is wealth inequality) as well as the unemployment rates by skill.

The targets in the calibration are averages of asset-to-income ratios and earnings inequality, but no wealth inequality. Table 13 shows some moments of the wealth distribution in the data (first row) and the model (second row). The moments are how much of total wealth is held by different wealth percentiles (the top 5%, top 20%, the top 50% and the bottom 10%). The model captures wealth inequality but falls a bit short at the very top—in the SIPP data, the top 5% hold 75% of the wealth, while in the model, they hold 53%. Nonetheless, the model aligns well with the data for the top 20%, 50%, and bottom 10%. Since our focus is on debt, the fact that the model and data are that close for wealth held by the bottom 10% (6.4% vs 5.04%) is encouraging.

Table 13: Summary of Net Worth Percentiles

	Bottom 10%	Top 50%	Top 20%	Top 5%
Data	-6.44%	106.58%	96.29%	75.38%
Model	-5.04%	112.98%	96.90%	53.33%

One of our model's main ingredients is unemployment risk, and we want it to reflect the risk faced by US workers. The separation rates are exogenous and taken from the data, but job-finding rates are endogenous. A significant model overprediction of unemployment rates may indicate that job-finding rates are too low so that unemployment is not that costly. Fortunately, the unemployment rates in the model are close to those in the data. This is particularly true for the most educated workers. The unemployment rates in our SIPP panel and in the model are given in Table 14. The only unemployment rate that deviates slightly is that of lower-skilled workers. The model delivers an unemployment rate of 5.66% while in the data is 4.05%. For the other two groups of workers, the unemployment rate in the model is virtually the same as the empirical analog in SIPP. To calculate the aggregate or overall unemployment rate, we use the shares of the three groups of workers in SIPP, to calculate the aggregate rate in the model. These shares are 36.5%, 51.1%, and 12.3% for the low, medium, and high skill groups, respectively. The aggregate unemployment rate in the model is 3.6%, while in the data is 3.1%.

Table 14: Summary of Unemployment Rates

	Aggregate	Low Skill	Medium Skill	High SKill
Data	3.01%	4.05%	2.72%	1.44 %
Model	3.64%	5.66%	2.72%	1.51%

Tables 15–17 present the results of regressions examining the relationship between assets or debt and either unemployment duration or the first wage after an unemployment spell. In Section 2, we established that a household's level of wealth is a significant predictor of unemployment duration. Consistent with this finding, Table 15 shows that, in the model, wealth is positively associated with longer unemployment duration. In the model, an increase in wealth equivalent to the average wage of a low-skilled worker (normalized to 1), represents a 16% rise in wealth. This change extends unemployment duration by approximately two days. Thus, the impact of assets on duration is relatively small. Furthermore, conditional on the same level of wealth, more educated workers tend to experience shorter periods of unemployment. Unemployment is a less desirable state for higher-skill workers as their earnings, relative to unemployment benefits, tend to be higher. That makes their unemployment spells shorter. This feature and the associated negative coefficients for medium and high skills are common to all reported model-based regressions with unemployment duration as the dependent variable.

Figure 5 shows graphically the relationship between duration and wealth/debt. The horizontal axis has ten wealth bins and the vertical axis has the median unemployment duration. The different lines represent the three different skill levels. The figure shows that the relationship is steeper, the lower the skill. This is especially clear for the lowest skill group, for whom duration rises rapidly with wealth (the median duration rises by 5 months when wealth rises from the first bin to the fourth bin). While duration also rises

Table 15: Regression: Unemployment Duration on Wealth

Variable	Intercept	Wealth	Medium Skill	High Skill
Coefficient	4.853***	0.044***	-1.858***	-2.266***
Std. Error	*(0.034)*	*(0.001)*	*(0.052)*	*(0.064)*
R-squared	0.09			

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

for the other two skill groups, the pattern is flatter, except perhaps for the change between the first and the third bin.

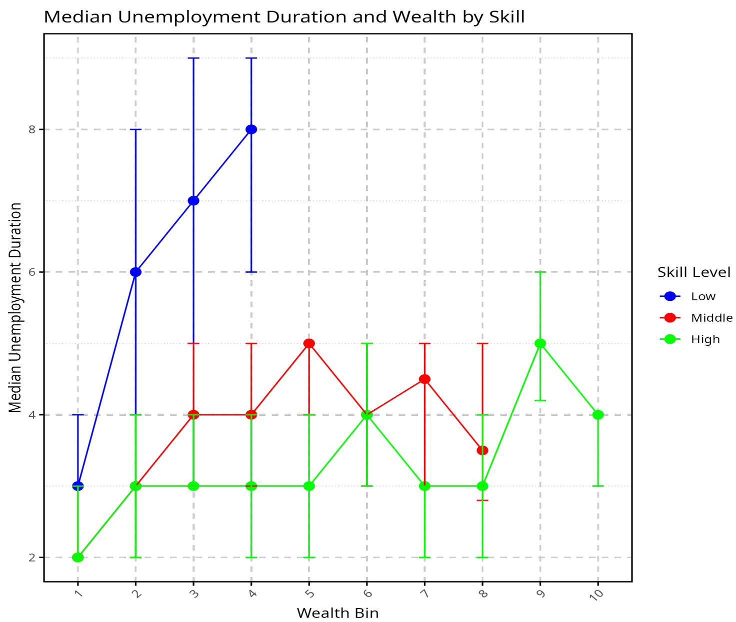

Figure 5: Median Unemployment Duration by Skill Level. The figure plots the median unemployment duration (as well as the 40th and 60th percentiles of duration) as a function of wealth (represented by 10 bins). Each line corresponds to a different skill level.

Table 16 shows that household debt is negatively related to duration, with a large coefficient (-0.575), which implies that workers who start an unemployment spell with a higher level of debt, experience shorter unemployment spells. An increase in debt equal to the average wage of the unskilled reduces unemployment duration by about two weeks. The effect of debt is quantitatively important.

Table 16: Regression: Unemployment Duration on Debt

Variable	Intercept	Debt	Medium Skill	High Skill
Coefficient	5.478***	-0.575***	-1.620***	-1.592***
Std. Error	*(0.038)*	*(0.019)*	*(0.052)*	*(0.062)*
R-squared	0.09			

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Finally, Table 17 illustrates the relationship between the level of wealth at the start of an unemployment spell and the initial wage earned upon re-employment. According to our hypothesis, households with higher levels of assets should be able to continue searching for better job opportunities, leading to higher starting wages. The model's simulations appear to support this idea, showing that greater initial wealth is indeed associated with higher initial wages upon returning to work. Quantitatively, an increase in wealth equal to the average level of unskilled wages raises wages by 0.6%. As can be inferred from the positive coefficients for the two skill levels, being a medium or high-skill worker is associated with a higher post-unemployment wage than being a low-skill worker.

Table 17: Regression: First Employment Wage on Wealth

Variable	Intercept	Starting Wealth	Medium Skill	High Skill
Coefficient	-0.354***	0.006***	0.459***	0.872***
Std. Error	*(0.0048*	*(0.00)*	*(0.012)*	*(0.015)*
R-squared	0.81			

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Overall, we have established that the model replicates both targeted and non-targeted moments. In what follows, we conduct the main exercise of the study, comparing the model's steady state outcomes under two different interest rate levels.

6 Results

In this section, we conduct the study's primary counterfactual exercise to explore the following question: How did the rise in household debt, driven by a decline in real interest rates, impact labor market dynamics? To address this, we compare two theoretical economies—one with a low interest rate and another with a relatively higher rate. Using the 2017–2019 calibration as a baseline, the exercise adjusts only the interest rate while keeping all other structural parameters unchanged. While some parameters (e.g., separation rates) have likely evolved over time, the goal of this analysis is to isolate the model's predictions for labor market dynamics when the real interest rate is the sole variable that changes. We then compare a set of key endogenous outcomes between the high-interest-rate and low-interest-rate economies.

The annual nominal interest rate in 1982 was about 12% and the year-over-year inflation rate was roughly 6%, so we set the 1982 real interest rate to 6% annually, which implies a 0.50% monthly rate. Recall that the baseline interest rate is 0.18% monthly, so the fall in real interest rates between 1982 and 2018 was roughly 32 basis points at the monthly frequency. We generate a long time series for each agent type by drawing one million compensation proposals from the wage distribution. These draws in combination with the consumption, savings, and reservation wage policy functions, generate a million draws from the model's stationary distribution over assets, employment status, and accepted wages. From these simulations, any moment related to the model's endogenous variables can be readily computed.

Table 18 presents the endogenous outcomes for two economies: one with the baseline calibration and another identical economy where the only difference is a higher real interest rate. We refer to the first as the 2018 economy and the second as the 1982 economy to reflect the observed decline in interest rates between these years. According to our model, this decline in interest rates has several effects. We focus on six endogenous equilibrium outcomes: the wealth-to-earnings ratio, the percent of indebted agents, the labor share, the skill premium, and the unemployment rate.

Table 18: High (1982) vs Low (2018) Real Interest Rate Economies

	Wealth-to-Earnings	Percent in Debt	Labor Share	Var $log(w)$	Skill Premium	Unemp. Rate
1982	4.28	46.5%	61%	0.66	1.39	3.93%
2018	4.24	49.7%	55%	0.75	1.55	3.64%

Note: The skill premium is defined as the ratio of average earnings of the middle-skill group of workers to the average earnings of the low-skill group of workers.

First, lower interest rates lead to higher indebtedness and lower savings. In the model, the proportion of those in debt (negative liquid net worth) declines from 49.7% to 46.5%, so slightly over 3 percentage points. The decline in assets is reflected in a decrease in the wealth-to-earnings ratio, which falls from 4.28 to 4.24. Notably, the drop in assets is even more pronounced because earnings also decline, from 1.58 to 1.42. As a result, the reduction in agents' liquid wealth is substantial.

To quantify the impact of lower interest rates on the labor's share, we follow a two-step approach. First, we define the labor share as the ratio of average wages (earnings) to average productivity. We estimate the economy's average productivity in 1982 by multiplying the average earnings (1.58) by the observed labor share for that year (61%), yielding an average productivity of 2.59. Next, assuming this level of productivity remains constant from 1982 to 2018, an earnings level of 1.42 in 2018 implies a labor share of approximately 55%. In other words, relative to productivity, the labor's share of earnings declined by six percentage points over this period. This result aligns with estimates from the BLS, which indicate a decline of approximately seven percentage points over the same period, decreasing from 63.6% to 56.4%.

The decline in asset levels and the increase in debt contributed to greater earnings inequality. The model attributes this rise in inequality to the concavity of the reservation wage function. At lower asset levels, the reservation wage declines rapidly, leading to greater dispersion in earnings as more workers accumulate fewer assets or fall into debt. According to the model, the variance of log earnings increased from 0.66 in 1982 to 0.75 in 2018, reflecting this growing inequality. This result is consistent with other studies, such as Heathcote et al. (2023), which find that individual earnings inequality has increased by approximately 9 log points on average for both men and women during this period. Other authors, such as Lippi and Perri (2023) and Heathcote et al. (2020), identify similar household earnings dynamics that have contributed to rising inequality.

We also calculate the skill premium, which, in line with the literature, is defined as the ratio of average earnings of college graduates (medium skill) to those of high school graduates (low skill). Using this measure, the model estimates a skill premium of 1.39 in 1982. As interest rates rise, the skill premium increases to 1.55 in 2018. This result is consistent with studies like Ohanian et al. (2023) and Krusell et al. (2000), among others, which also find that the skill premium has increased following similar patterns.

In the model, the rise in the skill premium follows a similar pattern to the overall increase in earnings inequality. Since low-skill workers have fewer assets, a decline in interest rates reduces their average earnings more significantly due to the concavity of the reservation wage function. The decline in labor's share, along with the rise in earnings inequality and the skill premium, suggests that these trends may not be driven solely by technological factors. Instead, the model interprets these shifts as labor market responses to changes in household balance sheets. As noted in the introduction, this perspective presents an unexplored explanation within the extensive literature on these long-term trends.

Finally, the unemployment rate declines, though the effect is relatively small. The model predicts a decrease of 0.3 percentage points, from 3.93% to 3.64%, driven by lower asset accumulation and shorter unemployment duration. Since the model does not account for business cycles, we compare this unemployment rate to the noncyclical unemployment rate estimated by the U.S. Congressional Budget Office, which decreased by approximately 1.6 percentage points over the same period.

7 Conclusions

This study offers a novel explanation for the decline in the U.S. labor share and the increase in earnings inequality between 1982 and 2019, attributing it to the fast rise in household debt. By linking increased household debt, and earnings and unemployment dynamics, including a reduction in the labor share, this research challenges traditional explanations that center on technological or institutional changes.

This conjecture is supported by several compelling arguments. First, it aligns with existing studies, such as those cited by Chaumont and Shi (2022), which indicate that individuals with higher wealth tend to engage in more extensive job searches and secure higher-paying positions. Second, it is consistent with the idea that financially stable unemployed workers can afford to spend more time job searching, thereby increasing their chances of finding better-paying opportunities. Third, this explanation challenges the view that capital deepening is the primary driver of the labor share's decline by highlighting that most empirical studies, as noted by Lawrence (2015) suggest that capital and labor are gross complements rather than substitutes.

This paper's model suggests that the rise in household debt contributed to the decline in labor's share and the increase in earnings inequality. As household savings rates fell, real interest rates also declined—a trend inconsistent with a closed-economy assumption for the U.S. during this period. Consequently, the model takes the decline in interest rates as given and examines its impact on labor markets through rising personal debt.

With imperfect unemployment insurance, workers engage in precautionary savings to buffer against a potential job loss. As financial positions weakened and unemployment became less sustainable, workers accepted lower wages to exit unemployment. This reduced average earnings relative to productivity, lowering labor's share. Earnings inequality also increased due to the concavity of the reservation wage function: when liquid net worth is negative, accepted wages drop sharply because unemployment becomes more costly.

Given the parsimony of our model and the straightforward nature of our main counterfactual exercise, we primarily interpret our quantitative results as an upper bound on the predicted effects of declining interest rates on labor market outcomes. A richer framework might yield results of a different magnitude. However, the qualitative conclusion remains robust: extended periods of low interest rates likely played a significant role in shaping labor market dynamics and earnings inequality, contributing meaningfully to the changes observed in the data.

Overall, this study offers a fresh perspective on the forces shaping U.S. labor share trends and earnings inequality, highlighting the significant role of rising household debt. It provides empirical support for this hypothesis using data from two U.S. household surveys: the Survey of Income and Program Participation from 2017 to 2019 and the 2019 Survey of Consumer Finances. Additionally, the study presents a parsimonious theoretical framework that, while omitting certain factors that could influence the quantitative results, nonetheless introduces a mechanism that plausibly explains the decline in the labor share and proposes a model capable of capturing the relevant empirical moments. Incorporating further complexity into this mechanism is the focus of ongoing and future research.

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Appendix A Literature Review

Our work contributes to several interconnected areas of research, including the rise in earnings inequality, the dynamics between wealth and labor market behavior, the relationship between interest rates and household borrowing, and the long-term decline in labor's share of income.

Several theories have been proposed to explain the long-term decline in labor's share of income. Technological advancements, such as improved computers and automation, reduce the cost of capital investment and incentivize firms to substitute labor with machines. Karabarbounis and Neiman (2013) argue that the falling relative price of investment goods is a primary driver of labor share decline, estimating an aggregate elasticity of substitution greater than one. However, Lawrence (2015) challenge this conclusion, suggesting that substitution between capital and labor is more limited. The transmission of automation effects is complex; new technology can both displace workers and enhance productivity. Glover and Short (2020) and Koh et al. (2020) analyze capital deepening as a potential driver, while Acemoglu and Restrepo (2020) highlight that robots uniquely displace workers from tasks previously performed by humans.

Increased trade and foreign competition have also been cited as factors. Elsby et al. (2013) find that industries most exposed to import competition experienced the largest declines in labor share. Similarly, Abdih and Danninger (2017) note that sectors with high offshoring potential show a weak but positive correlation with labor share shifts. Castro-Vincenzi and Kleinman (2020) document that industries reliant on intermediate inputs saw the most significant labor share declines. Alongside globalization, rising firm market power is another potential culprit. De Loecker et al. (2020) provide evidence that average markups in the U.S. increased sharply after 1980, indicating a shift in income distribution from labor to capital. However, Jaumandreu and Doraszelski (2019) and Raval (2023) question whether these markups truly explain labor share trends. Finally, deunionization has weakened worker bargaining power, reducing wages relative to productivity. Stansbury and Summers (2020) and Farber et al. (2018) link this to the decline in the union wage premium, while Bentolila and Saint-Paul (2003) argue that weaker unions lower the labor share when capital-labor substitution is inelastic. Holmes et al. (2012) further suggests that deunionization may accelerate automation, reinforcing labor's declining share of income.

One leading explanation for the rise in earnings inequality since 1980 is skill-biased technological change (SBTC). As computerization and automation advanced, the demand for highly educated and technically skilled workers grew more rapidly than the demand for less-skilled labor. This shift in labor demand led to a widening wage gap between these two groups of workers (Katz and Murphy, 1992). Subsequent refinements to SBTC theory highlight job polarization, where middle-skill jobs (often routine and easily automated) declined, while high-skill and low-skill occupations expanded (Autor et al., 2008). This polarization pushed earnings at the top and bottom ends further apart, contributing to overall income inequality (Acemoglu and Autor, 2011).

A second explanation focuses on institutional factors. The decline of labor unions, particularly in the United States, reduced the bargaining power of workers and contributed to stagnant wages in many middle- and low-wage occupations (Western and Rosenfeld, 2011). Additionally, policy changes such as lower minimum wage relative to median wages and deregulation in various industries have played a part in widening the earnings distribution (Card and DiNardo, 2002). Globalization and increased trade also exposed lower- and middle-skilled jobs to international competition, which restrained wage growth in those sectors while enabling higher-skilled workers to benefit from expanding global markets (Feenstra and Hanson, 1999).

Lastly, a growing body of research highlights how falling interest rates have contributed to rising household indebtedness, with various mechanisms and heterogeneities emphasized. Emiris and Koulischer (2023) develop a model of credit-constrained households and show that lower interest rates primarily increase borrowing among wealthier and less constrained individuals. Empirical evidence from Belgian credit registry data confirms this, indicating that older households with existing housing wealth were most responsive to rate declines, with a 1 percentage point drop in interest rates associated with a 7% increase in household debt. Martins and Villanueva (2006) exploit a quasi-natural experiment in Portugal to show that reforms reducing mortgage interest subsidies led to a significant drop in borrowing, confirming that household borrowing is elastic to interest rates, particularly among low- and middle-income borrowers. Fuster and Willen (2017) focus on the U.S. housing market and find that reductions in mortgage payment sizes—due to lower adjustable interest rates—substantially decreased mortgage default risk, indicating that interest rates influence not only borrowing but also repayment behavior. Rannenberg (2023) presents a macroeconomic model linking rising income inequality to a decline in the natural interest rate, which in turn fuels increased borrowing among non-rich households. This occurs as lower rates reduce borrowing costs and stimulate housing demand, particularly in the presence of collateral-based credit constraints. Finally, DeFusco et al. (2020) study the effects of macroprudential regulation targeting high-leverage mortgages and find that even modest regulatory costs significantly reduced borrowing volumes, underscoring the sensitivity of household debt to interest rates and lending conditions.

Appendix B Alternative SCF Samples

Table 19: 2019 vs 2022 SCFs. Mean Net worth by selected family characteristics (thousands of USD)

Characteristic	**2019**	**2022**
All	865.7	1,063.7
Income Percentile		
≤ 20	131.3	129.7
20 - 39.9	159.1	218.7
40 - 59.9	252.6	385.4
60 - 79.9	489.2	436.8
80 - 79.9	995.5	1,264.7
90 - 79.9	5,595.8	6,629.6
Education of reference person		
No high school diploma	171.1	175.6
High school diploma	310.1	413.3
Some College	340.1	541.1
College degree	1,572.2	2,003.4
Race or ethnicity of reference person		
White non-Hispanic	1,034.5	1,367.2
African American non-Hispanic	166.7	211.5
Hispanic or Latino	240.4	227.5
Asian	n.a.	1,826.9
Age of reference person (years)		
≤ 35	88.5	183.5
35-44	507.5	549.6
45-54	966..5	975.8
55-64	1,363.8	1,566.9
65-74	1,409.5	1,794.6
≥ 75	1,110.1	1,624.1

Table 20: 2019 SCF v.s. sample. Mean net worth by selected family characteristics (thousands of USD)

Characteristic	Sample	SCF
All	821.7	865.7
	(28.0)	(18.0)
Income Percentile		
≤ 20	85.3	131.3
20 - 39.9	64.0	159.1
40 - 59.9	139.4	252.6
60 - 79.9	302.8	489.2
80 - 89.9	685.4	995.5
90 - 100	4,569.7	5,595.8
Education of reference person		
No high school diploma	171.1	159.5
High school diploma	310.1	353.1
Some College	340.1	433.6
College degree	1,572.2	1,758.4
Race or ethnicity of reference person		
White non-Hispanic	1,034.5	1,102.8
African American non-Hispanic	166.7	162.0
Hispanic or Latino	240.4	222.8
Asian	n.a.	n.a.
Age of reference person (years)		
≤ 35	101.8	88.5
35-44	542.3	507.5
45-54	917.2	966.5
55-64	1,418.6	1,363.8
65-74	2,452.2	1,409.5
≥ 75	2,368.2	1,110.1

Table 21: 2019 SCF. Mean Net worth by selected family characteristics (thousands of USD)

Characteristic	Work + Min Wage	Unmarried
All	812.7	345.4
	(28.0)	(18.9)
Income Percentile		
≤ 20	85.3	n.a.
20 - 39.9	64.0	n.a.
40 - 59.9	139.4	n.a.
60 - 79.9	302.8	n.a.
80 - 79.9	685.4	n.a.
90 - 79.9	4,569.7	n.a.
Education of reference person		
No high school diploma	171.1	66.3
High school diploma	310.1	177.7
Some College	340.1	196.4
College degree	1,572.2	731.6
Race or ethnicity of reference person		
White non-Hispanic	1,034.5	467.7
African American non-Hispanic	166.7	95.3
Hispanic or Latino	240.4	129.1
Asian	n.a.	n.a.
Age of reference person (years)		
≤ 35	101.8	40.0
35-44	542.3	173.2
45-54	917.2	387.1
55-64	1,418.6	382.6
65-74	2,452.2	546.8
≥ 75	2,368.2	682.0

Appendix C Evidence from SCF regressions

Tables 22 and 23 below present regression results examining the relationship between wage income and both net worth and liquid net worth, alongside various control variables across different subsamples. We define liquid net worth as a household's total net worth excluding any home equity. The tables include five models, each representing a distinct subset of the data: All Data (Levels), Non-Negative Net Worth (Levels), Non-Negative Net Worth (Logs), Negative Net Worth (Levels), and Negative Net Worth (Logs). The number of observations varies across models, with the "All Data" model containing 3,208 observations, while models restricted to negative net worth have significantly fewer. Each column reports regression coefficients for the corresponding model, with standard errors in parentheses. Statistical significance is denoted by asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Net worth generally exhibits a positive relationship with wage income. As expected, educational attainment plays a significant role in wage determination, with individuals who have completed high school, some college, or a college degree earning substantially higher wages. This effect is particularly pronounced for those with a college degree, which is associated with the highest wage premium across all models. The results also highlight disparities across race and gender. Black/African American and Hispanic individuals generally earn significantly lower wages than the reference group, reflecting persistent wage gaps. Likewise, female workers earn considerably less than their male counterparts across all models, reinforcing well-documented gender wage disparities. Finally, while age is positively associated with wage income in some cases, the effect size remains relatively small.

Table 22: Wage Income on Net Worth plus Controls

Variable	**All Data** (Levels)	**Non-Neg NW** (Levels)	**Non-Neg NW** (Logs)	**Negative NW** (Levels)	**Negative NW** (Logs)
(Intercept)	3,396	12,652	9.289***	49,733***	10.489***
	(7,543)	(8,211)	(0.098)	(9,145)	(0.204)
Net Worth	0.006***	0.006***	0.173***	-0.029	0.032**
	(0.002)	(0.002)	(0.010)	(0.022)	(0.015)
High School or GED	25,358***	24,280***	0.168***	8,101	0.131
	(3,608)	(3,935)	(0.033)	(6,916)	(0.107)
Some College	39,274***	37,842***	0.221***	21,797***	0.270***
	(3,826)	(4,090)	(0.038)	(6,285)	(0.095)
College Degree	109,388***	116,718***	0.508***	29,472***	0.362***
	(5,466)	(5,956)	(0.041)	(6,487)	(0.097)
Black/African American	-18,863***	-16,961***	0.021	-7,357**	-0.090**
	(4,114)	(4,737)	(0.022)	(3,404)	(0.041)
Hispanic	-13,780***	-14,425***	-0.056*	5,332	0.068
	(3,692)	(4,118)	(0.031)	(5,411)	(0.066)
Other Race	37,709**	39,865**	0.124***	-10,288*	-0.096
	(11,890)	(12,462)	(0.039)	(5,263)	(0.073)
Female	-62,111***	-64,948***	-0.369***	-16,771***	-0.207***
	(3,712)	(4,293)	(0.022)	(2,842)	(0.040)
Age	1,542***	1,377***	-0.0027**	96.21	0.0015
	(168)	(180)	(0.0007)	(140)	(0.0021)
Observations	3,208	2,918	2,918	288	288

Note: Asterisks indicate significance levels: * p<0.10; ** p<0.05; *** p<0.01.

Table 23: Wage Income on Liquid Net Worth (NWL) plus controls

Variable	**All Data** (Levels)	**Non-Neg NWL** (Levels)	**Non-Neg NWL** (Logs)	**Negative NWL** (Levels)	**Negative NWL** (Logs)
(Intercept)	1,474	10,283	9.355***	38,259***	10.713***
	(7,389)	(8,292)	(0.078)	(9,575)	(0.122)
NWL	0.006***	0.006***	0.171***	-0.0015	-0.020*
	(0.002)	(0.002)	(0.009)	(0.017)	(0.012)
High School or GED	25,572***	24,932***	0.168***	16,121**	0.174**
	(3,658)	(4,328)	(0.037)	(5,847)	(0.069)
Some College	39,665***	39,316***	0.216***	28,823***	0.319***
	(3,869)	(4,666)	(0.046)	(5,494)	(0.064)
College Degree	110,808***	120,908***	0.501***	43,902***	0.452***
	(5,416)	(6,346)	(0.045)	(6,708)	(0.071)
Black/African American	-19,329***	-18,281***	0.011	-9,001**	-0.127**
	(4,118)	(4,778)	(0.023)	(4,751)	(0.050)
Hispanic	-13,868***	-12,782***	-0.022	-7,104	-0.087
	(3,719)	(4,384)	(0.031)	(5,826)	(0.070)
Other Race	38,598**	41,832**	0.161***	-10,753*	-0.128
	(12,079)	(13,081)	(0.037)	(5,455)	(0.071)
Female	-62,780***	-65,143***	-0.335***	-28,775***	-0.297***
	(3,700)	(4,403)	(0.022)	(3,607)	(0.037)
Age	1,597***	1,434***	-0.0017**	499.46**	0.004
	(161)	(175)	(0.0007)	(183)	(0.002)
Observations	3,208	2,884	2,884	382	382

Note: Asterisks indicate significance levels: * p<0.10; ** p<0.05; *** p<0.01.

Appendix D Evidence from SIPP regressions

This section reports all the coefficients of the regressions estimated in Section 2. These regressions relate unemployment duration as the dependent variable and assets, debt, and earnings data as independent variables. All the models are of the form:

$$UnempDur = \alpha + \beta_0 FIN + \gamma X$$

, and where X is a set of controls.[14] The variable FIN refers to a financial variable (e.g. unsecured debt to income, checking account to income, etc). While the model structure is the same, we estimate several relationships between unemployment duration and different FIN variables. Tables 24 and 25 report the coefficients. Each columns shows coefficients when the FIN variable is changed: $USECD/W > 0$ is an indicator variable representing positive levels of unsecured debt to income. We define analogous indicators for credit card debt, $CCD/W > 0$; for mortgage debt, $MD/W > 0$; and net worth, $NW/W > 0$. We also set FIN to the values of the ratios themselves, not an indicator of whether the ratio is positive. In Table 25 we show results for having a positive balance in a checking account $CHECK/W > 0$ (and the ratio $CHECK/W$ itself) or having a positive balance in a saving account SAV/W (and the ratio SAV/W itself). The last column of Table 25 substitutes the log of the first wage after an unemployment spell. For that specification, the vector of controls X also includes occupational dummies (OCC_2, OCC_3, etc). These dummies represent broad occupational groups that account for a substantial amount of wage differences.

[14]The controls are: an indicator variable for not being married (Not Married), for receiving unemployment benefits ($UI > 0$), for having a college degree (College), for being black (Race), for being female (Female) and year dummies (2019 and 2020). In addition, we control for age and for the square fo age.

Table 24: Model Specifications 1-8

Specification	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Intercept	1.630*	1.511	1.486	1.422	1.477	1.474	1.449	1.412
$USECD/W > 0$	-0.248*	–	–	–	–	–	–	–
$USECD/W$	–	-0.014**	–	–	–	–	–	–
$CCD/W > 0$	–	–	-0.426***	–	–	–	–	–
CCD/W	–	–	–	-0.089**	–	–	–	–
$MD/W > 0$	–	–	–	–	-0.392**	–	–	–
MD/W	–	–	–	–	–	-0.005	–	–
$NW/W > 0$	–	–	–	–	–	–	0.211	–
NW/W	–	–	–	–	–	–	–	-0.005
Not Married	0.519***	0.526***	0.476***	0.506***	0.458***	0.502***	0.430**	0.436**
$UI > 0$	-1.289***	-1.353***	-1.254***	-1.324***	-1.250***	-1.296***	-1.418***	-1.429***
Year=2019	0.087	0.100	0.074	0.093	0.110	0.100	–	–
Year=2020	0.014	0.021	0.012	0.028	0.034	0.029	0.016	0.016
Female	0.049	0.059	0.036	0.043	0.050	0.059	-0.080	-0.067
Race	0.443**	0.457**	0.440**	0.429**	0.392**	0.408**	0.488*	0.458*
Age	0.114**	0.115**	0.122**	0.119**	0.117**	0.116**	0.115	0.118
Age^2	-0.001*	-0.001*	-0.001**	-0.001**	-0.001*	-0.001*	-0.001	-0.001
College	-0.440***	-0.401***	-0.418***	-0.434***	-0.432**	-0.462***	-0.326	-0.287
Observations	2,342	2,342	2,349	2,349	2,332	2,332	1,639	1,639
Residual DF	2,332	2,332	2,339	2,339	2,322	2,322	1,630	1,630
AIC	12,593	12,591	12,625	12,626	12,545	12,550	8,707	8,706

Note: Asterisks indicate the level of significance of the parameters: * p<0.10; ** p<0.05; *** p<0.01.

Table 25: Model Specifications 9-13

Specification	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
Intercept	0.589	0.619	1.680	1.947	-10.186
$CHECK/W > 0$	0.047	–	–	–	–
$CHECK/W$	–	-0.033	–	–	–
$SAV/W > 0$	–	–	0.173	–	–
SAV/W	–	–	–	-0.021	–
log(First Wage)	–	–	–	–	2.831***
OCC_2	–	–	–	–	2.811
OCC_3	–	–	–	–	-1.303
OCC_5	–	–	–	–	0.689
OCC_6	–	–	–	–	-1.186
OCC_7	–	–	–	–	12.421***
OCC_9	–	–	–	–	2.501
Female	0.075	0.070	-0.077	-0.083	-2.696*
Race	0.124	0.103	-0.165	-0.188	4.628*
Age	0.149**	0.150**	0.088	0.080	0.300
Age^2	-0.0016*	-0.0016*	-0.0010	-0.0009	-0.004
College	-0.543***	-0.525***	-0.457**	-0.420*	-4.639***
$UI > 0$	-1.233***	-1.249***	-0.769**	-0.790**	-1.693
Not Married	0.585***	0.597***	0.373	0.373	-1.784
Year = 2019	0.116	0.131	–	-4.791***	–
Year = 2020	0.262	0.264	0.234	0.236	-1.348
Observations	1,338	1,338	694	694	32
Residual DF	1,327	1,327	684	684	15
AIC	7,142.5	7,141.2	3,519.7	3,519.2	150.88

Note: Asterisks indicate the level of significance of the parameters: * p<0.10; ** p<0.05; *** p<0.01.

Appendix E Household Debt Evolution

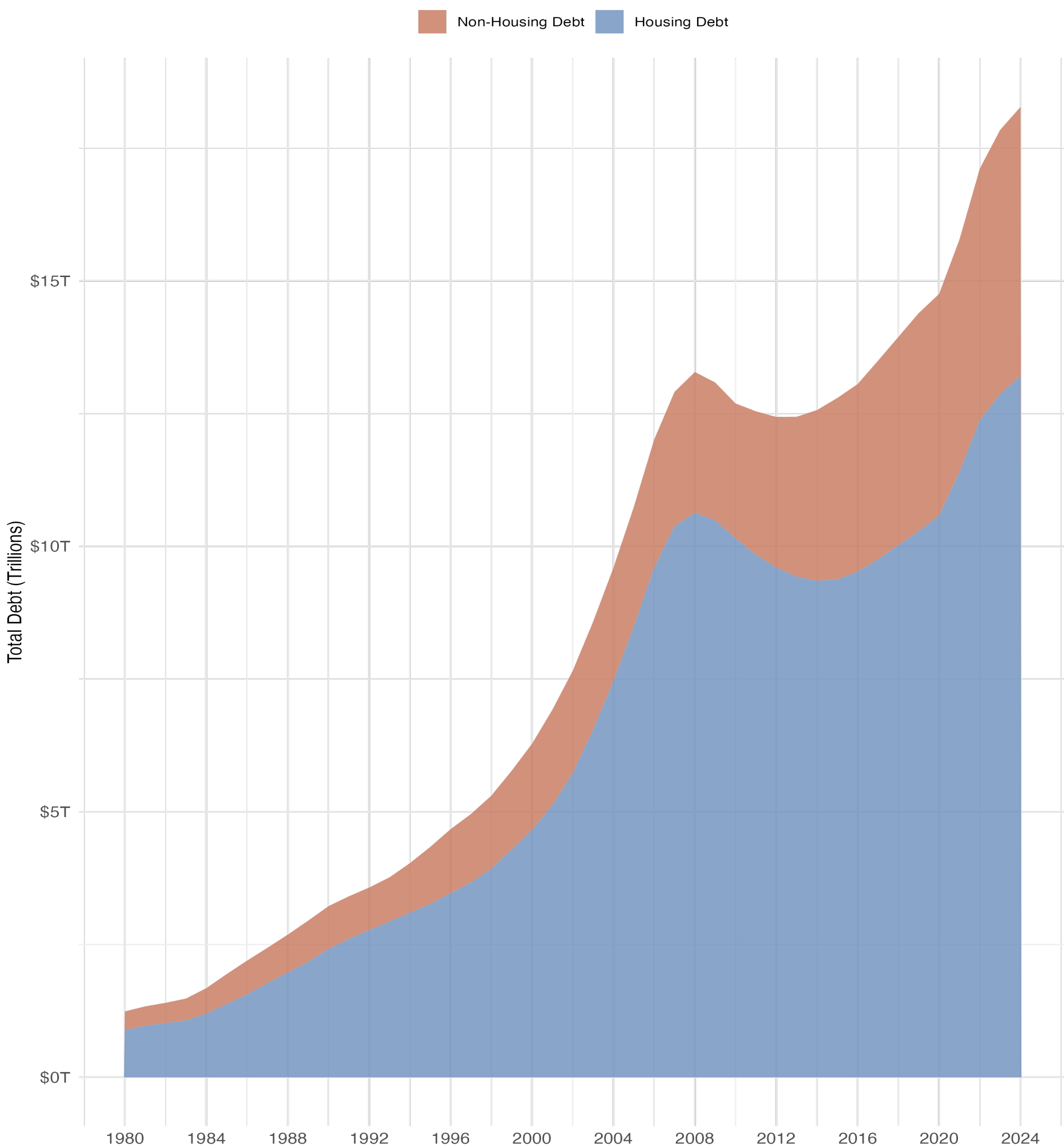

Figure 6: Housing vs. Non-housing Debt

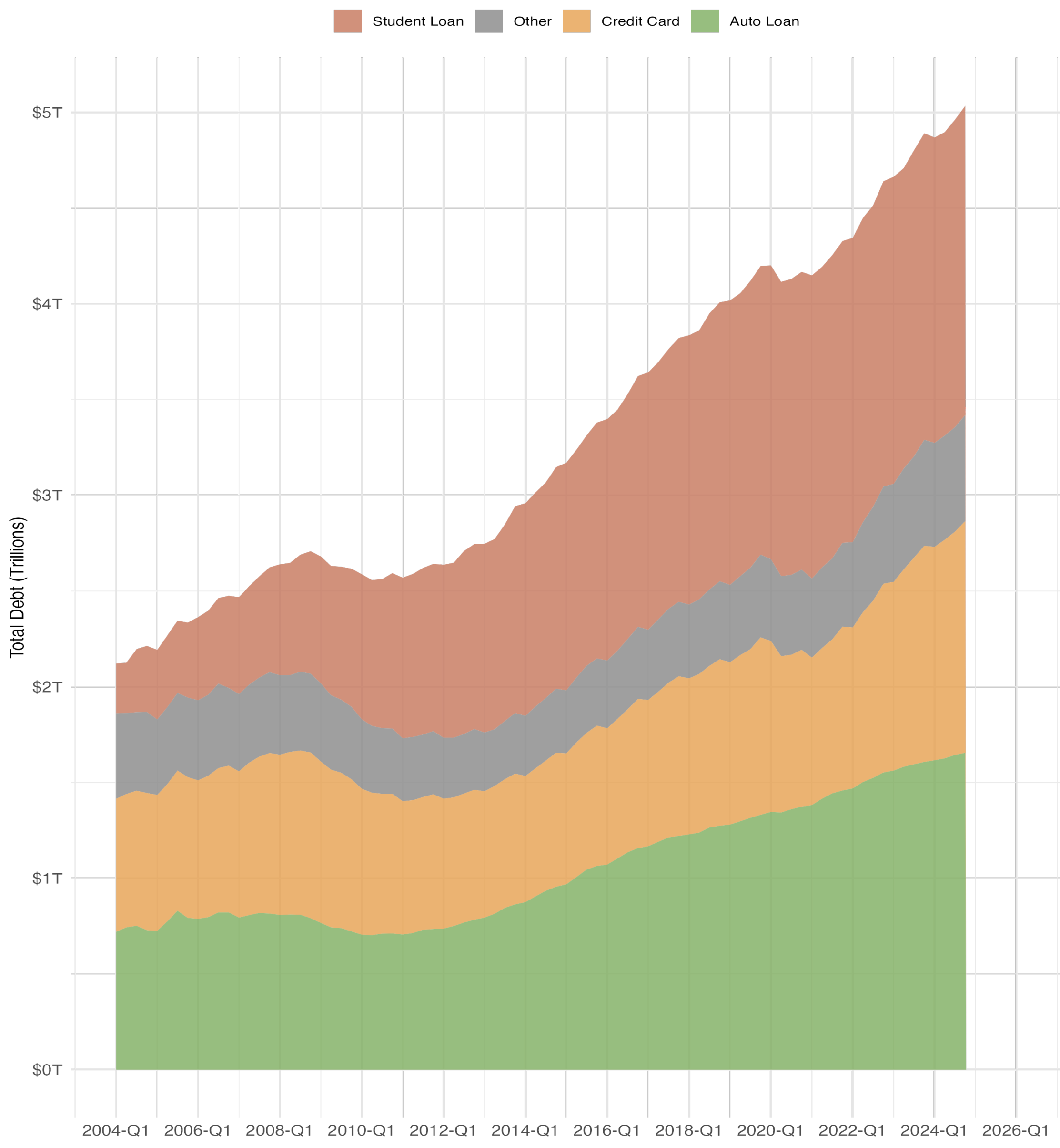

Figure 7: Non-housing Debt Balance