Income and Wealth Inequality in America, 1949-2013*

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Abstract

This paper studies the distribution of U.S. household income and wealth over seven decades of U.S. postwar history. We introduce a newly compiled household-level dataset based on archival data from historical waves of the Survey of Consumer Finances (SCF) starting in 1949. Covering a representative cross-section of American households, the long-run survey data give a granular picture of trends among the bottom 90% of the population, complementing recent work on top incomes. We show that the main loser of rising income concentration at the top was the American middle class – households between the 25th and 75th percentile of the income distribution. The household data equally reveal that income inequality increased earlier and more strongly than wealth inequality. Differences in the composition of household portfolios along the wealth distribution explain the divergence. While incomes stagnated, the American middle-class enjoyed substantial gains in housing wealth from highly concentrated and leveraged portfolios, mitigating wealth concentration at the top. The housing bust of 2007 put an end to this counterbalancing effect and triggered the largest spike in wealth inequality in postwar history. Our findings highlight the role of portfolio composition, leverage and asset prices for wealth dynamics in postwar America.

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1 Introduction

We live in unequal times. The income share of the richest 10 percent of U.S. households has grown substantially over the past decades. The causes and consequences of increasing inequality has become one of the defining debates of our time. This paper aims to fill a number of important gaps in our understanding of this trend and its drivers. The backbone of our study is a new dataset that builds on household-level information spanning the entire U.S. population over seven decades of postwar American history.

We unearthed historical waves of the Survey of Consumer Finances (SCF) that were conducted by the Economic Behavior Program of the Survey Research Center at the University of Michigan from 1948 to 1977. Individual studies such as Malmendier and Nagel (2011) or Herkenhoff (2013) have used extracts of these data to address specific questions of historical interest. But the pre-1983 SCF survey data have not yet been systematically processed and linked to the modern SCFs. In extensive data work, we harmonized the historical and modern surveys in a consistent way, creating a new long-run micro-level data spanning nearly 70 year of postwar history. We call this new resource for inequality research the *Harmonized Historical Survey of Consumer Finances* (HHSCF). The HHSCF data closely match aggregate trends in the National Income and Product Accounts (NIPA) and the Flow of Funds Accounts (FFA).

This paper introduces the HHSCF and exploits it to address a number of pivotal questions that were beyond the reach of existing studies. Income tax data used in the seminal studies of Piketty and Saez (2003) and Saez and Zucman (2016) are a fitting source to determine top income and wealth shares. Yet it is widely accepted that income tax data are not ideal to study the lower half of the distribution as they do not cover non-taxable income and non-filers. On the basis of the tax data we can not say much about the bottom 90% – the losers of increasing income concentration at the top. As a consequence, until today we know relatively little about trends in income inequality among groups in the middle and at the bottom of the distribution. Similar issues arise with respect to trends in wealth inequality. Previous studies relied on a capitalization method to infer wealth stocks from observable income flows. Yet outside the top 10%, most wealth is held in forms that do not generate income subject to income tax. By and large, previous studies had to work with cursory estimates of the evolution of the wealth distribution outside the top 10%. In the long-run HHSCF data, we observe income and wealth *jointly* at the household level and can study the income and wealth distribution across the entire population.

The household survey data confirm a substantial widening of income and wealth disparities over the past seven decades. The magnitudes are comparable to the trends observed in the income tax data. Yet while both data sources produce broadly similar results with respect to trends in income and wealth concentration at the top, the survey data add considerable nuance for the bottom 90%. We document that main street America – the 25th to 75th percentile of the distribution – was the main loser of increasing income concentration at the top. Out of every additional dollar of income that the American economy generated since 1970s, the middle class received only about 15 cents, less than half its share of 40 cents in the 1960s and 1970s. By contrast, the top 10% received about 75 cents of every additional dollar that the U.S. economy generated since 1970, more than double its earlier share of 30 cents.

Using the joint information on income and wealth in the HHSCF, we expose divergent trajectories of income and wealth inequality. In standard models of wealth inequality rising income inequality leads to a simultanoeus increase in wealth inequality that will even exceed the increase in income inequality if income-rich households save more – as existing research argues (Dynan, Skinner, and Zeldes (2004), Saez and Zucman (2016)). The HHSCF data show that for a long time the opposite was the case in postwar America. Wealth concentration decreased in the 1970s and 1980s, the time when income concentration at the top rose most strongly. Afterwards wealth concentration began to rise slowly but by 2007 wealth concentration barely exceeded its 1971 level. Yet the financial crisis of 2007/08 produced the largest spike in wealth concentration in postwar America. In the six years after the financial crisis wealth concentration at the top rose as much as in the six decades before.

The reason for these differential trends in income and wealth inequality can be found in the heterogeneity of household portfolios along the wealth distribution. While the portfolios of rich households are dominated by business equity and financial assets, middle-class household portfolios are highly concentrated in residential real estate and also highly leveraged. Before the crisis, rising house prices led to substantial wealth gains of middle-class households that counterbalanced the gains in business wealth recorded at the top of the distribution.

We calculate that the middle class received 75% of the total wealth gains from the housing boom of the 1990s and the mid-2000s. Asset price induced gains in middle class housing wealth slowed down the pace of wealth concentration at the top by two thirds. Without the boost from rising house prices, middle-class wealth would have been 40% lower in 2007. It is conceivable that these healthy wealth gains helped dispel middle class discontent about stagnant incomes for some time. When house prices collapsed after 2006, the same leveraged portfolio position of the middle class led to substantial wealth losses and a corresponding increase of wealth inequality. For instance, the 90-50 wealth ratio jumped from about 8 in 2007 to 12 in 2013, potentially driving the perception of rising inequality after the crisis.

In the light of the long-run HHSCF data, the interaction of heterogeneous portfolios with differential asset price changes emerges as a important driver of wealth inequality. Heterogeneity of household portfolios gives rise to highly divergent exposures to asset price changes and induces substantial rate of return differences between different groups. This mechanism constitutes an important avenue for future research aiming to explain inequality trends with structural macroeconomic models (Kaymak and Poschke (2016), Hubmer, Krusell, and Smith Jr (2016)).

The structure of the paper is as follows. Section 2 introduces the new dataset, and discusses the construction of the new long-run series. The next section benchmarks aggregate trends to NIPA and Flow of Funds data. Section 4 discusses the evolution of income and wealth inequality at the top and among the bottom 90% of the population. Importantly, we demonstrate that middle-class households have been the losers of rising income and wealth concentration at the top. Section 5 compares the rise in income and wealth inequality. We show that the trends diverged considerably. Section 6 explains this divergence through differences in household portfolios, leverage and asset price dynamics across the wealth distribution. Section 7 concludes.

Related literature: Our paper is closely related to and complements the pioneering work of Piketty and Saez (2003) and Saez and Zucman (2016) who use income tax data to document the evolution of income and wealth concentration over the last century. Saez and Zucman (2016) use a capitalization approach to impute wealth based on observed income flows. Their method is particularly powerful at the top of the income distribution where a significant portion of wealth is held in assets that generate taxable income flows. For portfolio positions that do not generate taxable income such as housing, Saez and Zucman (2016) rely on an imputation based on survey data. The HHSCF data we introduce in this paper corroborate their overall findings while providing additional evidence for the bottom 90%. Recently, Piketty, Saez, and Zucman (2016) combined micro data from tax records and household survey data to derive the distribution of income reported in the national accounts.[1]

Emphasizing the importance of asset price changes for inequality, our paper also relates to the work of Bach, Calvet, and Sodini (2016). Studying administrative Swedish data, they find that wealthy households receive higher returns on their portfolios, but also face higher risks. Kuhn and Rıos-Rull (2016) use data from the "modern" SCF to analyse household balance sheets based on SCF data from 1989 to 2013. Decomposing the relative importance

[1] In particular, Piketty, Saez, and Zucman use survey data from the Current Population Survey (CPS) to impute the distribution of transfers in terms of synthetic micro data. For income, they rely on the work done by Piketty and Saez (2003) that utilizes tax data. They also add wealth to their synthetic micro data set that is based on the capitalization method developed in Saez and Zucman (2016).

of different balance sheet positions for wealth inequality, they show that due to their size houses and mortgages are an important driver of wealth inequality.

Theoretical work explaining rising wealth inequality is still in its infancy. In a recent paper, Hubmer, Krusell, and Smith Jr (2016) use variants of incomplete market models to explore how different explanations for the rise in wealth inequality hold up quantitatively.[2] While tax progressivity emerges as a central driver of rising wealth inequality in their model, they also discuss differences in asset returns along the wealth distribution as a mechanism that the workhorse macro models does not (yet) feature. Our empirical results confirm that this is indeed an important gap to fill in future research. De Nardi and Fella (2017) survey the existing literature on macroeconomic models of wealth inequality. They discuss different models from the canonical incomplete market model to models with intergenerational transmission of financial and human capital, rate of return risk on financial investments, and more sophisticated earnings dynamics.

2 The Harmonized Historical Survey of Consumer Finances

This section presents our efforts to process the historical surveys to construct the long-run dataset that is the backbone of our study. We are hopeful that the new *Harmonized Historical Survey of Consumer Finances* can become a valuable resource for future research. We therefore go into some detail to describe the construction and contents of the dataset. We also discuss challenges that we encountered when linking the historical waves of the SCF with its modern counterparts.

The SCF is a key resource for research on household finances in the United States. The SCF is a triennial survey and data sets for various survey waves starting in 1983 are easily available on the Federal Reserves website. Other than ease of access, the comprehensiveness and quality of the SCF explains its popularity among researchers (see, for example, Kuhn and Rıos-Rull (2016) and references therein). Selected historical data for the period before 1983 such as the 1962 Survey of Financial Characteristics of Consumers (SFCC) and the 1963 Survey of Changes in Family Finances (SCFF) are also available from the Federal Reserves website.

However, the first consumer finance surveys were conducted much earlier, namely as far back as 1948. The early SCF waves were directed by the Economic Behavior Program of the Survey Research Center of the Institute for Social Research at the University of Michigan.

[2]See Castaneda, Díaz-Giménez, and Ríos-Rull (2003) for a benchmark model of cross-sectional income and wealth inequality and Kaymak and Poschke (2016) for another recent attempt to explain time trends.

Figure 1: Codebook of survey of consumer finances in 1949

Project # 42 -4- Card III

Col. No.

23-27 Income from wages and salaries: (Add amounts entered after questions 33, 34, 35) (in farm schedule, item 44a)

Code the amount in dollars

00000. No income from wages and salaries
Y0000. Income from wages and salaries exceeds $99,999
X0000. Income from wages and salaries not ascertained (code here if Schedule II contains only a total at the bottom of the page)

28 - Income from wages and salaries, in class intervals:

1. $1-$499
2. $500-$999
3. $1,000-$1,999
4. $2,000-$2,999
5. $3,000-$3,999
6. $4,000-$4,999
7. $5,000-$7,499
8. $7,500-$9,999
9. $10,000 and over

0. No income from wages and salaries

X. Income from wages and salaries not ascertained

29 Did you (R and SU) receive any money from interest, dividends, rents, trust fund, or royalties? (Question 37) (Farm Schedule 44b)

1. Yes, recieved income from this source; less than $100
2. Yes, received income from this source; $100-499
3. Yes, received income from this source; $500-1,999
4. Yes, received income from this source; $2,000-4999
5. " " " " " " ; $5000 or over
6 " " " " " " ; Amount not ascertained
0. No, did not receive income from this source

X. Not ascertained whether received income from this source

30-34 Income from interest, dividends, royalties, rents, trust funds, business, professional practice: (Add amounts entered after questions 37, 39, 40, 41, 43 minus 42; Farm Schedule 44b)

Code the amount in dollars

00000. No income from these sources
Y0000. Income from these sources larger than $99,999*
X0000. Income from these sources not ascertained
XY000. Negative income *

The historical SCF waves were taken annually between 1948 and 1971, and then again in 1977. The raw data are kept at the Inter-University Consortium for Political and Social Research (ICPSR), at the Institute for Social Research in Ann Arbor. The historical survey contains all the important variables that are needed to construct long-run series for the joint evolution of income, financial and non-financial assets, and housing and non-housing debt. In addition, the SCFs contain information on age, sex, race, marital status, family size, and educational attainment. Figure 1 shows an example of a survey questionnaire from the year 1949.

For our analysis, we use all underlying data and abstain from any sample selection. We extract cross-sectional data for the financial situation of U.S. households from 1949 to 1977, and then link the series to the post-1983 SCFs. The surveys start in 1948 but the first year with comprehensive coverage of debt and assets is 1949, our starting point. We had to drop a few selected outliers that are likely due to coding or transmission errors in the SCF files. Moreover, we adjust all data for inflation using the CPI and report results in 2013 Dollars. It is worth noting that the SCF is a household survey and as such income, debt, and wealth are all reported at the household level. This implies that in most cases households with fewer adult members have less income, debt, and wealth. The HHSCF data provides detailed demographic information together with the financial situation of U.S. households over time and allow us to take into account the effects of demographic changes.

2.1 Variables

The variables covered in the historical surveys generally correspond to those in the contemporary SCFs, but the exact wording of the questions may differ from survey to survey. Financial innovations impact continuous coverage of the various surveys. For instance, data on credit card balances become available after their introduction and proliferation. The appearance of new financial products like credit cards does, however, not impair the construction of consistent data over time. Implicitly, these products are counted as zero for years before their appearance. Some variables are not continuously covered so that we have to impute values in some years. We explain our imputation in the next section. Our subsequent analysis looks at four variables that are of particular importance for the analysis of household finances: income, assets, debt, and wealth.

Income: We construct total income as the sum of wages and salaries, income from professional practice and self employment plus rental income, interest, dividends, transfer payments as well as business and farm income. Income variables are available for all years. Capital gains are not reported in the early surveys. We therefore exclude them from our measure of income.

Assets: The historical SCF waves contain detailed information on household assets. We group assets into the following categories: liquid assets, housing, bonds, equity, the cash value of life insurance, other real estate, and business equity. The coverage is comprehensive for liquid assets and housing. Liquid assets comprise the sum of checking, saving, call/money market accounts, and certificates of deposits. Information on liquid assets is available for almost every year of the data set, except for 1964 and 1966. For bonds, variables are imputed for the 1960s, but the data are comprehensive for the 1950s. The coverage of other real estate as well as corporate and non-corporate equity is imputed for several years before 1977. Data on defined contribution pensions are only available from 1983 onwards, however, according to the FFA, this variable makes up a very small part of household wealth before the 1980s. Missing information before 1983 is unlikely to alter the wealth data significantly.[3] Table 2 below outlines the years and variables for when imputation is used.

Debt: Total debt consists of housing and non-housing debt. Housing debt is calculated as the sum of debt on owner-occupied homes and debt on other real estate. All surveys except those of 1952, 1961 and 1977 include explicit information on housing debt. For 1977, only the origination value (instead of the current value) of mortgages is available. Using information on the year the mortgage was taken out, remaining maturity and an estimated annual interest rate, we create a proxy for debt on homes for 1977.[4] All debt other than housing debt refers to and includes car loans, education loans, and loans for the purchase of other consumer durables. For several survey years, there is no information on non-housing debt, but if the components of non-housing debt, such as installment debt and credit card debt are available, we calculate the sum of these components and report the sum as non-housing debt.

Wealth: We construct wealth as the consolidated value of the household balance sheet by subtracting debt from assets. Wealth constitutes households net worth.

2.2 Weights and imputations

The SCF is designed to be representative of the U.S. population. Yet capturing the top of the income and wealth distribution is a challenge for most surveys. The modern SCF applies a two-frame sampling scheme to oversample wealthy households. Besides the coverage of wealthy households in the historical surveys, we also need to ensure representative coverage of demographic characteristics such as race, age, and education. In the following section, we explain how we adjusted the historical data to arrive at long-run series. This also includes imputing missing variables in the household balance sheet for particular survey years.

[3]Up to 1970, defined contribution plans correspond to less than 1% of average household wealth. Until 1977 this share increases to 1.7%.

[4]The surveys of 1952, 1956, 1960-1967 and 1971 contain no information on debt non-owner occupied real estate. While the overall amounts tend to be small, this may reduce the debt of rich households in early survey years as they are more likely to have debt from other real estate.

Oversampling of wealthy households: Since its redesign in 1983, the SCF consists of two samples. The first sample is drawn using an area probability sampling of the entire U.S. population and is selected by using information from the U.S. Census. To oversample wealthy households, the second so-called *list sample* contains households at the top of the wealth distribution. These households are selected using income tax information.[5] For both samples, survey weights are constructed separately. In the list sample, survey weights have to be disproportionally adjusted for non-responses. The weight of each household supposedly corresponds to the number of similar households in the U.S. In a final step, both samples are combined. To ensure that the combined sample is representative of the U.S. population survey weights of both samples are adjusted (see Kennickell, Woodburn, and McManus (1996)).[6]

Before 1983, the SCF rests on a sample that is representative of the U.S. population on the basis of Census data. There is no second list sample, so that the fact that non-responses are more frequent at the top of the distribution might lead to an under-representation of wealthy households. To account for this under-representation, we mimic the oversampling of rich households that is done in the surveys after 1983 to the pre-1983 survey. We adjust observation weights in the top of the income and wealth distribution. To do this, we rely on information on the distribution of the list sample in the 1983 SCF. The weighted number of households of the list sample in 1983 corresponds to about 2% of all households.

We determine where the households of the list sample would have been located along the income and wealth distribution after we excluded the households of the list sample. We find that most observations of the list sample would have been in the top 5% of both the income and wealth distribution. Weights for surveys before 1983 are then adjusted in three steps. First, we determine percentiles of the income and wealth distribution in each survey year. Second, we extract observations that are at the same time in the top 5% of the income and wealth distribution for each survey year. Third, we adjust the weights of these observations so that we add 2% of households to the sample. This implies that we apply two weight adjustment factors, one to adjust the sample weight of the bottom of the distribution and

[5] As tax data only provides information on income, a wealth index is constructed by capitalizing the income positions. Asset positions are estimated by dividing each source of capital income with the average rate of return of the corresponding asset.

[6] The adjustment is done by sorting all households into subgroups according to their gross asset holdings. Each subgroup may contain households from the first and second sample. Within each subgroup the weight of households from the first and second sample are then adjusted depending on how many U.S. households they are thought to represent. If N_1 and N_2 are the number of weighted households of sample 1 and 2, respectively, then n_1 and n_2 are the number of unweighted households. W_1 and W_2 weights are constructed for each sample separately. The adjusted weights for the combined samples, W_{12}, are then given by $W_{12} = \frac{n_i}{N_i} \frac{1}{\frac{n_1}{N_1} + \frac{n_2}{N_2}}$ for $i = 1, 2$. The less households an observation is thought to represent, the higher $= = \frac{n_i}{N_i}$ and the more the original weight W_i is adjusted upwards.

one to adjust weights in the top of the distribution so that we add 2 % of observations to the top of the distribution.

Table 1: Share of high income sample at the top of the distribution

	Income			Wealth		
	top 10%	top 5%	top 1%	top 10%	top 5%	top 1%
SFCC 1962	21 %	35 %	63 %	20 %	28 %	48 %
SCF 1983	17 %	34 %	88 %	17 %	32 %	72 %

Notes: Share of respondents from list sample in different parts of the income and wealth distribution. Left side shows shares in the top of the income distribution in the 1983 SCF and the 1963 SFCC data. Right side shows shares in the top of the wealth distribution in the 1983 SCF and the 1963 SFCC data. Shares are computed using weighted observations.

A key concern with this adjustment routine is that it relies on information from a single sample year in 1983. The list sample is not available for any of the later years. However, the 1962 SFCC sample used a similar two-frame sampling scheme to the 1983 survey with a sample of rich households that was selected based on tax records.

Table 1 shows non-response pattern at the top of the income and wealth distribution from the two surveys. The distribution of households at the top of the income and wealth distribution is relatively stable in the 1962 SFCC and the 1983 SCF. We find that non-response as the key reason for the under-representation of rich households in most surveys appears to have not changed over time. We conclude that there is no indication that our calibration of the adjustment routine to 1983 data is impacted by time trends in non-response pattern.

As a test to assess the reliability of our approach, we compare income shares at the top of the income distribution with information from pre-1983 tax data. We explain this process in further detail in section 4.1 where we will show that using the weight-adjusted data the top income shares very closely mirror each other in trend and level. This provides additional support for the validity of the approach. As a proof of concept, we apply in section A.3 of the appendix our adjustment to the 1983 data itself after we have dropped the list sample. We find that the adjustment works well for the top 10 % and deteriorates towards the very right tail. The very right tail has been extensively studied using tax data and is not at the focus of our study.

Demographic characteristics: We compare the coverage of demographic characteristics in the surveys before 1983 with data from the U.S. Census from 1940 to 1990. In particular, the described adjustment of sample weights might distort the distribution of demographic characteristics.[7]

[7] For example, as mainly white college households are in the top of the income and wealth distribution,

To obtain samples that match the Census data, we subdivide both the Census and the HHSCF data into 24 demographic subgroups. Subgroups are determined by age of the household head, whether the head attended college, and whether the head is black. We adjust HHSCF weights by minimizing the difference between the share of each subgroup in the HHSCF and the respective share in the Census.[8] As Census data are only available on a decennial basis, we linearly interpolate values between the dates.[9]

Figure 2 shows the shares of 10-year age groups, college households, and black households in the Census (black squares) and in the HHSCF with the adjustment of survey weights (gray dots). Population shares in surveys after 1983 are close to Census shares. Looking at the shares before 1983 without adjustment of survey weights, we find that households aged between 25 and 34 are overrepresented in most years while household aged 65 and above are underrepresented. In addition, the share of college households is 5 to 10 pp higher in the SCFs before 1983 without adjustment compared to the Census. Using adjusted weights, the distributions of age, education and race closely match the Census data.

Missing variables: The imputation of missing variables is done by predictive mean matching as proposed in Schenker and Taylor (1996). This imputation method assigns variable values to the missing observations by finding observations that are closest to the respective missing observations. The variable values of these "closest neighbors" are then employed to the respective observation for which information on the variable is missing.

In addition, we account for a potential underrepresentation of business wealth before 1983. High-wealth households who hold most of business wealth and equity are partly imputed before 1983. To account for their business wealth, we follow the method proposed by Saez and Zucman (2016) and adjust the observed holdings in the micro data using FFA data. For this purpose, we rely on data from the 1983 and 1989 surveys. We adjust business wealth and stock holdings in the earlier surveys so that the ratio of business wealth and stocks relative to the FFA aggregates matches the ratios in 1983 and 1989.[10] This provides consistent estimates taking into account the conceptual differences between SCF and FFA data.

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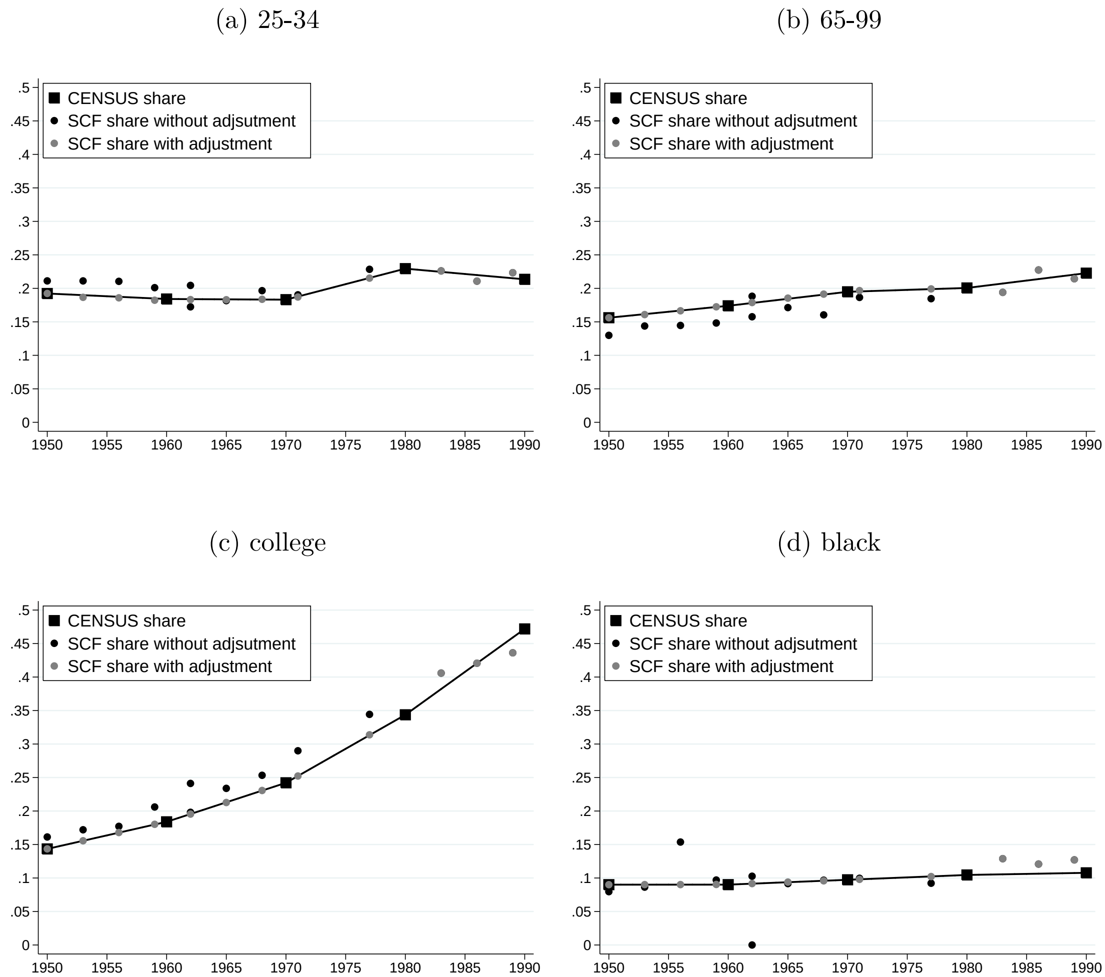
it is likely that their share in the survey population is too high.

[8] Similar to the adjustment of weights done previously, we calculate factors for each subgroup. By multiplying observations with the respective factor of their subgroup, the share of each group in the HHSCF corresponds to the respective share in the Census.

[9] The distributions of demographic characteristics such as age, education and race change gradually over time. Therefore, interpolation is a good approximation.

[10] Let X_{it} be business wealth or stocks of observation i in period t. $\bar{\mathrm{X}}_t$ is the respective mean in period t and X_t^{FFA} is the corresponding FFA position per household in t. The adjusted values of business wealth and stocks are then calculated as follows. $\mathrm{X}_{it}^{adj} = \mathrm{X}_{it} \dfrac{\mathrm{X}_t^{FFA}}{\bar{\mathrm{X}}_t} \dfrac{\bar{\mathrm{X}}_{1983,1989}}{\mathrm{X}_{1983,1989}^{FFA}}$

Figure 2: Shares of 10-year age groups, college and black households in the population



Notes: The large black dots refer to the share of the respective age group in the U.S. census. The small black dots are the shares using the original survey weights. The small gray dots are the shares using the new weights.

Table 2 details all available variables and their coverage, as well as the years in which we imputed data. An "O" in the table indicates that original information of the variable is available for the year. An "I" signifies that observations for this variable were imputed. If a variable is missing in a year, we report the years of adjacent surveys that are used for the imputation in Tables A and B of the appendix.[11]

We refer to the final data set as the *Harmonized Historical Survey of Consumer Finances* (HHSCF) data. It comprises 35 survey years with cross-sectional data – totaling $112,669$

[11]We exclude the survey years 1948, 1952, 1961, 1964 and 1966 due to lacking information on housing, mortgages or liquid assets. These three wealth components are held by a large fraction of households, but can only poorly be inferred from information on other variables (see R^2 in Tables B, D and E.)

Table 2: Data availability

	income			financial assets			non-financial assets			debt			
Survey year	total	labor	labor + business	liquid assets	bonds	equity	housing	other real estate	business	total	housing	other real estate	non-housing
1949	O	O	O	O	O	O	O	O	I	O	O	O	O
1950	O	O	O	O	O	O	O	O	O	O	O	O	O
1951	O	O	O	O	O	I	O	I	I	O	O	O	O
1952	O	O	O	O	O	O	I	O	O	I	I	I	O
1953	O	O	O	O	O	O	O	O	O	O	O	O	O
1954	O	O	O	O	O	I	O	I	I	O	O	O	O
1955	O	O	O	O	O	O	O	I	I	O	O	O	O
1956	O	O	O	O	O	I	O	I	I	I	O	I	O
1957	O	O	O	O	O	I	O	I	I	O	O	O	O
1958	O	O	O	O	O	I	O	I	I	O	O	O	O
1959	O	O	O	O	O	I	O	I	I	O	O	O	O
1960	O	I	O	O	O	O	O	O	O	I	O	I	O
1961	O	I	O	O	O	I	I	I	I	I	I	I	O
1962	O	I	O	O	O	O	O	O	O	I	O	I	O
1963	O	I	O	O	O	O	O	O	O	I	O	I	O
1964	O	I	O	I	I	O	O	I	I	I	O	I	O
1965	O	I	O	O	O	I	O	I	I	I	O	I	O
1966	O	O	O	I	I	I	O	I	I	I	O	I	I
1967	O	O	O	O	O	O	O	I	I	I	O	I	O
1968	O	O	O	O	O	O	O	O	I	O	O	O	O
1969	O	O	O	O	O	O	O	O	I	O	O	O	O
1970	O	O	O	O	O	O	O	O	O	O	O	O	O
1971	O	O	I	O	I	I	O	I	I	I	O	I	O
1977	O	O	I	O	O	O	O	O	I	O	O	O	O
1983	O	O	O	O	O	O	O	O	O	O	O	O	O
1989	O	O	O	O	O	O	O	O	O	O	O	O	O
1992	O	O	O	O	O	O	O	O	O	O	O	O	O
1995	O	O	O	O	O	O	O	O	O	O	O	O	O
1998	O	O	O	O	O	O	O	O	O	O	O	O	O
2001	O	O	O	O	O	O	O	O	O	O	O	O	O
2004	O	O	O	O	O	O	O	O	O	O	O	O	O
2007	O	O	O	O	O	O	O	O	O	O	O	O	O
2010	O	O	O	O	O	O	O	O	O	O	O	O	O
2013	O	O	O	O	O	O	O	O	O	O	O	O	O

Notes: "O" indicates that original observations of this variables are used, i.e. no imputed observations. "I" indicates that observations of this variable are imputed.

household observations with demographic information and 13 continuously covered financial variables. The number of observations varies from a minimum of $1,327$ in 1971 to a maximum of $6,482$ in 2010. Table A.1 in the appendix reports the number of observations for all years.

3 Aggregate trends

Our aim is to use the micro data to study the evolution of income and wealth distribution over time. For such an investigation, it is important that the micro data is consistent with aggregate data. In this section, we therfore benchmark trends from the HHSCF data to the National Income and Product Accounts (NIPA) and the Flow of Funds (FFA).

Even high quality micro data do not always correspond one-to-one to aggregate data as measurement concepts differ between micro surveys and national account data. For instance, Heathcote, Perri, and Violante (2010) discuss that data from the NIPA and Current Population Survey (CPS) differ substantially. They explain the observed differences with indirect capital income from pension plans, non-profit organizations and fiduciaries, as well as employer contributions for employee and health insurance funds. These positions are measured in the NIPA, but not in household surveys such as the CPS or the SCF.

With respect to the FFA, several wealth components of the household sector are measured as residuals obtained by subtracting the positions of all other sectors from the economy-wide total (see Antoniewicz et al. (1996), Henriques and Hsu (2013)). These residuals contain asset positions held by nonprofit organizations as well as domestic hedge funds that are not included in the SCF. Antoniewicz et al. (1996) thoroughly discusses the measurement concepts in the SCF and FFA and concludes that there are reasons for measurement error in both data sets.

Despite the conceptual differences in measuring income and wealth, we will see that the HHSCF data match aggregate trends closely – effectively alleviating most of the previously indicated concerns.[12] Figure 3 compares income and wealth of the HHSCF with the corresponding NIPA and FFA values. Income components of the NIPA tables that are included are wages and salaries, proprietors income, rental income, personal income receipts, social security, unemployment insurance, veterans benefits, other transfers and other net current transfer receipts from a business. FFA wealth data are calculated following Henriques and

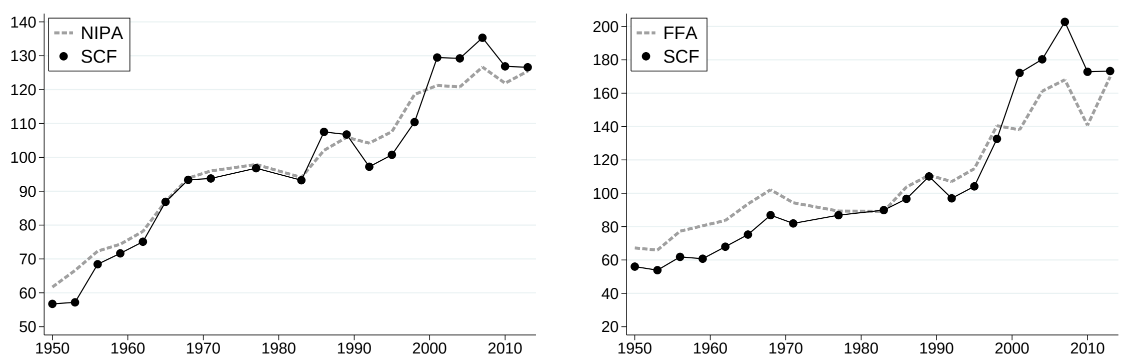
[12] The unit of analysis in the SCF is the primary economic unit (PEU) that contains persons in a household who share finances. The SCF sampling weights are constructed to be representative of all U.S. households following the household definition of the U.S. Census Bureau. The Census household definition deviates slightly from that of a PEU as it groups people living together in a housing unit. In some cases this may be several PEUs living together. Although the two concepts will lead to identical units of observation in the vast majority of cases, Kuhn and Rıos-Rull (2016) report that in 2013 the average SCF household is slightly smaller than a Census household. The analyses by Piketty and Saez (2003) and Saez and Zucman (2016) use tax units as their unit of observation. However, tax units differ from households. A tax unit can be a single adult or a married couple and both can have dependent children. In 2012 there are about 1/3 more tax units (160.7 million) than households (121.1 million) in the U.S.

Hsu (2013) who construct wealth from the FFA to be comparable to the SCF.[13] The base period for comparisons is 1983 to 1989 as these are the first surveys that incorporate the oversampling of wealthy households.

Figure 3: HHSCF, NIPA, and FFA: income and wealth

(a) Income

(b) Wealth



Notes: Income and wealth data from HHSCF in comparison to income data from NIPA and wealth data from FFA. All data has been indexed to the 1983 - 1989 period (= 100). HHSCF data is shown as black lines with circles, NIPA and FFA data as a gray dashed line. Over indexing period HHSCF value corresponds to 84% for income, 118% for wealth.

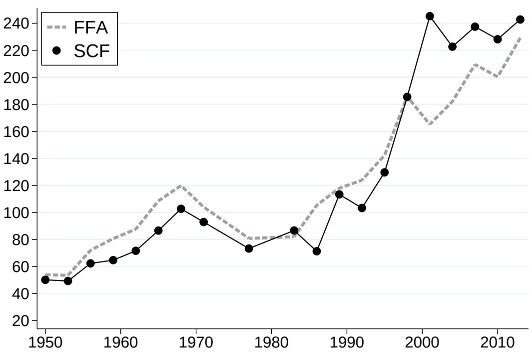
For the base period of 1983-1989, the HHSCF matches 84 percent of income from NIPA and 118 percent of FFA wealth. Figure 3 shows that the trend in income is very similar for HHSCF and NIPA data throughout the 1949-2013 time period. Looking at wealth, the trends differ only slightly. Before 1983, wealth in the HHSCF is below that of the FFA. From 1983 to 1998, the two measures are about the same and from then onwards the HHSCF is somewhat higher. Both wealth measures show an upward trend over time, the increase is steeper in the HHSCF.

To evaluate which specific asset and debt positions generate the divergence in wealth estimates, Figures 4 and 5 show different asset and debt positions. Figure 4a shows financial assets. Financial assets in the HHSCF increase more strongly in the 1980s than the corresponding FFA values. This difference between is mainly due to distinct trends in corporate equity during the stock market boom in the second half of the 1990s. Figure 4c shows that corporate equity in the household data nearly doubled in value between 1995 and 1998 while

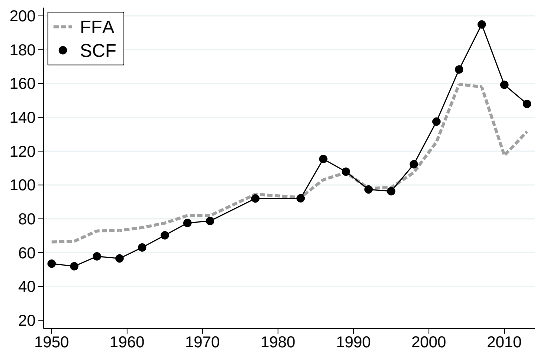
[13]This means that defined-benefit pension plans are excluded since these are not measured in the SCF and asset positions of nonprofit organizations are subtracted when possible (e.g., information on housing is provided separately for the household sector and nonprofit organizations). In addition, only mortgages and consumer credit are included as FFA debt components. However, the main adjustment to the SCF is that non-residential real estate is excluded from 1989 onwards (no distinction is available before 1989).

Figure 4: HHSCF, NIPA, and FFA: financial and non-financial assets

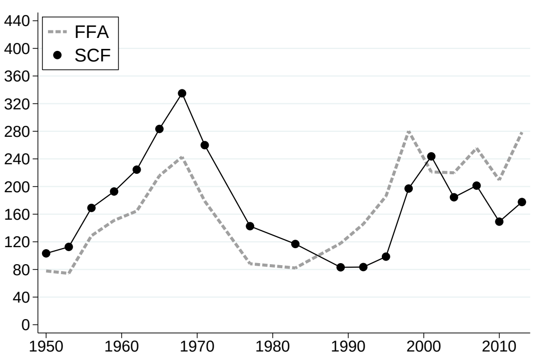
(a) Financial assets



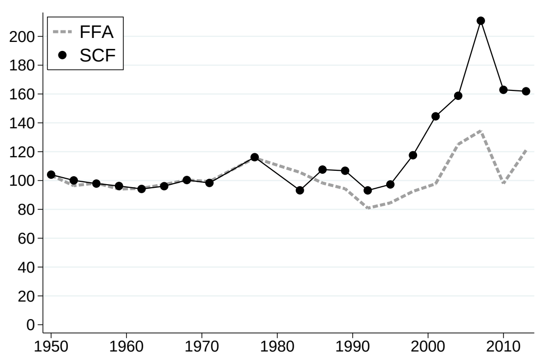
(b) Non-financial assets



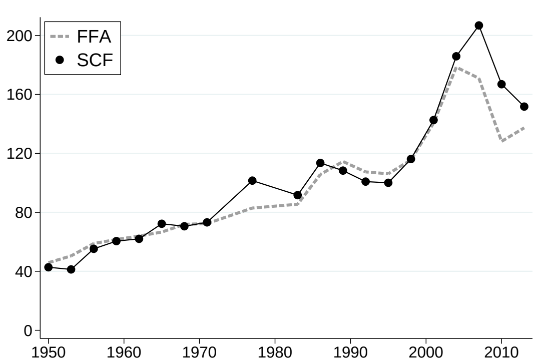
(c) Equity



(d) Business wealth



(e) Housing



Notes: Financial and non-financial assets from HHSCF in comparison to data from FFA. All data has been indexed to the 1983-1989 period (= 100). HHSCF data is shown as black lines with circles, FFA data as a gray dashed line. Over the indexed period, HHSCF values correspond to 76% for financial assets, 45% for deposits, 61% for bonds and 82% for corporate equity.

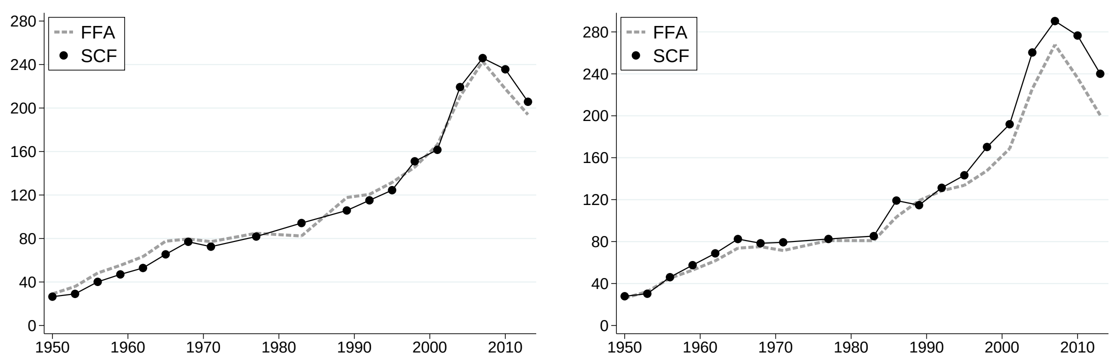
it increased by about 60% in the FFA.

Figure 4b shows that trends for non-financial assets are similar in the micro and macro data. The HHSCF shows a stronger increase between 1977 and 1983, and the decrease of non-financial assets is lower in the HHSCF after 2007. Differences in trends of non-corporate equity (Figure 4d) cause a stronger increase in non-financial assets between 1977 and 1983. Figure 4e shows housing as the most important non-financial asset. HHSCF data matches the FFA data closely.

Figure 5: HHSCF, NIPA, and FFA: debt

(a) Total debt

(b) Housing debt



Notes: Debt from HHSCF in comparison to data from FFA. All data has been indexed to the 1983-1989 period (= 100). HHSCF data is shown as black lines with circles, FFA data as a gray dashed line. Over the indexed period, HHSCF values correspond to 86% for total debt, 92% for housing debt and 69% for non-housing debt.

The household balance sheet component for which the HHSCF matches the aggregate data best is debt as shown in Figure 5. There is a level difference of about 15% throughout the whole time period, but the trend is almost identical in the HHSCF and FFA. The underlying reason why these trends are so similar is that the dominant component for both data sources is housing debt (Figure 5b). With respect to non-housing debt, the SCF data show somewhat lower values than the FFA. However, non-housing debt represents a relatively small share of total household debt, and the differences do not affect the overall trend in total debt.

In conclusion, the HHSCF matches aggregate trends of NIPA data and FFA asset and debt positions. In particular, the HHSCF data and the FFA show very similar trends for the important categories of housing wealth and mortgage debt. For some asset categories like corporate and non-corporate equity, some gaps remain. Yet this is true for both the historical and post-1983 SCF data and points to conceptual differences in measurement rather than specific problems of the historical series.

4 Income and wealth distribution in America, 1949-2013

The previous section discussed the aggregate increase of U.S. households income and wealth over the past seven decades. In this section, we will use the HHSCF data to study how the distribution of income and wealth changed over time. We will first look at income and wealth concentration at the top, corroborating stylized facts for the trajectories of U.S. income and wealth distribution since the end of World War II that emerged from well-known studies such as Piketty and Saez (2003) and Saez and Zucman (2016). In a second step, we will exploit the micro data to provide new and more detailed evidence for distributional trends within the bottom 90% of the population.

We will demonstrate that trends for top income and wealth shares in the HHSCF confirm the picture painted by tax data. Focusing on trends within the bottom 90%, we will show that the gains of the top 10% were accompanied by income losses in the middle of the distribution, i.e., for the 25th to 75th percentiles of income. By contrast, both the upper middle-class (75th-90th percentiles) and the poorest Americans in the bottom quartile of the distribution did not witness major income losses. With respect to wealth inequality, our data point to different dynamics that we subsequently analyze in greater detail.

4.1 Income and wealth concentration at the top

The recent debate on the evolution of income inequality focused on the concentration of income and wealth at the top. In Figure 6a, we compare the income shares of the top 10, 5, and 1 percent of the income distribution in the HHSCF to those first calculated by Piketty and Saez (2003) using IRS income tax data and a comparable definition of total income.[14] Figure 6b compares wealth shares of households at the top of the wealth distribution in the HHSCF with those obtained by Saez and Zucman (2016).[15] The wealth shares displayed in the chart show that wealth inequality in the U.S. decreased until the mid 1980s and started to rise at the beginning of the 1990s. Today, wealth inequality is at a postwar peak. In other words, the new data confirm a marked polarization of incomes in the past four decades, as well as increasing top wealth shares.

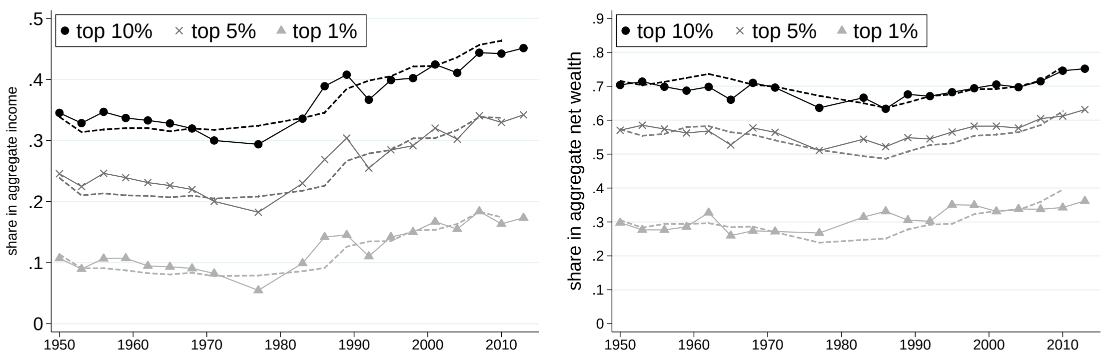
The remaining small differences are likely due to different measurement concepts. Total household wealth before 1983 is lower in the SCF than in the FFA. The difference is mainly

[14] Piketty and Saez (2003) include salaries and wages, small business and farm income, partnership and fiduciary income, dividends, interest, rents, royalties and other small items reported as other income. Both income measures do not include capital gains.

[15] See appendix C for a detailed discussion of their method.

Figure 6: Top income and wealth shares

(a) Income   (b) Wealth



Notes: The dots refer to income and wealth shares derived from the SCF. The dashed lines are the corresponding shares calculated by Piketty and Saez (2003) using IRS tax data or Saez and Zucman (2016) using IRS data and the capitalization method. The blue dots and line refer to households in the top 10% of the income (wealth) distribution, the red ones to top 5%, and the green ones to top 1%.

due to lower corporate and non-corporate equity. As this equity is mainly held by wealthy households, it potentially explains why the shares of top wealth households are smaller in the HHSCF compared to the capitalization method employed by Saez and Zucman (2016). Another difference is likely due to the fact that the pre-1962 estimates of Saez and Zucman (2016) had to be adjusted as tax units before are sorted by income rather than wealth. In the HHSCF data, we have micro data for the entire period and can sort households by wealth without having to rely on adjustments based on a ranking by income.[16]

4.2 Gini coefficients

In this section, we start the discussion with Gini coefficients as a comprehensive statistic to measure income and wealth inequality. Unlike top income and wealth shares, the Gini coefficient provides a summary measure of inequality along the entire distribution. Table 3 reports Gini coefficients of income and wealth at selected points in time. We report the full time series in Table D.3. The first row reports the Gini coefficient for all households. To capture at least partly changes in the bottom of the distribution, we exclude in the second

[16] As the HHSCF data provide the joint distribution of income and wealth, we can study trends in income and wealth concentration among alternative groups. Two alternatives of particular interest are the income concentration among wealth-rich households and wealth concentration among income-rich households. Looking at these groups, we find that the facts on trends are very similar (see Figure D.7 in the appendix). While the levels of income and wealth shares go down by construction, the pattern of changes in income and wealth concentration remain unaffected.

row the top 1% and only consider the bottom 99% of the income and wealth distribution. The third row considers the bottom 90% of the income and wealth distribution.

Table 3: Gini coefficient (×100) of income and wealth

		1950	1971	1989	2007	2013
income	all	44	43	52	55	55
	bottom 99 %	39	38	45	46	48
	bottom 90 %	31	33	38	37	38
wealth	all	76	76	76	79	82
	bottom 99 %	69	68	68	71	74
	bottom 90 %	53	52	56	57	61

Measured by Gini coefficients, income and wealth inequality have increased in the entire population (across all households), but also among the bottom 99% and bottom 90% of households. Yet unsurprisingly, there is a substantial drop in inequality once the top 1% of the distribution is excluded.

The overall trajectory of the Gini coefficients follows that of the top income and wealth shares. Between 1950 and 1989, the Gini for wealth did not change much. It rose slightly between 1989 and the financial crisis of 2007, and then increased strongly during the financial crisis and its aftermath. The income Gini coefficient, by contrast, rose already between 1971 and 1989 and further between 1989 and 2007 but it remained constant after 2007. These pattern also hold if we look among the bottom 90 % or 99 %.

Although a key advantage of the Gini coefficient is that it summarizes inequality in a single number, this comes at a price. As a summary measure, the Gini coefficient does not allow us study changes in different parts of the distribution, for example, focusing on the fortunes of the middle class. Furthermore, comparing trends in income and wealth inequality using the Gini coefficient is difficult because initial levels differ considerably. For the remainder of our analysis, we will therefore use alternative approaches to quantify the time path of the income and wealth distribution.

4.3 The declining income share of the middle class

A major advantage of the HHSCF data is that it enables us to go beyond top income shares and study the entire distribution. The mirror image of increasing concentration of resources in top 10% must, by definition, be (relative) income losses among the bottom 90%. But which strata of the bottom 90% were hit particularly hard by the growing income share of the top 10%?

Table 4 shows the evolution of income and wealth shares of different strata since Worl War II. Starting with income on the left side of the table, the HHSCF data document an increasing concentration of income at the top of the distribution. The top 10% have grown their income share from 34.5 percent to 44.7 percent between 1950 and 2013. At the same time, the income share of the middle class (25th to 75th percentiles) fell from about 40% to 30%. This substantial fall in middle-class incomes corresponds virtually one-for-one to the 10 pp increase of the income share of the top 10%.

The 1970s and 1980s witnessed the most extreme rise in the income share of the top 10% (+ 7.9 pp). During this period, the bottom 25% and the middle class lost ground, while the upper middle class between the 75th and 90th percentile maintained their income share. In a second phase, in the 1990s and 2000s, the top 10% continued to expanded their income shares (+ 4.1 pp), but in contrast to the earlier years the bottom 25% maintained their income. Households in the middle of the distribution were again hit most by income concentration at the top during this period.

Table 4: Shares in aggregate income and wealth

	Income					Wealth				
	1950	1971	1989	2007	2013	1950	1971	1989	2007	2013
bottom 25%	6.1	6.1	4.5	4.6	4.7	0.2	0.0	0.0	0.0	-0.5
25-50%	15.5	15.2	12.1	11.1	10.7	3.8	3.7	3.0	2.6	1.7
50-75%	23.4	24.7	21.8	20.1	19.4	11.2	11.0	11.7	10.2	8.3
75-90%	20.4	21.7	21.5	20.0	20.4	16.4	15.8	17.8	15.8	15.4
top 10%	34.5	32.2	40.1	44.2	44.7	68.4	69.6	67.5	71.4	75.1

Looking at wealth on the right side of Table 4, two distinct episodes of rising wealth concentration at the top stand out. Until 1989, the wealth share of the top 10% fell while middle class households gained ground. Wealth inequality began to rise slowly in the 1990s. But it was in the 2007/08 global financial crisis and its aftermath that the bottom and the middle class wealth shares dropped precipitously, and wealth shares at the top surged.

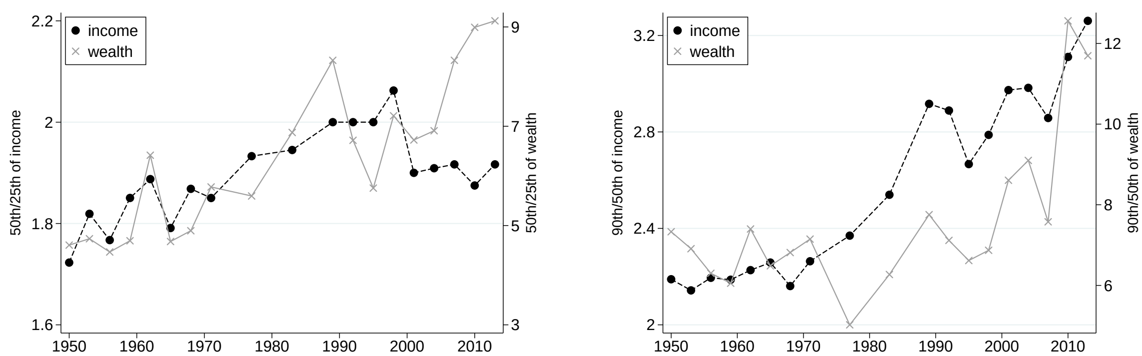
An interesting insight that emerges from Table 4 is that the trends in income and wealth inequality can diverge quite substantially over longer periods. Income concentration at the top rose most strongly in the 1970s and 1980s. Yet this was a period when the wealth share of the top 10% actually declined. The years from 2007-2013 saw the largest rise in wealth inequality in postwar American history. Wealth concentration in the six years from 2007 to 2013 increased as much as during the six decades from 1950 to 2007. Yet at the same time, income inequality barely budged. We will discuss the reasons for the divergence between income and wealth inequality in greater detail below.

Quantile ratios offer an intuitive perspective on shifts in relative fortunes over time. Figure 7 explores inequality trends among the bottom 90%. The left graph shows the 50-25 quantile ratio, the right graph the 90-50 ratio. While the 50-25 quantile ratio captures inequality trends within the lower middle class, the 90-50 ratio measures the relative fortune of the median household to the top 10%. The black lines show quantile ratios with respect to income, the gray lines show the same ratios for wealth.

Figure 7: Quantile ratios of income and wealth (in %)

(a) 50-25 ratio

(b) 90-50 ratio



Notes: Quantile ratios of income and wealth for all U.S. households from 1950 to 2013. Income ratios are plotted against the left axis, wealth ratios against the right axis. The horizontal axis shows calender time.

Starting with the 50-25 ratio, changes are relatively small and show no clear trend. The 50-25 ratio for income and wealth fluctuate in a narrow range until the financial crisis. Income inequality among the lower middle class actually decreased in the 2000s. However, as the right hand panel shows the 90-50 quantile ratio for income has risen sharply since 1970. The 1980s stand out as a decade of particularly rapid shift of income inequality, while the 1990s and early 2000s saw some leveling off. Yet the overall impression is quite stark. The distance between the middle class and the top 10% has widened substantially. A household at the 90th percentile of the income distribution used to earn about twice as much as the median household until the 1970s. Today, incomes between the two households differ by a factor of three.

The picture is very different for the 90-50 ratio of wealth. In 2007, on the eve of the financial crisis, a household at the 90th percentile of wealth was about eight times richer than the median household. The ratio was virtually the same in 1950, 1970 and 1990. Yet the 2007/08 financial crisis upset this relative constancy. Between 2007 and 2013, the 90-50 wealth ratio jumped from around 8 to 12 – the largest spike in wealth inequality in postwar history.

4.4 The distribution of aggregate income and wealth growth

As the American economy grew over time, additional dollars of income and wealth were created. How were these gains distributed across the population? This question offers another illuminating perspective on inequality dynamics. Looking back at the aggregate growth, we can ask how at any point in time the fruits of aggregate growth were distributed: What share of the additional income went to the top, the middle, and the bottom of the distribution?

Figure 8 shows the shares of the top 10% and the middle class in aggregate income and wealth growth over a backward looking 10-year moving window.[17] Until the mid 1970s, the middle class received about 40 cents out of each dollar of income growth and 20 cents out of each dollar of wealth growth.

The losing out of the middle class began in the mid-1970s when middle-class shares in income growth declined sharply, even dipping into negative territory in the 1980s. In the 1990s and 2000s, the middle class income share recovered slowly to about 10-20 cents out of each dollar of income growth – still less than half of the earlier share.

The middle-class share in wealth growth displays a different trajectory. It increased until the mid-1980s at a time when its income share had already fallen for more than a decade. From the mid-1980s onwards, the middle class shares in wealth growth declined slowly, but did not fall substantially until the financial crisis.

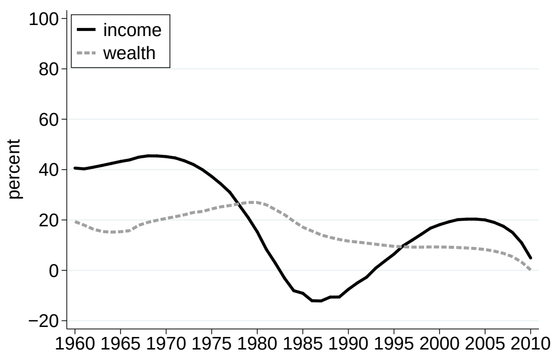
The top 10 % shares for income and wealth are the mirror image of the middle class. From the mid-1980s to the mid-1990s almost the entire income growth in the American economy went to the top 10%. Yet their share in wealth growth is reasonably smooth throughout the period. The share declined somewhat in the 1960s and 1970s, but then increased steadily since the 1980s. In the aftermath of the financial crisis, more than 80 cents of each additional dollar of wealth went to the richest 10 % of households.

Figure 9 shows the cumulative distribution of income and wealth growth between 1971 and the last pre-crisis survey in 2007. Over these 36 years, the richest 10% of Americans received 76 cents out of every additional dollar of income and 73 cents of every additional dollar of wealth. Put differently, the bottom 90% received less than 30 percent of the growth in income and wealth as the top 10% captured the lion's share of the aggregate increase.

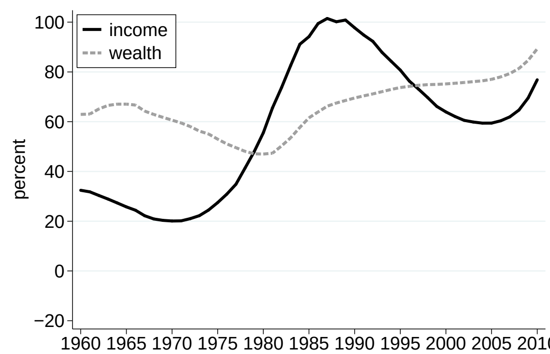
[17] We construct shares based on smoothed and interpolated time series. We use kernel-weighted local polynomial smoothing with a bandwidth of 12 years and a polynomial of degree 3 for interpolation.

Figure 8: Shares in income and wealth growth rates

(a) Middle class



(b) Top 10 %



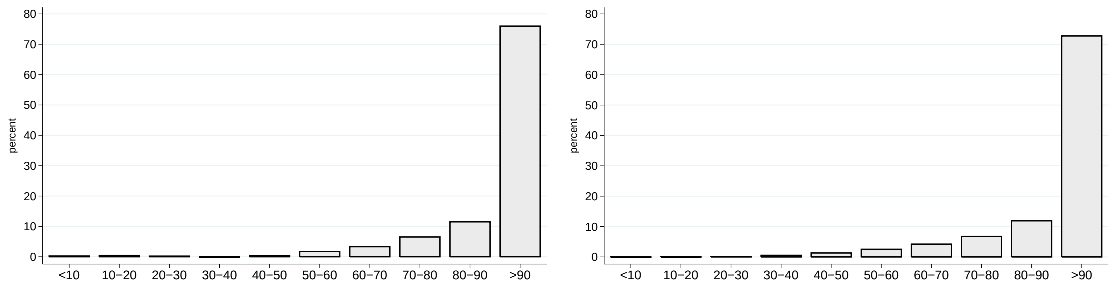
Notes: Shares in aggregate income and wealth growth over time. The current year is shown on the horizontal axis and income and wealth growth is considered over the preceding decade at each point in time. The solid line shows the share in income growth the dashed line shows the share in wealth growth. Shares are shown in percentage points.

However, this comparison of shares in aggregate income and wealth growth does not take into account different starting points. For inequality to change over time, the distribution of additional dollars of income and wealth must be different from the distribution at the beginning. If income growth had been proportional to initial income, the top 10 % would have received only 32 cents of every dollar of income growth between 1971 and 2007, considerably less than the 76 cents they pocketed.

For wealth, the initial distribution was more unequal as the top 10% owned approximately 70% of total wealth in 1971. In an inequality-neutral wealth growth path, the top 10% would have also received 70 cents of every additional dollar. In reality, they secured 73 cents of every additional dollar of wealth. Wealth inequality increased somewhat, but the shifts appear much less pronounced than for income. We will formalize this intuitive relationship between initial levels and the distribution of additional income and wealth in the next step and study the divergent trends of wealth and income inequality in greater detail.

Figure 9: Shares in aggregate income and wealth growth 1971 - 2007

(a) Income (b) Wealth



Notes: Shares in aggregate income and wealth growth for the period from 1971 to 2007. Horizontal axis shows income and wealth deciles.

5 Differential trends in income and wealth inequality

The preceding discussion already hinted at the fact that trends in income and wealth inequality diverged quite substantially in recent decades. In this section, we compare the change in inequality of income and wealth. Such a comparison must take into account the differences in the initial levels of income and wealth inequality. Wealth tends to be considerably more concentrated than income.

We construct a novel measure for the time path of changes in income and wealth inequality relative to their initial levels. We call this measure the *inequality gradient*. The inequality gradient measures what fraction of the total increase in income (or wealth) a particular group i received over a time period, relative to its initial share in total income ($x_{i,t}$). In other words, it measures income (or wealth) growth relative to an inequality-neutral growth path of income (or wealth). The inequality gradient is constructed as follows:

$$\Delta^i_{t,t+1} = \frac{\overbrace{x_{i,t+1}\bar{y}_{t+1} - x_{i,t}\bar{y}_t}^{\text{group i's income increase}}}{\underbrace{\bar{y}_{t+1} - \bar{y}_t}_{\text{total income increase}}} - x_{i,t} = (x_{i,t+1} - x_{i,t})\frac{\bar{y}_{t+1}}{\bar{y}_{t+1} - \bar{y}_t}$$

where $x_{i,t}$ denotes the share of household group i in total income (wealth) at time t and $\bar{y}_t$ denotes average income (wealth) of all households at time t.

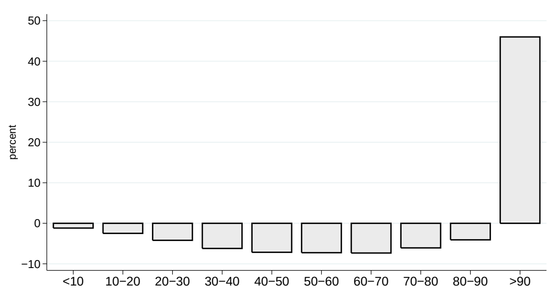
Consider the following example. Suppose group i had an income share of 20% at t ($x_{i,t} = 0.2$). Suppose now that total income in the economy increased between t and $t+1$ by \$20 and group is income increased by \$10 – we obtain $\Delta^i_{t,t+1} = \frac{10}{20} - 0.2 = 0.3$. If every group received exactly its current income share out of the income increase, i.e. if group is income grew by $0.2 \times \$20 = \$4$, then $\Delta^i_{t,t+1} = 0$ for all i. We refer to this as inequality-neutral growth.[18] The inequality gradient provides also a clear distinction between the winners (positive gradient) and the losers (negative gradient) over time.[19]

We chose the inequality gradient for the subsequent discussion for two reasons. First, potential alternatives such as the Gini coefficient suffer from the drawback that they are bounded between zero and one, so that changes are also bounded and magnitudes difficult to compare. Second, the inequality gradient allows us to get a clearer picture of who the winners (positive gradient) and the losers (negative gradient) are.

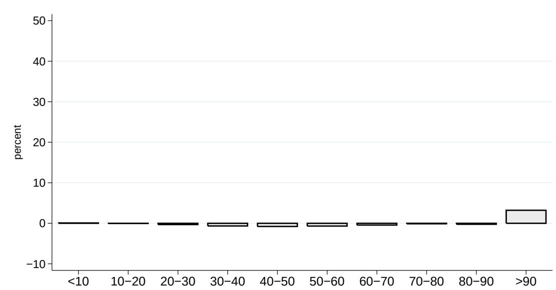
Figure 10a shows substantial relative income gains of the top 10%, measured by the steep income inequality gradient. Between 1971 and 2007 the top 10% received 76 cents out of every additional dollar of income in the economy. Their initial share in total income was 32%. The rich thus received 44 cents more than their initial share of 32 cents – leading to an inequality gradient of 44. By contrast, the inequality gradients for all other deciles are negative.

Figure 10: Inequality gradient for income and wealth 1971 - 2007

(a) Income



(b) Wealth



Notes: Inequality gradients for income and wealth for the period from 1971 to 2007. Horizontal axis shows income and wealth deciles.

Figure 10b shows the inequality gradient of wealth. The gains of the top 10% are much smaller, and there are small gains in the bottom decile. The inequality gradient for wealth in the top decile "only" stands at about 3, and is hence orders of magnitude smaller than for

[18]The inequality gradient can be formally derived as the outcome from a simple thought experiment on redistributive taxation where a more redistributive tax leads to a steeper inequality gradient (larger absolute values of $\Delta^i_{t,t+1}$). We demonstrate this in Appendix B.

[19]This assumes the typical case of positive income and wealth growth during a period. With negative income and wealth growth in the period from 2007 to 2013, the imbalance in growth can be still read off the absolute value of the gradient but the interpretation of winners and losers changes.

income. Recall that a gradient of zero implies constant wealth shares over time (inequality neutral wealth growth). A gradient of 3 means that over the period from 1970 to 2007, the top 10 % received 73 cents out of each additional dollar of wealth relative to an initial share of 70%. In other words, the increase in wealth inequality between the early 1970s and the onset of the financial crisis was relatively small.

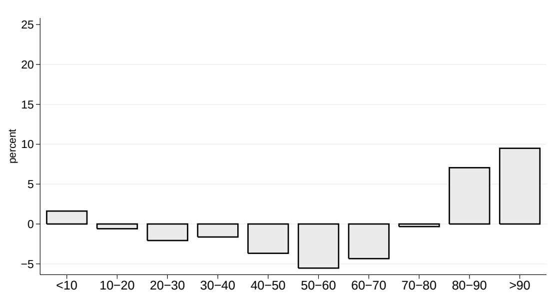
This overall picture – a pronounced increase in income inequality and a comparatively small rise in wealth concentration before 2007 (figure 10) – changed dramatically in the financial crisis and its aftermath. The years from 2007 to 2013 saw a much stronger rise of wealth concentration relative to income concentration (figure 11). Inequality gradients for wealth exceeded those for income now as Figure 11 shows. The top 10% wealth gradient is now almost twice as large as the corresponding income gradient.

Why is the case? Overall, the years 2007-2013 were associated with substantial aggregate wealth and income *losses*. Inequality gradients for this period turn negative as total income falls. The question is which groups lost more than others. As only absolute values of the inequality gradient matter for changes in inequality, we present in Figure 11 in this way. The Figure shows that the wealth losses in the financial crisis were unevenly distributed. In relative terms, the top 10% managed to protect their wealth much better than the bottom 90 %.

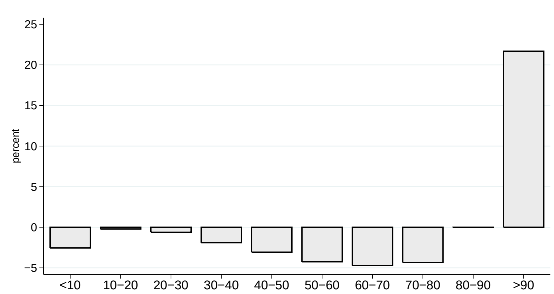
We will explore the reasons in the next section. Suffice it to say here that the portfolio composition appears to have played an important role: the typical portfolio of the wealthy lost much less in value than the typical portfolio of the middle class.

Figure 11: Inequality gradient for income and wealth 2007 - 2013

(a) Income



(b) Wealth

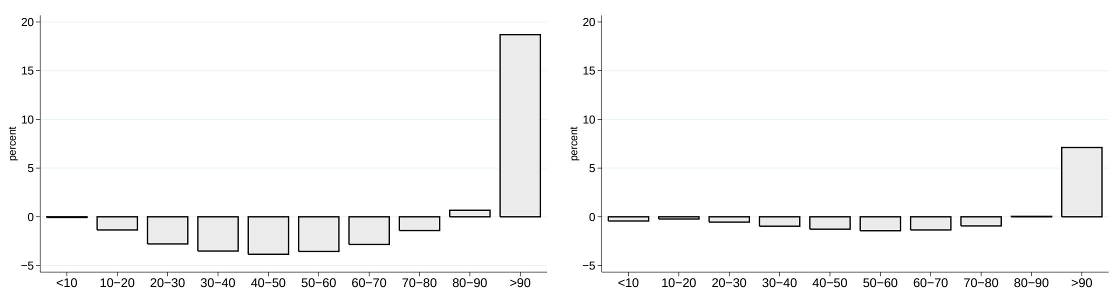


Notes: Absolute value of inequality gradients ($|\Delta|$) for income and wealth for the period from 2007 to 2013. Horizontal axis shows income and wealth deciles.

To what extent does the fall in income inequality and the surge of wealth inequality in the financial crisis change the long-run patterns discussed above? In Figure 12 we zoom out and track income and wealth concentration for the entire sample period from 1950 to 2013. The basic patterns remain the same. Income concentration at the top increased almost three times more than wealth concentration. This stronger polarization of incomes is mainly a function of the pronounced increase in income concentration between 1971 and 2007. Wealth inequality surged in the years after the 2008 financial crisis, but the increase was not strong enough to overturn the overall pattern of a more salient increase in income concentration.

Figure 12: Inequality gradient for income and wealth, 1950 - 2013

(a) Income (b) Wealth



Notes: Inequality gradients for income and wealth for the period from 1950 to 2013. Horizontal axis shows income and wealth deciles.

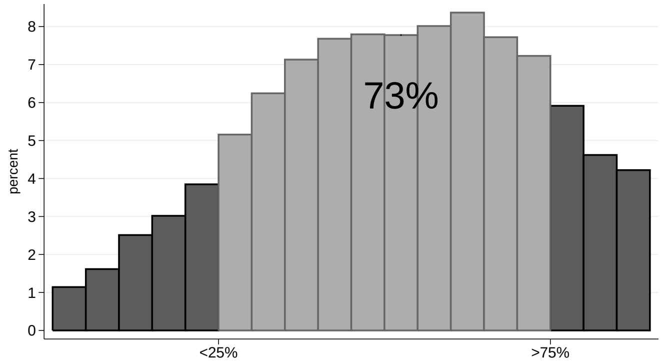
Figure 12 also hints at the main (relative) losers of income concentration since World War II: the inequality gradient for income is most strongly negative for households in the middle of the distribution. We can quantify the aggregate losses of different income groups by adding up the inequality gradients of the bottom 90% and then comparing them to the relative gradient share of each group

$$\lambda^i_{t,t+1} = \frac{\Delta^i_{t,t+1}}{\sum\limits_{j=1}^{J-1} \Delta^j_{t,t+1}}.$$

Remember that, by construction, inequality gradients sum to zero and given that we leave out the gradient from the top decile (resulting in $J-1$ in the denominator), $\lambda^i_{t,t+1}$ measures the contribution of each group i to the overall losses among the bottom 90%.

We plot the distributions of the relative income losses in Figure 13. The light gray area highlights the losses of households between the 25th and 75th percentiles of income. These households account for 73% of total income losses among the bottom 90%. To put this into perspective, if the losses had been shared proportional among households in the bottom 90%, the middle class should have only taken 59 % of the losses instead of the 73 % that we observe in the data. The middle class has hence taken over-proportional losses compared to other income groups. Main street America was the (main) relative loser of income polarization.

Figure 13: Distribution of losses ($\lambda^i_{t,t+1}$) among the bottom 90 %



Notes: Distribution of the loss in income shares among the bottom 90% of the income distribution. Total losses sum to 100%. Red bars show losses incurred by the middle class. The middle class is defined to be all households between the 1st and 3rd quartile.

6 The portfolio channel of wealth inequality

Wealth inequality in postwar America has risen less than income inequality. This central finding of the previous section is surprising in light of evidence that income-rich households have higher saving rates than poor households, as argued by Dynan, Skinner, and Zeldes (2004). With higher savings propensities at the top, increasing income concentration should translate into an even stronger increase in wealth inequality, all else equal. Saez and Zucman (2016) also find that saving rates increase with wealth and underscore the prominent role of differentials in savings rates for the trajectory in wealth inequality.

In this section, we explore the importance of a distinct *portfolio* channel for wealth dynamics that operates alongside the savings channel. The HHSCF data show that the composition and leverage of household portfolios varies substantially along the wealth distribution. Heterogeneity in the portfolio composition of households gives rise to different exposures to asset price changes. and hence differences in returns on wealth that can drive a wedge between income and wealth inequality.

Such differences in income and wealth dynamics are beginning to receive attention in the theoretical literature. For instance, Benhabib and Bisin (2016) point to return differences of assets as one potential channel to explain diverging trends between income and wealth inequality. Saez and Zucman (2016) also discuss that price effects can strongly change inequality trends relative to those implied by saving rate differences.

We will argue in this section that the portfolio channel played an important independent role for the path of wealth inequality in postwar America – and, at times, even the most important role. As homes dominate the asset side of the balance sheet of the bottom 90% of the wealth distribution, residential real estate is of particular importance for the observed phenomena. Housing is also the only asset that is held with substantial leverage so that the effect of house price changes on wealth is amplified over and above its portfolio share.

We will see that rising house prices interacted with highly concentrated and leveraged portfolios to produce substantial middle class gains in housing wealth. These gains mitigated the effects of rising income concentration at the top since the 1970s. Yet the same forces – portfolio concentration and leverage – produced a sharp drop in middle class wealth when house prices collapsed in the financial crisis. The housing bust after 2007 triggered the greatest surge of wealth inequality in postwar American history.

6.1 Portfolio heterogeneity

Figure 14 displays the heterogeneity of household portfolios along the wealth distribution.[20] We focus on four different subgroups. The upper left graph shows portfolios of the bottom 25% of the wealth distribution, the upper right shows portfolios of households in the middle class, the lower left graph shows households between the 75th and 90th percentile, and the bottom right shows households in the top 10%. Assets are shown as positive values and debt as negative values. Wealth corresponds to the consolidated value of all portfolio positions and is indicated by a dashed line in each of the figures.

It becomes immediately apparent from the graph that the composition of household portfolios differs substantially along the wealth distribution. Two core observations stand out and will be particularly important for the subsequent discussion. First, households in the bottom 90% of the wealth distribution are not diversified in their asset positions. Houses are *the* asset of the bottom 90%. Retirement accounts are another sizable asset, but come a distant second.

The second key observation is that portfolios along the wealth distribution differ substantially in leverage. The extent of leverage can be inferred from the sum of assets in excess of wealth. The top 10% of the wealth distribution owe hardly any debt relative to their assets, so that the sum of assets correspond approximately to their wealth. The upper middle class between the 75th and 90th percentile has little leverage overall but holds mortgage debt against housing. By contrast, the two middle quartiles of the wealth distribution are highly leveraged, with housing debt being the dominant debt component and assets exceeding wealth by a factor

[20] Online appendix III provides further results on differences in portfolio composition along the wealth distribution and its changes over time.

of 1.5 to 2. The bottom 25% hold hardly any net wealth. However, their zero net position also hides substantial gross positions of assets and debt on either side of the balance sheet. The third observation is that business equity and other financial assets are by far the most important asset category of households at the top of the wealth distribution. As a consequence, their wealth position is particularly sensitive to changes in the prices of these assets. Note that for our analysis we group households according to their wealth holdings. The income and the wealth poor (rich) are not identical groups. However, when we group households according to income rather than wealth, the overall patterns are similar.[21]

Summing up, the portfolios of middle-class households are non-diversified and highly leveraged with housing being the main asset. The top 10% have little leverage and hold portfolios that contain a substantial share of business equity. Such heterogeneity in gross portfolio position implies different exposures to asset price changes and potential difference in rate of returns. In the following, we will study the importance of both factors, leverage and diversification, for trends in wealth inequality in the postwar era.

6.2 Leverage ratios

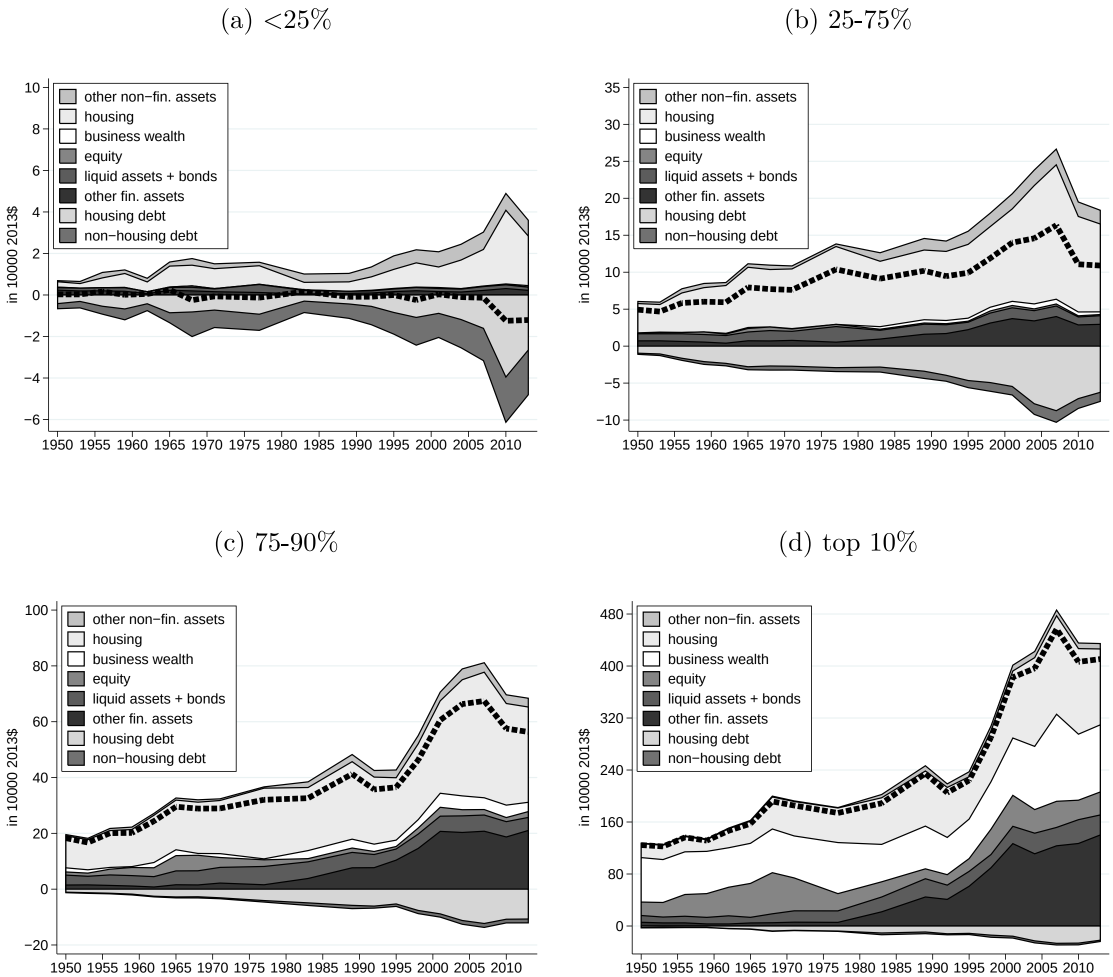
As noted above, household portfolios differ not only in their asset composition, but also in the degree of leverage. Table 6 shows the differences in leverage along the wealth distribution. More precisely, we see how the loan-to-value ratios of home owners are distributed across wealth groups.

The table shows overall wealth is negatively correlated with leverage. In 2007, 72.1 percent of home owners in the bottom 25% of the wealth distribution had a loan-to-value ratio greater than 75%. The table also demonstrates that leverage has increased over time across all wealth groups. The long-run evolution and distribution of household debt has rarely been studied. We refer the reader to the detailed analysis of the evolution of U.S. household debt in Kuhn, Schularick, and Steins (2016) where debt trends are discussed in detail alongside the income and wealth distribution.

Can such differences in leverage have quantitatively large effects? We perform a simple simulation experiment for the period after 1970 when trends in income and wealth inequality diverged. In Figure 15, we track the value of four hypothetical portfolios that contain the

[21] The most notable difference is that the bottom of the income distribution holds positive wealth and substantially less leverage than the bottom quartile of the wealth distribution. The main reason is that the bottom of the income distribution includes many retirees who have paid down most of their debt. By contrast, at the bottom of the wealth distribution households are relatively young and have often just bought a house with considerable leverage. Yet, for the middle class and the top 10 % of the income distribution, the patterns are very similar. The middle class is more leveraged and the portfolios are highly concentrated in housing. A more detailed discussion of the joint distribution of income and wealth based on the modern SCF surveys can be found in Kuhn and Ríos-Rull (2016).

Figure 14: Heterogeneity of household portfolios



Notes: Household portfolios for four wealth groups. Light gray areas show non-financial assets, dark gray bars financial assets, and negative areas show housing and non-housing debt, respectively. The upper left graph shows portfolios of the bottom 25% of the wealth distribution, and the upper right the 25% to 75% (middle class). The lower left graph shows the 75% to 90%, and the bottom right graph shows the top 10%. Portfolio components are shown in 10,000 CPI-adjusted U.S. Dollars. All Dollar values are in 2013 Dollars. Wealth groups are separately defined for each survey year.

same amount of equity invested in 1970 – yet with different amounts of leverage. We consider three portfolios for housing investment. The first without leverage (light gray solid line), the second with a leverage ratio of 50% (gray solid line), and the third with a leverage ratio of 75% (dark gray solid line). We also study a fourth portfolio of listed equities (black dashed line). Given the data in Table 5, we can think of the housing portfolio with high leverage as the portfolio representative of the bottom 25%, the portfolio with low leverage as that of the top 10%, and the portfolio in between as the portfolio of the middle class.

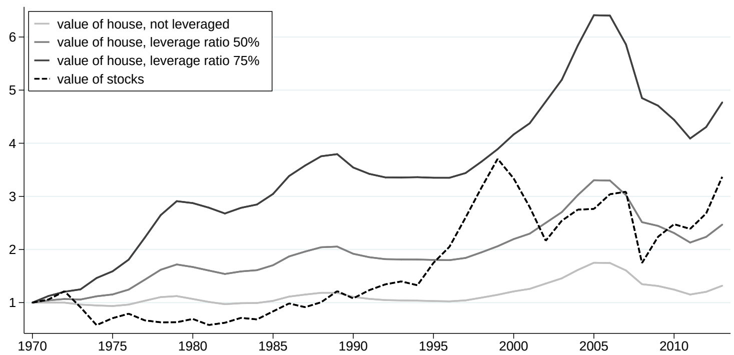
Table 5: Distribution of loan-to-value ratios of home owners by wealth groups

wealth group	leverage ratio	1950	1971	1989	2007	2013
bottom 25%	0%	53.8	36.7	39.6	19.6	9.2
	< 50%	7.7	5.0	1.3	2.8	1.7
	50% – 75%	6.2	6.2	4.8	5.5	4.8
	> 75%	32.3	52.1	54.3	72.1	84.3
25 % - 75 %	0%	58.2	42.9	36.4	26.7	33.3
	< 50%	27.1	27.2	32.6	27.3	18.3
	50% – 75%	10.4	20.2	19.7	25.9	19.9
	> 75%	4.2	9.7	11.3	20.0	28.5
75% – 90%	0%	71.2	57.4	36.1	33.6	41.0
	< 50%	24.8	30.9	46.1	45.4	29.2
	50% – 75%	3.1	8.4	13.8	16.7	18.1
	> 75%	0.8	3.3	3.9	4.4	11.7
top 10%	0%	70.9	57.4	48.7	36.5	40.4
	< 50%	21.1	29.3	40.3	48.4	37.8
	50% – 75%	5.0	10.2	8.4	10.2	16.3
	> 75%	3.0	3.1	2.5	4.9	5.6

Looking at the light gray line in Figure 15, we see that the value of housing investment without debt stays roughly at one until the end of the 1990s. From then onwards the value increases up to 2 in 2007 as house prices double. The investment with a leverage ratio of 75% increases more than sixfold over the same period. A leverage ratio of 50% represents an intermediate case with a slightly more than threefold increase of wealth. For consolidated household portfolios such differences translate into substantial differences in wealth growth that are orthogonal to differences in active saving rates, as conventionally defined. In our simulation, savings rates are zero over time and all wealth changes result from price effects and leverage.

Clearly, higher leverage also implies higher losses in the case of declining house prices. Figure E.8 in the appendix makes this point. It is also important to note that we do not compare total returns on different investments. Comparing returns is complex for several reasons: First, there is a service flow from housing that we would have to factor into financial returns. These returns differ across portfolios due to different house sizes. Second, there is a special tax treatment of mortgage deductions so that some of the service flow from housing is tax-exempt. Third, depreciation has to be accounted for when calculating housing returns. This constitutes an additional complication if the composition of land relative to structures in the total value of a house changed over time. For these reasons, we only consider the evolution

Figure 15: Effect of leverage on housing wealth



Notes: Evolution of the equity value of different portfolios invested in housing and stocks from changes in asset prices. The housing portfolios differ in their degree of leverage. All portfolios are constructed to start with an equity of 1 Dollar in 1970. See text for further details.

of equity in the different portfolios.[22]

6.3 House price exposure

Middle class households hold non-diversified and highly leveraged housing portfolios. Such portfolio positions imply that the wealth of middle class America is highly sensitive to changes in house prices. This section quantifies the exposure of different households to house price changes. We measure the exposure to house price changes as the elasticity of wealth with respect to house prices, which is equal to $\frac{\text{Housing}}{\text{wealth}}$, the ratio of the asset value of housing to wealth.

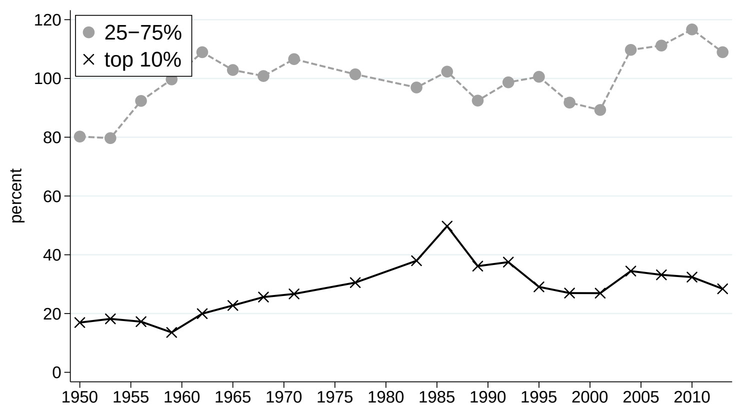
Figure 16 shows exposure to house prices for middle class households and households in the top 10%. It is immediately apparent that the top 10% have a much lower exposure to house price changes. The elasticity of wealth to house price changes is between 0.2 and 0.4 while the elasticity for the middle class is up to 5 times higher ranging from 0.8 to 1.2. For the period after 1970, house price exposure of the middle class stood at 1 or above, so that a 1% increase in house prices translates at least one-to-one to wealth growth. For the top 10%, the same 1% increase in house prices leads to a wealth growth of only about 0.3%. Hence,

[22] See Knoll, Schularick, and Steger (2017) for a discussion of changes in land values. The change in housing equity between two points in time is calculated in the following way. Denote inflation between period 0 and 1 by $\pi = \frac{p_1}{p_0} - 1$ and house price growth by $\Delta = \frac{p_1^H}{p_0^H} - 1$, with p_t^H being the nominal house price in period t. Assume that the initial leverage ratio is $L_0 = \frac{D_0}{H_0}$ and normalize initial housing equity to $H_0 - D_0 = 1$. Real housing equity E_1 in period 1 is then given by

$$E_1 = H_1 - D_0 = \left(\frac{1+\Delta}{1-L_0} - \frac{L_0}{1-L_0} \right) \frac{1}{1+\pi}.$$

the differences in portfolio composition between the middle class and the top 10% imply quantitatively sizable differences in the sensitivity of their wealth to house prices changes.

Figure 16: House price exposure $\left(\frac{\text{Housing}}{\text{Net wealth}} \times 100\right)$ by wealth groups



Notes: House price exposure for middle class households (25% - 75%), and households in the top 10% of the wealth distribution. House price exposure is measured by the elasticity of household wealth with respect to house price changes. See text for details.

To complete the picture, the house price elasticity of wealth can be further broken down into a *diversification component* that is determined by the share of housing in assets and a *leverage component* measured by the debt-to-wealth ratio

$$\frac{\text{Housing}}{\text{Wealth}} = \underbrace{\frac{\text{Housing}}{\text{Assets}}}_{\text{diversification}} \times \left(1 + \underbrace{\frac{\text{Debt}}{\text{Wealth}}}_{\text{leverage}}\right)$$

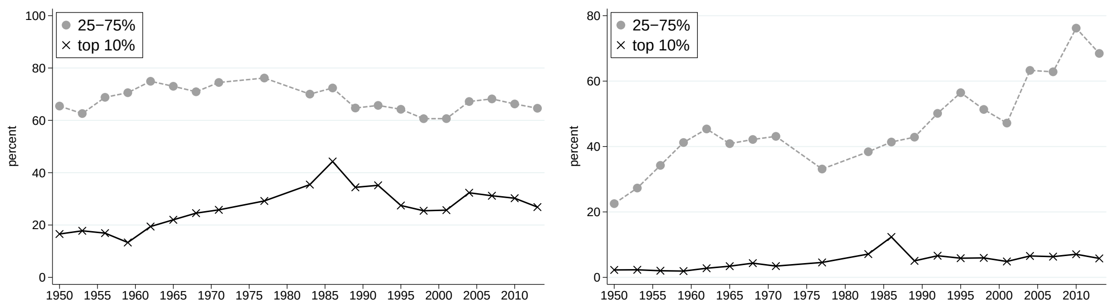
The leverage component also comprises other types of debt but these parts are small relative to housing debt (see Figure 14).

Figure 17 shows the two components of house price exposure for the middle class and the top 10% over time. The left graph displays the diversification component and the right graph the leverage component. The share of housing in total assets of the middle class varies between 60% and 80% over time. For rich households, it varies between 30% and 35% and remains substantially lower than for the middle class throughout.

With respect to leverage, it is clear that the middle class is much more highly leveraged. Middle-class leverage increases from 20% in 1950 to a stunning 80% in 2010. Moreover, this strong exposure from low diversification and high leverage is not itself the result of rising house prices. Even in the 30 years between 1950 and 1980 – when real house prices were relatively stable (see Knoll, Schularick, and Steger (2017)) – the middle class held about 70%

Figure 17: Components of house price exposure by wealth groups (in %)

(a) Diversification ($\frac{\text{Housing}}{\text{Assets}} \times 100$) (b) Leverage ($\frac{\text{Debt}}{\text{Wealth}} \times 100$)



Notes: Decomposition of house price exposure for middle class households (25% - 75%) and households in the top 10% of the wealth distribution. The left panel shows the diversification component while the right panel shows the leverage component. See text for details on the actual decomposition.

of its total assets in housing and leverage amplified house price changes by approximately 40%.

6.4 House prices and wealth inequality

Up to this point, our analysis has demonstrated that a households exposure to house prices differs substantially along the wealth distribution. This implies that house price changes will affect the time path of wealth inequality. This section quantifies the effects of changes in house prices on wealth inequality in postwar America. We employ our measure of house price exposure to break down wealth growth as follows

$$\underbrace{\frac{\Delta W_{t+1}}{W_t}}_{\text{wealth growth}} = \underbrace{\frac{H_t}{W_t}\frac{\Delta p_{t+1}}{p_t}}_{\text{house price component}} + \underbrace{g_t^R}_{\text{residual component}}$$

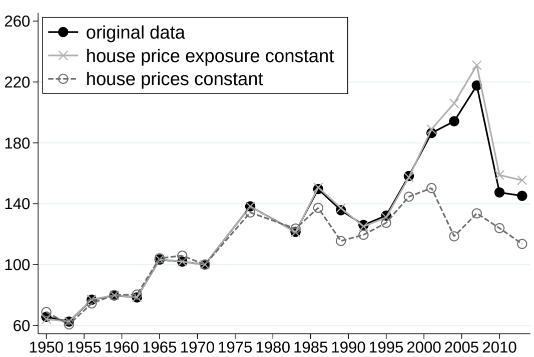
The first term on the right captures the part of wealth growth that results from changes in house prices, $\frac{\Delta p_{t+1}}{p_t}$, adjusted for house price exposure, $\frac{H_t}{W_t}$. Hence, for a given change in house prices, higher exposure will lead to stronger wealth growth. The second term, g_t^R, is a residual that accounts for wealth growth due to all other reasons. Hence, the house price component captures a pure price effect while differences in saving rates of households are captured in the residual component.

In a first step, we feed in observed data for the house price component to back out the residual over time. In a second step, we construct counterfactual wealth growth under two scenarios. First, we keep house prices constant ($\Delta p_{t+1} = 0$). Wealth growth in this case is equal to the residual component, g_t^R. Second, we construct wealth growth with constant house price exposures $\frac{H_t}{W_t}$ but changing prices. This isolates price effects from changes in portfolio allocation. We fix the elasticity of wealth to house price changes, $\frac{H_t}{W_t}$, to the level in 1971 and use home equity instead of wealth when the wealth of a group is negative in 1971. This only applies to few households in the bottom 25%.

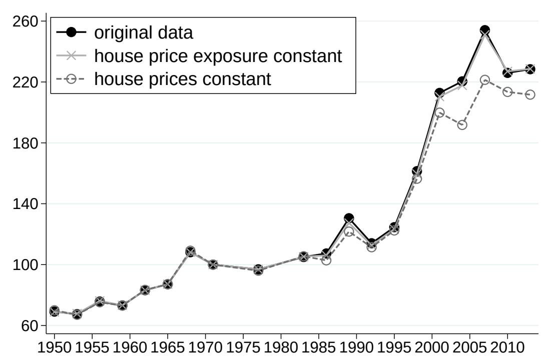
Figure 18 shows counterfactual change in wealth under the assumption of constant house price exposures and the counterfactual with changing house prices but constant house price exposures. The left panel shows the middle class and the right panel the top 10%. House price changes had modest effects on wealth growth of the top 10%. The wealth of the top 10% would have been only 15% lower if house prices had been constant for 4 decades after 1971.

Figure 18: Price and exposure effect of wealth by wealth groups

(a) 25-75%



(b) top 10%



Notes: Realized and counterfactual wealth with constant house prices and exposure at the 1971 level. All data has been indexed to 1971 (= 100).

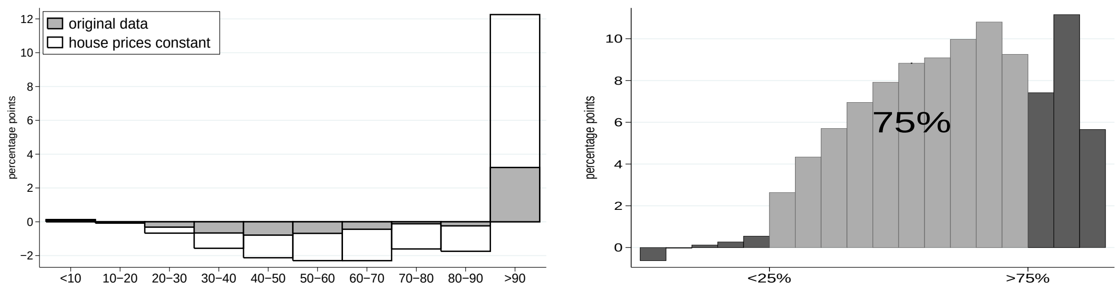
By contrast, wealth of the middle class would have been almost 40% lower at the peak of the house price boom in 2007 compared to the observed level. Middle class households were the main winners of the house price boom. However, the high exposure also explains the middle class wealth collapse after 2007 when house prices crashed. The house price bust shows up as a closing of the gap between counterfactual wealth and observed wealth. However, even after the collapse of house prices in the crisis, middle class households wealth would have been about 20% lower had house prices stayed constant at their 1971 level.

Figure 19a compares inequality gradients for wealth taken from Figure 10b (gray bars) to the counterfactual without house price changes (sum of gray and white bars). It clearly shows that the bottom 90% were the winners of rising house prices between 1971 and 2007.

Figure 19: Inequality gradients for wealth and distribution of wealth gains (1971 - 2007)

(a) wealth gradient

(b) distribution of wealth gains



Notes: Left panel: Inequality gradients for wealth and counterfactual wealth with constant house prices for the period of 1971 to 2007. The horizontal axis shows wealth deciles. Right panel: Distribution of wealth gains from house price effect. See text for details.

With constant house prices the inequality gradient for wealth of the top 10% shoots up to 12, about 4 times as steep as in the data.

We can identify the winners of the house price boom in a similar way to the identification of the losers of rising income concentration before. For this, we take the house price effect (white bars) from figure 19a among the bottom 90% and compute its distribution. We use the equivalent construction for the distribution of gains to that of the losses ($\lambda^i_{t,t+1}$) from Section 5. This time the losers are the top 10% as the middle class received 75% of the total wealth gains from rising house prices during the period from 1971 to 2007.

Finally, Table 6 shows the resulting wealth changes relative to the base year 1971 and the associated wealth gains from the house price effect (Δ house price) over time. The wealth gains from the house price effect are derived as the difference between the observed change in the wealth share (original data) and the wealth change without house price change (no house price effect).

In 2007, without the house price effect the wealth share of the top 10% would have been 4.4 pp higher, and the middle class share 3.2 pp lower. Rising house prices slowed down wealth concentration at the top by almost two thirds. The associated boost of middle-class wealth was very sizable. House price induced wealth gains corresponded to almost 100 % of the annual income of the middle class and could have financed additional annual income growth of 1.9 % between 1970 and 2007. In comparison, realized income growth of the middle class was a meager 0.5 % per year over this period.

Clearly, the survey year 2007 also coincided with the peak in house prices so that wealth gains were particularly large. Yet even after the housing bust, in 2013, the observed increase

Table 6: Changes in wealth shares relative to 1971

		1971	1989	2007	2013
bottom 25 %	original data	0	0.0	0.0	-0.5
	no house price effect		0.0	-0.1	-1.6
	constant exposure		0.0	0.1	-0.4
	Δ house price		0	0.1	1.1
25 -75 %	original data	0	0.2	-1.7	-4.5
	no house price effect		-0.8	-4.9	-5.8
	constant exposure		0.6	-1.0	-4.0
	Δ house price		1.0	3.2	1.3
75% - 90%	original data	0	1.8	-0.2	-0.5
	no house price effect		1.4	-1.2	-1.0
	constant exposure		2.0	0.4	-0.1
	Δ house price		0.4	1.0	0.5
Top 10%	original data	0	-2.0	1.9	5.5
	no house price effect		-0.6	6.3	8.3
	constant exposure		-2.6	0.6	4.5
	Δ house price		-1.4	-4.4	-2.8

in the top 10% wealth share of 5.5 pp was still about one third lower than the counterfactual increase of 8.3 pp in the absence of house price effect. The difference corresponds to about 20 % of total annual household income, indicating how substantial price-induced wealth shifts can be. We conclude that price effects from the housing market had quantitatively strong distributional effects on wealth inequality in postwar America.

7 Conclusions

This paper introduces a new dataset to study inequality dynamics over seven decades of postwar American history. The micro data from the *Harmonized Historical Survey of Consumer Finances* (HHSCF) are consistent with aggregate trends for income and wealth in the NIPA and FFA. We are confident that this dataset will prove valuable for future research in inequality, household finance, and beyond.

In this paper, we used the data to investigate the changes in the distribution of income and wealth in the U.S. since World War II. Previous research documented strong income and wealth concentration at the top but data limitations prevented a more detailed exploration of the trends in the bottom 90%. This paper completes the picture of rising income and wealth concentration by documenting how inequality changed outside the top 10%. Importantly, we document that the American middle class – households between the 25th and 75th income percentile – was the main loser of increasing income concentration at the top.

The new data equally reveal that differences in portfolio composition along the wealth distribution played an important role for the trajectory of wealth inequality. Differences in the composition of household portfolios along the wealth distribution help understand the observed divergence between income and wealth inequality. While incomes were under pressure, the American middle-class profited from substantial gains in housing wealth resulting from highly concentrated and leveraged portfolios. These gains mitigated the increase of wealth concentration at the top. However, the housing bust of 2007 triggered the biggest jump in wealth inequality in postwar history. In the six years from 2007 to 2013 wealth concentration increased as much as in the six preceding decades.

The paper shows that a deeper understanding of household portfolio allocation and the distributional consequences of asset price movements are essential for the analysis of the evolution of wealth inequality. In this sense, we are confident that the long-run micro data presented in this paper can provide a solid empirical foundation for future research on inequality trends in America.

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A Data details

A.1 Sample size

Table A.1 reports the sample sizes for the different survey years in the final HHSCF data. One observation corresponds to one household interview. Sample weights are used to make the sample consistent with the number of households in the U.S. population.

Table A.1: Sample size across survey years

survey year	sample size	survey year	sample size	survey year	sample size
1948	3,044	1960	2,708	1977	2,563
1949	2,988	1961	1,799	1983	4,103
1950	2,940	1962	4,476	1986	2,822
1951	2,938	1963	1,819	1989	3,143
1952	2,435	1964	1,540	1992	3,906
1953	2,663	1965	1,349	1995	4,299
1954	2,599	1966	2,419	1998	4,305
1955	2,766	1967	3,165	2001	4,442
1956	2,660	1968	2,677	2004	4,519
1957	2,726	1969	2,485	2007	4,417
1958	2,764	1970	2,576	2010	6,482
1959	2,790	1971	1,327	2013	6,015

A.2 Imputation of missing variables

This section provides further details on the imputation of missing variables by predictive mean matching. This imputation method involves three steps. First, a linear regression model is estimated using observations for which the variable of interest is available. Using the estimated coefficient vector and its variance, the distribution of the coefficients is calculated. In the second step, a coefficient vector is drawn from this distribution and predicted values of the variable are generated. This is done both for observations for which the variable is available and for when it is missing. Third, we compare the predicted values obtained from missing observations with those obtained from observations for which we have information on the variable. For each missing observation we choose the three observations among the available observations that have predicted values most similar to the respective missing observation. Out of these three, we choose one observation randomly and assign the value of the variable of interest to the corresponding missing observation.

In order to determine which adjacent survey years are most suitable for imputing missing

values we implement the following optimization before imputation. First, we determine all income, asset, debt, and demographic variables that are available in the year for which the variable is missing. For each combination of adjacent years, we then construct a subset of variables that are both available in the year with missing values and in the adjacent years. As the predictive accuracy decreased with the number of explanatory variables, we select those variables with the highest predictive power by using the lasso method. This method sets regression coefficients to zero for variables with small predictive power. For each combination of survey years we then regress the variable of interest of those variables selected by the lasso method.[23] Finally, we calculate the R^2 for each regression. This is used as a measure of how well the combination of adjacent years is able to predict the missing variable. The combination with the highest R^2 is chosen for the imputation.
Tables A to E of the Online appendix report the detailed combination of survey years and the adjacent survey years used in the imputation together with the R^2 from the regression.

A.3 Weight adjustment to account for non-response

We describe in section 2.2 how we account for non-response at the top of the income and wealth distribution before 1983. As a proof of concept to this approach, we apply our adjustment routine here to the 1983 data itself. We drop the list sample from the data and adjust the weights using our proposed adjustment approach. Table A.2 compares income and wealth shares of the sample, including the list sample from 1983 with those values obtained using our weight adjustment method on the sample excluding the list sample. The results show that the adjustment works very well. For income, it only slightly overestimates shares between the top 10% and 5% and slightly underestimates the top 5% to 1% share. Unsurprisingly, the fit deteriorates towards the right tail above the top 1%. Deviations are, however, always less than 2 percentage points (pp). For wealth shares, the picture is similar. After applying the weight adjustment, the shares up to the top 1% match reasonably well and the fit deteriorates within the top 1%.

[23] Only survey years conducted less than 15 years before or after the missing year are considered. Out of these surveys, we choose the four closest to the missing year.

Table A.2: Income and wealth shares of original and reweighted sample of SCF 1983

	income		wealth	
	original sample	reweighting	original sample	reweighting
top 10-5%	10.8	12.2	12.1	15.5
top 5-1%	13.2	12.6	22.8	24.7
top 1-0.5%	3.0	2.1	7.4	6.2
top 0.5-0.1%	4.5	1.9	11.4	6.2
top 0.1%	3.3	1.5	12.8	5.7

B Inequality gradient and taxation

In the main text we use the change in income and wealth shares as a measure for the change in income and wealth inequality. This measure can be derived from the following thought experiment. We focus our illustration on the case of the change in income inequality. First, we group households in N groups where each group is size p_i so that $\sum_{i=1}^{N} p_i = 1$. A tax authority now collects a share τ of income from each group i. The tax authority has to run a balanced budget and uses a transfers schedule $\{\delta_i\}_{i=1}^{N}$ to transfer all tax revenues back to households. If we denote average income of households in group i at time t by $y_{i,t}$ and average income of all households at time t by $\bar{y}_t$, then the balanced budget requirement is $\sum_{i=1}^{N} y_i p_i \tau = \tau \bar{y}_t = \sum_{i=1}^{N} \delta_i p_i$. To compare how much inequality has changed over time, we ask what the regressivity/progressivity of the transfer schedule $\{\delta_i\}_{i=1}^{N}$ has to be in order to implement the distribution of income shares at $t+1$ starting from income shares at t. For now, we utilize a case, shown below, that has no income growth but has a straightforward extension.

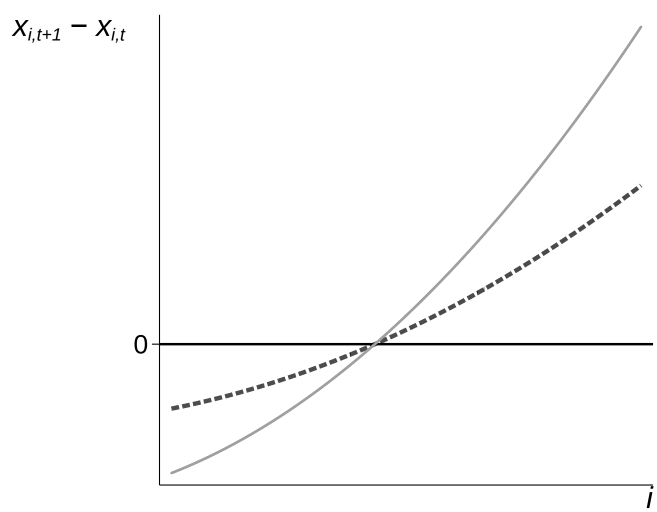
We denote the share of household group i in total income at time t by $x_{i,t}$. It holds that $x_{i,t} = p_i \frac{y_{i,t}}{\bar{y}_t}$. Each household pays taxes $\tau y_{i,t}$ in t so that after-tax income is $\tilde{y}_{i,t} = (1-\tau) y_{i,t}$. As the tax shares are constant across households, the income shares in after-tax income are not altered. Total tax revenues will be redistributed so that the budget of the tax authority is balanced. Using the assumption that aggregate income stays constant, i.e. $\bar{y}_t = \bar{y}_{t+1} = \bar{y}$, the change in income shares from t to $t+1$ can be written in the following way:

$$x_{i,t+1} - x_{i,t} = \frac{p_i y_{i,t+1} - p_i y_{i,t}}{\bar{y}} = p_i \frac{y_{i,t}(1-\tau) + \delta_{i,t} - y_i, t}{y} = p_i \frac{\delta_{i,t} - \tau y_{i,t}}{\bar{y}}$$

where the last expression on the right-hand side is simply the net transfer from the redistribution system as a share of average income $\bar{y}$ multiplied by the population share. With constant population shares $p_i = \frac{1}{N}$ we can just look at the change in income shares to learn about the implied regressivity/progressivity of the redistribution scheme to assess if the change in inequality was larger or smaller for a particular group.

Figure B.1 shows a stylized example of a change in inequality of two variables for example income and wealth. Both lines show the change in income and wealth shares for the example of income and wealth changes for the different groups $i = 1, \ldots, N$ connected by a continuous function. Both functions are positively sloped implying that we saw an increase in inequality for both variables. A positive slope means that income and wealth shares at the top of the distribution increased while they decreased at the bottom of the distribution. We also see that the gray solid line has a steeper slope compared to the black dashed line. In this case, inequality in the variable underlying the gray line increased by more than in the variable underlying the black line. If income inequality had not changed between t and $t+1$ the distribution would be a flat line equal to zero.

Figure B.1: Stylized inequality change



Therefore it logically follows, to include income and wealth growth in our analysis. In this case, we express the share a household has in an increase or decrease of aggregate income in the following way:

$$\Delta^i_{t,t+1} = \frac{x_{i,t+1}\bar{y}_{t+1} - x_{i,t}\bar{y}_t}{\bar{y}_{t+1} - \bar{y}_t} - x_{i,t} = (x_{i,t+1} - x_{i,t})\frac{\bar{y}_{t+1}}{\bar{y}_{t+1} - \bar{y}_t}$$

The change in income (wealth) shares is multiplied in addition by a time-varying constant $\frac{y_{t+1}}{y_{t+1}-y_t}$.

C Comparison to the capitalization approach

In their pioneering work, Saez and Zucman (2016) construct a measure of net wealth based on a capitalization technique using income data from tax records and aggregate data from the Flow of Funds. First, they use information on individual capital income from the tax data and calculate aggregate capital income from different asset categories, such as bonds and corporate equity. In a second step, they use the corresponding asset category of the Flow of Funds and divide its aggregate value by the respective aggregate income obtained from the tax data. This factor is called a capitalization factor. Asset positions of individuals are then constructed by multiplying the individual income components of the tax data with this factor. The approach, in its construction, matches the aggregate data from the Flow of Funds but makes strong assumptions of the stock-flow relationship between assets and incomes. While ingenious, there are a number of drawbacks when using this method.

First, housing wealth, which accounts for a large share of household wealth, can only be inaccurately estimated. That is the value of housing is inferred by using information on property taxes. Similar problems exist with respect to housing debt which Saez and Zucman (2016) estimate by employing information on interest payments and other important information for estimating current mortgage debt. They use for example the maturity or the initial level of the mortgage but the actual values are unknown. Moreover, wealth components that do not generate direct income flows like retirement accounts with retained earnings can only be estimated using survey data. Asset classes such as non-corporate equity that may from time to time generate negative income flows violate the assumption of a close stock-flow relationship inherent in the multiplier method.

Using Norwegian data, Fagereng, Guiso, Malacrino, and Pistaferri (2016) demonstrate that the existing small correlations between assets and income can lead to the overstatement of the wealth inequality when using the capitalization method. In addition, Saez and Zucman (2016) discuss within their paper how to improve wealth inequality estimates relative to their capitalization approach. They discuss the value of homes, employer-provided pensions, business equity, and mortgages. Our HHSCF data builds upon several of these suggestions. It includes the value of homes and mortgages that match aggregate numbers from the Flow of Funds so that reliable information on two important components of the household balance sheets that are hard to measure based on the capitalization method are provided. We also incorporate information on business equity and retirement accounts. For these assets, differences to the Flow of Funds become evident. In the case of business equity, measurement concepts are different between the two preexisting data sets. While the SCF reports market values, the Flow of Funds reports book values for non-incorporated businesses.

Furthermore, in our data we directly analyze asset and debt positions so that we do not have to impose a correlation between assets stocks and income flows. The assumption of uniform returns is at the center of the concerns raised by Fagereng, Guiso, Malacrino, and Pistaferri (2016) regarding the capitalization method. Kuhn and Rıos-Rull (2016) report very low correlations between wealth and capital income even for very restrictive definitions of financial wealth. Similarly, debt and no income assets like housing can only be imputed under the capitalization method based on itemized deductions and property taxes. The SCF data also has the advantage of observing these positions directly.
Using tax data has the advantage that the top of the income distribution is captured well. Arguably, income-generating assets constitute a larger fraction of the household port- folio at the top of the distribution. The capitalization method is therefore likely to provide a good estimate when it comes to the very right tail of the wealth distribution. We therefore consider our approach complementary to the capitalization approach, in particular, due to its strength regarding the lower part of the distribution.

D Income and wealth inequality

This section provides complementary evidence to the inequality trends documented in the main part of the paper. We document inequality trends based on gini coefficients, quantile ratios, and the effect of demographic change, and household size on inequality as measured by the gini coefficient.

D.1 Gini coefficients, quantile ratios, and demographic change

Our discussion of inequality trends has focused mainly on changes in income and wealth shares. Gini coefficients and quantile ratios provide alternative ways to study trends in inequality. We apply an approach proposed by Fortin, Lemieux, and Firpo (2011) to adjust Gini coefficients for demographic changes over time. We also report Gini coefficients after adjusting income and wealth using OECD equivalent scales. Our findings are summarized as follows.
Gini coefficients confirm the secular rise in inequality for both income and wealth. Unlike income or wealth shares, the Gini coefficient does not provide information about how a particular part of the distribution has changed but summarizes inequality along the entire distribution in a single number. As discussed in Kuhn and Rıos-Rull (2016), it does so in a way that is particularly sensitive to changes in the middle of the distribution. The observed large changes in the Gini coefficients are therefore consistent with a hollowing out of the

middle class that we document the main discussion.

Quantile ratios provide a different angle to look at inequality changes among the bottom 90% of the population. They allow us to track developments in different parts of the distribution. Our results on changes in quantile ratios confirm our findings based on the inequality gradient. They show declining income inequality at the bottom of the income distribution (25-50 ratio) during the 1990s and a simultaneous increase of the 75-90 ratio. A decreasing 25-50 ratio and an increasing 75-90 ratio are both phenomena that are in line with a hollowing out of the middle class.

The U.S. population has undergone large secular changes in terms of educational attainment, age structure, and household size. We use an approach proposed by Fortin, Lemieux, and Firpo (2011) to remove demographic changes when computing inequality statistics. We find the effects on Gini coefficients to be generally small except for the case of education. The rising share of college-educated household heads has led to an additional increase in income and wealth inequality. Without increasing college attainment, the Gini coefficient of income would today stand at 0.5 compared to its actual value of 0.55. The Gini coefficient of wealth would stand at 0.82 in comparison to its actual value of 0.83.

Finally, we use OECD equivalent scales to adjust for changing household sizes. The average number of persons per household declined in the U.S. between 1949 and 2013 from 3.42 to 2.54. This decline in average household size did not lead to notable changes in inequality when looking at Gini coefficients. This finding is in line with results from Kuhn and Rıos-Rull (2016) for post-1989 data.

As an alternative to the Gini coefficient, income and wealth shares have been popularized by the works of Piketty and Saez (2003) and Saez and Zucman (2016) that emphasize the concentration of income and wealth at the top of the distribution. We discuss income and wealth shares in Section 4.1. Unlike the Gini coefficient, income or wealth shares of particular groups contain information about single points on the Lorenz curve. The Gini coefficient collapses all information of the Lorenz curve into a single number. It therefore includes information about the entire distribution but loses conciseness regarding single parts of the distribution. Below, we will take a granular look at the distributional changes among the bottom 90% by looking at changes in income and wealth shares. However first, we will demonstrate that the HHSCF data is consistent with the income and wealth concentration at the top of the distribution in level and trend .

Table D.3: Gini coefficients for income and wealth

year	income			wealth		
	all	bottom 99%	bottom 90%	all	bottom 99%	bottom 90%
1950	44	39	31	76	69	53
1953	43	38	31	76	70	52
1956	44	39	31	76	68	50
1959	44	39	32	74	66	49
1962	44	40	33	77	68	54
1965	43	39	32	74	67	51
1968	42	38	32	77	70	52
1971	43	38	33	76	68	52
1977	41	39	33	72	66	51
1983	46	41	35	76	67	54
1986	48	42	36	75	64	52
1989	52	45	38	76	68	56
1992	49	44	37	76	67	55
1995	51	44	37	76	66	54
1998	51	44	37	77	68	55
2001	54	46	37	79	70	58
2004	52	45	37	79	70	59
2007	55	46	37	79	71	57
2010	54	47	37	81	74	61
2013	55	48	38	82	74	61

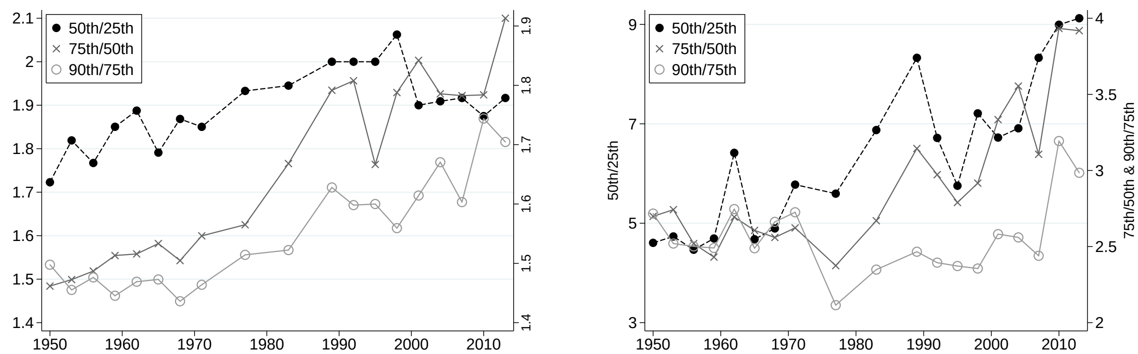
Notes: Gini coefficients for income and wealth for all households and bottom 99% and 90% of the income or wealth distribution. For the bottom 99% and 90% we exclude the top 1% and 10%, respectively, in the case of the income Gini of the income distribution and in the case of wealth, from the wealth distribution.

D.2 Changes in quantile ratios

The changes in income and wealth shares provide on way to look at the changes of income and wealth inequality among the bottom 90%. In Figure D.2, we look at quantile ratios of the income and wealth distribution to provide an alternative view of distributional changes over time. Looking at income in Figure D.2a, we find the same two episodes of changes in income inequality that we have previously identified. The first episode was during the 1970s and 1980s and shows rising inequality along the entire income distribution with all three quantile ratios increasing. The second episode, starting in the 1990s, paints again a distinct picture of the developments of inequality along the income distribution. Income inequality at the bottom, the 50-25 ratio, decreased. This decrease in income inequality at the bottom accelerates during the 2000s and continues until 2013. This finding matches the rising income shares of the bottom 25% from Table 4. During the same episode, the 75-50 ratio is constant and only increases between 2010 and 2013. The 90-75 ratio shows an upward trend starting in the 1990s and lasting until 2013. This supports the observation above where the declining income share of the middle class and a hollowing out of the middle class during the second episode of rising income inequality was also evident.

Figure D.2: Quantile ratios of income and wealth (in %)

(a) Income (b) Wealth



Notes: Left panel: Quantile ratios of income for all U.S. households from 1950-2013. Right panel: Quantile ratios of wealth for all U.S. households from 1950-2013. Black dashed lines show 50-25 ratios (left axis). Gray lines with crosses show 75-50 ratios and light gray lines with dots 90-75 ratios (right axis).

Looking at wealth in Figure D.2b, we find decreasing wealth inequality until the 1980s. Afterwards and until 2013, wealth inequality increases in line with our findings on wealth shares. The 50-25 ratio is much higher than the 75-50 ratio due to the low level of wealth at the bottom quartile. However, in relative terms the increase of the 75-50 ratio and the 50-25 ratio is similar over the period from 1980-2013. A large increase in inequality happens from 2007 to 2013 during the financial crisis, which is also in line with our previous findings. We conclude that the findings on the shifts in wealth shares and quantile ratios paint very similar pictures about the rising wealth inequality among the bottom 90

Table D.4: Quantile ratios of income (x100)

year	50th to 25th	75th to 50th	90th to 75th
1950	172.3	146.4	149.5
1953	182.2	147.4	145.4
1956	176.7	148.8	147.5
1959	185.9	151.5	145.2
1962	188.9	151.4	147.3
1965	179.6	153.7	147.3
1968	186.1	150.7	143.9
1971	185.3	156.2	145.6
1977	190.0	156.3	151.6
1983	194.4	166.7	152.3
1986	200.0	166.7	150.0
1989	200.0	179.2	162.8
1992	200.0	180.8	159.8
1995	200.0	166.7	160.0
1998	206.3	178.8	155.9
2001	194.2	180.3	162.9
2004	190.9	178.6	168.0
2007	191.7	178.3	160.9
2010	191.7	176.1	172.8
2013	184.8	190.4	170.5

Table D.5: Quantile ratios of wealth (x100)

year	50th to 25th	75th to 50th	90th to 75th
1950	437.2	264.7	255.0
1953	473.5	271.0	248.9
1956	546.6	250.3	245.1
1959	621.9	249.2	238.3
1962	628.4	269.6	271.2
1965	484.9	262.2	251.4
1968	567.3	263.9	256.5
1971	555.6	255.1	263.0
1977	515.9	235.1	215.3
1983	680.1	266.9	234.5
1986	368.9	256.7	212.5
1989	809.2	312.0	246.4
1992	667.1	297.6	239.2
1995	571.4	279.1	237.4
1998	697.1	290.9	236.1
2001	659.2	332.1	257.2
2004	688.7	352.6	255.9
2007	826.7	310.0	244.8
2010	877.8	391.8	318.5
2013	900.9	390.9	298.3

D.3 Demographic changes

The HHSCF data provides detailed information about the demographic characteristics of households. The U.S. population has undergone large secular changes in its household composition in terms of educational attainment, age, and household size. In this section, we explore how much these changes can account for in observed inequality trends. We use the approach proposed by Fortin, Lemieux, and Firpo (2011) to adjust for demographic changes over time. This is done by pooling data from the basis year with each survey year and calculate the probability of being surveyed in the basis year by running a probit regression. We use 1971 as our basis year. As explanatory variables, we include age, educational attainment, the number of adults and children in a household, and race of the household head. Next, we use this probability to re-weight observations in other survey years by multiplying the survey weights with the probability. We then compute counterfactual inequality measures where we fix demographic characteristics to the basis year.[24]

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[24] Reweighting factors are calculated in the following way: $D_Y = 0$ is a dummy indicating to which survey year the observation belongs. It is equal to 0 for the reference year and 1 otherwise. X are the explanatory variables. $\hat{P}(D_Y = 1|X)$ is the estimated probability of being surveyed in year Y given explanatory variables X. $\hat{P}(D_Y = 0|X)$ is the corresponding probability of being interviewed in the reference year. $\hat{P}(D_Y = 1)$ and $\hat{P}(D_Y = 0)$ are the sample proportions of households in the survey and reference year, respectively. The reweighting factor $\hat{\Psi}(X)$ is then given by:

$$\hat{\Psi}(X) = \frac{\hat{P}(D_Y = 1|X)/\hat{P}(D_Y = 1)}{\hat{P}(D_Y = 0|X)/\hat{P}(D_Y = 0)}$$

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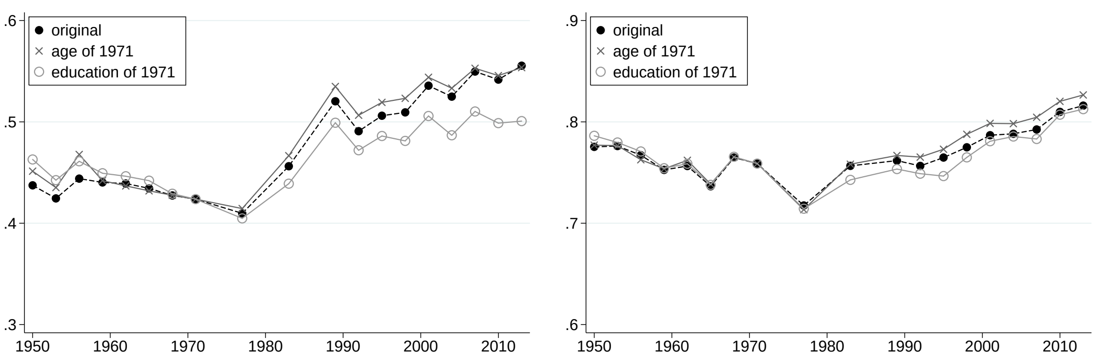
Here, we focus on Gini coefficients and only consider counterfactuals where we fix educational attainment and age structure over time. Figure D.3 shows the Gini coefficients of income and wealth for three cases. The black line with circles shows the original data, the gray line with crosses shows the Gini coefficient for a counterfactual where we fix the population shares across age groups, and the light gray line with dots shows the Gini coefficients if we fix educational attainment at the 1971 shares. We find that population aging had a negligible effect on income and wealth inequality. The Gini coefficients are only slightly lower than in the original data. Looking at the counterfactual with constant educational attainment, we find that changes in educational attainment lead to an increase in both income and wealth inequality. This is in line with a rising college wage premium beginning in the 1980s. Our decomposition shows that exploring educational choice and rising returns of college education will be key dimensions when studying trends in income and wealth inequality.

Figure D.3: Gini coefficients of income and wealth accounting for demographic change

(a) Income (b) Wealth



Notes:

Besides changes in educational attainment a second secular trend has been the decrease of average household size in the U.S. The average number of persons per household declined in the U.S. between 1949 and 2013 from 3.42 to 2.54 according to U.S. Census data. The number of household members 18 and older declined from 2.33 to 1.93 over the same period.

X. $\hat{P}(D_Y = 0|X)$ is the corresponding probability of being interviewed in the reference year. $\hat{P}(D_Y = 1)$ and $\hat{P}(D_Y = 0)$ are the sample proportions of households in the survey and reference year, respectively. The reweighting factor $\hat{\Psi}(X)$ is then given by:

$$\hat{\Psi}(X) = \frac{\hat{P}(D_Y = 1|X)/\hat{P}(D_Y = 1)}{\hat{P}(D_Y = 0|X)/\hat{P}(D_Y = 0)}$$

Given that HHSCF data is at the household level, changes in household size can potentially affect measures of household-level inequality.

Therefore as a follow up, we consider the effects that changes in household size that took place over previous decades had on inequality. We do this by adjusting household-level income and wealth by household-adult-equivalent members. We use the OECD equivalent scale. Figure D.4 reports Gini coefficients for income and wealth with and without adjustment for household size. We find that inequality for adult-equivalent income is slightly higher up to 1980 and shows a slight declining trend between 1950 to 1980. Starting in 1992, inequality for adult-equivalent income is lower but shows the same trend as unadjusted household income. For wealth, there is a small divergence of inequality when looking at adult-equivalent wealth for the period from the mid-1960s to the mid-1980s. Although there have been large changes in the size of U.S. households, adjusting for these changes did not alter the conclusions about trends of income and wealth inequality over time. This matches results from Kuhn and Rıos-Rull (2016) who find that adjusting for household size in the post-1989 SCFs has only a minor effect on inequality.

Figure D.4: Gini coefficients for adult-equivalent income and wealth

(a) Income (b) Wealth

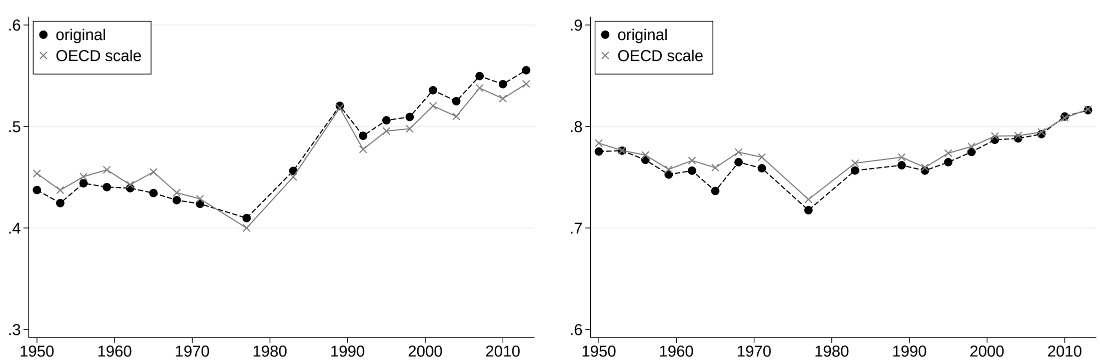


Figure D.5: Shares in aggregate income and wealth

(a) Income (b) Wealth

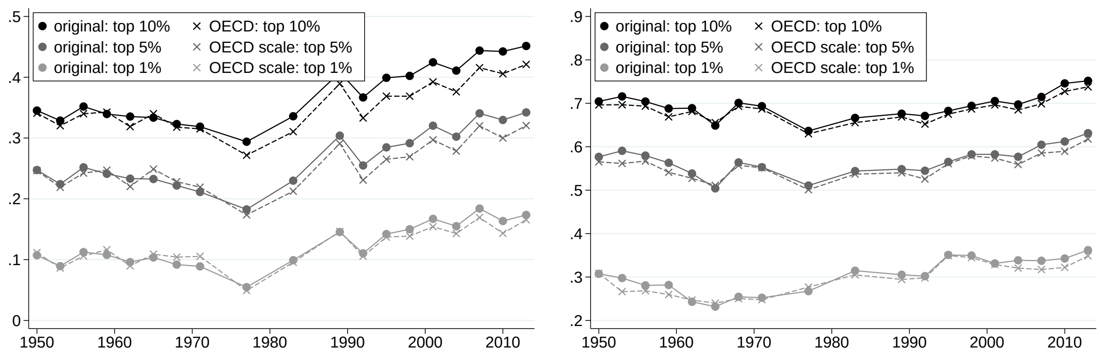
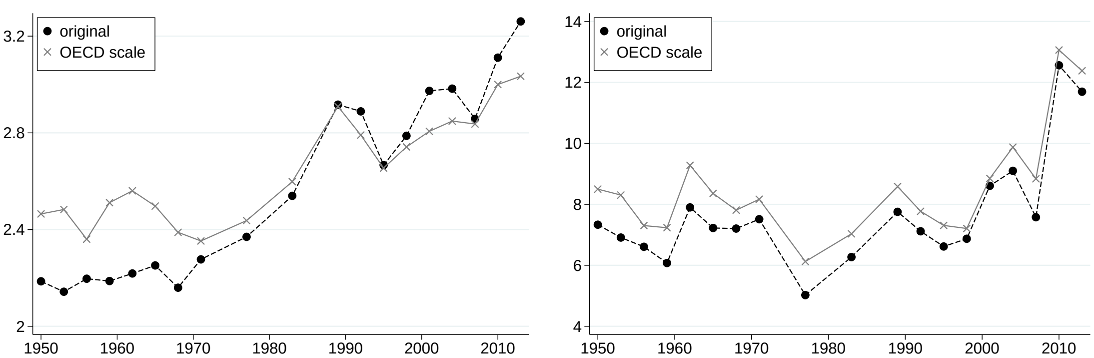


Figure D.6: Ratio of 90th to 50th percentile

(a) Income (b) Wealth

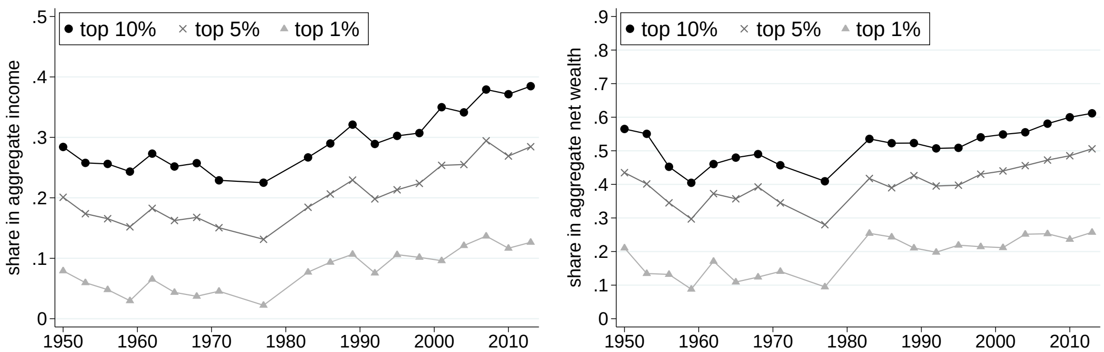


D.4 Income and wealth concentration

Households who are at the top of the income distribution need not be at the top of the wealth distribution and vice versa. The HHSCF data provides independent information on income and wealth so that we can explore the income concentration at the top of the wealth distribution and the wealth concentration at the top of the wealth distribution. Figure D.7 shows in the left panel the shares in total income of the top 10, 5, and 1 percent wealth-richest-households over time. The right panel shows the shares in total wealth of the top 10, 5, and 1 percent income-richest households. Compared to figure 6 from the main text the shares have to go down in level. The pattern of the change in income and wealth concentration remain however unaffected when we look at income concentration among the wealth-rich or wealth concentration among the income-rich.

Figure D.7: Shares in aggregate wealth and income

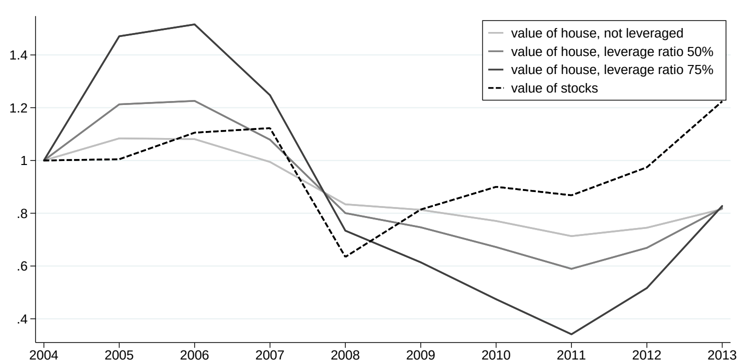
(a) Income Shares by Wealth Groups (b) Wealth Shares by Income Groups



E Leverage effect during the financial crisis

Figure E.8 shows the leverage effect in case of an investment done in 2004. In Figure 15 of the main part of the paper, we show the corresponding investment done in 1970. The large decline in house prices during the financial crisis is now amplified by the leverage effect. High leverage leads to particularly large losses from the decline in house prices. All portfolios recover starting in 2011. Still in 2013, one dollar invested in housing in 2004 is only worth 80 cents.

Figure E.8: Effect of leverage on housing value



Notes: Evolution of the equity value of different portfolios invested in housing and stocks from changes in asset prices. The housing portfolios differ in the degree of leverage. All portfolios are constructed to start with an equity of 1 Dollar in 2004. See text for further details.

Online Appendix
Not for Publication

This online appendix accompanies the paper *'Wealth and Income Inequality in America, 1949-2013'*.

I Information on imputation of missing variables

Tables A to E provide the information used to imputed missing variables. See Section A.2 from the published appendix for further details.

Table A: Imputation of income variables

	survey year	years in imputation	R^2
labor income	1960	1959	97
	1961	1959	97
	1962	1959	96
	1963	1959	96
	1964	1966	88
	1965	1966	78
labor income + business	1971	1968	83
	1977	1968	84

Notes: The number of years used for the imputation is intentionally not set to one. Rather, the R^2 was calculated using all possible combinations of years. However, the R^2 was highest using only one year for the imputation.

Table B: Imputation of financial variables

	survey year	years in imputation	R^2
liquid assets	1964	1961	42
	1966	1968	38
bonds	1964	1963	42
	1966	1967	23
	1971	1970	67
equity	1948	1952	98
	1951	1952	73
	1954	1955	74
	1956	1955	75
	1957	1955	75
	1958	1962	76
	1959	1962	76
	1961	1962	77
	1965	1963	64
	1966	1968	52
	1971	1970	96

Notes: The number of years used for the imputation is intentionally not set to one. Rather, the R^2 was calculated using all possible combinations of years. However, the R^2 was highest using only one year for the imputation.

Table C: Imputation of cash value of life insurance

survey year	years in imputation	R^2
1948	SFCC1962	45
1949	SFCC1962	47
1950	SFCC1962	49
1951	SFCC1962	48
1952	SFCC1962	46
1953	SFCC1962	49
1954	SFCC1962	47
1955	SFCC1962	40
1956	SFCC1962	40
1957	SFCC1962	41
1958	SFCC1962	41
1959	SFCC1962	41
1960	SFCC1962	48
1961	SFCC1962	35
1963	SFCC1962	41
1964	SFCC1962	44
1965	SFCC1962	47
1966	SFCC1962	38
1967	SFCC1962	38
1968	SFCC1962	47
1969	SFCC1962	57
1970	SFCC1962	58
1971	SFCC1962	38
1977	SFCC1962	43

Notes: The SFCC 1962 is intentionally not used for the imputation. Information on pension wealth is available both in the SFCC 1962 and in the SCF 1983. However, using variables available in the respective survey resulted in a higher R2 for the SFCC 1962.

Table D: Imputation of non-financial variables

	survey year	years in imputation	R^2
value of home	1948	1951	42
	1952	1954	50
	1961	1960	30
other real estate	1948	1952	37
	1951	1952	59
	1954	1952	50
	1955	1952	57
	1956	1952	58
	1957	1962	50
	1958	1963	55
	1959	1963	55
	1961	1963	56
	1964	1963	61
	1965	1968	61
	1966	1963	50
	1967	1968	59
	1971	1968	54
business assets	1948	1953	48
	1949	1950	51
	1951	1953	52
	1954	1953	49
	1955	1953	50
	1956	1953	51
	1957	1953	51
	1958	1962	95
	1959	1962	94
	1961	1962	96
	1964	1962	96
	1965	1962	96
	1966	1970	30
	1967	1970	33
	1968	1963	61
	1969	1963	62
	1971	1962	94
	1977	1970	40

Notes: The number of years used for the imputation is intentionally not set to one. Rather, the R^2 was calculated using all possible combinations of years. However, the R^2 was highest using only one year for the imputation.

Table E: Imputation of debt variables

	survey year	years in imputation	R^2
housing	1948	1951	24
	1952	1954	45
	1961	1962	27
other real estate	1948	1949	72
	1952	1954	70
	1960	1959	88
	1961	1959	87
	1962	1959	87
	1963	1968	96
	1964	1968	88
	1965	1968	95
	1966	1968	81
	1967	1968	84
	1971	1968	94
non-housing	1966	1968	29

II Time series on income and wealth shares

Tables F and G show the income and wealth shares of five groups in the income and wealth distribution: the bottom 25%, 25% to 50%, 50% to 75%, 75% to 90%, and the top 10%. Income and wealth shares are reported for the different survey years of the HHSCF data.

Table F: Shares in aggregate income

year	bottom 25%	25-50%	50-75%	75-90%	top 10%
1950	6.1	15.5	23.4	20.4	34.5
1953	5.9	15.9	24.4	21.0	32.8
1956	5.2	15.6	23.9	20.6	34.7
1959	5.8	15.3	24.3	21.2	33.4
1962	5.7	15.3	24.3	21.4	33.3
1965	6.3	15.5	24.3	21.4	32.6
1968	6.1	15.6	25.0	21.5	31.8
1971	6.1	15.2	24.7	21.7	32.2
1977	6.4	15.5	25.4	23.1	29.6
1983	5.7	13.9	24.2	22.7	33.5
1986	4.8	13.1	23.1	21.5	37.5
1989	4.5	12.1	21.8	21.5	40.1
1992	5.0	12.7	23.2	22.7	36.4
1995	4.1	12.7	22.6	21.8	38.8
1998	4.4	12.2	22.2	21.6	39.6
2001	4.5	11.4	20.9	20.8	42.3
2004	4.8	11.8	21.0	21.3	41.1
2007	4.6	11.1	20.1	20.0	44.2
2010	4.8	11.1	20.0	20.4	43.6
2013	4.7	10.7	19.4	20.4	44.7

Table G: Shares in aggregate wealth

year	bottom 25%	25-50%	50-75%	75-90%	top 10%
1950	0.2	3.8	11.2	16.4	68.4
1953	0.1	3.6	11.2	15.7	69.4
1956	-0.1	3.8	11.2	15.3	69.9
1959	-0.2	3.9	11.7	15.8	68.9
1962	0.1	3.2	10.6	16.4	69.7
1965	0.1	4.1	11.8	17.2	66.7
1968	-0.3	3.4	10.3	15.1	71.5
1971	0.0	3.7	11.0	15.8	69.6
1977	0.2	5.0	14.1	17.7	63.1
1983	0.2	3.8	12.4	17.2	66.5
1986	0.5	4.6	12.6	17.0	65.3
1989	0.0	3.0	11.7	17.8	67.5
1992	-0.1	3.4	12.1	17.5	67.0
1995	0.0	3.6	11.5	16.7	68.2
1998	-0.1	3.1	11.1	16.6	69.2
2001	0.0	2.7	10.2	16.7	70.3
2004	0.0	2.6	10.3	17.5	69.6
2007	0.0	2.6	10.2	15.8	71.4
2010	-0.5	1.8	8.4	15.9	74.4
2013	-0.5	1.7	8.3	15.4	75.1

III Additional results from portfolio composition

Tables H, I, and J show the composition of household portfolios for three groups of the wealth distribution. The portfolios are shown for preselected years of the HHSCF data.

Table H: Shares of wealth components in wealth portfolios of bottom 50% (in%)

year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt
1950	10.3	79.3	0.9	5.3	25.0	31.4	-14.3	-38.0
1953	15.2	80.0	0.4	5.1	29.5	31.4	-20.5	-41.1
1956	28.8	129.7	0.1	5.2	29.4	11.1	-24.4	-72.3
1959	25.2	166.8	0.1	8.3	31.0	1.1	-33.9	-98.6
1962	18.4	155.5	1.2	1.6	26.7	12.7	-23.8	-92.3
1965	15.6	167.2	0.3	5.3	20.2	10.5	-23.3	-95.8
1968	26.2	181.8	0.1	6.3	28.7	10.9	-51.7	-102.3
1971	15.5	166.1	0.3	5.8	22.4	15.1	-36.3	-89.0
1977	8.8	136.5	0.6	2.9	31.3	0.6	-9.3	-71.3
1983	30.3	118.0	1.7	2.5	18.6	13.4	-26.8	-57.7
1989	38.9	123.2	2.2	2.1	19.4	18.8	-38.2	-66.4
1992	38.7	148.7	4.5	1.5	17.1	19.2	-40.1	-89.7
1995	44.7	150.1	3.3	1.6	14.5	26.8	-41.0	-99.8
1998	41.6	160.5	3.5	1.9	15.8	30.6	-48.7	-105.1
2001	40.0	138.3	2.5	2.0	14.2	26.4	-37.4	-86.0
2004	41.3	178.2	2.6	1.7	13.4	24.9	-44.0	-118.1
2007	39.2	191.6	3.2	1.8	13.1	27.1	-45.0	-131.2
2010	83.7	394.4	7.0	1.5	23.5	49.4	-117.5	-341.9
2013	89.4	343.7	6.1	2.3	27.3	46.7	-126.6	-288.9

Table I: Shares of wealth components in wealth portfolios of 50-90% (in%)

year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt
1950	3.0	64.6	5.3	8.8	17.6	11.0	-1.3	-9.4
1953	3.5	67.0	5.6	9.3	17.4	10.8	-1.9	-11.7
1956	5.4	76.1	1.9	10.0	18.2	4.1	-2.0	-13.4
1959	5.7	79.2	1.5	13.8	17.4	1.1	-2.6	-16.2
1962	3.6	81.5	6.0	8.5	15.1	4.4	-2.1	-17.0
1965	3.5	77.7	3.8	12.7	16.0	4.1	-2.1	-15.7
1968	4.2	77.1	1.0	14.4	18.2	3.3	-2.5	-15.7
1971	2.8	79.5	2.9	8.7	19.0	5.9	-2.4	-16.6
1977	1.9	88.0	0.6	5.3	20.4	0.8	-1.3	-15.7
1983	7.7	78.6	7.0	2.7	15.8	10.8	-3.7	-18.9
1989	8.5	75.3	6.6	2.9	13.0	17.4	-4.3	-19.3
1992	8.6	76.2	6.3	2.5	12.8	20.3	-3.5	-23.1
1995	10.1	73.1	5.5	2.1	10.4	25.9	-4.1	-23.0
1998	8.5	67.3	5.7	3.8	11.1	29.5	-4.1	-22.0
2001	7.4	64.1	6.9	4.2	9.4	31.6	-3.2	-20.3
2004	7.7	75.9	6.6	2.7	9.0	28.1	-3.8	-26.2
2007	6.8	78.6	5.5	2.5	8.5	28.5	-3.7	-26.5
2010	8.0	75.8	6.6	2.2	9.4	30.1	-4.2	-28.0
2013	7.8	72.5	5.1	2.9	8.8	33.9	-4.0	-27.0

Table J: Shares of wealth components in wealth portfolios of top 10% (in%)

year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt
1950	0.7	17.5	55.8	14.9	8.5	4.8	-0.5	-1.9
1953	0.8	18.4	54.2	17.3	7.5	4.2	-0.6	-1.7
1956	0.9	18.1	49.8	23.6	7.8	1.8	-0.2	-1.5
1959	1.0	14.5	50.8	27.2	8.3	0.3	-0.3	-1.8
1962	0.8	19.9	40.6	30.8	8.5	2.1	-0.2	-2.5
1965	0.8	23.1	39.7	32.2	5.9	1.6	-0.3	-3.0
1968	0.7	26.4	35.0	33.7	7.1	1.6	-0.5	-3.9
1971	0.5	29.3	35.4	27.3	8.0	3.0	-0.2	-3.4
1977	0.4	31.1	46.5	15.8	10.4	0.7	-0.8	-4.2
1983	2.7	38.1	30.2	12.4	12.1	11.6	-1.4	-5.7
1989	3.4	36.1	28.0	6.5	12.0	19.0	-1.1	-3.9
1992	2.7	37.4	27.9	7.9	10.7	20.0	-0.8	-5.8
1995	3.4	29.0	27.1	8.8	10.2	27.3	-0.8	-5.0
1998	2.6	26.8	25.2	13.4	7.0	31.0	-1.1	-4.8
2001	2.3	26.9	23.0	12.5	7.0	33.1	-0.7	-4.1
2004	2.4	34.4	24.5	9.2	8.0	28.0	-0.7	-5.8
2007	1.9	33.2	29.1	8.8	6.2	27.1	-0.6	-5.8
2010	2.1	32.2	24.9	7.4	9.0	31.3	-0.6	-6.4
2013	2.0	28.4	25.1	8.6	7.5	34.1	-0.5	-5.3

IV Additional results of house price exposure

Tables K, L, and M show the house price exposure and its decomposition for the three wealth groups that were highlighted in the main part of the paper: the bottom 50%, 50% - 90%, and the top 10%. Tables N, O, and P show the distribution of leverage for these three wealth groups across all survey years of the HHSCF.

Table K: House price exposure of bottom 50% of wealth distribution

year	$\frac{\text{Housing}}{\text{Net wealth}}$	$\frac{\text{Housing}}{\text{Assets}}$	$\frac{\text{Debt}}{\text{Net wealth}}$
1950	79.3	52.1	52.2
1953	80.0	49.5	61.6
1956	129.7	63.5	104.3
1959	166.8	71.7	132.4
1962	155.5	72.0	116.1
1965	167.2	76.3	119.0
1968	181.8	71.6	153.9
1971	166.1	73.7	125.3
1977	136.5	75.6	80.6
1983	118.0	64.0	84.5
1986	123.7	69.4	78.3
1989	123.2	60.2	104.6
1992	148.7	64.7	129.8
1995	150.1	62.3	140.9
1998	160.5	63.2	153.8
2001	138.3	61.9	123.4
2004	178.2	68.0	162.1
2007	191.6	69.4	176.1
2010	394.4	70.5	459.4
2013	343.7	66.7	415.5

Table L: House price exposure of 50-90% of wealth distribution

year	$\frac{\text{Housing}}{\text{Net wealth}}$	$\frac{\text{Housing}}{\text{Assets}}$	$\frac{\text{Debt}}{\text{Net wealth}}$
1950	64.6	58.5	10.5
1953	67.0	59.0	13.6
1956	76.1	65.8	15.7
1959	79.2	66.7	18.8
1962	81.5	68.4	19.1
1965	77.7	66.0	17.8
1968	77.1	65.2	18.2
1971	79.5	66.9	18.8
1977	88.0	75.1	17.1
1983	78.6	64.1	22.6
1986	83.1	66.9	24.3
1989	75.3	60.9	23.6
1992	76.2	60.2	26.6
1995	73.1	57.5	27.1
1998	67.3	53.4	26.1
2001	64.1	51.9	23.5
2004	75.9	58.3	30.0
2007	78.6	60.3	30.2
2010	75.8	57.3	32.2
2013	72.5	55.3	31.0

Table M: House price exposure of top 10% of wealth distribution

year	$\frac{\text{Housing}}{\text{Net wealth}}$	$\frac{\text{Housing}}{\text{Assets}}$	$\frac{\text{Debt}}{\text{Net wealth}}$
1950	17.5	17.1	2.3
1953	18.4	17.9	2.4
1956	18.1	17.7	2.0
1959	14.5	14.2	2.1
1962	19.9	19.3	2.6
1965	23.1	22.4	3.3
1968	26.4	25.3	4.4
1971	29.3	28.3	3.6
1977	31.1	29.7	4.9
1983	38.1	35.6	7.1
1986	41.3	37.5	9.9
1989	36.1	34.4	5.0
1992	37.4	35.1	6.6
1995	29.0	27.4	5.8
1998	26.8	25.3	6.0
2001	26.9	25.7	4.8
2004	34.4	32.3	6.4
2007	33.2	31.2	6.3
2010	32.2	30.1	7.0
2013	28.4	26.8	5.8

Table N: Leverage on housing for bottom 50% of wealth distribution

	0%	<50%	50-75%	>75%
1950	55.3	18.9	14.0	11.8
1953	44.2	23.6	16.4	15.7
1956	38.0	21.6	22.8	17.6
1959	33.6	18.8	25.3	22.3
1962	32.4	17.6	20.8	29.2
1965	32.5	16.4	23.8	27.3
1968	33.4	14.8	24.3	27.5
1971	35.8	16.5	23.4	24.3
1977	48.3	12.5	18.1	21.1
1983	37.1	21.4	23.7	17.8
1986	37.1	21.8	21.2	19.9
1989	35.2	18.2	21.4	25.2
1992	32.5	18.0	19.3	30.2
1995	26.9	17.6	18.9	36.6
1998	28.0	13.5	19.3	39.1
2001	27.9	13.5	21.5	37.2
2004	24.4	11.9	25.3	38.4
2007	22.1	15.4	23.8	38.6
2010	17.3	8.4	17.3	57.0
2013	24.3	7.5	13.7	54.5

Table O: Leverage on housing for 50-90% of wealth distribution

	0%	<50%	50-75%	>75%
1950	64.3	28.7	5.7	1.3
1953	57.2	33.0	8.4	1.4
1956	56.7	31.8	10.0	1.5
1959	53.1	34.3	10.9	1.7
1962	48.7	33.2	14.3	3.8
1965	49.5	33.9	13.0	3.6
1968	51.6	29.6	15.1	3.7
1971	52.0	32.3	12.0	3.6
1977	62.2	28.0	8.1	1.7
1983	42.2	45.1	10.0	2.6
1986	41.8	42.5	12.6	3.1
1989	37.1	42.7	15.8	4.4
1992	41.6	31.6	19.8	7.0
1995	41.0	30.1	18.8	10.1
1998	38.2	30.7	20.1	11.1
2001	35.3	33.8	21.5	9.4
2004	31.8	34.3	22.9	11.1
2007	31.4	38.9	21.7	8.0
2010	35.1	29.7	19.6	15.6
2013	37.9	26.1	20.6	15.4

Table P: Leverage on housing for top 10% of wealth distribution

	0%	<50%	50-75%	>75%
1950	70.9	21.1	5.0	3.0
1953	68.8	26.7	3.6	0.9
1956	65.6	26.9	5.6	1.9
1959	63.2	24.5	9.4	2.9
1962	51.3	37.8	10.2	0.7
1965	49.8	31.1	14.3	4.7
1968	56.6	28.3	11.9	3.2
1971	57.4	29.3	10.2	3.1
1977	64.7	29.9	3.9	1.5
1983	49.4	40.7	8.6	1.3
1986	43.2	47.8	6.5	2.5
1989	48.7	40.3	8.4	2.5
1992	41.1	42.8	11.0	5.1
1995	41.1	38.3	15.0	5.6
1998	37.9	37.6	18.8	5.7
2001	43.0	41.0	13.7	2.3
2004	40.7	41.2	14.8	3.3
2007	36.5	48.4	10.2	4.9
2010	39.9	38.5	16.8	4.8
2013	40.4	37.8	16.3	5.6