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 the past seven decades. We introduce a newly compiled household-level dataset based on archival data from historical waves of the Survey of Consumer Finances (SCF). Complementing recent work on top income and wealth shares, the long-run survey data give a granular picture of trends in the bottom 90% of the population. The new data confirm a substantial widening of income and wealth disparities since the 1970s. We show that the main loser of rising income and wealth concentration at the top was the American middle class – households between the 25th and 75th percentile of the distribution. The household data also reveal that the paths of income and wealth inequality deviated substantially. Differences in the composition of household portfolios along the wealth distribution explain this divergence. While incomes stagnated, the 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 importance of portfolio composition, leverage and asset prices for wealth dynamics in postwar America.

JEL: D31, E21, E44, N32

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1 Introduction

We live in unequal times. The causes and consequences of widening disparities in income and wealth have become a defining debate of our age. This paper aims to fill a number of important gaps in our understanding of the long-run evolution of inequality. The backbone of our study is a new dataset that builds on detailed household-level information spanning the entire U.S. population over seven decades of postwar American history. The paper introduces this new dataset and uses it to study the development of income and wealth inequality.

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. The pre-1983 SCF data have not yet been systematically processed and linked to the modern SCFs. Only a few studies such as Malmendier and Nagel (2011) or Herkenhoff (2013) used parts of the data to address specific questions. In extensive data work, we harmonized the historical and modern surveys in a consistent way, creating a long-run micro-level dataset spanning nearly 70 years. We are terming this new resource for inequality research the *Historical Survey of Consumer Finances* (HSCF). The HSCF data closely match aggregate trends in the National Income and Product Accounts (NIPA) and the Flow of Funds Accounts (FFA).

This paper presents the dataset and addresses a number of 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. However, income tax data are not ideal to study the lower echelons of the distribution as non-taxable income and non-filers are not well covered. Until today, we know relatively little about the losers of increasing income concentration at the top. Similar issues arise with respect to trends in the wealth distribution. Recent studies rely on a capitalization method to infer wealth from the income flows reported in the tax data. However, outside the top 10% considerable wealth is held in forms that do not generate income subject to income tax. As in the case of income, until now estimates of the evolution of the wealth distribution for the bottom 90% had to remain somewhat cursory. In this paper, we close both gaps as we directly observe income and wealth across the entire distribution.

The long-run survey data show a substantial widening of income and wealth disparities since World War II. The observed levels and trends of income and wealth concentration corroborate the patterns described by Piketty and Saez (2003) and Saez and Zucman (2016). Yet while both data sources – income tax data and survey data – produce broadly similar conclusions with respect to trends in income and wealth concentration, the HSCF adds considerable nuance. We show that the American middle class – defined here as 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 1970, the middle class received only 15 cents, less than half its share of 40 cents in the 1950s and 1960s. The top 10% received 75 cents of every new 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 HSCF data, we also expose divergent trajectories of income and wealth inequality. In standard models an increase in income inequality typically leads to a simultaneous increase in wealth inequality. The increase in wealth inequality can even exceed that of income inequality if income-rich households save more – as existing research argues (Dynan, Skinner, and Zeldes (2004), Saez and Zucman (2016)). The HSCF data show that the opposite was the case over extended periods in postwar America. Wealth inequality decreased in the 1970s and 1980s when income concentration at the top surged. Wealth concentration began to increase in the 1990s, but even in 2007 the top 10% wealth share barely exceeded its 1971 level. The financial crisis of 2007/08 produced the largest spike in wealth inequality in postwar America. In the six years after the financial crisis, wealth concentration at the top rose more than in the six decades before. In the postwar era, the distribution of wealth in America has never been more unequal than it is today.

The reason for differential trends in income and wealth inequality can be found in the heterogeneity of household portfolios along the wealth distribution. We show that portfolio compositions vary systematically across the distribution. This gives rise to heterogeneous returns on wealth, which can have substantial effects on the wealth distribution (Benhabib and Bisin (2016)). In particular, the top and the middle of the distribution are affected differentially by stock and house price changes. While the portfolios of rich households are dominated by business equity and financial assets, the portfolio of the typical middle class households is highly concentrated in residential real estate and also highly leveraged. As a consequence, rising house prices lead to substantial wealth gains of middle class households. Higher equity prices primarily boost the wealth of households at the top of the wealth distribution as their portfolios are dominated by business equity.

Highlighting the importance of heterogeneous portfolios and differential wealth gains for the dynamics of wealth inequality in postwar America is a core contribution of this paper. The magnitude of changes in the wealth distribution induced by this portfolio channel is large. We calculate that the middle class received 75% of the total wealth gains from the housing boom of the 1990s and the mid-2000s. Without the boost from rising house prices, middle class wealth in 2007 would have been 40% lower. Growing middle class housing wealth played an important role in mitigating the overall increase in wealth inequality. Asset-price induced gains in housing wealth slowed down wealth concentration in the hands of the top 10% by about two thirds. It is conceivable that such substantial wealth gains helped dispel middle class discontent about stagnant incomes for some time. When house prices collapsed in the crisis, the same leveraged portfolio position of the middle class led to substantial wealth losses. Surging post-crisis wealth inequality might in turn have contributed to the perception of rising inequality in recent years.

The structure of the paper is as follows. Section 2 introduces the new dataset, and discusses the construction of the 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 evolution of income and wealth inequality and shows that the trends diverged. 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) rely on 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) also rely on an imputation based on survey data. As we will see, the HSCF data we introduce in this paper corroborate their overall findings but add considerable nuance, in particular with respect to the importance of portfolio heterogeneity for changes in wealth inequality. Kopczuk (2015) compares different approaches to estimate top wealth shares using tax data, the SCF and estate tax records. He finds that notable differences exist in estimates of wealth shares of the very rich, i.e., the top 1% (and above). However, the top 10% wealth shares typically align closely in level and trend. 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] Kopczuk, Saez, and Song (2010) study the long-run evolution of individual earnings in the United States using Social

[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).

Security Administration micro data and find a pronounced increase in earnings inequality since the 1970s.

Emphasizing the importance of asset price changes for changes in wealth inequality, our paper also relates to the work of Bach, Calvet, and Sodini (2016). Studying administrative Swedish data, they find that wealthy households earn higher returns on their portfolios, but also face higher risks. With regard to heterogeneity in returns along the wealth distribution, Fagereng, Guiso, Malacrino, and Pistaferri (2016) use administrative Norwegian tax data and document substantial heterogeneity in wealth returns and intergenerational persistence. Kuhn and Rıos-Rull (2016) use SCF data to analyze household balance sheets from 1989 to 2013. Decomposing the relative importance of different balance sheet positions for the evolution of wealth inequality, they show that houses and mortgage debt are important drivers of wealth inequality.

Theoretical work modeling the dynamics of wealth inequality is growing quickly. 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 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 an important gap to fill in future research. Benhabib and Bisin (2016) and Benhabib, Bisin, and Luo (2017) discuss heterogeneous asset returns as a driver of wealth inequality. Fella and De Nardi (2017) survey the existing literature and 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 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 *Historical Survey of Consumer Finances* can become a valuable resource for future research. We therefore go into some detail to describe the construction of the dataset and discuss the challenges we faced linking the historical waves of the SCF to their modern counterparts.

The SCF is a key resource for research on household finances in the United States. The SCF is a triennial survey and datasets for various survey waves starting in 1983 are easily avail-

[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.

able on the Federal Reserve's website. Other than ease of access, the comprehensiveness and quality of the SCF explain 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 Reserve's 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. 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 page from the survey codebook in 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. Given that the HSCF data provides detailed demographic information together with the financial situation of U.S. households over time, we will also explore the effects of demographic changes on the income and wealth distribution as part of our analysis.

2.1 Variables

The variables covered in the historical surveys correspond to those in the contemporary SCF, but the exact wording of the questions may differ from survey to survey. Financial innovations impact continuous coverage of variables across the various surveys. For instance, data on credit card balances become available after their introduction and proliferation.

Figure 1: Survey of Consumer Finances codebook from 1949

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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 *

However, the appearance of new financial products like credit cards does not impair the construction of consistent data series. Implicitly, these financial 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 the imputation procedure in the next section. Our analysis focuses on four variables that are of particular importance for 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 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, cars, and business equity. The coverage is comprehensive for liquid assets and housing. Liquid assets comprise of 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, the data are comprehensive for the 1950s, but imputation is needed in the 1960s. 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] The current value of cars is available in the historical files for 1955, 1956, 1960, and 1967. We impute the value in other years using information on age, model, and size of the car.[4] 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.[5] All debt other than

[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]Surveys up to 1971 include information on age, model and size of the car a households owns. If a household bought a car during the previous year, the purchasing price of this car is also available. We impute the car value using the average purchasing price of cars bought in the previous year that are of the same age, size, and model. In 1977, only information on the original purchasing price and the age of the car is given. For this year, we construct the car value assuming a 10% annual depreciation rate.

[5]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.

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. In addition to the adequate 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 constructed the HSCF to meet these criteria.

Oversampling of wealthy households: Since its redesign in 1983, the SCF consists of two samples. The first sample is drawn using area probability sampling of the entire U.S. population based on Census information. In addition, a second so-called *list sample* is drawn based on tax information. Tax information is used to identify households that are likely to be at the top of the wealth distribution.[6] For both samples, survey weights are constructed separately. In the list sample, survey weights have to be over-proportionally adjusted for non-responses. The weight of each household corresponds to the number of similar households in the population. In a final step, both samples are combined and survey weights are adjusted so that the combined sample is representative of the U.S. population (see Kennickell, Woodburn, and McManus (1996)).[7] This two-frame sampling scheme yields a representative coverage of the entire population including wealthy households.

[6] 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.

[7] 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 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 represents, the higher $= \frac{n_i}{N_i}$ and the more the original weight W_i is adjusted upwards.

Before 1983, the historical SCF sample is not supplemented by a second list sample. As a consequence, non-responses of wealthy households are likely to be more frequent. This could lead to an under-representation of rich households in the data. We use information from the 1983 list sample to adjust for a potential under-representation in the pre-1983 data. In a first step, we determine the share of households from the list sample among all households. Their share corresponds to approximately 2%. In a second step, we determine where the households from the list sample are located in the income and wealth distribution. We find that most observations are among the top 5% of the income and wealth distribution. Note that we determine these percentiles after we have dropped the list sample. Using this information, we adjust survey weights in all surveys before 1983 in two steps. First, we extract separately for each year all observations that are simultaneously in the top 5% of the income and wealth distribution. Secondly, we increase the weighting of these households in such a way that we effectively add 2% of wealthy households to the sample. We adjust the remaining weights accordingly.

A concern with this adjustment might be that it relies on information from a single sample year in 1983. The list sample information 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: Share of respondent from list 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.

In Table 1, we show non-response patterns 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 data. Put differently, we do not find evidence for a time trend in non-responses of wealthy households and there is no indication that our calibration of the adjustment routine to 1983 data might be impacted by time trends in non-response pattern. Moreover, in section 4.1 we compare the top income shares derived from the HSCF with top income shares calculated on the basis of tax data. The comparison shows that the weight-adjustment does not produce any unusual breaks in the time-series between the 1977 and 1983 surveys.[8]

Demographic characteristics: We compare the demographic characteristics in the surveys before 1983 with data from the U.S. Census from 1940 to 1990. The described adjustment of sample weights might affect the distribution of demographic characteristics.[9]
To obtain samples that match the Census data, we subdivide both the Census and the HSCF 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 HSCF weights by minimizing the difference between the share of each subgroup in the HSCF and the respective share in the Census.[10] As Census data are only available on a decennial basis, we linearly interpolate values between the dates.[11]
Figure 2 shows the shares of 10-year age groups, college households, and black households in the Census (black squares) and in the HSCF 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 SCF 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 described in Schenker and Taylor (1996). This multiple 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 observation for which information on the variable is missing. We impute five values for each missing observation. A detailed description of the imputation method is provided in Appendix A.2.
In addition, we account for a potential under-coverage of business wealth before 1983 and follow the method proposed by Saez and Zucman (2016) to adjust the observed holdings in

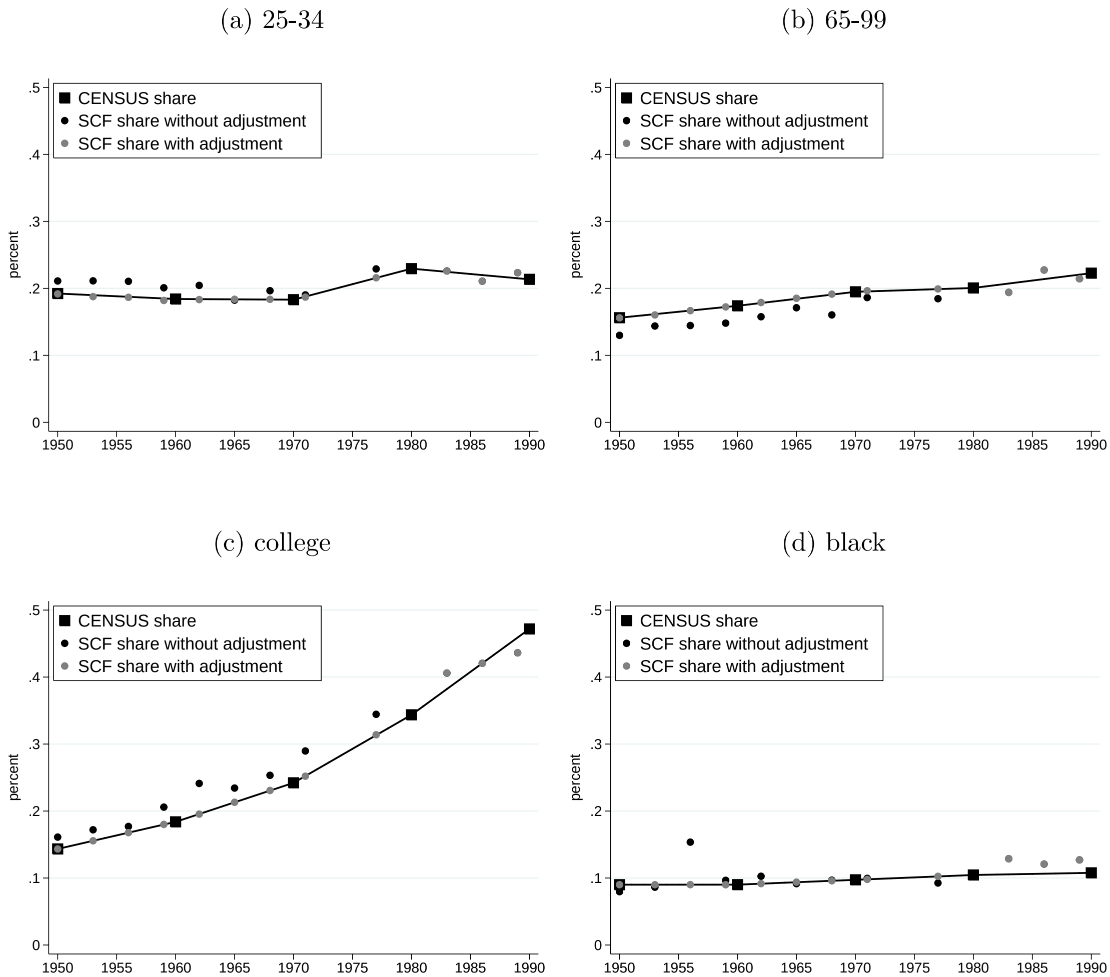
[8] As a proof of concept, we also apply in section A.1 of the appendix the adjustment to the 1983 data itself after dropping the list sample. We find that the adjustment works well for the top 10% but deteriorates towards the very right tail of the distribution. However, the very right tail of the distribution has been extensively studied with tax data and is not the focus of our study.

[9] For example, as mainly white college households are in the top of the income and wealth distribution, it is likely that their share in the survey population is too high.

[10] 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 HSCF corresponds to the respective share in the Census.

[11] The distributions of demographic characteristics such as age, education, and race change gradually over time, hence, linear interpolation provides a good approximation.

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



Notes: The large black squares refer to the share of the respective demographic group in the census data. Census data is linearly interpolated in between years. The small black dots are the shares of the respective group using the original survey data. The small gray dots are the shares using the adjusted survey data. Horizontal axes show calender time and vertical axes population shares.

the micro data with information from the FFA. For this purpose, we rely on data from the 1983 and 1989 surveys and 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.[12] This provides consistent estimates taking into account the conceptual differences between SCF and FFA data.

[12]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. $\mathrm{X}_{it}^{adj} = \mathrm{X}_{it} \frac{\mathrm{X}_t^{FFA}}{\bar{\mathrm{X}}_t} \frac{\bar{\mathrm{X}}_{1983,1989}}{\mathrm{X}_{1983,1989}^{FFA}}$

Table 2 details the 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 to E of the online appendix.[13]

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

The overall goal of this paper is to exploit our new micro data to study the evolution of income and wealth distribution over the past seven decades. For this purpose, it is important that the micro data are consistent with aggregate trends. In this section, we benchmark aggregate trends from the HSCF 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 (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 (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 HSCF

[13]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 of the online appendix.)

Table 2: Data availability

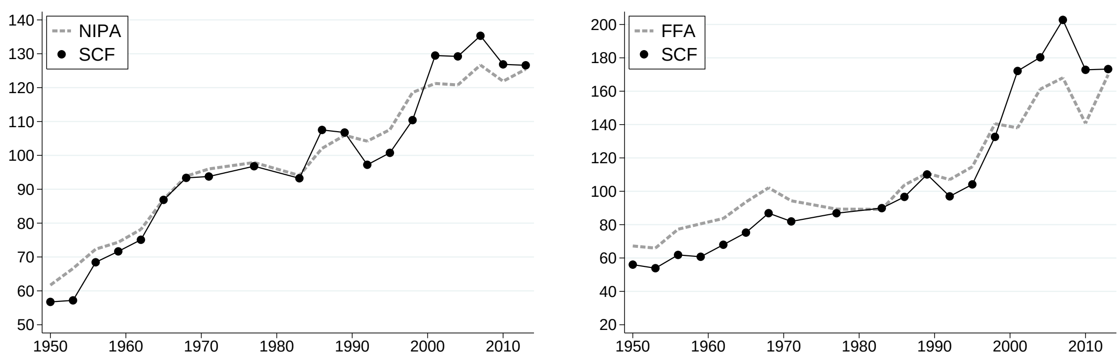
	income			financial assets			non-financial assets			debt			
Survey year	total	labor	labor + business	liquid assets	bonds	equity	housing	other real estate	business	total	housing	other real estate	non-housing
1949	O	O	O	O	O	O	O	O	I	O	O	O	O
1950	O	O	O	O	O	O	O	O	O	O	O	O	O
1951	O	O	O	O	O	I	O	I	I	O	O	O	O
1952	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: Data availability for different survey years. First column shows survey year. Each column refers to one variable in the HSCF data. "O" indicates that original observations of this variables are used, i.e. no imputed observations. "I" indicates that observations of this variable are imputed.

data match aggregate data closely – effectively alleviating most of the previously indicated concerns. Figure 3 compares income and wealth of the HSCF with the corresponding NIPA and FFA values. Income components of the NIPA 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 Hsu (2013) who construct wealth from the FFA to be comparable to the SCF.[14] The base period for comparisons is 1983 to 1989 as these are the first surveys that incorporate the oversampling of wealthy households.

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

(a) Income (b) Wealth



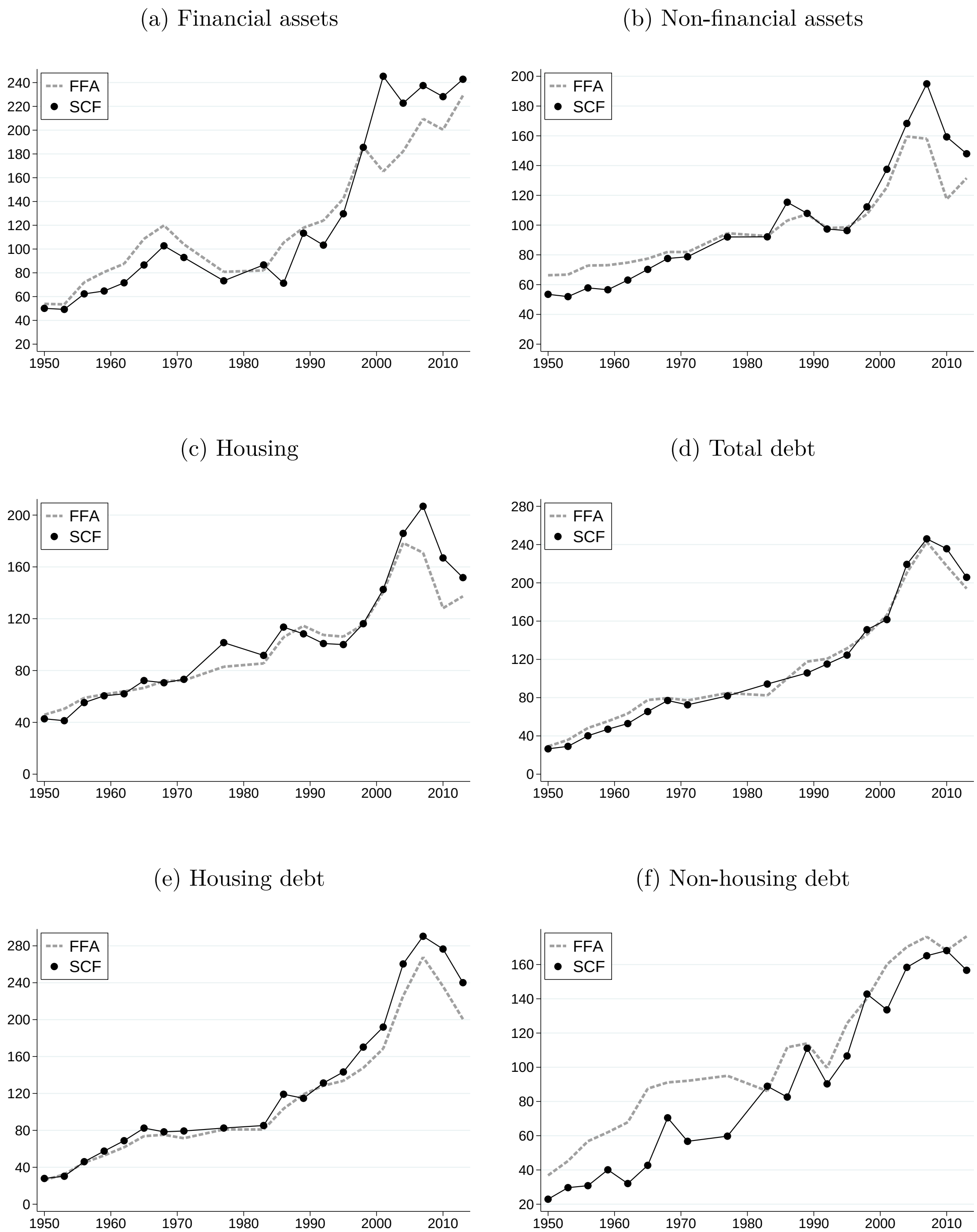
Notes: Income and wealth data from HSCF in comparison to income data from NIPA and wealth data from FFA. All data has been indexed to the 1983 - 1989 period (= 100). HSCF data is shown as black lines with circles, NIPA and FFA data as a gray dashed line. For the indexing period HSCF data corresponds to 80% of NIPA income and118% of FFA wealth.

For the base period of 1983-1989, the HSCF 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 HSCF and NIPA data throughout the 1949-2013 time period. Looking at wealth, the trends differ only slightly. Before 1983, wealth in the HSCF is below that of the FFA. From 1983 to 1998, the two measures are about the same and from then onwards the HSCF is somewhat higher. Both wealth measures show an upward trend over time, but the increase is somewhat steeper in the HSCF.

To evaluate which asset and debt positions generate the divergence in wealth estimates, Figures 4 shows different asset and debt components from the household balance sheet.

[14]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: HSCF, NIPA, and FFA: financial and non-financial assets



Notes: Asset and debt components of household balance sheets from HSCF in comparison to data from FFA. All data has been indexed to the 1983-1989 period (= 100). HSCF data is shown as black lines with circles, FFA data as a gray dashed line. For the indexed period HSCF data correspond to 80% of financial assets, 137% of non-financial assets, 98% of housing, 86% of total debt, 93% of housing debt, and 70% of non-housing debt.

Figure 4a shows financial assets. Financial assets in the HSCF increase more strongly in the 1990s than the corresponding FFA values. This difference is mainly due to distinct trends in corporate equity during the stock market boom in the second half of the 1990s. Figure 4b shows that trends for non-financial assets are similar in the micro and macro data. One reason for the close alignment can be seen in Figure 4c that shows housing as the most important non-financial asset is covered well in the survey data. The household balance sheet component for which the HSCF matches the aggregate data best is debt as shown in Figure 4d. There is a level difference of about 15% throughout the whole time period, but the trend is almost identical in the HSCF and FFA. The underlying reason why these trends are so similar is that the dominant component for both data sources is housing debt (Figure 4e). With respect to non-housing debt (Figure 4f), the SCF data show somewhat lower values in the early years than the FFA but in general a similar trend. However, non-housing debt represents a relatively small share of total household debt.

In conclusion, the HSCF matches aggregate trends of NIPA data and FFA asset and debt positions. In particular, the HSCF data and the FFA show very similar trends for the important categories of housing wealth and mortgage debt. For financial assets comprising corporate and non-corporate equity some gaps remain. 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 data.

4 Income and wealth distribution, 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 HSCF 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 by 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.[15]

We will demonstrate that trends for top income and wealth shares in the HSCF 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 of the middle class, households between the 25th to 75th percentiles. For the wealth distribution, we also find that most of

[15] Appendix B.2 provides a detailed analysis how changes in the demographic composition of U.S. households (educational attainment, age, household size) affect levels and trends of income and wealth inequality.

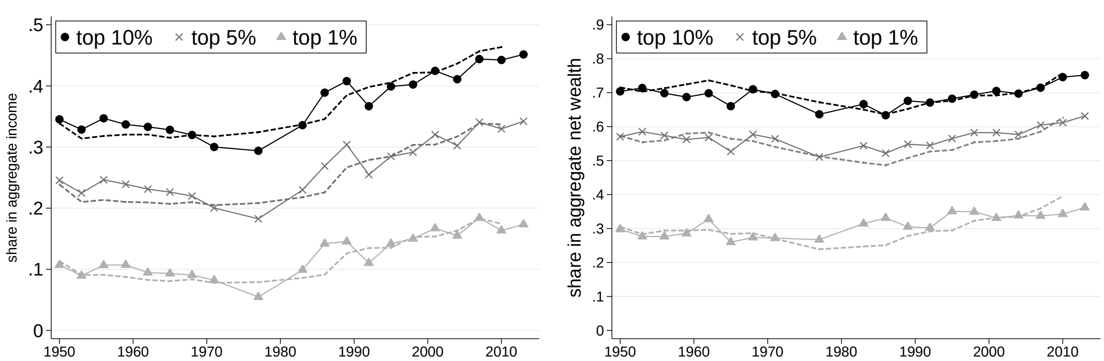
the gains in wealth shares at the top show up as losses in wealth shares of the middle class. Comparing trends in income and wealth inequality, our data point to different dynamics that we subsequently analyze in greater detail.

4.1 Income and wealth concentration at the top

The recent debate on the evolution of income and wealth inequality focused on the concentration of income and wealth at the top. In Figure 5a, we compare the income shares of the top 10%, 5%, and 1% of the income distribution in the HSCF to those first calculated by Piketty and Saez (2003) using IRS income tax data and a comparable definition of total income.[16] The HSCF data corroborates their finding of high and rising income concentration both in levels and trends. Figure 5b compares wealth shares of households at the top of the wealth distribution in the HSCF with those obtained by Saez and Zucman (2016). 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.

Figure 5: Top income and wealth shares

(a) Income (b) Wealth



Notes: Top income and wealth shares from HSCF data and Piketty and Saez (2003) and Saez and Zucman (2016). The dots show income and wealth shares from HSCF data, the dashed lines income shares from Piketty and Saez (2003) using IRS tax data or wealth shares from Saez and Zucman (2016) using IRS data and the capitalization method. The black dots show income (wealth) shares of the top 10%, dark gray crosses show the top 5% shares, and the light gray triangles show top 1% shares. Horizontal axes show calender time and vertical axes income and wealth shares.

[16] 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.

Some small differences especially for estimates of wealth concentration remain. One reason could be that the pre-1962 estimates of Saez and Zucman (2016) had to be adjusted, because tax units before are sorted by income rather than wealth. In the HSCF 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. In Figure C.4 of the appendix, we consider income concentration among wealth-rich households and wealth concentration among income-rich households. While the levels of income and wealth shares change by construction, the pattern of changes in income and wealth concentration remain unaffected. Kopczuk (2015) provides a detailed discussion of the different methods to estimate wealth concentration at the top. He shows that estimates for the top 10% wealth shares are similar across different methods, but they can diverge for the top 1% and above.

4.2 Gini coefficients

In this section, we start our discussion on the distributional changes among the bottom 90% 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 B.4 in the appendix. The first row reports the Gini coefficient for all households. To describe changes in the bottom of the distribution, we exclude in the second 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 ($\times$100) for 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 from 1989 to the eve of the financial crisis in 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 at 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 to 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 rely on income and wealth shares of different groups to describe changes of the income and wealth distribution over time.

4.3 The declining income share of the middle class

A major advantage of the HSCF 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 World War II.[17] Starting with income on the left side of the table, the HSCF data document an increasing concentration of income at the top of the distribution. The top 10% have grown their income share from 34.5% to 44.7% 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

[17] Online appendix II reports the full time series.

at the top during this period but also households between the 75th and 90th percentiles lost income shares.

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. 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. 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.

In appendix B.1, we also explore quantile ratios as an alternative and intuitive approach to study shifts in relative income and wealth over time. The quantile ratios paint a similar picture and point to divergent trends in income and wealth inequality over longer stretches of postwar U.S. history.

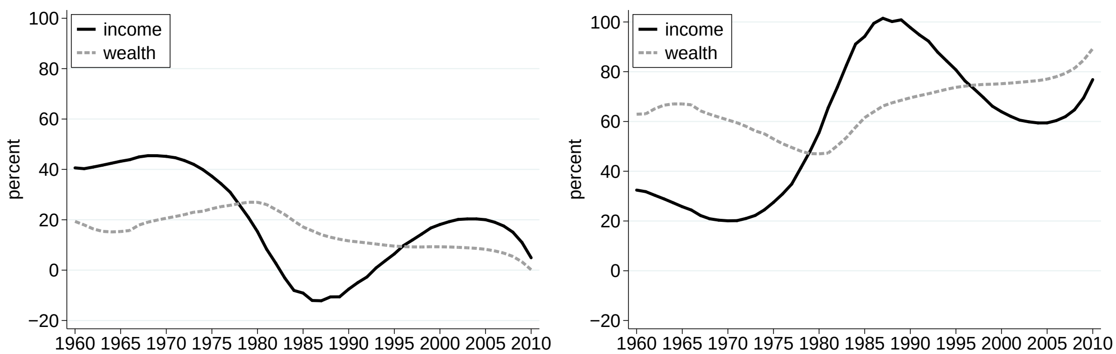
4.4 The distribution of aggregate income and wealth growth

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 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 6 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.[18] 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.

Figure 6: Shares in income and wealth growth rates

(a) 25-75%

(b) Top 10 %



Notes: Shares in aggregate income and wealth growth over time. Left panel shows shares for the 25th to 75th percentiles (middle class). Right panel shows shares for the top 10%. 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 and the dashed line shows the share in wealth growth. Shares are shown in percentage points.

The middle class began to lose ground in the mid-1970s. Middle class shares in income growth declined sharply, even dipping into negative territory at times 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 share until the 1970s. However, the middle-class share in wealth growth has a different trajectory. It increased until the mid-1980s at a time when the middle class 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.

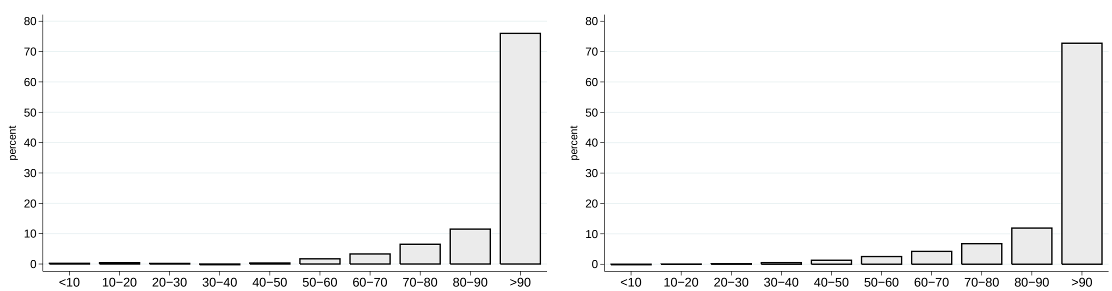
The top 10% shares for income and wealth are essentially the mirror image of the middle class. From the mid-1980s to the mid-1990s almost the entire income growth in the American economy went to the top 10%. In the 2000s, the share was a little lower, but still about

[18]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.

twice the level it reached before the 1970s. By contrast, the top-10% share in wealth growth remained reasonably smooth throughout the period. It fell a little in the 1960s and 1970s, but surged in the 1980s. Since the financial crisis, about 80 cents of each additional dollar of wealth generated by the American economy went to the richest 10 % of households.
Figure 7 zooms in on the period between 1971 and the last pre-crisis survey in 2007. It shows the cumulative distribution of income and wealth growth. 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 growth of the U.S. economy.

Figure 7: 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.

The above comparison of shares in aggregate income and wealth growth does not take into account different initial income and wealth shares. For inequality to change over time, the distribution of additional dollars of income or wealth must be different from the distribution at the beginning. Put differently, if income growth had been proportional to initial income, the top 10% would have received 32 cents of every dollar of income growth between 1971 and 2007, and income inequality would not have widened. Yet, the top 10% pocketed considerably more, namely 76 cents of every additional dollar.
For wealth, the initial distribution was more unequal. The top 10% already owned approximately 70% of total wealth in 1971. Under inequality-neutral wealth growth, the top 10% would have also received 70 cents of every additional dollar. That number is very close to the 73 cents of very new dollar of wealth that they secured in the data. In other words, wealth inequality increased somewhat, but the shifts are much less pronounced than for income. In the next section, we will formalize this intuitive relationship between the initial level of

inequality and the distribution of new dollars of income (wealth) and study the divergent trends of wealth and income inequality in greater detail.

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 changes in the distribution of income and wealth over time. Such a comparison must take into account the differences in the initial levels of income and wealth inequality. Clearly, wealth tends to be considerably more concentrated than income.

We propose the *inequality gradient* as a novel measure for the time path of changes in income and wealth inequality. 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. 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 i's 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 i's 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.

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 are 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.[19]

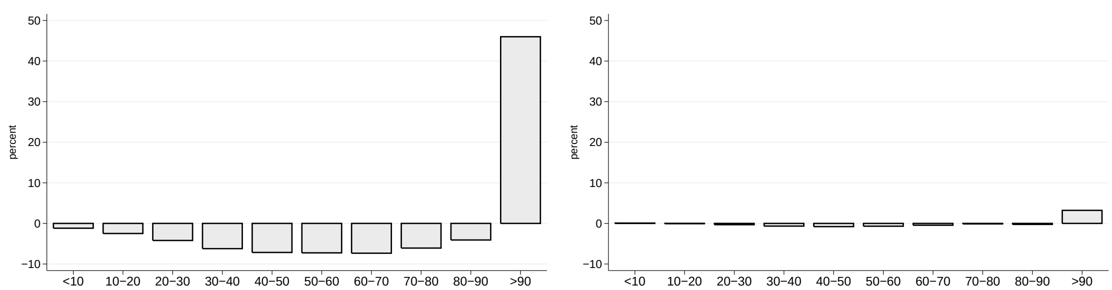
Figure 8a shows the inequality gradient for income. We find substantial relative income gains of the top 10%, measured by the steep income inequality gradient. Between 1971 and

[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.

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. Hence, their participation in income growth was less than their initial income share.

Figure 8: 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 8b 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 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 1971 to 2007, the top 10 % received 73 cents out of each additional dollar of wealth relative to an initial wealth 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.

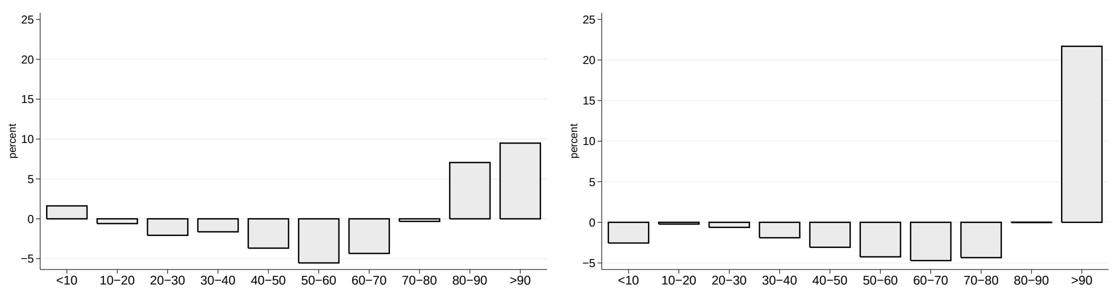
This overall picture – a pronounced increase in income inequality and a comparatively small rise in wealth concentration before 2007 (figure 8) – changed dramatically in the financial crisis and its aftermath. The years from 2007 to 2013 saw a much stronger rise of wealth concentration relative to income concentration. Inequality gradients for wealth exceeded those for income over this time period as Figure 9 shows. The top 10% wealth gradient is now more than twice as large as the corresponding income gradient. The years 2007-2013 were associated with substantial aggregate wealth and income *losses*. Inequality gradients for this period turn negative. 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 9 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. The larger change in wealth inequality compared to income inequality during the financial crisis highlights a second important result. The fact that wealth inequality exceeds income inequality and that the bottom 50% hold hardly any wealth does not automatically imply that changes in income inequality must exceed changes in wealth inequality over time.

Figure 9: 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 10 we zoom out and track income and wealth concentration for the entire sample period from 1950 to 2013.

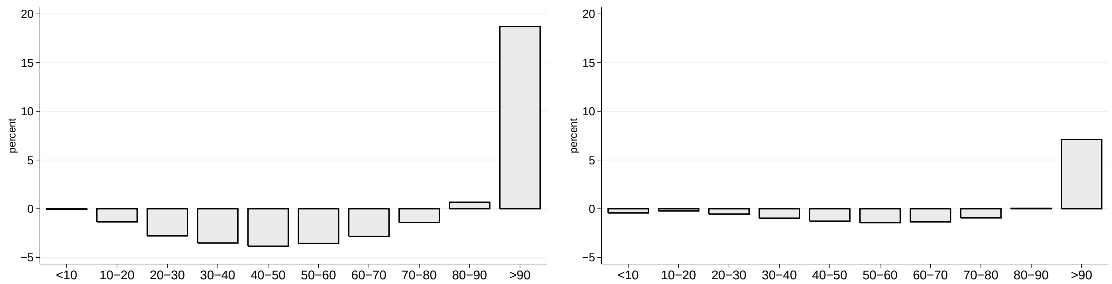
The basic patterns remain the same. Income concentration at the top increased almost three times more than wealth concentration. This stronger polarization of incomes is mainly a result of the pronounced increase in income concentration between 1971 and 2007. Wealth inequality surged in the years after 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 10 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 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

Figure 10: Inequality gradient for income and wealth, 1950 - 2013

(a) Income (b) Wealth



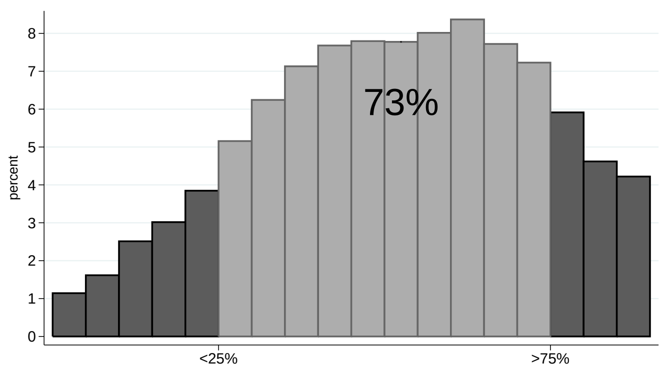
Notes: Inequality gradients for income and wealth for the period from 1950 to 2013. Horizontal axis shows income and wealth deciles.

group

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

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%.

Figure 11: Distribution of losses ($\lambda^i_{t,t+1}$) among the bottom 90%, 1971 - 2007



Notes: Distribution of the loss in income shares among the bottom 90% of the income distribution for the period from 1971 to 2007. Total losses sum to 100%. Red bars show losses incurred between the 25th and 75th percentile (middle class).

We plot the distributions of the relative income losses for the period from 1971 to 2007 in Figure 11. 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 witnessed over-proportional losses compared to other income groups and was the (main) relative loser of income polarization.

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 highlight the 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 HSCF 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 trends in 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. Using a similar theoretical approach, Garbinti, Goupille-Lebret, and Piketty (2017) argue that price effects played an important role in shaping the French wealth distribution over the past 200 years.

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 dominant role. As homes are the most important asset on 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 over long stretches of U.S. postwar history. 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 12 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 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 of 1.5 to 2. The bottom 25% have hardly any wealth. However, their zero net position also hides substantial gross positions of assets and debt on either side of the balance sheet.

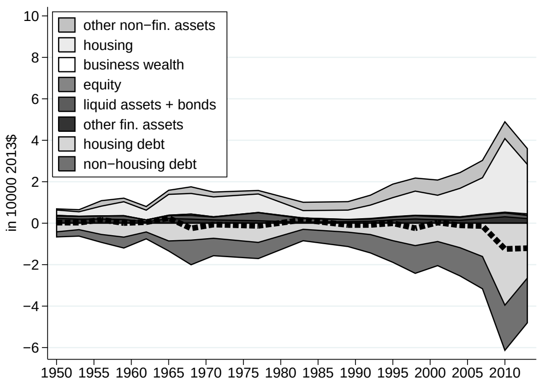
The third observation is that business equity and other financial assets are by far the most important asset category of households at the top of the wealth distribution. As a consequence, their wealth position is particularly sensitive to changes in the prices of these assets. Note that for our analysis 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]

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

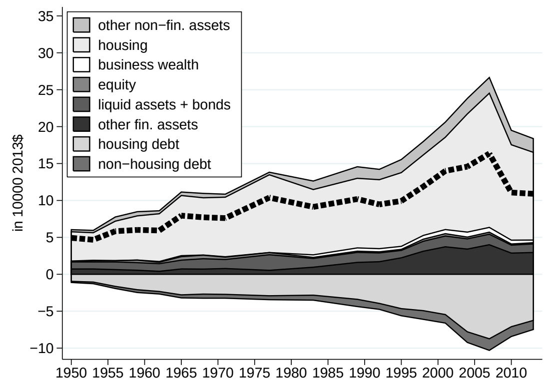
[21] The most notable difference is that the bottom of the income distribution holds positive wealth and

Figure 12: Heterogeneity of household portfolios

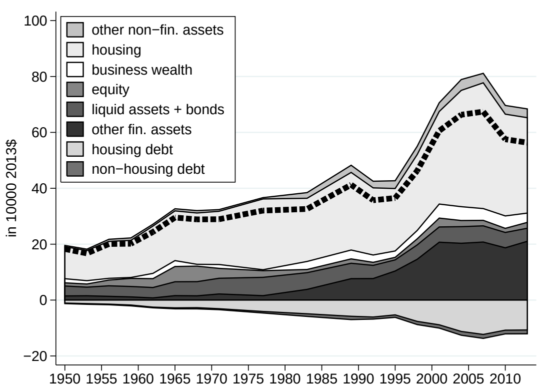
(a) <25%



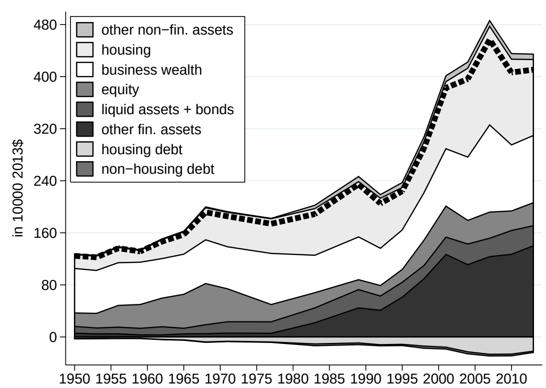
(b) 25-75%



(c) 75-90%



(d) top 10%



Notes: Household portfolios for four wealth groups. Light gray areas show non-financial assets, dark gray areas 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 25th to 75th percentile (middle class). The lower left graph shows the 75th to 90th percentile, 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.

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

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 detailed discussion of the joint distribution of income and wealth based on the modern SCF surveys can be found in Kuhn and Rıos-Rull (2016).

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 5 shows the differences in leverage along the wealth distribution. More precisely, we show loan-to-value ratios of home owners for different wealth groups.[22]

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

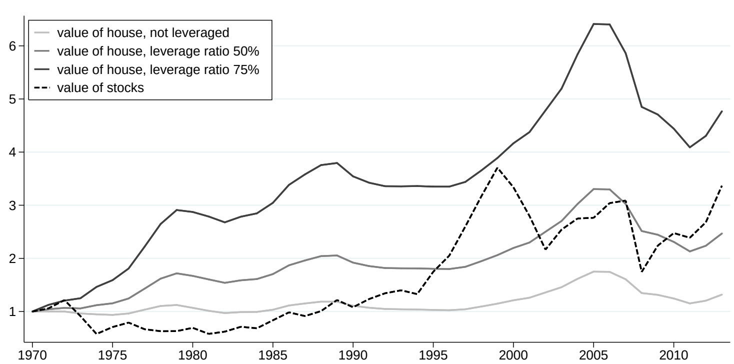
The table shows overall wealth is negatively correlated with leverage. In 2007, 72.1 percent of home owners in the bottom 25% of the wealth distribution had a loan-to-value ratio greater than 75%. The table also demonstrates that leverage has increased over time across all wealth groups. The long-run evolution and distribution of household debt has rarely been studied. We refer for a detailed analysis of the evolution of U.S. household debt to Kuhn, Schularick, and Steins (2017) where we explore household debt trends over the past seven decades using the HSCF data.

[22] We show average loan-to-value for wealth groups. Tables P, Q, R and S in the online appendix show the full time series.

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 13, we track the value of four hypothetical portfolios that contain the 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).[23] Given the data in Table 5, we can think of the housing portfolio with high leverage as the portfolio representative of homeowners in the bottom 25%, the portfolio with low leverage as that of homeowners in the top 10%, and the portfolio in between as the portfolio of homeowners in the middle class.

Looking at the light gray line in Figure 13, 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.

Figure 13: 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 over time. The housing portfolios differ in their degree of leverage. All portfolios are constructed to start with equity of 1 Dollar in 1970. See text for further details.

Clearly, higher leverage also implies higher losses in the case of declining house prices. Figure D.5 in the appendix makes this point. It is also important to note that we do not compare

[23] We use throughout the updated house and stock price series from Shiller (2015).

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 of equity in the different portfolios.[24]

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 14 shows exposure to house prices for middle class households and households in the top 10%.[25] 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, 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.

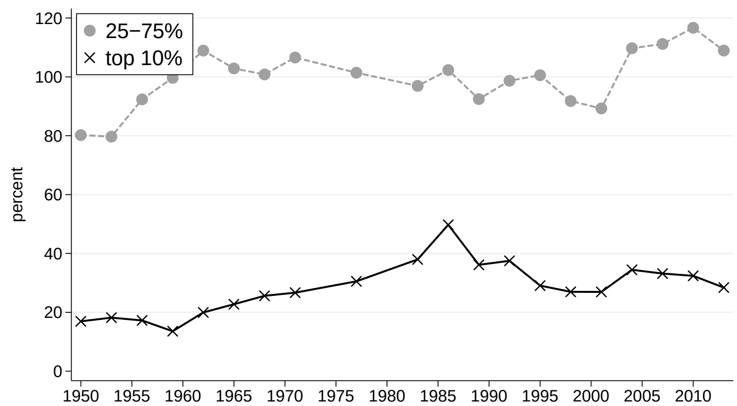
To complete the picture, the house price elasticity of wealth can be further broken down into a *diversification component* that is determined by the share of housing in assets and a

[24]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

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

[25]Online appendix IV provides further results on house price exposure along the wealth distribution and its changes over time.

Figure 14: House price exposure $\left(\frac{\text{Housing}}{\text{Net wealth}} \times 100\right)$ by wealth group



Notes: House price exposure for households between the 25th and 75th percentile (middle class) 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. Horizontal axis shows calender time and vertical axis house price exposure in percentage points.

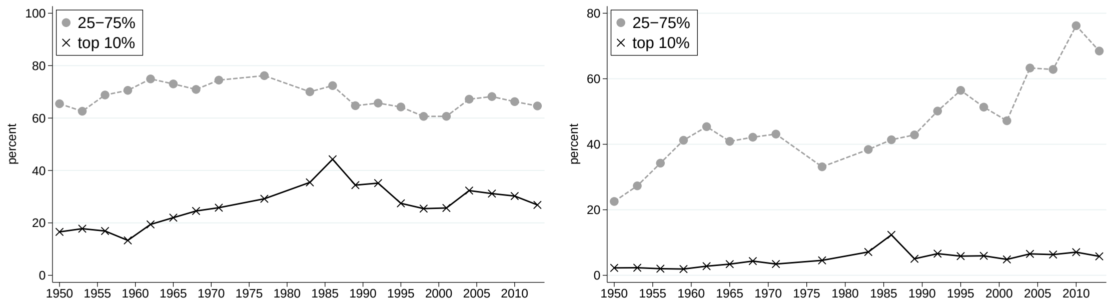
leverage component measured by the debt-to-wealth ratio

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

The leverage component also comprises other types of debt but these parts are small relative to housing debt (see Figure 12). Figure 15 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 leveraged. Middle-class leverage increases from 20% in 1950 to a stunning 80% in 2010. Moreover, the 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% of its total assets in housing and leverage amplified house price changes by approximately 40%.

Figure 15: Components of house price exposure by wealth group

(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 households between the 25th and 75th percentile (middle class) and households in the top 10% of the wealth distribution. The left panel shows the *diversification* component and the right panel shows the *leverage* component. See text for further details. Horizontal axes show calender time and vertical axes components in percentage points.

6.4 House prices and wealth inequality

Up to this point, our analysis has demonstrated that a household's 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

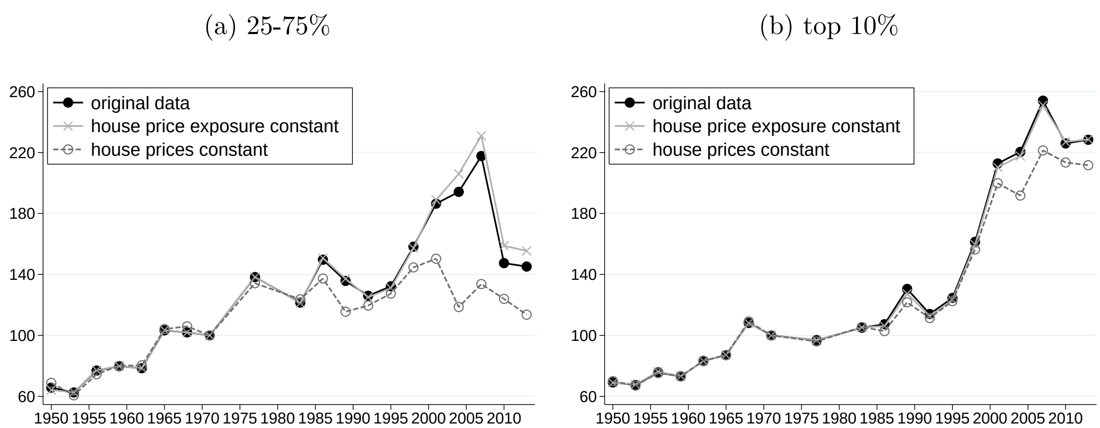
$$\underbrace{\frac{\Delta W_{t+1}}{W_t}}_{\text{wealth growth}} = \underbrace{\frac{H_t}{W_t}\frac{\Delta p_{t+1}}{p_t}}_{\text{house price component}} + \underbrace{g_t^R}_{\text{residual component}}$$

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 16 shows the counterfactual change in wealth under the assumption of constant house price exposure 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 four decades after 1971.

Figure 16: Price and exposure effect of wealth by wealth groups

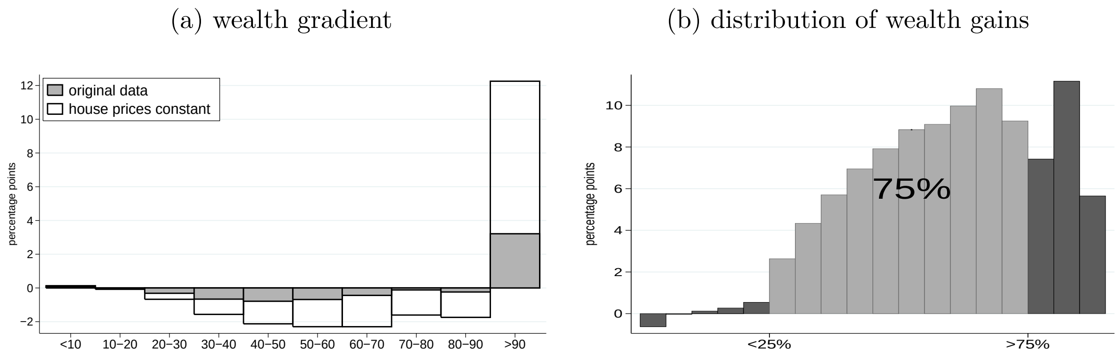


Notes: Realized and counterfactual wealth for households between the 25th and 75th percentile (middle class) and the top 10% of the wealth distribution. Black dots show original data. Gray dashed line with circles shows wealth under the assumption of constant house prices and house price exposure at the 1971 level. Gray solid line with crosses shows wealth under the assumption of constant house price exposure at the 1971 level. All data has been indexed to 1971 (= 100). Horizontal axes show calender time.

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 17a compares inequality gradients for wealth taken from Figure 8b (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. With

Figure 17: Inequality gradients for wealth and distribution of wealth gains (1971 - 2007)



Notes: Left panel shows inequality gradients for wealth and wealth with constant house prices for the period from 1971 to 2007. The horizontal axis shows wealth deciles. Right panel shows the distribution of wealth gains from house price growth across the wealth distribution. See text for further details.

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 17a 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. In other words, rising house prices slowed down wealth concentration at the top by almost two thirds (1.9 pp vs 6.3 pp) and gave a sizable boost to middle class wealth. House price induced wealth gains could have finance 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 in the top 10% wealth share of 5.5 pp was still about one third lower than the counterfactual

Table 6: Changes in wealth shares relative to 1971

		1971	1989	2007	2013
bottom 25 %	original data		0.0	0.0	-0.5
	no house price effect	0	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		0.2	-1.7	-4.5
	no house price effect	0	-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		1.8	-0.2	-0.5
	no house price effect	0	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		-2.0	1.9	5.5
	no house price effect	0	-0.6	6.3	8.3
	constant exposure		-2.6	0.6	4.5
	Δ house price		-1.4	-4.4	-2.8

Notes: Changes in wealth shares relative to 1971 for different wealth groups. The first row for each welath group shows the change in the original data. The second row ("no house price effect") shows the change in wealth share with constant house prices and the third row ("constant exposure") shows the change in wealth with changing house prices but constant exposure. The last row ("Δ house price") shows the difference between the original data and the case with no house price effect. See text for further details.

increase of 8.3 pp in the absence of the 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 trends in the housing market had quantitatively strong distributional effects on wealth inequality in postwar America.

In appendix E, we show that because of the high concentration of business wealth at the top, stock price changes play a similar role for wealth shares of the top 10%. Assuming that stocks and business wealth evolve in line with the S&P500 equity market index, we show that the wealth of the top 10% is equally sensitive to equity prices as middle class wealth is sensitive to trends in house prices. Our results demonstrate that the race between returns in stock and housing markets was a powerful driver of wealth inequality dynamics in postwar America.

7 Conclusions

This paper introduced the *Historical Survey of Consumer Finances* (HSCF), a new household-level dataset covering the financial situation of U.S. households since 1949. The long-run survey data provide detailed information on income, assets, and debts of American households over the past seven decades. Importantly, the HSCF allows researchers to analyze time trends of the income and wealth distribution jointly. We are hopeful that the new dataset will prove valuable for future research on inequality, household finance, political economy, and beyond.

In this paper, we used the data to shed a new light on the evolution of income and wealth inequality since World War II. Previous research documented a trend towards increasing polarization of income and wealth. The new data confirm this finding. We complete the picture by documenting how income and wealth changed outside the top 10%. Importantly, we show that the American middle class – households between the 25th and 75th percentiles – was the main loser of increasing income and wealth concentration at the top.

The new data also reveal that differences in portfolio compositions along the wealth distribution have played an important and sometimes dominant role for the evolution of wealth inequality in the U.S. Systematic differences in the portfolio composition of households lead to heterogeneous wealth gains from asset price changes. Owing to concentrated and leveraged portfolios, middle-class wealth in America is highly sensitive to fluctuations in real estate prices while the wealth of the top 10% is primarily driven by changes in equity prices. In the two decades before the crisis, the American middle class profited from substantial gains in housing wealth. These high wealth gains on housing counterbalanced increasing business wealth at the top and mitigated the overall increase in wealth inequality. The house price bust in the financial crisis triggered the largest jump in wealth inequality in postwar history. The long-run survey data show that portfolio heterogeneity and differential wealth gains were of first-order importance for the evolution of wealth inequality in postwar America. This core finding opens up new avenues for future research.

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A Data details

Table A.1 reports the sample sizes for the different survey years in the final HSCF 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.1 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, we apply our adjustment 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 results for income and wealth shares of the original sample including the list sample with those values obtained using our weight adjustment on the sample excluding the list sample. The results show that the adjustment works well. For income, it slightly overestimates shares between the top 10% and 5% and slightly underestimates the top 5% to 1% share. The fit deteriorates towards the right tail above the top 1%. Deviations are, however, always less than 2 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%.

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

A.2 Imputation of missing variables

This section provides further details on the imputation of missing variables by predictive mean matching as described in Schenker and Taylor (1996). Following the modern SCF, we use multiple imputation and produce five imputed values for each missing variable. The imputation involves several steps. First, a linear regression model of the variable of interest is estimated on a sample with non-missing observations. For each of the multiple imputations, a random realization of the regression coefficients is drawn using the estimated variance-covariance matrix. Using this coefficient vector and the linear regression model, a prediction for the variable of interest is generated. The predicted values on missing and non-missing observations are compared to find non-missing observations that produce the closest prediction. For each missing observation, we choose the three observations among the non-missing 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. Hence, the linear regression model is only used to define the distance between missing and non-missing observations. The imputed values for the variables are all observed values. We refer to Schenker and Taylor (1996) for an in-depth discussion of the topic.

For each missing variable, there are several adjacent surveys that in principle could be used as non-missing sample for the imputation. 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 on those variables selected by the lasso method.[26] Finally, we calculate the R^2 for each regression. We use the R^2 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.

B Additional results on trends in income and wealth inequality

This section provides complementary evidence to the inequality trends documented in the main part of the paper. We first document inequality trends using quantile ratios. Second, we report the entire time series of Gini coefficients and explore afterwards how demographic change and changes in household size have impacted inequality trends.

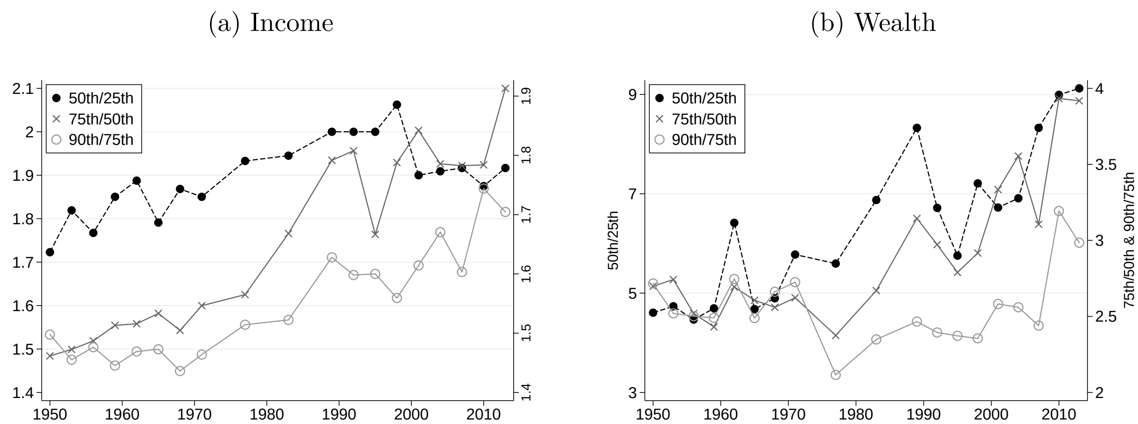
B.1 Quantile ratios

Quantile ratios provide a different angle to look at changes in inequality. They allow us to track developments in different parts of the distribution and offer an intuitive perspective on shifts in relative fortunes over time.

Figure B.1 shows the 50-25, 75-50, and 90-75 ratios for income and wealth. Looking at income in figure B.1a, we clearly see the onset of rising income inequality starting in the 1970s. All quantile ratios rise until the mid-1990s when the 50-25 ratio and the 75-50 ratio level off. These patterns match table 4 in the main part. Income shares decline in the middle and bottom up until the 1990s and decrease below the top afterwards. Looking at wealth in figure B.1b, we find that trends in quantile ratios match again the pattern observed for wealth shares in section 4.3. We see little changes in inequality up until the beginning of the 1990s. The 50-25 ratio fluctuates but mostly because wealth at the 25th percentile is very volatile. Persistent changes start in the 1990s and a large jump in inequality happens after 2007 with the financial crisis and the drop in house prices. We report in table B.3 the entire time series of different quantile ratios for income and wealth.

[26] 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.

Figure B.1: Quantile ratios of income and 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).

Table B.3: Quantile ratios of income and wealth (x100)

year	income			wealth		
	50th/25th	75th/50th	90th/75th	50th/25th	75th/50th	90th/75th
1950	172.3	146.4	149.5	437.2	264.7	255.0
1953	182.2	147.4	145.4	473.5	271.0	248.9
1956	176.7	148.8	147.5	546.6	250.3	245.1
1959	185.9	151.5	145.2	621.9	249.2	238.3
1962	188.9	151.4	147.3	628.4	269.6	271.2
1965	179.6	153.7	147.3	484.9	262.2	251.4
1968	186.1	150.7	143.9	567.3	263.9	256.5
1971	185.3	156.2	145.6	555.6	255.1	263.0
1977	190.0	156.3	151.6	515.9	235.1	215.3
1983	194.4	166.7	152.3	680.1	266.9	234.5
1986	200.0	166.7	150.0	368.9	256.7	212.5
1989	200.0	179.2	162.8	809.2	312.0	246.4
1992	200.0	180.8	159.8	667.1	297.6	239.2
1995	200.0	166.7	160.0	571.4	279.1	237.4
1998	206.3	178.8	155.9	697.1	290.9	236.1
2001	194.2	180.3	162.9	659.2	332.1	257.2
2004	190.9	178.6	168.0	688.7	352.6	255.9
2007	191.7	178.3	160.9	826.7	310.0	244.8
2010	191.7	176.1	172.8	877.8	391.8	318.5
2013	184.8	190.4	170.5	900.9	390.9	298.3

B.2 Gini coefficients, demographic change, and changes in household size

Table B.4 shows the time series of Gini coefficients over time. The table shows Gini coefficients every three years or between 1971 and 1983 for all available surveys. We discuss the observed time trends in section 4.2 of the main part of the paper.

Table B.4: 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.

In this section, we explore in the first part effects of the large secular changes in terms of educational attainment, age structure, and household size of the U.S. population on income and wealth inequality over the postwar history. We use an approach proposed by Fortin, Lemieux, and Firpo (2011) to remove changes in the age structure and educational attainment over time. In the second part, we account for changes in household size. We adjust income and wealth at the household level to per-adult equivalents using OECD equivalent scales.

For both parts of the analysis, we exploit a key strength of the HSCF data, namely, that it provides detailed information about the demographic characteristics of households. We use characteristics of the household head as the characteristics of the household and we use 1971 as our basis year. We implement the approach by Fortin, Lemieux, and Firpo (2011) 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. As explanatory variables, we include age, educational attainment, the number of adults and children in a household, and race of the household head. We use the estimated probability to re-weight observations in other survey years by multiplying the survey weights with the estimated probability. This allows us to compute counterfactual inequality measures fixing demographic characteristics to the basis year.[27] We consider two counterfactuals relative to the observed data. In the two counterfactuals, we fix educational attainment and the age structure over time. Figure B.2 shows Gini coefficients and wealth and income shares for the original data and the two counterfactual cases. The black line with circles shows the original data, the gray line with crosses shows the counterfactual when we fix the population shares across age groups and the light gray line with dots shows the counterfactual when we fix educational attainment to 1971. We find the effects on income to be small for the case when we fix the age structure but sizable for the case when we fix educational attainment. This finding is in line with a rising college wage premium and more college-educated household heads. The experience premium and life-cycle income profiles changed too little to have a notable impact. The effects flip for wealth. For wealth, the effect of changing educational attainment is rather small but the effect of aging is more pronounced. This aligns with an increased need for retirement savings and retirement savings being a driver of cross-sectional wealth inequality. To summarize, demographic changes have some effects, they do however not change the overall pattern of income and wealth inequality in the United States since World War II.

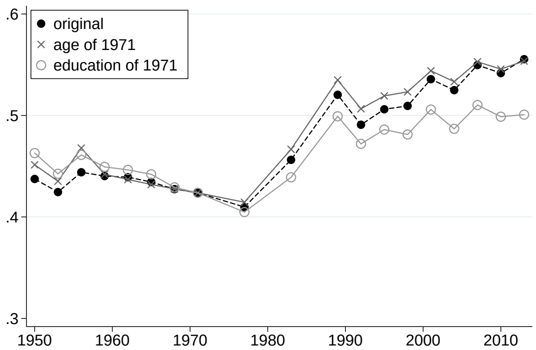
A second secular trend in the United States has been the decrease of average household size.

[27] 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:

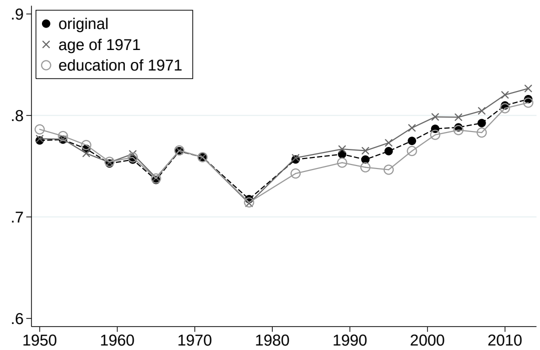
$$\hat{\Psi}(X) = \frac{\hat{P}(D_Y = 1|X)/\hat{P}(D_Y = 1)}{\hat{P}(D_Y = 0|X)/\hat{P}(D_Y = 0)}$$

Figure B.2: Gini coefficients and income and wealth shares after accounting for demographic change

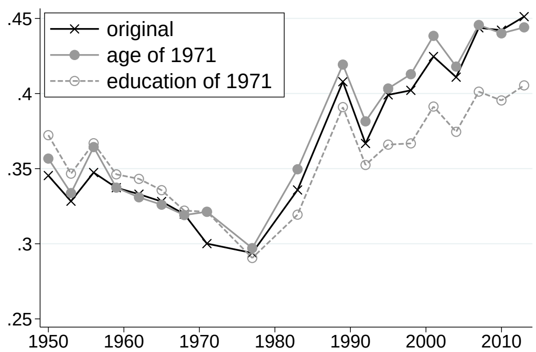
(a) Income gini



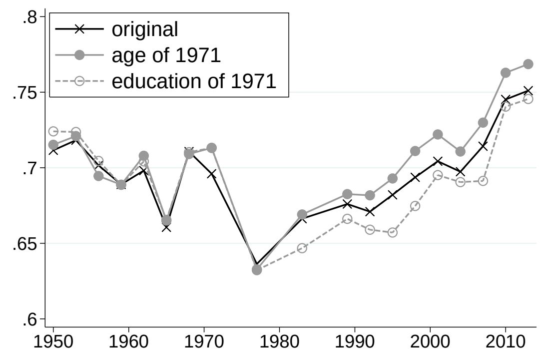
(b) Wealth gini



(c) Income top 10% share



(d) Wealth top 10% share



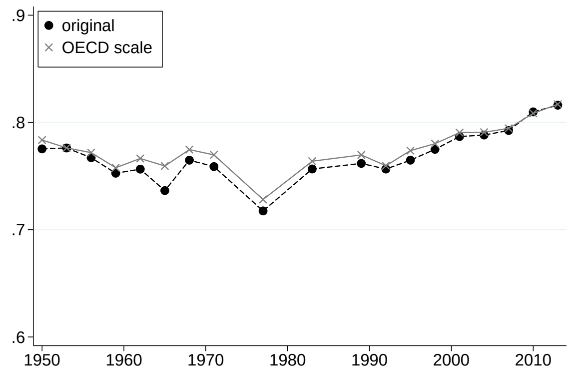
Notes: The upper two graphs show gini coefficients for income and wealth, the lower two graphs the income and wealth shares of the top 10%. The black dashed lines are the results using the original data. For the dark gray solid lines with crosses the age distribution is held constant at the 1971 distribution. For the light gray solid lines with dots the distribution of education is held constant at the 1971 distribution. Age and education refer to head of household.

The average number of persons per household declined 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. Given that HSCF data is at the household level, changes in household size can potentially affect measures of household-level inequality. We adjust household-level income and wealth to per-adult-equivalent member of the household. We use the OECD equivalent scale for adjusting. Figure B.3 reports Gini coefficients and income and wealth shares with and without adjustment for household size. We find that the Gini coefficient for adult-equivalent income is slightly higher up to 1980 and shows a slightly declining trend between 1950 to 1980. Starting in 1992, inequality for adult-equivalent income is lower but shows the same trend as total 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. Income concentration at the top becomes lower once we look at adult-equivalent income. Such a trend is consistent with stronger assortative mating and increasing female labor force participation. For wealth, there is hardly any notable effect. Although there have been large changes in the size of U.S. households, adjusting for these changes does not notably 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.

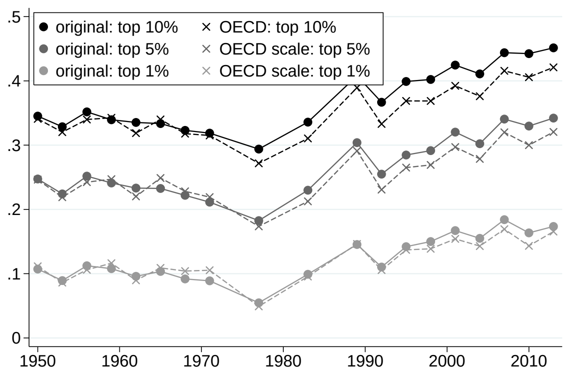
Figure B.3: Gini coefficients and income and wealth shares for adult-equivalent income and wealth

(a) Income gini

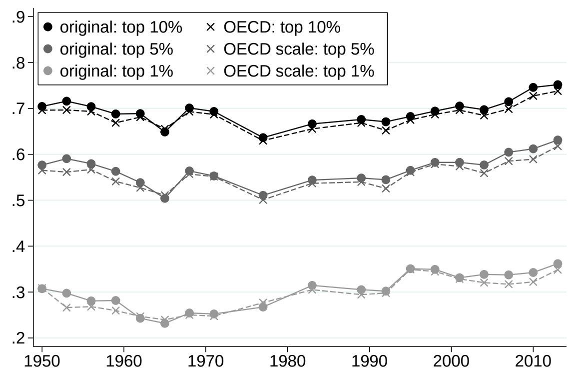
(b) Wealth gini



(c) Income shares



(d) Wealth shares



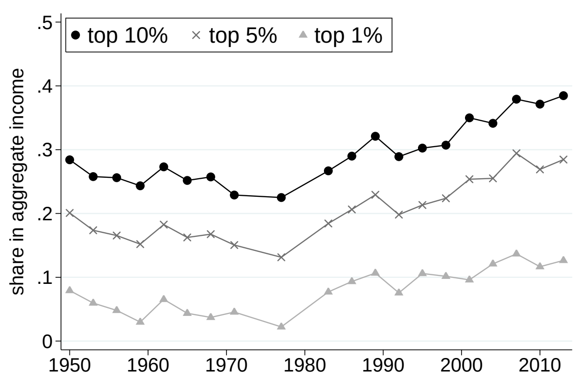
Notes: The upper two graphs show Gini coefficients for income and wealth. The black dashed lines are the results using the original data. For the gray solid lines with crosses the data was adjusted with the OECD equivalent scale. The lower two graphs show the income and wealth shares of the top 10%, 5%, and 1% of the income and wealth distribution. The solid lines with dots are the shares using the original data. The dashed lines with crosses show shares after the data was adjusted using the OECD equivalent scale.

C Income and wealth concentration

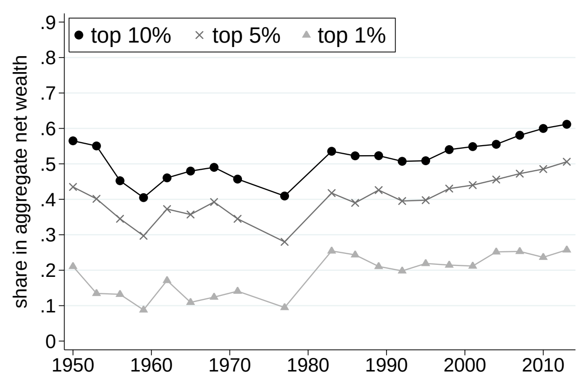
In the main part of the paper, we report income and wealth concentration separately along the income and wealth distribution. There are important cases where households who are at the top of the wealth distribution are not at the top of the income distribution and vice versa, for example, retired households who typically hold a lot of wealth but have little income. The HSCF 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 C.4 shows in the left panel the shares in total income of the top 10%, 5%, and 1% wealth-richest-households over time. The right panel shows the shares in total wealth of the top 10%, 5%, and 1% income-richest households. Compared to figure 5 the shares decline, yet the patterns with respect to the level of income and wealth concentration remain unaffected. Wealth is much more concentrated than income. Comparing the trends to those discussed before, the evolution of income and wealth concentration appears very similar when we consider income concentration among the wealth-rich or wealth concentration among the income-rich.

Figure C.4: Shares in aggregate wealth and income

(a) Income Shares by Wealth Groups



(b) Wealth Shares by Income Groups

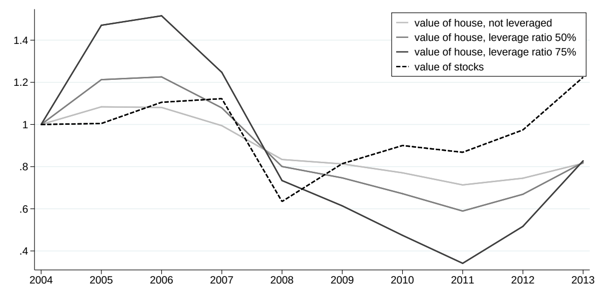


Notes: The left graph shows income shares for the top 10%, 5%, and 1% of the wealth distribution. The right graph shows wealth shares of the top 10%, 5%, and 1% of the income distribution.

D Leverage effect during the financial crisis

Figure D.5 complements the analysis of the effect of leverage from section 6.2. It shows the leverage effect in case of an investment done in 2004. In Figure 13 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 D.5: 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 have an equity value of 1 Dollar in 2004. See text for further details.

E Stock prices and wealth inequality

The main part of the paper explores the effect of house price changes on the evolution of wealth inequality over the past four decades. We document that household portfolios differ along the wealth distribution. The middle class is highly exposed to house price changes because houses are the most important asset on the household balance sheet and highly leveraged. By contrast, the top 10% of the wealth distribution are mostly invested in stocks and business wealth. In the following, we perform a counterfactual experiment coresponding to the one for house prices in section 6.4. We aim to measure the effect of stock price changes on wealth. We assume that privately held business wealth and holdings of publicly traded equity are equally affected by stock price changes. Figure E.6 shows the evolution of wealth for the middle class and the top 10% relative to 1971 (indexed to 100). Constant stock prices would not have affected middle class welath by much. However, the effect on wealth of the top 10% is pronounced. If stock prices had stayed constant at their 1971 level, wealth of the top 10% today would be 40% lower than what we observe in the data.

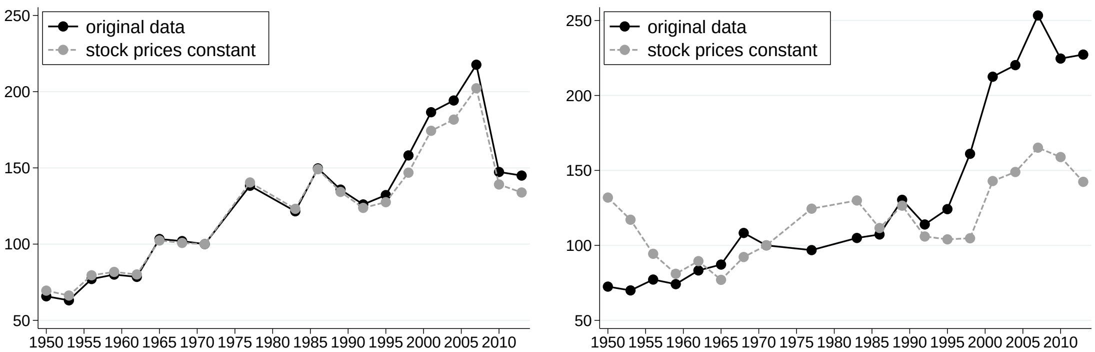
Figure E.7 combines the two counterfactual experiments and keeps stock and house prices constant at their 1971 level. This experiment shows the strong exposure of the middle class to house prices and that of the top 10% to stock prices. House prices do not matter much for the wealthy; stock prices do not matter much for the middle class.

Figure E.8 shows the resulting shifts in wealth shares as in figure 17a in the main part of the paper. Grey bars show the observed inequality gradients for wealth for the period from 1971 to 2007. White bars show the inequality gradients under the counterfactual scenario for asset prices. Figure E.8a shows the case of constant stock prices. The wealth share of the top 10% would have declined strongly. While houses increased strongly in value, stocks and business wealth that are important assets at the top of the wealth distribution did not

Figure E.6: Stock price effect by wealth groups

(a) 25-75%

(b) top 10%



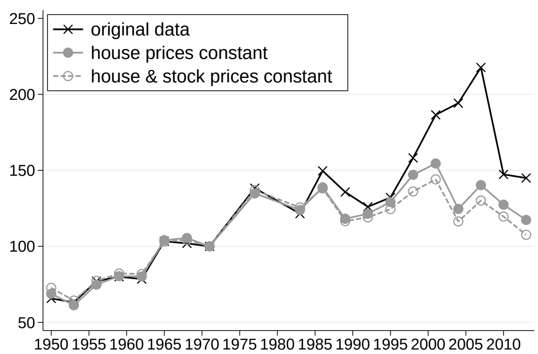
Notes: Realized and counterfactual wealth for households between the 25th and 75th percentile (middle class) and the top 10% of the wealth distribution. Black solid lines show original data. Gray dashed lines show wealth under the assumption of constant stock prices at the 1971 level. All data has been indexed to 1971 (= 100).

increase in value. The winners of this scenario are all households above the median and below the 90th percentile. Shutting down house price growth in addition restores the finding that the middle class has been the winner of rising house prices (Figure E.8b). Yet absent increasing stock and business values, the wealth would have increased the most in the upper middle class between the 75th and 90th percentile.

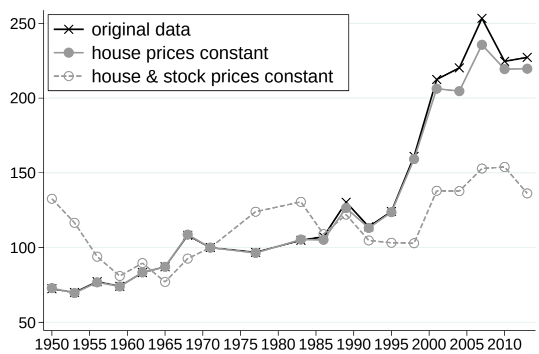
These results reinforce our conclusion from the main part of the paper that the large price changes since the 1970s and a strong portfolio channel leading to large differences in price exposure also led to large shifts in the U.S. wealth distribution.

Figure E.7: House and stock price effect by wealth groups

(a) 25-75%



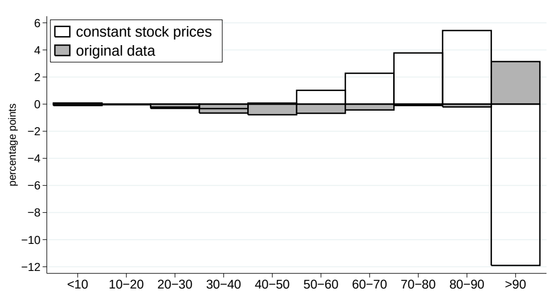
(b) top 10%



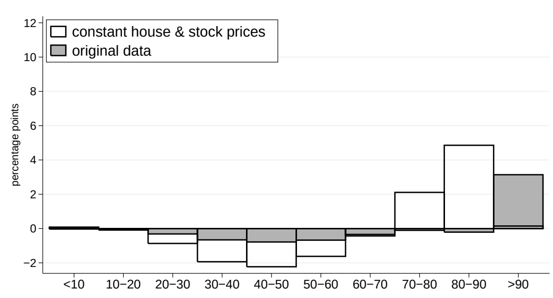
Notes: Realized and counterfactual wealth for households between the 25th and 75th percentile (middle class) and the top 10% of the wealth distribution. Black solid lines with crosses show original data. Dark gray lines lines show wealth under the assumption of constant house prices at the 1971 level. Bright gray dashed lines show wealth under the assumption of constant house and stock prices at the 1971 level. All data has been indexed to 1971 (= 100).

Figure E.8: Inequality gradients for wealth (1971 - 2007)

(a) constant stock prices



(b) constant house & stock prices



Notes: Left panel shows inequality gradients for wealth and wealth with constant stock prices for the period from 1971 to 2007. The right panel shows inequality gradients for wealth and wealth with constant house and stock prices for the period from 1971 to 2007. The horizontal axis shows wealth deciles.

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 on the adjacent survey years used to impute missing variables in some of the survey years. We describe the imputation procedure in detail in Section A.2 of the appendix. In most cases, our imputation method selects a single survey years to impute missing information. This restriction to a single year is not predetermined as part of the imputation routine but the outcome that yields the best fit. We describe the method to select survey years as part of the imputation approach in the appendix.

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: First column shows name of imputed variable, second column shows year for which imputation is done, and the third column shows the survey years from which information is used for the imputation. The number of years used for the imputation is not restricted to be one but chosen as part of the imputation routine. See description of imputation routine for further details.

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: First column shows name of imputed variable, second column shows year for which imputation is done, and the third column shows the survey years from which information is used for the imputation. The number of years used for the imputation is not restricted to be one but chosen as part of the imputation routine. See description of imputation routine for further details.

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: First column shows name of imputed variable, second column shows year for which imputation is done, and the third column shows the survey years from which information is used for the imputation. The imputation is not restricted to use only SFCC 1962 data. Information on pension wealth is available in both the SFCC 1962 and the SCF 1983. The SFCC 1962 data is chosen as part of the imputation routine. See description of imputation routine for further details.

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: First column shows name of imputed variable, second column shows year for which imputation is done, and the third column shows the survey years from which information is used for the imputation. The number of years used for the imputation is not restricted to be one but chosen as part of the imputation routine. See description of imputation routine for further details.

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

Notes: First column shows name of imputed variable, second column shows year for which imputation is done, and the third column shows the survey years from which information is used for the imputation. The number of years used for the imputation is not restricted to be one but chosen as part of the imputation routine. See description of imputation routine for further details.

II Time series on income and wealth shares

Tables F and G show income and wealth shares for five income and wealth groups over time. The groups are the bottom 25%, 25% to 50%, 50% to 75%, 75% to 90%, and the top 10%. By adding the second and third group, the income and wealth shares for the middle class (25% - 75%) can be derived. Income and wealth shares are reported for surveys in three year intervals except for the 1970s and 1980s when all results for all conducted surveys are shown.

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, J and K show the portfolio composition of households for the four wealth groups considered in the main part of the paper. These groups are the bottom 25 %, 25% to 75%, 75 to 90%, and the top 10%. Portfolio shares are reported for surveys in three year intervals except for the 1970s and 1980s where all results for all conducted surveys are shown. The first six columns show shares in assets, the next two columns show share in debt, and the last column shows the debt-to-asset ratio.

Table H: Shares of wealth components in wealth portfolios of bottom 25% (in%)

	assets						debt		
year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt	$\frac{\text{debt}}{\text{assets}}$
1950	7.9	36.6	0.2	4.9	16.5	33.9	37.2	62.9	96.0
1953	15.4	33.2	0.0	1.0	20.3	30.0	50.2	49.8	94.9
1956	24.1	43.2	0.3	0.8	13.0	18.5	36.2	51.2	97.2
1959	14.3	55.6	0.0	1.2	14.1	14.8	43.8	56.2	99.1
1962	22.1	58.1	0.1	0.3	11.6	7.9	44.2	55.8	93.7
1965	12.3	63.4	0.0	1.7	8.5	14.1	35.8	64.2	84.9
1968	18.1	56.1	0.0	4.6	9.8	11.3	60.6	39.4	116.1
1971	15.7	63.8	0.0	1.0	9.0	10.5	53.7	46.3	104.7
1977	10.7	56.6	0.0	0.8	24.4	7.5	45.7	54.3	108.1
1983	39.8	35.2	0.7	2.7	16.7	5.0	65.0	35.0	83.8
1989	39.2	43.4	0.6	0.2	9.1	7.6	61.7	38.3	108.3
1992	35.3	47.8	1.9	0.3	7.6	7.1	61.8	38.2	106.1
1995	34.5	48.7	0.8	0.6	6.8	8.6	55.4	44.6	100.1
1998	28.9	53.6	0.6	0.4	7.1	9.4	55.3	44.7	111.1
2001	35.2	47.6	1.4	0.8	7.1	7.9	56.8	43.2	98.3
2004	31.1	56.3	0.3	0.7	5.7	5.8	53.5	46.5	104.2
2007	27.6	58.1	0.3	0.6	6.1	7.3	49.2	50.8	104.4
2010	16.7	72.3	0.7	0.2	3.7	6.4	35.2	64.8	125.0
2013	21.2	66.3	1.8	0.3	4.2	6.2	44.8	55.2	133.6

Table I: Shares of wealth components in wealth portfolios of 25-75% (in%)

year	assets: other non-fin. assets	assets: real estate	assets: business wealth	assets: equity	assets: liquid assets + bonds	assets: other fin. assets	debt: non-housing debt	debt: housing debt	**debt / assets**
1950	4.6	65.5	0.9	1.1	16.0	11.9	14.0	86.2	18.4
1953	5.3	62.7	1.3	2.9	15.9	12.0	17.1	82.9	21.3
1956	7.3	68.8	0.2	2.2	13.4	8.1	14.5	82.8	25.5
1959	6.7	70.6	0.2	4.0	12.1	6.5	15.3	84.7	29.1
1962	4.7	74.9	1.4	2.3	11.9	4.7	12.6	87.4	31.2
1965	4.2	73.0	0.9	4.8	10.6	6.6	12.9	87.1	29.0
1968	5.5	70.9	0.2	4.1	12.9	6.4	16.5	83.6	29.7
1971	3.7	74.5	0.5	2.9	11.2	7.1	16.1	84.2	30.1
1977	2.5	76.2	0.1	2.1	15.3	3.9	15.4	84.6	24.9
1983	9.1	70.0	2.7	1.2	9.4	7.6	19.2	80.8	27.7
1989	10.7	64.7	3.0	1.1	9.3	11.0	22.4	77.6	30.0
1992	9.9	65.7	3.0	1.0	8.4	12.0	17.0	83.0	33.4
1995	11.4	64.2	2.6	0.9	6.5	14.3	17.2	82.8	36.1
1998	10.1	60.6	2.8	1.6	7.5	17.4	19.2	80.8	33.9
2001	9.9	60.7	2.7	1.5	7.1	18.1	17.5	82.5	32.0
2004	8.8	67.2	2.8	1.0	5.8	14.3	15.6	84.4	38.8
2007	8.0	68.2	2.4	1.0	5.3	15.0	15.3	84.7	38.6
2010	10.0	66.3	2.7	0.8	5.5	14.7	15.7	84.3	43.3
2013	10.1	64.7	1.9	0.9	6.3	16.0	16.4	83.6	40.7

Table J: Shares of wealth components in wealth portfolios of 75-90% (in%)

	assets						debt		
year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt	$\frac{\text{debt}}{\text{assets}}$
1950	2.3	57.6	9.1	6.1	17.5	7.5	15.0	91.1	5.9
1953	2.6	58.0	7.4	6.8	16.8	8.4	15.1	85.6	7.9
1956	3.5	60.6	3.0	9.4	17.3	6.2	12.6	84.8	7.8
1959	4.0	60.0	1.7	12.5	16.8	5.1	14.4	86.1	9.3
1962	2.3	63.1	7.5	10.5	13.3	3.2	9.9	90.1	10.4
1965	2.4	56.2	5.3	16.1	15.2	4.9	11.4	88.6	10.0
1968	2.8	58.0	1.9	16.4	16.0	4.8	13.2	86.8	9.8
1971	1.9	60.1	3.0	10.3	17.9	6.9	10.7	90.5	10.8
1977	1.3	69.1	0.9	6.5	17.9	4.3	11.7	88.6	12.6
1983	5.3	58.8	7.5	3.0	15.5	10.0	16.0	84.0	15.2
1989	5.3	57.5	6.6	3.3	11.4	15.9	16.9	83.1	14.5
1992	5.6	56.5	6.2	2.5	11.1	18.1	10.8	89.2	16.0
1995	6.5	52.3	5.3	2.2	9.4	24.3	14.3	85.7	14.5
1998	5.3	49.4	5.5	3.9	9.3	26.6	13.0	87.0	16.0
2001	4.4	46.9	7.1	4.5	7.7	29.3	11.7	88.3	14.2
2004	4.9	52.7	6.3	2.8	7.5	25.7	10.8	89.2	15.9
2007	4.1	55.5	5.2	2.4	7.1	25.6	10.3	89.7	16.9
2010	4.5	52.4	6.4	2.0	7.9	26.8	11.0	89.0	17.4
2013	4.6	49.9	4.8	3.1	6.9	30.8	11.4	88.6	17.7

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

	assets						debt		
year	other non-fin. assets	real estate	business wealth	equity	liquid assets + bonds	other fin. assets	non-housing debt	housing debt	$\frac{\text{debt}}{\text{assets}}$
1950	0.6	15.7	50.8	20.7	7.8	4.3	22.7	81.2	2.1
1953	0.8	17.0	50.2	21.5	6.9	3.7	27.6	73.2	2.2
1956	0.9	16.5	46.3	25.7	7.3	3.4	12.5	77.4	1.9
1959	0.9	13.1	47.7	28.2	7.6	2.6	14.7	86.5	1.9
1962	0.7	19.4	39.6	30.1	8.2	1.9	6.6	93.4	2.7
1965	0.8	22.0	38.4	30.6	5.5	2.8	9.0	91.0	3.3
1968	0.7	24.5	33.2	32.3	6.8	2.5	9.1	90.9	4.2
1971	0.5	25.8	35.2	27.3	8.5	2.8	6.7	94.1	3.3
1977	0.4	29.2	43.1	14.6	9.7	3.1	6.9	97.4	4.4
1983	2.5	35.5	28.4	11.6	11.3	10.8	20.1	79.9	6.6
1989	3.2	34.4	26.7	6.2	11.4	18.1	22.5	77.5	4.8
1992	2.5	35.2	26.2	7.4	10.0	18.7	12.1	87.9	6.2
1995	3.2	27.5	25.4	8.3	9.7	25.9	14.1	85.9	5.5
1998	2.4	25.5	23.8	12.6	6.6	29.1	18.9	81.1	5.6
2001	2.2	25.7	22.0	11.9	6.6	31.6	15.4	84.6	4.6
2004	2.2	32.3	23.0	8.6	7.5	26.3	12.0	88.0	6.1
2007	1.8	31.2	27.5	8.3	5.8	25.4	8.8	91.2	6.0
2010	2.0	30.1	23.3	6.9	8.5	29.3	9.1	90.9	6.6
2013	1.9	26.9	23.7	8.2	7.0	32.2	8.3	91.7	5.5

IV Additional results of house price exposure

Tables L, M, N, and O show the house price exposure and its decomposition for the four wealth groups that we discuss in the main part of the paper: the bottom 25%, 25% - 75%, 75% - 90%, and the top 10% of the wealth distribution. Tables P, Q, R and S show the distribution of leverage for these four wealth groups. House price exposure and leverage are reported for surveys in three year intervals except for the 1970s and 1980s where all results for all conducted surveys are shown.

Table L: House price exposure of bottom 25% of wealth distribution

year	Housing / Net wealth	Housing / Assets	Debt / Net wealth
1950	46.5	33.3	134.2
1953	57.2	30.9	175.9
1956	51.7	41.7	120.5
1959	55.2	54.8	99.8
1962	52.6	56.2	87.6
1965	53.4	61.6	73.6
1968	54.5	51.9	121.9
1971	56.3	60.2	97.9
1977	49.1	52.9	100.4
1983	54.5	34.1	134.0
1989	51.9	40.5	138.9
1992	55.9	44.4	133.5
1995	53.2	48.0	110.8
1998	52.1	50.0	115.9
2001	52.4	45.9	112.4
2004	53.6	56.0	99.8
2007	52.1	57.2	95.1
2010	47.2	67.6	87.3
2013	47.2	61.7	102.1

Notes: As net wealth of the bottom 25% is negative in several years, it is replaced by net housing wealth.

Table M: House price exposure of 25-75% of wealth distribution

year	$\frac{\text{Housing}}{\text{Net wealth}}$	$\frac{\text{Housing}}{\text{Assets}}$	$\frac{\text{Debt}}{\text{Net wealth}}$
1950	77.8	63.5	22.5
1953	76.3	60.1	27.1
1956	89.2	66.4	34.2
1959	99.0	70.2	41.1
1962	100.0	68.8	45.4
1965	93.7	66.5	40.9
1968	89.5	62.9	42.1
1971	95.4	66.6	43.1
1977	93.4	70.2	33.1
1983	87.8	63.4	38.4
1989	86.5	60.6	42.9
1992	90.9	60.5	50.1
1995	94.1	60.1	56.5
1998	85.3	56.4	51.4
2001	82.7	56.2	47.2
2004	103.1	63.2	63.3
2007	102.5	62.9	62.9
2010	109.0	61.8	76.3
2013	101.2	60.1	68.6

Table N: House price exposure of 75-90% of wealth distribution

year	$\frac{\text{Housing}}{\text{Net wealth}}$	$\frac{\text{Housing}}{\text{Assets}}$	$\frac{\text{Debt}}{\text{Net wealth}}$
1950	50.8	47.8	6.3
1953	56.0	51.6	8.6
1956	57.9	53.3	8.5
1959	65.1	59.1	10.2
1962	53.6	48.0	11.6
1965	50.4	45.4	11.1
1968	48.8	44.0	10.9
1971	52.2	46.6	12.1
1977	62.0	54.2	14.4
1983	55.4	47.0	17.9
1989	56.3	48.2	16.9
1992	56.9	47.8	19.1
1995	52.0	44.4	17.0
1998	47.5	39.9	19.0
2001	45.9	39.4	16.5
2004	52.1	43.8	19.0
2007	55.3	46.0	20.4
2010	51.4	42.5	21.1
2013	49.6	40.8	21.5

Table O: 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	10.8	10.5	2.1
1953	10.8	10.6	2.2
1956	13.0	12.7	2.0
1959	13.0	12.8	1.9
1962	13.7	13.4	2.8
1965	14.2	13.7	3.4
1968	11.7	11.2	4.3
1971	11.9	11.5	3.4
1977	19.8	18.9	4.6
1983	18.9	17.7	7.1
1989	18.2	17.3	5.0
1992	19.1	17.9	6.6
1995	16.0	15.1	5.9
1998	15.6	14.7	6.0
2001	15.6	14.8	4.9
2004	20.1	18.9	6.5
2007	19.7	18.5	6.3
2010	18.7	17.5	7.1
2013	16.9	16.0	5.8

Table P: Leverage on housing for bottom 25% of wealth distribution

	0%	<50%	50-75%	>75%
1950	52.9	6.1	9.5	31.6
1953	38.1	8.7	4.9	48.2
1956	35.5	7.5	12.7	44.3
1959	26.6	5.9	13.9	53.6
1962	27.5	4.8	3.5	64.2
1965	26.1	2.4	8.3	63.2
1968	23.3	4.6	9.1	63.0
1971	34.3	4.6	5.4	55.7
1977	41.6	2.6	6.5	49.3
1983	25.8	6.3	21.7	46.2
1989	40.1	1.1	3.2	55.6
1992	26.9	10.4	10.0	52.6
1995	31.2	4.2	10.4	54.3
1998	20.9	5.4	5.6	68.2
2001	22.1	1.6	6.3	70.1
2004	18.5	5.5	12.4	63.6
2007	20.3	2.8	5.5	71.4
2010	7.9	1.6	3.0	87.6
2013	8.8	2.0	5.0	84.2

Table Q: Leverage on housing for 25-75% of wealth distribution

	0%	<50%	50-75%	>75%
1950	56.9	27.9	10.9	4.2
1953	48.9	31.9	14.3	4.9
1956	45.8	30.0	18.0	6.1
1959	42.6	29.6	20.0	7.7
1962	39.3	29.5	18.9	12.3
1965	41.2	27.9	20.9	9.9
1968	42.1	24.6	22.4	10.9
1971	43.2	26.7	20.1	9.9
1977	57.1	20.8	14.5	7.6
1983	40.0	35.5	16.7	7.7
1989	36.4	32.5	19.8	11.2
1992	37.0	24.8	22.0	16.1
1995	32.4	25.2	20.9	21.4
1998	34.1	23.0	20.5	22.4
2001	32.3	23.6	24.8	19.3
2004	27.5	22.9	26.7	22.9
2007	26.7	27.3	25.9	20.2
2010	27.0	20.0	22.0	30.9
2013	33.2	18.3	20.0	28.6

Table R: Leverage on housing for 75-90% of wealth distribution

	0%	<50%	50-75%	>75%
1950	72.8	24.0	2.5	0.7
1953	67.0	28.5	3.5	1.1
1956	66.2	28.5	4.2	1.1
1959	63.5	30.6	4.7	1.2
1962	56.8	28.3	11.8	3.1
1965	54.0	32.0	8.9	5.1
1968	58.2	29.0	10.2	2.6
1971	56.9	30.9	8.8	3.4
1977	60.9	31.8	5.7	1.5
1983	43.8	46.5	7.7	2.0
1989	36.2	46.1	13.8	3.9
1992	44.7	35.5	15.2	4.6
1995	46.7	32.8	15.1	5.4
1998	39.0	33.5	21.4	6.1
2001	35.9	40.6	15.7	7.9
2004	36.3	40.2	18.6	4.9
2007	33.5	45.4	16.8	4.4
2010	40.3	34.5	16.5	8.6
2013	40.9	29.1	18.3	11.7

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

	0%	<50%	50-75%	>75%
1950	72.8	19.7	4.3	3.2
1953	68.0	27.0	3.6	1.3
1956	65.4	26.3	5.8	2.5
1959	59.9	27.9	9.0	3.2
1962	51.2	37.6	10.5	0.7
1965	49.0	32.0	13.2	5.8
1968	57.7	27.9	11.7	2.7
1971	56.6	29.8	10.8	2.8
1977	64.1	30.8	3.3	1.7
1983	49.3	40.9	8.6	1.3
1989	48.6	40.3	8.5	2.5
1992	41.1	42.8	11.0	5.2
1995	41.2	38.1	15.1	5.6
1998	38.1	37.6	18.6	5.7
2001	43.0	41.1	13.7	2.3
2004	40.7	41.2	14.8	3.4
2007	36.4	48.5	10.1	5.0
2010	39.8	38.7	16.6	4.8
2013	40.5	37.5	16.3	5.7