Income and Wealth Inequality in America, 1949-2013*

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Abstract

Relying on newly coded data from historical waves of the Survey of Consumer Finances (SCF) going back to 1949, this paper studies the distribution of U.S. household income and wealth over seven decades of U.S. postwar history. The new micro-level data allow us to address central questions about the evolution of income and wealth inequality that have been beyond reach with existing data and methods. We provide new evidence for the evolution of income and wealth inequality among the bottom 90 % of households. We document how increasing income and wealth concentration at the top was accompanied by a hollowing out of the middle class. The historical household surveys also make it possible to study trends in income and wealth concentration jointly. We show that income inequality rose earlier and more strongly than wealth inequality. Differences in household portfolios and leverage play the central role for the observed divergence of income and wealth inequality.

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1 Introduction

We live in unequal times. In 2013, the richest 10 percent of households in the United States received almost 50 percent of all income and possessed 75 percent of wealth. The secular rise of income and wealth inequality since the second half of the 20th century is a defining debate of our times. It is also the main focus of this paper. Our factual knowledge of the process and its driving forces is still impeded by a lack of detailed micro data spanning the entire population over several decades. This paper aims to close this gap. We unearthed historical household-level data from early waves of the Survey of Consumer Finances (SCF) going back to 1949. We combine these data with the modern SCF and assemble a new consistent micro dataset covering the financial situation of U.S. households since World War 2. This new data source that we call the *harmonized historical Survey of Consumer Finances* (HHSCF) allows us to address a number of important questions that have been beyond reach with existing data sources and methods.

The HHSCF data confirm a substantial widening of income and wealth disparities in the past decades but also add a number of new stylized facts. Importantly, the new data allows us to complete the picture of the evolution of income and wealth inequality by documenting how and where inequality changed in the bottom 90 % of the distribution. The HHSCF data reveal a substantial *hollowing out of the middle class* with the middle of the income and wealth distribution being the main losers from rising income and wealth concentration at the top.

The new data also make it possible to observe and analyze the evolution of income and wealth inequality over time, based on the joint observations in the surveys. We show that income inequality rose earlier and more strongly than wealth inequality. We also point out that diverging trends between income and wealth inequality can be traced back to the interaction of asset prices and differences in the portfolio structure across the wealth distribution. In a nutshell, rising house prices and highly concentrated and leveraged household portfolios of the middle-class led to substantial wealth gains that, at least until the crisis, mitigated the increase in wealth inequality. Our results highlight the importance of price effects and differences in portfolio composition to understand trends in wealth inequality.

Our paper contributes to the study of income and wealth inequality in three different ways: new data, new measurement, and new explanations. First, we assemble the *Harmonized Historical Survey of Consumer Finances* (HHSCF) data on the financial situation of U.S. households. HHSCF data provide information on income, assets, debt, and wealth over the entire post-World War II period. We expect the dataset to become a valuable source for future research.

Second, we use HHSCF data to document trends in income and wealth inequality independently of existing studies. The debate about rising inequality has so far, mainly due to data limitations, focused on income and wealth concentration among the richest households (Piketty and Saez (2001), Saez and Zucman (2014)). The HHSCF data add the missing piece about inequality trends among the bottom 90 %.

Third, we exploit that HHSCF data provides independent information on income and wealth to contrast the timing and gradient of the rise in income and wealth inequality. We find an asynchronous and asymmetric increase. Over the past seven decades, income inequality rose earlier and substantially more than wealth inequality. We explain these differential trends by heterogeneity of household portfolios along the wealth distribution. Rising house prices hit non-diversified, highly leveraged household portfolios of the middle class. The resulting wealth gains mitigated the rise in wealth inequality relative to a rise in income inequality.

To construct the HHSCF dataset, we coded historical waves of the Survey of Consumer Finances (SCF) from data archives at the University of Michigan. These surveys were taken on an annual basis from 1948 to 1971 and then again in 1977. After extensive data work, we were able to link the historical survey data to the "modern" SCF data starting in 1983 in a consistent way. The result are *Historical Harmonized Survey of Consumer Finances* (HHSCF) files. We describe the steps we take to compile the data and demonstrate that the HHSCF data closely match aggregate trends in the National Income and Product Accounts (NIPA) and Flow of Funds accounts (FFA). The HHSCF micro data is therefore well-suited to study the distributional changes underlying macroeconomic trends. We expect that other researchers working with the data in the future will profit from this detailed new dataset.

The HHSCF data contain detailed information on income, financial and non-financial assets as well as housing and non-housing debt, together with demographic information like age, education, and household composition. The excellent coverage of houses and housing debt allows us to gain a granular picture of developments among the bottom 90 % of the wealth distribution as houses are by far the most important asset for this income group. Tax data has to impute income of non-filers at the bottom of the income distribution and the capitalization method proposed by Saez and Zucman (2014) has to construct major parts of wealth for the median household. Existing data has therefore to remain largely silent on the evolution of inequality among the bottom 90 %. We show that the middle 50 percent of the distribution were the main losers of rising income and wealth concentration at the top. This hollowing out of the middle class is the missing piece in the picture of rising inequality

in recent decades.
To analyze the joint evolution of income and wealth inequality, we exploit the fact that income and wealth are reported independently in the HHSCF data. Yet a comparison of trends in income and wealth inequality is still intricate because wealth inequality exceeds income inequality in levels. We construct what we call the *inequality gradient* that quantifies inequality in income and wealth growth relative to inequality-neutral growth. When we compare changes of income and wealth inequality over time, we find an asynchronous and asymmetric increase. Income inequality increased earlier and more than wealth inequality.
With respect to the timeline of the trends in inequality, we find the strongest increase of income concentration at the top during the two decades after 1970. During the same time period, wealth concentration at the top was actually decreasing. Wealth concentration at the top started to increase only after the 1980s and jumped during the financial crisis and its aftermath. Such differential trends in the evolution of income and wealth inequality provide important information to discriminate between different sources of rising inequality in structural macroeconomic models (Kaymak and Poschke (2016), Hubmer, Krusell, and Anthony A. Smith (2016)).
We explain this divergent increase of inequality by changes in house prices and differences in the composition of household portfolios along the wealth distribution. We document that the bottom 90 % of the wealth distribution hold non-diversified, highly leveraged portfolios. Rising house prices led to particularly large wealth gains for middle-class households and mitigated wealth inequality relative to income inequality. We find that the middle class received 73 % of the wealth gains form the house price increase of the 1990s and 2000s. However, the same effect aggravated wealth inequality during the financial crisis due to the drop in house prices. We also find that low diversification and high leverage are no phenomena of periods with rising house prices but were also present in the three decades from 1950 to 1980 in a period of stable real house prices (see Knoll, Schularick, and Steger (2016)). This finding suggests that the allocation of assets in the household portfolio and gross positions in assets and debt with different exposure to macroeconomic trends will be a fruitful avenue for future research trying to understand the forces driving changes in wealth inequality.
The structure of the paper is as follows. In section 2, we introduce the harmonized historical SCF (HHSCF) data and present more details on the substantial data work necessary to generate the long-run series presented here. We compare aggregated data trends from the micro data to data from NIPA and Flow of Funds. Section 3 discusses trends in income

and wealth inequality among the bottom 90 % and documents the hollowing out of the middle class. Section 4 compares the intensity and timing of the rise in income and wealth inequality. Section 5 discusses the underlying household portfolios in connection with price dynamics to explain the different trends in income and wealth inequality. Counterfactual simulations demonstrate wealth trends absent price changes. Section 6 concludes.

Related literature: Our paper is closely related to pioneering work of Piketty and Saez (2001) and Saez and Zucman (2014). Our analysis is complimentary to these papers due to different data and focus. Piketty and Saez (2001) use tax data to document the evolution of income concentration at the top of the U.S. income distribution over the last century. Saez and Zucman (2014) develop a capitalization approach using tax data to impute wealth from the flow of funds to households based on observed income flows. Their method is particularly powerful at the top of the income distribution where a lot of wealth is held in financial assets that generate taxable income flows. For assets that do not generate taxable income like housing and for debt positions like mortgages, Saez and Zucman (2014) had to rely on imputation based on survey data. We demonstrate below that our independent data corroborates their findings on rising income and wealth concentration at the top. This complements their work by providing additional, independent evidence for their findings. We also complement their work in terms of focus by exploring the changes in the distribution among the bottom 90 % of the income and wealth distribution.

There has been a recent attempt by Piketty, Saez, and Zucman (2016) to shed more light on the developments in the entire distribution of households by combining micro data from tax records and household survey data to derive the distribution of income reported in the national accounts over time. National income that is at the focus of their study is different to household income that we study in this paper. Their analysis, while focusing on a similar group of households, looks at a different object of interest. Piketty, Saez, and Zucman use survey data from the Current Population Survey (CPS) to impute the distribution of transfers in a synthetic micro data. For income, they rely on the work by Piketty and Saez (2001) that uses tax data. They also add wealth to their synthetic micro data based on the capitalization method developed in Saez and Zucman (2014). Given their ambitions, their method has to rely on a series of assumptions to operationalize the distribution of all national income to households.

Regarding the importance of asset price changes for inequality Bach, Calvet, and Sodini (2016) is a related paper. They study administrative Swedish data on income and wealth and find that wealthy household receive higher returns on their portfolios but face also more risk. In line with our findings that asset price changes are important to understand trends in wealth inequality, they find that for the rather short period from 2001 to 2007 covered by their data, asset price changes explain most of the changes in wealth concentration at the top.

Kuhn and Rıos-Rull (2016) use data from the “modern” Survey of Consumer Finances from 1989 to 2013. They provide detailed information on cross-sectional inequality and document facts on inequality over the life-cycle, for different educational attainment, for different employment types, and marital status. They provide already a first glance on household balance sheets based on SCF data starting in 1989 to 2013 and decompose the relative importance of different balance sheet positions for wealth inequality. They find that houses and mortgages are due to their sheer size on the household balance sheet an important driver of wealth inequality as measured by the Gini coefficient. In their discussion on the trends in inequality they put a particular focus on the period of the Great Recession.

Theoretical work trying to explain rising wealth inequality is still scare. In a recent paper, Hubmer, Krusell, and Anthony A. Smith (2016) use variants of incomplete market models as the workhorse macroeconomic model to study inequality and explore how different explanations for the rise in wealth inequality perform in a quantitative model. Their analysis highlights the challenges faced by theoretical models to account for the level and the change of wealth inequality. They find that changes in tax progressivity is the most important driver for rising wealth inequality. They conjecture that asset returns and differences in asset returns along the wealth distribution is a potentially important driver of wealth inequality that the workhorse model does not feature. Our results provide support to their conjecture.

Kaymak and Poschke (2016) explore the role of the tax and transfer system and technological change in shaping wealth inequality over the past decades. They use a standard incomplete markets framework that is calibrated to the 1960s and explore how subsequent changes in the tax and transfer system and technological change affected inequality. They attribute more than 50 % of the rise in wealth inequality to changes in the tax and transfer system.

De Nardi and Fella (2017) provide an excellent survey of the existing literature on macroeconomic models of wealth inequality. They discuss different models from the canonical incomplete market model to models with intergenerational transmission of financial and human capital, entrepreneurship, preference heterogeneity, health expenditure risk, rate of return risk on financial investments, and more sophisticated earnings dynamics. The authors discuss the strengths and weaknesses of existing theoretical models in matching dimensions of wealth inequality.

2 The Harmonized Historical Survey of Consumer Finances (HHSCF)

This section describes our efforts to process and clean the historical data to construct the long-run dataset that is the backbone of our study. The new *harmonized historical Survey of Consumer Finances* data (HHSCF) is an important contribution of the paper and the resulting data may be valuable to future researchers, so we go into somewhat greater detail than usual to describe some of the gory details of the construction of the underlying dataset. We also discuss challenges we had to overcome when linking the historical waves of the SCF with its modern counterparts.

The SCF is a key resource for research on household finances in the United States. The SCF is a triennial survey and data for the various survey waves starting in 1983 are available for download from the website of the Federal Reserve. 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 Fed's website.

However, the first consumer finance surveys were conducted much earlier, namely as far back as 1948. The early SCF waves have been conducted by the Economic Behavior Program of the Survey Research Center of the Institute for Social Research at the University of Michigan. While individual studies such as Malmendier and Nagel (2011) or Herkenhoff (2013) have used extracts of the data to address questions of historical interest, to the best of our knowledge, the pre-1983 SCF data have not yet been systematically processed and harmonized so they can be linked to the modern SCFs.

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 contain 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 additional information on age, sex, race, marital status, family size, and educational attainment.

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. We only drop some obvious outlier that are likely due to coding or transmission errors in the SCF files. We adjust all data for inflation using the CPI and report results in 2013 Dollars. It is worth keeping in mind that the SCF is a household survey so that income, debt, and wealth are all reported at the household level. This implies that in most cases households with fewer adult members have less income, debt, and wealth. The household as the unit of observation is most widely used when studying trends in inequality. We exploit the fact that HHSCF data provides detailed demographic information together with the financial situation and explore the effects of secular demographic changes on income and wealth inequality as part of our analysis.

2.1 Variables

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

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

Assets: The historical SCF waves contain detailed information on household assets. We summarize assets in the following asset categories: liquid assets, housing, bonds, equity, other real estate, and business equity. The coverage is comprehensive for liquid assets and housing. Liquid assets comprise the sum of checking, saving, call/money market accounts, and certificates of deposits. Information on liquid assets is available for almost all years, except for 1964 and 1966. Housing data is missing in 1952 and 1961. We impute values for missing variables in intermediate survey years. We describe our imputation procedure in detail below. Regarding bonds, variables are imputed for the 1960s, but the coverage is comprehensive for the 1950s. The coverage of other real estate as well as corporate and non-corporate equity is imputed in several years before 1977. Data on defined contribution pensions is 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 should not alter wealth data significantly.[1] Table 3 below reports for which years and variables 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 direct 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.[2] All debt other than housing debt refers to and includes car loans, education loans, and loans for the purchase of other consumer durables. For several survey years, there is no information on non-housing debt, but if the components of non-housing debt, such as installment debt and credit card debt are available, we calculate the sum of these components and report the sum as non-housing debt.

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

2.2 Weights and imputations

The SCF is designed to be representative of the U.S. population. Capturing the top of the income and wealth distribution is a challenge for most surveys. Since its redesign in 1983, the SCF therefore applies a two-frame sampling scheme to oversample wealthy households. Besides the coverage of wealthy households in the historical survey, concerns might also exist with respect to representative coverage of demographic characteristics such as race, age, and education. We explain how we adjust the historical data to get a harmonized data series over time. This also includes imputing missing variables to the household balance sheet in some survey years.

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

[2]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 the early years as they are more likely to have debt on other real estate.

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 and is selected by using information from the U.S. Census. To oversample wealthy households, the second so-called *list sample* contains households at the top of the wealth distribution. These households are selected using income tax information.[3] For both samples, survey weights are constructed separately. In the list sample, survey weights have to be disproportionally adjusted for non-response. The weight of each household is supposed to correspond to the number of similar households in the U.S. population. In a final step, both samples are combined. To ensure that the combined sample is representative of the U.S. population survey weights of both samples are adjusted (see Kennickell, Woodburn, and McManus (1996)).[4]

Before 1983, the SCF contains a sample that is representative of the U.S. population on the basis of Census data. There is no second list sample, so that more prevalent non-response at the top of the distribution might lead to a under-representation of wealthy households. To account for this under-representation, we mimic the oversampling of rich households that is done from 1983 onwards in the samples before 1983. We do this by adjusting observation weights in the top of the income and wealth distribution. We rely on information on the distribution of the list sample in the 1983 SCF. In 1983, we can identify the households from the list sample. This is not possible in any of the later survey years. The weighted number of households of the list sample in 1983 corresponds to 2% of U.S. households. We determine how the households from the list sample are distributed along the income and wealth distribution. We compare it to the remaining sample and determine excluding all households of the list sample at which percentiles the list sample observations are located. We find that most observations of the list sample are in the top 5% of both the income and wealth distribution. Weights for surveys before 1983 are then constructed as follows: we calculate percentiles of the income and wealth distribution in each survey year and extract

[3]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.

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

observations that are in the top 5% of the income and the wealth distribution. We adjust weights of these observations so that the resulting weights correspond to 2% of all households. We calculate two weight adjustment factors, one for the unadjusted sample and one for the adjusted sample. Multiplying observations of both samples with their respective adjustment factor results in a sample weight of 2% out of all households for the weight-adjusted sample in the final sample.

Table 1: Share of high income sample at top of 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 part shows shares in the top of the income distribution in the 1983 SCF and the 1963 SFCC data. Right part shows shares in the top of the wealth distribution in the 1983 SCF and the 1963 SFCC data. Shares are computed using weighted observations.

One concern with this adjustment routine is that it relies on information from a single sample year in 1983. The list sample cannot be identified in any of the later years.[5] The 1962 SFCC sample used a similar two-frame sampling scheme to the 1983 survey with a sample of rich households that has been selected based on tax records. In the 1962 data, we can identify this high-income sample. Table 1 shows that non-response pattern at the top of the income and wealth distribution in the 1962 SFCC and 1983 SCF. We find that the distribution of households in the top of the income and wealth distribution are very stable over time. We conclude based on these numbers that non-response as the key reason for the under-representation of rich households in most surveys appears to have not changed over the decades before 1983. We found no indication that our calibration of the adjustment routine to 1983 data will suffer from problems due to time trends in non-response pattern.

As a further proof of concept, we apply our adjustment routine to 1983 data. We do this by dropping the list sample in 1983 from the data and adjust weights using our proposed adjustment approach. Table 2 compares income and wealth shares of the sample including the list sample in 1983 with those obtained using our weight adjustment method on the sample excluding the list sample in 1983. The results show that our adjustment works very well. For income, it only slightly overestimates shares between the top 10 % and 5% and

[5]The Federal Reserve Board must not release any information about the distribution of the list sample in the data set.

slightly underestimates the top 5 % to 1% share. Little surprisingly, the fit deteriorates towards the right tail above the top 1 %. Deviations are, however, always less than 2 percentage points. For wealth shares, we get a similar picture. After weight adjustment the shares up to the top 1 % are matched reasonably well and the fit deteriorates within the top 1%.

Table 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

As a further test to assess the reliability of our approach, we compare income shares at the top of the income distribution with information from tax data before 1983. We will do this in section 3.1. We will see that using the weight-adjusted data, we match the top income shares very closely in trend and level. This provides additional support for the validity of our approach.

Demographic characteristics: We compare the coverage of demographic characteristics in the surveys before 1983 with data from the U.S. Census from 1940 until 1990. In particular, the described adjustment of sample weights might distort the distribution of demographic characteristics.[6]

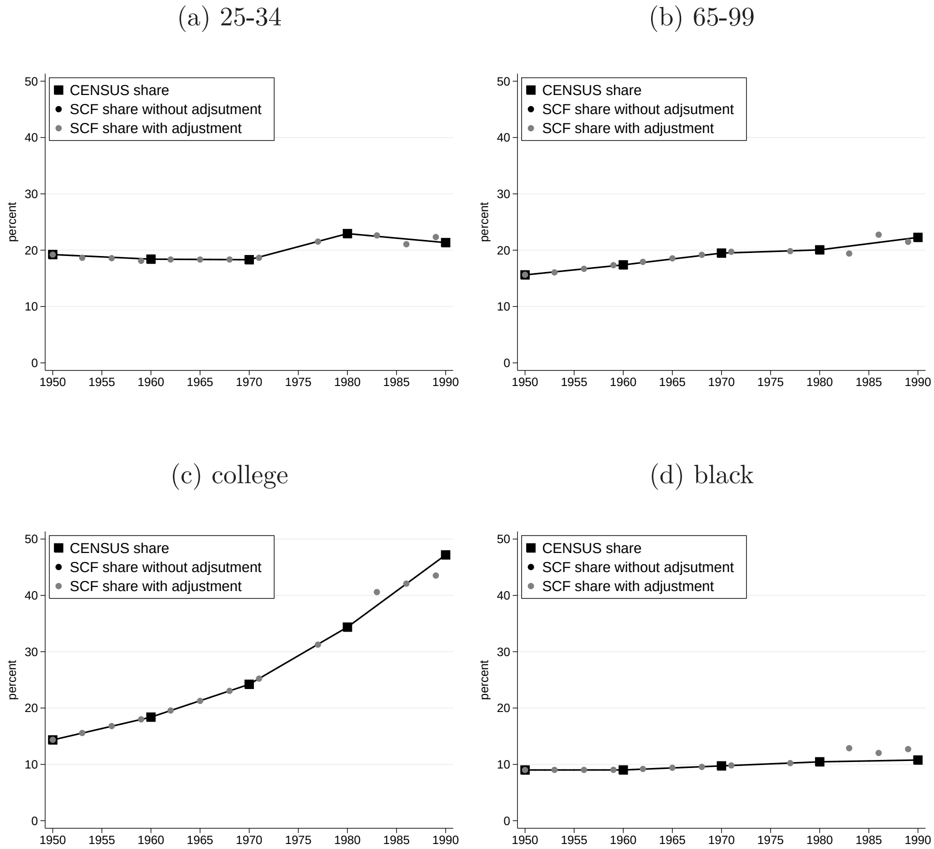
To obtain samples that match the Census data, we subdivide both the Census and the HHSCF data into 24 demographic subgroups. Subgroups are determined by age of the household head, whether the head has attended college, and whether the head is black. We adjust HHSCF weights by minimizing the difference between the share of each subgroup in the HHSCF and the respective share in the Census.[7] As Census data are only available on a decennial basis, we linearly interpolate values between Census dates.[8]

[6]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.

[7]Similar to the adjustment of weights before, we calculate factors for each subgroup. Multiplying observations with the respective factor of their subgroup the share of each group in the HHSCF corresponds to the respective share in the Census.

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

Figure 1: Shares of 10-year age groups, college and black households in population



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

Figure 1 shows the shares of 10-year age groups, college households, and black households in the Census (black squares) and in the HHSCF with the adjustment of survey weights (gray dots). Population shares in surveys after 1983 are close to Census shares. Looking at the shares before 1983 without adjustment of survey weights, we find that households aged between 25 and 34 are overrepresented in most years while household aged 65 and above are underrepresented. In addition, the share of college households is 5 to 10 percentage points higher in the SCFs before 1983 without adjustment compared to the Census. Using adjusted weights, the distributions of age, education and race matches closely Census data.

Missing variables: The imputation of missing variables is done by predictive mean matching as described in Schenker and Taylor (1996). This imputation method assigns variable

values to the missing observations by finding observations which are most closely to the respective missing observations. The variable values of these "closest neighbors" are then employed to the respective observation for which information on the variable is missing.
In addition, we account for an underrepresentation of business wealth in years before 1983. The fact that business wealth is underrepresented results from the fact that high wealth households who hold most of business wealth and stocks are in part imputed before 1983. To impute also their business wealth and stocks, we follow ideas similar to Saez and Zucman (2014) and adjust the observed holdings in the micro data based on FFA observations. We do not match the aggregate amount of business wealth and stocks from the FFA directly like in the approach by Saez and Zucman (2014) but adjust in a consistent way with later surveys and measurement in the SCF. We use data from the 1983 and 1989 HHSCF surveys and adjust business wealth and stocks holdings in the earlier survey so that the ratio of business wealth and stocks relative to the FFA aggregates is equal to the respective ratio of 1983 and 1989.[9] This provides consistent estimates taking into account conceptual differences between SCF and FFA data.
Table 3 details the variables and their coverage, as well as the years for which imputations were necessary. An "O" in the table indicates that original information of the variable is available in the respective year, i.e. original observations of the respective variable are used. An "I" means that observations of this variable are imputed. If a variable is missing in a year, we report the years of adjacent surveys that are used for the imputation in Tables A and B of the appendix.[10]

We refer to the final data as the *harmonized historical Survey of Consumer Finances* (HH-SCF) data. The data provides 35 survey years with cross-sectional data with a total of 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.[11] In order to avoid fluctuations due to small sample size in some of the HHSCF data, we pool three consecutive surveys up to 1971 when reporting time

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

[10] We exclude the survey years 1948, 1952, 1961, 1964 and 1966 in which there are either no 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, E and F.)

[11] Table A.1 in the appendix reports the number of observations for all years.

Table 3: 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
1948	O	O	O	O	O	I	I	I	I	I	I	I	O
1949	O	O	O	O	O	O	O	O	I	O	O	O	O
1950	O	O	O	O	O	O	O	O	O	O	O	O	O
1951	O	O	O	O	O	I	O	I	I	O	O	O	O
1952	O	O	O	O	O	O	I	O	O	I	I	I	O
1953	O	O	O	O	O	O	O	O	O	O	O	O	O
1954	O	O	O	O	O	I	O	I	I	O	O	O	O
1955	O	O	O	O	O	O	O	I	I	O	O	O	O
1956	O	O	O	O	O	I	O	I	I	I	O	I	O
1957	O	O	O	O	O	I	O	I	I	O	O	O	O
1958	O	O	O	O	O	I	O	I	I	O	O	O	O
1959	O	O	O	O	O	I	O	I	I	O	O	O	O
1960	O	I	O	O	O	O	O	O	O	I	O	I	O
1961	O	I	O	O	O	I	I	I	I	I	I	I	O
1962	O	I	O	O	O	O	O	O	O	I	O	I	O
1963	O	I	O	O	O	O	O	O	O	I	O	I	O
1964	O	I	O	I	I	O	O	I	I	I	O	I	O
1965	O	I	O	O	O	I	O	I	I	I	O	I	O
1966	O	O	O	I	I	I	O	I	I	I	O	I	I
1967	O	O	O	O	O	O	O	I	I	I	O	I	O
1968	O	O	O	O	O	O	O	O	I	O	O	O	O
1969	O	O	O	O	O	O	O	O	I	O	O	O	O
1970	O	O	O	O	O	O	O	O	O	O	O	O	O
1971	O	O	I	O	I	I	O	I	I	I	O	I	O
1977	O	O	I	O	O	O	O	O	I	O	O	O	O
1983	O	O	O	O	O	O	O	O	O	O	O	O	O
1989	O	O	O	O	O	O	O	O	O	O	O	O	O
1992	O	O	O	O	O	O	O	O	O	O	O	O	O
1995	O	O	O	O	O	O	O	O	O	O	O	O	O
1998	O	O	O	O	O	O	O	O	O	O	O	O	O
2001	O	O	O	O	O	O	O	O	O	O	O	O	O
2004	O	O	O	O	O	O	O	O	O	O	O	O	O
2007	O	O	O	O	O	O	O	O	O	O	O	O	O
2010	O	O	O	O	O	O	O	O	O	O	O	O	O
2013	O	O	O	O	O	O	O	O	O	O	O	O	O

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

trends below.

2.3 Comparison to aggregate trends

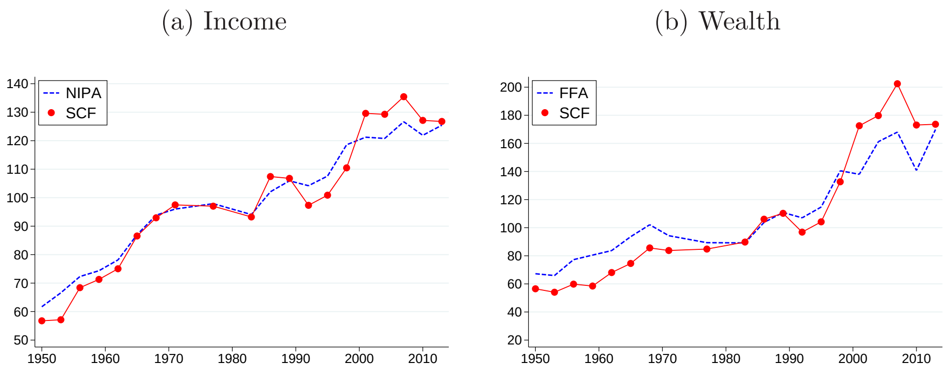
We will use the micro data to investigate distributional changes in income and wealth over time. For such an investigation, it is important that the micro data is consistent with aggregate trends. We benchmark trends from the HHSCF data to trends in aggregate data from the National Income and Product Accounts (NIPA) and the Flow of Funds (FFA). Household-level surveys often struggle to match aggregate data when the micro data is aggregated to the level of the macroeconomy. In many cases, measurement concepts differ between micro surveys and macro data, explaining at least in part why even high quality micro data do not correspond one-for-one to aggregate data. For instance, Heathcote, Perri, and Violante (2010) compare NIPA income to the Current Population Survey (CPS). They explain that observed differences are due to the fact that NIPA income includes 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 not measured 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 respective positions of all other sectors from the economy-wide total (see Antoniewicz et al. (1996), Henriques and Hsu (2013)). These residuals contain asset positions held by nonprofit organizations as well as domestic hedge funds which are not included in the SCF. Antoniewicz et al. (1996) provides a very careful discussion about the measurement concepts in the SCF and FFA and summarizes that there are reasons for measurement error in both data sets. We demonstrate that despite the conceptual differences in measuring income and wealth the HHSCF data match aggregate trends closely, effectively alleviating such concerns.[12]

Figure 2 compares income and wealth of the HHSCF with the corresponding NIPA and FFA values. Income components of the NIPA tables that are included are wages and salaries, proprietors income, rental income, personal income receipts, social security, unemployment

[12]There is also a difference in the unit of analysis. The SCF sampling weights are constructed to be representative of all U.S. households following the household definition of the U.S. Census Bureau. The unit of analysis in the SCF is the primary economic unit (PEU) that contains only persons in the household who share finances. The Census household definition groups people living together in a housing unit. In some cases this may be several PEUs living together. Although the two concepts will lead to identical units of observation in the vast majority of cases, Kuhn and Rıos-Rull (2016) report that in 2013 the average SCF household is slightly smaller than a Census household. The analyses by Piketty and Saez (2001) and Saez and Zucman (2014) consider tax units as their unit of observation. Tax units differ from households. A tax unit can be a single adult or a married couple both can have dependent children. In 2012 there are about 1/3 more tax units (160.7 million) than households (121.1 million) in the U.S.

insurance, veterans benefits, other transfers and net other current transfer receipts from business. FFA wealth data are calculated following Henriques and Hsu (2013). Henriques and Hsu carefully construct wealth from the FFA to be most closely comparable to the SCF. In practice, this means that defined-benefit pension plans are excluded as these are not measured in the SCF and asset positions of nonprofit organizations are subtracted if possible (e.g., information on housing is provided separately for the household sector and nonprofit organization). In addition, only mortgages and consumer credit are included as FFA debt components. The main adjustment to the SCF is that non-residential real estate is excluded from 1989 onwards (no distinction is available before 1989). The base period for comparisons is 1983 to 1989. These are the first surveys which incorporate the oversampling of wealthy households. We remove level differences that are likely due to conceptual differences and compare trends from aggregate data to those we get from aggregating the micro data.

Figure 2: HHSCF, NIPA, and FFA: income and wealth



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

For the base period 1983 and 1989, the HHSCF matches 84 percent of income from NIPA and 118 percent of FFA wealth. Figure 2 shows the trend in income is similar for HHSCF and NIPA data throughout the 1948-2013 time period. Looking at wealth, the trend in the HHSCF and the FFA differs slightly. Before 1983, wealth in the HHSCF is below that of the FFA. From 1983 to 1998, the HHSCF and FFA measure are about the same and from then onwards the HHSCF exceeds the FFA values. Both wealth measures show an upward trend over time, but the increase is steeper in the HHSCF.

To evaluate which specific asset and debt positions generate the divergence between wealth in the HHSCF and FFA, Figures 3 and 4 show different asset and debt positions. Figure 3a shows financial assets (liquid assets, bonds, corporate equity). We see that financial assets in the HHSCF increase more strongly starting in the 1980s than FFA values. This difference between HHSCF and FFA data is mainly due to distinct trends in corporate equity during the stock market boom in the second half of the 1990s. Figure 3c shows that corporate equity in the HHSCF nearly doubled in value (from 99 to 197) between 1995 and 1998 while it increased by about 60 % in the FFA (from 188 to 283).

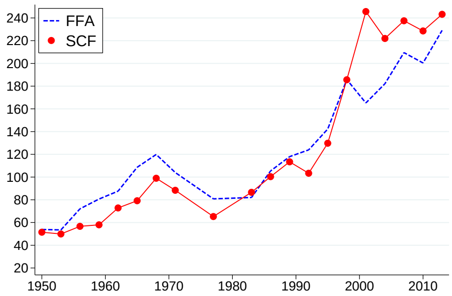
Figure 3b shows that trends for non-financial assets are similar in the micro and macro data. The HHSCF shows a stronger increase between 1977 and 1983, and the decrease of non-financial assets is lower in the HHSCF after 2007. Differences in trends of non-corporate equity (Figure 3d) causes a stronger increase of non-financial assets between 1977 and 1983. Figure 3e shows housing as the most important non-financial asset matches the FFA closely.

The household balance sheet component for which the HHSCF match the aggregate data best is debt – as shown in Figure 4. There is a level difference of about 15% throughout the whole time period, but the trend is almost identical in the HHSCF and FFA. The reason is that the dominant component is housing debt for which the trends are very similar in both data sources (Figure 4b).

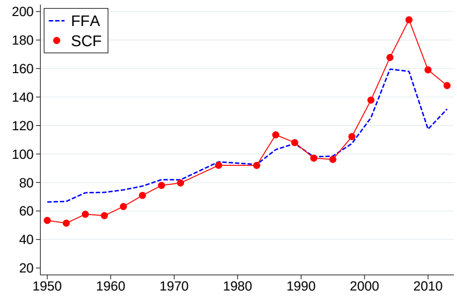
Summing up, the HHSCF matches trends of NIPA income data and FFA asset and debt positions closely. The HHSCF matches in particular trends of major categories of housing and mortgages in the FFA data very well. For some asset categories like corporate and non-corporate equity some gaps exist. Yet, this is true for both the historical and post-1983 HHSCF data and points to conceptual differences in measurement rather than specific problems of the historical survey data. With respect to overall wealth, i.e., the sum of all asset and debt components, the post-1980 increase appears somewhat stronger in the HHSCF. But our overall conclusion is that the HHSCF provides reliable micro-data to study trends in income and wealth over the long-run. We now turn to our investigation of the distributional changes over time.

Figure 3: HHSCF, NIPA, and FFA: financial and non-financial assets

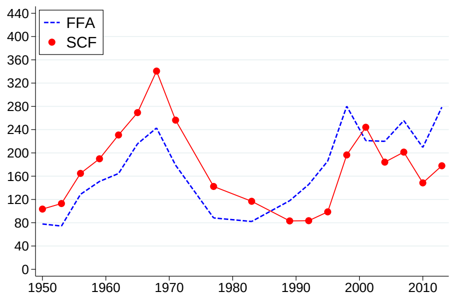
(a) Financial assets



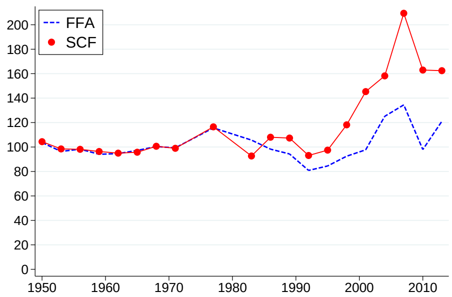
(b) Non-financial assets



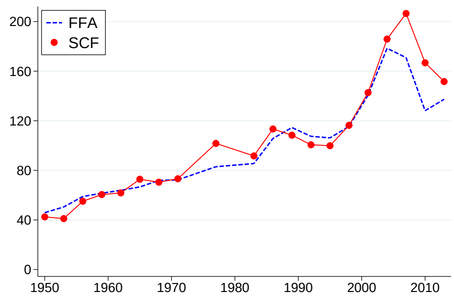
(c) Equity



(d) Business wealth



(e) Housing

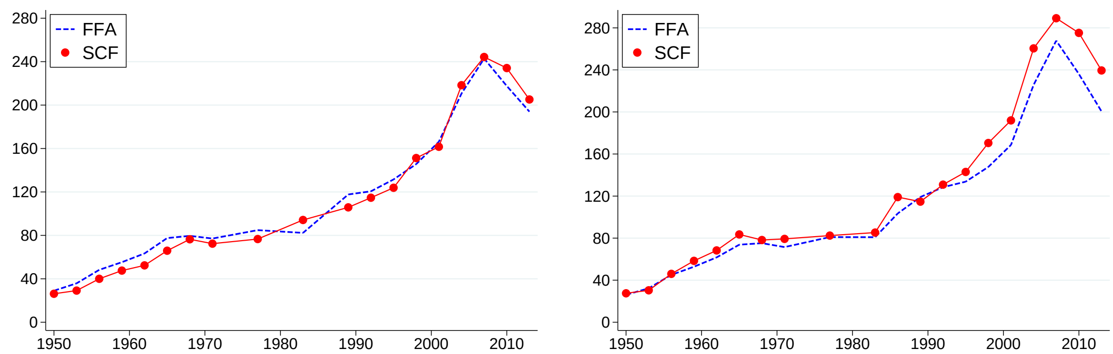


Notes: Financial and non-financial assets from HHSCF in comparison to data from FFA. All data has been indexed to 1983 and 1989 period (= 100). HHSCF data is shown as red lines with circles, FFA data as blue dashed line. Over indexing period HHSCF value corresponds to 76% for financial assets, 45% for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

Figure 4: HHSCF, NIPA, and FFA: debt

(a) Total debt

(b) Housing debt



Notes: Debt from HHSCF in comparison to data from FFA. All data has been indexed to 1983 and 1989 period (= 100). HHSCF data is shown as red lines with circles, FFA data as blue dashed line. Over indexing period HHSCF value corresponds to 86% for total debt, 92% for housing debt and 69% for non-housing debt.

3 The view from below: who lost out?

The last section showed the aggregate increase of U.S. households' income and wealth over the past seven decades. Over this period, income doubled and wealth tripled. Our HHSCF micro data matches these aggregate trends closely. Much of the recent debate on inequality focuses on income and wealth shares of the top of the distribution (Piketty and Saez (2001), Saez and Zucman (2014)). For instance, it is well established that the top 10 % of the income and wealth distribution have been the winners – and among them in particular the top 1%. While we know that the losers must be outside the top 10%, the bottom 90 % are a large and heterogenous group and we know very little distributional trends within this part of the population. The key advantage of the HHSCF data is that it covers the portfolio of the "main street" household very well, and arguably better than IRS income tax data. The typical U.S. household owns a house, has mortgage debt, and nowadays a retirement account. Analyses based on tax data do not only have to impute incomes of non-filers at the bottom of the distribution, they also have to impute both assets and debt of a typical U.S. household portfolio without observing the corresponding income flows in tax returns. In brief, while tax data provides a very granular picture of the right tail of the distribution, they are less ideal to study developments among the bottom 90 % of the population.

In the following, we will first revisit and corroborate existing stylized facts for the trajectory of U.S. wealth and income distribution since WW2 with the HHSCF data. In a second step, we will provide new and detailed evidence for the bottom 90 % and document a pronounced *hollowing out of the middle class*. We find that the gains of the top 10 % were accompanied by pronounced losses of income in the middle of the distribution. We will also point out that the trajectories of income and wealth inequality diverged strongly over the past seven decades.

3.1 Income and wealth concentration at the top

The recent debate on the evolution of income inequality focused on the concentration of income and wealth at the top of the distribution. Tax data is very effective in measuring income at the top of the income distribution.[13] In Figure 5a, we compare the income shares of the top 10, 5, and 1 percent of the income distribution in the HHSCF to those calculated

[13] Income shares have a particular advantage when using tax data because the income share of a particular group constitutes a single point on the Lorenz curve and it does not require to take a stand on the shape of the Lorenz curve below that point. Top income and wealth shares are therefore independent on the distribution among the bottom 90 %.

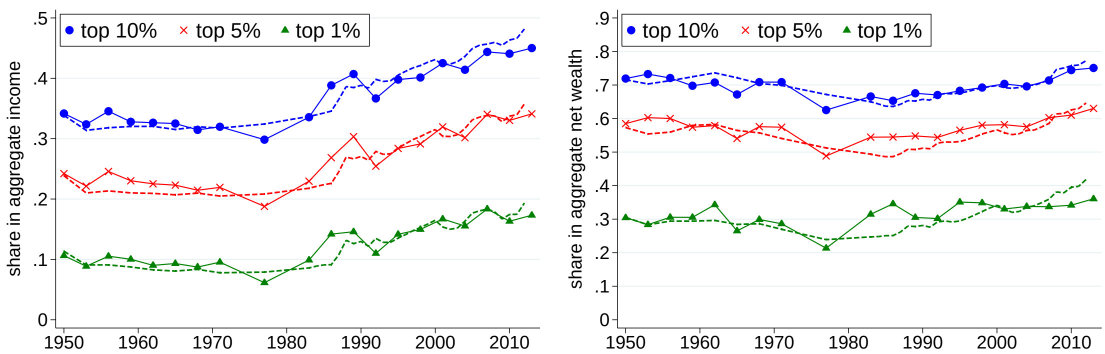
by Piketty and Saez (2001) using IRS income tax data. The definition of total income is comparable to that in the HHSCF.[14]

Saez and Zucman (2014) introduce a capitalization method to distribute wealth from the FFA to the cross section of households based on income flows from tax returns.[15] Figure 5b compares wealth shares of households at the top of the wealth distribution in the HHSCF with those obtained by Saez and Zucman (2014). The wealth shares show that wealth inequality in the U.S. decreased until the mid 1980s and started to increase at the beginning of the 1990s. Today, wealth inequality is at a historical peak.

In sum, the HHSCF data display the same levels of income concentration at the top and a marked polarization of incomes in the past four decades, as well as similar trends for top wealth shares. We can thus independently confirm the increase of income and wealth concentration at the top, pointed out by Piketty and Saez (2001) and Saez and Zucman (2014) in their important contributions. At the same time, we will be able to say more about the losers in the process and about the different trajectories of income and wealth inequality. This is what we turn to now.

Figure 5: Top income and wealth shares

(a) Income (b) Wealth



Notes: The dots refer to income and wealth shares derived from the SCF. The dashed lines are the corresponding shares calculated by Piketty and Saez (2001) using IRS tax data or Saez and Zucman (2014) using IRS data and the capitalization method. The blue dots and line refer to households in the top 10% of the income (wealth) distribution, the red ones to top 5%, and the green ones to top 1%.

[14]Piketty and Saez (2001) include salaries and wages, small business and farm income, partnership and fiduciary income, dividends, interest, rents, royalties and other small items reported as other income. Both income measures do not include capital gains.

[15]We discuss their method in detail in appendix C.

3.2 The bottom 90%

Table 4 shows income and wealth shares of different groups over time. Starting with income in the left half of the table, we see the increasing concentration of income at the top over time. The top 10 % have grown their income share from 34.5 percent to 44.7 percent between 1950 and 2013. We uncover two distinct episodes underlying the rise in income concentration at the top. The first episode was during the 1970s and 1980s with the most extreme rise in the income share of the top 10 % (+ 7.9 pp.). During this episode, the bottom 25 % and the middle class lost ground, while the upper middle class between the 75th and 90th percentile retained a stable income share.

The second episode took place during the 1990s and 2000s. This episode led to redistribution of income shares towards the top 10 % (+ 4.1 pp.) but in contrast to the first episode the bottom 25 % now kept their income share constant and households between the median and the top decile all lost income shares. But in both episodes, the income groups in the middle were the main losers of the distributional changes.

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 in the right half of table 4, we can also identify two distinct episodes. The first episode of rising wealth concentration occurred during the 1990s and 2000s, much later than the beginnings of income concentration. The wealth share of the top 10 % rose by 3.9 pp in these two decades. Households above the median up to the top decile were the main losers of that episode. The second episode of wealth concentration at the top happened in the financial crisis and its aftermath between 2007 and 2013. The bottom and the middle class lost ground (-3.3 pp) while households between the 75th and the 90th percentile had a roughly stable wealth share, and the rich gained strongly.

An interesting insight that emerges from Table 4 is that the trends in income and wealth inequality diverge. The period of the strongest income concentration at the top during the

1970s and 1980s was a period when the wealth share of the top 10 % declined. The period from to 2007 and 2013 saw the strongest rise in wealth inequality, but income inequality barely changed. We will discuss the reasons for this divergences in greater detail below. In essence, we will argue that differences in portfolio positions, coupled with leverage and asset price trends, explain why the middle class lost less ground.

3.2.1 Quantile ratios

We continue the discussion of trends within the bottom 90% by looking at quantile ratios in Figure 6. Quantile ratios provide an intuitive approach to study changes in the distribution over time. They are unbounded and changes in magnitude allow for a comparison over time despite differences in initial levels of inequality.The blue lines are ratios with respect to income, the red lines with respect to wealth.

The left graph shows 50-25 quantile ratios, the right graph 90-50 ratios. The 50-25 quantile ratio captures inequality in the bottom half of the middle class. The changes for the income ratio are small and show now clear trend. The ratio increases from 1.8 to about 2 and decreases afterwards to 1.8. In contrast to the overall trends, income inequality decreased at the bottom of the middle class in the 2000s, a pattern generally consistent with a hollowing out of the middle class if households in the middle of the distribution see meager income growth. The ratio for wealth is constant up until the 1980s and shows a slight increase afterwards, yet, with ups and downs. Clearly, there is a large increase during and after the financial crisis.

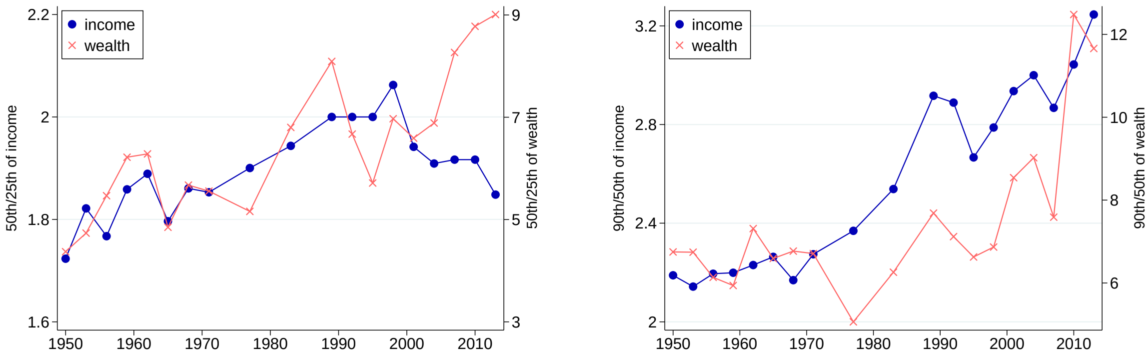
The 90-50 ratio measures the distance between the middle of the distribution and the top. The chart shows that income inequality started to rise considerably earlier than wealth inequality. The quantile ratio for income started to increase in 1970, while that for wealth only in the 1980s. In addition, income differences grew more than wealth differences until 2007 when the 90-50 ratio jumped up.

3.2.2 The inequality gradient

To get a better understanding of the relative changes in inequality over time, we construct an *inequality gradient*. It measures how much the income or wealth share of a group changed from the initial level. Specifically, we construct the inequality gradient for income as follows

Figure 6: Quantile ratios of income and wealth (in %)

(a) 50-25 ratio (b) 90-50 ratio



Notes: Quantile ratios of income and wealth for all U.S. households from 1950 to 2013. See text for details on the construction of income and wealth.

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

where $x_{i,t}$ denotes the share of household group i in total income at time t and $\bar{y}_t$ denotes average income of all households at time t. We construct the equivalent inequality gradient for wealth.

The inequality gradient has a very intuitive interpretation. The inequality gradient measures how much a particular group i received from the increase in total income (or wealth) $(\bar{y}_{t+1} - \bar{y}_t)$ over and above its initial share in total income $(x_{i,t})$. In other words, it measures the inequality of income (or wealth) growth relative to an "inequality-neutral" growth of income (or wealth). 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, then we get $\Delta^i_{t,t+1} = \frac{10}{20} - 0.2 = 0.3$. 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. [16]

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

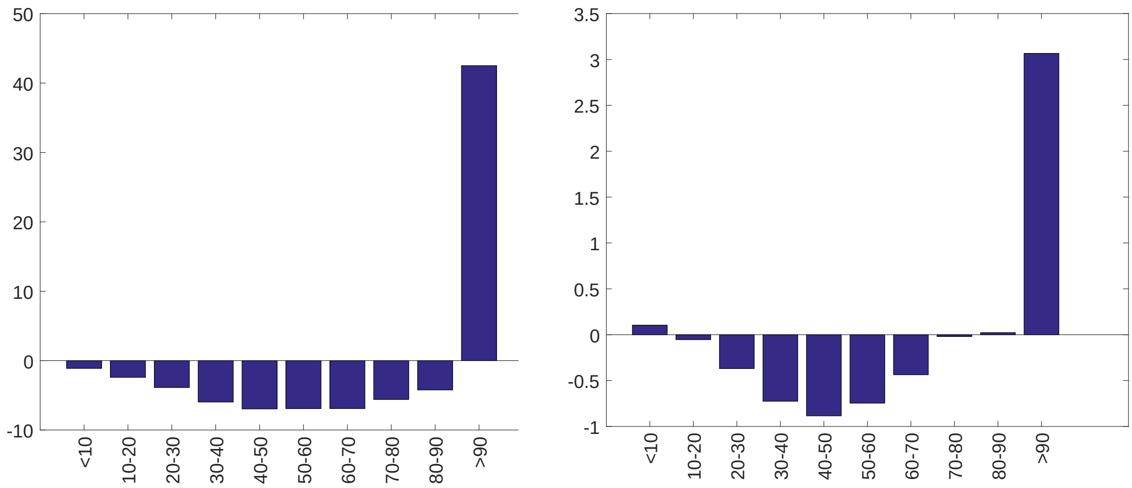
We chose the inequality gradient for the subsequent discussion for two reasons. First, a potential alternative such as the Gini coefficient has the drawback that it is bounded between zero and one, so that changes in the Gini coefficient are also bounded and magnitudes of changes are difficult to compare. Second, the inequality gradient allows us to get a more granular picture of who the winners (positive gradient) and the losers (negative gradient) are.

Figure 7a shows the substantial income gains of the top 10%. The income gradient is very steep. For the top 10 %, it is at 40. This implies that after adding in their initial share, between 1971 and 2007 the top 10 % received 72 cents out of every additional Dollar in the economy – 40 cents more than their initial share of 32 cents in the early 1970s. This demonstrates that the fruits of aggregate growth have been divided in a highly unequal way. At the same time, inequality gradients for all other deciles are negative. Everybody in the bottom 90 % lost relative income but the gradients in the middle of the income distribution are the steepest. The middle class (around the median) has been the main loser of the distributional change.

Figure 7: 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 7b shows the inequality gradient of wealth. Again, the top 10 % stand out as the clear winners of the distributional change although there are tiny gains in the bottom decile and in the 9th decile. As for income, we find that inequality gradients are steepest in the middle of the distribution.

3.3 Distribution of losses among the bottom 90%

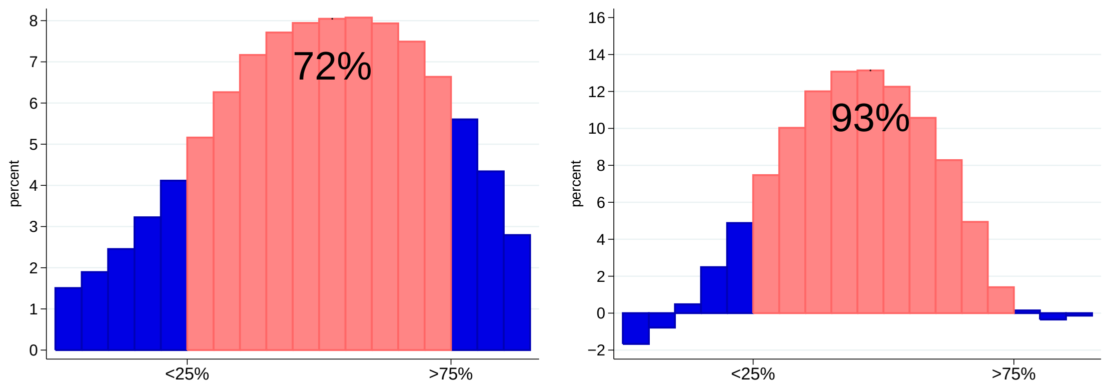
Having zoomed in on the relative winners and losers among the bottom 90%, we saw that inequality gradients are almost always negative for the bottom 90%. The relative size of the inequality gradients is informative about the size and the distribution of the losses among the bottom 90 % are. It is important to keep in mind that the inequality gradient does not measure absolute losses in income or wealth but only losses relative to inequality-neutral income and wealth growth.
We construct the distribution of losses by summing inequality gradients of the bottom 90 % and look at the relative gradient share of each group

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

Remember that by construction inequality gradients sum to zero and given that we leave out the gradient of the top decile (summation to $J-1$ in the denominator), $\lambda^i_{t,t+1}$ measures the contribution of each group i to the overall losses among the bottom 90 %.
We plot the distributions of the losses for income and wealth in Figure 8. It shows that most losses are concentrated in the middle of the distribution. The red area indicates the losses of the middle class, all households between the 25th and 75th percentile. We see that for income, the middle class took 72 % of all losses among the bottom 90 %. This hollowing out of the middle class is the matching part to the rising income concentration at the top. The growing fortunes of the top 10% came at the expense of large losses (relative to the income and wealth neutral growth path) of the middle strata of the income distribution.
To summarize, we document that rising income and wealth shares at the top have not hit everybody among the bottom 90 % equally but were accompanied by a hollowing out of the middle class both for income and wealth.

Figure 8: Distribution of losses ($\lambda^i_{t,t+1}$) among bottom 90 %

(a) income (b) wealth



Notes: Distribution of loss in income and wealth shares among the bottom 90 % of the income and wealth distribution. Total losses sum to 100 %. Red bars show losses of the middle class. The middle class is defined to be all households between the 1st and 3rd quartile. For income, the middle class experiences 72 % of all losses, for wealth the middle class experiences 93 % of all losses.

4 Income vs. wealth inequality

Have income and wealth inequality taken different trajectories since WW2? Some of the data presented in the previous section suggested the answer is affirmative. The inequality gradient allows us to answer this question and track the differential evolution of both income and wealth inequality over time independent of differences in the initial level of inequality. However, we will start the discussion with a brief look at Gini coefficients as a popular method to compare changes in inequality over time.

4.1 Gini coefficients for income and wealth

In Table 5, we start by looking at Gini coefficients of income and wealth as the most widely-used measure of inequality. We also report the full time series in Table D.2. The first row always reports the Gini coefficient for all households, the second row excludes the top 1 % and only considers the bottom 99 % of the income and wealth distribution, and the third row considers the bottom 90 % of the income and wealth distribution.

Gini coefficients of income and wealth are increasing over time for all households, the bottom 99 %, and the bottom 90 %. Comparing the level of inequality, we see a substantial drop in

Table 5: Gini coefficient (×100) of income and wealth

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

inequality once the top 1% of the distribution are excluded; once we exclude the top 10 %, there is less but still substantial inequality.

However, the Table also shows that the increase of wealth inequality has been slower than in the case of incomes. Between 1950 and 1989, the wealth Gini did not change at all, and actually fell for the bottom 99%. . Between 1989 and the financial crisis, wealth inequality increased by three percentage points.

Income inequality, by contrast, already rose by 9 percentage points between 1971 and 1989 when wealth inequality remained stable. However, statements about the relative strength of the increase in inequality based on changes in Gini coefficients are intricate due to level differences. That's why we turn again to the inequality gradient.

4.2 Inequality gradients for income and wealth

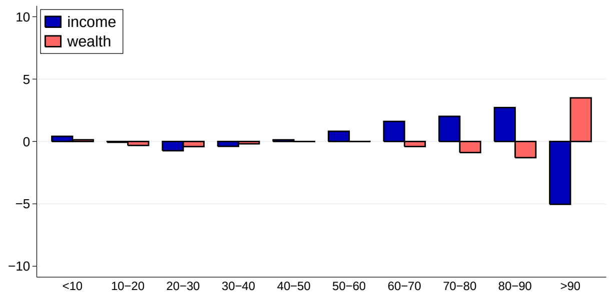
Figure 9 shows inequality gradients for income and wealth for three sub-periods from 1950 to 1971, 1971 to 2007, and 2007 to 2013. Comparing inequality gradients of income and wealth, we see immediately that income gradients exceed wealth gradients by a considerable margin. As they share the same distributional properties, the difference in size of the gradient points towards a substantially stronger rise in inequality for income than for wealth.

The chart also allows us to compare the difference in "steepness" of inequality gradients for various sub-periods. We see that income and wealth shares hardly changed in the 1950s and 1960s. Inequality gradients barely exceed 2 in absolute value so that income and wealth growth were close to inequality neutral. Regarding wealth, households in the top 10% of the wealth distribution received about 2 percentage points more of the aggregate wealth increase relative to their wealth share in 1950 while the top 10% of the income distribution received about 2 percentage points less. Yet overall, the period until 1970 has largely been one of inequality-neutral income and wealth growth.

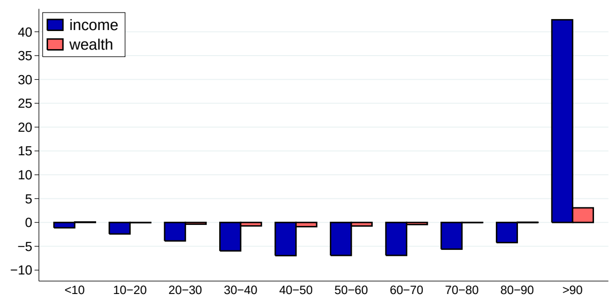
It also becomes apparent that the income inequality gradient is much steeper for the 1971-2007 period. From 1970 to 2007 inequality evolved asymmetrically with a much stronger rise in income inequality than for wealth. The inequality gradient of income increases strongly and shifts towards a distinct separation of winners and losers between the top 10 % and the bottom 90 %. By contrast, the inequality gradient for wealth rises only marginally and remains much smaller than for income.

Figure 9: Change in income and wealth shares (percentage points)

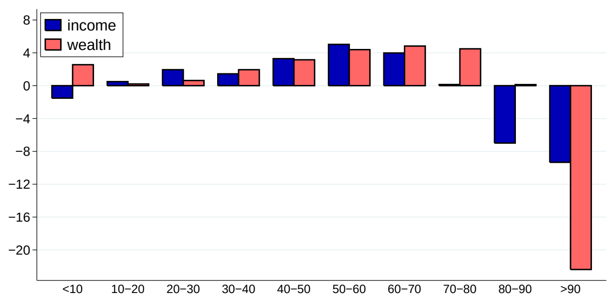
(a) 1950 - 1971



(b) 1971 - 2007



(c) 2007 - 2013



Notes: Changes in income and wealth shares of all income deciles for time periods 1950 to 1971 (left panel) and from 1971 to 2007 (right panel). Horizontal axis shows income deciles from 1 (bottom 10 %) to 10 (top 10 %). Income deciles are determined at the beginning of indicated time period. Vertical axis shows the change in the income (wealth) share in total income (wealth) in percentage points.

4.3 Effects of the financial crisis

The picture is different when we looki at the financial crisis and its recessionary aftermath from 2007 to 2013. Figure 9c shows that inequality gradients of income are at the level of wealth or below for the bottom 75 % of the distribution. For the top 10 %, the inequality gradient of wealth exceeds the income gradient by a factor of more than 2.

Inequality gradients of the top 10 % are negative. However, these numbers have to be interpreted with caution. The period from 2007 to 2013 was associated with large losses in wealth triggered by the financial crisis. A negative wealth gradient implies that a group had to take smaller losses relative to the aggregate loss than their initial wealth share. Hence, the large negative gradient at the top of the wealth distribution implies a concentration of wealth as the richest households lost less wealth than their wealth share. The same interpretation applies to income over this period.

However, the inequality gradient of income for the top 10 % is not even half as steep as for wealth. This points to much less income concentration over this period. In other words, inequality trends have been asymmetric during the financial crisis and its aftermath with a stronger rise of wealth concentration compared to income.

Summing up, wealth inequality increased more than income inequality between 2007 to 2013, but overall the changes in income concentration from 1971 to 2007 dominate the picture over the last seven decades. These differences between income and wealth inequality have so far received little attention. They do, however, provide testable implications for theories to explain changes in income and wealth inequality over time [17] Kopczuk (2015) discusses that the joint evolution of income and wealth inequality remains under-researched given its potential to inform models to explain the underlying mechanisms. Benhabib and Bisin (2016) discuss return differences of assets as one potential channel. This is what we turn to next. We will investigate the reasons for these strikingly different trends in income and wealth inequality and explain them based on differences in household portfolios, leverage and rising house prices over the period from 1971 to 2007.

[17] See Castaneda, Díaz-Giménez, and Ríos-Rull (2003) for a benchmark model, De Nardi and Fella (2017) for a survey, or Kaymak and Poschke (2016) and Hubmer, Krusell, and Anthony A. Smith (2016) for recent attempts).

5 Why did wealth inequality rise less than income inequality?

Wealth inequality increased less than income inequality. In this section, we demonstrate that the portfolio composition of households is critical to understand these differential trends in inequality. When asset prices change, differences in the composition of household portfolios imply differences in exposure, and thereby, difference in wealth dynamics. Our focus will be on houses and house prices, first, because houses are the single most important asset in the portfolios of the bottom 90 % of the wealth distribution, and second, because house prices changed strongly over the period of diverging inequality trends. Being the most important asset alone makes households' wealth particularly exposed to changes in house prices, but in addition, housing is also a particular asset because it is virtually the only asset that is held with substantial leverage. As a consequence, the effect of house price changes on wealth is amplified over and above the direct exposure. Putting pieces together, we will demonstrate that highly non-diversified portfolios of the middle class, and a particular house price episode during the 1990s and 2000s provide an explanation for the mitigated rise of wealth inequality compared to income inequality in the period from 1970 to 2007. The same forces lead after the drop in house prices during the financial crisis to a quick and strong rise in wealth inequality between 2007 and 2013.

5.1 Housing and Leverage

Figure 10 shows household portfolios along the wealth distribution.[18] We group households along the wealth distribution in four groups. 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%. We show asset positions as positive values and debt positions as negative values. Wealth corresponds to the consolidated value of all portfolio positions and is shown as dashed line in each of the figures. It becomes immediately apparent that the composition of household portfolios differs along the wealth distribution. Leaving aside many interesting observations about U.S. household portfolios and their changing composition over time, we make two observations on trends with respect to housing and housing debt that are key for the subsequent discussion.

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

The first observation is that households in the bottom 90 % of the wealth distribution are little diversified in their asset positions. They hold by far the largest part of their assets in housing. Other financial assets that are mostly comprised of retirement accounts are the second most important asset position today after a large increase over the past 35 years.
The second observation is that portfolios differ along the wealth distribution in leverage. The extend of leverage can be inferred from the sum of assets in excess of wealth. The top 10 % of the wealth distribution hold 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 is still little leveraged but holds mortgage debt against housing. The middle class is already substantially leveraged. Housing debt is the dominant debt component and assets exceed wealth by a factor of between 1.3 to 2. The bottom 25 % hold hardly any wealth sometimes even negative wealth, yet, this approximate zero net position hides substantial gross positions of assets and debt. Unlike for the other groups, debt comprises a substantial share of non-housing debt. Still, housing and housing debt dominate the portfolio of the bottom 25 % of the wealth distribution. Their strong leverage implies, as we will demonstrate in detail below, that house price changes will be strongly amplified in their effect on wealth.
We conclude based on these observations that middle-class households and households in the top 10 % of the wealth distribution are very differentially exposed to house price changes. While middle-class households are highly non-diversified and leveraged with respect to housing, the top 10 % are little leveraged and less exposed to house price changes due to more diversification. Before we quantify and explore the consequences of these portfolio differences for trends in wealth inequality, we look at the consequences of differences in leverage in isolation. Leverage effects are rarely studied in macroeconomic models of wealth inequality but are, as we will demonstrate, quantitatively important to understand differential wealth dynamics.

5.2 House prices and leverage

In a first step, we take a more detailed look at leverage by looking at the distribution of loan-to-value ratios within and across wealth groups. In a second step, we demonstrate how the empirically observed differences in leverage affect housing equity, and thereby, wealth over time.
Table 6 shows the shares of households having a loan-to-value ratio of zero, a loan-to-value ratio of up to 50%, between 50% and 75%, or above 75%. We make two observations

Table 6: Distribution of loan-to-value ratios by wealth groups

	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

on leverage. First, at each point in time more wealth is positively correlated with a larger fraction of households without debt and fewer households having a loan-to-value ratio of over 75%. Starting at the 75th percentile, we see that the upper middle class between the 75th and 90th percentile and the top 10 % show very similar distributions of loan-to-value ratios. Second, going from the cross-section to the time dimension, we find increasing leverage. For all wealth groups the share of households without debt is decreasing until 2007.

Household debt has been rarely studied but has recently received increasing attention after the financial turmoil of the Great Recession. We refer the interested reader for an in-depth analysis of the evolution of U.S. household debt to Kuhn, Schularick, and Steins (2016). There, we discuss in detail debt trends along the income and wealth distribution based on HHSCF data. We demonstrate that although rich households are little leveraged, they still hold most of the aggregate debt and are responsible for the increase of U.S. household debt over the past decades.

In the second step, we demonstrate the quantitative importance of the observed differences in leverage on wealth dynamics. We perform a simple simulation experiment in which we focus on the period of diverging trends in income and wealth inequality after 1970. This period also includes the unprecedented house price increase starting in the mid-90s up to the financial crisis. In appendix E, we look at an episode of falling house prices to document how the same forces that will lead to amplification of house price dynamics on wealth in the presence of rising house prices will also lead to amplification of losses when house prices are falling.

In Figure 11, we consider the value of four portfolios that all contain the same amount of equity initially invested in 1970 but carry different amounts of leverage. We consider three portfolios for housing investment: One with no leverage (red solid line), one with a leverage ratio of 50 % (blue solid line), and one with a leverage ratio of 75 % (green solid line). We consider as a fourth portfolio a portfolio of stocks (black dashed line). Given the data in table 6, we think of the housing portfolio with high leverage as the portfolio of the bottom 25 %, the portfolio with low leverage as that of the top 10 %, and the portfolio in between as the portfolio of the middle class.

Looking at the red line in Figure 11, we see that the value of the housing investment without any debt stays roughly at one until the end of the 1990s. From then onwards the value increases up to 2 in 2007 tracking house prices one-to-one. Looking at the green line, i.e. the investment with a leverage ratio of 75%, we see that the growth in value is much stronger. Between 1970 and 2007 the value increases more than sixfold. The case with a leverage ratio of 50 % represents an intermediate case with a slightly more than threefold increase. These differences in wealth dynamics highlight the importance of considering household gross positions to understand wealth dynamics over time. For consolidated portfolios these differences in wealth growth would show up as differences in returns on wealth. Benhabib and Bisin (2016) discuss return differences as one potential channel to drive a wedge between income and wealth inequality in structural models of inequality. It is important to emphasize that these differences in wealth growth are orthogonal to differences in saving rates. Conventionally defined saving rates, see for example Saez and Zucman (2014), are zero over time in all cases. All wealth changes result from pure price effects. Saez and Zucman (2014) discuss that such price effects can strongly change inequality trends relative to those implied by saving rate differences.

Higher leverage also implies higher losses in case of declining house prices. Figure E.7 in the appendix illustrates this point. It shows the evolution of the same portfolios but with investments made in 2004. As in Figure 11, we find that up to 2007 the gains are the higher, the more debt is taken out. Without any leverage the value increases by about 5%; the investment with a leverage ratio of 75% increases by almost 50%. In the course of the financial crisis, the value of the latter investment decreases to less than 40% of the initial value, meaning a loss of 60 % of initially invested equity by 2011. By contrast, the investment without debt is at the trough still at about 75 % of the initial investment. In 2013, after a recovery in house prices all portfolios recovered to 80 % of the initial investment.

It is important to empathize at this point that we do not compare returns of the different investments. Comparing returns is intricate 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 the service flow from housing is tax-exempt. Third, housing returns have to be accounted for depreciation. This constitutes an additional complication if the composition of land relative to structures in the total value of houses changed over time. For these reasons, we only consider the evolution of equity in the different portfolios.[19]

Our focus on changes in housing equity rather than returns on housing is further justified by our interest in the evolution of the stocks of wealth rather than the income or consumption flows. The differences in returns directly affect income and consumption inequality because they affect income flows and service flows from housing. It is therefore important to note that we do not argue that house price returns are larger than returns on stocks or equity. Indeed, the effects on inequality that we discuss below do not depend on the sign of the return differential but only on the *relative* changes of the return differential over time. What we demonstrate is that periods when house prices rise above trend, then wealth in portfolios with large housing exposure rises *relatively* more. While wealth concentration at the top might rise overall, the rise is mitigated during periods of rising house prices if households in the bottom of the distribution experience stronger wealth growth due to strong house price growth.

[19]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

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

5.3 House price exposure

The two previous sections highlight that middle-class households in comparison to households in the top 10 % hold highly non-diversified and highly leveraged portfolios in housing. Such portfolios lead to a high sensitivity of household wealth to changes in house prices. This section quantifies the exposure of households' wealth to house price changes over time. 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 12 shows exposure to house prices for middle-class households and households in the top 10 %. It becomes immediately apparent that the top 10 % have a much lower exposure to house prices. The wealth elasticity of the top 10% is between 0.2 and 0.4 while the elasticity of the middle class is up to 5 times higher ranging from 0.8 to 1.2. For most of the period after 1970, house price exposure is at 1 or above, meaning that a 1 % increase in house prices translates at least one-to-one in wealth growth. For the top 10 %, the same 1 % increase in house prices leads to wealth growth of only about 0.3 % over the same period. Hence, the differences in portfolio composition between the middle class and the top 10 % implies quantitatively sizable differences in the sensitivity of their wealth to house prices changes.

The house price elasticity can be further decomposed in a *diversification component* that is determined by the share of housing in assets and a *leverage component* measured by the debt-to-wealth ratio

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

The leverage component also comprises other types of debt but these parts are small relative to housing debt (see figure 10).

Figure 13 shows the two components of house price exposure for the middle class and the top 10 % over time. The left graph shows the diversification component, the right graph the leverage component. The difference in diversification is much smaller than in leverage. The share of housing in total asset of the middle class varies between 60% and 80% over time. It always stays at high levels confirming little diversification of household portfolios in this part of the wealth distribution. There is an upward trend in the diversification component of the top 10% during the two decades after 1960 leading to a stronger exposure to house prices. Still, their diversification component varies between 30 % and 35 % and remains substantially lower than for the middle class.

The leverage component is small for households in the top 10 % of the wealth distribution so that there is little amplification of the diversification component trough leverage. For the middle class, we find a much stronger amplification of the diversification component through leverage. Their leverage component increases from 20% in 1950 to stunning 80 % in 2010. This implies that the direct effect of house prices on wealth by the diversification component is further amplified by 80 % through leverage. We find that such strong exposure from low diversification and high leverage are no phenomena of episodes of rising house prices. Even in the 30 years between 1950 and 1980 with relatively stable real house prices (see Knoll, Schularick, and Steger (2016)), the middle class held about 70 % of all its assets as housing and leverage amplified any house price change by 40 %.

5.4 House prices and wealth inequality

The analysis has demonstrated that exposure of households to house prices differs substantially along the wealth distribution. This implies that house price changes will affect wealth dynamics and wealth inequality. This section quantifies the effects of changes in house prices on wealth inequality. We employ our measure of house price exposure to decompose 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 is the house price component that captures the part of wealth growth due to 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 more exposure will lead to stronger wealth growth. The second term, g_t^R, is a residual accounting for wealth growth due to all other reasons. Hence, the house price component captures a pure price effect. Differences in saving rates of households are captured in the residual component. As a first step of the decomposition, we feed in observed data for the house price component to back out the residual component over time.[20] In a second step, we construct counterfactual wealth growth rates under two scenarios. First, we construct wealth growth if house prices had stayed constant at the level of 1971 ($\Delta p_{t+1} = 0$). Wealth growth in this case is equal to the residual growth component, g_t^R. Second, we construct wealth growth if prices did change but house price exposure $\frac{H_t}{W_t}$ had not changed. This isolates, ignoring general equilibrium effects, price effects from changes in

[20] We assume one period to last three years with the first time period being 1950. As there is no survey in 1974 and and 1980, we linearly interpolate wealth and housing for these two periods.

the adjustment of household portfolios over time, for example, from an increase in leverage. For the counterfactual with constant exposure, we fix exposure, $\frac{H_t}{W_t}$, to its level of 1971.[21] Figure 14 shows the resulting counterfactual wealth changes for the middle class and the top 10 % relative to observed wealth growth. Negative numbers mean lower wealth than observed in the data and positive numbers mean more wealth than observed in the data. The left graph of Figure 14 shows the change in wealth with constant house prices. The right graph shows the counterfactual with changing house prices but constant house price exposures.

We find that effects from changes in house prices on wealth of the top 10 % are modest. Their wealth would have been even at the peak of the house price boom only 15 % lower; this reflects their low exposure to house price changes. 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 their observed wealth. This shows that middle-class households are major winners of the house price boom. Their high exposure lead to large wealth gains from the increase in house prices. On the other hand, their high exposure also explains their wealth decline after 2007 when house prices collapsed. This collapse shows up as a closing of the gap between counterfactual wealth and observed wealth. But even after the collapse of house prices, middle-class households' wealth would have been 20 % lower had house prices stayed constant at their 1971 level.

The right panel of Figure 14 shows the effect on wealth growth from changes in exposure. For both the top 10 % and the middle class there are hardly any effects until the mid-1990s mirroring both relative constant exposure but also relatively constant house prices. For the top 10 %, there is still hardly any effect from changes in exposure after 1995. For the middle class, we find 8 % higher wealth in the absence of exposure changes. This reflects their high exposure to house price changes in 1971 compared to 1995 and the increase in house prices over this period. These results show that shifts in portfolios, for example through changes in leverage, had only minor effects on wealth dynamics of the middle class. We conclude that middle-class households are the winners of the house price boom because they backed the right horse over the past decades with a strong exposure to house prices in their portfolios.

Ultimately, we are interested in the effects of house price changes on wealth inequality. Figure 15a demonstrates this effect. It compares inequality gradients for wealth from Figure 9 (blue bars) to the counterfactual without house price changes (sum of blue and white bars). We

[21] We use home equity instead of wealth if wealth of a group is negative in 1971. This only applies to households in the bottom 25 %.

see that the bottom 90 % have been the winners of rising house prices between 1971 and 2007. The wealth concentration at the top today would be much stronger had the rise in house prices not occurred. With constant house prices the inequality gradient for wealth of the top 10 % shoots up to 13, more than 4 times as steep as in the data.

As in the case where we identified the losers of rising income and wealth concentration, we can now look at who the winners of the house price increase have been. For this, we take the house price effect (white bars) from figure 15a among the bottom 90 % and compute the distribution among the bottom 90 %. This time the losers are the top 10 %. We use the equivalent construction for the distribution of gains to that of the losses ($\lambda^i_{t,t+1}$) from section 3.3. We find that the middle class has been the major winner of the house price increase. They received 73 % of the gains from rising house prices over the period from 1971 to 2007. Rising house prices prevented therefore an even stronger hollowing out of the middle class than what has been observed over this time period.

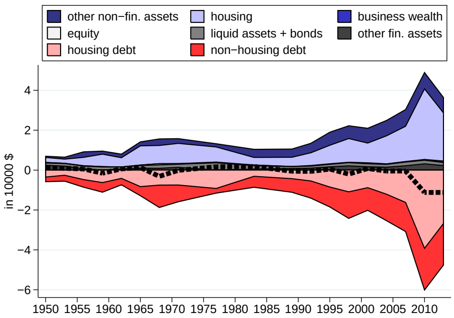
Table 7 shows the resulting wealth shares under the different scenarios over time. In 2007, the wealth share of the middle class would have been 3.2 pp. or 25 % lower without the rise in house prices. By contrast, had they kept their exposure to house prices constant in the presence of rising house prices, their wealth share in 2007 would have been 0.6 pp. larger than their observed share of 12.8 % in 2007. Without the rise in house prices, wealth concentration at the top would have been stronger. The wealth share of the top 10 % would have been at 75.8 % another 4.4 pp. larger than their observed share of 71.4 %. Adding wealth shares of the bottom 90 %, we find that their wealth share in 2013 even after the collapse in house prices is 2.6 pp. higher than what it would have been without an increase house prices over time. Such 2.6 pp. correspond to a large shift in wealth. It is more than twice the total wealth of all households in the bottom 50 % of the wealth distribution (1.2 %). This shows that price effects from the housing market have quantitatively strong distributional effects on wealth inequality over time.

Table 7: Shares in aggregate wealth

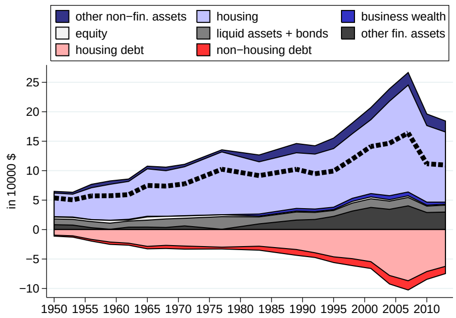
		1950	1971	1989	2007	2013
bottom 25 %	original data	0.2		0.0	0.0	-0.5
	no house price effect	0.2	0.0	-0.1	0.0	-1.3
	constant exposure	0.2		0.0	0.0	-0.5
25 -75 %	original data	15.0		14.7	12.8	10.0
	no house price effect	15.4	14.7	13.7	9.6	8.7
	constant exposure	14.7		15.0	13.4	10.5
75% - 90%	original data	16.4		17.8	15.8	15.4
	no house price effect	16.6	15.8	17.4	14.7	14.9
	constant exposure	16.4		17.9	16.2	15.8
Top 10%	original data	68.4		67.5	71.4	75.1
	no house price effect	67.9	69.6	69.0	75.8	77.7
	constant exposure	68.7		67.1	70.3	74.2

Figure 10: Wealth components in portfolios

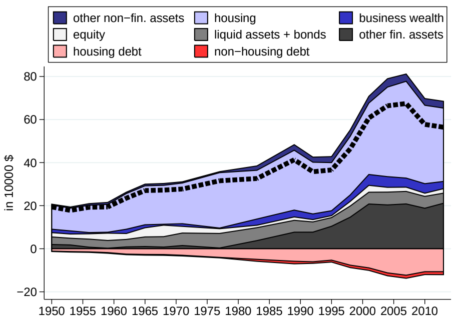
(a) <25%



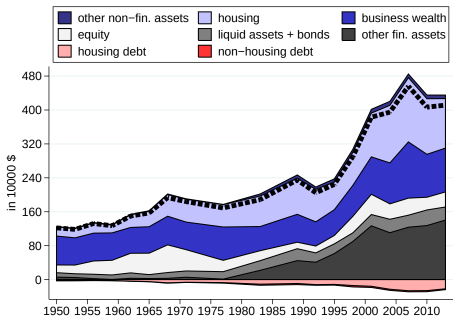
(b) 25-75%



(c) 75-90%

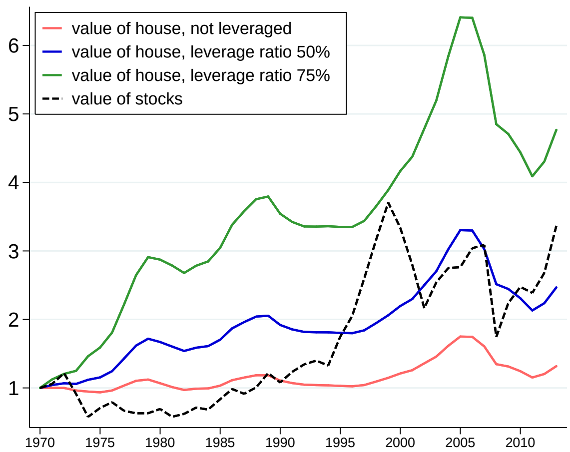


(d) top 10%



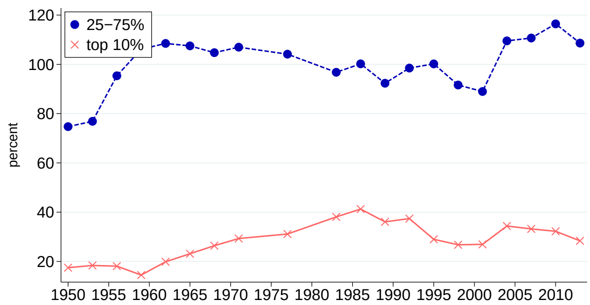
Notes: Household portfolios for four wealth groups. Blue areas show non-financial assets, gray bars financial assets, and red areas show housing and non-housing debt, respectively. The upper left graph shows portfolios of the bottom 25% of the wealth distribution, the upper right the 25 % to 75% (middle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

Figure 11: Effect of leverage on housing value



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

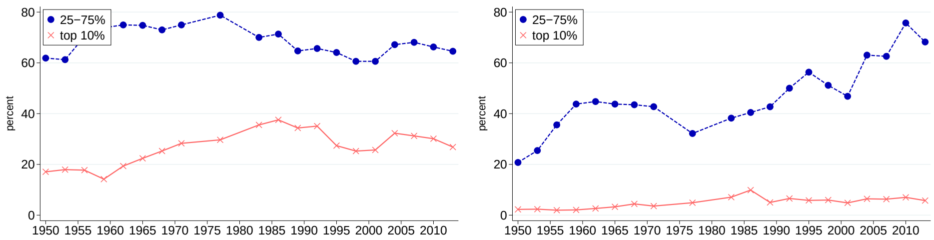
Figure 12: House price exposure $\left(\frac{\text{Housing}}{\text{Net wealth}} \times 100\right)$ by wealth groups



Notes: House price exposure for middle class households (25 % - 75 %) and households in 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.

Figure 13: Components of house price exposure by wealth groups (in %)

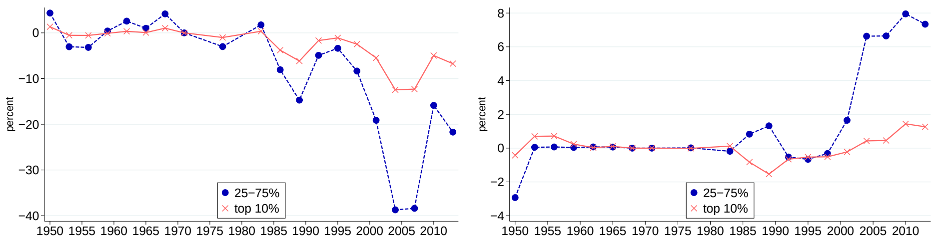
(a) Diversification ($\frac{\text{Housing}}{\text{Assets}} \times 100$) (b) Leverage ($\frac{\text{Debt}}{\text{Wealth}} \times 100$)



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

Figure 14: Price and exposure effect of wealth growth by wealth groups

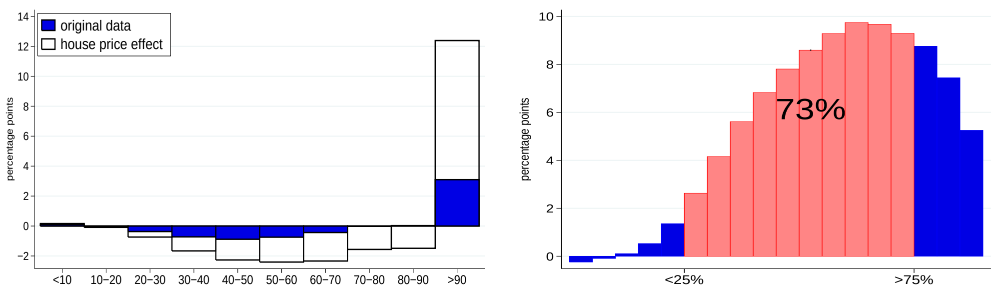
(a) house prices constant (b) house price exposure constant



Notes: Difference between realized and counterfactual wealth growth. Left panel counterfactual growth with constant house prices at 1971 level. Right panel constant house price exposure at 1971 level.

Figure 15: Inequality gradients for wealth and distribution of wealth gains (1971 - 2007)

(a) wealth gradient (b) distribution of wealth gains



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

6 Conclusions

This paper introduces newly compiled *Harmonized Historical Survey of Consumer Finances* (HHSCF) data covering the financial situation of U.S. households for the entire post-WW2 period. We show that the micro data from the HHSCF are consistent with aggregate trends for income and wealth from NIPA and FFA. We expect this data to be valuable to other researchers in the future to study important questions on the evolution of U.S. household portfolios. In this paper, we used the data to investigate the changes in the the distribution of income and wealth that occurred in the U.S. over the last two generations.

Previous research documented strong income and wealth concentration at the top but data limitations prevented a more detailed exploration of the trends in the bottom 90%. This paper completes the picture of rising income and wealth concentration by documenting how inequality changed outside the top 10% and highlight the losers in the process. Most importantly, we document a strong hollowing out of the middle class.

We also show that income inequality increased earlier and more strongly than wealth inequality. We demonstrate that differences in portfolio composition along the wealth distribution led to substantial differences in gains from the house price boom of the 1990s and 2000s. These gains mostly concentrated in the middle class had a mitigating effect on the rise in wealth inequality. This effect reversed with the drop in house prices during the financial crisis. Our paper suggests that a deeper understanding of household portfolio allocation and the distributional consequences of asset price movements are essential for the analysis of wealth inequality. We provide the empirical foundation for future explorations of this topic.

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A Data details

A.1 Sample size

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

Table A.1: Sample size across survey years

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

A.2 Imputation of missing variables

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

In order to determine which adjacent survey years are most suitable for imputing missing values we implement the following optimization before imputation. First, we determine all income, asset, debt, and demographic variables that are available in the year for which the variable is missing. For each combination of adjacent years, we then construct a subset of variables that are both available in the year with missing values and 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.[22]Finally, we calculate the R^2 for each regression. This is used as a measure of how well the combination of adjacent years is able to predict the missing variable. The combination with the highest R^2 is chosen for the imputation.

Tables A to F 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 Inequality gradient and taxation

We use in the main text the change in income and wealth shares as a measure for the change in income and wealth inequality. This measure can be derived from the following though experiment. We focus for illustration on the case of the change in income inequality. First, we group households in N groups where each group is of size p_i so that $\sum_{i=1}^{N} p_i = 1$. A tax authority now collects a share τ of income from each group i. The tax authority has to run a balanced budget and uses a transfers schedule $\{\delta_i\}_{i=1}^{N}$ to transfer all tax revenues back to households. If we denote average income of households in group i at time t by $y_{i,t}$ and average income of all households at time t by $\bar{y}_t$, then the balanced budget requirement is $\sum_{i=1}^{N} y_i p_i \tau = \tau \bar{y}_t = \sum_{i=1}^{N} \delta_i p_i$. To compare how much inequality has changed over time, we ask what the regressivity/progressivity of the transfer schedule $\{\delta_i\}_{i=1}^{N}$ has to be to implement the distribution of income shares at $t+1$ starting from income shares at t. For now, we are looking at a case without income growth but the extension is straightforward as shown below.

We denote the share of household group i in total income at time t by $x_{i,t}$. It holds that $x_{i,t} = p_i \frac{y_{i,t}}{\bar{y}_t}$. Each household pays taxes $\tau y_{i,t}$ in t so that after-tax income is $\tilde{y}_{i,t} = (1-\tau) y_{i,t}$.

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

As the tax shares are constant across households, the income shares in after-tax income are not altered. Total tax revenues will be redistributed so that the budget of the tax authority is balanced. Using the assumption that aggregate income stays constant, i.e. $\bar{y}_t = \bar{y}_{t+1} = \bar{y}$, the change in income shares from t to $t+1$ can be written in the following way:

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

where the last expression on the right-hand side is just the net transfer from the redistribution system as a share of average income $\bar{y}$ multiplied by the population share. With constant population shares $p_i = \frac{1}{N}$ we can just look at the change in income shares to learn about the implied regressivity/progressivity of the redistribution scheme to assess if the change in inequality was larger or smaller.
Figure B.1 shows a stylized example of a change in inequality of two variables for example income and wealth. Both lines show the change in income and wealth shares for the example of income and wealth changes for the different groups $i = 1, \ldots, N$ connected by a continuous function. Both functions are positively sloped implying that we saw an increase in inequality for both variables. A positive slope means that income and wealth shares at the top of the distribution increased while they decreased at the bottom of the distribution. We also see that the red solid line has a steeper slope compared to the blue dashed line. In this case, we will say that inequality in the variable underlying the red line increased by more than in the variable underlying the blue line. If income inequality had not changed between t and $t+1$ the distribution would be a flat line equal to zero.
It is straightforward to include income and wealth growth. In this case, we write the share a household has in an in- or decrease of aggregate income in the following way:

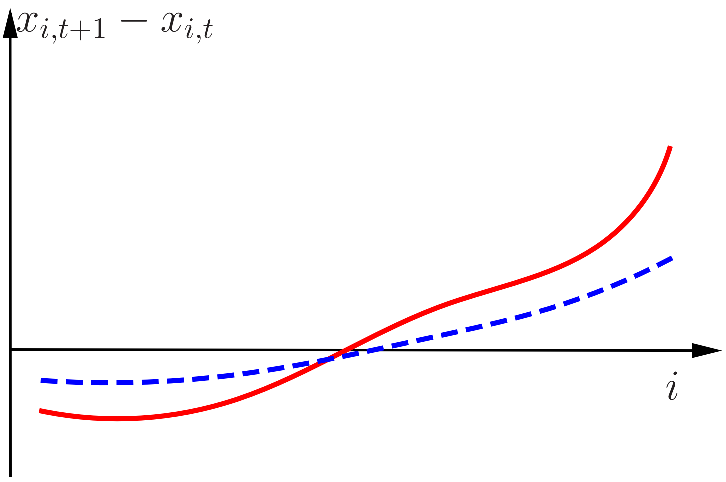
$$\Delta^i_{t,t+1} = \frac{x_{i,t+1}\bar{y}_{t+1} - x_{i,t}\bar{y}_t}{\bar{y}_{t+1} - \bar{y}_t} - x_{i,t} = (x_{i,t+1} - x_{i,t})\frac{\bar{y}_{t+1}}{\bar{y}_{t+1} - \bar{y}_t}$$

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

C Comparison to the capitalization approach

In pioneering work, Saez and Zucman (2014) construct a measure of net wealth based on a capitalization technique using income data from tax records and aggregate data from the

Figure B.1: Stylized inequality change



Flow of Funds. In a first step, Saez and Zucman (2014) use information on individual capital income from the tax data and calculate aggregate capital income from different asset categories, such as bonds and corporate equity. In a second step, they use the corresponding asset category of the Flow of Funds and divide its aggregate value by the respective aggregate income obtained from the tax data. This factor is called capitalization factor. Asset positions of individuals are then constructed by multiplying the individual income components of the tax data with this factor. The approach matches by construction the aggregate data from the Flow of Funds but has to make strong assumptions on the stock-flow relationship between assets and incomes. While ingenious, there are a number of drawbacks of this method.
First, housing wealth, which accounts for a large share of household wealth, can only be estimated inaccurately so that the value of housing is inferred by using information on property taxes. Similar problems exist with respect to housing debt which Saez and Zucman (2014) estimate by employing information on interest payments, other important information for estimating current mortgage debt, for example the maturity or the initial level of the mortgage, is not known. Moreover, wealth components that do not generate direct income flows like retirement accounts with retained earnings can only be estimated using survey data. Asset classes such as non-corporate equity that may from time to time generate negative income flows violate the assumption of a close stock-flow relationship inherent in the multiplier method. Fagereng, Guiso, Malacrino, and Pistaferri (2016) demonstrate using Norwegian data that already small correlations between assets and income can lead to overstating wealth inequality using the capitalization method and Saez and Zucman (2014)

already discuss themselves how to improve wealth inequality estimates relative to their capitalization approach. They discuss the value of homes, employer-provided pensions, business equity, and mortgages. Our data makes progress on several of these suggestions. We observe the value of homes and mortgages that match aggregate numbers from the Flow of Funds so that we provide reliable information on two important components of the household balance sheets that are hard to measure based on the capitalization method. We also have information on business equity and retirement accounts. For these assets differences to the Flow of Funds arises. For business equity measurement concepts are different. While the SCF reports market values the flow of funds reports book values for non-incorporated businesses. Furthermore, we observe in our data asset and debt positions directly so that we do not have to impose a correlation between assets stocks and income flows. The assumption of uniform returns is at the center of the concerns raised by Fagereng, Guiso, Malacrino, and Pistaferri (2016) regarding the capitalization method. Kuhn and Rıos-Rull (2016) report very low correlations between wealth and capital income even for very restrictive definitions of financial wealth. Similarly, debt and "no income" assets like housing can only be imputed under the capitalization method based on itemized deductions and property taxes. The SCF data has the advantage of observing these positions directly.

Using tax data has the advantage that the top of the income distribution is captured very well. Arguably, income generating assets constitute a larger fraction of the household portfolio at the top of the distribution. The capitalization method is therefore likely to provide a good estimate when it comes to the very right tail of the wealth distribution. We consider our approach therefore as complementary to the capitalization approach, in particular, due to its strength regarding the lower part of the distribution.

D Income and wealth inequality

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

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

Our discussion of inequality trends has focused mainly on changes in income and wealth shares. Gini coefficients and quantile ratios provide alternative ways to study trends in inequality. We relegate a detailed discussion of inequality trends based on these statistics to appendix D. There we also discuss the effects of demographic changes on observed inequality. We apply an approach proposed by Fortin, Lemieux, and Firpo (2011) to adjust Gini coefficients for demographic changes over time. We also report Gini coefficients after adjusting income and wealth using OECD equivalent scales. Our findings can be summarized as follows.

Gini coefficients confirm the secular rise in inequality for both income and wealth. Unlike income or wealth shares, the Gini coefficient does not provide information about how a particular part of the distribution has changed but summarizes inequality along the entire distribution in a single number. As discussed in Kuhn and Rıos-Rull (2016), it does so in a way that is particularly sensitive to changes in the middle of the distribution. The observed large changes in the Gini coefficients are therefore consistent with a hollowing out of the middle class that we document.

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

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

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

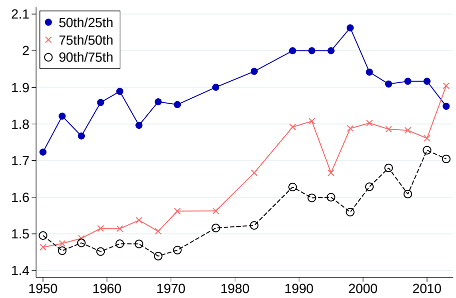
As an alternative to the Gini coefficient, income and wealth shares have been popularized by the works of Piketty and Saez (2001) and Saez and Zucman (2014) that emphasize the concentration of income and wealth at the top of the distribution. We discuss income and wealth shares in section 3.1. Unlike the Gini coefficient, income or wealth shares of particular groups contain information about single points on the Lorenz curve. The Gini coefficient collapses all information of the Lorenz curve in a single number. It includes therefore information about the entire distribution but loses the conciseness regarding single parts of the distribution. Below, we will take a granular look at the distributional changes among the bottom 90 % by looking at changes in income and wealth shares. Before, we demonstrate that the HHSCF data is consistent with the income and wealth concentration at the top in level and trend.

D.2 Changes in quantile ratios

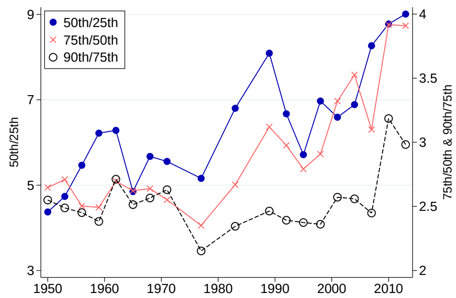
The changes in income and wealth shares provide a view from one angle to look at changes of income and wealth inequality among the bottom 90 %. In Figure D.2, we look at quantile ratios of the income and wealth distribution to provide an alternative view at distributional changes over time. Looking at income in figure D.2a, we find the same two episodes of changes in income inequality that we identified before. The first epsiode during the 1970s and 1980s shows rising inequality along the entire income distribution with all three quantile ratios increasing. The second episode starting in the 1990s, paints again a distinct picture on the developments of inequality along the income distribution. Income inequality at the bottom, the 50-25 ratio, decreased. This decrease of income inequality at the bottom accelerates during the 2000s and continues until 2013. This finding matches the rising income share of the bottom 25 % from table 4. During the same episode, the 75-50 ratio is constant and only increases between 2010 and 2013. The 90-75 ratio shows an upward trend starting in the 1990s and lasting until 2013. This matches the observation from above of a declining income share of the middle class and a hollowing out of the middle class during the second episode of rising income inequality.
Looking at wealth in figure D.2b, we find decreasing wealth inequality until the 1980s. Afterwards and until 2013, wealth inequality increases in line with our findings on wealth shares. The 50-25 ratio is much higher than the 75-50 ratio due to the low level of wealth at the bottom quartile but in relative terms the increase of the 75-50 ratio and the 50-25 ratio is similar over the period from the 1980 to 2013. A large increase in inequality happens from 2007 to 2013 during the financial crisis in line with our previous findings. We conclude that the findings on the shifts in wealth shares and quantile ratios paint very similar pictures

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

(a) Income



(b) Wealth



Notes: Left panel: Quantile ratios of income for all U.S. households from 1950 to 2013. Right panel: Quantile ratios of wealth for all U.S. households from 1950 to 2013. Blue lines show 50-25 ratios (left axis). Red lines show 75-50 ratios and black lines 90-75 ratios (right axis).

about the rising wealth inequality among the bottom 90 %.

Table D.2: 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 in case of the income gini the top 1 and 10%, respectively, of the income distribution and in case of wealth from the wealth distribution.

Table D.3: Quantile ratios of income (x100)

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

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

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

D.3 Demographic change

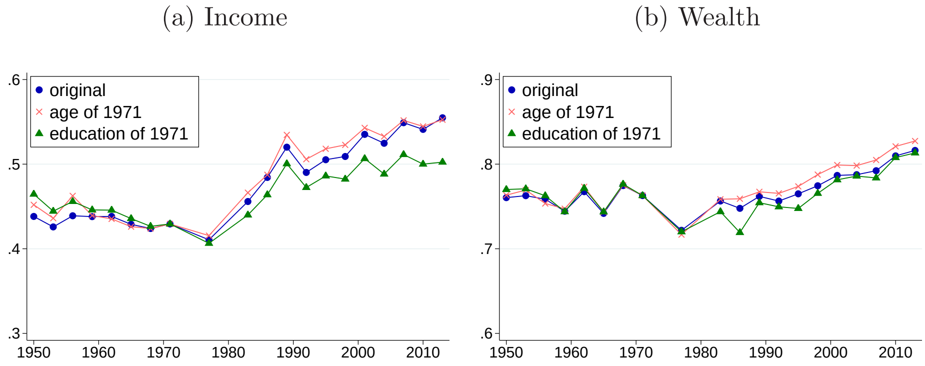
The HHSCF data provides detailed information about the demographic characteristics of households. The U.S. population has undergone large secular changes in its household composition in terms of educational attainment, age, and household size. In this section, we explore how much these changes can account for in observed inequality trends. We use the approach proposed by Fortin, Lemieux, and Firpo (2011) to adjust for demographic changes over time. This is done by pooling data from the basis year with each survey year and calculate the probability of being surveyed in the basis year by running a probit regression. We use 1971 as our basis year. As explanatory variables, we include age, educational attainment, the number of adults and children in a household, and race of the household head. Next, we use this probability to re-weight observations in other survey years by multiplying the survey weights with the probability. We then compute counterfactual inequality measures where we fix demographic characteristics to the basis year.[23] Here, we focus on Gini coefficients and only consider counterfactuals where we fix educational attainment and age structure over time. Figure D.3 shows the Gini coefficients of income and wealth for three cases. The blue line with circles shows the original data, the red line with crosses shows the Gini coefficient for a counterfactual where we fix the population shares across age groups, and the green line with triangles shows the Gini coefficients if we fix educational attainment at the 1971 shares. We find that population aging had a negligible effect on income and wealth inequality. The Gini coefficients are only slightly lower than in the original data. Looking at the counterfactual with constant educational attainment, we find that changes in educational attainment lead to an increase in both income and wealth inequality. This is in line with a rising college wage premium since the 1980s. Our decomposition shows that exploring educational choice and rising returns to college education will be key dimensions when studying trends in income and wealth inequality.

Besides changes in educational attainment a second secular trend has been the decrease of average household size in the U.S. The average number of persons per household declined in

[23] 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 D.3: Gini coefficients of income and wealth accounting for demographic change

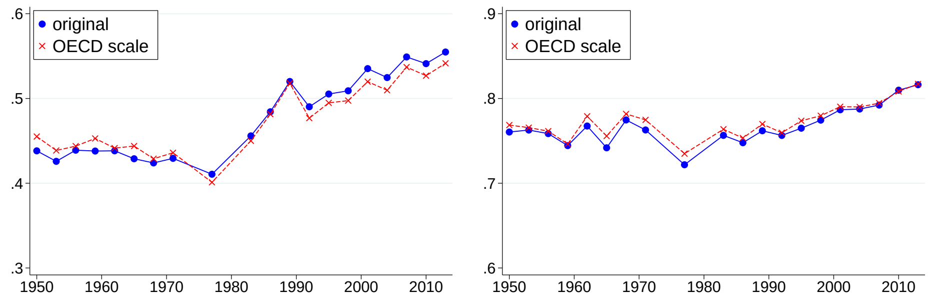


Notes:

the U.S. between 1949 and 2013 from 3.42 to 2.54 according to U.S. Census data. The number of household members 18 and older declined from 2.33 to 1.93 over the same period. Given that HHSCF data is at the household level, changes in household size can potentially affect measures of household-level inequality. In a second step, we therefore consider the effects of changes in household size that took place over past decades on inequality. We do this by adjusting household-level income and wealth by household adult-equivalent members. We use the OECD equivalent scale. Figure D.4 reports Gini coefficients for income and wealth with and without adjustment for household size. We find that inequality for adult-equivalent income is slightly higher up to 1980 and shows a slightly declining trend for the three decades between 1950 to 1980. Starting from 1992, inequality for adult-equivalent income is lower but shows the same trend as unadjusted household income. For wealth, there is a small divergence of inequality when looking at adult-equivalent wealth for the period from the mid-1960s to the mid-1980s. Although there have been large changes in the size of U.S. households, adjusting for these changes did not alter the conclusions about trends of income and wealth inequality over the past decades. This matches results from Kuhn and Ríos-Rull (2016) who find that adjusting for household size in the post-1989 SCFs has only a minor effect on inequality.

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

(a) Income (b) Wealth



Notes:

Figure D.5: Shares in aggregate income and wealth

(a) Income (b) Wealth

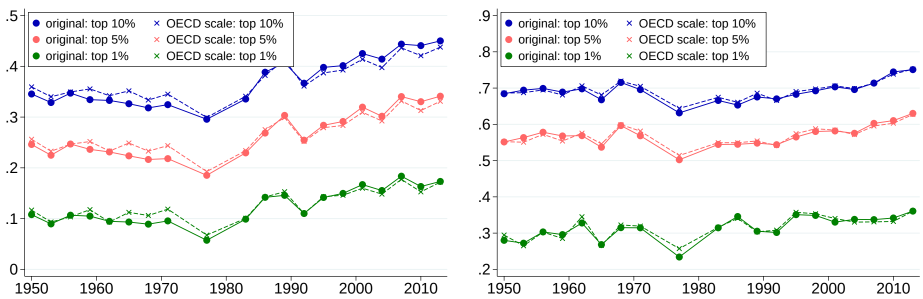
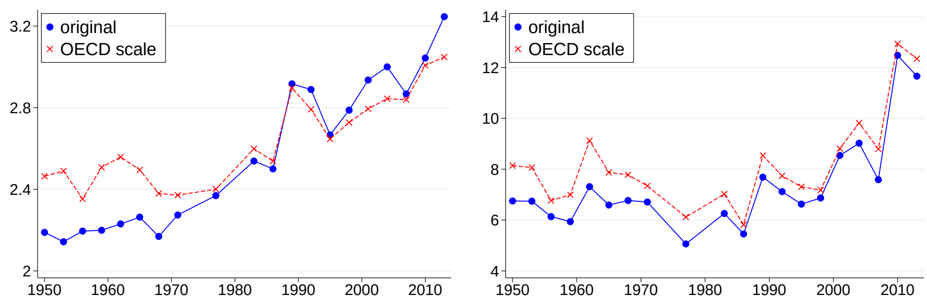


Figure D.6: Ratio of 90th to 50th percentile

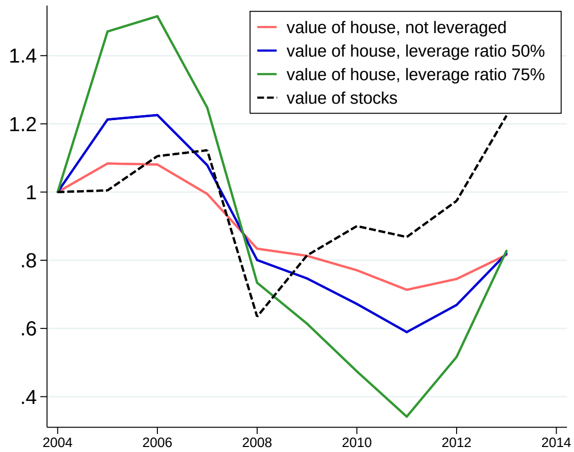
(a) Income (b) Wealth



E Leverage effect during the financial crisis

Figure E.7 shows the leverage effect in case of an investment done in 2004. In figure 11 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 2004 in housing is only worth 80 cents.

Figure E.7: Effect of leverage on housing value



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

Online Appendix
Not for Publication

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

I Information on imputation of missing variables

Tables A to F provide the information used to imputed missing variables. See section A.2 from appendix for further details.

Table A: Imputation of income variables

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

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

Table B: Imputation of financial variables

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

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

Table C: Imputation of pension wealth

survey year	years in imputation	R^2
1948	SFCC1962	38
1949	SFCC1962	43
1950	SFCC1962	42
1951	SFCC1962	45
1952	SFCC1962	42
1953	SFCC1962	40
1954	SFCC1962	45
1955	SFCC1962	41
1956	SFCC1962	41
1957	SFCC1962	45
1958	SFCC1962	42
1959	SFCC1962	42
1960	SFCC1962	37
1961	SFCC1962	38
1962	SFCC1962	37
1963	SFCC1962	37
1964	SFCC1962	34
1965	SFCC1962	38
1966	SFCC1962	31
1967	SFCC1962	36
1968	SFCC1962	39
1969	SFCC1962	39
1970	SFCC1962	40
1971	SFCC1962	35
1977	SFCC1962	38

Notes: The SFCC 1962 is not used for the imputation by construction. Information on pension wealth is available both in the SFCC 1962 and in the SCF 1983. However, using variables available in the respective survey resulted in a higher R^2 for the SFCC 1962.

Table D: Imputation of cash value of life insurance

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

Notes: The SFCC 1962 is not used for the imputation by construction. Information on the cash value of a life insurance is available both in the SFCC 1962 and in the SCF 1983. However, using variables available in the respective survey resulted in a higher R^2 for the SFCC 1962.

Table E: Imputation of non-financial variables

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

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

Table F: Imputation of debt variables

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

II Time series on income and wealth shares

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

Table G: 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 H: 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 on portfolio composition

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

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

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

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

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

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

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

IV Additional results on house price exposure

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

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

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

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

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

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

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

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

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

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

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

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

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