Income and Wealth Inequality in America, 1949-2016*

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Abstract: This paper introduces a new long-run data set based on archival data from historical waves of the Survey of Consumer Finances. The household-level data allow us to study the joint distribution of household income and wealth since 1949. We expose the central importance of portfolio composition and asset prices for wealth dynamics in postwar America. Asset prices shift the wealth distribution because the composition and leverage of household portfolios differ systematically along the wealth distribution. Middle-class portfolios are dominated by housing, while rich households predominantly own business equity. An important consequence is that the top and the middle of the distribution are affected differentially by changes in equity and house prices. Housing booms lead to substantial wealth gains for leveraged middle-class households and tend to decrease wealth inequality, all else equal. Stock market booms primarily boost the wealth of households at the top of the distribution. This race between the equity market and the housing market shaped wealth dynamics in postwar America and decoupled the income and wealth distribution over extended periods. The historical data also reveal that no progress has been made in reducing income and wealth inequalities between black and white households over the past 70 years, and that close to half of all American households have less wealth today in real terms than the median household had in 1970.

JEL: D31, E21, E44, N32

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1 Introduction

We live in unequal times. The causes and consequences of widening disparities in income and wealth have become a defining debate of our age. Recent studies have made major inroads into documenting trends in either income or wealth inequality in the United States (Piketty and Saez (2003), Kopczuk *et al.* (2010), Saez and Zucman (2016)), but we still know little about how the joint distributions of income and wealth evolved over the long run. This paper fills this gap.

The backbone of this study is a newly compiled dataset that builds on household-level information and spans the entire U.S. population over seven decades of postwar American history. We unearthed historical waves of the Survey of Consumer Finances (SCF) that were conducted by the Economic Behavior Program of the Survey Research Center at the University of Michigan from 1947 to 1977. In extensive data work, we linked the historical survey data to the modern SCFs that the Federal Reserve redesigned in 1983.[1] We call this new resource for inequality research the SCF+.

The SCF+ complements existing datasets for long-run inequality research that are based on income tax and social security records, but also goes beyond them in a number of important ways. Importantly, the SCF+ is the first dataset that makes it possible to study the joint distributions of income and wealth over the long run. As a historical version of the SCF, it contains the same comprehensive income and balance sheet information as the modern SCFs. This means that we do not have to combine data from different sources or capitalize income tax data to generate wealth holdings. Moreover, the SCF+ contains granular demographic information that can be used to study dimensions of inequality —such as long-run trends in racial inequality— that so far have been out of reach for research.

Our analysis speaks to the quest to generate realistic wealth dynamics in dynamic quantitative models (Benhabib and Bisin (2016), Fella and De Nardi (2017), Gabaix *et al.* (2016), Hubmer *et al.* (2017)). A key finding of our paper is that a channel that has attracted little scrutiny so far has played a central role in the evolution of wealth inequality in postwar America: asset price changes induce large shifts in the wealth distribution. This is because the composition and leverage of household portfolios differ systematically along the wealth distribution. While the portfolios of rich households are dominated by corporate and non-corporate equity, the portfolio of a typical middle-class household is highly concentrated in residential real estate and, at the same time, highly leveraged. These portfolio differences

[1] A few studies such as Malmendier and Nagel (2011) or Herkenhoff (2013) exploited parts of these data to address specific questions, but no study has attempted to harmonize modern and historical data in a consistent way. Note that we leave the post-1983 modern SCF unchanged. Its value for studying distributional trends has been demonstrated in recent contributions by Bricker *et al.* (2016) and Wolff (2017).

are persistent over time. We document this stylized fact and expose its consequences for the dynamics of the wealth distribution.

An important upshot is that the top and the middle of the distribution are affected differentially by changes in equity and house prices. Housing booms lead to substantial wealth gains for leveraged middle-class households and tend to decrease wealth inequality, all else equal. Stock market booms primarily boost the wealth of households at the top of the wealth distribution as their portfolios are dominated by listed and unlisted business equity. Portfolio heterogeneity thus gives rise to a race between the housing market and the stock market in shaping the wealth distribution. We show that over extended periods in postwar American history, such portfolio valuation effects have been predominant drivers of shifts in the distribution of wealth.

A second consequence of portfolio heterogeneity is that asset price movements can introduce a wedge between the evolution of the income and wealth distribution. For instance, rising asset prices can mitigate the effects that low income growth and declining savings rates have on wealth accumulation. Looking at income and wealth growth of different parts of the wealth distribution, we find such a divergence played a prominent role in the four decades before the financial crisis. The middle class (50th-90th percentile) rapidly lost ground to the top 10% with respect to income but, by and large, maintained its wealth share thanks to substantial gains in housing wealth. The SCF+ data show that incomes of the top 10% more than doubled since 1971, while the incomes of middle-class households (50th-90th percentile) increased by less than 40%, and those of households in the bottom 50% stagnated in real terms. In line with previous research, the SCF+ data thus confirm a strong trend toward growing income concentration at the top (Piketty and Saez (2003); Kopczuk *et al.* (2010)). However, when it comes to wealth, the picture is different. For the bottom 50% of the wealth distribution, wealth doubled between 1971 and 2007 despite zero income growth. For the middle class and for the top 10%, wealth grew at approximately the same rate, rising by a factor of 2.5. As a result, wealth-to-income ratios increased most strongly for the bottom 90% of the wealth distribution. That the SCF+ data reach back to the 1950s and 1960s, that is, before the income distribution started to widen substantially, makes it possible to expose these divergent trends.

Importantly, price effects account for a major part of the wealth gains of the middle class and the lower middle class. We estimate that between 1971 and 2007, wealth of the bottom 50% grew by 97% only because of price effects — essentially a doubling of wealth without any (active) saving. For the bottom 50%, virtually all wealth growth over the 1971-2007 period came from higher asset prices, and even in the middle and at the top of the distribution, asset price induced gains accounted for close to half of total wealth growth, comparable to the contribution of savings flows. From a political economy perspective, it is conceivable that the strong wealth gains for the middle and lower middle class helped to dispel discontent about stagnant incomes. They may also help to explain the disconnect between trends in income and consumption inequality that have been the subject of some debate (Attanasio and Pistaferri, 2016). When house prices collapsed in the 2008 crisis, the same leveraged portfolio position of the middle class brought about substantial wealth losses, while the quick rebound in stock markets boosted wealth at the top. Relative price changes between houses and equities after 2007 have produced the largest spike in wealth inequality in postwar American history. Surging post-crisis wealth inequality might in turn have contributed to the perception of sharply rising inequality in recent years.

Thanks to its demographic detail, we can also exploit the SCF+ to shed new light on the long-run evolution of racial inequalities. The SCF+ covers the entire postwar history of racial inequality and spans the pre- and post-civil rights eras. With information on income and wealth at the household level, we do not only complement recent studies of the long-run evolution of racial wage inequality (Bayer and Charles, 2017), but we add new dimensions. Most importantly, the SCF+ data offer a window on long-run trends in racial *wealth inequality* that have so far remained uncharted territory. We expose persistent and, in some respects, growing inequalities between black and white Americans. Income disparities today are as big as they were in the pre-civil rights era. In 2016, black household income is still only half of the income of white households. The racial wealth gap is even wider and is still as large as it was in the 1950s and 1960s. The median black household persistently has less than 15% of the wealth of the median white household. We also find that the financial crisis has hit black households particularly hard and has undone the little progress that had been made in reducing the racial wealth gap during the 2000s (Wolff, 2017). The overall summary is bleak. The typical black household remains poorer than 80% of white households.

Related literature: Research on inequality has become a highly active field, and our paper speaks to a large literature. Analytically, the paper is most closely related to recent contributions emphasizing the importance of heterogeneity in returns on wealth for the wealth distribution. On the empirical side, this literature has mainly worked with European data, while our paper addresses the issues with long-run micro data for the United States. Bach *et al.* (2016) study administrative Swedish data. With regard to heterogeneity in returns along the wealth distribution, Fagereng *et al.* (2016) use administrative Norwegian tax data and document substantial heterogeneity in wealth returns and intergenerational persistence. For France, Garbinti *et al.* (2017) analyze the long-run distribution of wealth as well as the role of return and savings rate differentials. In the American context, Wolff (2016) demonstrates the sensitivity of middle-class wealth to the house price collapse in the Great Recession, and his earlier research (Wolff, 2002) is closely related as it discusses the sensitivity of the U.S. wealth distribution to asset price changes. In the policy debate, the role of asset prices for the wealth distribution has also been discussed, for example, by Yellen (2014). Moreover, Kuhn and Ríos-Rull (2016) argue that housing wealth plays an important role for the wealth distribution.

With respect to data production and the emphasis on long-run trends, our paper complements the pioneering work of Piketty and Saez (2003) and Saez and Zucman (2016), as well as the work of Kopczuk *et al.* (2010). Our paper also speaks to the more recent contribution of Piketty *et al.* (2016), who combined micro data from tax records and household survey data to derive the distribution of income reported in the national accounts. Saez and Zucman (2016) estimate the wealth distribution by capitalizing income flows from administrative data. This approach is advantageous for households at the top of the distribution that hold a significant part of their wealth in assets that generate taxable income flows. Yet many assets in middle-class portfolios do not generate taxable income flows — housing being a prime example. The SCF+ provides long-run data on all sources of income (including capital and non-taxable income) as well as the entire household balance sheet with all assets (including residential real estate) and liabilities (including mortgage debt). Playing to the strength of our data, our paper focuses on the bottom 90% of households, not on changes in inequality at the very top. We also connect our paper to the recent paper by Bricker *et al.* (2016) that demonstrates the potential of the modern SCFs to study distributional trends even at the top, and discuss the differences between the more advanced modern SCF and the historical SCF waves.[2]

Theoretical work modeling the dynamics of wealth inequality has grown quickly. A common thread is that models based on labor income risk alone typically produce too little wealth concentration and cannot account for substantial shifts in wealth inequality that occur over short time horizons. Our paper speaks to recent work by Benhabib and Bisin (2016), Benhabib *et al.* (2017), and Gabaix *et al.* (2016), who discuss the importance of heterogeneous returns for the wealth distribution and its changes over time. In another recent paper, Hubmer *et al.* (2017) use variants of incomplete markets models to quantify the contribution of different drivers for rising wealth inequality and point to return differences and portfolio differences as a neglected line of research. Our findings support the emphasis on asset returns.[3] Glover

[2]Work in labor economics often relies on data from the CPS. Examples are Gottschalk and Danziger (2005) and Burkhauser *et al.* (2009). Most relevant for our work is Burkhauser *et al.* (2012), who show that trends in income inequality derived from the CPS are similar to the inequality series based on tax data in Piketty and Saez (2003). They also provide a detailed discussion of the conceptual differences in measuring income in the tax and CPS data.

[3]See also Castaneda *et al.* (2003) for a benchmark model of cross-sectional income and wealth inequality and Kaymak and Poschke (2016) for another recent attempt to explain time trends.

et al. (2017) quantify the welfare effects of wealth changes resulting from portfolio differences and asset price changes during the Great Recession. Fella and De Nardi (2017) survey the existing literature and discuss different models from the canonical incomplete market model to models with intergenerational transmission of financial and human capital, rate of return risk on financial investments, and more sophisticated earnings dynamics.

Outline: The paper is divided into three parts. The first part documents the extensive data work that we have undertaken over the past years to construct the SCF+ and what we did to align the historical and modern SCF data. The second part then exploits the new data and presents stylized facts for long-run trends in income and wealth inequality, including racial inequalities, that emerge from the SCF+. The third part studies the joint distributions of income and wealth and exposes the central importance of asset price changes for the dynamics of the wealth distribution in postwar America. The last section concludes.

2 Constructing the SCF+

The SCF is a key resource for research on household finances in the United States. It is a triennial survey, and the post-1983 data are available on the website of the Board of Governors of the Federal Reserve System[4]. Yet the first consumer finance surveys were conducted as far back as 1947. The early SCF waves were directed by the Economic Behavior Program of the Survey Research Center of the Institute for Social Research at the University of Michigan. The surveys were taken annually between 1947 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, Michigan.

For this paper, we linked the archival survey data to the post-1983 SCF. To do this, we harmonized and re-weighted the historical data to make them as compatible as possible with the modern SCF. Note that we do not adjust the post-1983 SCF data. On the contrary, we take the advanced survey design of the modern SCF as the benchmark and adjust the historical surveys so that they come as close as possible to this benchmark. We discuss in detail below and in the Appendix B how we proceeded and how consistent the historical and modern data are, especially when it comes to the top of the distribution. The combined data set adds four decades of household-level micro data, effectively doubling the time span covered by the SCF. As a new resource for long-run research on household finances, we refer to this historically extended version of the SCF as the *SCF+*.

The SCF+ complements the data sets for long-run trends in the distribution of income and

[4] `https://www.federalreserve.gov/econres/scfindex.htm`. See Bricker *et al.* (2017) for results from the 2017 SCF data and for general information on the SCF data and sampling.

wealth in the U.S. that Piketty and Saez (2003) and Saez and Zucman (2016) have compiled using administrative tax data. Other researchers have used the 1962 Survey of Financial Characteristics of Consumers (SFCC) that provides a snapshot of the financial conditions of U.S. households in 1962 (Wolff, 2017).[5] But so far the income tax data constitute the only data set that covers the entire post-war period on a continuous basis. The SCF+ provides an opportunity to corroborate and improve our understanding of postwar trends in the distribution of income and wealth.

For future researchers, it is important to have a good understanding of the relative strengths and weaknesses of the SCF+ for inequality research. A key advantage of the long-run tax data is their compulsory collection process resulting in near-universal coverage at the top of the distribution, whereas survey data have to cope with non-response of rich households. This being said, the tests carried out in a recent paper by Bricker *et al.* (2016) show that the modern SCF with its combined administrative and survey data methodology also captures households at the very top of the distribution.

The strengths of the administrative data in terms of accuracy and coverage at the top of the distribution also have to be weighed against the attractive properties of survey data in other respects. Most importantly, the survey data contain direct measurements of assets and debt plus the information to stratify households by demographic characteristics. The survey data also cover people who do not file taxes, and the unit of analysis is the household, not the tax unit. This structure is in line with economic models in which the household is the relevant unit for risk and resource sharing.[6]

Moreover, specific challenges arise when income tax data are used to construct wealth estimates. The capitalization method of Saez and Zucman (2016) relies on observable income tax flows that are capitalized to allocate aggregate wealth positions in the cross section. While ingenious as an approach, some gaps remain because a substantial part of wealth does not generate taxable income flows and has to be imputed (often on the basis of survey data). The key asset here is owner-occupied housing as well as its corresponding liability, mortgage debt. Pension assets also do not generate taxable income flows, and unrealized capital gains do not show up on tax returns until they are realized.

In the estimates of Saez and Zucman (2016), about 90% of the total wealth outside the top 10% has to be imputed. And even for the top 10%, the share of imputed wealth stands at 40%. Saez and Zucman (2016) correctly stress that the exact distribution of these assets is of

[5]For the construction of the SCF+, we have set the distributional information from the 1962 SCF against the SFCC data and generally found the differences to be small. More details below.

[6]In 2012, there were about one-third more tax units (160.7 million) than households (121.1 million) in the United States. Bricker *et al.* (2016) argue that relying on tax units could lead to higher measured income concentration toward the top of the distribution.

minor importance for the very top of the wealth distribution. Yet for researchers interested in long-run distributional changes outside the very top, these are binding constraints that the SCF+ overcomes. The capitalization method also has to derive returns for individual asset classes from a combination of capital income from tax data and aggregate estimates from the flow of funds. Kopczuk (2015) provides an illustration of how this method can lead to an upward bias of wealth concentration during low interest rate periods, and the recent paper by Bricker *et al.* (2018) quantifies this bias and discusses in detail other conceptual differences between survey estimates and estimates based on tax data.

2.1 Variables in the SCF+

The variables covered in the historical surveys of the SCF+ correspond to those in the contemporary SCF, but the exact wording of the questions can differ from survey to survey. Some variables are not continuously covered, so we have to impute values in some years. We explain the imputation procedure in the following section. Our analysis focuses on the four variables that are of particular importance for household finances: income, assets, debt, and wealth. In the analysis, we use all data and abstain from any sample selection. We adjust all data for inflation using the consumer price index (CPI) and report results in 2016 dollars. Table 2 provides a general overview over variables and years when imputation is used. Online Appendix A.1 contains additional information.

Income: We construct total income as the sum of wages and salaries, income from professional practice and self-employment, rental income, interest, dividends, transfer payments, as well as business and farm income. Note that we do not include imputed rental income of homeowners in the baseline, but we provide additional results in the Appendix.

Assets: The historical SCF waves contain detailed information on household assets. We group assets into the following categories: liquid assets, housing, bonds, stocks and business equity, mutual funds, the cash value of life insurance, defined-contribution retirement plans[7], other real estate, and cars. Liquid assets comprise the sum of checking, savings, call/money market accounts, and certificates of deposits. By contrast, Social Security as a key asset for most families is not measured as part of household wealth. The wealth concept used here hence follows the literature by focusing on marketable household wealth. A more detailed discussion of the importance of Social Security for household wealth and its distribution can be found in Bricker *et al.* (2016).

[7]Data on defined contribution retirement plans are only available from 1983 onward. However, according to the flow of funds accounts (FFA), this variable makes up a small part of household wealth before the 1980s, so missing information before 1983 is unlikely to change the picture meaningfully. Up to 1970, defined contribution plans correspond to less than 1% of average household wealth.

Debt: Total debt consists of housing and non-housing debt. Housing debt is calculated as the sum of debt on owner-occupied homes, home equity loans, and home equity lines of credit. 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. All debt other than housing debt refers to and includes car loans, education loans, and other consumer loans.

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. As Bricker *et al.* (2016) discuss, the modern SCF applies a sophisticated two-frame sampling scheme to oversample wealthy households, combining administrative and survey data. The historical surveys did not oversample households at the top. In this section and in the Appendix, we outline how we dealt with the issue and discuss the implications for the representativeness of the SCF+. In addition to the adequate coverage of wealthy households, we also need to ensure representative coverage of demographic characteristics such as race, age, and education.

Oversampling of wealthy households: Since its redesign in 1983, the SCF consists of two samples. The first sample is drawn using area probability sampling of the entire U.S. population based on Census information. In addition, a second so-called *list sample* is drawn based on tax information.[8] 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 corresponds to the number of similar households in the population. In a final step, both samples are combined and survey weights are adjusted so that the combined sample is representative of the U.S. population (Kennickell and Woodburn, 1999). Before 1983, the historical SCF data are not supplemented by a list sample. As a consequence, the challenge of adequately representing households at the very top is likely to be more pervasive (Sabelhaus *et al.*, 2015). Missing households at the top could potentially lead to an under-representation and bias historical inequality measures downwards.

For the construction of the SCF+, we use information from the 1983 list sample to adjust the coverage of rich households in the pre-1983 data. In a first step, we determine the proportion

[8]The methodology has evolved over time and uses a combination of income capitalization with income from several tax years and regression evidence based on existing surveys. See Kennickell (2017) and Bricker *et al.* (2017) for details and further references.

of households in the 1983 list sample relative to all households. Their share corresponds to approximately 2%. In a second step, we determine where the households from the list sample are located in the income and wealth distribution in 1983. We find that most observations are among the top 5% of the income and wealth distribution. Using this information, we adjust survey weights in all survey years before 1983 in two steps. First, for each year we extract all observations that are simultaneously in the top 5% of the income and wealth distribution. Secondly, we increase the weighting of these households in such a way that we effectively add 2% of wealthy households to the sample and adjust the remaining weights accordingly. This approach is similar in spirit to Bricker *et al.* (2018), who adjust SCF weights inversely proportional to the overlap of the SCF sample with the Forbes list.

The list sample of the modern SCF is concentrated in the top 1% of the wealth distribution, and great effort goes into identifying these households as Bricker *et al.* (2016) discuss. A potential concern with our adjustment of the historical data is that we can only increase the weight of households that are sampled. This could be problematic if non-response rates have changed over time, or if the older surveys failed to identify and contact wealthy households in sufficient numbers. One way to get a better sense of how pervasive these issues are, is to compare the 1983 data with the 1962 Survey of Financial Characteristics of Consumers (SFCC). The SFCC was the only historical survey that also used a two-frame sampling scheme similar to the 1983 list sample on the basis of income tax records.

Table 1: Share of respondents from list sample at the top of the distribution

	Income		Wealth	
	top 10%	top 5%	top 10%	top 5%
SFCC 1962	21 %	35 %	20 %	28 %
SCF 1983	17 %	34 %	17 %	32 %

Notes: Share of respondents from list sample in different parts of the income and wealth distribution. The left panel shows shares in the top of the income distribution in the 1983 SCF and the 1962 SFCC data. The right panel shows shares in the top of the wealth distribution in the 1983 SCF and the 1962 SFCC data.

Table 1 compares the non-response patterns at the top of the income and wealth distribution from these two surveys. Importantly, we find little evidence for a pronounced time trend in non-response of wealthy households. For the modern SCF surveys, the reported response rates for the list sample also do not point to any trends in non-response rates for the list sample over time (see Bricker *et al.* (2016), Bricker *et al.* (2017)). In Appendix B we apply a battery of tests to the historical data that were proposed in a recent paper by Bricker *et al.* (2016) to examine how well the modern SCFs perform in capturing the top of the distribution relative to the tax data. More precisely, we test how many households in the SCF+ are above the 99th percentile threshold for income and wealth from the tax data, and how mean income and wealth above this threshold compare. Although these tests do not signal systematic deviations, the strength of the SCF+ data clearly lies in their comprehensive coverage of the lower ranks of the distribution. A lot of research has already been devoted to small groups at the very top of the distribution, but less is known about long-run distributional trends among the bottom 99% of households. Consequently, in this paper we will not talk about the top 1% of households, but will focus on income and wealth trends of the remaining 99% of American families.

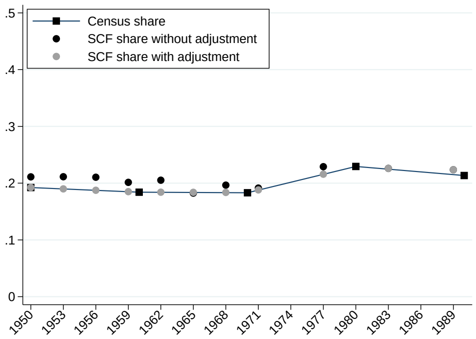
Demographic characteristics: We compare the demographic characteristics in the surveys before 1983 with data from the U.S. Census from 1940 to 1990. To obtain samples that match the Census data, we subdivide both the Census and the SCF+ data into demographic subgroups. Subgroups are determined by age of the household head, college education, and race. In addition to these demographic characteristics, we include homeownership as an additional dimension. We adjust SCF+ weights by minimizing the difference between the share of each subgroup in the SCF+ and the respective share in the Census. As Census data are only available on a decennial basis, we linearly interpolate values between the dates. Figure 1 shows the shares of 10-year age groups, college households, and black households in the Census (black squares) and in the SCF+ with the adjustment of survey weights (gray dots). Using adjusted weights, the distributions of age, education, and race closely match the Census data. We match the homeownership rate equally well after the adjustment (see Figure A.1).

Missing variables: The imputation of missing variables is done by predictive mean matching as described in Schenker and Taylor (1996). This multiple imputation method assigns variable values by finding observations that are closest to the respective missing observations. In line with the post-1983 data, we impute five values for each missing observation. We account for a potential undercoverage of business equity before 1983 and follow the method proposed by Saez and Zucman (2016) to adjust the observed holdings in the micro data with information from the FFA. A detailed description of these steps is provided in Appendix A.1.

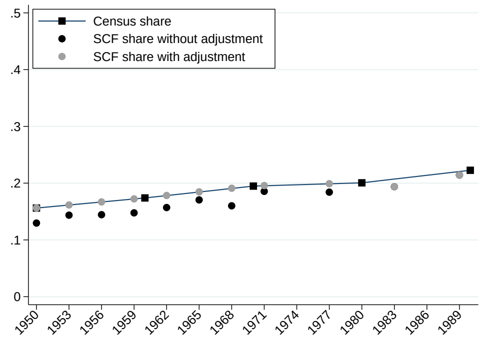
Table 2 shows the variables and their coverage, as well as the years in which we imputed data.[9] In Appendix A.1, we also explain how we impute the value of cars for selected years based on model and purchasing year.

[9] We exclude the survey years 1947, 1948, 1952, 1961, 1964 and 1966 because we lack information on housing, mortgages, and liquid assets. These three wealth components are held by a large fraction of households but can only be poorly inferred from information on other variables.

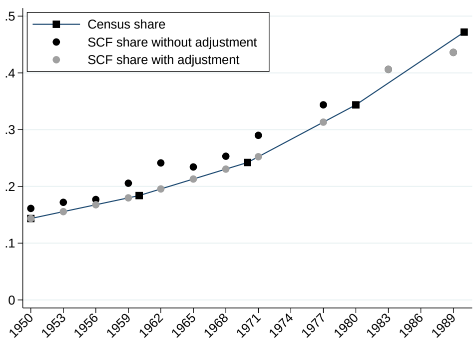
Figure 1: Shares of 10-year age groups, college households, and black households in the population



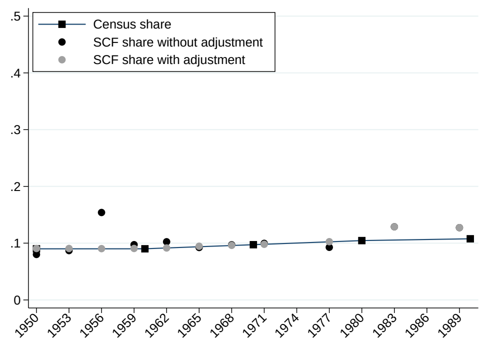
(a) 25-34



(b) 65-99



(c) college



(d) black

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

The final SCF+ data set comprises 35 survey years with cross-sectional data, totaling $102,304$ household observations. The number of observations varies from a minimum of $1,327$ in 1971 to a maximum of $6,482$ in 2010. Table A.1 in the appendix reports the number of observations for all survey years.

2.3 Aggregate trends

Before looking in detail at the evolution of the income and wealth distributions since World War II, the first step is to benchmark aggregate trends from the SCF+ to the national income and product accounts (NIPA) and the flow of funds accounts (FFA). To do so, we have to take into account that even high-quality micro data do not always correspond one-to-one to aggregate data as measurement concepts differ. We follow Henriques and Hsu (2013) and

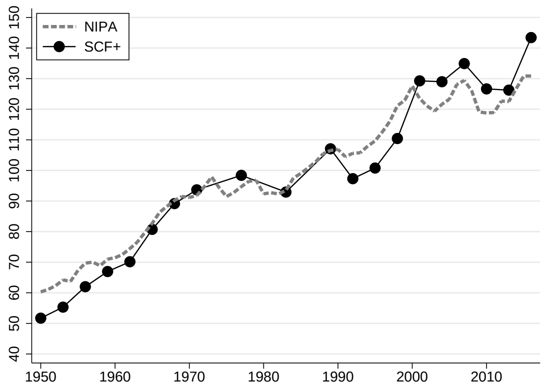
Table 2: Data availability

	income			financial assets			nonfinancial assets			debt			
Survey year	total	labor	labor + business	liquid assets	bonds	equity	housing	other real estate	business	total	housing	other real estate	nonhousing
1949	O	O	O	O	O	O	O	I	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
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	O	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	O	O	I	O
1962	O	I	O	O	O	O	O	O	O	O	O	I	O
1963	O	I	O	O	O	O	O	O	O	O	O	I	O
1965	O	I	O	O	O	I	O	I	I	O	O	I	O
1967	O	O	O	O	I	O	O	I	I	O	O	I	O
1968	O	O	O	O	I	O	O	O	I	O	O	O	O
1969	O	O	O	O	I	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	O	O	I	O
1977	O	O	I	O	O	O	O	O	I	O	O	O	O

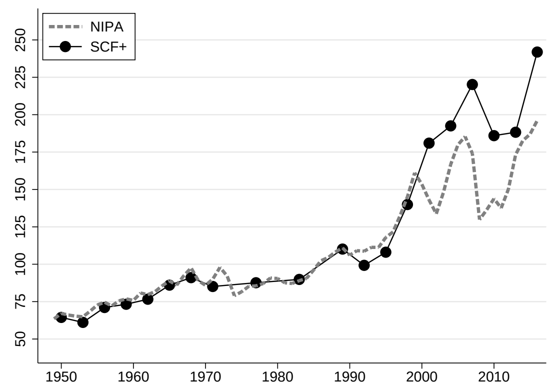
Notes: Data availability for different survey years. The first column shows the survey year. The letter *O* indicates that original observations are used, the letter *I* indicates that the variable has been imputed. In some years totals are available but components not separately reported had to be imputed. Totals are marked as imputed if any component is imputed. Equity includes stocks and mutual funds. Income in 1977 imputed based on interval information.

Dettling *et al.* (2015) to account for the conceptual differences when constructing income and wealth series. We relegate the details to Appendix A.5. For the modern SCF data, Henriques and Hsu (2013) and Dettling *et al.* (2015) conclude that after accounting for the conceptual differences between micro and macro data align well. They also provide detailed discussions for observed differences. Figure 2 compares indexed time series for average household income and wealth from the SCF+ with the corresponding series constructed from NIPA and FFA. Figure 2a shows that the trend in income is very similar for SCF+ and NIPA data throughout the 1949-2016 time period. For the base period of 1983-1989, the SCF+ matches 87% of

Figure 2: SCF+, NIPA, and FFA: income and wealth



(a) Income

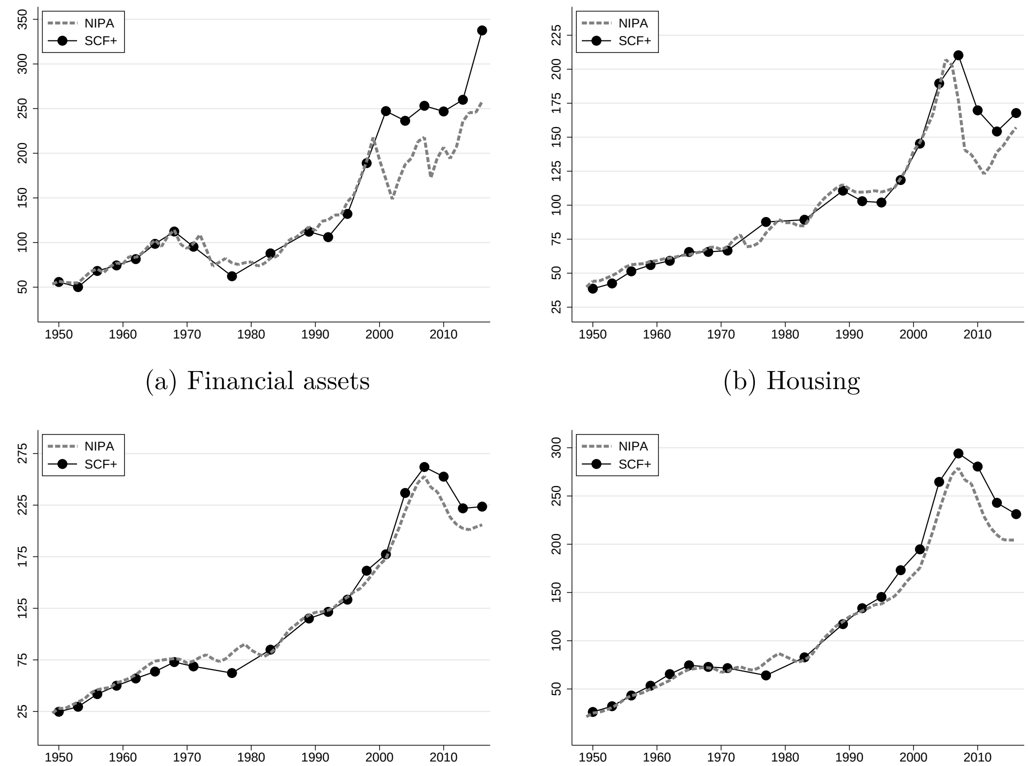


(b) Wealth

Notes: Income and wealth data from SCF+ in comparison to income data from NIPA and wealth data from FFA. All data have been indexed to the 1983-1989 period (= 100). SCF+ data are shown as black lines with circles, NIPA and FFA data as a gray dashed line. For the indexing period, SCF+ data correspond to 87% of NIPA income and 90% of FFA wealth.

income from the NIPA. Looking at wealth, the trends differ only slightly. Before 1995, wealth trends from the SCF+ and FFA hardly differ. There appears to be a persistent level shift in the late 1990s that Henriques and Hsu (2013) trace back to differences in business wealth and owner-occupied houses. Looking at different wealth components, we find that financial assets in the SCF+ (Figure 3a) increase more strongly in the early 2000s than the corresponding FFA values. Henriques and Hsu (2013) attribute most of the difference to the coverage of retirement accounts in the SCF data. Figure 3b shows that housing as the most important non-financial asset is covered well in the survey data. Debt is the household balance sheet component for which the SCF+ matches the aggregate best, as shown in Figure 3c. Summing up, the SCF+ matches aggregate trends of NIPA data and FFA asset and debt positions. In particular, the SCF+ data and the FFA show similar trends for the important categories of housing wealth and mortgage debt.

Figure 3: SCF+, NIPA, and FFA: financial and nonfinancial assets



(a) Financial assets

(b) Housing

(c) Total debt

(d) Housing debt

Notes: Asset and debt components of household balance sheets from the SCF+ and the FFA. All data have been indexed to the 1983-1989 period (= 100). SCF+ data are shown as black lines with circles, FFA data as a gray dashed line. For the indexed period, SCF+ data correspond to 68% of financial assets, 98% of housing, 73% of total debt, and 75% of housing debt.

3 Income and wealth inequality in the SCF+

This section presents stylized facts for long-run trends in income and wealth inequality that the SCF+ data bring to light. We begin by documenting the evolution of Gini coefficients for income and wealth as a comprehensive measure of inequality. We go on and look at the income and wealth inequality trends in different parts of the distribution. For this step, we will rely on the strength of the SCF+ data in covering the bottom 90% of the distribution. We also look at the long-run trends in the share of hand-to-mouth households and use the demographic information in the SCF+ data to analyze the importance of demographic factors in distributional change. Importantly, we present evidence on long-run trends in inequalities in income and wealth between black and white households.

3.1 Gini coefficients

The Gini coefficient is a comprehensive summary measure of inequality along the entire distribution. Table 3 reports Gini coefficients for income and wealth at selected points in time. The first row reports the Gini coefficient for all households; the other rows focus on the bottom 99% and the bottom 90%, respectively.[10]

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

		1950	1971	1989	2007	2016
income	all	44	43	53	55	58
	bottom 99%	39	39	46	47	49
	bottom 90%	31	33	39	38	39
wealth	all	81	80	79	82	86
	bottom 99%	74	74	72	74	79
	bottom 90%	61	62	63	63	70

The Gini coefficients show that income and wealth inequality has increased not only across the entire population (across all households) but also among the bottom 99% and bottom 90% of households. The overall income Gini has risen from its postwar low of 0.43 in 1971 to 0.58 in 2016 (Figure 4a). Unsurprisingly, there is a substantial drop in inequality once we look at the bottom 99% of the distribution, but the increase in the Gini coefficient is still substantial. Also, within the bottom 90% income inequality has widened, yet this has mainly occurred between 1971 and 1989. In Section 3.3 below, we explore in detail changes within the bottom 90% over time.[11]

Turning to wealth, it is well known that wealth is considerably more unequally distributed than income. The wealth Gini has fluctuated around 0.8 for most of the postwar period and did not change much, if at all, between 1950 and 2007 (Figure 4b). By 2007, it stood at 0.82 and was only marginally higher than in both 1950 and 1971. The marked decline in the wealth Gini between 1971 and 1977 stands out. We will trace this decline back to asset price shifts in Section 4.3 below. A substantial increase in the Gini coefficient occurred between

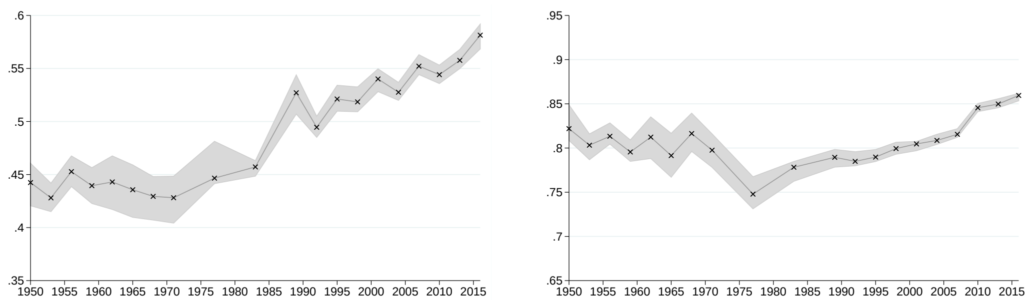
[10] We report the full time series in Table E.5 in the Appendix. We include negative-wealth households in the calculation. Figure D.9 of the Appendix shows that time trends are very similar when we restrict the analysis to positive income and wealth households.

[11] Our baseline income does not include rental income of owner-occupiers. As a sensitivity check, we imputed this rental income using historical rental yields from Jordà *et al.* (forthcoming) in the Appendix D.2. We find the Gini coefficient for income after imputing rents to be slightly lower.

2007 and 2016, and the wealth Gini reached its postwar peak in 2016.

The confidence bands in Figure 4 also show that Gini coefficients for both income and wealth are tightly estimated, although the confidence bands are somewhat wider in the historical data.[12] The observed long-run trends are clearly statistically significant. America is considerably more unequal today than it was in the 1970s, with respect to both income and wealth.

Figure 4: Gini coefficients with confidence bands



(a) Income

(b) Wealth

Notes: Gini coefficient of income (panel (a)) and wealth (panel (b)) with 90% confidence bands. Confidence bands are shown as gray areas, and point estimates are connected by lines. Confidence bands are bootstrapped using 999 different replicate weights constructed from a geographically stratified sample of the final dataset.

3.2 Income and wealth shares

Decomposing inequality trends, we start with an exploration of changes in income and wealth shares at the top, following the recent literature.[13] Broadly speaking, the SCF+ data corroborate the trajectories of the U.S. income and wealth distribution that emerged from the well-known studies by Piketty and Saez (2003) and Saez and Zucman (2016).

Figure 5a compares the income shares of the top 10% and 5% of the income distribution in the SCF+ to those calculated by Piketty and Saez (2003) using IRS data.[14] On the right-hand side, Figure 5b compares top wealth shares from the SCF+ with those from

[12] All confidence bands are computed using 999 replicate sample weights. Replicate weights are provided for the modern SCF surveys after 1983. For the historical surveys, we construct comparable 999 replicate weights (see Appendix A.2).

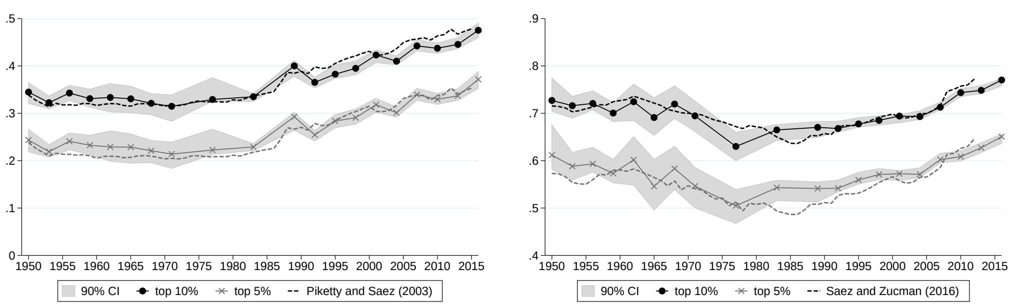
[13] We follow the recent literature in considering synthetic income and wealth groups. Households from a group need not be the same across surveys due to mobility. Exploring wealth mobility using data from the Panel Study of Income Dynamics (PSID), we find high persistence of households within wealth groups. More than 70% of households typically remain within wealth groups between survey dates. We report detailed results in Online Appendix C.

[14] Piketty and Saez (2003) include salaries and wages, small business and farm income, partnership and fiduciary income, dividends, interest, rents, royalties, and other small items reported as other income.

Saez and Zucman (2016). Figure 5 also shows estimated 90% confidence bands resulting from sampling error in the SCF+ data for the top income and wealth shares. The confidence bands underscore that the reported increases in income and wealth inequality are statistically significant. Despite some minor discrepancies, the SCF+ and tax data align in levels and trends of inequality so that they tell a similar story about the long-run trajectory of wealth and income inequality in postwar America. The increase in wealth inequality since the 1990s initially appeared somewhat stronger in the capitalized income tax data, but the gap has narrowed substantially with the 2016 SCF data.[15]

The 1962 SFCC constitutes an alternative data point to our SCF+ data for that year. The survey shows a nearly identical top 10% wealth share and a somewhat lower top 10% income share. This implies that the increase in income concentration at the top since the 1960s is even stronger when using the 1962 SFCC datapoint. However, the income tax data are actually much closer to the SCF+ data and also show a higher top 10% share than the SFCC. For consistency reasons, we use the SCF+ data throughout.

Figure 5: Income and wealth shares



(a) Income

(b) Wealth

Notes: Top income and wealth shares from SCF+ data and Piketty and Saez (2003) and Saez and Zucman (2016). The dots show income and wealth shares from SCF+ data, the dashed lines income shares from Piketty and Saez (2003) using IRS tax data or wealth shares from Saez and Zucman (2016) using IRS data and the capitalization method. The black dots show income (wealth) shares of the top 10%, dark gray crosses show the top-5% shares. Gray areas around the time series show 90% confidence bands.

In the next step of our decomposition, we move down the distribution and turn to the evolution of income and wealth among the bottom 90% (Table 4). The mirror image of increasing concentration of income in the hands of the top 10% must, by definition, be (relative) income losses among the bottom 90%. But which strata of the bottom 90% were hit particularly hard by the growing income share of the top 10%?

[15]Kopczuk (2015) provides a detailed discussion of this phenomenon. We also note some small differences in the trajectory of the wealth distribution in the earlier decades between the IRS and the SCF+ data. One reason for the divergence could be that Saez and Zucman (2016) had to adjust the pre-1962 estimates as households have been sorted by income rather than wealth.

Table 4 reports the income shares of different groups of the income distribution and wealth shares of different strata of the wealth distribution.[16] Starting with income on the left, the SCF+ shows that the top 10% have grown their income share by close to 15 percentage points from 34.5% to 48.2% between 1950 and 2016. The income share of the bottom 50% of Americans has fallen by roughly a third from 21.6% to 14.5%, and middle-class households (50th to 90th percentiles) have lost about 6 percentage points in income shares. In other words, we do observe a hollowing out of middle-class America, with households around the median having witnessed the largest relative income losses.

Table 4: Shares in aggregate income and wealth

	Income					Wealth				
	1950	1971	1989	2007	2016	1950	1971	1989	2007	2016
bottom 50%	21.6	21.6	16.2	15.4	14.5	3.0	3.0	2.9	2.5	1.2
0%- 25%	6.1	6.2	5.0	4.5	4.5	-0.1	-0.2	-0.1	-0.1	-0.4
25%-50%	15.5	15.4	11.3	11.0	10.1	3.1	3.2	3.0	2.6	1.6
50%-90%	43.9	47.7	43.8	40.3	37.9	24.7	26.3	29.5	26.0	21.5
50%-75%	23.5	24.9	22.5	20.3	18.4	9.8	10.5	11.7	10.2	7.2
75%-90%	20.4	22.8	21.4	20.0	19.5	14.8	15.8	17.8	15.8	14.3
top 10%	34.5	30.7	39.9	44.3	47.6	72.3	70.7	67.6	71.5	77.4

The right side of Table 4 studies the change in wealth shares (households are now stratified by wealth). The main insight here is that until the 2008 financial crisis, changes in wealth shares were modest. If anything, the bottom 90% wealth share was slightly higher in 2007 than it was in 1950, and very close to its 1971 level. In contrast to the observed changes in the income distribution, middle-class households managed to maintain their wealth shares until the mid-2000s. The 50%-90% wealth share was higher in 2007 than in 1950, and only slightly lower than in 1989. It is equally clear that the financial crisis had a substantial effect on the wealth distribution. Middle-class wealth shares collapsed across the board, while the wealth share of the top 10% surged by 6 percentage points within less than a decade. The decade since the financial crises witnessed the largest spike in wealth concentration in postwar America.

[16] Appendix E.3 reports the full time series.

The overall outcome was a more pronounced shift in the income distribution than in the wealth distribution since the 1970s. We return to this important fact in section 4. In the next step, we zoom in on the bottom 90% and study long-run distributional trends in the lower parts of the distribution, as well as low and negative-wealth households.

3.3 The bottom 90%

Much of recent research on seminal trends in inequality has focused on developments at the very top of the distribution. This emphasis on the top 1% (and beyond) plays to the strength of the income tax data that were, at least so far, the only source spanning the postwar decades on a continuous basis. However, the income tax data can only provide a relatively coarse picture of developments in the lower parts of the distribution. The SCF+ fills this gap.

We start the analysis with income and wealth trends for percentiles across the bottom 90%. Figure 6a documents that income grew at a similar rate across the 25th, 50th, and 75th percentiles in the first two postwar decades. From the 1970s to the 1990s, the 25th and 50th percentile experienced real income losses while incomes at the 75th percentile stagnated. All groups saw a return to real income growth from the mid-1990s to mid-2000s, but only incomes at the 75th percentile have recovered from the 2008 crisis.

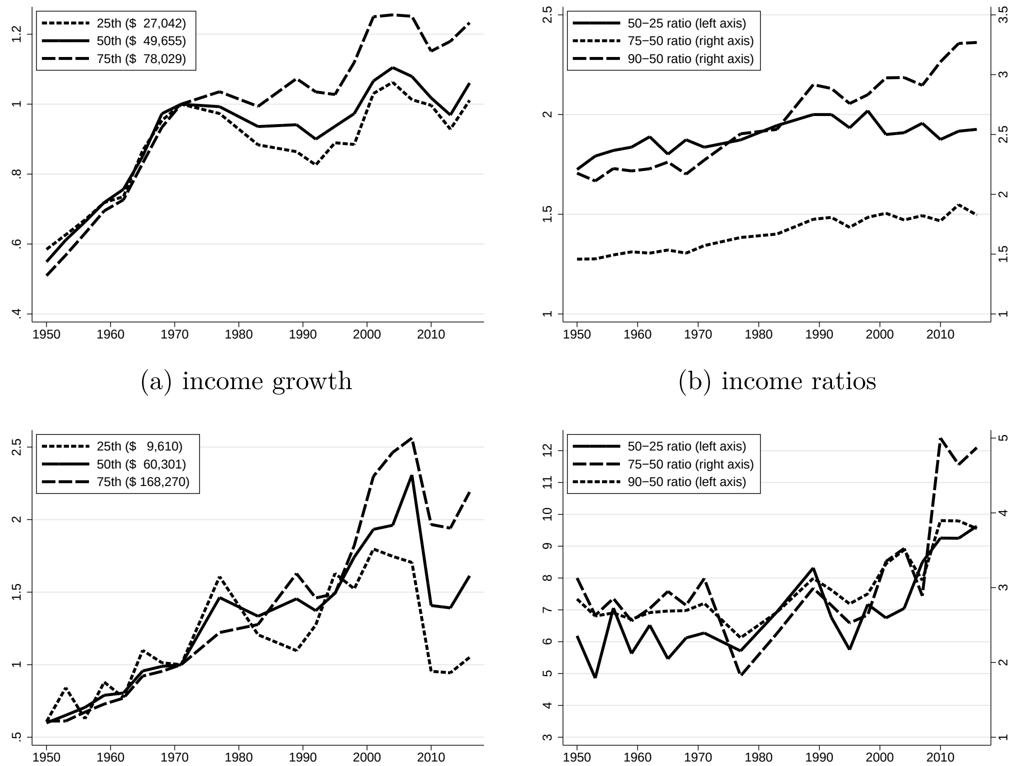
Looking at percentile ratios in Figure 6b, we see that since 1980 income at the median evolved similarly to income at the 25th percentile so that the 50-25 ratio did not change much over the last four decades. By contrast, since the 1970s the 75th and 90th percentile left the median behind leading to a pronounced widening of the 75-50 and 90-50 percentile ratios.

Figure 6c presents the same analysis for wealth. The picture is markedly different. First, wealth between groups started to persistently diverge only in the 2000s, not in 1970s as in the case of income. Second, households at all three percentiles saw major wealth drops after 2007, but there was considerable variation. The outcome is a substantial polarization of wealth and pronounced widening of the 90-50 and 50-25 ratios. The Figure also shows that nearly all wealth gains that households at the 25th percentile had made since 1971 have been wiped out by the crisis.

3.3.1 Low and negative wealth households

Low and negative wealth households (net debtors) are key groups when it comes to the consequences of wealth inequality for macroeconomic dynamics (Krusell and Smith, 1998). Using the SCF+ data, we show in Figure 7 how the shares of low and negative wealth households evolved over the last seven decades. The share of net debtors has doubled from its low of the 1980s, but remains within its postwar range that fluctuated between 5% and

Figure 6: Percentiles and percentile ratios for income and wealth



(a) income growth

(b) income ratios

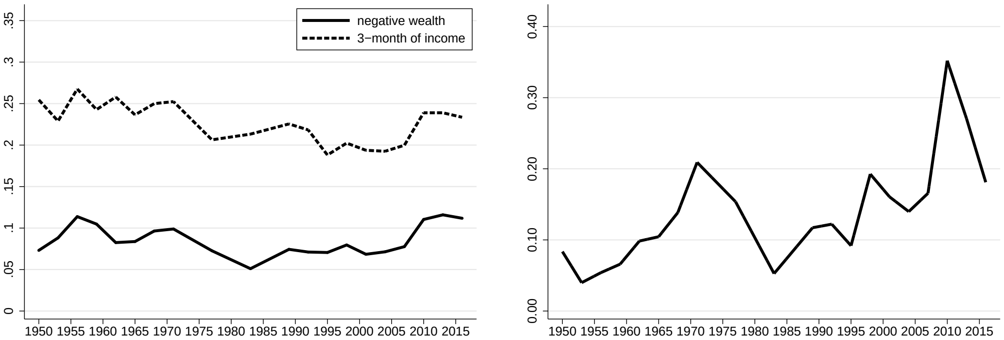
(c) wealth growth

(d) wealth ratios

Notes: Left panels show growth of the 25th, 50th, and 75th income and wealth percentiles relative to 1971. Right panels show 90-50, 75-50 and 50-25 percentile ratios for income and wealth. For percentiles in left panel legend shows 1971 levels in 2016 dollars.

12% (see Figure 7a). A broader measure of low-wealth households includes all households that have positive wealth but whose wealth is low relative to their income. We use a threshold of three months of income, implying a wealth-to-income ratio of 0.25 or below. This group can self-insure only to a limited extent by accessing savings, for instance, in the case of a job loss. The share of this group is large: close to one quarter of American households are low-wealth households according to this definition. The share of these households has risen since the crisis, but remains within its postwar range. One reason why households have negative wealth is negative home equity, and Figure 7b reports the share of homeowners among negative-wealth households. The ratio reached its all-time high in 2007 when house prices collapsed and highly leveraged households ended up *under water*.

Figure 7: Low-wealth households



(a) low wealth households

(b) negative wealth homeowner

Notes: Share of low-wealth households over time and share of homeowners among net debtors. Left panel shares shares for two measures of low-wealth households: *3 month of income* shows households with wealth less than three months of income ($\frac{3}{12}$ of annual income), *net debtors* shows share of households with negative wealth. Right panel shows the share of homeowners among net debtors.

3.3.2 Wealthy hand-to-mouth households

Kaplan and Violante (2014) argue that the group of households that behave like hand-to-mouth consumers, i.e., as if they had no wealth for consumption smoothing, is much larger as many households hold wealth in illiquid assets that cannot be easily accessed. Kaplan and Violante (2014) coined the term *wealthy hand-to-mouth households* and documented that from 1989 to 2010 about one in three American households can be classified as "hand-to-mouth" and that about two-thirds of these households are wealthy hand-to-mouth consumers.

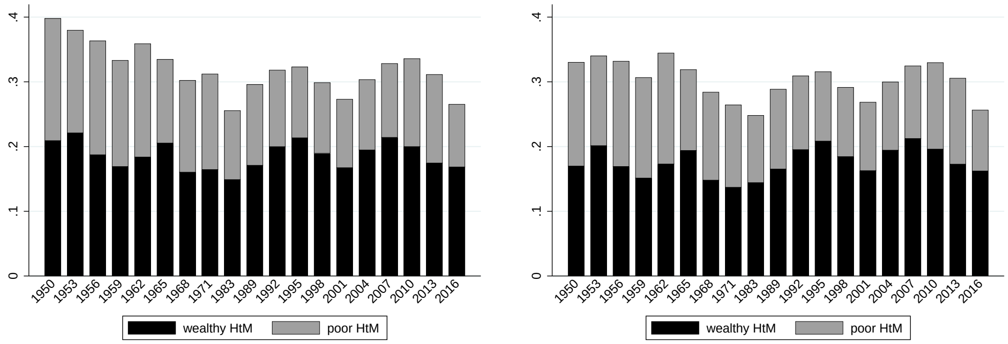
Using the SCF+, we can provide estimates for the share of wealthy hand-to-mouth consumers for the entire postwar period. We follow Kaplan *et al.* (2014) in identifying hand-to-mouth households in the data and relegate details to Appendix A.7. We also provide estimates for cash holdings of households going back until 1973 using data from the National Crime Victimization Survey (NCVS).[17]

Figure 8 provides two different estimates of the share of hand-to-mouth and wealthy hand-to-mouth households in the United States over the post-WW2 period.[18] Figure 8a shows the baseline estimate following the approach for cash holdings in Kaplan *et al.* (2014). It shows a slight downward trend for hand-to-mouth households over the time period of the historical data and a rising proportion of wealthy-hand-to-mouth households. Figure 8b

[17]Although the survey is designed to collect data on victims of crime, it also records details of the incidence, including theft. Online Appendix A.7 provides details on the construction of estimates and Figure A.2 shows cash estimates as fraction of median SCF+ income.

[18]We do not provide estimates for 1977 because income in 1977 is reported in intervals so that the share of hand-to-mouth is estimated imprecisely.

Figure 8: Share of Poor and Wealthy Hand-to-Mouth Households



(a) Baseline

(b) Alternative Cash Adjustment

Notes: Panel (a) shows the share of poor and wealthy hand-to-mouth consumers over time, following the baseline specification of Kaplan *et al.* (2014). Panel (b) estimates cash holdings from the NCVS. We do not report an estimate for 1977 due to data limitations (see footnote 18).

provides estimates for hand-to-mouth households using our estimates for cash holdings from the NCVS data. Both Figures show a relatively stable ratio of wealthy hand-to-mouth households since 1950, albeit with some variation over shorter horizons.

3.4 Demographic change

What were the effects of secular changes in terms of educational attainment, age structure, and household size of the U.S. population on income and wealth inequality? Using the demographic information in the SCF+, we provide answers to these questions. In a first step, we implement an approach proposed by Fortin *et al.* (2011) to remove changes in the age structure and educational attainment over time.[19] In a second step, we account for changes in household size by adjusting income and wealth at the household level to per-adult equivalents using the OECD equivalent scale.[20]

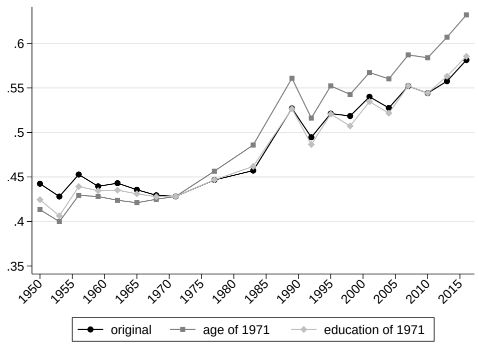
Figure 9a shows Gini coefficients for the original data and the two counterfactual cases where we add the marginal effects from fixing educational attainment and the age structure at the 1971 distributions. The effect from shifts towards more highly educated household heads on income appear rather small, but the effects coming from an older population are more sizable.

[19]We use 1971 as our base year for which we fix the distribution of demographic characteristics. We then estimate a probit model including age, educational attainment, the number of adults and children in a household, and the race of the household head as controls to derive adjustment weights. We relegate a detailed description to Appendix A.6.

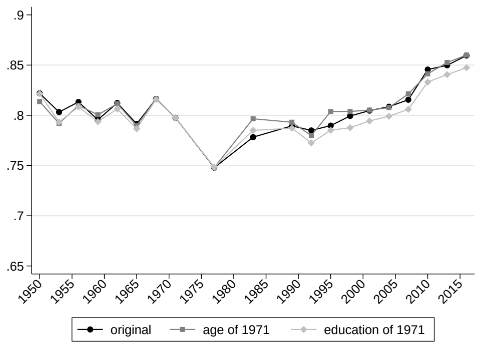
[20]The OECD equivalence scale assigns a value of 1 to the first household member, 0.7 to each additional adult, and 0.5 to each child (see OECD `http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf`).

Note that this finding is in line with a rising college wage premium as we only consider the effect from changes in quantities (number of households) not prices (wages). In the case of wealth (Figure 9b), the effect of changing educational attainment and aging are small.[21] All in all, demographic changes have some effects, but do not change the overall pattern of income and wealth inequality in the United States since World War II.

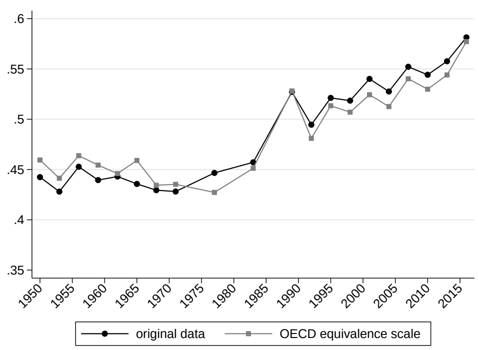
Figure 9: Gini coefficients accounting for demographic change



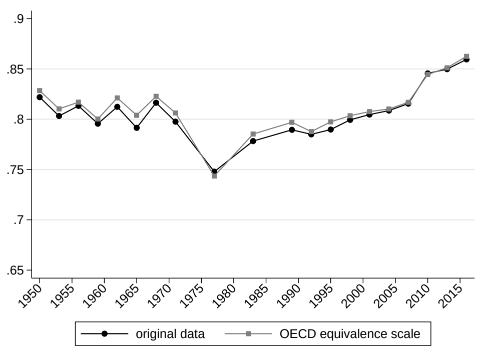
(a) Income Gini



(b) Wealth Gini



(c) Income Gini



(d) Wealth Gini

Notes: The top two graphs show the effects of demographic changes on Gini coefficients. The black dashed lines are the results using the original data. For the dark gray solid lines with crosses, the age distribution is held constant at the 1971 distribution. For the light gray solid lines with dots, the distribution of education is held constant at the 1971 distribution. Age and education refer to the head of household. The bottom two graphs show Gini coefficients for adult-equivalent income and wealth. The black dashed lines are the results using the original data. For the gray solid lines with crosses, the data were adjusted with the OECD equivalence scale (see footnote 20).

A second secular trend in the United States has been the decrease in average household size from an average of 3.4 household members in 1949 to an average of 2.5 in 2013 according to Census data. Given that the SCF+ is a household survey, changes in household size can potentially affect measures of household-level inequality. We adjust income and wealth to

[21] Bartscher *et al.* (2018) provide a detailed analysis on the trends in the financial situation of college and non-college households in the United States based on the SCF+ data.

per-adult-equivalent member of the household with the OECD equivalence scale. Figure 9c reports that income concentration at the top falls somewhat when we look at adult-equivalent income. This trend is consistent with stronger assortative mating and increasing female labor force participation. For wealth (Figure 9d), we do not observe big effects.

3.5 The persistence of racial disparities in income and wealth

Race is an important stratifying dimension of the U.S. population. In a recent paper, Bayer and Charles (2017) provide long-run evidence on the black-white earnings gap using data from the U.S. Census Bureau and the American Community Survey. They document persistent earnings differences for working-age men. The SCF+ data complement recent work on the long-run evolution of racial inequality along three dimensions.[22]

First, in addition to earnings, we study household income from all sources. Second, our unit of observation is the household, not working-age male individuals. We thus capture the effects of changing marriage patterns, higher labor force participation of women, as well as changes in transfers, education, and retirement decisions of households. Third, the SCF+ data also allow us to analyze the long-run evolution of *wealth* differentials between black and white households. So far, the racial wealth gap has remained uncharted territory as long-run data were simply not available. With data reaching back to the pre-civil rights era, our analysis extends recent work by Wolff (2017), who studied wealth differences between black, white, and Hispanic households in the modern SCF data starting in 1983. For the analysis, we group households into black and white households according to the race of the household head.[23]

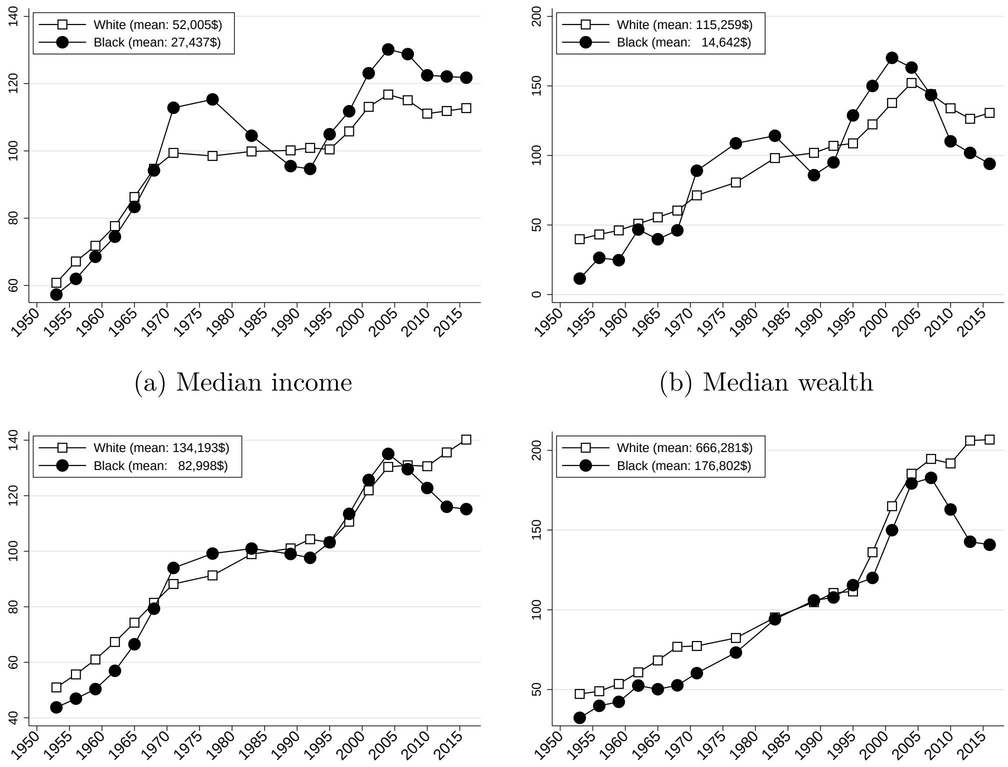
Figure 10 shows the trends in income and wealth of the median household and of the household at the 90th percentile for both white and black households. The racial divide will fall if black households' income or wealth increases more strongly over time. A lockstep evolution of the series for black and white households (equal growth rates) signals persistence of existing racial disparities.

Three facts stand out. First, income has grown at a comparable rate for black and white households. This means that pre-civil rights era disparities have largely persisted as black income growth did not accelerate relative to white households. Second, as the numbers indicate, the size of the racial income divide remains substantial. The median black household has about half of the income of the median white household. Third, the wealth gap is much

[22] Thompson and Suarez (2017) and Dettling *et al.* (2017) analyze racial inequality using SCF data.

[23] The number of interracial marriages is growing but remains small. Fryer (2007) reports that for whites about 1% of marriages were interracial and about 5% for black Americans. We drop all other racial categories. The survey questions for race in the SCF changed little over time. An important change happened in 1989, when the information was obtained as part of the interview rather than coded directly by the interviewer.

Figure 10: Income and wealth trends for black and white households



(a) Median income

(b) Median wealth

(c) Income 90th percentile

(d) Wealth 90th percentile

Notes: Panels (a) and (b) show median income and wealth of black and white households over time. Panels (c) and (d) show the 90th percentiles for income and wealth of black and white households over time. We show moving averages over three neighboring observations. Average wealth levels for 1983-1989 (in 2016 dollars) are shown in the legend.

larger than the income gap and equally persistent. The median black household disposes of 12% of the wealth of a median white household. In the 1980s, the wealth of the median black household stood at about $15,000 in 2016 prices — equivalent to the value of a car. The median white household had about $140,000 — corresponding to the value of a small house. Looking at the time trends in more detail, we note two periods when the racial disparities narrowed temporarily. In the 1970s, the income of the median black household grew about 20% faster than the income of the median white household. However, the trend reversed in the 1980s when the share of black households headed by women increased strongly.[24] The 2000s are the second period in which the racial income gap narrowed somewhat for the median household.

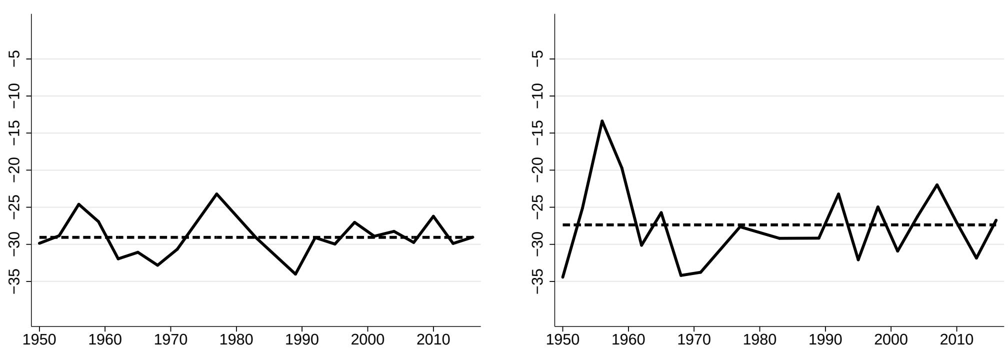
Figure 10b exposes an equally persistent racial wealth gap. The difference in wealth narrowed

[24]When adjusting incomes for household size, the decline in relative incomes for black households during the 1980s becomes less pronounced.

temporarily in the housing boom of the 1990s and early 2000s, but widened again after the financial crisis. After 2007, the wealth levels of households at the 90th percentile of the black wealth distribution collapsed, while the 90th percentile of the white wealth distribution remained largely unaffected.

As an alternative to study the evolution of earnings differences over time, Bayer and Charles (2017) apply the concept of a racial "rank gap". Adapted for wealth, the rank gap is the percentage point difference between the rank of a given percentile in the black and white wealth distribution. For instance, a number of -30 for the median of the black wealth distribution means that the place of that household would be 30 percentage points lower in the wealth distribution of white households, that is, only at the 20th percentile.

Figure 11: Racial wealth rank gaps



(a) Rank gap median

(b) Rank gap 90th percentile

Notes: Racial wealth rank gaps at the median and 90th percentile. The racial rank gap is the difference in percentage points between the rank of the median (90th percentile) in the wealth distribution of black households and the position that this wealth level takes in the distribution of white households. Dashed lines show the long-run average of the racial wealth rank gaps.

Figure 11a shows the wealth rank gap at the median and the 90th percentile. For the median, the long-run average is close to -30, implying that the median black household is at the 20th percentile of the wealth distribution of white households. Put differently, the typical black household is poorer than 80% of white households. The rank gap fluctuates, tracking what we have seen for levels in Figure 10b, but is highly persistent over time. Our main conclusion is that virtually no progress has been made over the past 70 years in reducing wealth inequality between black and white households.

4 Asset prices and the wealth distribution

In the previous section, we discussed changes in the income and wealth distributions separately, as in the existing literature. Yet it is precisely the link between the income and wealth distributions that plays a central role in theoretical models of wealth inequality. A central advantage of the SCF+ is that it allows us to study the long-run evolution of the *joint* distributions of income and wealth. This topic is what we turn to now.

In the simplest model of the dynamics of the wealth distribution, changes in the income and wealth distributions are closely linked. With saving rates that are constant over time and uniform across wealth classes, and uniform returns on wealth along the wealth distribution, changes in the wealth distribution would be solely driven by changes in the income distribution. Or, put differently, the differential growth rates of wealth would be a function of the differential growth rates of income. Recent studies have questioned this assumption, as models based on labor income risk typically produce too little wealth concentration at the top and cannot account for substantial shifts in wealth inequality that occur over short time horizons (Benhabib and Bisin (2016), Gabaix *et al.* (2016), Hubmer *et al.* (2017)).

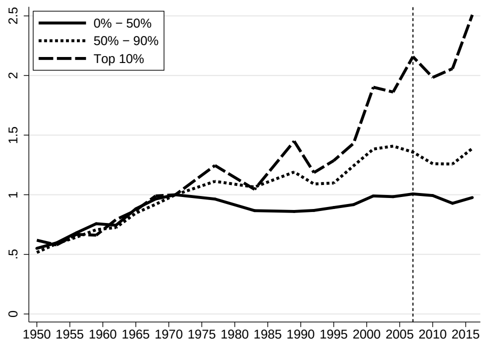
As a first check, in Figure 12 we compare the time path of income and wealth growth in the United States since 1971. Note that we stratify all households by wealth and index income and wealth levels to 1 in 1971. Figure 12a highlights a substantial divergence in income growth for different groups of the wealth distribution. Income growth was low for the bottom 90% and particularly meager for households in the lower half. For the bottom 50%, real incomes have stagnated since the 1970s. For households between the 50th and 90th percentiles of the wealth distribution, real incomes rose modestly by about a third over nearly 40 years, implying annual growth rates of much less than 1% per year. By contrast, income growth at the top was strong. The incomes of households within the top 10% of the wealth distribution have doubled between 1971 and 2007.[25]

Yet when we turn to wealth growth for the same groups in Figure 12b, the contrast is stark. From 1971 to 2007 (the last pre-crisis survey), wealth growth has been, by and large, identical for the top 10% and the bottom 90% of the wealth distribution. More precisely, middle-class (50%-90%) wealth increased by 140%, exactly at the same rate as top 10% wealth. And even the bottom 50% did not do too badly when it comes to wealth growth, as their wealth still doubled between 1971 and 2007. Wealth and income growth rates have decoupled over an extended period, in marked contrast to the simple model sketched above. We will return to this point below.

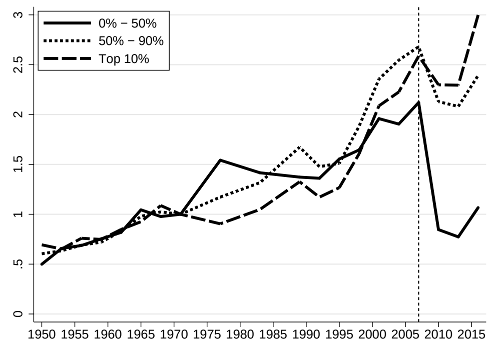
Figure 12b also shows how devastating the 2007-2008 financial crash was to lower middle-

[25] Online Appendix E.3 reports income shares for households along the wealth distribution comparable to the income shares along the income distribution in Table 4.

Figure 12: Income and wealth growth along the wealth distribution



(a) Income growth



(b) Wealth growth

Notes: Growth of income and wealth for different wealth groups. All time series are indexed to 1 in 1971. The solid lines show growth rates for the bottom 50%, the short dashed lines for the middle class (50%-90%), and the long dashed lines for the top 10%. See text for further details.

class wealth, while the impact of the crisis on wealth at the top was rather minor. By 2013, the absolute level of real wealth below the median household was 20% below its 1971 level. Within a few years, the crisis wiped out all gains in household wealth that the bottom 50% of the distribution had made over the preceding four decades. As of 2016, still close to half of the American population dispose of less wealth in real dollar amounts than in 1971.

One upshot is that before the financial crisis, wealth-to-income ratios increased most strongly in the middle and at the bottom of the wealth distribution and then also fell most strongly for those groups during the crash. Figure 13 illustrates this phenomenon. The bottom 50% and the middle class experienced the strongest increase in wealth-to-income ratios, followed by a substantial decline. At the top, wealth-to-income ratios increased only slightly between 1971 and 2007 and hardly changed after 2007.

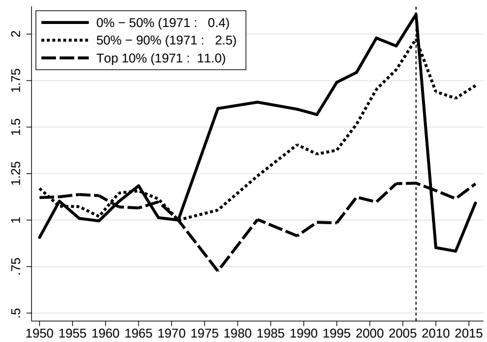
4.1 The dynamics of the wealth distribution

If we are to understand the dynamics of the wealth distribution in America over the past seven decades, we must look beyond income growth. In the following, we demonstrate that asset price changes played an important role in the observed dynamics of wealth inequality in postwar America.[26]

Asset prices affect the dynamics of the wealth distribution through two channels. First, asset prices lead to differential capital gains if portfolios differ across the distribution. We

[26] For the French case, Garbinti *et al.* (2017) show that price effects played an important role in shaping the French wealth distribution over the past 200 years. In the American context, Saez and Zucman (2016) discuss that price effects can change inequality trends relative to those implied by income and saving rate differences but focus on saving rate differences in their discussion.

Figure 13: Change in wealth-to-income ratios by wealth group, 1950-2016



Notes: Wealth-to-income ratios are constructed as a ratio of averages within each group. The solid lines refer to the bottom 50%, the short dashed lines to the middle class (50%-90%), and the long dashed lines to the top 10%. All series are indexed and show growth relative to 1971. The legend reports levels of wealth-to-income ratios for all wealth groups in 1971. See text for further details.

document this important stylized fact for the U.S. economy below. As changes in asset prices revalue existing wealth, they can induce shifts in wealth shares that are unrelated to income changes. Moreover, they can do so over short horizons as they immediately affect the value of accumulated assets. We will document that in America, persistent differences in portfolio composition between middle-class households and rich households essentially give rise to a race between the stock market and the housing market in shaping the dynamics of the wealth distribution.

The second channel through which asset prices matter for the dynamics of wealth inequality is through their effect on wealth-to-income ratios. The level of the wealth-to-income ratio determines the relative importance of savings flows for wealth dynamics. When wealth-to-income ratios are high, income growth and savings flows become relatively less important for the wealth distribution, simply because the stock of wealth is high relative to income flows. This second channel is particularly relevant for the time period from 1970 to 2007, when the aggregate wealth-to-income ratio increased from 4 to more than 7, driven by rising house prices and a booming stock market.

To see how asset prices affect wealth inequality when portfolios are heterogeneous, consider a household i in period t with a portfolio of assets $\{A^i_{j,t}\}^J_{j=1}$, for instance, houses, stocks, and saving accounts. For household i, the capital gain Π^i_t from asset price changes between period t and $t+1$ is the asset-weighted average of price changes

$$\Pi^i_t = \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) A^i_{j,t},$$

where $p_{j,t}$ denotes a (real) price index for asset j in period t. Denote the household's wealth in t by W_t^i and divide both sides of the equation by wealth to get

$$
\begin{aligned}
\frac{\Pi_t^i}{W_t^i} &= \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) \frac{A_{j,t}^i}{W_t^i} \\
q_t^i &= \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) \alpha_{j,t}^i, \qquad (1)
\end{aligned}
$$

where $\alpha_{j,t}^i$ denotes the portfolio share $\frac{A_{j,t}^i}{W_t^i}$ of asset j for household i in period t and q_t^i is the growth rate of household wealth from capital gains. Equation (1) shows that portfolio differences (i.e., differences in $\alpha_{j,t}^i$ across households) lead to differences in capital gains q_t^i.
To fix ideas and structure the discussion about how this affects the wealth distribution, we rely on an illuminating accounting framework adapted from Saez and Zucman (2016).[27]
Consider a simplified law of motion for wealth of household i:

$$W_{t+1}^i = W_t^i(1 + r_t^i + q_t^i) + Y_t^i - C_t^i$$

where r_t^i are returns on wealth other than capital gains (e.g., dividends), Y_t^i denotes income from all other sources, and C_t^i denotes consumption.[28] The savings flow S_t^i of household i in period t corresponds to total income net of consumption $S_t^i = r_t^i W_t^i + Y_t^i - C_t^i$. Define further the saving rate s_t^i as $s_t^i = \frac{S_t^i}{Y_t^i}$, so that the law of motion for wealth becomes

$$W_{t+1}^i = W_t^i(1 + q_t^i) + S_t^i = W_t^i(1 + q_t^i) + s_t^i Y_t^i = (1 + q_t^i + \sigma_t^i) W_t^i \qquad (2)$$

with $\sigma_t^i = \frac{s_t^i Y_t^i}{W_t^i}$ capturing the contribution of savings to wealth growth and the term q_t^i captures the effect of capital gains to wealth growth.
In the next step, we move from the law of motion for wealth *levels* to a law of motion for wealth *shares* of different wealth strata. We construct "synthetic" saving flows and capital gains for specific wealth groups, again taking the lead from Saez and Zucman (2016). Savings flows and capital gains for wealth groups are "synthetic" in the sense that they assume that households stay in their wealth group from one period to the next. Using PSID data, we show

[27] A micro-founded analysis of household saving behavior and portfolio choice requires a more complex approach. Hubmer *et al.* (2017) discuss why such a framework remains beyond reach for the time being but must become a topic for future research.

[28] Income denotes income from all sources excluding capital. This approach simplifies wealth dynamics by abstracting from bequests and death, divorce, marriage or other life-cycle events that affect households' wealth accumulation. We adjust the framework by Saez and Zucman (2016) slightly with respect to the timing convention by assuming that capital gains accrue together with savings flows, but the underlying mechanism remains the same. Saez and Zucman (2016) focus on the heterogeneity in savings behavior and assume homogeneity of capital gains. Our discussion focuses on the comparison of the relative importance of savings and capital gains as drivers of wealth accumulation.

in Online Appendix C that while there is some mobility in practice, the synthetic method yields a good approximation of wealth dynamics.

Note that we will now use i to refer to the group of households in a specific wealth stratum. The wealth share of group i in period t is $\omega_t^i = \frac{W_t^i}{W_t}$ where W_t is aggregate wealth in period t. All aggregate variables are defined according to group-level variables; for example, the aggregate savings rate is $s_t = \frac{S_t}{Y_t}$. Applying some straightforward transformations to equation (2) yields the law of motion for the wealth share ω_t^i:

$$\omega_{t+1}^i = \frac{1 + q_t^i + \sigma_t^i}{1 + q_t + \sigma_t} \omega_t^i \qquad \Longleftrightarrow \qquad \frac{\omega_{t+1}^i}{\omega_t^i} = \frac{1 + q_t^i + \sigma_t^i}{1 + q_t + \sigma_t}. \tag{3}$$

The law of motion has an intuitive interpretation: the wealth share of any group i increases if the group's wealth growth rate exceeds the average wealth growth rate in the economy. Differences in growth rates result from the two components of wealth growth in equation (2). First, group i's capital gains q_t^i can be higher (or lower) than the average capital gain q_t in the economy. Second, different rates of wealth growth can result from the difference between group i's savings component σ_t^i relative to the average savings σ_t. This is the channel through which differences in income growth translate into wealth inequality: higher incomes of group i will, all else equal, increase the group's saving flows and its wealth level relative to other groups in the economy.

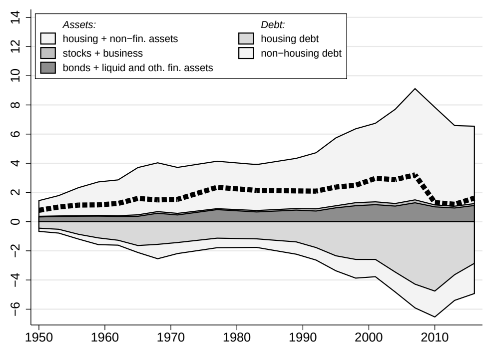
The savings term σ_t^i comprises the inverse of the wealth-to-income ratio. With higher wealth-to-income ratios, the importance of savings flows declines and tends to zero. This implies that the relative importance of differences in savings flows diminishes with higher wealth-to-income ratios. This effect is independent of portfolio composition and is operative even when households have identical wealth portfolios (so that capital gains are identical). Also note that the two components q_t^i and σ_t^i are independent, so that a low savings component relative to the average can go hand-in-hand with a large capital gains component relative to the average for group i, and vice versa. This can decouple the evolution of the income and wealth distributions.

4.2 Portfolio heterogeneity and asset price exposures

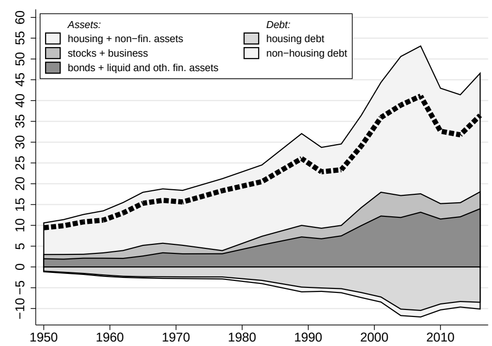
If portfolios differ systematically along the wealth distribution, asset price changes will lead to differential capital gains along the wealth distribution. These in turn can induce changes in the wealth distribution that are unrelated to changes in the income distribution. The necessary condition for such effects is that portfolios are heterogeneous. For the first time, the SCF+ provides us with long-run balance sheet information to study the composition of household portfolios over a long time horizon. The evidence points to systematic and highly persistent differences in wealth portfolios across groups and hence a potentially important role for asset prices in shifting the wealth distribution, as we will now demonstrate.

Figure 14 displays the heterogeneity of household portfolios. It tracks the portfolio composition of the bottom 50%, the 50%-90%, and the top 10% of the wealth distribution since 1949. As a benchmark, we also track the average portfolio of the macroeconomy. In the figures, assets enter with positive values and debt as negative values. Household wealth corresponds to the consolidated value of all portfolio positions and is indicated by a dashed line in each of the figures. The degree of leverage in household portfolios can be inferred by looking at the sum of assets in excess of wealth. We provide time series in the Appendix E.5.

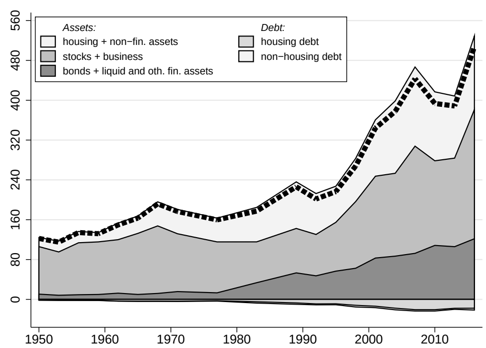
Figure 14: Heterogeneity of household portfolios



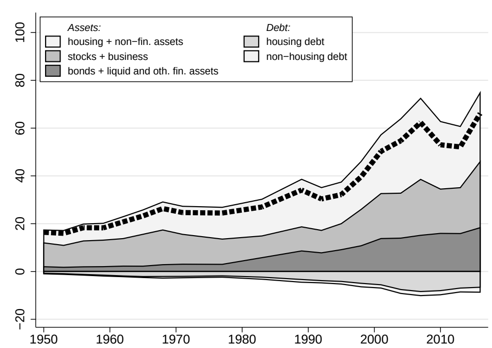
(a) <50%



(b) 50-90%



(c) 90-100%



(d) all households

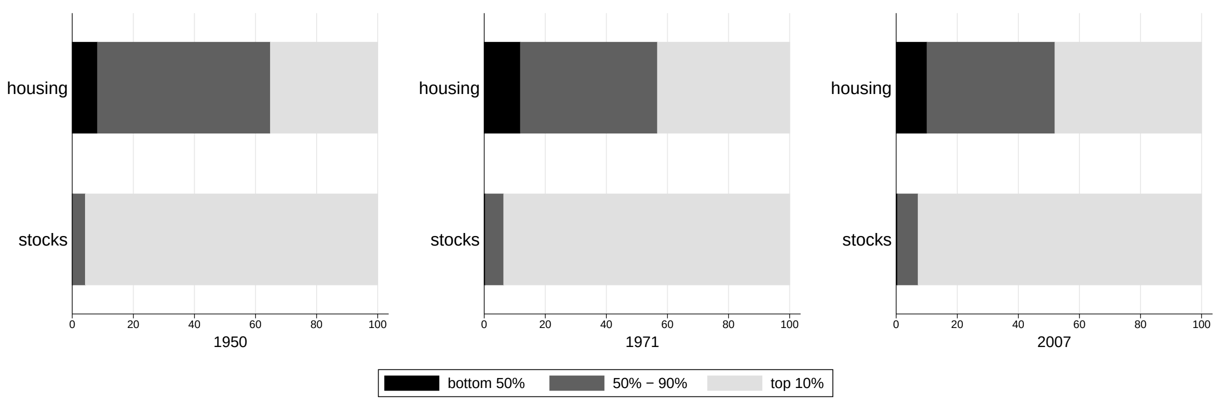
Notes: The dashed line indicates wealth. Panel (a) shows the portfolio of the bottom 50% of the wealth distribution, panel (b) the portfolio of the 50%-90%, and panel (c) the portfolio of the top 10%. Panel (d) shows the portfolio of all households. The portfolio components are shown in 10,000 CPI-adjusted 2016 dollars. Wealth groups are separately defined for each survey year.

Bottom 50%: The bottom 50% have little wealth, yet their small wealth position masks substantial gross positions. Houses and other nonfinancial assets, mainly cars, make up more than 80% of the asset side of the balance sheet. Financial assets play a minor role in bottom 50% portfolios. On the liability side, housing debt is the dominant form of debt, but compared to other wealth groups, the bottom 50% also have a high share of non-housing debt. In recent years, education loans make up a growing share of this debt (Bartscher *et al.* (2019)). Assets exceed wealth by a large margin, indicating a high degree of leverage.

Middle class (50%-90%): The middle-class portfolio is dominated by nonfinancial assets. About two-thirds of the middle-class portfolio consists of houses and other nonfinancial assets. Direct stock holdings are typically below 5%. The large growth of other financial assets in the portfolio comes mainly from defined contribution pension plans. The middle class is also leveraged, with housing debt being the dominant debt component and assets exceeding wealth by 10% to 30%.

Top 10%: The top 10% are different when it comes to portfolio composition. The bulk of wealth is held in stocks and business equity. Houses as an asset class gained in importance for the top 10% but constitute a comparatively small fraction of assets. Other financial assets have grown strongly, mainly because of the proliferation of defined contribution pension plans. Leverage is low, so that for the top 10%, the sum of assets corresponds approximately to wealth.

Figure 15: Asset distribution by wealth group for selected years



Notes: Housing includes the asset value of the house, and equity consists of stocks and business wealth. The black part of the bar on the left is the share of the bottom 50%, the gray bar is the share of households in the 50%-90%, and the light gray bar at the right is the share of the top 10%.

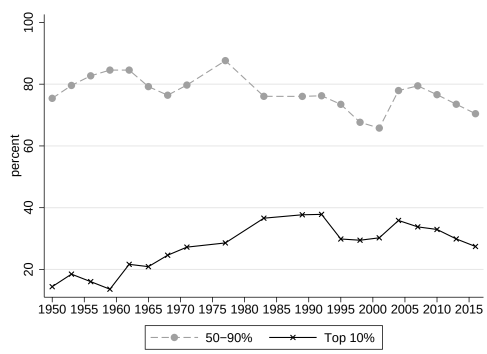
Portfolio composition thus varies substantially along the wealth distribution. These differences are also highly persistent. The portfolios of the bottom 90% are non-diversified and highly leveraged. Houses are *the* asset of the bottom 90%, making residential real estate the most egalitarian asset. Figure 15 highlights this point by showing the ownership structure of housing and stocks at different points in time.[29] The bottom 90% hold about half of all

[29]We include mutual funds in the stock holdings. Results change little if we only consider direct stock holdings.

housing wealth, but only a tiny fraction of stocks. Stocks are *the* asset of the wealthy in the sense that the top 10% consistently hold more than 90% of stocks. Looking at the Gini coefficient for individual asset classes confirms that housing is the most equally distributed asset and that the distribution of housing wealth has not changed substantially over time. We report Gini coefficients for all asset classes in the Appendix E.1.

An important consequence of non-diversified and leveraged portfolio positions is that the wealth of middle-class households is highly exposed to changes in house prices. We quantify this exposure as the elasticity of wealth with respect to house prices, which is equal to $\frac{\text{Housing}}{\text{Wealth}}$, the ratio of the asset value of housing to wealth. Figure 16 shows the resulting exposure to house prices for middle-class households and households in the top 10% over time. The figure confirms that the elasticity of middle-class wealth to house prices is three to four times higher than at at the top. A 10% increase in house prices increases middle-class wealth by 6%-7%.[30] For changes in stock prices, the exposures are reversed. The top 10% are highly exposed, the rest very little.

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



Notes: House price exposure for different wealth groups. House price exposure is measured by the elasticity of household wealth with respect to house price changes. See text for details. Horizontal axis shows calendar time and vertical axis house price exposure in percentage points.

4.3 The race between the stock market and the housing market

Such pronounced portfolio differences between households along the wealth distribution give rise to what we call the race between the stock market and the housing market: owing to their larger exposure, the middle class gains relatively more than top-wealth households when house prices rise. All else equal, rising house prices make the wealth distribution more equal,

[30]We do not show the bottom 50% in this graph because of their large exposure. Appendix E.2 provides further results on house price exposure along the wealth distribution and changes over time and decomposes the house price elasticity of wealth further into a *diversification component* and a *leverage component*.

while stock market booms have the opposite effect: they primarily boost wealth at the top and lead to a more unequal distribution of wealth.

To explore how important this race between the stock market and the housing market has been for the wealth distribution in postwar America, we estimate the following regression relating changes in the top 10% wealth share over the three-year survey intervals to asset price movements:

$$\Delta \log(\omega_{t+1}^{top10}) = \beta_0 + \beta_h \Delta \log(p_{t+1}^h) + \beta_s \Delta \log(p_{t+1}^s) + \varepsilon_t,$$

where Δ is the first-difference operator, $\Delta x_{t+1} = x_{t+1} - x_t$, the superscript h denotes house prices and the superscript s stock prices. We use the S&P 500 stock market index and the Case-Shiller House Price Index obtained from the latest version of the Macrohistory Database (Jordà *et al.*, 2017).

Table 5 reports the estimated coefficients for the baseline regression in the first column. The signs of the estimated coefficients demonstrate how the race between the housing market and the stock market shaped wealth dynamics: rising house prices are associated with a falling top 10% wealth share. Rising stock prices boost the top 10% wealth share. Note that in the baseline specification, the error term comprises all other effects related to differences in savings or wealth-to-income ratios. Wolff (2002) estimated similar regressions relating the top 1% and top 5% wealth share to fluctuations in stock and house prices.

We control for these factors in additional regressions in columns (2)-(4) by adding the income share of the top 10% and changes in the ratio of income to wealth as regressors. As expected, the coefficients β_h and β_s become larger and significance rises. Clearly, while the effects are economically large, the sample is small and statistical significance varies.

The estimated regression coefficients have an intuitive interpretation as they correspond to the average elasticity of the top 10% wealth share with respect to asset prices.[31] From the law of motion for the wealth share, we can derive the elasticity of the wealth share of group i with respect to the price of asset j:

$$\frac{\partial\left(\frac{\omega_{t+1}^i}{\omega_t^i}\right)}{\partial\left(\frac{p_{t+1}^j}{p_t^j}\right)} = (1 + q_t + \sigma_t)^{-1}\left(\alpha_{t,j}^i - \alpha_{t,j}\frac{\omega_{t+1}^i}{\omega_t^i}\right).$$

Figure 17 shows the time series for the elasticity constructed from the portfolio shares in the SCF+ data. The house price elasticity of the top 10% fluctuates around a mean of -0.17, very close to the point estimate of -0.16 in the wealth share regression (4) above. All else

[31] The portfolio share $\alpha_h = \frac{H}{W}$ in Figure 16 corresponds to the elasticity of the wealth level.

Table 5: The race between equity and house prices

	(1)	(2)	(3)	(4)
β_h	-0.104	-0.116	-0.138*	-0.157**
β_s	0.043*	0.044*	0.052**	0.043*
θ^{top10}	no	yes	no	yes
$\frac{Y}{W}$	no	no	yes	yes
N	19	19	19	19
R^2	0.162	0.246	0.352	0.468

Notes: Regression of changes in the top 10% wealth share on asset price growth and controls. Growth rates computed using log differences. θ^{top10} denotes the income share of the top 10% of households in the wealth distribution. $\frac{Y}{W}$ denotes controls for the inverse of the wealth-to-income ratio of the top 10% of households in the wealth distribution and for the aggregate economy. Asterisks show significance levels (* $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$). All observations from the surveys from 1950 to 2016 are used.

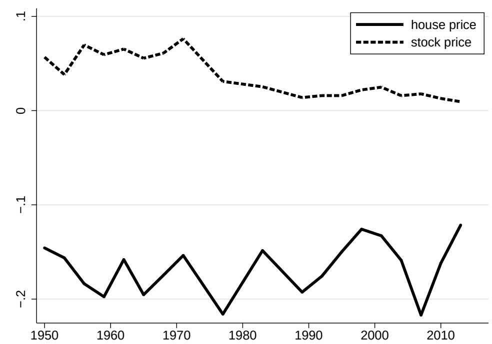
equal, a 10% increase in house prices will lower the top 10% wealth share by 1.6%. Assuming a top 10% wealth share of 75%, this corresponds to a decrease in the top 10% wealth share of 1.2 percentage points.

The magnitudes are large. A hypothetical 40% increase in real house prices would reduce the wealth share of the top 10% from 75% to 70%, bringing it back to its 1971 level. For stock prices, the long-run average elasticity stands at 0.036 and is only slightly lower than the point estimate from the regression of 0.043. A 130% real increase in the stock market — comparable to the period between 1998 to 2007 — increases the wealth share of the top 10% by about 6 percentage points. By the same token, the fall in the stock market in the 1970s contributed to the decline in wealth inequality in the 1970s that we discussed above. Because of the substantial portfolio heterogeneity along the wealth distribution, asset prices have first-order effects on the evolution of wealth inequality.

4.4 Wealth gains from asset prices

The results of the previous section demonstrate that over short horizons, asset price fluctuations are closely associated with changes in wealth shares. We now quantify the contribution of asset price changes to wealth accumulation of different groups over the past four decades. We concentrate on wealth growth over two distinct periods. The first period comprises the nearly four decades from 1971 to the 2007-2008 financial crisis (the last pre-crisis survey was carried out in 2007). This was a period in which the income distribution widened substantially, but measures of wealth inequality changed very little. We will see that house-

Figure 17: Asset price elasticity of top 10% wealth share

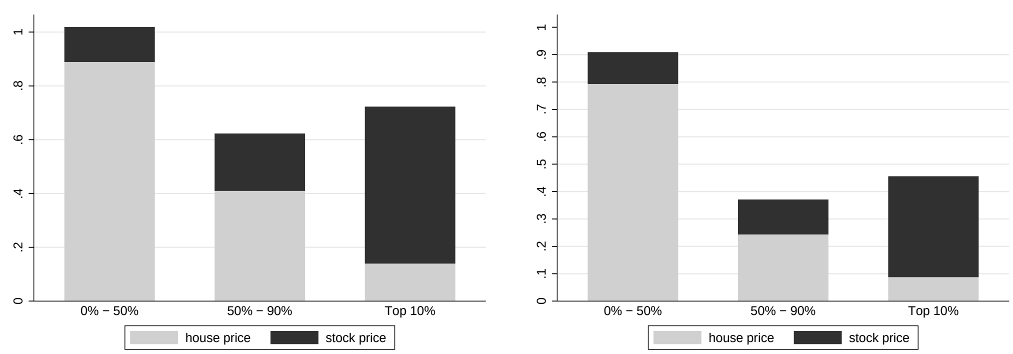


Notes: Elasticity of the top 10% wealth share with respect to stock and house prices. See text for details.

price-induced wealth gains for the bottom 90% of the population played a central role in the observed stability of the wealth distribution.

The second period that we study covers the decade after the financial crisis. As discussed above, this decade has witnessed the largest increase in wealth inequality in postwar history. The income distribution, by contrast, changed only modestly over this period. We will see that asset prices are again central in accounting for the large shift in the distribution of wealth over a relatively short period.

Figure 18: Wealth growth from asset prices, 1971-2007



(a) Wealth growth from asset prices (b) Share in total wealth growth

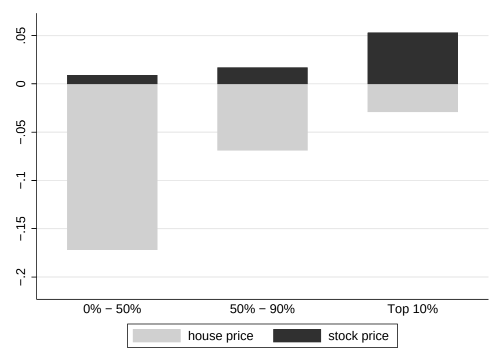
Notes: Wealth growth component from the housing market and the stock market (q_t^i) in levels and as share of total growth for the bottom 50%, 50%-90%, and top 10% of the wealth distribution for the period from 1971 to 2007. The growth component in panel (a) is computed by fixing the housing and equity position at the beginning of the time period and then adjusting asset prices. Asset price gains or losses are expressed relative to the initial wealth level of the respective group. Panel (b) shows the wealth growth component from asset prices as a share of total wealth growth over the period from 1971 to 2007 for the different wealth groups.

Figure 18a shows how much wealth grew between 1971 and 2007 because of price changes in the stock market and the housing market. As before, we track wealth growth across three different wealth groups: the bottom 50%, the 50%-90%, and the top 10%. While Figure 18a displays the wealth growth from asset price changes, Figure 18b highlights the share of such asset-price-induced wealth growth in total wealth growth, including changes in wealth coming from savings flows.

Two observations stand out. First, over the entire period, wealth gains from rising asset prices were substantial across the distribution. As Figure 18a shows, the wealth of the bottom 50% grew by 90% only because of price effects. Also for the 50%-90% group and the top 10%, asset price changes induced sizable wealth growth of about 60%. It is easy to spot the race between the stock market and the housing market in the data: wealth growth from house price effects dominate for the bottom 90% of the wealth distribution, and stock price gains account for the bulk of the wealth gains at the top.

How much of the total wealth increase in the different groups is explained by price effects? Figure 18b shows that for the bottom 50% virtually all wealth growth over the 1971-2007 period came from higher asset prices. But even in the middle and at the top, asset prices still account for 40% of total wealth growth, with the rest accounted for by savings. Note that these estimates for the role of asset prices for wealth growth are likely conservative as households increased their exposure to the housing market over this period. The variation in the contribution to wealth growth along the distribution helps us to understand why wealth and income growth decoupled in the decades before the crisis: relative to income, wealth grew most strongly for the bottom 90%.

Figure 19: Wealth growth from asset prices since 2007



Notes: Wealth growth component from the housing market and the stock market (q_t^i) for the bottom 50%, 50%-90%, and top 10% of the wealth distribution for the period 2007 to 2016. The growth component is computed by fixing the housing and equity position at the beginning of the time period and adjusting asset prices. Asset price gains or losses are expressed as share of the initial wealth level of the respective group.

Asset price movements also explain why wealth concentration spiked after the financial crisis. House prices plummeted after 2007 and recovered only slowly in recent years. By 2016, they were still 10% below their 2007 peak level. By contrast, the stock market recovered more quickly and the main stock market indices were about 30% above their 2007 levels in real terms in 2016. Figure 19 shows the race between the housing market and the stock market between 2007 and 2016. The bottom 50% lost 15% of wealth relative to 2007 levels, mainly because of lower house prices. By contrast, the top 10% were the main beneficiary from the stock market boom and were relatively less affected by the drop in residential real estate prices. The consequence of substantial wealth losses at the bottom and in the middle of the distribution, coupled with wealth gains at the top, produced a large spike in wealth inequality.

What would the distribution of wealth in America look like today without asset price effects? To construct a counterfactual, we use the law of motion for wealth levels from equation (2), keeping all parameters constant but adjusting the asset return term, q_t^i, so that nominal house prices (or stock prices) only increased with the rate of CPI inflation since 1971 (i.e., we keep prices constant in real terms). Note that this is an accounting exercise, not a general equilibrium analysis. Our aim here is to illustrate the potential of asset prices to shift the wealth distribution.

Table 6 shows the measured change in the wealth shares of the three groups relative to 1971, as well as the counterfactual change under two scenarios. In the first scenario, we keep real house prices constant. In the second scenario, we fix real stock prices at their 1971 level. The table shows counterfactual changes in wealth shares under these two corner assumptions.

Table 6: Changes in wealth shares relative to 1971

		1989	2007	2016
bottom 50 %	observed change	-0.1	-0.6	-1.9
	constant house prices	-0.3	-1.5	-2.6
	constant stock prices	-0.1	-0.2	-1.7
50% - 90%	observed change	3.2	-0.3	-4.8
	constant house prices	2.8	-2.4	-6.5
	constant stock prices	3.7	3.0	-1.3
Top 10%	observed change	-3.1	0.8	6.7
	constant house prices	-2.4	3.9	9.1
	constant stock prices	-3.7	-2.8	3.0

Notes: Changes in wealth shares relative to 1971 for different wealth groups. The first row for each wealth group shows the observed change in wealth shares (including changing house prices). The second row ("constant house prices") shows the change in wealth shares with constant real house prices. The third row ("constant stock prices") shows the change in wealth shares with constant real stock prices.

The key message from Table 6 is that the asset price effects were potentially large. From 1971 to 2007, rising house prices slowed down wealth concentration in the hands of the top 10% by 3.1 percentage points. Without higher house prices, the increase in wealth concentration at the top would have been four times higher than what we observe in the data. The house price crash after 2007 largely reversed these effects, but even in 2016, the observed increase in the top 10% wealth share of 6.7 percentage points was still about one-third lower than the counterfactual increase of 9.1 percentage points. Again, it is important to realize the magnitude of these shifts in wealth shares. A difference of 2 percentage points corresponds to over 14% of total annual household income. The last row for each wealth group in Table 6 also reports the corresponding counterfactual for constant stock prices. Without the stock market boom, the top 10% wealth share would have been 3 percentage points lower in 2007 than in 1971, and even over the whole period, the middle class (50%-90%) would not have lost ground relative to the top. These counterfactual simulations are suggestive only, but they highlight to what extent the wealth distribution is sensitive to asset price dynamics.

5 Conclusions

This paper makes three contributions to the literature on income and wealth inequality. First, we introduced the SCF+, an extended version of the Survey of Consumer Finances. The SCF+ covers as household-level dataset the financial situation of U.S. households since World War II. The SCF+ complements existing datasets for long-run inequality research that are based on income tax and social security records. The SCF+ makes it possible to study the joint distributions of income and wealth over time as it contains both income and balance sheet information, coupled with extensive demographic information. We expect that the SCF+ data will become a valuable resource for future empirical and theoretical research on inequality, household finance, political economy, and beyond.

Second, we exploited the new data to study the trends in income and wealth inequality. Previous research documented a trend toward increasing polarization of income and wealth since the 1970s. The data confirm this finding and underscore that the American middle class was the main loser of increasing income concentration at the top. We also track the racial wealth gap between black and white households over the long run. The picture that the SCF+ paints is one of a persistent income and wealth divide between white and black households. Importantly, we expose divergent trends in the income and wealth distribution for extended periods. Before the crisis in 2008, incomes of households in the lower half of the distribution stagnated, but their wealth grew substantially. However, a large part of these wealth gains have been undone in the crisis. We link these findings to the importance of asset price changes for wealth dynamics.

The third main contribution of the paper is to expose systematic and highly persistent differences in portfolio composition and leverage of households along the wealth distribution. An important consequence of these differences is that asset price changes have first-order effects on the wealth distribution. They lead to capital gains and losses that induce shifts in the wealth distribution that are unrelated to changes in the income distribution. The magnitude of changes in the wealth distribution induced by this asset price channel can be large. By highlighting the crucial role that portfolio composition, leverage, and asset prices play for the wealth distribution, our paper opens up new avenues for future empirical and theoretical research on the determinants of wealth inequality.

References

Attanasio, O. P. and Pistaferri, L. (2016). Consumption inequality. *Journal of Economic Perspectives*, **30** (2), 3–28.

Bach, L., Calvet, L. E. and Sodini, P. (2016). *Rich Pickings? Risk, Return, and Skill in the Portfolios of the Wealthy*. Tech. Rep. 11734, Centre for Economic Policy Research.

Bartscher, A., Kuhn, M., Schularick, M. and Steins, U. I. (2019). *The Great American Debt Boom, 1949-2016*. Tech. rep., University of Bonn.

Bartscher, A. K., Kuhn, M. and Schularick, M. (2018). *The College Wealth Divide: Education and Inequality in America, 1956-2016*. Tech. rep., University of Bonn.

Bayer, P. and Charles, K. K. (2017). Divergent paths: A new perspective on earnings differences between black and white men since 1940. *The Quarterly Journal of Economics*.

Benhabib, J. and Bisin, A. (2016). *Skewed Wealth Distributions: Theory and Empirics*. Working Paper 21924, National Bureau of Economic Research.

—, — and Luo, M. (2017). Earnings inequality and other determinants of wealth inequality. *American Economic Review*, **107** (5), 593–97.

Bricker, J., Dettling, L. J., Henriques, A., Hsu, J. W., Jacobs, L., Moore, K. B., Pack, S., Sabelhaus, J., Thompson, J. and Windle, R. A. (2017). Changes in us family finances from 2013 to 2016: Evidence from the survey of consumer finances. *Fed. Res. Bull.*, **103**, 1.

—, Henriques, A. and Hansen, P. (2018). *How much has wealth concentration grown in the United States? A re-examination of data from 2001-2013*. Tech. rep., Discussion Paper.

—, —, Krimmel, J. and Sabelhaus, J. (2016). Measuring income and wealth at the top using administrative and survey data. *Brookings Papers on Economic Activity*, **2016** (1), 261–331.

Burkhauser, R. V., Feng, S. and Jenkins, S. P. (2009). Using the p90/p10 index to measure us inequality trends with current population survey data: A view from inside the census bureau vaults. *Review of Income and Wealth*, **55** (1), 166–185.

—, —, — and Larrimore, J. (2012). Recent trends in top income shares in the united states: reconciling estimates from march cps and irs tax return data. *Review of Economics and Statistics*, **94** (2), 371–388.

Castaneda, A., Díaz-Giménez, J. and Ríos-Rull, J.-V. (2003). Accounting for the u.s. earnings and wealth inequality. *Journal of Political Economy*, **111** (4), 818–857.

Dettling, L. J., Devlin-Foltz, S., Krimmel, J., Pack, S. and Thompson, J. P. (2015). *Comparing micro and macro sources for household accounts in the United States: evidence from the Survey of Consumer Finances*. Tech. rep., Federal Reserve Board.

—, Hsu, J. W., Jacobs, L., Moore, K. B. and Thompson, J. P. (2017). *Recent trends in wealth-holding by race and ethnicity: evidence from the survey of consumer finances*. Tech. rep., Board of Governors of the Federal Reserve System (US).

Díaz-Giménez, J., Glover, A. and Ríos-Rull, J.-V. (2011). Facts on the distributions of earnings, income, and wealth in the united states: 2007 update. *Federal Reserve Bank of Minneapolis Quarterly Review*, **34** (1), 2–32.

Fagereng, A., Guiso, L., Malacrino, D. and Pistaferri, L. (2016). *Heterogeneity and Persistence in Returns to Wealth*. Tech. rep., Discussion Paper.

Fella, G. and De Nardi, M. (2017). Saving and wealth inequality. *Review of Economic Dynamics*.

Fortin, N., Lemieux, T. and Firpo, S. (2011). Chapter 1 - decomposition methods in economics. In O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, vol. 4a, Elsevier, pp. 1 – 102.

Fryer, J., Roland G. (2007). Guess who's been coming to dinner? trends in interracial marriage over the 20th century. *Journal of Economic Perspectives*, **21** (2), 71–90.

Gabaix, X., Lasry, J.-M., Lions, P.-L. and Moll, B. (2016). The dynamics of inequality. *Econometrica*, **84** (6), 2071–2111.

Garbinti, B., Goupille-Lebret, J. and Piketty, T. (2017). *Accounting for wealth inequality dynamics: Methods, estimates and simulations for France (1800-2014)*. Tech. rep., Discussion Paper.

Glover, A., Heathcote, J., Krueger, D. and Rios-Rull, J.-V. (2017). Intergenerational redistribution in the great recession. *Working Paper*.

Gottschalk, P. and Danziger, S. (2005). Inequality of wage rates, earnings and family income in the united states, 1975–2002. *Review of Income and Wealth*, **51** (2), 231–254.

Heathcote, J., Perri, F. and Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006. *Review of Economic Dynamics*, **13** (1), 15–51.

Henriques, A. and Hsu, J. W. (2013). *Analysis of wealth using micro and macro data: A comparison of the Survey of Consumer Finances and Flow of Funds Accounts*. Tech. rep., FEDS Working Paper.

Herkenhoff, K. F. (2013). The impact of consumer credit access on unemployment. *University of Califomia Los Angeles mimeo*.

Hubmer, J., Krusell, P. and Smith, A. A. (2017). The historical evolution of the wealth distribution: A quantitative-theoretic investigation. *Working Paper*.

Jordà, Ò., Knoll, K., Kuvshinov, D., Schularick, M. and Taylor, A. M. (forthcoming). The rate of return on everything, 1870–2015. *Quarterly Journal of Economics*.

—, Schularick, M. and Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER macroeconomics annual*, **31** (1), 213–263.

Kaplan, G. and Violante, G. L. (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica*, **82** (4), 1199–1239.

—, Violante, G. l. and Weidner, J. (2014). The wealthy hand-to-mouth. *Brookings Papers on Economic Activity*.

Kaymak, B. and Poschke, M. (2016). The evolution of wealth inequality over half a century: The role of taxes, transfers and technology. *Journal of Monetary Economics*, **77**, 1–25.

Kennickell, A. B. (2017). Modeling wealth with multiple observations of income: Redesign of the sample for the 2001 survey of consumer finances. *Statistical Journal of the IAOS*, **33** (1), 51–58.

— and Woodburn, R. L. (1999). Consistent weight design for the 1989, 1992 and 1995 scfs, and the distribution of wealth. *Review of Income and Wealth*, **45** (2), 193–215.

Knoll, K., Schularick, M. and Steger, T. (2017). No price like home: global house prices, 1870–2012. *The American Economic Review*, **107** (2), 331–353.

Kopczuk, W. (2015). What do we know about the evolution of top wealth shares in the united states? *Journal of Economic Perspectives*, **29** (1), 47–66.

—, Saez, E. and Song, J. (2010). Earnings inequality and mobility in the united states: evidence from social security data since 1937. *The Quarterly Journal of Economics*, **125** (1), 91–128.

Krusell, P. and Smith, A. A., Jr. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, **106** (5), 867–896.

Kuhn, M. and Ríos-Rull, J.-V. (2016). 2013 update on the us earnings, income, and wealth distributional facts: A view from macroeconomics. *Federal Reserve Bank of Minneapolis Quarterly Review*, **37** (1).

Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, **126**, 373–416.

Piketty, T. and Saez, E. (2003). Income inequality in the united states, 1913–1998. *The Quarterly Journal of Economics*, **118** (1), 1–41.

—, — and Zucman, G. (2016). *Distributional National Accounts: Methods and Estimates for the United States*. Tech. rep., National Bureau of Economic Research.

Sabelhaus, J., Johnson, D., Ash, S., Swanson, D., Garner, T. I., Greenlees, J., Henderson, S., Sabelhaus, J., Ash, S. and Garner, G. (2015). Is the consumer expenditure survey representative by income? *Improving the Measurement of Consumer Expenditures*, **74**, 241.

Saez, E. and Zucman, G. (2016). Wealth inequality in the united states since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics*, **131** (2), 519–578.

Schenker, N. and Taylor, J. M. (1996). Partially parametric techniques for multiple imputation. *Computational Statistics & Data Analysis*, **22** (4), 425–446.

Thompson, J. P. and Suarez, G. (2017). *Updating the Racial Wealth Gap*. Tech. rep., Federal Reserve Board.

Wolff, E. N. (2002). Top heavy: The increasing inequality of wealth in america and what can be done about it.

— (2016). Household wealth trends in the united states, 1962 to 2013: What happened over the great recession? *RSF: The Russell Sage Foundation Journal of the Social Sciences*, **2** (6), 24–43.

— (2017). *Household Wealth Trends in the United States, 1962 to 2016: Has Middle Class Wealth Recovered?* Working Paper 24085, National Bureau of Economic Research.

Yellen, J. (2014). Perspectives on inequality and opportunity from the survey of consumer finances. Remarks by Janet L. Yellen, Chair Board of Governors of the Federal Reserve System at the Conference on Economic Opportunity and Inequality, Federal Reserve Bank of Boston, Boston, Massachusetts, October 17, 2014 [Accessed : March 22, 2019].

Appendix for Online Publication

Income and Wealth Inequality in America, 1949-2016

April 2019

This appendix accompanies the paper *Income and Wealth Inequality in America, 1949-2016*. Section A provides further details on the SCF+ data and its construction. We also explain how we implement the approaches for demographic adjustment and how we identify hand-to-mouth households in the data. Section B discusses the coverage of the SCF+ at the top of the income and wealth distribution. Section C discusses evidence on mobility between wealth groups based on Panel Study of Income Dynamics (PSID) data. Section D provides sensitivity tests for Gini coefficients excluding negative wealth or income observations and for imputing rental income from owner-occupied housing. Section E provides additional results on Gini coefficients for different asset classes, a decomposition of house price exposure for different wealth groups over time, and presents time series for income and wealth shares, Gini coefficients for income and wealth, and for the portfolio composition along the wealth distribution.

A Data

This section provides details on the imputation of missing variables, construction of replicate weights, number of household observations across years, home ownership rates after weight adjustment, and construction of consistent income and wealth concepts for comparison with NIPA and FFA data.

A.1 Imputation of missing variables

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

For each missing variable, several adjacent surveys could in principle be used as nonmissing samples for the imputation. In order to determine which adjacent survey years are most suitable for imputing missing values, we implement the following optimization before imputation. First, we determine all income, asset, debt, and demographic variables that are available in the year for which the variable is missing. For each combination of adjacent years, we then construct a subset of variables that are available both in the year with missing values and in the adjacent years. As the predictive accuracy decreased with the number of explanatory variables, we select those variables with the highest predictive power by using the lasso method. This method sets regression coefficients to zero for variables with small predictive power. For each combination of survey years, we then regress the variable of interest on those variables selected by the lasso method. Finally, we calculate the R^2 for each regression. We use the R^2 as a measure of how well the combination of adjacent years is able to predict the missing variable. The combination with the highest R^2 is chosen for the imputation.

We account for a potential undercoverage of business equity before 1983 and follow the method proposed by Saez and Zucman (2016) to adjust the observed holdings in the micro data with information from the FFA. We rely on data from the 1983 and 1989 surveys and adjust business wealth and stock holdings including other managed assets in the earlier surveys so that the ratio of business wealth and stocks matches the 1983 and 1989 values. Let X_{it} be business wealth or stocks of observation i in period t. The variable $\bar{\mathrm{X}}_t$ is the respective mean in period t, and X_t^{FFA} is the corresponding FFA position per household in t. The adjusted values of business wealth and stocks are then calculated as follows

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

For cars, the current value is available in the historical files for 1955, 1956, 1960, and 1967. We impute the value in other years using information on age, model, and size of the car.

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

A.2 Confidence intervals for income and wealth shares

Bricker *et al.* (2018) provide a discussion of *modeling error* in the capitalization approach to the wealth distribution. Survey data are immune to modeling error as income and wealth are directly observed from the answers of survey participants. The survey data, however, contain measurement and sampling error. To provide estimates of the variability that results from these errors, replicate weights for the modern SCF data have been constructed and provided to researchers. We construct replicated weights for the historical surveys following as closely as possible the practice for the modern samples. We draw 999 samples from the data stratified by geographical units and adjust weights to get a nationally representative sample. We use these replicate weights to construct all confidence bounds of our estimates shown in the main paper.

A.3 Sample size

Table A.1 reports the number of household observations for the different sample years. As described in Section A.1, there are five implicates for each household observation in the final data. For the historical data, we pool sample years when surveys were conducted annually to increase the accuracy of our estimates. We show the number of observations for single survey years and after pooling sample years in Table A.1. The years highlighted in bold are used for all results in the main part of the paper using the pooled samples.

Table A.1: Number of household observations

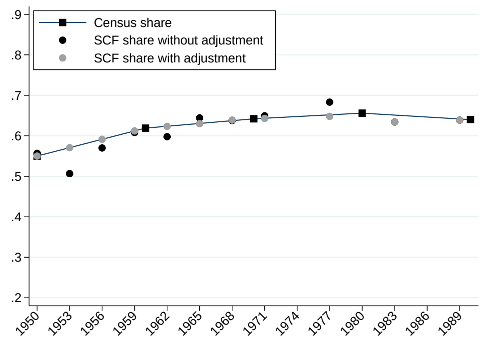
year	observations	pooled	year	observations	pooled	year	observations
1949	2,988		1960	2,708		**1983**	4,103
1950	2,940	5,928	**1962**	1,922	4,630	**1989**	3,143
1951	2,938		1963	1,819		**1992**	3,906
1953	2,663	5,601	**1965**	1,349	3,168	**1995**	4,299
1954	2,599		1967	3,165		**1998**	4,305
1955	2,766		**1968**	2,677	5,842	**2001**	4,442
1956	2,660	8,025	1969	2,485		**2004**	4,519
1957	2,726		1970	2,576		**2007**	4,417
1958	2,764		**1971**	1,327	6,388	**2010**	6,482
1959	2,790	8,280	**1977**	2,563		**2013**	6,015
Total number observations: 102,304						**2016**	6,248

Notes: Number of household observations in SCF+ data. The first column shows the survey year. Survey years in bold are used for time series in the main paper. The second column shows the number of household observations for different survey years. The third column shows the number of observations after pooling survey years. For results in the main paper, pooled survey years are always used. Horizontal lines indicate the pooled annual survey years.

A.4 Homeownership rates

In Section 2.2, we discuss the adjustment of survey weights to match population shares for age of the household head, college education, and race to be consistent with Census data. In the same step, we also target homeownership rates. Figure A.1 shows the homeownership rate in the Census (black squares) and in the SCF+ with the adjustment of survey weights (gray dots) and without adjustment (black dots).

Figure A.1: Homeownership rates



Notes: The large black squares show homeownership rates in the Census data. Census data are linearly interpolated between years. The small black dots are the homeownership rates using the original survey data. The small gray dots are the homeownership rates using the adjusted survey data.

A.5 Comparison to NIPA and FFA

It is well known that even high-quality micro data do not correspond one-to-one to aggregate data due to differences in measurement. For instance, Heathcote *et al.* (2010) discuss that data from the NIPA and CPS differ substantially. Indirect capital income from pension plans, nonprofit organizations, and fiduciaries, as well as employer contributions for employee and health insurance funds, are measured in the NIPA but not in household surveys such as the CPS or the SCF. Henriques and Hsu (2013) and Dettling *et al.* (2015) provide detailed discussions of the differences between SCF micro data and FFA and NIPA data and explain how to construct equivalent income and wealth measures.

For the construction of incomes for the comparison in Section 2.3, we follow Dettling *et al.* (2015). We start with personal income from NIPA table 2.1 and subtract/add components as described in Table A1 of Dettling *et al.* (2015). Our SCF+ income measure does not include capital gains. We also abstain from subtracting any components from *other income* as we do not have the detailed breakdown by source that is used in the adjustment by Dettling *et al.* (2015) for this position. We adjust NIPA income by CPI and divide totals by the number of households from the Census.

To construct wealth from the FFA data, we add the following FFA positions using annual data:

NW (wealth)	=	FIN (financial assets) + NFIN (nonfinancial assets) TDEBT (debt)
FIN	=	DEPOS (deposits) + BONDS (bonds)
		+ CORPEQUITY (corporate equity) + MFUND (mutual funds)
		+ DCPEN (defined contribution pension wealth)
NFIN	=	BUS (noncorporate businesses) + HOUSE (houses)
TDEBT	=	HDEBT (housing debt) + PDEBT (personal debt)
DEPOS	=	LM153091003(A) + FL153020005(A) + FL153030005(A) + FL153034005(A)
BONDS	=	FL153061105(A) + FL153061705(A) + FL153062005(A) + FL153063005(A)
CORPEQUITY	=	LM153064105(A)
MFUND	=	LM153064205(A)
DCPEN	=	FL574090055(A) + FL224090055(A) + FL344090025(A)
BUS	=	LM152090205(A)
HOUSE	=	LM155035015(A)
HDEBT	=	FL153165105(A)
PDEBT	=	FL153166000(A)

This construction of wealth excludes the identifiable components of wealth of nonprofit organizations that comprise real estate, equipment, intellectual property products, open market paper, other loans and advances, municipal securities, commercial mortgages, and trade payables. We exclude consumer durables and assets related to life insurance, security credit, and miscellaneous assets and loans. These positions are excluded either because they belong to nonprofit organizations that are not part of the SCF household survey, or because of non-comparability. Dettling *et al.* (2015) explain the reasons for this selection in detail in Appendix B of their paper. We do not subtract the wealth of the Forbes 400 from the FFA total, because these estimates only exist since 1982. We adjust FFA values by CPI and divide totals by the number of households from Census data.

A.6 Accounting for demographic change

We implement the approach proposed by Fortin *et al.* (2011) to construct counterfactual wealth and income distributions when holding individual demographic characteristics constant over time. We choose 1971 as the base year. The counterfactual relies on changing the conditional distribution of a certain demographic variable X_d. This is achieved by a re-weighting approach. We follow the steps in Fortin *et al.* (2011) for the case of general covariates. In the first step, we pool the data from the base year and the year for which we want to compute the counterfactual. In the second step, we estimate a re-weighting factor

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

D_Y is a dummy which is equal to 1 in the base year and else zero. The estimate is obtained by combining the predicted probabilities from a probit or logit regression of D_Y on the covariates X, and the pooled sample proportions of the two groups, $\hat{P}(D_Y = j)$, $j = 0, 1$. In the third step, we estimate a similar re-weighting factor using all covariates except X_d, $\hat{\Psi}_{X_{-d}}(X_{-d})$. Finally, we adjust survey weights by the factor $\frac{\hat{\Psi}_X(X)}{\hat{\Psi}_{X_{-d}}(X_{-d})}$. In order to obtain the marginal effect of covariate X_d, we subtract from the statistic of interest derived using the adjusted weights the statistic derived using survey weights adjusted by $\hat{\Psi}_X(X)$. We add the marginal effect to the baseline estimate without adjustment. We used a probit model, including age, educational attainment, the number of adults and children, as well as race as explanatory variables in X. We first fix the age distribution to its 1971 level, and then fix the share of households whose head has at least attained some college to the base year.

A.7 Identifying hand-to-mouth households

We follow Kaplan *et al.* (2014) and restrict the sample to households with a household head between 22 and 79 years of age. We also exclude households without other income than self-employment income and households with negative income. We refer to this sample as the restricted sample in the empirical results. Following Kaplan *et al.* (2014), we classify a household as *hand-to-mouth* if one of the following two conditions applies:

$$0 \leq a \leq \frac{1}{2}\frac{y}{\theta}$$
$$a < 0 \qquad \text{and} \qquad a \leq \frac{1}{2}\frac{y}{\theta} - \underline{a}$$

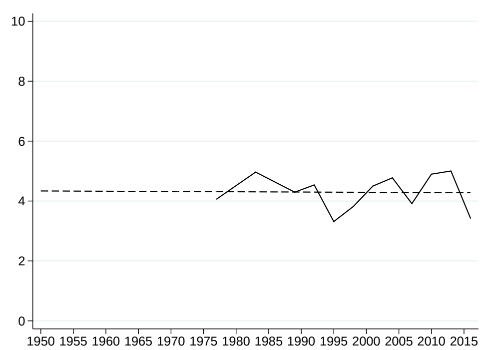
where a denotes liquid assets of the household, y denotes monthly household income net of capital income, θ is the payment frequency for income, and $\underline{a}$ denotes the borrowing limit. The factor $\frac{1}{2}$ is due to the assumption that resources are consumed at a constant rate over the month.

We follow the baseline parametrization in Kaplan *et al.* (2014) and set $\theta = 2$ and the borrowing limit to one times monthly income ($\underline{a} = y$). According to the first definition, a household is *hand-to-mouth* if liquid assets are positive but less than 25% of monthly labor income. Alternatively, a household is *hand-to-mouth* according to the second definition if it has negative liquid assets and the remaining credit line $\underline{a} + a$ is less than 25% of monthly labor income.

Following Kaplan *et al.* (2014), we distinguish between *wealthy* and *poor* hand-to-mouth households. We classify a household as a *wealthy* hand-to-mouth household if the household is hand-to-mouth according to one of the definitions from above and if the household has positive illiquid assets. Illiquid assets are the sum of housing, other real estate, certificates of deposits, retirement accounts, the cash value of life insurances, and savings bonds. From this asset position, we subtract housing debt associated with the primary residence and other real estate. The net position is the estimate for illiquid assets. Liquid assets comprise all assets held in checking, savings and call accounts, money market deposit accounts, money market mutual funds and (since 2016) prepaid debit cards.

Cash holdings are not recorded in the SCF data and have to be estimated using other data sources. We rely on different estimates for cash holdings for the historical data. The first estimate relies on Kaplan *et al.* (2014) who use evidence from the 2010 Survey of Consumer Payment Choice (SCPC). Based on this evidence, they adjust the assets in transaction accounts by a factor $1 + \frac{138}{2{,}500}$ to account for cash holdings, i.e. they increase the money held in transaction accounts by roughly 5.5%. This estimate is the ratio of average individual cash holdings from the SCPC (excluding large-value holdings), divided by the median of assets in transaction accounts from the restricted 2010 SCF sample. It seems plausible that households historically relied more on cash during the era when credit or debit cards and ATMs were not yet widely available.

Figure A.2: Cash Holdings Estimated from NCVS Relative to Median Income



Notes: The figure shows the ratio of the average amount of cash stolen in theft incidences from the National Crime Victimization Survey (NCVS) relative to median total household income in the restricted SCF+ sample. The series was extended backwards before 1983 by linear extrapolation. The NCVS data are at the individual level.

Providing alternative estimates on cash holdings is difficult, as data on cash holdings are notoriously hard to find. We provide new estimates on U.S. individual cash holdings by relying on data from the National Crime Victimization Survey (NCVS). The survey explores if individuals have been victims of crime and asks about details of the incidence, including theft. An advantage of using data on the theft of cash is that victims are likely to accurately remember the amount. Like Kaplan *et al.* (2014), we exclude particularly large cash amounts stolen as they might be more systematically selected and less exogenous. In particular, we exclude values above the 99th percentile of the stolen cash distribution. The data from the

NCVS exist since 1973. Figure A.2 shows the cash estimates as a share of median income from the SCF. For the period prior to 1973, we extrapolate this series using a linear fit, which is plotted as a dashed line in the figure.

B Coverage at the top of the distribution

The main part of the paper analyzes inequality trends using three wealth groups: the bottom 50%, 50%-90%, and the top 10% of households of the wealth distribution. A large part of the literature on trends in wealth and income concentration focuses on smaller groups in the right tail of the income and wealth distribution such as the top 1% (Piketty and Saez (2003), Saez and Zucman (2016), Bricker *et al.* (2016)). Capturing the far right tail is challenging for survey data, because non-response becomes prevalent at the top of the distribution (Sabelhaus *et al.*, 2015). Starting in 1983 the modern SCF introduced a two-frame sampling scheme that heavily oversamples households based on information from tax data. The historical SCF data do not feature a similarly sophisticated sampling scheme. As explained in the paper, we use a re-weighting approach to account for more prevalent non-response at the top of the distribution. This re-weighting approach is calibrated to the 1983 data and described in detail in the paper. A core assumption is that non-response patterns do not change systematically over time.

Bricker *et al.* (2016) provide a comprehensive discussion of the modern SCF data and the oversampling approach. They also propose a series of tests to examine the coverage of the (modern) SCF data at the top of the distribution in comparison to the tax data. In this section, we apply the tests suggested by Bricker *et al.* (2016) to the historical data. The aim is to better understand how the historical SCFs perform in capturing the right tail of the distribution relative to the tax data.

B.1 The top of the distribution: SCF+ vs. tax data

B.1.1 Income

For the modern SCFs, Bricker *et al.* (2016) use the income thresholds from tax data and compute the share of households in the survey data that is above this threshold. The data collected by Piketty and Saez (2003) allow us to implement the same test for the historical survey data. If the share of households is lower in the historical data, it could be an indication that top-income households are under-represented in the historical surveys.

We use the 90th, 95th, and 99th income percentiles reported by Piketty and Saez (2003). We adjust all data so that incomes are expressed in 2016 dollars, and calculate income thresholds excluding capital gains (Table A4 from Piketty and Saez (2003)) to align the tax data with income from the SCF+ data.

Figure B.3 shows the share of households in the SCF+ data who are above the 99th percentile (Figure B.3a), the 90th, and the 95th percentile (Figure B.3b). Looking first at the share of households above the 99th percentile in Figure B.3a, we observe that the share of households is in all years larger than 1%. Bricker *et al.* (2016) discuss this finding and the reasons behind it for the post-1989 data. If the historical data systematically miss households above the 99th percentile, we either expect a positive time trend in the share of households in case the coverage of the top improves over time, or a pronounced level shift from the 1970s to the 1980s, when we transition from the historical data to the modern SCF data. This is not the case. The data show neither a time trend nor any indication that there has been a pronounced level shift between the 1970s and 1980s in the share of households above the 99th percentile. The share fluctuates around its long-run mean (dashed line). We repeat the exercise for households above the 90th and 95th percentiles of the income tax distribution in Figure B.3b. We confirm the same pattern: the shares fluctuate around their long-run means with no indication of a secular trend or level shift from the 1970s to the 1980s.

Figure B.3: Population shares for income

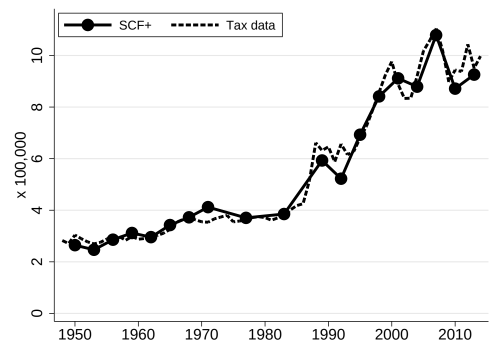
(a) 99th percentile (b) 90th/95th percentile

Notes: Share of households in the SCF+ data above 90th, 95th, and 99th percentile of the income distribution from the tax data. Left panel: Share of households in the SCF+ data above the 99th percentile from tax data. Dashed line shows sample average. Right panel: Share of households in the SCF+ data above the 90th and 95th percentile of the income distribution from tax data. Dashed line shows sample average for both time series.

As a second test, Bricker *et al.* (2016) propose to compare the incomes of households above the 99th percentile threshold. Even if there is no trend in the share of households above the 99th percentile, the historical surveys might have too few households in the very right tail of the income distribution. If this is the case, average income for households above the 99th percentile will be too low and we should see mean incomes jump (compared to the tax data)

when we move from the historical to the modern SCFs.
Figure B.4 compares mean income of households who are above the 99th percentile of the tax-data income distribution. The two series co-move closely over time. Importantly, there is no indication of a level shift in the average income series from the 1970s to the 1980s, when the historical and modern SCF data are combined.

Figure B.4: Income level of households above the 99th percentile of tax data



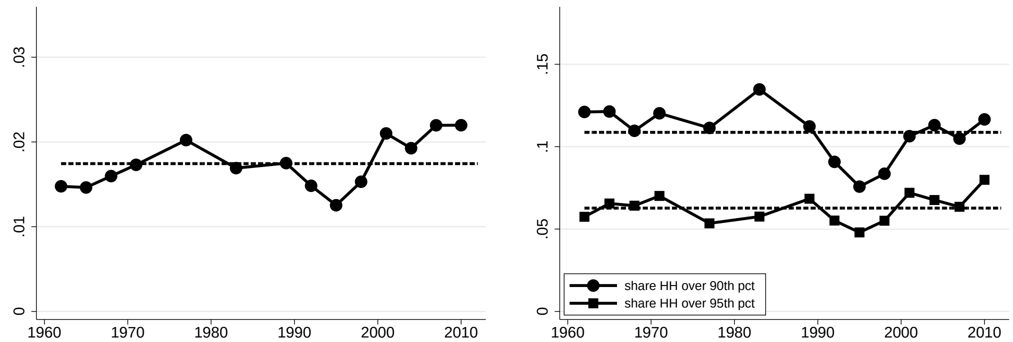
Notes: Mean income for households above the 99th percentile of the income distribution from tax data. All data have been transformed to 2016 dollars using the CPI and levels are shown in 100,000 dollars.

B.1.2 Wealth

For wealth the comparison is less comprehensive because we have to rely on indirect estimates for wealth thresholds from Saez and Zucman (2016) that are based on the capitalization method. These estimates start in 1962 only. As in the case of income, we report in the first step households above the 90th, 95th, and 99th percentiles from the estimated wealth distribution in Saez and Zucman (2016). In the second step, we again compare the conditional mean wealth level above the 99th percentile using the tax-data estimated and the estimate from the SCF+ data.
Looking at the share of households above the 99th percentile of the wealth distribution in Figure B.5a, we see a similar picture as for the income distribution. The share is greater than 1% and fluctuates around its long-run mean over the entire sample period. Again, there is no evidence of a structural break between the 1970s to the 1980s. Figure B.5b shows results for the 95th and 90th percentile of the wealth distribution.
How does the conditional mean wealth level for these households above the 99th percentile compare between the two sources? To get comparable estimates in terms of covered asset classes, we remove retirement accounts from wealth in the SCF+ and tax data.[32] As in the

[32]The tax-based estimates by Saez and Zucman (2016) include defined-benefit retirement accounts while retirement accounts in the SCF+ data only comprise defined-contribution retirement accounts.

Figure B.5: Population shares for wealth

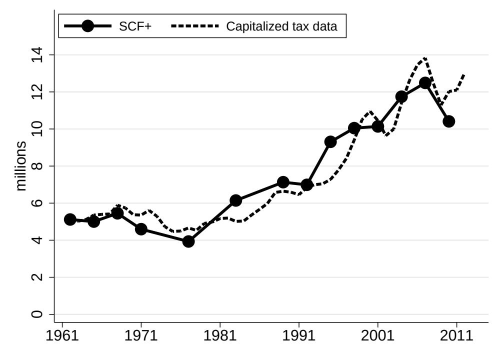


(a) 99th percentile (b) 90th/95th percentile

Notes: Share of households in the SCF+ data above 90th, 95th, and 99th percentile of the estimated wealth distribution based on tax data and the capitalization method. Left panel: Share of households in the SCF+ data above the 99th percentile from tax data. Dashed line shows sample average. Right panel: Share of households in the SCF+ data above the 90th and 95th percentile of the estimated wealth distribution. Dashed line shows sample average.

case of income, we find a close alignment for wealth levels. Comparing the pre-1983 to the post-1983 period, we find no evidence of a break in the time series when the historical and modern SCF data are merged.

Figure B.6: Wealth level of households above the 99th percentile of capitalized tax data



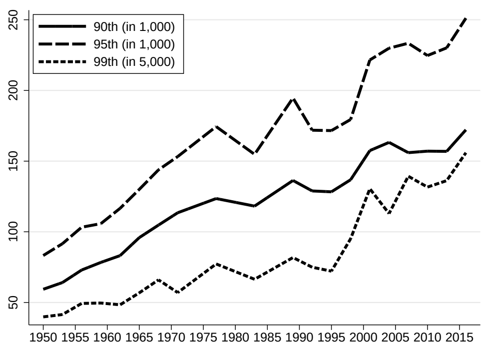
Notes: Mean wealth for households above the 99th percentile of the wealth distribution estimated using capitalized tax data. All data have been transformed to 2016 dollars using the CPI and levels are shown in millions dollars.

It is important to add a cautionary note. The evidence presented here does not support the conclusion that the SCF+ data match the distribution *within* the top 1% over time. The evidence presented only offers support for the notion that the re-weighted historical data capture the representative top 1% household reasonably well (measured against the benchmark of the tax data). The distribution within the top 1% is beyond reach without the heavy oversampling of the modern SCFs.

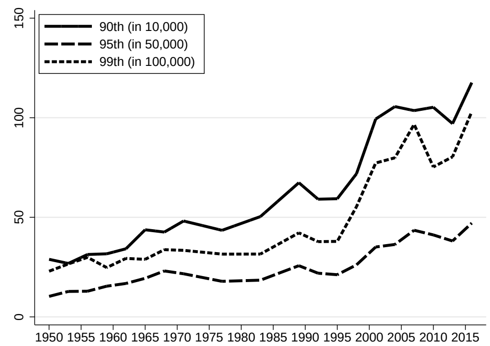
B.2 Percentiles

Another way to gauge the coverage at the top is to follow the levels of income and wealth of the top percentiles over time. Figure B.7 shows the 90th, 95th, and 99th percentiles of the income and wealth distribution over time, as well as the growth of these percentiles relative to 1971.

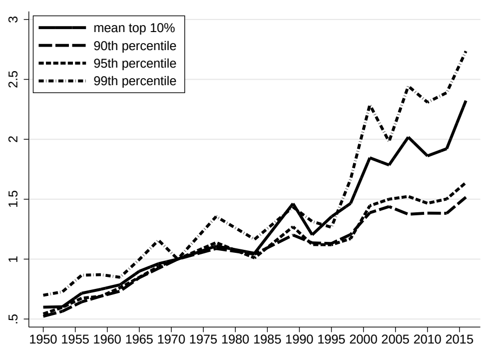
Figure B.7: Top percentiles for income and wealth over time



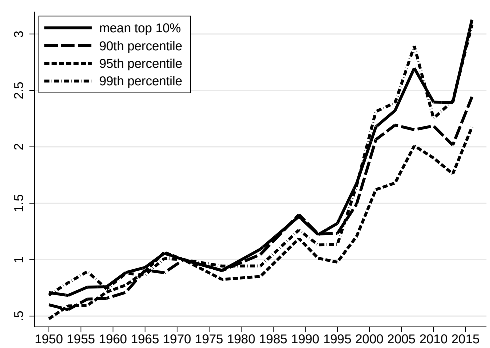
(a) income



(b) wealth



(c) income growth



(d) wealth growth

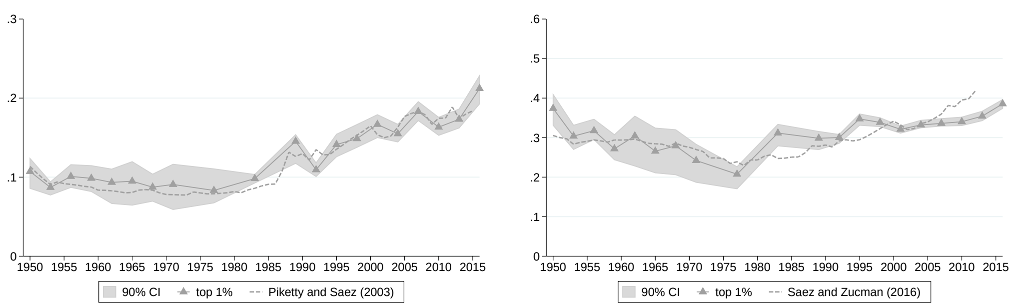
Notes: Percentile levels for income and wealth and growth of these percentiles relative to 1971. Top left panel: 90th, 95th, and 99th percentiles of the income distribution (2016 dollars). Top right panel: 90th, 95th, and 99th percentiles of the wealth distribution (2016 dollars). Bottom left panel: Growth of 90th, 95th, and 99th percentile of the income distribution relative to 1971. Bottom right panel: Growth of 90th, 95th, and 99th percentile of the wealth distribution relative to 1971.

Starting with income levels, all three percentiles evolve smoothly over time, and there is no indication of a shift in the early 1980s when we move from the historical to the modern surveys. The levels of the wealth percentiles in Figure B.7b also do not display level shifts. Figures B.7c and B.7d show the growth relative to the base 1971. Once more the transition from the adjusted historical surveys to the modern SCF does not lead to breaks in the time series.

B.3 Top income and wealth shares

Figure B.8 shows top 1% income and wealth shares from the SCF+ and compares them to the estimates by Piketty and Saez (2003) and Saez and Zucman (2016). Looking at the income share of the top 1% in Figure B.8a, the SCF+ and the tax data align closely in levels and trends for the historical period. The tax data and the combined SCF and SCF+ data both show a large increase of the top 1% income share between 1971 and 2016. Importantly, the increase in the top 1% income share is concentrated in the period after 1980 where we rely on modern SCF data that capture the very right tail of the income distribution. For wealth in Figure B.8b there is some divergence in trends over the last two decades. Bricker *et al.* (2016) and Kopczuk (2015) argue that trends from the capitalized tax data overstate the increase in wealth concentration over this time period.

Figure B.8: Top 1% income and wealth shares



(a) Income (b) Wealth

Notes: Top 1% income and wealth shares from SCF+ data and Piketty and Saez (2003) and Saez and Zucman (2016). The triangles show income and wealth shares from SCF+ data, the dashed lines income shares from Piketty and Saez (2003) using IRS tax data or wealth shares from Saez and Zucman (2016) using IRS data and the capitalization method. Gray areas around the SCF+ estimates show 90% confidence bands. Confidence bands are bootstrapped using 999 different replicate weights constructed from geographically-stratified sample of the final data set.

C Wealth mobility

The SCF+ data provide detailed information on the financial situation of U.S. households over the last seven decades. The survey is a repeated cross section and does not track households over time.[33] For our analysis in the main part of the paper, we follow the synthetic panel approach of Piketty and Saez (2003) and Saez and Zucman (2016). Households are grouped by wealth or income and then group-level income and wealth are traced over time.

In this section, we use additional data from the Panel Study of Income Dynamics (PSID) to quantify the degree of income and wealth mobility between survey dates. Díaz-Giménez *et al.* (2011) provide a similar analysis for the period from 2001 to 2007. We extend their analysis for the time period from 1983 to 2010. The main advantage of the PSID data is that it tracks the same households over time in a panel, but there are also limitations because the PSID is not designed as a wealth survey. When the PSID started in 1968, there was no systematic coverage of households' balance sheets. This changed in 1983, but the collected financial data are generally seen as lower quality compared to the SCF data as the PSID relies heavily on imputations. While this is less of a concern for cross-sectional analysis, imputation in the panel dimension tends to increase mobility due to imputation errors. Furthermore, it is important to note that for the period from 1983 to 1993, the time intervals between wealth surveys are five years and therefore longer than after 1998, when the time intervals reduce to two years. Hence, the persistence of households in wealth groups should be expected to be lower during the 1983-1993 period compared to the post-1998 period with shorter intervals between survey dates.

With these caveats in mind, we use the PSID data to explore mobility across the three wealth groups from the analysis in the main part of the paper: the bottom 50%, 50%-90%, and top 10%. For this analysis, we follow Kaplan *et al.* (2014) by restricting the sample to household heads from the SRC sample but abstain from any further sample selection.

Table C.2 shows the share of households that remain within their respective wealth group between survey dates. The share is generally high.[34] For two-year periods, the data show that more than 83% of households from the bottom 50% of the wealth distribution stay within their wealth group across surveys. We find equally high stability for the 50%-90% where around 80% of households remain in this wealth group between survey dates, and also the persistence at the top of the wealth distribution recently increased to close to 80%. Moreover, most households that move out of the top 10% between survey dates, remain close to the top. For instance, the share of households from the top 10% that is still within the top 20% at the next survey date is around 90% for the two-year periods and 86% for the five-year period.

[33]The 1983 and the 2007 SCF provide information on a subset of households from the initial survey at a second interview three years later.

[34]We always require households to be present at both survey dates when computing flows.

Table C.2: Wealth mobility

	bottom 50%	50%-90%	top 10%
1983	0.774	0.748	0.647
1988	0.750	0.740	0.672
1993	0.748	0.758	0.679
1998	0.833	0.793	0.681
2000	0.830	0.781	0.687
2002	0.838	0.796	0.729
2004	0.840	0.803	0.742
2006	0.846	0.802	0.735
2008	0.829	0.790	0.739
2010	0.848	0.811	0.774

Notes: Wealth mobility between survey dates based on PSID data. Columns show the wealth group and rows the initial survey year. Mobility is shown as the share of households who remain in the wealth group between survey dates. Difference between survey dates is five years for the first three surveys and two years starting in 1998.

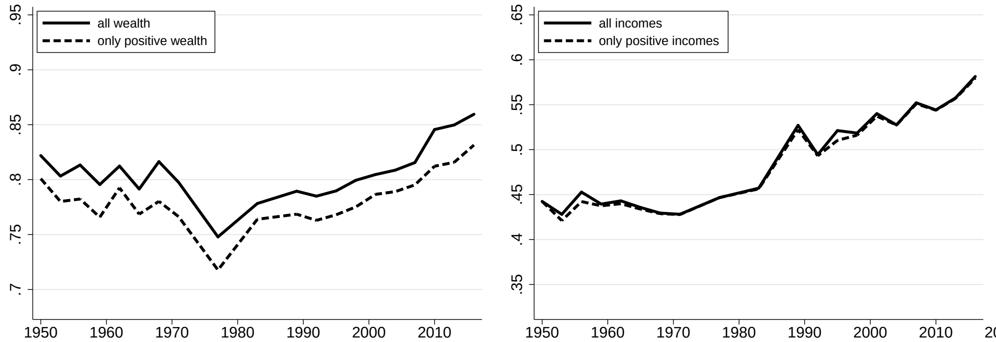
D Sensitivity analysis

This section provides a sensitivity analysis of Gini coefficients for income and wealth and explores the diverging income and wealth inequality trends using quantile ratios instead of group averages. For Gini coefficients, we explore the effect of excluding negative-wealth and income observations and the effect of imputing rents from owner-occupied housing to income. The sensitivity analysis complements the discussion from Section 3. For quantile ratios, we explore changes of the 95-50 and 90-50 ratios for income and wealth relative to 1971 to demonstrate that the pattern of diverging income and wealth inequality trends from Section 4 do not depend on trends in the very right tail of the distribution.

D.1 Excluding negative income and wealth observations

Figure D.9 shows the effect of excluding negative wealth (income) observations when computing Gini coefficients. We find that the Gini coefficients are lower when excluding negative wealth observations, but the time trends remain unaffected. For income, the effect from excluding negative income observations is negligible. Negative income observations can result, for example, from business losses.

Figure D.9: Gini coefficients for income and wealth



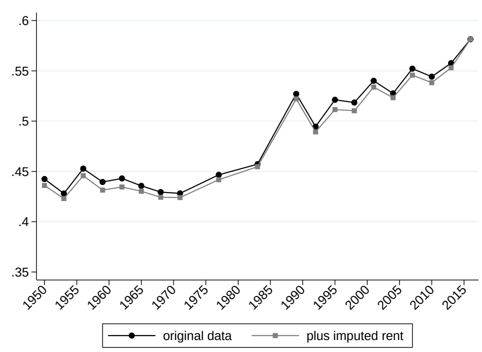
(a) wealth (b) income

Notes: Gini coefficients for income and wealth over time. Solid lines show Gini coeffients if all observations are included, dashed lines show Gini coefficients if only positive values for income or wealth are included.

D.2 Imputed rental income of owner occupiers

The main part of the paper does not include rental income of owner-occupied housing in total income. This section uses rental yields from Jordà *et al.* (forthcoming) to impute rental income for homeowners. Rental yields are average rental yields for the U.S. On average, imputed rental income accounts for 8% to 12% for households in the 50% - 90% of the wealth distribution and 6% to 10% for the top 10%. For the bottom 50%, the share accounts for only 2% to 6% due to lower homeownership rates in this part of the distribution. The share of imputed income is rising over time for all wealth groups. Including imputed rental income slightly decreases measured income inequality, but the overall effects are small (Figure D.10).

Figure D.10: Gini coefficient for income with imputed rents

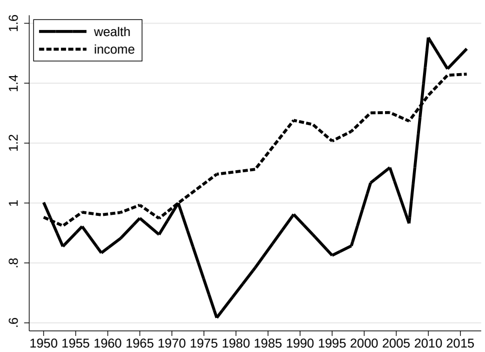


Notes: Gini coefficient for income over time. Black line with dots shows income Gini for baseline definition of income. Gray line with squares shows income Gini with imputed rents for owner-occupied housing using rental yields from Jordà *et al.* (forthcoming).

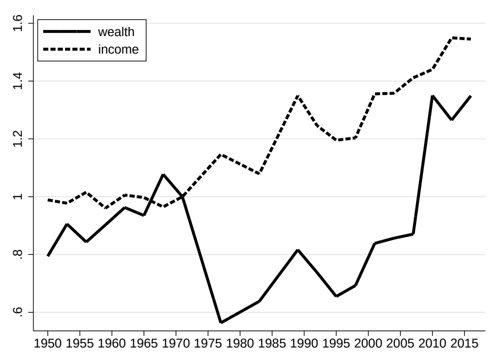
D.3 Trends in quantile ratios for income and wealth

In Section 4, we document diverging income and wealth inequality trends for the period between 1971 and 2007 based on group averages. We also document a strong rise in wealth inequality after 2007. For the top 10%, the trends in average income or wealth could be driven by changes in the very right tail of the distribution. Figure D.11 shows changes in the 95-50 and 90-50 ratios for income and wealth relative to 1971. These quantile ratios are robust to particularly high income or wealth growth in the very right tail of the distribution. We find that the stylized fact of hardly changing wealth inequality between 1971 and 2007 is a robust finding also when considering quantile ratios.[35] For income inequality, we also find the documented trends of rising income inequality since 1971 to be robust. The increase in wealth inequality after 2007 shows up even more strongly for the quantile ratios. Both the 95-50 and the 90-50 ratio jump up after 2007 and remain higher compared to historical levels.

Figure D.11: Changes in quantile ratios over time



(a) 90-50 ratios



(b) 95-50 ratios

Notes: Change in quantile ratios for income and wealth relative to 1971. The left panel shows growth relative to ratio levels in 1971 for 90-50 quantile ratios, the right panel changes in 95-50 quantile ratios of income and wealth.

E Additional results

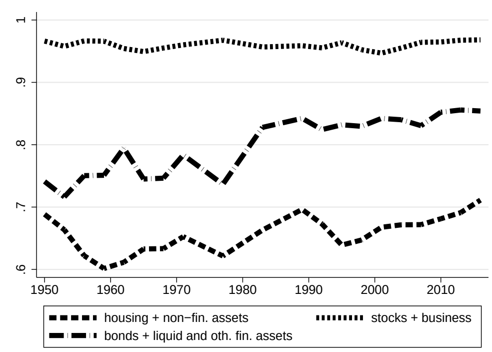
This section provides additional results that complement the analysis on portfolio composition from Section 4. First, we show Gini coefficients for different asset classes. Second, we provide a decomposition of house price exposure for different wealth groups. Finally, we report the estimated time series for Gini coefficients, wealth and income shares, and portfolio shares.

[35] We also explored trends in the 99-50 ratios and found very similar results.

E.1 Gini coefficients for different asset classes

Section 4.2 in the main paper documents systematic differences in the household portfolios along the wealth distribution. We document that the distribution of stock holdings is highly skewed, while houses are in comparison relatively equally distributed. Here we offer an alternative view on the distribution of assets in the population by looking at Gini coefficients within asset classes. Kuhn and Ríos-Rull (2016) report large differences in inequality of asset holdings within asset classes. The SCF+ data allow us to extend such an analysis over the long run and document that such inequalities in the asset distributions have been a long-run phenomenon. Figure E.12 presents Gini coefficients for different asset classes. The time series are reported in Table E.3.

Figure E.12: Gini coefficients for different asset classes over time



Notes: Gini coefficients for different asset classes over time.

Corroborating the pattern from Figure 15, we find that housing is the most equally distributed asset, with a Gini coefficient fluctuating around 0.6 and only recently exceeding 0.7. We observe a slight upward trend since 1960. By contrast, business equity and stocks show a very high degree of inequality, with high and stable Gini coefficients in excess of 0.95.

Table E.3: Gini coefficients for different asset classes over time

year	housing + nonfin. assets	stocks + business	bonds + liq. and oth. fin. assets
1950	0.69	0.97	0.74
1953	0.66	0.96	0.72
1956	0.62	0.97	0.75
1959	0.60	0.97	0.75
1962	0.61	0.95	0.79
1965	0.63	0.95	0.74
1968	0.63	0.96	0.75
1971	0.65	0.96	0.78
1977	0.62	0.97	0.74
1983	0.66	0.96	0.83
1989	0.70	0.96	0.84
1992	0.67	0.96	0.82
1995	0.64	0.96	0.83
1998	0.65	0.95	0.83
2001	0.67	0.95	0.84
2004	0.67	0.96	0.84
2007	0.67	0.96	0.83
2010	0.68	0.96	0.85
2013	0.69	0.97	0.86
2016	0.71	0.97	0.85

E.2 Decomposition of house price exposure

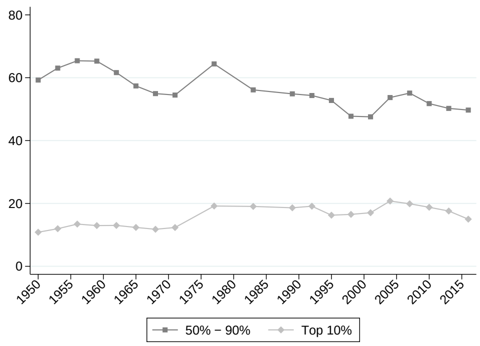
The house price elasticity of wealth from Figure 16 in the main part of the paper can be further broken down into a *diversification component* that is determined by the share of housing in assets and a *leverage component* measured by the debt-to-wealth ratio

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

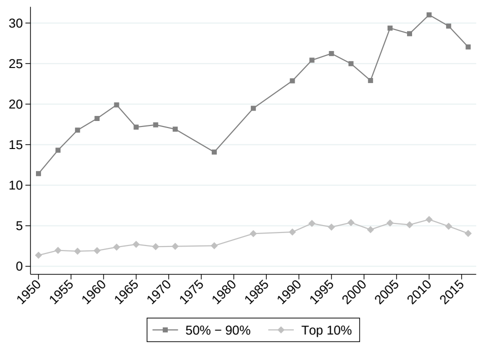
Figure E.13 shows these two components of house price exposure for the middle class and the top 10% over time. Panels (a) and (c) show the diversification component, panels (b) and (d) the leverage component.

We find that the bottom 90% are always less diversified in their asset holdings and that the share of housing in total assets remained more or less constant at 60% over the past seven decades. The top 10% are substantially more diversified with housing accounting for at most 20% of their assets (Figures E.13a and E.13c). The middle class (50%-90%) is substantially much more leveraged than the top 10% and their leverage increased over time. In 1950, debt was equivalent to only about 10% of wealth. By 2016, this number has almost tripled (Figure E.13b). For the top 10%, as share of wealth also increased over time but accounts for only 5% of their total wealth by 2016. Leverage for the bottom 50% is substantially higher (Figure E.13d). Until 2007, debt was on average roughly as much as their total debt. This changed dramatically during the financial crisis and its aftermath. In 2016, the ratio of debt to wealth for the bottom 50% is roughly 3. Strong exposure from low diversification and high leverage is not itself the result of rising house prices. Even in the 30 years between 1950 and 1980 — when real house prices were relatively stable (Knoll *et al.*, 2017) — the bottom 90% were highly exposed to the housing market.

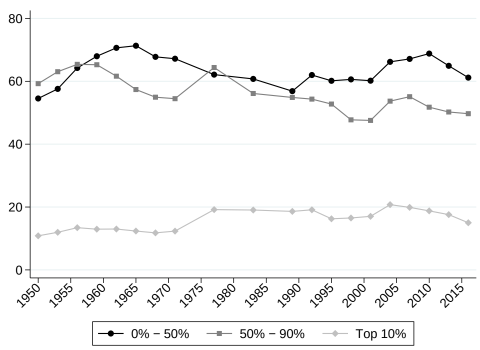
Figure E.13: Components of house price exposure by wealth group



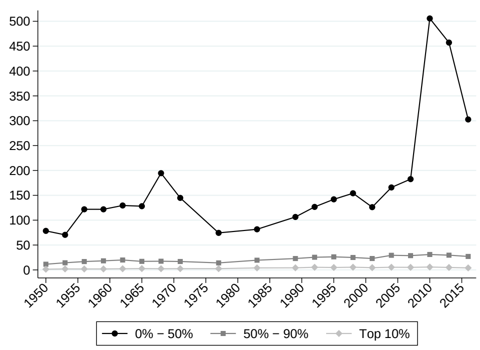
(a) Diversification ($\frac{\text{Housing}}{\text{Assets}} \times 100$)



(b) Leverage ($\frac{\text{Debt}}{\text{Wealth}} \times 100$)



(c) Diversification ($\frac{\text{Housing}}{\text{Assets}} \times 100$)



(d) Leverage ($\frac{\text{Debt}}{\text{Wealth}} \times 100$)

Notes: Decomposition of house price exposure for households in the bottom 50%, the 50%-90%, and the top 10% of the wealth distribution. Panels (a) and (c) show the *diversification* component, panels (b) and (d) the *leverage* component. See text for further details. Horizontal axes show calendar time, and vertical axes components are in percentage points.

E.3 Time series of income and wealth shares

Table E.4 shows income shares for three income and wealth groups over time. The groups are the bottom 50%, the 50%-90%, and the top 10%. Table 4 in the main paper shows the data for selected years. The last three columns show the income shares by wealth groups corresponding to the discussion in Section 4 in the paper.

Table E.4: Shares in aggregate income and wealth

	income shares by income groups			wealth shares by wealth groups			income shares by wealth groups		
year	0%-50%	50%-90%	top 10%	0%-50%	50%-90%	top 10%	0%-50%	50%-90%	top 10%
1950	21.7	43.9	34.5	2.6	24.7	72.7	33.9	37.7	28.4
1953	22.1	45.7	32.2	3.4	25.0	71.6	34.4	38.9	26.7
1956	21.1	44.6	34.3	2.8	25.1	72.1	34.7	38.4	26.8
1959	21.2	45.7	33.1	3.4	26.5	70.1	35.8	38.6	25.6
1962	21.1	45.6	33.4	3.0	24.6	72.4	34.2	38.7	27.1
1965	21.6	45.3	33.1	3.5	27.4	69.1	34.2	39.5	26.3
1968	21.6	46.3	32.1	2.6	25.5	72.0	34.4	38.7	26.9
1971	21.6	46.9	31.5	3.0	27.5	69.5	34.0	40.4	25.6
1977	20.4	46.7	32.9	4.9	32.1	63.0	31.4	43.6	24.9
1983	19.6	46.9	33.5	3.9	29.6	66.5	30.0	43.3	26.7
1989	16.3	43.7	40.0	3.0	30.0	67.0	25.9	42.0	32.1
1992	17.7	45.7	36.5	3.4	29.9	66.8	28.7	42.4	28.9
1995	16.4	45.3	38.3	3.6	28.6	67.8	28.5	41.2	30.3
1998	16.6	43.9	39.5	3.0	28.5	68.5	26.7	42.5	30.7
2001	15.9	41.7	42.3	2.8	27.8	69.4	24.7	40.4	34.9
2004	16.6	42.4	41.0	2.6	28.1	69.3	24.6	41.3	34.2
2007	15.5	40.3	44.2	2.5	26.2	71.3	24.0	38.0	37.9
2010	16.0	40.2	43.7	1.2	24.4	74.4	25.3	37.6	37.1
2013	15.3	40.1	44.6	1.1	24.1	74.8	23.7	37.7	38.7
2016	14.6	37.9	47.5	1.2	21.8	77.0	21.9	36.6	41.5

E.4 Time series of Gini coefficients

Table E.5 shows the time series of Gini coefficients over time. We discuss the observed time trends in Section 3.1 of the main paper.

Table E.5: Gini coefficients for income and wealth

	Income			Wealth		
year	all	bottom 99%	bottom 90%	all	bottom 99%	bottom 90%
1950	44	39	31	81	74	61
1953	43	39	32	79	73	58
1956	46	41	34	79	73	58
1959	44	39	33	79	71	58
1962	44	40	33	80	72	61
1965	44	39	32	78	72	59
1968	43	39	32	81	74	62
1971	43	39	33	80	74	62
1977	42	40	34	76	70	60
1983	46	41	35	78	70	59
1989	53	46	39	79	72	63
1992	49	45	38	79	71	61
1995	52	46	39	79	70	60
1998	52	45	38	80	72	62
2001	54	46	38	81	74	63
2004	53	46	38	81	74	65
2007	55	47	38	82	74	63
2010	54	47	37	85	79	71
2013	56	48	38	85	79	71
2016	58	49	39	86	79	70

Notes: Gini coefficients for income and wealth for all households and bottom 99% and 90% of the income and wealth distribution.

E.5 Time series of portfolio composition

Tables E.6, E.7, and E.8 show the portfolio composition of households for the three wealth groups considered in the main paper. These groups are the bottom 50%, the 50%-90%, and the top 10%. The first six columns show shares in assets, the next two columns show shares in debt, and the last column shows the debt-to-asset ratio.

Table E.6: Shares of wealth components in wealth portfolios of bottom 50% (in%)

year	other nonfin. assets	real estate	bus. wealth	equity	liquid assets, bonds	other fin. assets	non housing debt	housing debt	debt-to-asset ratio
1950	8.1	48.5	0.6	1.7	18.6	22.4	33.6	66.4	38.3
1953	8.6	53.8	0.2	1.5	17.1	18.7	31.7	68.3	37.5
1956	13.5	58.2	0.1	1.4	13.7	13.1	27.1	72.9	44.5
1959	10.6	64.7	0.1	2.0	12.7	9.9	28.2	71.8	52.3
1962	8.3	73.0	0.5	0.8	11.8	5.6	20.3	79.7	54.0
1965	7.2	72.5	0.2	2.3	8.9	8.8	21.2	78.8	51.5
1968	9.7	68.0	0.0	3.0	10.7	8.6	38.3	61.7	60.5
1971	7.8	71.6	0.1	1.8	10.0	8.7	32.9	67.1	56.8
1977	5.1	69.4	0.0	1.6	18.8	5.2	29.0	71.0	51.6
1983	16.8	63.2	1.0	1.5	10.3	7.2	33.2	66.8	44.9
1989	19.5	59.4	1.3	1.3	9.5	9.0	37.8	62.2	51.5
1992	17.3	63.9	2.0	1.1	7.6	8.1	32.6	67.4	55.8
1995	18.8	61.7	1.4	1.2	6.1	10.9	30.6	69.4	58.5
1998	16.8	62.5	1.4	1.8	6.3	11.2	33.0	67.0	60.5
2001	18.1	61.7	1.1	1.8	6.4	10.9	31.3	68.7	55.7
2004	16.0	67.6	1.0	1.3	5.2	8.9	28.3	71.7	62.3
2007	14.5	68.9	1.2	1.0	4.8	9.7	27.5	72.5	64.4
2010	15.3	69.7	1.3	0.4	4.3	8.9	27.2	72.8	83.3
2013	17.8	65.8	1.2	0.7	5.4	9.0	32.6	67.4	81.9
2016	18.6	62.2	1.2	0.8	6.0	11.2	42.0	58.0	75.0

Table E.7: Shares of wealth components in wealth portfolios of 50%-90% (in%)

year	other nonfin. assets	real estate	bus. wealth	equity	liquid assets, bonds	other fin. assets	non housing debt	housing debt	debt-to-asset ratio
1950	3.0	62.8	4.7	3.8	17.1	8.6	14.3	85.7	9.5
1953	3.1	62.7	4.8	5.5	15.0	8.8	14.7	85.3	11.5
1956	4.5	65.5	2.0	5.9	15.5	6.7	13.7	86.3	12.9
1959	4.8	64.7	1.3	9.1	14.7	5.4	13.7	86.3	15.1
1962	3.0	68.2	5.2	7.4	12.5	3.6	11.4	88.6	15.4
1965	2.8	63.6	3.5	10.5	13.8	5.7	12.3	87.7	13.7
1968	3.6	62.8	0.8	12.3	15.0	5.4	15.6	84.4	14.5
1971	2.5	66.1	1.7	7.6	15.6	6.5	14.3	85.7	15.0
1977	1.6	71.8	0.7	5.0	17.3	3.6	16.6	83.4	12.7
1983	6.4	63.1	5.8	2.6	13.3	8.7	19.4	80.6	16.3
1989	6.9	60.6	5.4	3.2	10.6	13.3	19.1	80.9	18.4
1992	6.9	59.8	5.0	3.7	10.2	14.4	13.9	86.1	20.1
1995	8.0	57.2	4.3	4.0	8.2	18.2	15.7	84.3	20.6
1998	6.8	52.9	4.6	6.9	8.9	19.8	16.6	83.4	19.8
2001	6.0	51.6	5.6	7.0	7.7	22.0	14.4	85.6	18.3
2004	6.0	58.1	5.1	5.2	7.0	18.7	13.4	86.6	22.4
2007	5.3	59.8	4.2	4.1	6.6	19.9	13.1	86.9	22.0
2010	6.2	56.7	5.1	3.4	7.2	21.3	13.9	86.1	23.3
2013	6.1	54.7	3.9	4.1	6.8	24.3	13.8	86.2	22.6
2016	5.8	53.3	4.5	4.3	7.1	24.9	16.1	83.9	21.0

Table E.8: Shares of wealth components in wealth portfolios of top 10% (in%)

year	other nonfin. assets	real estate	bus. wealth	equity	liquid assets, bonds	other fin. assets	non housing debt	housing debt	debt-to-asset ratio
1950	0.6	16.0	49.9	21.1	8.0	4.3	30.3	69.7	1.4
1953	0.8	18.4	49.8	20.1	7.2	3.7	32.2	67.8	1.9
1956	0.8	15.9	45.4	27.2	7.1	3.5	17.2	82.8	1.5
1959	0.9	13.3	45.5	30.8	7.4	2.1	16.3	83.7	1.8
1962	0.7	19.6	38.9	30.1	8.5	2.2	7.2	92.8	2.5
1965	0.7	22.3	35.5	33.4	5.4	2.7	11.2	88.8	2.5
1968	0.7	22.8	33.4	32.9	7.5	2.7	10.3	89.7	2.2
1971	0.5	26.4	33.8	27.0	9.4	3.0	9.1	90.9	2.2
1977	0.4	27.8	43.7	15.6	9.6	2.9	12.9	87.1	2.2
1983	2.6	33.6	29.3	13.2	11.6	9.8	35.7	64.3	3.9
1989	3.3	33.8	26.9	8.5	11.5	16.1	27.8	72.2	3.9
1992	2.6	34.1	26.8	10.4	10.1	16.0	17.2	82.8	4.9
1995	3.2	26.6	25.9	14.7	9.8	19.8	17.8	82.2	4.5
1998	2.4	25.0	23.9	18.6	6.7	23.4	22.2	77.8	4.9
2001	2.2	25.3	22.1	17.9	6.7	25.9	17.7	82.3	4.1
2004	2.3	31.5	23.3	15.3	7.6	20.1	15.6	84.4	4.8
2007	1.8	30.3	27.9	15.6	5.9	18.5	11.4	88.6	4.7
2010	2.0	29.3	23.7	14.7	8.5	21.8	11.6	88.4	5.4
2013	1.9	26.1	24.1	16.1	7.1	24.6	10.4	89.6	4.5
2016	1.5	24.2	25.2	19.9	6.3	22.9	17.3	82.7	3.7