WORKING PAPER · NO. 2021-119

Top Wealth in America: New Estimates and Implications for Taxing the Rich

Matthew Smith, Owen M. Zidar, and Eric Zwick

OCTOBER 2021

Becker Friedman Institute
FOR ECONOMICS AT UCHICAGO

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

TOP WEALTH IN AMERICA:
NEW ESTIMATES AND IMPLICATIONS FOR TAXING THE RICH

Matthew Smith
Owen M. Zidar
Eric Zwick

October 2021

This work does not necessarily reflect the views of the US Treasury. We thank Anmol Bhandari, Jesse Bricker, Jediphi Cabal, Curtis Carlson, John Cochrane, Anil Kashyap, Pete Klenow, Henrik Kleven, Pat Kline, Wojciech Kopczuk, Ilyana Kuziemko, Dave Lee, Moritz Lenel, Adam Looney, Janet McCubbin, Ellen McGrattan, Kevin Moore, Stefan Nagel, Matt Notowidigdo, Luigi Pistaferri, Emmanuel Saez, Natasha Sarin, David Splinter, Juan Carlos Suarez Serrato, Amir Sufi, Larry Summers, Richard Thaler, Chris Tonetti, Rob Vishny, Alice Volz, Danny Yagan, Gabriel Zucman and many seminar participants for helpful comments. Joseph Battles, Drew Burd, Coly Elhai, Joseph Hancuch, Stephanie Kestelman, Laurence O'Brien, Shivani Pandey, Dustin Swonder, Samuel Wallach-Hanson, Blake Woods, and Caleb Wroblewski provided stellar research assistance. We thank Michael Batty, Joseph Briggs, David Fisher, Ravi Mattu, Enrico Moretti, Orie Paul, Caleb Pitters, Barry Ritholtz, Emmanuel Roman, John Sabelhaus, Natasha Sarin, Alexi Savov, David Splinter, Kamilla Sommer, Cathleen Stahl, Dan Wilson and their coauthors for sharing data. Zidar and Zwick thank the Kauffman Foundation for support. Zidar also thanks the NSF for support under Grant Number 1752431, and Zwick also thanks the Fama Research Fund, Neubauer Family Foundation, the Polsky Center, and the Hultquist Faculty Research Endowment at Chicago Booth.

Top Wealth in America: New Estimates and Implications for Taxing the Rich
Matthew Smith, Owen M. Zidar, and Eric Zwick
October 2021
JEL No. D31,E01,E21,H2

ABSTRACT

This paper uses administrative tax data to estimate top wealth in the United States. We assemble new data that links people to their sources of capital income and develop new methods to estimate the degree of return heterogeneity within asset classes. Disaggregated fixed income data reveal that rich individuals earn much more of their interest income in higher-yielding forms, and have much greater exposure to credit risk. Consequently, in recent years, the interest rate on fixed income at the top is approximately three times higher than the average. Using firm-level characteristics to value firms, we find that twenty percent of total pass-through business wealth accrues to those with losses. We combine this new data on fixed income and pass-through business returns with refined estimates of C-corporation equity, housing, and pension wealth to deliver new capitalized wealth estimates. Our approach---which builds on Saez and Zucman (2016) and Bricker, Henriques, and Hansen (2018)---reduces bias because wealth and rates of return are correlated. From 1989 to 2016, the top 1%, 0.1%, and 0.01% wealth shares increased by 7.6, 5.1, and 3.0 percentage points, respectively, to 31.5%, 15.0%, and 7.0%. While these changes are less dramatic than some prior estimates, wealth is very concentrated: the top 1% holds nearly as much wealth as either the bottom 90% or the "P90-99" class. We discuss implications for income inequality measures, capital tax policy, and savings behavior.

Matthew Smith
Office of Tax Analysis
U.S. Department of the Treasury
1500 Pennsylvania Avenue, NW
Washington, D.C. 20220
matthew.smith@treasury.gov

Owen M. Zidar
Department of Economics &
School of International and Public Affairs
Princeton University
237 Julis Romo Rabinowitz Building
Princeton, NJ 08544
and NBER
ozidar@princeton.edu

Eric Zwick
Booth School of Business
University of Chicago
5807 South Woodlawn Avenue
Chicago, IL 60637
and NBER
ezwick@chicagobooth.edu

How rich are the richest Americans? A thorough answer to this question is necessary to address public concern over rising inequality, whether the distribution of resources is fair, and how policy ought to respond. Evaluating tax policies that target the rich depends upon the quality of top wealth estimates. Measuring the concentration of wealth also matters for economic analysis of growth, savings, and capital accumulation.

There are three main approaches for estimating top wealth (Kopczuk, 2015). The first approach combines estate tax data and mortality statistics to map the wealth of decedents to estimates for the wealth of the living (Mallet, 1908; Kopczuk and Saez, 2004*a*). The second approach uses surveys such as the Federal Reserve's Survey of Consumer Finances (SCF)(Wolff, 1998; Bricker, Henriques, Krimmel and Sabelhaus, 2016; Bricker, Henriques and Hansen, 2018). The third approach scales up, or "capitalizes," income observed on tax returns to estimate top wealth (Giffen, 1913; Stewart, 1939; Saez and Zucman, 2016).

Recent estimates from these approaches tell starkly different stories about the level and evolution of top 0.1% wealth (Figure 1A). The estate tax series suggests the share of wealth held by the top 0.1% was around 10% in recent years, has changed little since 1975, but was twice as high in the era before the Great Depression. In contrast, the capitalization approach in Saez and Zucman (2016) (SZ)—which adopts the simplifying assumption of equal returns within asset class to map income to wealth—shows a dramatic U-shape in wealth concentration. Top 0.1% wealth matched the estate tax series in the early years, then diverged and surged spectacularly since 1980 to around 20% recently. The survey data from the SCF, available every three years since 1989, has hovered between the estate and capitalization series and shows modest growth.[1]

There is especially strong disagreement across series about the level, trend, and composition of top wealth within the top 1% in the twenty-first century. Even after harmonizing the SCF to match the tax data unit of observation and adding the Forbes 400, the gaps remain stark between an equal-returns capitalization series and the SCF for the top 0.1% and top 0.01% (Figure 1B). In terms of composition, the equal-returns series implies that half the portfolio of the top 0.01% is fixed income, whereas in the SCF the portfolio share is only 9%. By contrast, pass-through business wealth is nearly three times as large in top 0.1%

[1]SZ identify three factors that account for differences between their estimates and the SCF—the unit of observation, inclusion of the Forbes 400, and differences in household balance sheet aggregates—but find that adjusting for these factors leaves a residual gap. SZ attribute the residual gap to the possibility of sampling errors and underreporting, but Bricker, Henriques, Krimmel and Sabelhaus (2016) present compelling evidence that suggests the SCF sampling process does a good job of identifying and adjusting for differential response rates at the top of the distribution. As for the estate tax, Saez and Zucman (2019*a*) find that adjusting for mortality rate differentials can increase the trend in the estate tax series, though there is still uncertainty about this adjustment in the time series and estimates are sensitive to a small number of underlying observations and low mortality rates. Despite this progress in reconciling differences, several issues remain, which we describe and address using new data and methods.

portfolios in the SCF as in the equal-returns series.

This paper uses administrative tax data to estimate top wealth in the United States. We assemble new data that links people to their sources of capital income and develop new methods to estimate the degree of return heterogeneity within asset classes. We combine this new data on fixed income and pass-through business returns with refined estimates of C-corporation equity, housing, and pension wealth to deliver new capitalized wealth estimates. Our approach—which builds on SZ and Piketty, Saez and Zucman (2018) (PSZ) as well as Bricker, Henriques and Hansen (2018) (BHH)—reduces bias because wealth and rates of return are correlated. We provide new wealth estimates, new evidence on the rates of return, and a systematic analysis of the issues most consequential for capitalization.

We find less wealth concentration relative to the equal-returns, individual-level approach in PSZ, especially at the very top. Figure 1A shows that the top 0.1% wealth share in 2016 is 15% under our approach, and around 20% in PSZ. Top 1% and 0.01% shares fall by 24 percent and 36 percent, respectively, leaving the recent wealth estimates above the estate tax series and closer to the SCF. The growth in top wealth shares is also less dramatic, especially in the tail. For example, our approach reduces the growth in top 0.01% shares since 1989 by 45%. Nevertheless, wealth is very concentrated: the top 1% holds nearly as much wealth as either the bottom 90% or the "P90-99" class.

In terms of top portfolios, we find a larger role for pass-through business wealth and a much smaller role for fixed income wealth than PSZ, consistent with the composition of top wealth in the SCF, estate tax data, and surveys of family offices of the ultrarich. Pass-through business and C-corporation equity wealth are the primary sources of wealth at the top. At the very top, C-corporation equity is the largest component, accounting for 40% of top 0.01% wealth, but pass-through business looms large at 29%. In contrast, pension and housing wealth account for almost all wealth of the bottom 90%.

The capitalization approach estimates wealth W as a function of observed income y using the relationship, $W = \beta y$, where β is the capitalization factor. In the case of a bond, β is $1/r$ where r is the interest rate. We estimate the degree of heterogeneity and allow β to vary across groups of people within each major asset class: fixed income, C-corporation equity, pass-through business, housing, and pensions. For each category, we describe challenges in applying the capitalization approach, how we address them, and provide new evidence and methods to develop and support our estimates. We then add up these components and present results on the level, trends, and composition of wealth in America.

We introduce two innovations to estimate fixed income wealth. First, we construct a novel data set on the universe of taxable interest sources linked to owners using de-identified data from income tax records spanning 2001-2016. These 3.2 billion source-owner observations allow us to disaggregate taxable interest income into subcomponents. This disaggregation reveals that rich individuals earn a much larger share of their interest income in the tax data in higher-yielding forms (such as boutique investment partnerships of distressed debt or mezzanine funds). Disaggregation also allows us to estimate interest rates more accurately than prior work. These data reveal a striking amount of return heterogeneity across wealth groups, with the top 0.01% group receiving returns that are 3.3 times average returns. In 2016, our estimates increase from nearly 1% within the bottom 99.9 to 1.6% for P99.9-99.99 to 3.4% for the top 0.01%.

Second, we develop a complementary approach that uses the covariance structure of interest rates, assets, and returns to estimate fixed income returns by group. Intuitively, we estimate risk exposure to credit and interest rate risk for different groups by observing how their interest income flows vary and covary with aggregate risk factors. Consistent with our information-returns estimates and qualitative evidence, we find that top wealth groups have much greater exposure to credit risk. The resulting point estimate for interest rates on fixed income in 2016 is 3.7% (s.e.=0.7%) for the top 0.1% group and 1.4% (s.e.=0.9%) for the bottom group. We find that the ratio of the top interest rate to the equal-returns rate is around 3.5 in recent years, with a confidence interval from 2.8 to 4.3 in 2016.

Both the information-return and risk-exposure approaches result in substantially lower fixed income wealth estimates at the top in recent years relative to equal-returns. Accounting for the degree of return heterogeneity in our preferred approach lowers the top 0.1% wealth share by 4.1 percentage points in 2016.

To estimate pass-through business wealth, we use linked firm-owner data and industry-specific valuation multiples from public markets to develop bottom-up estimates of pass-through business wealth. Our estimates account for differences in risk, profitability, and the prevalence of losses and depreciation deductions across firms. We also account for labor income recharacterized as profits following Smith, Yagan, Zidar and Zwick (2019) (SYZZ), liquidity discounts of private firms, and missing pass-through income in tax data. We find that returns to private business rise sharply with income, but decline for those at the top of the wealth distribution. We also find that 20% of total pass-through business wealth accrues to those with losses in terms of pass-through income. Prior approaches that only capitalize positive business income, such as in SZ and BHH (who assume equal-returns in non-fixed income categories), will fail to assign substantial business wealth to these individuals because they do not incorporate return heterogeneity (i.e., tax losses of wealthy business owners).

Our aggregate pass-through business wealth estimates exceed the analogous concept in the Financial Accounts, which form the basis of the equal-returns approach. However, our aggregate estimates are below those in the SCF. We present evidence that suggests respondents' self-reported valuations in the SCF do not reflect liquidity discounts and appear overstated relative to market values, especially among small and mid-market firms that account for a substantial share of top 1% wealth in the SCF. We show that adjusting for this difference in private business valuations closes the gap between our top 1% shares and those in the SCF. We also use our data to produce estimates of rates of return for U.S. pass-through businesses and their owners, which are valuable independently of the main focus of the paper.

For C-corporation equity, we use both dividends and realized capital gains to estimate C-corporation equity wealth because both flows are informative about stock ownership. We estimate the weight placed on dividends and capital gains by minimizing the distance between top equity wealth shares in SCF data and in the equity wealth model. We find no evidence that the ultra wealthy have much lower dividend rates.

An important limitation of capitalizing equity flows—regardless of the weight on dividends and realized capital gains—is that it may miss some of the richest Americans, for whom the majority of capital gains are unrealized, especially in the very right tail. Following Bricker, Hansen and Volz (2019*a*), who apply this approach to the SCF, we add the Forbes 400 members and adjust the sampling weights to account for overlap between capitalized estimates and the additional observations from Forbes. Due to their relative size—Forbes individuals collectively account for 2.8% of total household wealth in 2016—and overlap with our estimates—owners of private businesses or dividend-paying public companies account for 77% of collective Forbes wealth in 2016—we find that incorporating the Forbes data has only a modest effect on our overall top share estimates.

For pension wealth, we capitalize an age-group specific combination of wages and pension distributions. This approach allows us to incorporate the life-cycle patterns in pension wealth and associated income flows. While less important for top wealth, pension wealth accounts for 63% of wealth for the bottom 90% and 36% for the P90-99 group. Although we do not account for the value of Social Security in our main specification, we show that doing so would further increase the role of this category of wealth and flatten the trend in measured wealth concentration (Sabelhaus and Volz, 2019; Catherine, Miller and Sarin, 2020).

Finally, for housing wealth, we allow effective property tax rates to vary across U.S. states when mapping property tax deductions to estimated housing assets. This heterogeneity matters less for the level of top wealth and more for its geographic distribution and evolution. For example, a dollar of property taxes paid in California is associated with four times as much housing wealth as a dollar paid in Illinois.

We consider the impact of parameter uncertainty and model uncertainty on our estimates. Accounting for estimated uncertainty in the parameters governing fixed income and equity wealth estimates yields top 0.1% shares that range from 14% to 16% in 2016. We also present a broader perturbation analysis that incorporates model uncertainty and alternative aggregate wealth category estimates. We then decompose the absolute difference between the PSZ wealth estimates and ours: for the top 0.1% share, 52% of the difference is due to fixed income, 23% is due to C-corporation equity, 13% is due to pass-through, 10% is due to pensions, and the remainder is due to housing, rental wealth, and other categories.

Prior work shows that allowing for interest rate heterogeneity materially reduces capitalized wealth shares in recent years. Kopczuk (2015) suggests that return heterogeneity is especially important when average returns are close to zero. Fagereng, Guiso, Malacrino and Pistaferri (2016) also challenge the equal-returns assumption using administrative records from Norway to construct individual rates of return and show how this assumption biases the trend upward.[2] Bricker, Henriques, Krimmel and Sabelhaus (2016) (BHKS) show that assigning the top 1% to have a higher interest rate—while also augmenting the SCF with the wealth of the Forbes 400 and reconciling the unit of measurement in the SCF from households to tax units—can close most of the gap between the SCF and capitalization series for the top 1%, but leaves some gap unexplained for the top 0.1%. Building on this work with income tax data matched to the SCF, BHH show that adjusting for top-1% heterogeneity in interest rates narrows most of the gap between the SCF and the capitalization approach for the top 1% (e.g., BHH Figure 6) and about one third of the gap for the top 0.1% (e.g., Appendix Figure 14).[3] To their credit, SZ do consider robustness analysis that assigns top groups modestly higher interest rates, which bring capitalization estimates down, although they use the equal-return approach for their headline results and subsequently in PSZ.

Our approach outperforms other ways of measuring interest rate heterogeneity—including SCF and linked income-and-estate tax returns—for a few reasons. First, past work (e.g., SZ, BHKS, BHH) has underestimated rates of return at the top because the interest rate is measured with a denominator that includes too many assets—specifically, fixed income and money market mutual funds—which are more prevalent at the top.[4] These assets pay non-qualified dividends, not interest, so should not be estimated by capitalizing interest flows. Removing non-taxable-interest-generating assets from the denominator increases the rate of

[2] Other contributions include Arrow (1987); Piketty (2014); Gabaix, Lasry, Lions and Moll (2016); Bach, Calvet and Sodini (2016); Guvenen, Kambourov, Kuruscu, Ocampo and Chen (2017).

[3] BHH only adjust fixed income estimates for heterogeneity. We also estimate and apply heterogeneous returns assumptions to derive capitalized wealth estimates for all major asset classes. Whereas BHH find a relatively small role for reranking in affecting capitalized wealth estimates with return heterogeneity, we find a larger role for reranking because we identify a significant amount of pass-through wealth among those with low or negative taxable incomes.

[4] We discuss the relationship between our work and contemporaneous and subsequent work, including SZ, PSZ, BHKS, BHH, and Saez and Zucman (2020*b*), in Appendix L. The revisions in Saez and Zucman (2020*b*) result in a similar top 0.1% share compared to the SZ series (Appendix Figure A.1), partly because they account for a smaller degree of return heterogeneity than we find for fixed income (Figure 5A).

return in 2016 in the SCF for the top 0.1% wealth group from 2.3% (s.e.=0.4%) to 3.9% (s.e.=1.0%). The same issue affects interest rates measured using estate tax records linked to income tax data. Moreover, in the SCF data and estate tax data, it is not possible to isolate the boutique funds that we find are key for generating the bulk of interest income for those at the very top in recent years. Consequently, disaggregating and separately capitalizing these flows is not possible in these other data sets. In contrast, our data permit us to characterize and incorporate heterogeneity across fixed income sources and further into the top tail.[5] Second, our ability to isolate these flows allows us to shed light on why different groups earn such different returns. Third, because we are measuring return heterogeneity with population data, our estimates are substantially more precise than those derived from either the SCF due to sampling error or the estate tax due to volatility from mortality rates and small sample sizes. Last, our risk-exposure approach permits us to generate standard errors for characterizing uncertainty in rates of return and capitalized wealth estimates.

By combining our estimates across asset classes, we shed new light on the levels, trends, composition, and geography of top wealth and provide estimates with implications for income inequality measures, capital tax policy, and savings behavior. Given the sensitivity of wealth estimates to assumptions about the degree of return heterogeneity, we hope that providing new estimates of this key input advances our understanding of wealth inequality in America.

1 Data

Our Data Sources. Aggregate wealth data come from the U.S. Financial Accounts (formerly the Flow of Funds) at the Federal Reserve Board, and national income data come from the National Income and Product Accounts at the U.S. Bureau of Economic Analysis (BEA). Fiscal income data comes from the IRS Statistics of Income (SOI) stratified random samples for 1965 to 2016. These data provide the core inputs for our wealth estimates.

We compare our estimates to other series, including the SCF for 1989 through 2016, supplemented with the Forbes 400 list, and the estate tax series from Kopczuk and Saez (2004*a*) and updated through 2016. We separately use aggregate data from SOI on portfolio composition from estate tax filings. We also consider the recent Distributional Financial Accounts (DFA) series, which maps the SCF onto Financial Accounts categories, providing a useful bridge between the SCF and the aggregate series in the capitalization approach.

[5]BHH primarily focus on the top 1% and do not attempt to measure interest rates further up the distribution. We show that there is considerable portfolio heterogeneity that contributes to quantitatively relevant return heterogeneity within the top 1%. Failing to account for this heterogeneity within the top 1% matters for accurate measurement of top wealth and we find that much of the difference is in the top 0.1% and top 0.01%.

We use numerous data sources to estimate wealth and validate our estimates for each asset class. First, for fixed income, we assemble novel source-owner linked data for the population of interest income recipients. These sources include large financial institutions, pass-throughs (partnerships and S-corporations), trusts, private loans to businesses, and savings bonds. We draw from a range of firm-level data, including balance sheet information on assets and income statement information on interest payments, to determine interest rates paid for each source. Section 3 describes these data in detail.

We also use data on asset holdings and fixed income flows from the SCF, yields on fixed income securities over time and bank deposits from Federal Reserve Economic Data (FRED) and Alexi Savov, respectively, and data on fixed income wealth and fixed income flows from a sample of estate tax filings merged to prior year individual tax filings.

Second, for pass-through business, we start with data for the population of individual owner-firm links among S-corporations and partnerships to apportion firm ownership among owners based on their share of ordinary business income. We use data from business tax returns to construct valuation inputs, including revenues, assets, 4-digit industry, and a measure of cash flow. We link both primary taxpayers and their spouses to the pass-through firms they own to provide novel estimates of pass-through business wealth. We draw on public company filings from Compustat to construct multiple-based valuation models. We estimate liquidity discounts for private firms using transaction data from Thomson Reuters SDC. We use aggregate estimates for underreported pass-through income from Auten and Splinter (2019) to estimate missing pass-through wealth.

Third, for C-corporation equity, we use data from the IRS Sales of Capital Assets files and population-level information returns (Form 1065 K1) to explore the composition of realized capital gains. We assemble an analogous data set to our pass-through fixed income funds for pass-through equity funds, which allows us to quantify dividend yield heterogeneity along the wealth distribution and characterize the sources of dividends and capital gains.

Fourth, for pension wealth, we incorporate estimates of defined benefit pension wealth from Sabelhaus and Volz (2019) into the SCF. We draw data on aggregate Social Security wealth from Sabelhaus and Volz (2020) and Catherine, Miller and Sarin (2020).

Fifth, for housing, we combine data on effective state property tax rates from ATTOM, assessed tax values for all residential units from DataQuick, state price indexes from Core-Logic, and state-by-year property tax revenues and population from the Census of States.

Harmonized SCF. We make several adjustments to the SCF to ensure comparability. First, our approach defines the relevant observation at the individual level based on equal splits within tax units, whereas the SCF unit of observation is the household. Second, the

SCF does not include estimates of defined benefit pension wealth, so we supplement SCF data with the Sabelhaus and Volz (2019) estimates. Third, as there is no flow concept on tax returns that corresponds to non-financial wealth, such as vehicles, jewelry, or art, our approach does not attempt to allocate these assets. Fourth, the SCF excludes the Forbes 400 from the sampling frame for privacy reasons.

Appendix Figure A.2 shows the importance of applying each adjustment and how the final series compares to our preferred approach for both the top 1% and top 0.1%. The most quantitatively important adjustments for the SCF shares are changes to the unit of observation, the inclusion of defined benefit pension wealth, and inclusion of the Forbes 400.[6]

We define private business using the SCF questions that cover both private C- and S-corporations, as well as non-corporate private business (see Appendix D for definitions).

Defining and Updating Macroeconomic Wealth Components. Our Financial Accounts aggregates draw from SZ, updated through 2014 in PSZ, and updated through 2016 by us. We make a few modifications to incorporate subsequent findings in our preferred wealth concept. First, we remove fixed-income mutual funds from the class of aggregates that generate taxable interest. These funds pay non-qualified dividends, not interest. Second, unlike SZ and PSZ, we do not assign residual wealth in Financial Accounts to fixed income, leaving it to be allocated in proportion to total wealth. Third, we reassign debt secured by commercial real estate from housing to non-corporate business (Mian, Straub and Sufi, 2020; Saez and Zucman, 2020*b*). Fourth, we do not include vehicle debt since the assets are excluded. We also scale down aggregate credit card debt so that it only reflects revolving balances (Batty, Bricker, Briggs, Holmquist, Hume McIntosh, Moore, Nielsen, Reber, Shatto, Sommer, Sweeney and Henriques Volz, 2019) (DFA 2019). Fifth, to separate C-corporation wealth from S-corporation wealth in the financial accounts, we adopt the updated S-corporation estimates from Saez and Zucman (2020*b*). Sixth, we retain Financial Accounts estimates of unfunded defined benefit pension wealth (DFA 2019).

These six modifications affect wealth estimates as follows. Reducing the fixed income aggregate lowers the bias from equal-returns for overall top wealth shares. We compare results using PSZ 2018 fixed income aggregates to those that use the updated aggregate. Reassigning debt to non-corporate business increases housing wealth and lowers sole proprietorship estimates. Updated non-mortgage debt definitions increase bottom 90% net worth.

[6] Specifically, going from household-level to an individual-level wealth concept materially reduces the top 1% and top 0.1% shares, as does adding defined benefit pension wealth because most of this wealth accrues to the bottom 99%. Adding the Forbes 400 and ranking the SCF using effective tax unit ranks (which increases the number of SCF households in the top groups) increases top shares. Saez and Zucman (2019*a*) make some but not all of these adjustments to the SCF.

Higher S-corporation aggregates reduce C-corporation aggregates. Retaining comprehensive pension estimates increases total wealth and mostly affects pensioners outside the top. We show the effect of these updates in the perturbation analysis and when presenting results for specific asset classes.

Appendix C, D, and E provide detailed definitions for each wealth component in the tax data, the SCF, and the DFA, respectively. Appendix F provides the sources for aggregate wealth components. Appendix G gives sources for other data used in this paper. Appendix I describes how we estimate portfolio composition for the Forbes 400.

2 Aggregate Wealth and Capital Income Components

The Level and Composition of Aggregate Wealth. Our goal is to estimate the distribution of wealth across individuals in the U.S. using aggregate wealth data and individual-level income data. We define aggregate wealth as total assets minus liabilities of individuals at market value, excluding durables, Social Security, non-profits, and human capital. This wealth concept is thus closer to private financial wealth than to permanent income.[7]

Figure 2A decomposes aggregate wealth and plots the evolution of five key components relative to national income. Other than pass-through business, each component is from the Financial Accounts. In 2016, national wealth amounts to 540% of national income. The largest component is pensions, which equals 203% of national income (of which 40 p.p. are unfunded defined benefit pensions).[8] Housing net of mortgages is the next largest (117%), followed by fixed income assets (94%), pass-through business—which includes proprietorship, partnership, and S-corporation equity (71%)—and C-corporation equity (67%). Combined C-corporation and pass-through business wealth gives 138%, fifty percent more than the amount of fixed income wealth and commensurate with funded pension wealth. Non-mortgage debt, which includes credit-card balances, debt secured by durable goods, student loans, and other loans, amounts to -16% of national wealth. Aggregate wealth is 77 percentage points of national income higher than in PSZ, of which 40 p.p., 15 p.p., 10 p.p., and 12 p.p. are from unfunded defined benefit pensions, our bottom-up pass-through estimates, adjustments to non-mortgage debt, and residual updates.

At the aggregate level, wealth has increased from 346% in 1966 to 540% of national income. Of that increase, 124 percentage points are from pensions, 38 are from net housing, 22 from pass-through business, 18 are from fixed income, and -7 from C-corporation equity.

[7] We also depart from SZ and follow PSZ in focusing on individual-level estimates rather than tax unit-level estimates, which helps account for evolving household structure over time and across the income distribution.

[8] We include unfunded DB pensions for consistency with and similar reasons as BHKS, BHH, and DFA.

Pension growth largely reflects the transition from defined benefit to defined contribution plans and the growth of defined contribution plans after policy reforms in the early 1980s.[9] Both aggregate housing and equity components mirror the rise and fall of asset prices associated with the stock market boom in the late 1990s and the housing boom and bust in the mid-2000s. Fixed income wealth has grown the least, though it has increased since its low point at 44% of national income in 2000 to a level last seen in the early 1990s.

The Financial Accounts are not perfect wealth measures. First, they do not include Social Security wealth, nor do they reflect the stock of human capital. Second, data limitations imply the value of non-public equity is imperfectly estimated. A significant share of non-public equity comes from multiplying the book value of private company assets by market-to-book ratios at the two-digit industry level and then applying a 25% discount for illiquidity. This procedure likely understates the value of private equity, motivating our bottom-up approach for valuing private business. Third, they may miss wealth held abroad by U.S. persons, which Zucman (2013) estimates to be 4% of U.S. financial wealth. Last, the household sector is a residual category that includes hedge funds and other entities with unclear ultimate ownership. Each of these considerations affects the total wealth to be distributed.

The Level and Composition of Observed Capital income. Figure 2B plots six types of capital income relative to national income from 1966 to 2016. Aggregate interest income of U.S. individuals increased in the late 1970s and boomed in the early 1980s. It then fell in the 1990s back to its initial share of national income. Since 2000, aggregate interest income has been falling and amounted to 0.6% of national income or $102 billion in 2016.

Pension and pass-through income are now the largest sources of fiscal capital income. Pension income has risen tenfold from 0.7% to 6% of national income from 1966 to 2016. Pass-through income was 6.8% in 1966, fell to 4% in the early 1980s, and then recovered following the Tax Reform Act of 1986 to 7.3% in 2016. Aggregate dividend income of U.S. individuals amounts to 1.6% and has fluctuated mildly around that level over this period. In contrast, aggregate capital gains of U.S. individuals is much more volatile and ranges from 2% to over 8%. Aggregate property tax payments, which are capitalized to estimate housing assets, amount to approximately 1.2% and grew modestly during the 2000s housing cycle.

[9] We plot an additional measure of pension and pass-through business wealth to compare our measures to those in other work. We show a pension series that excludes the unfunded portion of defined benefit pension wealth. We also show the Financial Accounts pass-through measure as defined in Saez and Zucman (2020*b*). Appendix Figure A.4 compares aggregates derived from the Financial Accounts in PSZ to those in the updated series with updated definitions in Saez and Zucman (2020*b*).

3 Fixed Income

3.1 Challenges in Capitalizing Interest Income

In individual tax return data, we observe interest income each year. Scaling this flow to estimate fixed income assets is challenging for four reasons. First, taxable interest income is a broad bucket that comprises many different categories of assets delivering fixed income to owners.[10] In particular, these categories include both low-yield deposits and payments from limited partnerships holding high-yield assets less traditionally thought of as fixed income, such as mezzanine securities, distressed debt, mortgage servicing rights, and leveraged loans.

Second, especially in the low interest rate environment of the mid-2000s and post-recession period, small differences in returns are quantitatively first order in terms of bias (Kopczuk, 2015; Fagereng, Guiso, Malacrino and Pistaferri, 2016).

Third, many traditional fixed income assets do not generate taxable interest. In particular, money market funds and mutual funds distribute all payments from fixed income assets in the form of non-qualified dividends, not interest.[11] These segments of the financial sector have grown in importance over time and are a large share of top portfolios. The assets that continue to pay taxable interest include bank deposits, directly held bonds, private direct loans, and indirectly held fixed income securities with non-mutual-fund intermediaries. An accurate mapping of macroeconomic targets to tax flows therefore requires separating assets that generate interest from those that generate dividends.

Fourth, fixed income portfolios for the wealthy differ in nature, risk, duration, and liquidity from those for the less wealthy. Therefore, a dollar of interest income for a wealthy person corresponds to a different level of assets than for a poorer person. Figure 3A uses the 2016 SCF to decompose fixed income holdings into two broad categories: liquid assets, including currency, deposits, and money market funds; and less liquid assets, including bonds, non-money-market fixed income mutual funds, and other fixed income assets. Among fixed income assets, high net worth households have more of their fixed income assets in bonds and other securities. The top 0.1% hold less than 20% of their fixed income portfolio in liquid assets. Bonds and fixed income mutual funds account for over 80%. In contrast, the bottom 90% hold more than 80% of their fixed income assets in liquid assets.

[10] Consider the instructions for Form 1099-INT, the information return for taxable fixed income that financial institutions provide taxpayers and the IRS. Box 1 is to "include interest on bank deposits, accumulated dividends paid by a life insurance company, indebtedness (including bonds, debentures, notes, and certificates other than those of the U.S. Treasury)."

[11] The term "non-qualified" implies that these dividends do not benefit from lower tax rates reserved for most dividend payments on equity claims.

3.2 New Data on Fixed Income Components

We construct a novel data set on the universe of taxable interest sources linked to owners using deidentified data from income tax records spanning 2001–2016. Unlike the top incomes data, these data are available on the full population. We construct these data as follows.

We first merge the population of tax returns for individuals and couples (Form 1040) to all information returns that report taxable interest (Forms 1099-INT, 1065-K1, 1120S-K1, 1041-K1). Form 1065, 1120S, and 1041 payments correspond to partnerships, S-corporations, and trusts, respectively, and "K1" refers to the information return issued by these entities for payments to owners. We further classify payments reported on Form 1099-INT into three categories: bank payments, loan payments, and savings bond payments. Bank payments and loan payments are those for which the total number of payees in a year is weakly greater than and less than 10, respectively. Savings bond payments are reported in a separate box on the information return.

The full sample comprises 3,166,087,481 source-owner-year observations (respectively, 2.8B, 120M, 110M, 27M, 21M, and 7.4M from banks, savings bonds, partnerships, S-corporations, estates, and loans). In 2016, the sample comprises 140,682,577 source-owner observations on 2,378,896 distinct sources and 64,716,434 distinct owners. From each taxpayer's Form 1040, we obtain non-qualified dividends, which includes payments from money market and fixed income mutual funds. Appendix Figure A.6 plots aggregate flows for each source over time. Interest income flows on information returns account for 80–90% of aggregate taxable interest.[12] Since 2001, the share of information-return interest coming from banks fell from 70% to 40%, and the share from partnerships increased from below 10% to nearly 30%.

Figures 3B–D plot participation rates and interest income composition in 2016 and bank participation rates over time, grouping taxpayers in adjusted gross income (AGI) percentiles. We partition the top 1% into three groups: P99-99.9, P99.9-P99.99, and the top 0.01%.

Four facts emerge. First, throughout the AGI distribution, the share of taxpayers with positive interest income from banks is much higher than for other sources of interest income. In 2016, the participation rate rises from 20% for below-median taxpayers to 60% at P90 to nearly 100% at the very top.

Second, in contrast to broad participation in banks, only top taxpayers receive interest

[12]This gap likely results from three forces. First, for small dollar payments, banks are not required to issue information returns but individuals may still report that income. Second, loans between individuals or issued by foreign entities do not trigger an information reporting requirement (see IRS Regulations Section 1.6049-5). Third, there may be some "line switching" in which income with similar tax treatment (such as real estate income) is reported in the interest box on the individual's Form 1040. This issue does not affect pass-through bottom-up estimates since the information returns are complete Cooper, McClelland, Pearce, Prisinzano, Sullivan, Yagan, Zidar and Zwick (2016).

income from partnerships, S-corporations, private loans, and trusts. Participation rates in these boutique sources rise sharply within the top decile, reaching 80% for the top 0.01%.

Third, during the 2000s and 2010s, bank participation rates declined substantially across the AGI distribution, except for the very top. From 2002, the median AGI taxpayer bank participation rate fell in half from 45% to 23%. This decline appears uniform along the AGI distribution below the top 5%. This trend coincides with a dramatic increase in taxable interest income concentration (Appendix Figure A.5B). It might appear that this fact points toward increased concentration in fixed income assets. However, substitution away from bank deposits into money market accounts and fixed income mutual funds is also consistent with rising taxable interest concentration.[13]

Fourth, the share of interest income coming from each source varies across the AGI distribution. In 2016, for those below P98, the majority of interest income comes from banks. Savings bonds account for an additional 20% of taxable interest for this group. In contrast, for top earners, partnerships generate the bulk of taxable interest, with S-corporations and private loans accounting for nontrivial shares. Bank payment shares fall sharply from 50% for P97 to 30% for P99-99.9 to just over 10% for the top 0.01%. These large and systematic differences in interest income composition reflect different portfolios: bank deposits differ from boutique investment funds available to the ultrarich. In the next section, we use these flow data to estimate individual-level returns and capitalized-fixed-income wealth.

3.3 Using Tax Data to Measure Return Heterogeneity

Source-Level Rates of Return. For each income component, we estimate a rate of return using tax data when possible and supplement these estimates with other data when necessary. For boutique sources of income, we construct new data that link the population of interest-paying partnerships (Form 1065) to their owners (via Form 1065-K1). For private loans, we link the SOI corporate sample (Form 1120 and 1120S) to the payees for their interest payments (via Form 1099-INT).

For boutique sources, we focus on interest-paying partnerships because they account for most top interest income relative to S-corporations and trusts. We construct an interest rate for each partnership as the ratio of total interest payments to all partners divided by the partnership's total assets. Both total interest payments and total assets appear on the

[13]Unlike for bank deposits, we do not see a sharp decline in participation in non-qualified-dividend-paying assets. In addition, as highlighted by BHKS, banks are not required to issue information returns when the income falls below $10. The decline in deposit rates since 2000 likely increased the share of accounts subject to this measurement issue; consistent with this idea, we find the number of information returns issued by banks falls from 238 million in 2001 to 126 million in 2016. In contrast to this participation trend, the share of respondents in the SCF reporting bank deposits remained stable over this time period.

partnership's Form 1065 business tax return.

Ideally, we could measure interest rates for fixed income holdings for all partnerships that distribute interest to individuals. However, partnerships that pay multiple types of income will have fixed income and other assets commingled such that we cannot recover the appropriate interest rate. For example, an investment partnership holding both stocks and bonds would distribute some dividends, some capital gains, and some interest, but total assets are not reported in sufficient detail to allow us to isolate the bonds. We therefore restrict the population of interest-paying partnerships to those for which the share of income distributed to partners via interest is at least 99% of all payments to partners. Thus, we restrict the data to firms that specialize in fixed income.[14]

Separately, for private loans we construct a firm-level interest rate as the sum of taxable interest reported on all information returns issued by the firm divided by the sum of mortgages, loans from shareholders, and other non-current liabilities reported on the firm's tax return (Form 1120 or 1120S, Schedule L). We restrict the sample to firms that issue fewer than 10 information returns to individuals and where total interest on information returns approximately matches the firm's total interest payments (Form 1120 or 1120S, Line 13). This restriction allows us to focus on firms with relatively simple liability structures where an interest rate can be more easily measured.

For deposits, savings bonds, and fixed income mutual funds, we are not able to use tax data to estimate returns. For deposits, we compute group-specific capitalization factors with groups partitioned by non-interest wealth into deciles from P0 to P90, percentiles from P90 to P99, and P99-P99.9 and top 0.1% groups. We use SCF data to estimate the share of total bank deposits for each group, then use these shares to allocate aggregate Financial Accounts deposits to these groups in the tax data. We define group-specific bank interest rates using the ratio of taxable interest from banks on information returns to deposits at the group level. Finally, these interest rates deliver capitalization factors for estimating bank deposit holdings at the individual level.

Group-specific factors are required because bank interest is a composite that we cannot disaggregate further. According to conversations with practitioners, wealthy individuals typically receive higher interest rates on bank deposits (see, e.g., Fagereng, Guiso, Malacrino and Pistaferri (2020) for evidence from Norway). Moreover, wealthy individuals also receive interest income on some wealth management products held through banks via the same clearinghouse payer that generates information returns for deposit income for the less wealthy.

[14] One potential concern with this approach is that total assets reported by these partnerships may be mismeasured, perhaps because they do not affect the firms' tax bill or because these firms have non-fixed-income assets that do not generate income. Such classical measurement error is less consequential for boutique assets because the means are well above zero.

Bank interest flows represent a combination of true deposits and these other sources, the relative importance of which varies along the wealth distribution. Ultimately, our approach allows us to estimate heterogeneous returns within fixed income assets at banks.[15]

We estimate returns for savings bonds using SCF data and following a similar approach to our approach for private loans.[16] In the case of fixed income mutual funds, we assign wealth in proportion to individual-level non-qualified dividends from individual tax returns (Form 1040), thus assuming equal returns within this segment of assets.

Figure 4A presents interest rates by source for 2016. Boutique interest rates vary along the AGI distribution, so we present AGI-group-specific rates for this source. We interpret this variation as reflecting differences in portfolio composition, risk exposure, and scale dependence. In 2016, rates across asset classes and groups vary from 0.3% for bottom-wealth bank deposits to 6.2% for top-AGI boutique funds. Interest rates for bank payments range from approximately 0.4% at the bottom to 1.2% for the top 0.1% in terms of non-interest wealth. This convexity is consistent with evidence from Norway, which shows an average premium in returns for safe assets of approximately 1% for top wealth groups relative to the median (Fagereng, Guiso, Malacrino and Pistaferri (2020), Figure 2B). Business loan rates are 4.5%. Savings bond rates are 5.3%.[17] Business loans and boutique rates are higher than savings bond rates and considerably higher than bank deposit rates. For both business loans and boutique funds, these rates likely reflect illiquidity, longer maturity, and higher default risk. Average realized rates on boutique assets increase somewhat with AGI, though the rate of the P99.9-99.99 slightly exceeds that of the top 0.01%. The key point is that interest rates vary substantially across interest source, even during the low-interest-rate period.

Individual-Level Rates of Return. The combination of interest rate heterogeneity across sources and greater exposure at the top to higher yielding fixed income assets results in substantial heterogeneity in rates of return across wealth groups. To quantify the

[15]In our preferred estimates, bank deposit shares are somewhat more concentrated relative to the SCF shares. For example, the SCF top-1% deposit share is 24%, whereas our top-1% deposit share is 43%. This fact suggests our approach may be conservative relative to the true underlying heterogeneity in bank returns. It also reflects the fact that bank interest flows represent both deposit and non-deposit assets, as well as the measurement issues at the bottom discussed in footnote 13.

[16]Specifically, we restrict the SCF sample to individuals for whom savings bonds make up more than 95% of their taxable-interest-generating assets. We estimate returns for this sample using the ratio of aggregate SCF interest to SCF taxable-interest-generating assets and SCF sampling weights. To interpolate rates for years between SCF sampling years, we use coefficients from a regression of the SCF savings bond rate on the 10-year US Treasury. We use these savings bond rates to generate yearly capitalization factors for capitalizing savings bond interest.

[17]Savings bond rates exceed current government bond rates for two reasons. First, interest payments for this source are reported as a cumulative distribution when individuals redeem their bonds. Second, these payments likely reflect bonds issued in earlier periods with higher rates.

degree of return heterogeneity across groups, we take the following steps. First, we use these different rates to capitalize the interest flows received from each source and by AGI group. For example, $1 of bank interest for the bottom 90% of the non-interest wealth distribution receives a capitalization factor of 312(=1/0.0032), whereas $1 of boutique interest for the top P99.9-99.99 of the AGI distribution receives a capitalization factor of 14(=1/0.0702). This step generates an amount of assets for each source at the individual level.[18]

Second, to match the total amount to the Financial Accounts, we scale fixed income assets in proportion to fixed income assets from the capitalization of information returns.[19] One reason our bottom-up aggregate fixed income wealth may not match the Financial Accounts is that, on average across AGI groups and years, information returns account for approximately 80–90% of taxable interest reported on individual tax returns. Another reason is that, because the Financial Accounts household fixed-income aggregate is itself a residual, the Financial Accounts include a broader portion of fixed income assets than when measured directly via tax returns. In robustness analysis, we present estimates that do not align our aggregates to the Financial Accounts.[20]

Figure 4B presents fixed income rates of return for 2016. We calculate rates of return as the group-level ratio of total interest income divided by total interest-generating fixed income assets. We plot these returns ranking individuals by our estimate of total wealth. Rates of return increase from 0.80% for P0-90 to 0.77% for P90-99 to 0.89% for P99-99.9 to 1.65% for P99.9-99.99 to 3.43% for P99.99-100. Rates of return that rank by AGI or by non-interest wealth display moderately greater heterogeneity in absolute terms though the differences are similar in relative terms. Overall, these data reveal a striking amount of return heterogeneity with the P99.99-100 wealth groups receiving returns that are 3.3 times average returns. At the same time, top rates of return are considerably below the top boutique rates, which reflects the mix of high- and low-yielding fixed income assets held by those at the top of the wealth distribution.

Figure 4C shows the time series of top 0.01%, top 0.1%, top 1%, and bottom 99% rates of return ranked by our preferred wealth estimates. We compare these rates to the equal-returns rate and to various capital market rates: the deposit rate from Savov, the 10-year

[18]Before assigning AGI-group boutique rates, we reassign some P0 taxpayers to the AGI group that corresponds with the absolute value of their AGI. This step is motivated by the observation in Figure 3B and in our private business estimates that those with very large losses (e.g., $> \$1M$) are likely to have substantial wealth and better resemble those at the top.

[19]For example, in 2016, aggregate capitalized fixed income assets equals $9.28T and aggregate fixed income assets in the Financial Accounts equals $9.34T. Effectively, this approach allocates the residual $0.06T in proportion to estimated fixed income assets. On average, from 2001 to 2016, the capitalized fixed income total is 9.6% below the Financial Accounts total.

[20]Unlike for pass-through business, we adhere to the Financial Accounts totals because the valuations in the Financial Accounts for marketable securities are more certain.

US Treasury rate, and the Moody's Aaa and Baa corporate bond rates. All interest rates reached a peak in the 1980s during the Volcker tightening and have been falling since then. In the years since 2000, the bottom-99% rate tracks the deposit rate closely, exceeding it by approximately 0.8% in the low-interest-rate period. The equal-returns yield, which fell from 9.5% in 1982 to 1.1% in 2016, exceeds the bottom-99% but is below the top-1% and top 0.1% rates. The top-1% rate tracks the 10-year US Treasury rate although is slightly lower since the Great Recession. The top-0.1% rate hovers between the 10-year US Treasury and the Aaa rate, moving toward the 10-year rate in the last few years of the sample. In our series, top-0.01% rate is below the riskier Baa corporate bond rate in almost all years and is slightly below the Aaa rate in 2016.

Are These Top Return Estimates Realistic? Our boutique interest rates are considerably higher than deposit or Treasury market rates. Are these reasonable? One way to approach this question is by looking at what these rates imply for aggregate quantities. The top 0.1% boutique rates in Figure 4A of 6–7% in 2016 correspond to $16B in taxable interest flows from boutique sources, which implies aggregate boutique assets for this group of $230–270B, equal to approximately 2% of top-0.1% wealth. This category of assets is not separately identified in the SCF; according to experts at the Federal Reserve Board, it is most likely to appear in the category of "Other Managed Assets." For the top 0.1% in the SCF in 2016, this category amounts to $620B, which includes both fixed income and non-fixed income holdings. Alternately, one can look at aggregate holdings of debt securities by the hedge fund sector in Financial Accounts Table B.101.f, which includes holdings by both individuals and non-individual investors such as pensions and endowments. In 2016, these holdings equal $670B in 2016. Thus, our approach appears to generate reasonable aggregates compared to external sources.[21]

As another way to assess the plausibility of these rates, Appendix Table B.1 presents additional evidence that boutique funds invest in riskier assets.[22] Many of these funds appear to invest in subordinate securities in private equity and real estate transactions, mezzanine and distressed debt, mortgage servicing rights, foreign bonds, etc., which carry considerably more credit risk than investments in government securities or bank deposits.

[21] In contrast, capitalizing these boutique interest flows using the equal-returns rate delivers aggregates of $1.5–2T, which appears much too large relative to these external sources. This total even exceeds aggregate non-bond liabilities of the non-financial corporate sector ($1.1T in 2016), which provides a benchmark for the amount of non-traditional fixed income assets that may be held in boutique partnerships.

[22] We group all 18,758 fixed income partnerships identified in 2016 and then assign each fund to one of many groups based on common words used in the fund's name. To preserve taxpayer confidentiality, the table only contains words that would not identify particular entities and restricts to those words that appear in more than 50 fund names. Categories with the highest asset-weighted interest rates use terms like MEZZANINE (6.62%), OFFSHORE (6.00%), DEBT (6.27%), HOLDCO (5.19%), CREDIT (4.99%), etc.

Appendix Table B.2 compares the interest rate distributions for boutique funds and private loans to that for different groups of corporate bonds. We collect corporate bond data from the Thomson Reuters eMaxx database merged to the WRDS Bond Returns database and report the distributions of yield-to-maturity at market values for bonds sorted into Moody's credit rating groups. The partnership and private loan interest rate distributions are quite similar to each other and overlap with corporate bond distributions for bonds with mid-tier and lower credit ratings. The most speculative corporate bonds appear to have higher yields on average than the loans and boutique funds. Overall, the table suggests our estimates from the tax data are indeed reasonable if we think of these partnerships as holding fixed income assets with substantial underlying credit risk.

As a third way of assessing the plausibility of our interest rates for the ultra high net worth population (i.e., net worth > \$50M), we collect data on fixed income portfolios from family office surveys and from conversations with wealth managers and fixed income fund managers.[23] According to PIMCO, the expected returns in 2019 for cash or equivalents, developed-market fixed income, emerging-market external debt, emerging-market local debt, and private credit are 2.2%, 3.3%, 3.3%, 5.3%, and 5.8%, respectively. Separately, PIMCO provided us with information on yield-to-maturity for some of the largest fixed-income funds that appear in high-net-worth portfolios: Short-Term, Total Returns, Income, Diversified Income. In 2016, average yields for these funds were 2.2%, 4.1%, 5.2%, 6.2%, respectively; in contrast, the average yield-to-maturity for the 10-year Treasury was 1.8%.

In terms of portfolio shares, North American family offices report 10% allocated to developed-market and developing-market bonds and 6% allocated to cash or equivalents. Half of the portfolio is allocated to "alternatives," including venture capital and direct private equity (12%), private equity funds (8%), hedge funds (9%), and direct real estate (13%). Private equity and hedge funds also include boutique private credit and distressed debt investments managed as limited partnerships. Expected returns in 2016 are 0.9%, 2.6%, and 5.5% for cash or equivalents, developed-market fixed income, and developing-market fixed income, respectively. Expected returns for hedge fund credit and distressed debt strategies are 7.5% and 11.2%, respectively, though these returns reflect both interest and capital gains.

In addition, we obtained from voluntary public disclosures the detailed tax returns with attachments for high wealth politicians.[24] Three of the wealthier politicians to release their

[23] Data on portfolio shares and expected returns for fixed income holdings come from the UBS-Campden Global Family Office Report from 2016 and from PIMCO's Family Office Portfolio Analysis from 2019. These portfolio shares refer to the invested portfolio, but do not include what the Family Office Report refers to as the "operating business," which accounts for approximately half of the typical family's net worth.

[24] *To be clear, no IRS data were used to collect this information.* Data were downloaded from `OpenSecrets.org`. Similar data are available at `https://www.taxnotes.com/presidential-tax-returns`.

tax returns and other financial information during presidential runs are Carly Fiorina, Tom Steyer, and Mitt Romney. On her 2013 tax return, Fiorina reported \$446,458 in taxable interest. Steyer reported \$11,963,299 in 2016. Romney reported \$3,012,775 in 2011.

The vast majority of Fiorina's interest comes from pass-throughs that appear to specialize in risky debt investments—the largest payments come from GS Mezzanine Partners V, LP (\$163,204); GS Concentrated Mezzanine and Distress (\$101,686); GS Mezzanine Partners 2006, LP (\$57,898); and Distressed Managers IV, LP (\$47,994). Steyer's financial disclosures exceed 2,600 pages, but do not appear to contain schedules that permit us to characterize his interest income. Nevertheless, his disclosures reveal substantial holdings of specialty private equity, venture capital, and other boutique investment funds. Romney's interest income is also somewhat difficult to characterize, but much of the income comes from pass-through holdings, directly-held off-the-run bonds, and non-traditional fixed income assets.[25]

Together, these data confirm that wealthy individuals tilt their fixed income portfolios toward riskier, higher-yielding strategies that are not widely held by the typical investor and likely require a certain level of wealth to access. As a result, these individuals expect much higher returns than the typical bank deposit holder, even in the low interest rate environment. The evidence presented here also supports our top return estimates quantitatively.

Nevertheless, our information returns approach has a few limitations. First, some taxable interest does not appear on information returns, which requires us to assign wealth for those subcomponents. Second, our boutique fund and private loan rates are estimates from a subset of interest-paying firms with capital structures that permit us to measure interest rates. Nonetheless, being able to decompose interest income reduces aggregation bias. Third, the information returns are not available prior to 2000. This limitation is less problematic because precise measurement of heterogeneity appears quantitatively more relevant for capitalization in the recent low interest rate period.

3.4 Using Risk Exposure to Estimate Return Heterogeneity

We complement the information-returns based series, which is available from 2001-2016, with a return series that uses the covariance structure of interest rates, assets, and returns

[25] Most of Romney's interest income derives from holdings in various family trusts that have separate financial disclosures. These holdings are broken down to \$1,061,639 coming from pass-through holdings and another \$1,935,479 coming from government bonds and other directly held obligations. Romney's financial disclosures from 2011 reveal holdings for some individual securities, including off-the-run bonds from the Federal Home Loan Bank (FHLB) with coupon rates ranging from 0.875% to 5.5%, as well as foreign government bond holdings with coupon rates ranging from 2.5% to 6.75%. He also reports receiving interest income from several dozen funds associated with his former company Bain Capital and their debt subsidiary Sankaty Credit Opportunities, which specializes in debt instruments from private equity deals. Romney also reports more than \$14,000 from a seller-financed mortgage and from a private loan.

to estimate risk exposure to credit and interest rate risk for different groups. We use this risk-exposure approach to estimate returns in the years when the information returns are not available and as a validation of the information-return approach.

Model Setup. Consider two groups $i \in \{1, 2\}$. Let $i = 1$ represent those in the top 0.1% of the non-fixed-income-wealth distribution, and $i = 2$ represent everyone else.[26] We use the non-fixed-income-wealth distribution (i.e., wealth other than fixed-income wealth) to rank individuals and estimate wealth in a non-circular way.

The following system of five equations explain the relationship between fixed income flows, assets, and returns across groups:

$$\ln y_{1t} = \ln r_{1t} + \ln a_{1t} \tag{1}$$

$$\ln y_{2t} = \ln r_{2t} + \ln a_{2t} \tag{2}$$

$$\ln a_t^{total} = s_1^a \ln a_{1t} + (1 - s_1^a) \ln a_{2t} \tag{3}$$

$$\ln r_t^I = \pi_1^I \ln r_{1t} + \pi_2^I \ln r_{2t} \tag{4}$$

$$\ln r_t^C = \pi_1^C \ln r_{1t} + \pi_2^C \ln r_{2t}. \tag{5}$$

The first two equations relate total fixed income flows y_{it} of group i in year t to their effective rate of return on fixed income assets r_{it} and their total fixed income assets a_{it}. Equation (3) is the log-linearized aggregation constraint that relates total fixed income assets a_t^{total} to the assets of both groups, where s_1^a is group 1's share of assets.

Equations (4) and (5) are reduced-form expressions that result from projecting the effective return of each group onto measures of interest rate risk r_t^I and of credit risk r_t^C on fixed income assets. Intuitively, a structural analogue of this projection for group 1, $r_{1t} = \gamma_1^I r_t^I + \gamma_1^C r_t^C$, resembles a CAPM setup in that their return reflects their factor loadings on two aggregate risk factors. This innovation is inspired by Begenau, Piazzesi and Schneider (2020) who estimate bank risk by projecting the returns of fixed income assets on interest rate risk and credit risk measures. A second innovation is to use the coefficient restrictions implied by the model to estimate the key parameters of interest, $(\pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C)$, which govern each group's risk-exposure and allow us to estimate returns for each group.

The model implies restrictions on elements of mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$, where

[26] Using other group definitions requires updating the flows that each group collectively receives (i.e., y_{1t},y_{2t}). To construct our three-tier estimate, we implement this procedure with 1 representing the top 0.1% of the non-fixed-income-wealth distribution, then run the same steps a second time with group 1 representing the top 1% of the non-fixed-income-wealth distribution, and then use the formulas in Appendix H.3 to construct estimates for the top 0.1%, P99-99.9, and bottom 99% from these results (see Appendix H.2 for step-by-step details).

$\boldsymbol{\mu}$ is the 5×1 vector of means of the five-equation system:

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_{r_1} + \mu_{a_1} \\ \mu_{r_2} + \mu_{a_2} \\ s_1^a \mu_{a_1} + (1 - s_1^a)\, \mu_{a_2} \\ \pi_1^I \mu_{r_1} + \pi_2^I \mu_{r_2} \\ \pi_1^C \mu_{r_1} + \pi_2^C \mu_{r_2} \end{bmatrix}, \tag{6}$$

where μ_x denotes the mean of $\ln x_t$. For example, the mean of equation (1), which describes the average log fixed income of group 1 ($\ln y_{1t}$), is equal to that group's average log rate of return plus the average log assets (i.e., $\mu_{r_1} + \mu_{a_1}$). The covariance matrix is:

$$\boldsymbol{\Sigma} = \begin{bmatrix} Var(\ln y_{1t}) & ... & ... & ... & ... \\ Cov(\ln y_{2t}, \ln y_{1t}) & Var(\ln y_{2t}) & ... & ... & ... \\ Cov(\ln a_t^{total}, \ln y_{1t}) & Cov(\ln a_t^{total}, \ln y_{2t}) & Var(\ln a_t^{total}) & ... & ... \\ Cov(\ln r_t^I, \ln y_{1t}) & Cov(\ln r_t^I, \ln y_{2t}) & Cov(\ln r_t^I, \ln a_t^{total}) & Var(\ln r_t^I) & ... \\ Cov(\ln r_t^C, \ln y_{1t}) & Cov(\ln r_t^C, \ln y_{2t}) & Cov(\ln r_t^C, \ln a_t^{total}) & Cov(\ln r_t^C, \ln r_t^I) & Var(\ln r_t^C) \end{bmatrix}. \tag{7}$$

We use the elements from $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ to define a 20×1 moment vector $\boldsymbol{m(\theta)}$ and a 19×1 parameter vector $\boldsymbol{\theta}$:

$$\boldsymbol{m(\theta)} = \left[\boldsymbol{\mu}, \Sigma_{11}, \Sigma_{21}, \Sigma_{31}, \Sigma_{41}, \Sigma_{51}, \Sigma_{22}, \Sigma_{32}, \Sigma_{42}, \Sigma_{52}, \Sigma_{33}, \Sigma_{43}, \Sigma_{53}, \Sigma_{44}, \Sigma_{54}, \Sigma_{55}\right]'$$
$$\boldsymbol{\theta} = \left[\mu_{r_1}, \mu_{r_2}, \mu_{a_1}, \mu_{a_2}, \sigma_{r_1}^2, \sigma_{r_2}^2, \sigma_{a_1}^2, \sigma_{a_2}^2, c_{r_1,r_2}, c_{r_1,a_1}, c_{r_1,a_2}, c_{r_2,a_1}, c_{r_2,a_2}, c_{a_1,a_2}, \pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C, s_1^a\right]'$$

where the moments are mean and covariance elements of equations (6) and (7). The parameters in $\boldsymbol{\theta}$ are means, variances, and covariances of the four unknowns $(r_{1t}, r_{2t}, a_{1t}, a_{2t})$ the $\boldsymbol{\pi}$ parameters governing each group's risk-exposure, and asset shares (s_1^a).[27]

Minimum Distance Estimation and Inference. We use a classical minimum distance (CMD) estimator to find the parameters that minimize the distance between the empirical

[27]For example, $\Sigma_{42} = Cov(\ln r_t^I, \ln y_{2t}) = \pi_1^I c_{r_1,r_2} + \pi_1^I c_{r_1,a_2} + \pi_2^I \sigma_{r_2}^2 + \pi_2^I c_{r_2,a_2}$, where c_{r_1,r_2} is the covariance of returns for group 1 and 2, c_{r_1,a_2} is the covariance of returns for group 1 and assets for group 2, $\sigma_{r_2}^2$ is the variance of returns $\ln r_{2t}$, and c_{r_2,a_2} is the covariance of returns and assets for group 2. Solving for $\pi_2^I = \frac{\Sigma_{42} - \pi_1^I (c_{r_1,r_2} + c_{r_1,a_2})}{\sigma_{r_2}^2 + c_{r_2,a_2}}$ helps provide some intuition for how this parameter can be identified. A bigger covariance between group 2's income and aggregate interest rate risk (i.e., Σ_{42}) indicates that π_2^I is larger. Appendix H.1 provides all of the explicit expressions of covariance moments in terms of parameters and additional discussion of how parameters can be identified.

and model moments:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \; [\hat{\mathbf{m}} - \mathbf{m}(\boldsymbol{\theta})]'[\hat{\mathbf{m}} - \mathbf{m}(\boldsymbol{\theta})], \tag{8}$$

where $\hat{\mathbf{m}}$ is the empirical estimate of mean and covariance terms, which are a function of data $(y_{1t}, y_{2t}, a_t^{total}, r_t^I, r_t^C)$. In particular, y_{1t}, y_{2t} are total fixed income flows in the tax data for group 1 and 2, respectively. In our baseline approach, group 1 is defined as individuals whose non-interest wealth ranks in the top 0.1% of the non-interest wealth distribution. Total taxable-interest-generating fixed income assets a_t^{total} are from the Financial Accounts, and r_t^I and r_t^C are the 5-year US Treasury rate and Baa index, which follows the approach of Begenau, Piazzesi and Schneider (2020) who show that these two series span interest rate space well.[28] We use a 27-year panel of annual data from 1989 to 2016 to align the sample with the SCF.

We focus on estimating the risk exposure parameters of each group (i.e., $\pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C$) and calibrate the other parameters to their corresponding SCF values. Appendix Table H.1 lists the calibrated parameter values. Although we use the SCF to calibrate some of these parameters, this approach only uses tax data to measure income flows over time, so the resulting estimates directly reflect patterns in the tax data.[29] Under regularity conditions, the vector of estimated moments will have a standard normal distribution with $\sqrt{T}(\hat{\mathbf{m}} - \mathbf{m}) \to N(0, \mathbf{V})$. Applying Hansen (1982), we have $\sqrt{T}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \to N(0, \Delta)$ where $\Delta = (\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'\mathbf{V}\mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}$ and $\mathbf{G} = \frac{\partial \boldsymbol{m}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$. We estimate $\hat{\mathbf{V}}$ via block bootstrap.[30]

The minimum distance analysis has a few limitations. First, there is a tradeoff between the dimension of heterogeneity and the precision of our estimates. Unlike the information returns approach, we cannot identify interest rate heterogeneity for a large number of groups. Second, we assume that the risk exposure parameters (i.e., the $\boldsymbol{\pi}$ terms) do not vary over time. In reality, portfolio exposure to credit and interest risk might deviate from these average risk exposures.

Estimates of Return Heterogeneity with Standard Errors. We can rearrange the risk exposure equations (4) and (5) to express each group's returns as a function of observ-

[28] Begenau, Piazzesi and Schneider (2020) use a swap instead of the 5-year US Treasury rate, but their Figure 1 shows the swap is essentially the same as the more widely available 5-year Treasury rate.

[29] Specifically, the SCF calibrated values only affect step 3 in the estimation steps enumerated in Appendix H.2. The empirical moments in step 2 do not depend on the SCF.

[30] In particular, we sample with replacement $(y_{1t}, y_{2t}, a_t^{total}, r_t^I, r_t^C)$ with overlapping blocks of length 3 (based on the rule of thumb $T^{\frac{1}{3}} = (2016 - 1989)^{\frac{1}{3}} \approx 3$, where T is the number of years in the sample).

ables and parameters:

$$\ln r_{1t} = \frac{\pi_2^C}{\pi_1^I \pi_2^C - \pi_2^I \pi_1^C} \ln r_t^I - \frac{\pi_2^I}{\pi_1^I \pi_2^C - \pi_2^I \pi_1^C} \ln r_t^C \tag{9}$$

$$\ln r_{2t} = \frac{-\pi_1^C}{\pi_1^I \pi_2^C - \pi_2^I \pi_1^C} \ln r_t^I + \frac{\pi_1^I}{\pi_1^I \pi_2^C - \pi_2^I \pi_1^C} \ln r_t^C. \tag{10}$$

We can exponentiate these expressions and plug in estimates of $\hat{\boldsymbol{\theta}}$ to obtain the estimates of r_{1t} and r_{2t}. We find the top wealth group has much stronger exposure to credit risk.[31] This finding is consistent with the information-return-based result that those at the top have higher exposure to boutique investment funds and lower exposure to bank deposits and savings bonds in their fixed income portfolios.

Figure 4D plots the resulting estimates of $\hat{r}_{1t}$ and $\hat{r}_{2t}$. The top wealth group's rate of return is 4.6% in the mid 1960s, rose to around 11.7% in the early 1980s, and has come down over time. In 2016, the top return $\hat{r}_{1,2016}$ is 3.7% with a 95% confidence interval from 3.0% to 4.5%. The bottom 99.9% return follows a similar evolution but is lower—starting at 4.2%, peaking around 9.6% in the early 1980s, and falling to around 1.4% in 2016 with a confidence interval from 0.4% to 2.3%.[32]

The confidence interval around the bottom rate includes zero in some of the recent years, which suggests capitalization estimates are likely to be very sensitive for the bottom group to the point of being unusable in some years. We therefore use the top rate estimates and then set the bottom rate such that the sum over groups adds up to the Financial Accounts aggregate for fixed income assets (see Appendix M for details).

Despite the instability of bottom rates in recent years, we can still use these estimates to quantify the extent of return heterogeneity. Figure 5A presents the point estimates and standard errors of a key ratio of the top rate relative to the equal-returns rate, $\frac{r_{1t}}{\bar{r}_t}$. This ratio summarizes the degree of heterogeneity, which is a key aspect of the debate about capitalizing top interest rates (e.g., Saez and Zucman (2020*a*) Figure 7). In recent years, the ratio's value is around 3.5 for the top 0.1% of the non-interest wealth distribution. Moreover, we can reject the null hypothesis that the top group earned the equal-returns rate. The confidence interval for this key ratio of top-to-average returns ranges from 2.8 to 4.3 in 2016. Therefore, prior approaches that assign the top group the average rate of return will overstate top returns by 180% to 330% in 2016, thereby substantially overstating top fixed income assets. Our

[31] Appendix Table H.2 reports the parameter estimates of the $\boldsymbol{\pi}$ terms as well as the coefficients in equation (9) and (10). For example, $\frac{\hat{\pi}_2^C}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} = 0.05$ ($s.e. = 0.14$). The resulting expressions are $\ln \hat{r}_{1t} = 0.05 \ln r_t^I + 0.84 \ln r_t^C$ and $\ln \hat{r}_{2t} = 0.82 \ln r_t^I + 0.06 \ln r_t^C$.

[32] Appendix Figure A.8 shows the average rates of return in 2016 when applying our preferred classical minimum distance (CMD) approach closely match those under our preferred information-returns approach.

estimates also reject the Saez and Zucman (2020*b*) approach, which assumes the top group's return exceeds the equal-returns rate by a factor of only 1.4. Figure 5A shows that the ratio for our preferred top 0.01% of the wealth distribution also increases sharply in recent years to a similar level of 3.3 as the minimum distance estimate.[33]

Figure 5B illustrates the capitalization factors, $\beta_t = 1/r_t$, that result from our minimum distance estimation and compares them to those implied by our information returns approach, by the equal-returns approach, and by other capital market rates. The difference in factors rapidly rises as aggregate interest rates approach zero.

The equal-returns series used in PSZ reflects a rate of return that includes non-interest-generating fixed income assets (namely mutual funds) and residual wealth in the numerator of the capitalization factor. It results in a capitalization factor of 124 in 2016. Removing these funds and using the latest vintage of Financial Accounts aggregates delivers an equal-returns factor of 95 in 2016. The Aaa and Treasury series imply factors of $\frac{1}{3.67\%} = 27$ and $\frac{1}{1.84\%} = 54$, respectively. When interest rates were further from zero in the 1990s, the equal-returns factor ranged from 14 to 25, whereas the more conservative Moody's Aaa factor ranged from 11 to 15. Our preferred top-0.01% estimates using information returns (or minimum distance for the top-0.1% of non-interest wealth) fall between that implied by the Treasury series and the Baa, with a value of 29 (and 27) in 2016. Our preferred top-0.1% factor tracks the Treasury-implied factor over time, and the top 1% factor exceeds it in recent years. Both are still much smaller than the equal-returns factor.

Figure 5C shows the impact on estimated fixed income wealth of the top 0.1% of the wealth distribution relative to total household wealth under different assumptions. For each series, we rank by preferred wealth to isolate the role of capitalization assumptions. The equal-returns factor from PSZ delivers an estimate in 2016 of 5.9% of household wealth. The equal-returns series using updated aggregates and definitions yields an estimate of 3.8%, highlighting the importance of mapping the right aggregates to taxable flows. Alternative factors deliver even lower estimates, including 2.4% for the 10-year Treasury, 1.8% under our preferred approach, and 1.4% and 1.1% when using the Aaa and Baa rates, respectively.[34] With the PSZ factor, top 0.1% fixed income wealth hovers between 1% and 3% of total household wealth between 1965 and 2000, rising modestly from the 1980s into the 1990s, but

[33]The top 0.1% group delivers a ratio of 2.1 in 2016, which is somewhat below the minimum-distance estimate. This difference reflects in part the different ranks used to define top groups (recall that in Figure 4B, the 2016 return ranked by wealth for the top group is 66% (= 3.4%/5.1%) of the return ranked by non-interest wealth). In other words, using this ratio of 2.1 for the top 0.1% ranked by wealth corresponds to 3.2 ranked by non-interest wealth.

[34]For the 10-year Treasury, Aaa, and Baa series, we use the respective interest rate to capitalize interest income for the top 1% ranked in terms of non-interest wealth. We then allocate the residual for capitalizing non-top-1% interest income.

then surges dramatically starting in 2000 to a peak of 6.3% of total household wealth in 2012. Top estimates using other factors show a significantly attenuated rise since 2000. Overall, the 4.1(=5.9-1.8) percentage point difference in the PSZ and preferred series accounts for a substantial portion of the gap between estimates shown in Figure 1.

Figure 5D compares actual taxable-interest-generating fixed income wealth in the SCF to predicted fixed income wealth using the equal-returns approach in PSZ versus the two-tier CMD approach.[35] Predicted fixed income wealth under equal returns vastly exceeds SCF wealth with a prediction error that increases with actual fixed income wealth. In 2016, the average top 1% household in the SCF has \$0.9M of actual fixed income wealth, whereas the PSZ 2018 estimate is \$2.6M or 291% too high. For the top 0.1% and top 0.01%, actual wealth is \$2.6M and \$4.5M, respectively, whereas the PSZ estimates are \$11.9M and \$37.1M, with corresponding prediction errors of 461% and 816%. The graph also shows that applying (i) equal returns with the updated aggregates or (ii) the return heterogeneity approach in SZ (2020b) both underperform the CMD method in predicting actual fixed income wealth.

3.5 Comparison to Prior Estimates of Return Heterogeneity

Prior approaches to capitalize interest income use either an equal returns assumption (SZ, PSZ) or map estimated interest rates from other data sources. In robustness analyses, SZ present results that scale down fixed income assets for those at the top using 10-year US Treasury rate and estate tax data.[36] BHKS also consider a top-0.1% capitalization factor chosen to match the 10-year US Treasury rate.[37] BHH use the 10-year US Treasury and estate approaches and compare these to an approach that matches households in the SCF to their individual tax returns. In the latter approach, they estimate interest rates as interest income divided by the sum of SCF fixed income assets. In each case, they then apply these interest rates for different top 1% groups (i.e., ranked by total wealth, total income, or interest income) to estimate capitalized fixed income wealth.[38]

These approaches suffer from three key limitations. The first is an absence of direct data on the degree of portfolio and return heterogeneity in terms of fixed income flows. Moreover,

[35] Taxable-interest-generating fixed income wealth is bank deposits, savings bonds, directly held bonds (excluding tax exempts), private loans, mortgage assets, and corresponding components of trust wealth.

[36] The scale factor that they use is the ratio of the equal-returns interest rate to the estimated interest rate for estate tax decedents with more than \$20 million in estates. They also alternatively use the 10-year US Treasury bond rate for the top 1% (ranked in terms of adjusted gross income less capital gains).

[37] They note that this rate appears "conservative" relative to estimated interest rates in the SCF, and that the capitalization model for creating the SCF sampling frame applies the Aaa corporate bond rate.

[38] The previous version of our paper followed these approaches and generalized the two-tier approach by assigning three different rates: the Aaa for the top 0.1% in terms of interest income, the 10-year US Treasury rate for the next 0.9%, and a residual rate that ensured the aggregates matched the Financial Accounts.

in the SCF data and estate tax data, it is not possible to isolate the boutique funds that we find are key for generating the bulk of interest income for those at the very top in recent years. The second is an imperfect mapping from the SCF and estate tax wealth data to the corresponding income flows. Specifically, the interest rates estimated in these papers include money market and fixed income mutual funds that do not pay taxable interest, thus downward biasing the estimated interest rates and the degree of return heterogeneity. Third, interest rates at the top in the SCF and estate tax data are imprecise due to sampling uncertainty, volatility from mortality rates, and small sample sizes.[39]

Figure 6 compares interest rates derived from the SCF following the BHH definition to a definition that removes non-taxable-interest-generating assets from the denominator. The numerator remains the same as in BHH, which equals interest income reported by SCF respondents based on the corresponding box for taxable interest on their tax return. In BHH, the denominator includes taxable-interest-generating assets (such as deposits and directly held bonds) as well as money market and fixed income mutual funds, whereas our preferred definition excludes these funds. Panel A shows that removing these non-taxable-interest-generating assets from the denominator increases the rate of return in 2016 in the SCF for the top 0.1% wealth group from 2.3% (s.e.=0.4%) to 3.9% (s.e.=1.0%). Figure 6B scales the interest rates in Panel A by the equal-returns rate from Figure 5A to show how this refinement affects the returns ratio. For the top 0.1%, the ratio in 2016 increases from 2.2 (s.e.=0.4) to 3.7 (s.e.=0.9), which is slightly above that from our information-return and minimum distance estimates. The confidence intervals are narrow enough to reject the equal-returns approach and the ratio of 1.4 in Saez and Zucman (2020*b*).[40]

The effects of this refinement increase within the top 1%, which reflects greater exposure to non-interest-generating funds at the very top. However, the return ratio estimate for the top 1% of 2.2 (s.e.=0.4) also suggests a factor of 1.4 is insufficient to account for return heterogeneity for this group. The figure also highlights the uncertainty in estimating interest rates for the very small sample of SCF respondents in the top 0.01% (e.g., there are 527 observations in 2016). For this group, standard errors for the BHH interest rate definition and our preferred definition are 1.3% and 2.8%, respectively, such that the confidence intervals include our preferred interest rates for both definitions. The returns ratio for this group

[39] Appendix Figure A.7 plots top interest rates under uncertainty for estate tax data using a definition that removes non-interest-generating fixed income funds from the fixed income asset definition. Appendix Section L.4 discusses other limitations of the estate tax data that also apply to this exercise.

[40] Saez and Zucman (2020*b*) also recognize this issue with the interest rate definition based on the SCF. Their approach is to remove an estimate of interest generated by boutique-style investments from the numerator, because such assets are hard to isolate in the SCF. This approach is uninformative about the relevant drivers of interest rate heterogeneity for those at the top, as our information returns data show that boutique sources account for the bulk of top taxable interest flows in tax data.

using our preferred definition has a similarly wide confidence interval, which nevertheless continues to reject both 1 and 1.4.

4 Pass-Through Equity

4.1 Challenges in Estimating Pass-Through Equity Wealth

Estimating pass-through equity wealth, which accounts for the bulk of private business wealth, is challenging for four reasons. First, as with fixed income, the information available on individual tax returns (Form 1040) is limited. Each individual tax return reports total profits across all firms owned by individuals with no additional information about the firms. Unlike in the case of stock wealth, private business wealth is typically undiversified. Thus, there is more scope for heterogeneous returns across private business owners due to differences in firm size, industry, and exposure to aggregate risk.

Second, unlike the case for marketable securities in fixed income and public equity, estimates of aggregate private business wealth are highly uncertain. For example, aggregate pass-through business values as reported by their owners in the SCF are approximately twice as large as the equivalent concept in the Financial Accounts. This difference, which amounts to 60% of national income in recent years, likely reflects a combination of factors, including self-reported valuations versus market valuations, liquidity adjustments, and missing data in the Financial Accounts.[41] An accurate valuation model is a necessary ingredient for the process of taxing business wealth, whether via an estate or wealth tax. Thus, this challenge is not only relevant for our measurement purposes, but also for implementing tax policy.

Third, because most private business wealth is closely held by active owner-managers, business income reflects a mix of payments for capital and for entrepreneurial labor services (SYZZ). A large share of the "assets" in private firms is inalienable human capital (Bhandari and McGrattan, 2021). Thus, estimating marketable private business wealth requires decomposing the flows to remove labor income prior to applying any capitalization approach.

Fourth, tax rules allow individuals to report large losses due to depreciation and investments. Such losses do not imply the value of the underlying businesses are negative or

[41] Based on conversations with economists who produce the Financial Accounts, closely-held business is likely understated in the accounts for several reasons. First, S-corporation equity is estimated using ratios of market value of equity to book value of assets at the 2-digit sector level, which may understate firm value in the asset-light service sector firms that predominate among S-corporations. Second, non-corporate business equity is estimated using a mix of market values for real estate and fixed income assets and book values for other assets, which may understate the value of these firms. Third, financial partnerships are not currently included in the accounts, which are among the largest 4-digit industries in our data. Fourth, closely held C-corporations with less than $1-2B in revenues are not included because of data limitations.

zero. Indeed, many privately-held real estate, hotels, and restaurant firms can generate such large taxable losses that the owners' AGI becomes negative even though these owners have considerable wealth in these assets. As a result, using profits alone to estimate business wealth—whether these profits appear on the individual tax return or on the business tax return—paints a biased picture of the level and distribution of private business wealth.

Finally, estimates depend on information reported to the IRS, but underreported income for pass-throughs amounts to hundreds of billions of dollars (Mazur and Plumley, 2007; Auten and Splinter, 2019; Guyton, Langetieg, Reck, Risch and Zucman, 2020). As a result, capitalizing flows in tax data may understate total pass-through business wealth.

4.2 Estimating Pass-Through Equity using Firm Characteristics

We estimate pass-through equity wealth using linked firm-owner data to develop bottom-up estimates that address these challenges. Pass-through wealth includes equity wealth associated with formal pass-throughs (i.e., S-corporations and partnerships) and informal pass-throughs (i.e., sole proprietorships). We use an industry-specific approach for formal pass-throughs, but do not have industry data for sole proprietorships, so we use a simple capitalization approach for this category of wealth.

For each firm j and owner i in year t, we begin with sales y_{ijt}^{sale}, assets y_{ijt}^{asset}, and modified EBITD y_{ijt}^{ebitd}, each apportioned to the owner based on his or her pro rata share of distributed profits or losses.[42] Modified EBITD equals interest plus depreciation plus 25% of profits, which reflects the non-human-capital contribution of pass-through profits estimated in SYZZ.[43] Our estimate of the owner's equity wealth across all firms is a liquidity-adjusted, equal-weighted average of capitalized pro rata sales, assets, and modified EBITD:

$$\hat{W}_{it}^{pthru} = 0.9 \times \sum_{j(i)} 1/3 \left(\beta_t^{sale,k(j)} \times y_{ijt}^{sale} + \beta_t^{asset,k(j)} \times y_{ijt}^{asset} + \beta_t^{ebitd,k(j)} \times y_{ijt}^{ebitd} \right), \qquad (11)$$

where $j(i)$ indicates that person i owns firm j, $k(j)$ denotes NAICS 4-digit industry k for firm j, and $\beta_t^{X,k(j)}$ denotes the valuation multiple for factor $X \in \{sale, asset, ebitd\}$ for industry $k(j)$. For example, $\beta_t^{sale,k(j)}$ is the valuation multiple for sales and y_{ijt}^{sale} is sales at firm j in industry $k(j)$ apportioned to owner i in year t. We define industry-specific multiples for all

[42] For firms with zero profits, we use a $1/N$ weight to apportion firm characteristics across owners.

[43] We consider a 50% profit parameter in a robustness exercise, which reflects the bottom of the 95% confidence interval from both equal-weighted and profit-weighted owner-death estimates in SYZZ (see their Appendix Table J.9, columns (1) and (4)).

NAICS 4-digit industries using data from Compustat:

$$\beta_t^{X,k} = \frac{\sum_{j\in k} V_{jt}}{\sum_{j\in k} X_{jt}},$$

where V_{jt} is the market value of equity for firm j. Industries with insufficient data or outlier multiples are assigned the market aggregate multiple for that factor.[44]

We apply the factor 0.9 to the estimated values to reflect a 10% liquidity discount. Our liquidity adjustment is the approximate median estimate using EBITDA multiples from data on 167 private acquisitions over 1984–2019 recorded in SDC. Our methodology for computing discounts follows Koeplin, Sarin and Shapiro (2000). Appendix J details this calculation.

Consider applying equation (11) to a typical top-owned pass-through firm: auto dealers (NAICS 4411) in S-corporation form. In 2016, auto dealers (NAICS 4411) have \$580B, \$168B, and \$6.15B dollars of sales, assets, and modified EBITD, respectively, and the corresponding multiples are 0.3, 0.56, and 6.36. We then average the three values to estimate S-corporation business wealth in that industry and apply the 10% liquidity discount. For auto dealers, this estimate amounts to \$92B in 2016. Note our method accounts for the low profit margins in this industry (i.e., $\$6.15B/\$580B = 1.1\%$) by averaging the high sales-based valuation with the low modified-EBITD-based valuation. This overall valuation implies a per-firm valuation of \$3M, in line with industry approaches to valuing auto dealerships.[45]

Our approach incorporates assets and sales to make valuations more accurate for industries for which accounting techniques that reduce profits (e.g., real estate) are prevalent. We use this method to estimate S-corporation and partnership wealth and follow the simpler approach for valuing proprietors, as we lack industry information for these firms. Since proprietors' income accounts for a small share of pass-through income at the top, a more involved model for proprietors' wealth will have modest impacts on top shares and composition.

For sole proprietorships, we begin with positive taxable proprietors' income y_{it}^{sole} for person i in year t. For each individual, we estimate proprietors' equity by scaling this flow by a common capitalization factor:

$$\bar{\beta}_t^{sole} = \frac{W_t^{sole+part}}{\sum_i (y_{it}^{sole} + y_{it}^{part})},$$

[44]Equity values are defined as the price of common stock (PRCC_C) times the number of common shares outstanding (CSHO). We consider multiples based on assets (AT), sales (SALE), and EBITD (profits before tax + XINT + DP). Outlier multiples are below 0 or above 5 for assets and sales, and above 40 for profits before tax. In cases with negative apportioned EBITD, we set the implied EBITD-based value to zero. We do not adjust Compustat EBITD using the 25% correction of profits, because that estimate is not appropriate for public C-corporations.

[45]See `https://www.forbes.com/2009/06/30/auto-dealership-valuation-entrepreneurs-finance-taulli.html` for an example analysis and discussion by an industry practitioner.

where y_{it}^{part} is positive partnership income for person i in year t and $W_t^{sole+part}$ is the aggregate wealth of unincorporated business in the Financial Accounts.

In 2016, aggregate proprietor and partnership flows are \$421B and \$320B, respectively, and aggregate unincorporated business wealth is \$8.5T.[46] Thus, the resulting capitalization factor is $\$8.5T/(\$421B + \$320B) = 11$. We use both proprietors' and partnership income to compute the capitalization factor because the Financial Accounts aggregate does not separate these types of businesses. Because we are only capitalizing proprietors' income using this factor, aggregate sole proprietorship wealth will be smaller than $W_t^{sole+part}$, equal to 57% of the Financial Accounts total (which includes both proprietorships and partnerships).

Finally, we estimate aggregate missing formal pass-through wealth. We start with estimates of underreported income for S-corporations and partnerships from Auten and Splinter (2019). We then apply the 75% recharacterized labor adjustment, and capitalize the resulting flows using a $\beta_t^{profits}$ multiple from Compustat. Last, we apply a 10% liquidity adjustment. Because we lack information on the distribution of this wealth, we allocate it in proportion to total wealth. In 2016, aggregate underreported flows for partnerships and S-corporations are \$212B and \$47B, and aggregate missing wealth is \$856B and \$191B, respectively.

4.3 Pass-Through Business Wealth Estimates

Figure 7A plots aggregate pass-through business valuation implied by applying our methodology to S-corporations and partnerships. We plot these aggregates as a share of national income by year and compare them to analogous measures from the U.S. Financial Accounts and from the SCF. We plot a long time series from 1989 through 2016 that applies the model average method to S-corporation and partnership equity after 2001, the first year in which our linked firm-owner data are available. Prior to 2001, we use the sole proprietorship capitalization factor to estimate partnership wealth and an analogous approach for S-corporation income as in SZ and PSZ.

The figure shows the range of disagreement between the Financial Accounts-based measure and the SCF-based measure. Our aggregates fall in between the Financial Accounts and SCF series in recent years and track the time series reasonably well. For example, in 2016, our estimates before liquidity and human-capital adjustments imply aggregate pass-through wealth equal to 90% of national income, approximately halfway between the SCF and Financial Accounts aggregates. Our preferred series is 15 percentage points lower relative to national income, but still exceeds the Financial Accounts total.

[46] Approximately \$20B of the proprietor flows are royalty flows and estate and trust flows earned from pass-through business.

Figures 7B and 7C quantify return heterogeneity across industries and individuals, respectively. To compute returns for a given group, we divide aggregate industry profits before tax by our estimate of group-specific wealth.[47] Figure 7B plots these returns for the thirty largest industries in aggregate S-corporation wealth and compares them to the aggregate S-corporation return. High return industries tend to be the industries in which we think the primary input is human capital, broadly defined, rather than non-human capital, including architects, engineers, lawyers, and doctors (SYZZ). This fact implies that these industries will have lower valuations compared to an equal-returns approach that does not adjust profits for recharacterized labor income. Conversely, pass-through owners with significant fixed capital (e.g., real estate) should be capitalized more because of low relative returns.

The figure shows large dispersion in implied returns across industries. The aggregate return is 10.5%, implying an equal-returns capitalization factor of 9.5. The low returns for real estate (0.4%) and high returns for lawyers (34.1%) respectively imply capitalization factors of 277 and 3. Thus, industries with returns far from the aggregate return will correspond to wealth estimates that can be understated or overstated by an order of magnitude.[48]

Figure 7C shows how pass-through returns vary across the wealth distribution in 2016. The ratio of profits to our valuation measure averages 14% for P75 to P95 before falling to around 5% for the top 0.01%. For this asset class, an equal-returns approach would understate top wealth concentration by allocating too little wealth to those with low returns.[49]

Figure 7D plots the share of pass-through business wealth in 2016 for percentile groups ranked by wealth, AGI, and pass-through income. We highlight three facts. First, 20% of pass-through wealth accrues to those with losses (P0) in terms of pass-through income. Approaches that only capitalize positive business income (e.g., SZ) will fail to assign substantial

[47] We focus on S-corporations in the industry returns analysis because they are more comparable than partnerships to traditional corporations. For example, C-corporations and S-corporations have similar accounting for compensation of active owners. This comparability makes it easier to build intuition about implied rates of return, especially for closely held firms.

[48] To provide more texture on which industries contribute to top pass-through wealth, Appendix Table B.6 presents characteristics for the largest thirty 4-digit industries. The largest five industries are other financial investment activity (5239, $1,044B), lessors of real estate (5311, $530B), restaurants (7225, $261B), management of holding companies (5511,$244B), and other professional and technical services (5419, $217B). More capital-intensive industries in real estate, finance, and oil and gas have high value per firm and are worth less per owner. In contrast, less capital-intensive industries such as law firms and consultancies are worth more per owner on average but are smaller and more numerous.

[49] This decreasing pattern contrasts with return heterogeneity when we rank individuals by AGI or pass-through income. Moving from lower to higher ranks, returns are weakly increasing in the case of AGI and sharply increasing in the case of pass-through income. This fact reflects the prevalence of human-capital-rich entrepreneurs in asset-light industries at the top of the income distribution (SYZZ). In addition, Appendix Table B.7 presents summary statistics on average returns to private business wealth for the population of pass- through businesses and their owners from 2001 to 2016. For S-corporations, mean unweighted and value-weighted returns are 11.26% and 9.88%, respectively. For partnerships, mean unweighted and value-weighted returns are 4.16% and 6.12%, respectively.

business wealth to these individuals. Second, ranking by preferred wealth estimates increases pass-through wealth concentration at the top relative to ranking by business income or AGI. This fact indicates those with losses collectively account for significant wealth at the top of the wealth distribution, which is captured by our approach. Third, private business wealth is exceptionally concentrated: when ranked by overall wealth, two-thirds of pass-through business wealth accrues to the top 1% and 40% accrues to the top 0.1%.

Comparison to the SCF. The SCF uses respondents' self-reported estimated value of the business. However, as we detail in Appendix L.1, there are a few reasons to believe these values are overstated. First, SCF-implied valuation ratios rival or substantially exceed public company valuations.[50] These valuations seem especially overstated for small and mid-market firms (i.e., with sales between $1M-$50M), which account for more than half of private business wealth in the top 1% (Appendix Table B.5). Second, these valuations are inconsistent with evidence on liquidity discounts for private targets in large firm acquisitions (Appendix J), evidence on private market sales data for mid-market firms (Bhandari and McGrattan, 2021), and the literature estimating private firm sales discounts (Officer, 2007), all of which point toward considerable private firm discounts. Third, SCF respondents appear to report high values for other assets without readily available market values such as housing (Gallin, Molloy, Nielsen, Smith and Sommer, 2021; Feiveson and Sabelhaus, 2019). Finally, even taking respondents' values as given, a wide range of total private business values is supported by the data, which reflects the relatively small number of top business owners in the sample and how the concentration of business wealth amplifies sampling uncertainty.

Comparison to Saez and Zucman (2016). SZ apply one equal-returns capitalization factor for the sum of positive proprietorship and positive partnership income and a separate equal-returns capitalization factor for positive S-corporation income. Three differences deserve note. First, this approach misses industry heterogeneity in the mapping of flows to stocks, including heterogeneity in financial and human capital components of pass-through income. Second, it estimates wealth of zero for firms that generate zero or negative taxable income despite having significant assets (e.g., real estate). Third, it relies on the Financial Accounts aggregates for the value of private business, which are likely understated.

[50] For example, Appendix Table B.4 shows that the average market value to sales ratio in the SCF is 2.6 and 2.5 for those in the P99-99.9 and top 0.1% of net worth, which is much higher than the market to sales ratio of 1.8 in Compustat. Similar valuation premia appear for ratios relative to profits (22.6 and 18.2 vs. 16.3) and cost basis (8 and 9.5 vs. either 3 or 6.5 depending on whether the measure of cost basis in Compustat is book equity or net capital).

5 C-corporation Equity

5.1 Challenges in Capitalizing C-corporation Equity Flows

Dividends and capital gains both provide information about C-corporation ownership. However, mapping these flows to an estimate of C-corporation wealth involves several challenges.

First, unlike fixed income and pass-through business wealth, we cannot link most C-corporations to their owners. Dividend payments are reported on information returns, but not all firms pay dividends. In addition, dividends on stock held through brokerage accounts appear as paid by intermediaries and do not reveal the underlying ownership.[51]

Second, while dividends derive exclusively from C-corporation ownership, realized capital gains do not.[52] Figure 8A presents the capital gains composition from the SOI Sale of Capital Assets study files for the years 1997 to 2012. While sale of corporate stock is one of the largest categories, it accounts for only 20% to 30% of total realized capital gains, whereas pass-through gains is the largest category. While pass-through gains might represent the sale of corporate stock as well, they likely also reflect sales in other categories and "carried interest" compensation to investment managers. The latter is an important source of income for general partners in hedge funds, venture capital, and private equity. We estimate that general partner distributed gains range from 15% to 35% of top 0.1% capital gains in recent years, or \$50B to \$100B per year between 2012 and 2016.[53] This result gives a reason why capital gains may provide inaccurate information about stock ownership, because carried interest does not map to current or future ownership of C-corporation stock.

A third challenge with using realized capital gains is that realizations are lumpy. Some high C-corporation wealth holders might not realize gains, while others will sell the majority

[51] Appendix Figure A.10 shows that 1099-DIVs from "broker" payers with greater than 10,000 payees are most common form of dividend payment, and they account for the bulk of dividends received for most groups except for the very top. Similarly, "brokers" for capital gains are the most common form besides 1099-Bs, which report capital gains and basis amounts at the asset level for certain assets (e.g., stock shares).

[52] As the IRS acknowledges in its instructions for reporting realized capital gains, the sale of capital assets comprises sales for a broad class of assets: "most property you own and use for personal purposes or investment is a capital asset. For example, your house, furniture, car, stocks, and bonds are capital assets" (Instructions for Form 1040, Schedule D, 2018, p.2). In their analysis of the composition of reported capital gains, the IRS SOI division lists 22 distinct categories. See `https://www.irs.gov/pub/irs-pdf/i1040sd.pdf` for 1040-D instructions, and `https://www.irs.gov/pub/irs-soi/soi-a-inca-id1604.pdf` for SOI's Sale of Capital Assets study for tax years 2007–2012.

[53] Appendix Figure A.13 presents evidence supporting our estimate. We first validate that SOCA capital gains closely track the SOI realized capital gains in our capitalized income estimates. We then show that the pass-through component of SOCA gains is large relative to SOI realized gains and the gains derived from different information return databases are comparable in magnitude and time series. General partners consistently receive 20% of all distributed gains and 60% of all distributed ordinary income, which strongly supports our approach to identifying active managers.

of their assets in a single year.[54] Thus, realized capital gains, when observed, may provide inaccurate information about the underlying distribution of wealth. This issue likely matters more in recent years as the rich own substantial stock wealth, and the tax preference for capital gains versus dividends has fluctuated over time generally in favor of capital gains.

Fourth, capitalizing equity flows may miss some of the richest Americans, for whom the majority of capital gains are unrealized. Some prominent Forbes individuals have their wealth concentrated in public firms, which do not pay dividends (e.g., Warren Buffett and Berkshire Hathaway, Mark Zuckerberg and Facebook, and Jeff Bezos and Amazon). Others do (e.g., Bill Gates and Microsoft, Larry Ellison and Oracle, the Waltons and Walmart, Phil Knight and Nike). Capitalization approaches that rely on observable fiscal capital income understate the wealth of non-dividend-generating public firms.

5.2 Capitalizing Dividends and Realized Capital Gains

We now describe how we address these challenges to estimate C-corporation equity wealth using a parameterized-combination of dividends and capital gains. Both flows provide information about C-corporation ownership, and we use data on flows and stocks from the SCF to discipline how to best combine these flows in the tax data.

Model Setup. Consider a simple case with two groups $i \in \{1, 2\}$. Let $i = 1$ represent the top 0.1% of the wealth distribution, and $i = 2$ represent everyone else. The following two expressions characterize the level and share of C-corporation wealth for group i in year t:

$$a^C_{it}(\alpha_i) = \beta^C_{it}(\alpha_i) \times \left(\alpha_i y^D_{it} + (1-\alpha_i) y^G_{it}\right) \tag{12}$$

$$s^C_{it}(\alpha_i) = \frac{a^C_{it}(\alpha_i)}{\sum_i a^C_{it}(\alpha_i)}, \tag{13}$$

where $a^C_{it}(\alpha_i)$ is C-corporation equity wealth of group i in year t and $\left(\alpha_i y^D_{it} + (1-\alpha_i) y^G_{it}\right)$ is an α_i-weighted average of group i's dividend income y^D_{it} and capital gains y^G_{it}. The capitalization factor $\beta^C_{it}(\alpha_i) = \frac{a^C_{it}(\alpha_i)}{\left(\alpha_i y^D_{it} + (1-\alpha_i) y^G_{it}\right)}$ scales up this composite flow and depends on α_i, which governs the magnitude of the total income flow $\left(\alpha_i y^D_{it} + (1-\alpha_i) y^G_{it}\right)$ for group i. Group i's share of C-corporation equity wealth is s^C_{it}.

[54] Appendix Figure A.14 uses panel data from the population of individual tax returns to compare the year-over-year persistence of realized capital gains to that for other sources of income. For those in the top 1% of realized gains in year t, the average rank in year $t + 1$ is the 75th percentile. In contrast, dividends, interest, wages, and adjusted gross income are much more persistent over time, with the top 1% having average rank of 99th, 97th, 97th, and 96th percentile, respectively, in the next year. This fact helps explain why dividends are a better predictor than realized capital gains for stock holdings in the SCF.

Minimum Distance Estimation using Equity Wealth Shares. For each group i, we find α_i that minimizes the distance between actual and model-based shares of C-corporation equity wealth:

$$\hat{\alpha}_i = \arg\min_{\alpha_i} \sum_t \left[\hat{s}_{it}^C - s_{it}^C(\alpha_i)\right]^2 \tag{14}$$

where $\hat{s}_{it}^C$ is the actual share of C-corporation equity wealth in the SCF and $s_{it}^C(\alpha_i)$ is the model-implied share given a value of α_i and data on group i's dividend income y_{it}^D and capital gains income y_{it}^G. We use this estimate of α_i to determine how to best define income flows, i.e., $\left(\hat{\alpha}_i y_{it}^D + (1-\hat{\alpha}_i) y_{it}^G\right)$, and how to capitalize them, i.e., scaling them by $\beta_{it}^C(\hat{\alpha}_i)$, to estimate C-corporate equity wealth for group i in year t. C-corporation wealth in the SCF is defined to include stocks, equity mutual funds, the equity share of mixed funds, as well as private businesses in C-corporation form.

A Regression-Based Approach on Individual-Level Data. We compare our minimum-distance approach with an alternative that estimates α_i using OLS with household-level data from the SCF. Specifically, we can fit the following model of C-corporation equity wealth:

$$a_{nt}^C = \beta^D y_{nt}^D + \beta^G y_{nt}^G + \varepsilon_{nt} \tag{15}$$

where a_{nt}^C is household n's C-corporation equity wealth in year t and y_{nt}^D and y_{nt}^G and their dividend and capital gains income, respectively. Relating the coefficients to the terms in equation (12) reveals that $\beta^D = \beta^C \alpha$ and $\beta^G = \beta^C(1-\alpha)$. These two expressions identify α in terms of coefficients: $\alpha = \frac{\beta^D}{\beta^D + \beta^G}$. Intuitively, if there is a common capitalization factor for the composite flow for all groups and if dividends are more related to C-corporation wealth empirically, then minimizing error at the person level requires more weight on dividends.

We can also investigate the degree of heterogeneity in α_i by fitting the model in equation (15) within certain wealth groups. Looking at these subsamples will produce estimates of α_i by group i. In addition, we also can weigh these regressions by wealth to put more focus on minimizing error for those of substantial means.

Results. Figure 8B presents results from the share-based approach using group-level data to estimate α_i. We present separate estimates for P0-90, P90-99, P99-99.9, P99.9-99.99, and for the top 0.01%. The error-minimizing weight on dividends $\hat{\alpha}_i$ for all groups is very close to 0.9. Except for the top 0.01%, we can precisely estimate this parameter and reject the hypothesis that $\alpha_i = 0.5$, which is the approach taken in SZ and PSZ.

Table 1 presents results from the regression-based approach using household-level data. We find C-corporation wealth is much more strongly related to dividends than realized capital gains in the full sample and for all subgroups. Interpreted through the lens of our model, the estimated αs range between 0.94 to 0.98, with the weight on dividends increasing as we move up the wealth distribution. These household-level regressions deliver more precision than the share-based approach, but at the cost of using household-level wealth as the estimand of interest rather than C-corporation wealth shares.

Both approaches strongly support placing substantially more weight on dividends when capitalizing flows to estimate C-corporation wealth. Moreover, they both suggest the degree of heterogeneity in mapping flows to stocks is relatively unimportant for this asset class.[55] Because there appears to be little heterogeneity across groups, we adopt a wealth-weighted average of parameter estimates to set α_i equal to 0.9 in our baseline capitalization.[56] The resulting capitalization factor $\beta_t^C(0.9) = \frac{\sum_i a_{it}^C}{\sum_i \left(0.9 y_{it}^D + 0.1 y_{it}^G\right)}$ is the ratio of aggregate C-corporation wealth from the Financial Accounts to the aggregate composite flow of 0.9 times dividends plus 0.1 times capital gains for each year.

Figure 8C shows how our preferred approach compares to alternative assumptions on the relative weight on capital gains for estimating C-corporation wealth. Putting positive weight on capital gains implies a much larger increase in top equity wealth and higher volatility through the stock market boom and bust in the 1990s. Since dividends are less volatile and less concentrated, the dividends-only series (i.e., 0% weight on capital gains) is more stable and lower. Reducing the weight on realized capital gains to zero, however, may be problematic because some people only hold non-dividend-paying stocks.[57] Relative to a dividends-only series, our preferred specification with 10% weight on capital gains better captures movements in the stock market.

Compared to SZ and PSZ, our approach reduces the weight on realized capital gains.[58] Instead of a weight of 0.9 on dividends and 0.1 on realized capital gains, PSZ sum both flows, which is equivalent to using weights of 0.5. Note that because aggregate realized capital gains are much larger than dividends—in 2016, total realized gains are \$614B versus \$254B for dividends (Figure 2)—the relative contribution of capital gains to estimating C-corporation equity wealth exceeds 50% when setting $\alpha = 0.5$. The $\alpha = 0.5$ assumption in the PSZ

[55] Figure A.10 shows that partnerships are an important source of dividend income for those at very top, analogous to results in Fig 8. Figure A.11 shows that heterogeneity in yields appears relatively small.

[56] The top 0.01% accounts for 6.8% of C-corporation equity wealth in 2016 in the SCF.

[57] Scholz (1992); Kawano (2014) test the dividend clientele hypothesis (Miller and Modigliani, 1961; Miller, 1977; Auerbach and King, 1983; Auerbach, 1983; Poterba, 2002) and find that high-income households reduce their exposure to dividend-yielding equities for tax reasons. This finding suggests that relying exclusively on dividend payments may not be optimal because it might underweight these high-income households.

[58] SZ and PSZ also apply "mixed" method for ranking. See Appendix L.2 for details.

series yields an estimate of 6.3% of household wealth for the top 0.1% with our preferred ranks in 2016. The $\alpha = 0.5$ assumption using updated aggregates and definitions in the equal-return series yields 5.8%, whereas our preferred series yields 4.9% and dividends only gives 4.5%. The difference between our preferred approach and the PSZ approach amounts to 1.4 (=6.3-4.9) percentage points of overall household wealth accruing to the top 0.1%.

Augmenting the Very Top with Forbes 400 Data. Following the method in Bricker, Hansen and Volz (2019*a*), we add the Forbes 400 members to our data and adjust the sampling weights to account for overlap between capitalized estimates and the additional observations from Forbes. Figure 8D shows how our approach and a few alternative adjustments affects top wealth shares. We compare results of alternative approaches that (a) do not account for Forbes, (b) replace the richest 400 in our capitalized data with the Forbes 400, and (c) add an estimate of non-dividend-generating C-corporation wealth to our preferred BHV blending approach. Due to their relative size—Forbes individuals collectively account for 2.8% of total household wealth in 2016—and overlap with our estimates—owners of private businesses or dividend-paying public companies account for 77% of collective Forbes wealth—we find that incorporating the Forbes data has only a modest effect on our overall top share estimates. Appendix L.3 provides additional discussion.

When allocating Forbes wealth to categories, we use public information on Forbes individuals in 2016 to allocate Forbes wealth to public and private equity. For each individual, we allocate fixed income, pensions, housing, and other wealth according to top 0.01% SCF portfolio shares, then allocate the rest (81%) to either public or private equity depending on whether they derive most of their wealth from public or private companies (Appendix I).

6 Pension Wealth

6.1 Challenges in Estimating Pension Wealth

Tax data do not provide a direct link between individuals and their pension wealth. Estimating pension wealth is thus similar to the case of C-corporation equity, as we must rely on relevant flows. These flows include wages for workers and pension distributions for those who have reached the eligibility age. An issue with the latter flow is separating regular distributions from rollovers of account balances due to employer-status change.

The life-cycle of pension wealth accumulation further complicates the capitalization approach. Figure 9A uses the SCF to plot average wages, pension income, and pension wealth in 2016 dollars, averaging across cohorts from 1989 to 2016. Wage income grows over the life cycle and then declines starting around age 55 to near zero by age 75. In contrast, pension income is nearly zero until age 60. Pension wealth has an inverse-U shape that reflects the accumulation and decumulation of savings.

These life cycle dynamics result in flow-to-stock ratios that vary by age. Figure 9B summarizes this heterogeneity by plotting the ratio of wage and pension income to total pension wealth, respectively. The blue bars depict the population average and the red bars show the ratios for four age groups: below 45, 45 to 59, 60 to 74, and above 75. Wage income of adults younger than 45 amounts to 108% of their pension wealth on average, whereas average wages for those above age 75 are only 3% of their pension wealth. The patterns for pension income are reversed. The ratios for those between 45 and 74 are closer to the population averages in blue, with the 45 to 59 aged group having a wage to pension wealth ratio that is similar to the overall average, while those aged 60 to 74 have smaller wage to pension wealth ratios, reflecting larger retirement rates. Overall, the heterogeneity in pension wealth and flow-to-stock ratios across age groups means that an age-group-invariant approach will induce large errors.

An additional challenge is determining an appropriate macro target for pension wealth. The Financial Accounts include the balance of defined contribution pensions, the funded balances of defined benefit plans, and estimates of the value of unfunded defined benefit plans. Our baseline uses the Financial Accounts, but in auxiliary series, we show the effects of including Social Security wealth estimates.

6.2 Capitalizing Wages and Pension Income

This section describes how we use each individual's flow of wages and pension income to estimate pension wealth. This component of wealth includes both defined contribution pensions and defined benefit pension entitlements, including an estimate of the value of unfunded defined benefit entitlements from Sabelhaus and Volz (2019).

We begin with wages y_{it}^{wage} and pension income y_{it}^{pen} for person i in year t.[59] For each flow, we apply an age-group-specific capitalization factor:

$$\beta_t^{penw,wage,a} = \frac{\sum_{i \in a} \gamma_a \bar{W}_{it}^{pen}}{\sum_{i \in a} y_{it}^{wage}} \qquad \beta_t^{penw,pen,a} = \frac{\sum_{i \in a} \gamma_a \bar{W}_{it}^{pen}}{\sum_{i \in a} y_{it}^{pen}},$$

where age group $a \in \{< 45, 45 \text{ to } 59, 60 \text{ to } 74, > 75\}$ and γ_a is the ratio of pension wealth per capita within an age group to aggregate pension wealth per capita.[60] Our estimate is an

[59]In our measure of y_{it}^{wage}, we include wage income and recharacterized wages from pass-through business, which amount to 75% of pass-through business income (SYZZ).

[60]We construct γ_a using the mean γ_{at} in the SCF from 1989 to 2016. Our measure of pension wealth is

age-group-specific convex combination of capitalized wages and capitalized pension income:

$$\hat{W}_{it}^{penw} = \theta^{penw,a} \left(\beta_t^{penw,wage,a} \times y_{it}^{wage}\right) + \left(1 - \theta^{penw,a}\right) \left(\beta_t^{penw,pen,a} \times \left(y_{it}^{pen}\right)\right), \tag{16}$$

where $\theta^{penw,a}$ is the weight on capitalized wages and $(1-\theta^{penw,a})$ is the weight on capitalized pension income for age group a. Younger individuals have more weight put on wages and older individuals have more on pensions. In particular, $\theta^{penw,a}$ is 0.92, 0.83, 0.36, and 0.07 for those younger than 45, 45 to 59, 60 to 74, and above 75, respectively.[61]

In 2016, this approach results in the following formula for estimated pension wealth using the defined-benefit-augmented SCF:

$$\hat{W}_{i,2016}^{pen,SZZ} = \begin{cases} .92\left(1.3 \times y_{i,2016}^{wage}\right) + (1-.92)\left(132.4 \times \left(y_{i,2016}^{pen}\right)\right) & \text{if } age < 45 \\ .83\left(4.3 \times y_{i,2016}^{wage}\right) + (1-.83)\left(94.8 \times \left(y_{i,2016}^{pen}\right)\right) & 45 \leq age < 60 \\ .36\left(10.6 \times y_{i,2016}^{wage}\right) + (1-.36)\left(23.5 \times \left(y_{i,2016}^{pen}\right)\right) & \text{if } 60 \leq age < 74 \\ .07\left(27.1 \times y_{i,2016}^{wage}\right) + (1-.07)\left(7.2 \times \left(y_{i,2016}^{pen}\right)\right) & \text{otherwise} \end{cases}. \tag{17}$$

The formula shows that older individuals have higher capitalization factors for wages and higher weights on capitalized pension income. The higher capitalization factors on wages reflect the feature that a dollar of wages corresponds to more pension wealth for older people, who have accumulated larger pensions. Capitalization factors for pension distributions decline in age because aggregate pension distribution flows are much smaller for younger groups than for older groups.

Figure 9C considers the effect on top shares of integrating estimates of Social Security wealth from Catherine, Miller and Sarin (2020) (CMS) and Sabelhaus and Volz (2019) (SV).[62] Were we to include this wealth in our household aggregate, the top 0.1% share in 2016 would fall by thirty percent, and the growth in the top 0.1% share would fall by sixty percent. The generosity of social insurance can therefore materially affect wealth concentration measures.

the defined-benefit-augmented SCF from Sabelhaus and Volz (2019). We find that γ_a is 0.32, 1.56, 1.83, and 0.76 for $a \in \{< 45, 45\text{to } 59, 60\text{to } 74, > 75\}$, respectively. For example, $\gamma_{60\text{to}74} = 1.83$ indicates that individuals aged 60 to 74 have 83% more much pension wealth relative to the overall population.

[61] We obtain these weights from regressions of pension wealth in the SCF on capitalized wages and capitalized pensions. We set the weight equal to the coefficient on capitalized wages divided by the sum of coefficients. The ratio of coefficients is fairly stable over time when we estimate the regression each year.

[62] CMS and SV estimate the value of Social Security wealth for U.S. households is $33T and $22T in 2016, respectively, and increased since 1989 from around 50% to 200% in the CMS series (Appendix Figure A.16). The SV series starts in 1995 and grows to 133% of national income in 2016. The reasons for this growth include demographic trends, increased program generosity, and lower interest rates. Both CMS and SV agree Social Security wealth lowers levels of top shares. However, in SV, augmenting with Social Security has a smaller impact on the trend, whereas the CMS approach lowers the trend a bit more due to their discounting and risk-adjustment approach.

7 Housing

7.1 Challenges in Estimating Housing Wealth using Tax Data

The principal challenge in deriving a measure of housing wealth from tax returns is that owner-occupied housing does not generate taxable income, so we must rely on other proxies to assign housing wealth. Following SZ, we use property tax payments and mortgage interest deductions to produce capitalized estimates of housing assets and debts. A second challenge is that property tax payments do not correspond uniformly to an underlying amount of assets because tax rates vary across locations and over time. Effective rates by year and substate geography do not exist at present, nor do state-level average property tax rates extending back in time.[63] Figure 10A plots a map of average state-level effective property tax rates collected from deeds data and computed by ATTOM for 2012. Property tax rates vary across the United States, from below 0.5% in the Southwest and Deep South to more than 2% in the Midwest and some states in the Northeast. Third, mortgage interest deductions do not reveal the underlying interest rates, which would ideally be used to assign mortgage debt. Instead, they reflect a combination of interest rates, the amount of debt outstanding, and mortgage points paid at the time of purchase. Finally, we only observe property taxes and mortgage interest deductions for itemizers.

7.2 Capitalization with Unequal Property Tax Rates

We use each individual's flow of property tax and mortgage interest deductions to estimate housing wealth. This component of wealth does not include rental real estate.[64]

We separately estimate owner-occupied housing assets and mortgage liabilities. For assets, we begin with property tax deductions y_{it}^{ptax} for itemizer i in year t. We estimate housing assets by scaling y_{it}^{ptax} by a location-year-specific capitalization factor β_{st}^{ptax}, which is the ratio of housing values to property tax payments in state s in year t. To derive capitalization factors for each state over time, we combine state-level data from four sources: (1) effective property tax rate data from ATTOM, (2) property tax assessor data from 2012 from DataQuick, (3) CoreLogic state-level house price indexes, and (4) state-level property tax revenues and population from the US Census of States. Appendix K describes our approach to estimating these capitalization factors.

For mortgage debt, we begin with mortgage interest deductions y_{it}^{mid} for itemizer i in

[63] Assessed values also vary within cities across people due to bias in the assessment process (Avenancio-Leon and Howard, 2019).

[64] Most rental housing is likely included in private business wealth. We estimate informal rental housing wealth by capitalizing rental income payments under equal-returns following SZ.

year t. We then apply an equal-returns capitalization factor to estimate mortgage debt. For non-itemizers, we assign average housing asset and mortgage values from the SCF for demographic groups g (i.e., income decile $\times$ married $\times$ old). Net housing wealth is given by assets less liabilities, each defined as:

$$\hat{A}_{it}^{hou} = \begin{cases} \beta_{st}^{ptax} y_{it}^{ptax} & \text{if itemizer} \\ \bar{A}_{gt}^{hou,SCF} & \text{otherwise, } i \in g \end{cases} \qquad \hat{D}_{it}^{hou} = \begin{cases} \bar{\beta}_{t}^{mid} y_{it}^{mid} & \text{if itemizer} \\ \bar{D}_{gt}^{hou,SCF} & \text{otherwise, } i \in g, \end{cases}$$

where $\bar{\beta}_t^{mid} = (\sum_i D_{it}^{hou})/(\sum_i y_{it}^{mid}/0.8)$ is the capitalization factor for itemizers, whose mortgage interest deductions are assumed to account to 80% of aggregate mortgages.

Accounting for state-specific capitalization factors is important for estimating the level and geographic distribution of housing assets. Figure 10B plots the capitalization factor implied by dividing aggregate housing assets by aggregate property tax payments. The factor varies between 90 and 120 over time but hovers around 100 from 1977 to 2016. Recall that a factor of 100 implies a property tax rate of 1%. Because property tax rates are low, small departures from the national average can lead to large bias in wealth estimates across states. Given the variation in actual rates between 0.4% and 2.3%, the equal-rates assumption for allocating housing assets assigns more than twice the amount to high-tax states and less than half to low-tax states. This issue is analogous to the bias for fixed income wealth estimated under an equal-returns assumption during low-interest-rate periods.

Figure 10B shows the effect of our unequal property tax rate estimates by comparing the implied California capitalization factor over time to the equal-rate benchmark. Three facts stand out. First, the factor we apply to property tax deductions in California in 2016 doubles relative to the equal rate benchmark, implying that California owns significantly more real estate under the unequal rate assumption. Second, our estimate reveals the amplified exposure of California to the housing boom and bust in the mid-2000s, as the California factor rises and falls much more dramatically than the national factor. Third, the 1978 passage of Proposition 13, which capped future property tax increases, causes a sharp and immediate increase in the California factor. This increase reflects house prices immediately capitalizing the value of reduced future property taxes.

Our approach for housing follows Saez and Zucman (2016) except for the estimation of state-year-specific capitalization factors.[65] They apply an equal-returns capitalization factor in a given year for mapping property tax deductions to housing assets. That approach misses

[65] In years prior to 1980, we follow Saez and Zucman (2016) for housing assets as well because state-level house price indices are not available. In those years, we use a capitalization factor for the property tax deductions for itemizers of $\bar{\beta}_t^{hou} = \frac{\sum_i A_{it}^{hou}}{\sum_i y_{it}^{ptax}/0.75}$, whose property taxes are assumed to account for 75% of aggregate property tax payments.

large cross-state differences in property taxes and regional house price dynamics.

8 Adding It Up: New Top Wealth Estimates

8.1 The Level of Top Wealth

Table 2 shows the number of individuals in each wealth group and the wealth thresholds defining each group. We then report average wealth and the share of total wealth for these groups when applying the equal-returns approach and ranking of PSZ.[66]

Panel A focuses on top wealth groups. The full population includes 239 million individuals whose average wealth is $364K in 2016. The top 1% includes 2.4 million individuals with wealth of at least $3.7M and average wealth equal to 32 times average wealth in the full population. In terms of shares, this group's share of total wealth is 31.5% under our preferred approach, compared to 36.6% under PSZ equal returns. Similarly, for the top 0.1%, who have wealth exceeding $17.8M, our estimates reduce their share from 18.6% under equal returns to 15.0% in our preferred specification. Thus, the combined effect of accounting for estimated heterogeneity, updating Financial Accounts aggregates, estimating private business values, adding Forbes 400 data, and including unfunded pension wealth materially affects the estimated concentration of top wealth. These adjustments are increasingly important within the very top group, as the top 1% share falls by 14% (5.1/36.6), the top 0.1% share falls by 19% (3.6/18.6), and the top 0.01% share falls by 26% (2.5/9.5).

Panel B focuses on intermediate wealth groups. A key result is that the bottom 90%, who collectively hold 34.3% of wealth, are allocated 5.6 p.p. more wealth than in PSZ. The "P90-99" class, a group with more than $717K but less than $3.73M in preferred wealth, hold 34.2% of total wealth, on par with the bottom 90% and more than the top 1%.

Figure 11 compares Forbes 400 wealth to aggregate wealth according to our preferred specification for telescoping subgroups of the top 1%: P99-99.9, P99.9-99.99, and the top 0.01%. We report totals and counts of individuals in each group as well as results using tax units. The wealth threshold to be in the top 0.01% in 2016 is $84M for individuals and $124M for tax units. The figure provides perspective on the relative importance of accounting for Forbes wealth if capitalization alone misses their unrealized stock wealth in non-dividend-paying companies. The Forbes 400 have considerable wealth ($2.4T in 2016), but the total wealth of the P99-99.9 and P99.9-99.99 tax unit groups exceeds this amount by factors of 6.2 and 3.0, respectively. Of course, Forbes members are much wealthier on

[66] Section L.2 discusses differences between our preferred approach and the PSZ equal-returns approach in more detail and component-by-component.

average: these groups respectively contain 1.5 million and 150 thousand tax units, whereas Forbes represents only 400. Our top 0.01% group contains \$6.6T of wealth, which includes the impact of blending Forbes into our data.[67]

8.2 The Composition of Top Wealth

Tables 3A and 3B show the wealth composition in 2016 for each wealth group in our preferred approach. Pass-through business, C-corporation equity, and fixed income account for 26%, 32%, and 23% of top 0.1% wealth, respectively, with the rest in housing and pensions. At the very top, C-corporation equity is the largest component, accounting for 40% of top 0.01% wealth, but pass-through business looms large at 29%. In contrast, the wealth composition for the bottom 90% is 63% pensions and 23% in housing. The portfolios of the P90-99 are more balanced, with almost equal shares from fixed income (18%), C-corporation plus pass-through equity (21%), housing (25%), and a larger role for pensions (36%).

Figure 12 plots the level and allocation of wealth across asset classes among the top 10%. We group individuals into percentile bins and further divide the top 1% into P99-99.9, P99.9-99.99, and the top 0.01%. Each plot shows the share of total household wealth accruing to that group in a particular asset class. We compare our preferred estimates to the PSZ equal-returns approach and the harmonized SCF with Forbes.

The figure displays where in the distribution and across assets differences in approach lead to differences in top wealth shares. Overall, the top 0.01% has 7.0% of total household wealth in our series, of which 1.3 p.p., 2.0 p.p., 2.8 p.p., and 0.9 p.p. are due to fixed income, pass-through business, public equity, and other categories, respectively. The largest difference between our series and the PSZ series is fixed income, for which the PSZ approach estimates fixed income assets of the top 0.01% account for 4.1% of total US household wealth. This difference is partially offset by our pass-through business estimate, which exceeds PSZ's estimate of 1.1% of total household wealth by 0.9 percentage points. The estimates for the other asset classes are similar for the top 0.01%.

In our series, those in the P99-99.9 hold a substantial amount of wealth that exceeds that held by the top 0.1% in terms of fixed income and have considerably more wealth in pensions and housing. For pass-through wealth, the P99-99.9 hold 2.9% of total household wealth, whereas the top 0.1% holds 3.9%. C-corporation equity is more concentrated, as the

[67] Without blending, this group would have \$6.1T. Replacing the top 400 capitalized tax units with Forbes estimates gives \$7.0T. We show the effects of these alternatives on top wealth shares in Figure 8D. With a Pareto parameter of 1.4, the amount of wealth between the Forbes 2016 cutoff of \$1.7B and \$124M is $[(1700/124)^{(1.4-1)} - 1] = 182\%$ of the wealth above \$1.7B in Forbes, which is \$2.4T. Thus, under the Pareto approximation and taking the Forbes estimate as given, the collective wealth of those with wealth above \$124M is \$2.4T $\times$ (2.82) = \$6.8T. Appendix L.3 provides additional discussion.

top 0.01% holds more wealth than the P99-99.9 and P99.9-99.99 groups despite representing 1/100th and 1/10th the number of individuals, respectively.

Pass-through business held by the P99-99.9 group accounts for much of the difference in overall top wealth shares for the top 1%. Compared to our series, pass-through business in the SCF for the P99-99.9, P99.9-P99.99, and top 0.01% groups respectively account for 3.8, 1.7, and 1.7 percentage points of the gap in top-1% shares. The gap with the equal-return series is even larger. The C-corporation estimates also show gaps between the SCF and capitalization approaches for the P99-99.9 group. The harmonized SCF series, which includes Forbes, allocates less public equity wealth to the top 0.01% than our series, which partly assuages concerns that we may undercount public equity wealth at the top due to limitations in the capitalization approach.

Comparing Portfolio Shares across Sources and Approaches. Figure 15 compares top portfolio shares in our preferred series in 2016 to alternative data sources for four groups: the top 0.001%, top 0.01%, top 0.1%, and top 1%. For capitalization series, we compare our preferred estimates to the equal-return series in PSZ. For all groups, we compare these two series to the harmonized SCF including Forbes. For the top 0.01% and top 0.001%, we add a fourth series from the UBS Family Office survey of ultrahigh net worth. For the top 0.1%, we compare these estimates to a mortality-rate-adjusted series from estate tax returns above the top 0.1% threshold. For the top 1%, we add portfolio shares from the DFA.[68]

Figure 15A presents portfolio shares for the top 0.001% across different series. Our preferred fixed income portfolio share (19%) is less than one-third of that in the equal-return series (59%). This shift is offset by C-corporation equity and pass-through business wealth, which increase from 36% to 54% and from 10% to 18%, respectively. The results are similarly stark for the top 0.01% (Figure 15B) and top 0.1% (Figure 15C), with fixed income shares in our specification falling form 49% to 19% and from 42% to 23%, respectively. For the top 1% (Figure 15D), differences in portfolio composition go in the same directions but are less dramatic. However, housing plays a larger role in our series at 15% relative to 9% in PSZ, reflecting the importance of top 1% individuals who live in low property tax states like California. Our preferred shares are closer to the SCF than the PSZ series, especially for fixed income. Pass-through business wealth is larger in the SCF (approximately half for the top 0.1% and above) versus 25 to 30% for our series. Our allocation to C-corporation wealth is larger than in the SCF among top groups, resulting in an overall equity share that

[68]Note our capitalization and SCF series use equal-split, individual-level definitions for groups and the estate tax returns cover single decedents, while the unit of observation is the household for the DFA and the family office for the UBS survey. This distinction does not affect portfolio shares as much as wealth levels and top shares.

accounts for the bulk of wealth in both series.

Asset composition figures from UBS family offices align well with the SCF although have pass-through business and C-corporation shares that are closer to ours. Asset composition figures from estate tax returns align well with our estimates of the top 0.1%. Estate tax portfolio shares have less public equity and fixed income, and more pass-through wealth. A smaller public equity share may reflect the importance of private C-corporations at the top, which are harder for us to distinguish from public equity because firm-owner links are not available for this type of firm. In addition, certain categories of managed assets on estate tax returns are difficult to allocate to underlying asset classes, which may account for some of the difference between our series and the estate series.[69]

8.3 The Growth of Top Wealth

Figure 1 plots our preferred estimates from 1966 to 2016 for the top 0.01%, top 0.1%, and the top 1%. For the top 0.1%, top wealth falls from 10% in the late 1960s to a low of 5.7% in 1978, then steadily rises to around 15% in recent years. Relative to the PSZ series, our preferred series not only shows a lower level in recent years but less growth since 1980. The PSZ top 0.1% series grew from 6.3% in 1978 to 18.6% in 2016; our preferred series grew from 5.7% to 15.0%. Focusing on the 1989-2016 period during which the SCF is available, the top 0.1% share grew 5.1% in our series, 4.3% in the SCF, and 8.1% in PSZ.

The gap between the PSZ and preferred series is even larger in recent years for the top 0.01%. Our series and the PSZ series track each other closely before 2000, but they diverge in 2000, especially since 2007. In our series, the top-0.01% shares increase from 5.8% in 2001 to 6.2% in 2006 to 7.0% in 2016; in the PSZ series, the increase from 2001 to 2006 is similar but the increase from 2006 to 2016 is three times larger.

For both of these top groups, our series closely tracks the harmonized SCF with Forbes in recent years. For the top 1%, we find a similar trend to the harmonized SCF with Forbes but a lower level. Since 2000, the SCF top 1% share is between the equal-returns series and our preferred series, though shows a sharper increase between 2013 and 2016 that appears to have partly reversed in the 2019 survey.

Figure 13 plots time series versions of Figure 12 for the five major asset classes for the top 0.01%, top 0.1%, and top 1% in our series, the PSZ equal-returns series, and the harmonized SCF. The figure helps provide a more systematic presentation of the composition of top wealth over time relative to the equal-returns approach. The figure also displays

[69] Evidence from administrative data in Scandinavia also shows small contributions of fixed income and large roles of equity and especially private business at the top (Fagereng, Guiso, Malacrino and Pistaferri, 2020; Bach, Calvet and Sodini, 2020).

when different updates occur (1980s for pension and housing, 2001 for pass-through and fixed income with information-returns) and the corresponding effects, and how policy and macroeconomic conditions affect the concentration and composition of wealth. For the top 1%, we include estimates from the DFA for comparison.[70]

In the PSZ equal-returns top-0.1% series, which rises by 3.9 percentage points between 2001 and 2016, fixed income wealth, C-corporation wealth, pass-through business, and the residual categories account for 4.5, -0.9, 1.3, and -1.0 percentage points, respectively. In our preferred series, which rises by 2.1 percentage points, these components respectively account for 0.7, 0.6, 0.8, and 0.0 percentage points. Thus, the largest difference between our approaches is in fixed income, followed by C-corporation equity, pass-through business, and other categories. These patterns apply in a more pronounced fashion for the top 0.01%. For example, fixed income accounts for 3.1 percentage points of the rise of the top-0.01% share of 3.9 percentage points in the equal-returns series; in our series, the contribution is only 0.1 percentage points of the 2.1 percentage point rise.[71]

In the SCF series for the top 0.1% and 0.01%, the trend is primarily driven by pass-through business. Across groups, the difference in top shares between the SCF and our series is mostly driven by level differences in pass-through business rather than trends.

For the top 1% in the PSZ series, the rise is 5.3 percentage points since 2001, of which 5.8, -1.7, 2.6, and -1.4 percentage points come from fixed income, C-corporation equity, pass-through business, and other categories, respectively. In our series, which rises by 4.2 percentage points, the contribution of these categories is 2.0, 0.6, 1.5, and 0.1, respectively. Housing volatility appears more important for this group than for groups further in the right tail, and as a result, the 1980s housing cycle affects the earlier trend for both capitalized specifications. Whereas the value of pass-through business rises in both capitalized specifications from 1989 to 2016, the SCF trend is flatter, fluctuating around 12% of total household wealth. The DFA series, which maps SCF shares onto Financial Accounts aggregates, shows a similar stability around 8% of total household wealth.

Figure 14A plots top 1%, P90-99, and P0-90 wealth shares over this time period under both our preferred and the equal-return approaches. The difference in growth between the PSZ and preferred approaches is less pronounced for the top 1% than for the top 0.1% and top 0.01%, with the growth of the top 1% share from 2001 to 2016 falling from 5.4 to 4.2

[70]Note the DFA data define the top 1% in terms of households and cannot be split in the same way we split the SCF and other series, which modestly affects the levels. Appendix Figure A.19 shows top 1% levels for each component in capitalized estimates at the tax-unit level compared to the DFA. The takeaways in terms of comparability across data sets are unchanged.

[71]Appendix Figure A.22 decomposes the 1989–2016 growth in concentration by asset class for the top 0.01%, top 0.1%, and top 1%. For both periods, fixed income accounts for a small share of the growth, whereas private business is more important.

percentage points. Overall, wealth is still concentrated: the top 1% holds nearly as much wealth as either the bottom 90% or the "P90-99" class.

The evolution of the P0-90 versus P90-99 shares from 1965 to 2000 reflects the evolution of pensions, housing, and public equity and relative exposures for different groups. Aggregate pension wealth rises secularly over this time, which is most important for the bottom group. Housing wealth rises and falls in the 1980s, affecting the bottom group and the P90-99 groups significantly. Public equity wealth falls in the 1970s, remains low, and then resurges in the mid-1990s, which drives the time series for the top 1%. In more recent years, the bottom 90 group loses ground relative to both the top 1% and the P90-99. These results are consistent with findings from other data sets (e.g., Kuhn, Schularick, and Steins (2020)). Saez and Zucman (2016) also highlight the decline of P0-90 wealth driven by housing and an increase in debt. Our series shows a less dramatic decline due to the increased role for pensions, including unfunded defined benefit plans, smaller aggregate non-mortgage debt, as well as the more concentrated nature of housing wealth in our unequal-property-tax-rate series. Average wealth of the bottom 90 increased modestly by 17% from 2001 to 2016 (from \$120K to \$140K in 2016 dollars), whereas average wealth for P90-99 and the top 1% rose by 40% and 49% (from \$1.0M to \$1.4M and from \$7.7M to \$11.5M), respectively.

9 Robustness and Comparison with Other Approaches

9.1 Characterizing Parameter and Model Uncertainty

We begin by accounting for estimated uncertainty in the parameters governing group-specific estimates of fixed income and equity wealth. In particular, we bootstrap the minimum distance parameters (i.e., $\hat{\boldsymbol{\theta}}$ and $\hat{\alpha}_i$) to develop a series of top interest rates on fixed income and weights on dividend flows, which we use to construct fixed income and equity wealth estimates for each parameter draw.[72] We then combine these estimates with other asset classes, which do not vary across draws, to define new top wealth groups. We present the 95% band of top wealth shares using this procedure. For the SCF, we sample SCF households using the replicate weights and following the procedure in BHKS to generate confidence bands for top shares.

Figure 16A plots the top share series for the top 0.01%, top 0.1%, and top 1% and

[72] In particular, we take draws for these parameters from a normal distribution with the respective means and variances using estimates in Appendix Table H.2 and Table 1. For each draw b, we form an estimate of r^b_{1t} using equation 9 and then follow the procedure described in the main text for forming estimates for P99-99.9 and everyone else for fixed income. Similarly, for each draw b, we form an estimate of α^b_i, which we use to form a composite flow of dividends and capital gains, which we then capitalize following the steps described in the main text.

compares them to our preferred series and the PSZ 2018 series. For the top 0.01% and top 0.1%, our preferred series tracks the upper confidence interval of the SCF. Although there is parameter uncertainty for fixed income and equity estimates, this uncertainty is less important for differences across estimates than modeling assumptions about the degree of heterogeneity and the weight on capital gains. For the top 1%, our preferred series is closer to the lower bound of the SCF confidence interval, and the PSZ 2018 series is well above it for most of the 2000s other than the 2016 estimate.

Figure 16B plots the consequences of changing other modeling assumptions that govern wealth component estimates. It combines series from Figures 5C, 8C, 8D, 9C, and A.15 and shows the implications for top 0.1% wealth shares.[73] We fix the ranks to isolate the role of each change. Perturbing our preferred specification results moderate differences in top 0.1% series. The estimates fall within the 95% confidence interval of the SCF in 2016. In contrast, the PSZ 2018 is well above all other series since 2000 and especially in recent years.

9.2 Reconciling Our Estimates with Other Sources

SCF. There are two main sources of difference between our top wealth shares and the harmonized SCF.[74] First, as noted above, the SCF shows considerably higher values for private business for the top 1%, with much of this wealth held by the P99-99.9 group. Scaling private business to match Financial Accounts aggregates closes all of the gap for our top 1% estimates (Appendix Figures A.24 and A.25). This force also explains why the DFA measures of top 1% shares are closer to ours. Second, the large aggregate level of deposits in the Financial Accounts relative to the SCF contribute to higher portfolio shares in fixed income in our series (Appendix Figures A.26 and A.27).

For groups outside the top 1%, forces that likely introduce differences between our series and the SCF include the total value of housing wealth and the allocation of pension wealth. Aggregate housing wealth is 10–20% higher in the SCF than in the Financial Accounts (Gallin, Molloy, Nielsen, Smith and Sommer, 2021). SCF-derived numbers augmented by SV show more pension wealth in the P90-99 group than we estimate, whereas our model predicts relatively more wealth in the bottom 90 and in the right tail. Estimating pension wealth via capitalization is challenging because we do not have information about worker

[73] These perturbations include using CMD 3-tier approach for fixed income instead of information returns after 2001, using a weight of $\alpha = .75$ on dividends, different labor and liquidity adjustments for private business, and excluding unfunded DB pensions.

[74] Many of the possible differences between our series and the raw SCF have been addressed by previous work, including SZ, BHKS, BHH, and SV and Henriques and Hsu (2014); Bricker, Hansen and Volz (2019*b*); Saez and Zucman (2020*b*). Moreover, concerns about response bias are addressed in BHKS, suggesting this cannot account for differences across methods.

tenure or public-sector employment status, characteristics that SV find are important for matching pension wealth in addition to age and income.

Overall, the SCF is a crucial input into the wealth inequality debate. It allows researchers using income tax data to say more than they otherwise could, provides a benchmark for inequality research, contains detailed portfolio information that is unavailable in other data sets, and enables analysis by characteristics (such as race) that cannot be studied elsewhere. At the same time, the SCF is of course too small of a sample for some things, for example, estimating precise top shares within the top 1%, characterizing private businesses held at the top, unpacking the portfolios and returns of the ultra rich, and the geography of wealth.

SZ and Other Sources. Appendix Table B.9 presents a systematic perturbation analysis that shows the effect on top shares and composition of changing several modeling assumptions.[75] Overall, for the top 0.1%, we find fixed income changes represent 52% of the absolute value of the differences with PSZ. C-corporation equity, pass-through, and pensions account for 23%, 13%, and 10%, respectively. The remainder is due to housing, rental wealth, and other categories. Appendix L.2 provides a detailed discussion of differences with SZ by asset class. Appendix L also compare results with the SCF, DFA, estate tax data, and Forbes.

10 Conclusion

This paper combines administrative tax data with a range of new data to provide estimates of wealth concentration and composition in the United States. We find the top 0.1% share of wealth has increased from 12.9% to 15% from 2001 to 2016. While this increase is lower than some prior estimates, wealth is very concentrated—the top 1% holds nearly as much wealth as either the bottom 90% or the "P90-99" class. We find that pass-through business and public equity wealth are the primary sources of wealth at the top, and pension and housing wealth account for almost all wealth for the bottom 90%.

We provide a systematic analysis of the conceptual and measurement issues most consequential for estimating wealth using capitalization methods. Though the capitalization approach has advantages over other methods, uncertainty remains inherent to the approach as estimates can be sensitive to different assumptions.

Our estimates have implications for inequality, capital tax policy, and savings behavior. First, a recent strand of the income inequality literature uses wealth estimates to appor-

[75] Model differences are more important than reranking, though reranking is non-trivial. For example, Panel C rows 5 and 6 show that ranking differences due to the pass-through business estimates can increase top 0.1% shares by 0.7 percentage points.

tion components of national income not captured by fiscal income data (Piketty, Saez and Zucman, 2018; Auten and Splinter, 2017; Smith, Yagan, Zidar and Zwick, 2019; Garbinti, Goupille-Lebret and Piketty, 2018). For example, the top 1% share of C-corporation retained earnings, which are not immediately distributed to their owners, is assumed to equal that group's share of C-corporation wealth within the household sector. Similar imputations are required for other components of national income that are not included on individual tax returns: untaxed interest income; pension income; corporate, property, and sales taxes; and imputed rents for owner-occupied housing. As a result, changes in top wealth estimates imply changes in the distribution of capital income. Relative to an equal-returns approach, our preferred wealth estimates likely reduce top capital income, may imply a lower level of top income shares, and indicate that income inequality is driven less by capital than labor, including the labor component of pass-through business income. A larger role for pass-through business wealth, lower concentration of financial wealth, and a less rapid rise in recent years in top financial wealth and capital shares all point to a larger role for human capital and a smaller role for non-human capital in top income growth.

In terms of capital tax policy, these estimates provide an input for estimates of the stock of unrealized capital gains, the estate tax base, wealth taxes, and other proposals that seek to harmonize labor and capital taxes. Given prominent wealth tax proposals focus on the extreme tail of the wealth distribution, our estimates would reduce mechanical wealth tax revenue estimates. We find a larger role for illiquid wealth categories where valuations are more contentious, which could imply higher administrative burdens for a wealth tax or proposals to tax unrealized capital gains.

For income taxation, our estimates affect the numerator and denominator for measuring broad effective tax rates along the income distribution. They also inform the mechanical revenue consequences of proposals that target top incomes by providing an estimate of the capital tax base. Our estimates provide information about the distribution of corporate tax incidence for equity held directly by households and indirectly through pensions.

One can combine our wealth estimates with assumptions about asset price growth to infer savings rates for different groups. Not only is analyzing savings behavior interesting on its own (Mian, Straub and Sufi, 2020; Feiveson and Sabelhaus, 2019), it also is relevant for tax policy for three reasons. First, differences in rates of time preference and thus in savings rates across groups can provide a theoretical basis for taxing capital income (Atkinson and Stiglitz, 1976; Saez, 2002). Moreover, the magnitude of savings rate disparities can affect optimal capital tax rates. Accounting for public and private savings vehicles is crucial for implementing optimal tax rate formulas. Second, if the recent rise of top wealth inequality is mostly due to asset prices and not new savings, then forecasting future asset prices becomes more important for the question of whether the recent growth in wealth concentration will continue (Piketty, 2014; Fagereng, Holm, Moll and Natvik, 2019). Indeed, if recent asset price changes reflect a transition from a high interest rate environment to a low one, then extrapolating into the future the trend in wealth concentration to measure the capital tax base may not be justified (Cochrane, 2020). Third, to the extent that wealth growth depends more on asset price growth, the magnitude of unrealized capital gains and corresponding potential tax revenues from taxing these gains are larger than if savings are more important. This consideration matters for evaluating capital tax proposals, such as repealing the "step-up" in basis at death for inheritances (Sarin, Summers, Zidar and Zwick, 2021).

We highlight a few avenues for future research. First, there are many ways to improve these wealth estimates and incorporate further refinements, such as the impact of tax avoidance and evasion (Guyton, Langetieg, Reck, Risch and Zucman, 2020), better measures of pension wealth and the accuracy of the Forbes 400, and social insurance programs such as Medicare and Social Security. Second, we hope our estimates for wealth and income inequality can improve our understanding of the drivers of inequality. For example, our estimates provide inputs to investigating how much of wealth is inherited and the relative importance of family firms versus self-made entrepreneurs (Gomez, 2019; Atkeson and Irie, 2020). Third, these estimates can be linked with estate tax data to estimate behavioral responses to capital taxation and inform policy design and enforcement.

References

Arrow, Kenneth J. 1987. "The demand for information and the distribution of income." *Probability in the Engineering and Informational Sciences*, 1(1): 3–13.

Atkeson, Andrew, and Magnus Irie. 2020. "Understanding 100 years of the evolution of top wealth shares in the U.S.: What is the Role of Family Firms?"

Atkinson, Anthony Barnes, and Joseph E. Stiglitz. 1976. "The design of tax structure: direct versus indirect taxation." *Journal of Public Economics*, 6(1-2): 55–75.

Auerbach, Alan J. 1983. "Stockholder tax rates and firm attributes." *Journal of Public Economics*, 21(2): 107–127.

Auerbach, Alan J., and Mervyn A. King. 1983. "Taxation, portfolio choice, and debt-equity ratios: A general equilibrium model." *Quarterly Journal of Economics*, 98(4): 587–609.

Auten, Gerald, and David Splinter. 2017. "Income Inequality in the United States: Using Tax Data to Measure Long-Term Trends."

Auten, Gerald, and David Splinter. 2019. "Using Tax Data to Measure Long-Term Trends in U.S. Income Inequality." *Treasury Office of Tax Analysis Working Paper.*

Avenancio-Leon, Carlos, and Troup Howard. 2019. "The assessment gap: Racial inequalities in property taxation." *Available at SSRN 3465010.*

Bach, Laurent, Laurent E. Calvet, and Paolo Sodini. 2016. "Rich pickings? Risk, return, and skill in the portfolios of the wealthy."

Bach, Laurent, Laurent E. Calvet, and Paolo Sodini. 2020. "Rich Pickings? Risk, Return, and Skill in Household Wealth." *American Economic Review*, 110(9): 2703–47.

Batty, Michael M. Batty, Jesse Bricker, Joseph S. Briggs, Elizabeth Holmquist, Susan Hume McIntosh, Kevin B. Moore, Eric R. Nielsen, Sarah Reber, Molly Shatto, Kamila Sommer, Tom Sweeney, and Alice Henriques Volz. 2019. "Introducing the Distributional Financial Accounts of the United States."

Begenau, Juliane, Monika Piazzesi, and Martin Schneider. 2020. "Banks' Risk Exposures." National Bureau of Economic Research Working Paper 21334.

Bhandari, Anmol, and Ellen R McGrattan. 2021. "Sweat equity in US private business." *The Quarterly Journal of Economics*, 136(2): 727–781.

Bhandari, Anmol, Serdar Birinci, Ellen McGrattan, and Kurt See. 2019. "What Do Survey Data Tell Us about US Businesses?" National Bureau of Economic Research.

Bricker, Jesse, Alice Henriques, and Peter Hansen. 2018. "How much has wealth concentration grown in the United States? A re-examination of data from 2001-2013."

Bricker, Jesse, Alice Henriques, Jacob Krimmel, and John Sabelhaus. 2016. "Measuring income and wealth at the top using administrative and survey data." *Brookings Papers on Economic Activity*, 2016(1): 261–331.

Bricker, Jesse, and Alice Henriques Volz. 2020. "Wealth concentration levels and growth: 1989-2016." Board of Governors of the Federal Reserve System (US).

Bricker, Jesse, Peter Hansen, and Alice Henriques Volz. 2019*a*. "Wealth concentration in the US after augmenting the upper tail of the survey of consumer finances." *Economics Letters*, 184: 108659.

Bricker, Jesse, Peter Hansen, and Alice Henriques Volz. 2019*b*. "Wealth concentration in the US after augmenting the upper tail of the survey of consumer finances." *Economics Letters*, 184: 108659.

Brown, Jeffrey, Jeffrey Liebman, and Joshua Pollet. 2002. "Estimating Life Tables That Reflect Socioeconomic Differences in Mortality." In *The Distributional Aspects of Social Security and Social Security Reform.* , ed. Martin Feldstein and Jeffrey Liebman. Chicago and London:University of Chicago Press.

Catherine, Sylvain, Max Miller, and Natasha Sarin. 2020. "Social Security and Trends in Inequality." Working Paper.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. "The Association Between Income and Life Expectancy in the United States, 2001-2014." *JAMA*, 315(16): 1750–1766.

Cochrane, John. 2020. "Wealth and Taxes." *Cato Institute, Tax and Budget Bulletin*, 86.

Cooper, Michael, John McClelland, James Pearce, Richard Prisinzano, Joseph Sullivan, Danny Yagan, Owen Zidar, and Eric Zwick. 2016. "Business in the United States: Who Owns It, and How Much Tax Do They Pay?" *Tax Policy and the Economy*, 30(1): 91–128.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy." *Quarterly Journal of Economics*, 132(4): 1819–1876.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2016. "Heterogeneity in returns to wealth and the measurement of wealth inequality." *American Economic Review Papers & Proceedings*, 106(5): 651–55.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2020. "Heterogeneity and Persistence in Returns to Wealth." *Econometrica*, 88(1): 115–170.

Fagereng, Andreas, Martin Blomhoff Holm, Benjamin Moll, and Gisle James James Natvik. 2019. "Saving Behavior Across the Wealth Distribution: The Importance of Capital Gains." *NBER Working Paper*, , (w26588).

Fajgelbaum, Pablo D., Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar. 2019. "State taxes and spatial misallocation." *Review of Economic Studies*, 86(1): 333–376.

Feiveson, Laura, and John Sabelhaus. 2019. "Lifecycle patterns of saving and wealth accumulation."

Gabaix, Xavier, Jean-Michel Lasry, Pierre-Louis Lions, and Benjamin Moll. 2016. "The Dynamics of Inequality." *Econometrica*, 84(6): 2071–2111.

Gallin, Joshua, Raven Molloy, Eric Nielsen, Paul Smith, and Kamila Sommer. 2021. "Measuring aggregate housing wealth: New insights from machine learning." *Journal of Housing Economics*, 51: 101734.

Garbinti, Bertrand, Jonathan Goupille-Lebret, and Thomas Piketty. 2018. "Income inequality in France, 1900–2014: Evidence from Distributional National Accounts (DINA)." *Journal of Public Economics*, 162: 63–77.

Giffen, Sir Robert. 1913. *Statistics.* Macmillan.

Gomez, Matthieu. 2019. "Displacement and the Rise in Top Wealth Inequality."

Guvenen, Fatih, Gueorgui Kambourov, Burhan Kuruscu, Sergio Ocampo, and Daphne Chen. 2017. "Use it or lose it: Efficiency gains from wealth taxation."

Guyton, John, Patrick Langetieg, Daniel Reck, Max Risch, and Gabriel Zucman. 2020. "Tax Evasion by the Wealthy: Measurement and Implications." *Measuring and Understanding the Distribution and Intra/Inter-Generational Mobility of Income and Wealth.* University of Chicago Press.

Hansen, Lars Peter. 1982. "Large sample properties of generalized method of moments estimators." *Econometrica: Journal of the econometric society*, 1029–1054.

Henriques, Alice M, and Joanne W Hsu. 2014. "Analysis of Wealth Using Micro- and Macrodata: A Comparison of the Survey of Consumer Finances and Flow of Funds Accounts." In *Measuring Economic Sustainability and Progress.* 245–274. University of Chicago Press.

Kawano, Laura. 2014. "The Dividend Clientele Hypothesis: Evidence from the 2003 Tax Act." *American Economic Journal: Economic Policy*, 6(1): 114–36.

Koeplin, John, Atulya Sarin, and Alan C. Shapiro. 2000. "The private company discount." *Journal of Applied Corporate Finance*, 12(4): 94–101.

Kopczuk, Wojciech. 2015. "What do we know about the evolution of top wealth shares in the United States?" *Journal of Economic Perspectives*, 29(1): 47–66.

Kopczuk, Wojciech, and Emmanuel Saez. 2004*a*. "Top wealth shares in the united states: 1916-2000: Evidence from estate tax returns." *National Tax Journal*, 57(2, part 2): 445–488.

Kopczuk, Wojciech, and Emmanuel Saez. 2004*b*. “Top wealth shares in the united states: 1916-2000: Evidence from estate tax returns.” National Bureau of Economic Research.

Mallet, Bernard. 1908. “A method of estimating capital wealth from the estate duty statistics.” *Journal of the Royal Statistical Society*, 71(1): 65–101.

Mazur, Mark J, and Alan H Plumley. 2007. “Understanding the tax gap.” *National Tax Journal*, 60(3): 569–576.

Mian, Atif R, Ludwig Straub, and Amir Sufi. 2020. “The Saving Glut of the Rich.”

Miller, Merton H. 1977. “Debt and taxes.” *Journal of Finance*, 32(2): 261–275.

Miller, Merton H., and Franco Modigliani. 1961. “Dividend policy, growth, and the valuation of shares.” *Journal of Business*, 34(4): 411–433.

Officer, Micah S. 2007. “The price of corporate liquidity: Acquisition discounts for unlisted targets.” *Journal of Financial Economics*, 83(3): 571–598.

Piketty, Thomas. 2014. *Capital in the 21st Century.* Cambridge, MA:Harvard University Press.

Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman. 2018. “Distributional national accounts: methods and estimates for the United States.” *Quarterly Journal of Economics*, 133(2): 553–609.

Poterba, James M. 2002. “Taxation, risk-taking, and household portfolio behavior.” In *Handbook of public economics*. Vol. 3, 1109–1171. Elsevier.

Raub, Brian, Barry Johnson, and Joseph Newcomb. 2010. “A comparison of wealth estimates for America’s wealthiest decedents using tax data and data from the Forbes 400.” 128–135.

Sabelhaus, John, and Alice Henriques Volz. 2019. “Are Disappearing Employer Pensions Contributing to Rising Wealth Inequality?” Board of Governors of the Federal Reserve System (US).

Sabelhaus, John, and Alice Henriques Volz. 2020. “Social Security Wealth, Inequality, and Lifecycle Saving.” In *Measuring and Understanding the Distribution and Intra/Inter-Generational Mobility of Income and Wealth*. University of Chicago Press.

Saez, Emmanuel. 2002. “The desirability of commodity taxation under non-linear income taxation and heterogeneous tastes.” *Journal of Public Economics*, 83(2): 217–230.

Saez, Emmanuel, and Gabriel Zucman. 2016. “Wealth inequality in the United States since 1913: Evidence from capitalized income tax data.” *Quarterly Journal of Economics*, 131(2): 519–578.

Saez, Emmanuel, and Gabriel Zucman. 2019*a*. "Progressive Wealth Taxation." *Brookings Papers on Economic Activity.*

Saez, Emmanuel, and Gabriel Zucman. 2019*b*. "Scoring of the Warren Wealth Tax Proposal." mimeo.

Saez, Emmanuel, and Gabriel Zucman. 2020*a*. "Comments on Smith, Zidar, and Zwick (2019)." mimeo.

Saez, Emmanuel, and Gabriel Zucman. 2020*b*. "Trends in US Income and Wealth Inequality: Revising After the Revisionists." NBER Working Paper No. 27921.

Sarin, Natasha, Lawrence H Summers, Owen M Zidar, and Eric Zwick. 2021. "Rethinking How We Score Capital Gains Tax Reform."

Scholz, John Karl. 1992. "A direct examination of the dividend clientele hypothesis." *Journal of Public Economics*, 49(3): 261–285.

Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick. 2019. "Capitalists in the Twenty-first Century." *Quarterly Journal of Economics*, 134(4): 1675–1745.

Stewart, Charles. 1939. "Income Capitalization as a Method of Estimating the Distribution of Wealth By Size Groups." In *Studies in Income and Wealth, Volume 3*. 95–146. NBER.

Wolff, Edward N. 1998. "Recent trends in the size distribution of household wealth." *Journal of Economic Perspectives*, 12(3): 131–150.

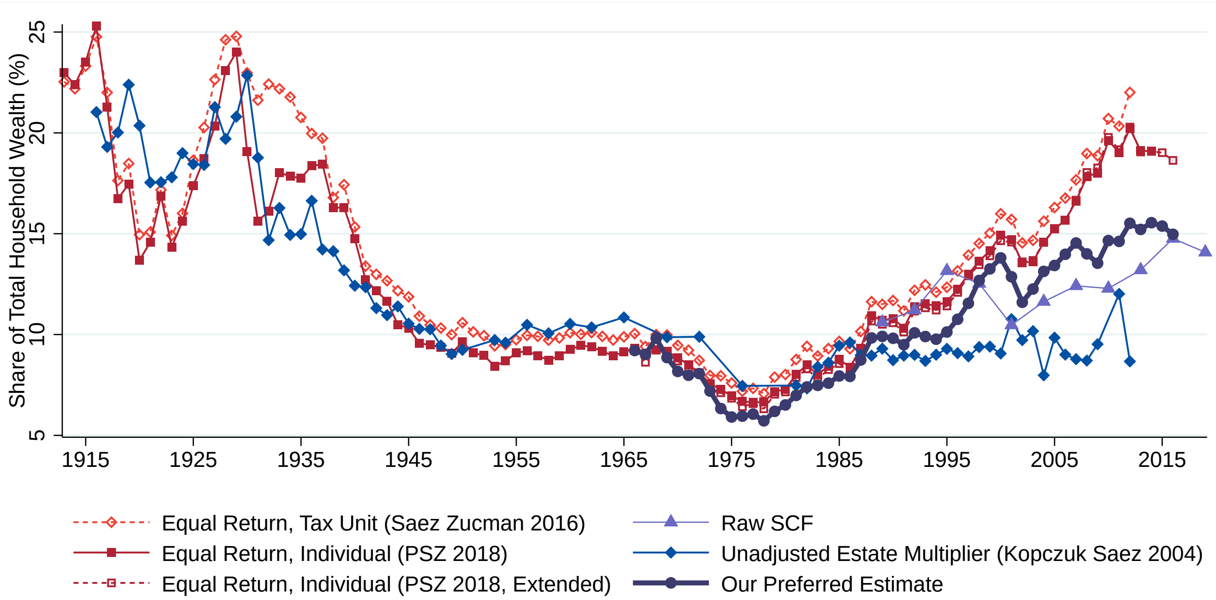
Yagan, Danny. 2015. "Capital tax reform and the real economy: The effects of the 2003 dividend tax cut." *American Economic Review*, 105(12): 3531–63.

Zucman, Gabriel. 2013. "The missing wealth of nations: Are Europe and the US net debtors or net creditors?" *Quarterly Journal of Economics*, 128(3): 1321–1364.

Zwick, Eric, and James Mahon. 2017. "Tax policy and heterogeneous investment behavior." *American Economic Review*, 107(1): 217–48.

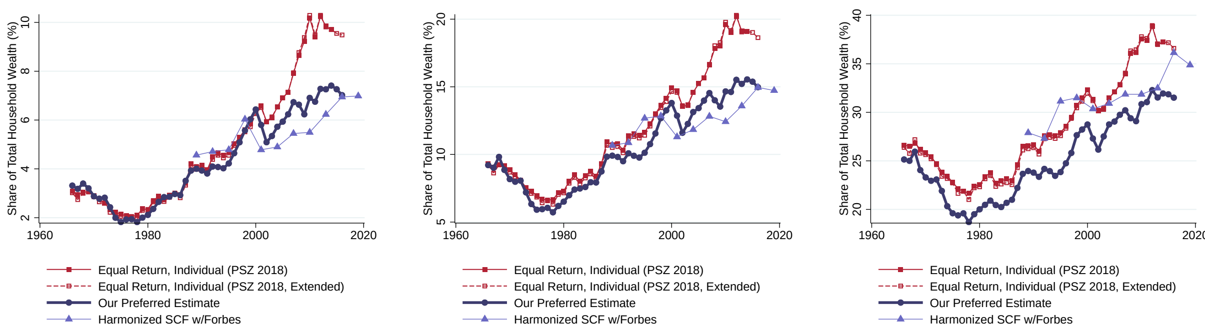
Figure 1: Wealth Concentration in the United States

A. Top 0.1% Share of Total Wealth, Unadjusted Series



B. Top Shares of Total Wealth, Harmonized Series

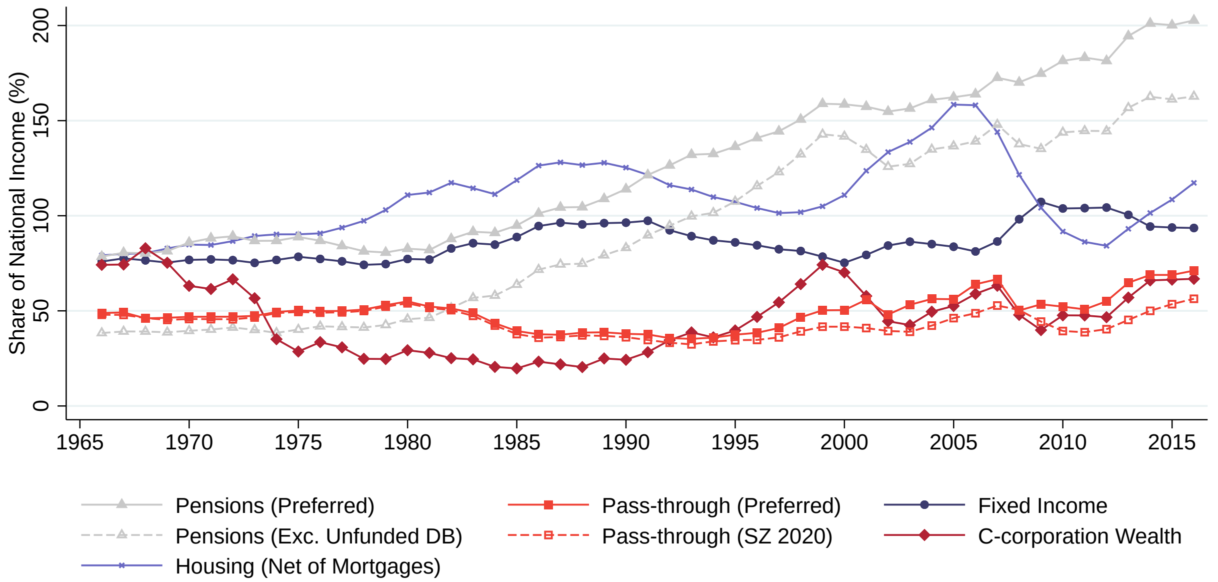
Top 0.01% | Top 0.1% | Top 1%



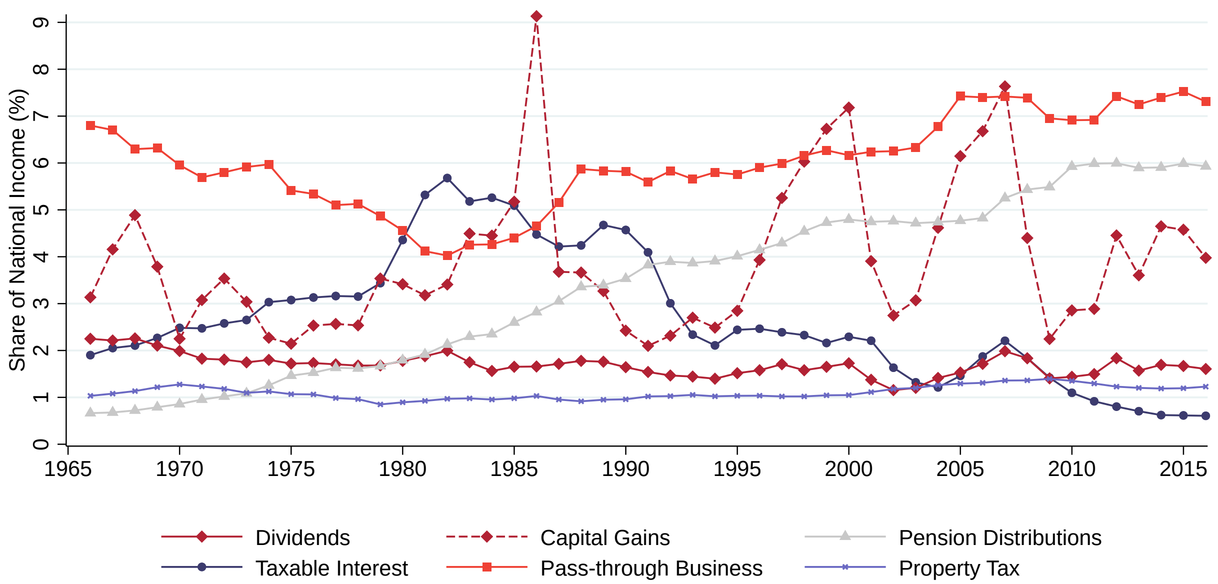
Notes: This figure plots the share of total household wealth for different wealth groups. Panel A graphs our preferred specification for the top 0.1% share of net household wealth, along with analogous series from Piketty, Saez and Zucman (2018), Saez and Zucman (2016), Kopczuk and Saez (2004*a*) (retrieved from and updated in the appendix of Saez and Zucman (2016)), and the SCF. Panel B compares our preferred estimates to the PSZ equal-returns approach and the harmonized SCF with Forbes series for the top 0.01%, 0.1%, and 1% share of net household wealth.

Figure 2: Aggregate Household Wealth and Fiscal Income Components

A. Components of Aggregate Household Wealth

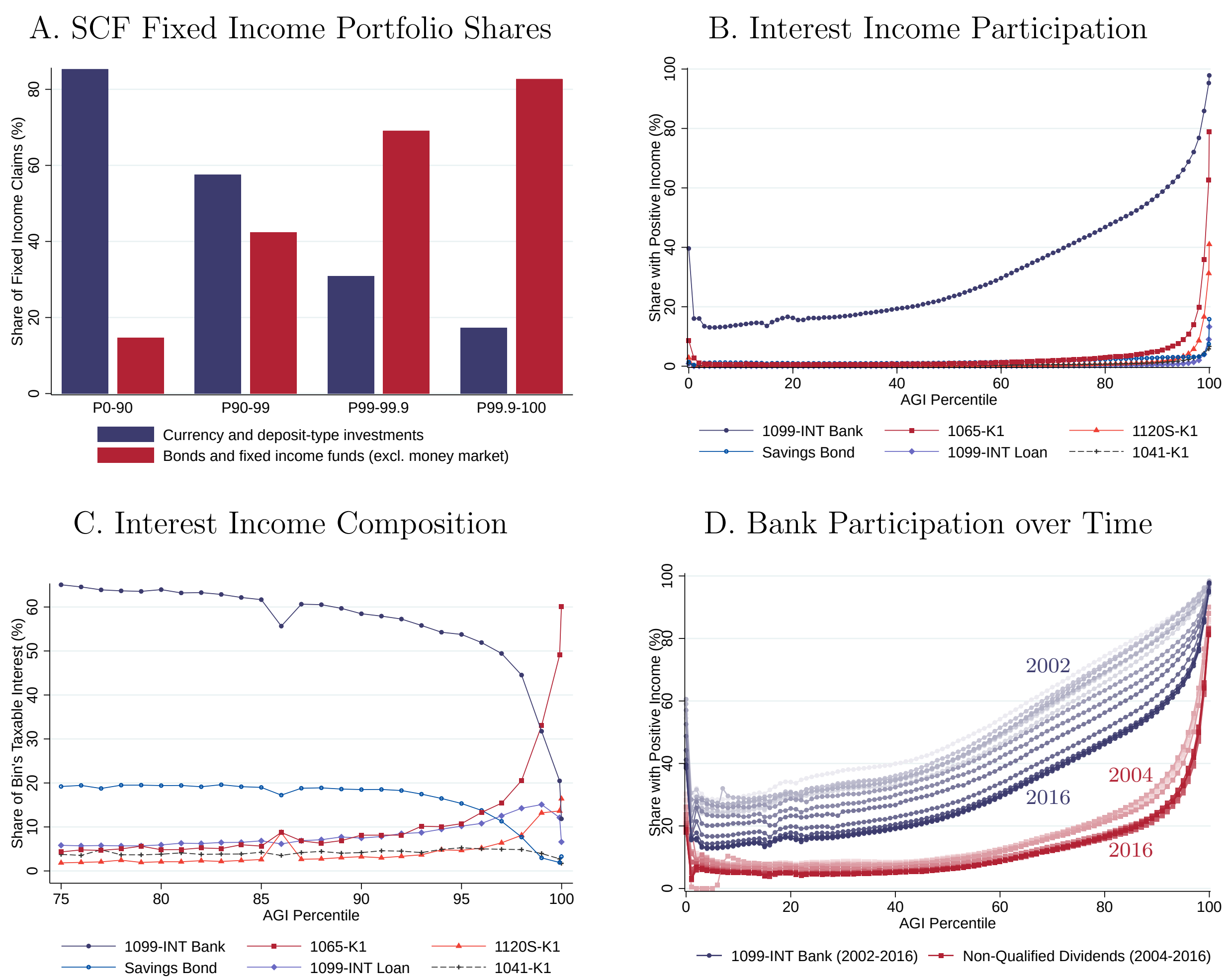


B. Components of Aggregate Fiscal Capital Income



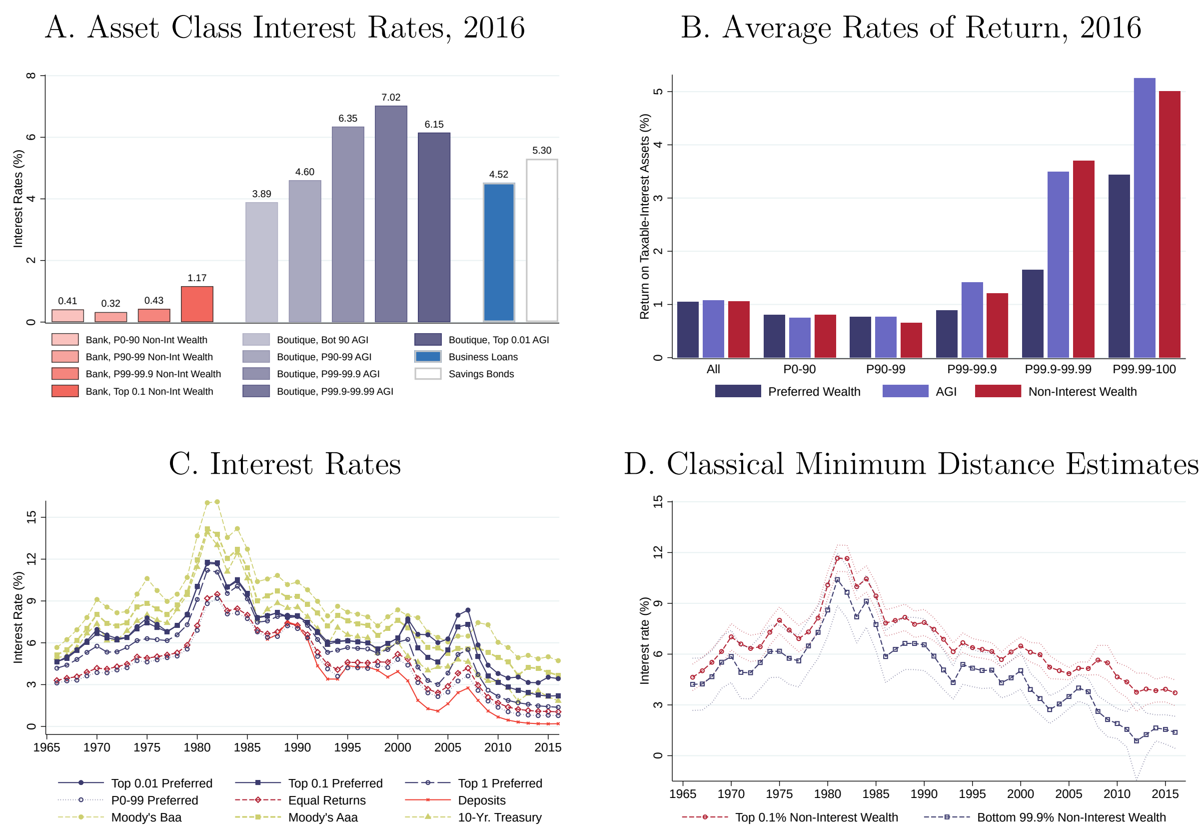
Notes: This figure plots the main components of aggregate national household wealth and fiscal capital income. Panel A plots net household wealth components relative to national income. Fixed income assets include taxable bonds, municipal bonds, currencies, and deposits. C-corporation wealth includes public and private C-corporations. Pass-through business includes S-corporation equity and non-corporate equities in sole proprietorships and partnerships. Housing denotes housing wealth net of mortgages. For pass-through business, the "SZ 2020" version follows the definitions in Saez and Zucman (2020*b*) for pass-through business wealth based on the Financial Accounts. We plot two pension series, one which includes funded and unfunded defined benefit (DB) wealth and one which only includes funded DB wealth. Panel B graphs the ratio of components of fiscal income relative to national income.

Figure 3: Fixed Income Portfolio Heterogeneity across Groups



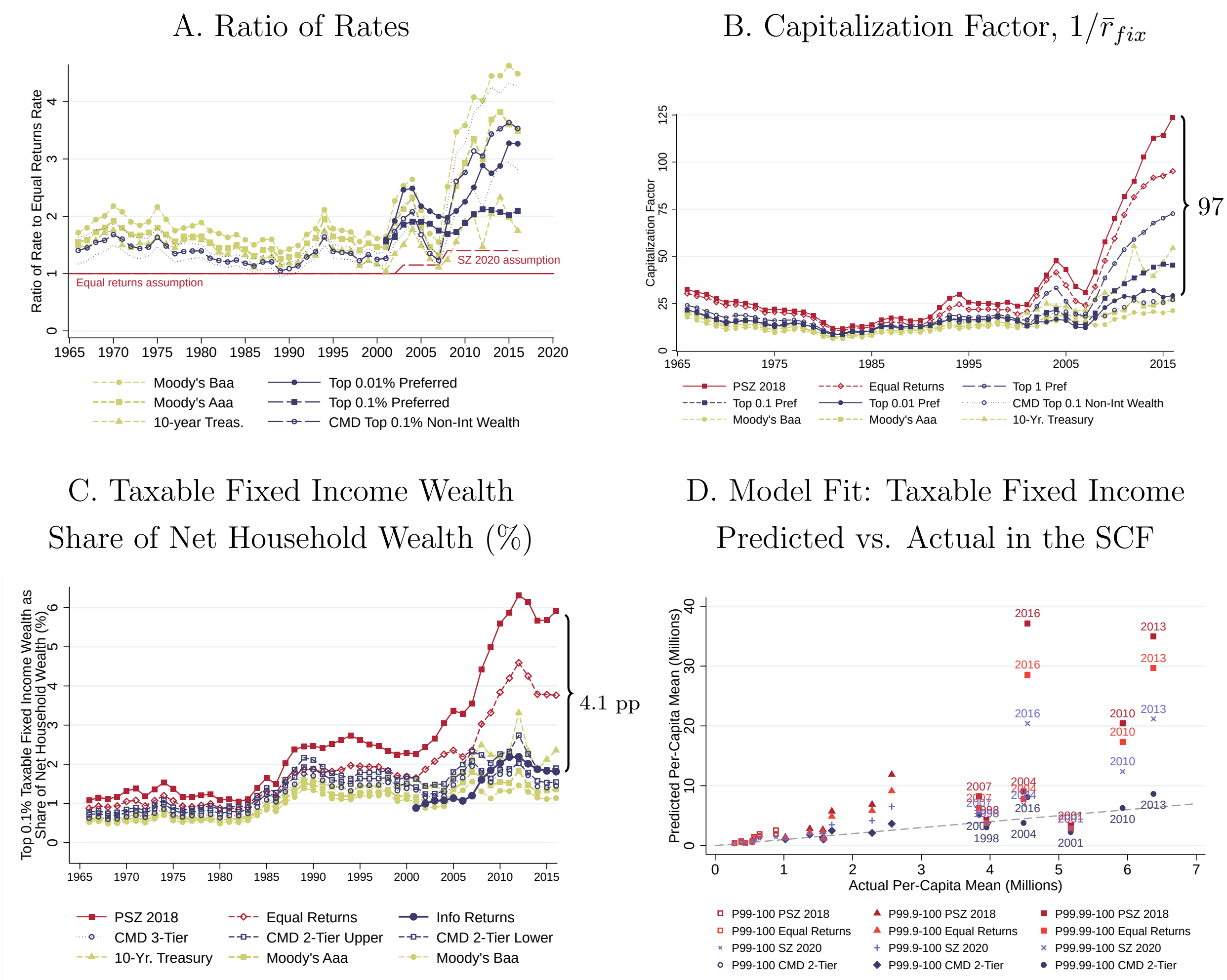
Notes: This figure uses SCF and tax data to document portfolio heterogeneity along the wealth distribution in the nature of interest-bearing assets. Panel A uses the 2016 SCF to decompose fixed income holdings into two broad categories: liquid assets, including currency, deposits, and money market funds; and less liquid assets, including bonds and non-money-market fixed income mutual funds. We present portfolio shares separately for the top 0.1%, P99-P99.9, P90-99, and for the bottom 90% of respondents, ranked in terms of preferred SCF net worth. Panels B–D use population-level tax data to present participation rates and interest income composition in 2016 and bank participation rates over time, with taxpayers grouped in adjusted gross income (AGI) percentiles. We partition the top 1% into three groups: P99-99.9, P99.9-P99.99, and the top 0.01%. We classify fixed income payments based on the information return on which interest income appears, further classifying payments reported on Form 1099-INT into three categories: bank payments (total payees > 10), loan payments (total payees < 10), and savings bond payments.

Figure 4: Fixed Income Rates of Return Vary across Wealth and Income Groups



Notes: This figure provides evidence on fixed income portfolio returns for different groups. Panel A presents interest rates by source for 2016, which serve as inputs into our information-return capitalization approach. Panel B plots the returns to taxable-interest-generating fixed income assets by percentile of preferred wealth, AGI, and non-interest wealth. Panel C plots different the preferred rate-of-return series from Panel B by year. Prior to 2001, these series use the three-tier classical minimum distance (CMD) estimates for return heterogeneity by non-interest wealth. Equal returns plots $\bar{r}_{fix}$ following the capitalization approach in Piketty, Saez and Zucman (2018) with updated aggregates that exclude fixed income assets that generate non-qualified dividends and miscellaneous wealth. 10-Yr. Treasury, Moody's Aaa, and Moody's Baa refer are capital market yields for Treasuries and different categories of investment-grade corporate bonds. Deposits are the bank deposit rate from Drechsler, Savov and Schnabl (2017). Panel D plots estimated interest rates and 95% confidence intervals from the two-group CMD estimates with individuals ranked by non-interest wealth.

Figure 5: Alternative Capitalization Factors for Fixed Income Wealth

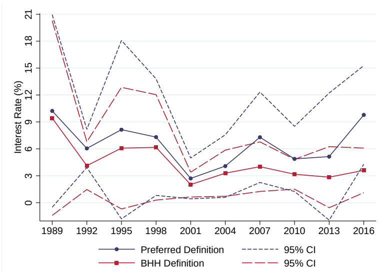


Notes: This figure compares capitalization factors under alternative assumptions of average returns to taxable-interest-generating fixed income wealth. Panel A presents the point estimates and standard errors of a key ratio of the top rate relative to the equal-returns rate, $r_{1t}/\bar{r}_t$, which summarizes the degree of heterogeneity. We plot this ratio for different wealth groups ranked by preferred wealth, for the top 0.1% non-interest-wealth group estimated via classical minimum distance (CMD), and for different capital market interest rates. Panel B plots capitalization factors, i.e., the reciprocal of the interest rates from Figure 4C. We add a series that uses the fixed income wealth definition and aggregates from Piketty, Saez and Zucman (2018) and a series based on the top 0.1% non-interest-wealth CMD estimates from Figure 4D. Panel C shows top 0.1% fixed income wealth (including funds that generate non-qualifying dividends) relative to total household wealth when using different capitalization approaches for the top group under wealth ranks from our preferred definition. As in Panel B, the PSZ 2018 series uses aggregates and definitions from Piketty, Saez and Zucman (2018), while the Equal Returns series updates aggregates and definitions. CMD 3-Tier refers to our preferred minimum distance approach. CMD 2-Tier Upper and 2-Tier Lower use the two-group approach and respectively apply the 95% upper and lower confidence interval for capitalizing top wealth. The capital market rate series apply these rates to the top 1% ranked by taxable interest. Panel D plots predicted versus actual SCF wealth using data on flows and stocks from the SCF. Predictions take flows as an input and produce estimates of fixed income wealth. The dashed line plots the 45-degree line. Points on the graphs show predicted wealth for different income groups for a given year using capitalization factors from Piketty, Saez and Zucman (2018) with unupdated and updated (i.e., Equal Returns) definitions and aggregates, from Saez and Zucman (2020*b*), and from applying the two-group CMD approach. We define SCF fixed income wealth to exclude funds that do not generate taxable interest.

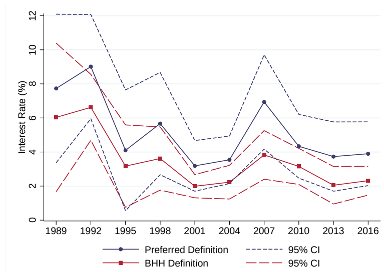
Figure 6: Interest Rates in the SCF for Taxable-Interest-Generating Assets

A. Interest Rates

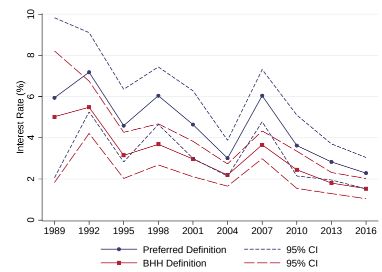
Top 0.01%



Top 0.1%

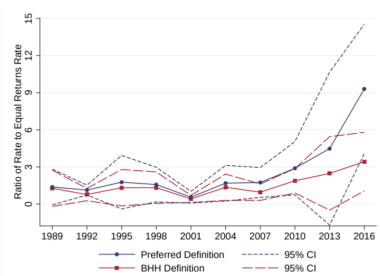


Top 1%

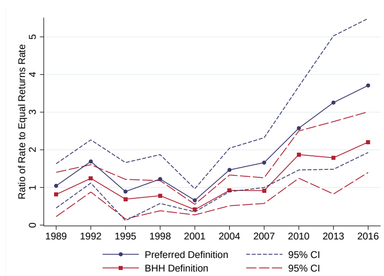


B. Ratio of SCF Top Rate to Equal Returns Rate

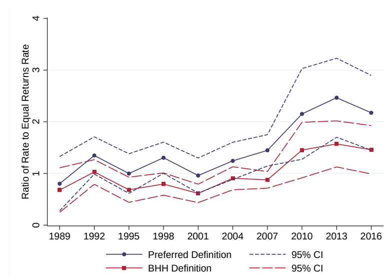
Top 0.01%



Top 0.1%

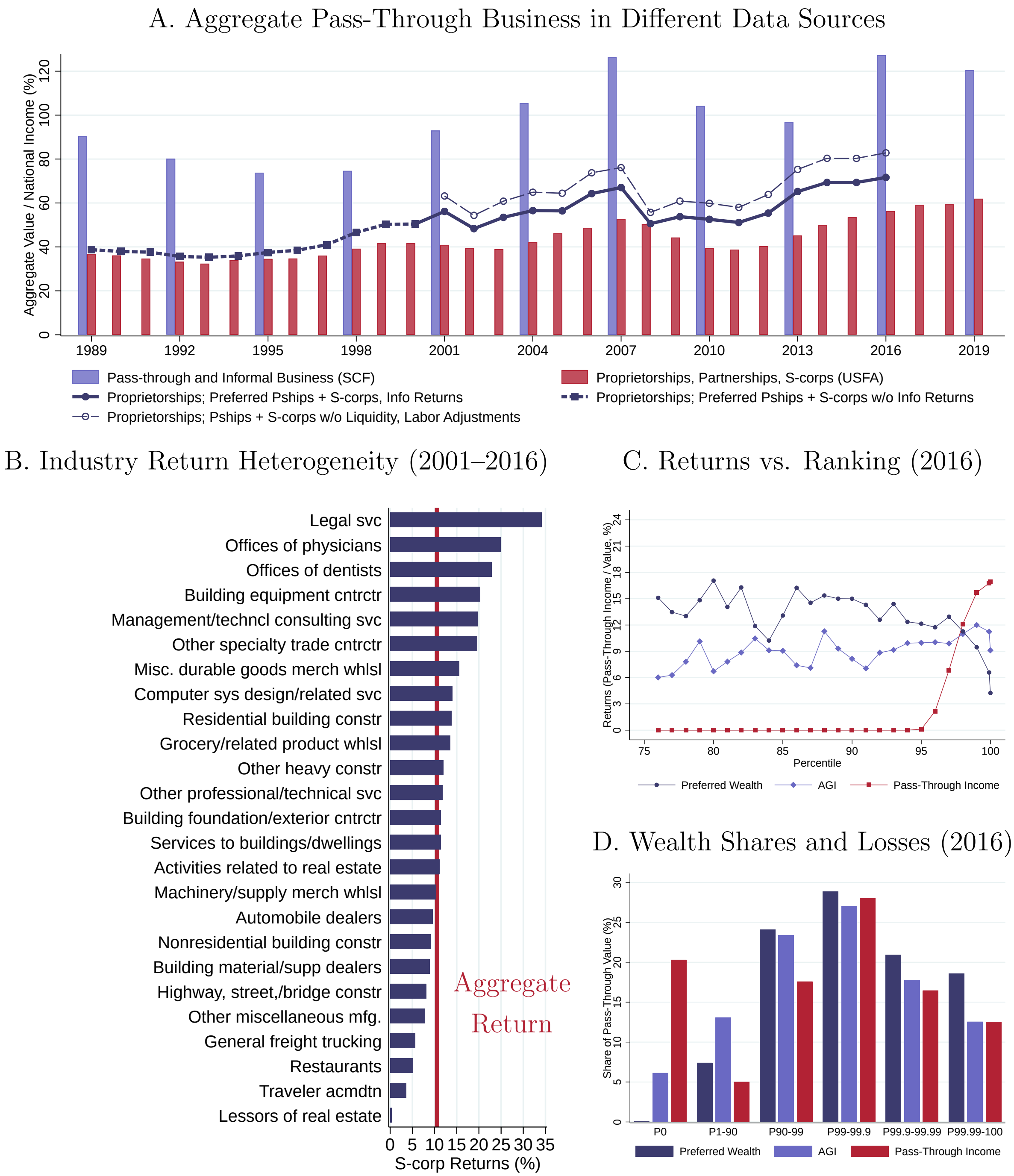


Top 1%



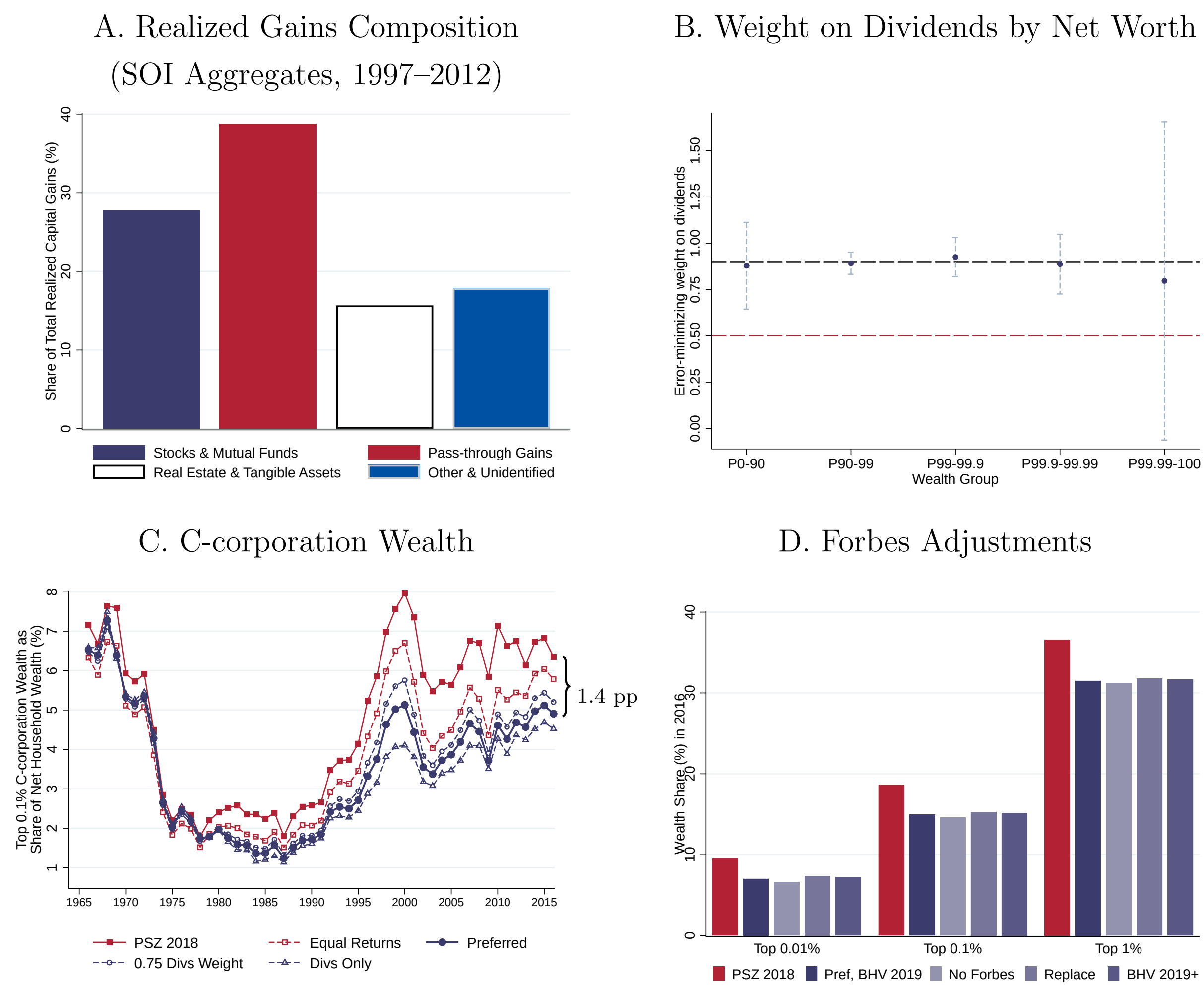
Notes: This figure plots top interest rates and return ratios under uncertainty for the SCF We sample SCF households using the replicate weights and following the procedure in Bricker, Henriques, Krimmel and Sabelhaus (2016). We report both our preferred definition, which removes non-interest-generating assets (i.e., fixed income mutual funds and money market funds, which pay non-qualified dividends) from the denominator of the interest rate, as well as the definition from Bricker, Henriques and Hansen (2018). The denominator of the return ratio is the equal-returns rate from Figure 5A.

Figure 7: Aggregate Pass-Through Equity and Unequal Returns across Groups



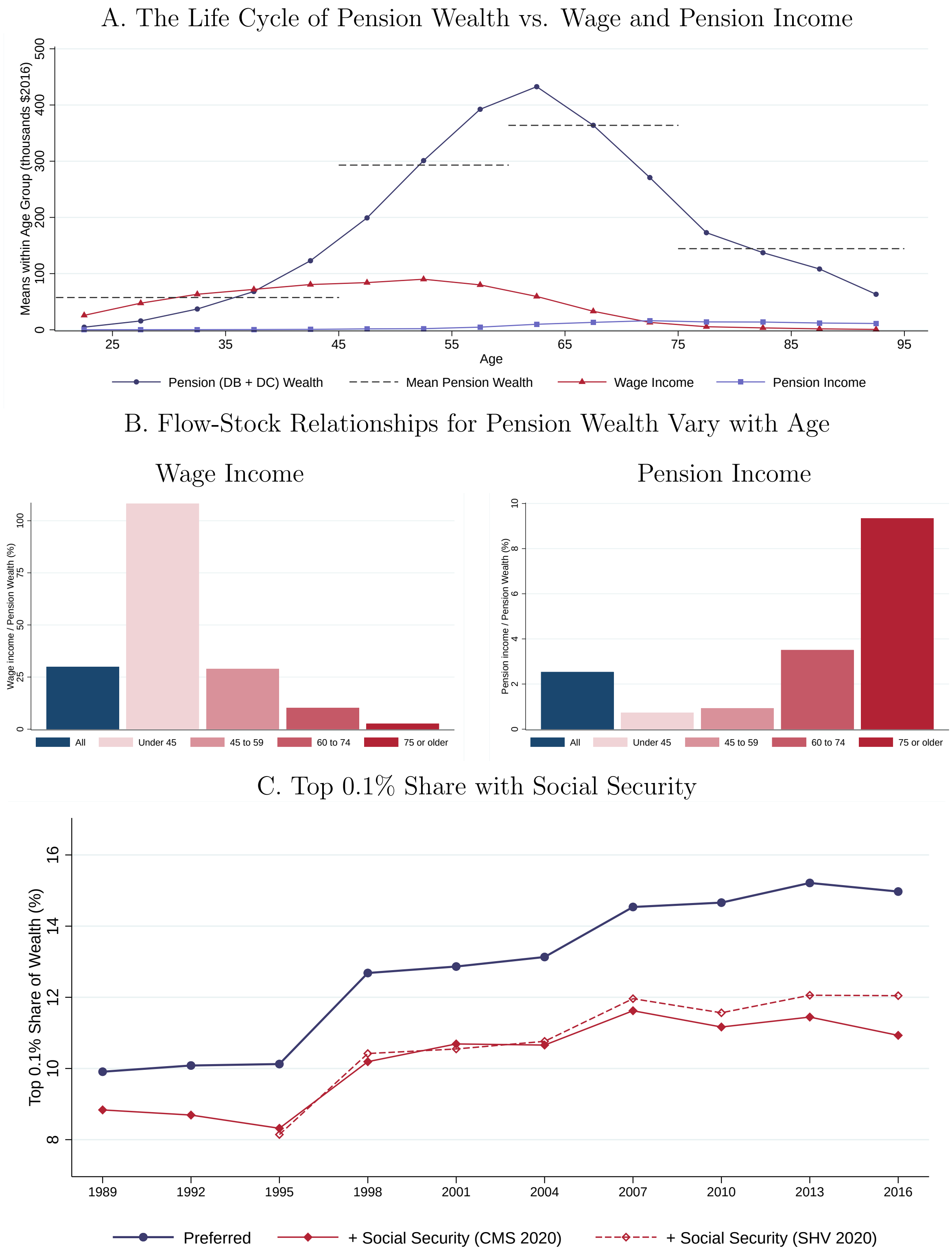
Notes: This figure documents differences in the aggregate value of private businesses across data sources and heterogeneity in effective returns on pass-through equity. Panel A compares aggregate pass-through business values from the Survey of Consumer Finances (SCF) to an analogous concept from the capitalization approach based on the US Financial Accounts, which combines non-corporate business wealth with S-corporation equity wealth. The panel also plots estimates of pass-through business wealth using our valuations for S-corporations and partnerships and our estimate for missing pass-through business wealth. We plot both our preferred series, which adjusts for liquidity discounts and labor income characterized as profits, and an unadjusted series. Prior to 2001, our approach follows the capitalization approach with Financial Accounts aggregates, as in Piketty, Saez and Zucman (2018) and Saez and Zucman (2020*b*), but adds missing pass-through business wealth. Panels B and C quantify return heterogeneity across industries and individuals, respectively. Returns equal aggregate industry profits before tax divided by our estimate of group-specific wealth. Panel D plots the share of pass-through business wealth in 2016 for groups ranked by wealth, AGI, and pass-through income. We divide the P0-90 group into a P0 and a P1-90 group to isolate those with losses and significant business wealth.

Figure 8: Dividends are More Informative than Realized Gains for Inferring Stock Wealth



Notes: This figure presents evidence supporting our approach to inferring stock wealth from dividends and realized capital gains, and considers the impact of augmenting capitalization estimates with Forbes 400 data. Panel A decomposes realized capital gains by component using IRS statistics of income aggregates from 1997-2012. Panel B uses minimum distance to estimate the optimal weight on dividends versus capital gains for different wealth groups in the SCF. Panel C is analogous to Figure 5C. We plot C-corporation equity estimates given different weights on dividends and realized capital gains, and applying the equal returns approach (0.5 weight on both dividends and capital gains) using updated aggregates and definitions and the unupdated series following Piketty, Saez and Zucman (2018). Panel D presents three alternative approaches that combine Forbes data with our capitalized estimates for the top 1%, top 0.1%, and top 0.01% in 2016. The first "Replace" replaces the richest 400 in our data with the Forbes 400. The second "Pref, BHV 2019" follows Bricker, Hansen and Volz (2019*b*) by blending the Forbes data into the tax sample and adjusting sampling weights to account for overlap. The third "BHV 2019+" adds an estimate of non-dividend-generating C-corporation wealth from Appendix L.3 to our preferred, BHV blending approach.

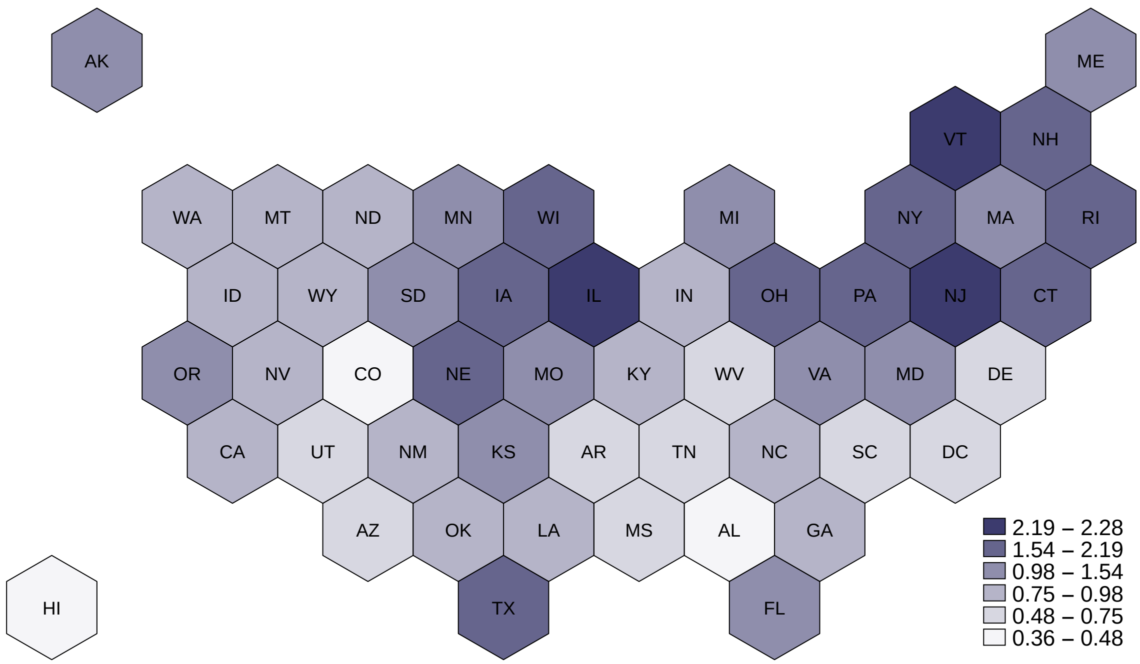
Figure 9: Using Wages and Pension Distributions to Infer Pension Wealth



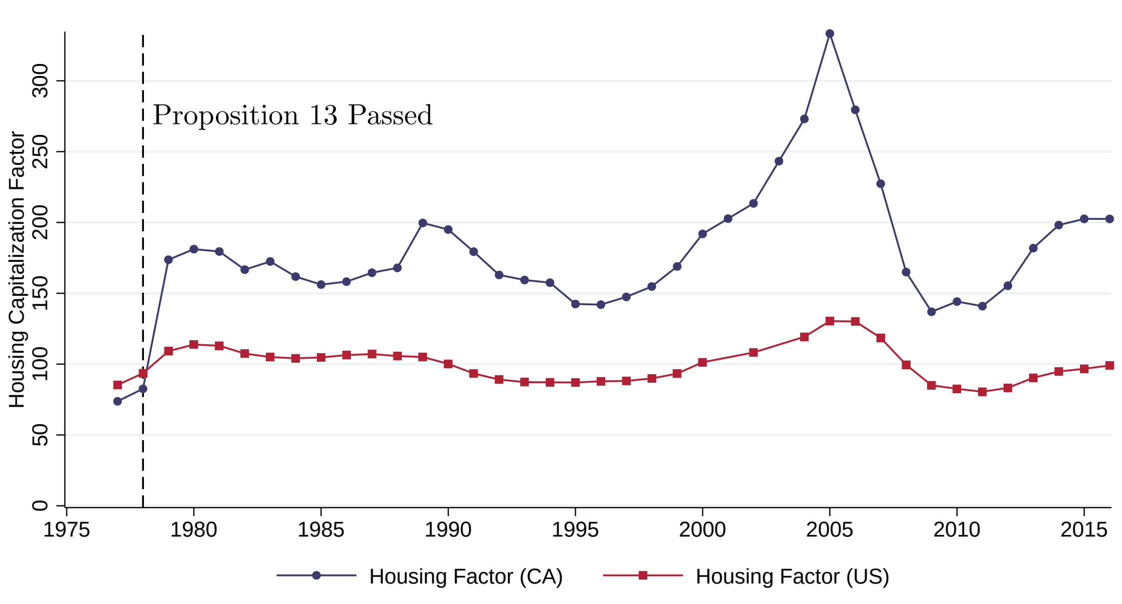
Notes: This figure explores the relative informativeness of wages and pension income for inferring pension wealth for different age groups. Panel A plots 1989–2016 data from the SCF on the life cycle of pension wealth, wage income, and pension income. Pension wealth is the defined-benefit-augmented SCF from Sabelhaus and Volz (2019). The dashed lines plot average pension wealth for that age group. Panel B plots the ratio of wage income or pension income to pension wealth for the full population, those under 45, those aged 45-59, those aged 60-64, and those over 75. Panel C plots our preferred top 0.1% wealth share and a modified series that includes total Social Security wealth in the denominator and top 0.1% Social Security wealth in the numerator (the latter of which is close to zero relative to total wealth). Social Security data come from Catherine, Miller and Sarin (2020) (CMS) and Sabelhaus and Volz (2019) (SHV).

Figure 10: Regional Variation in the Returns to Housing Assets

A. Geographic Variation in Property Tax Rates

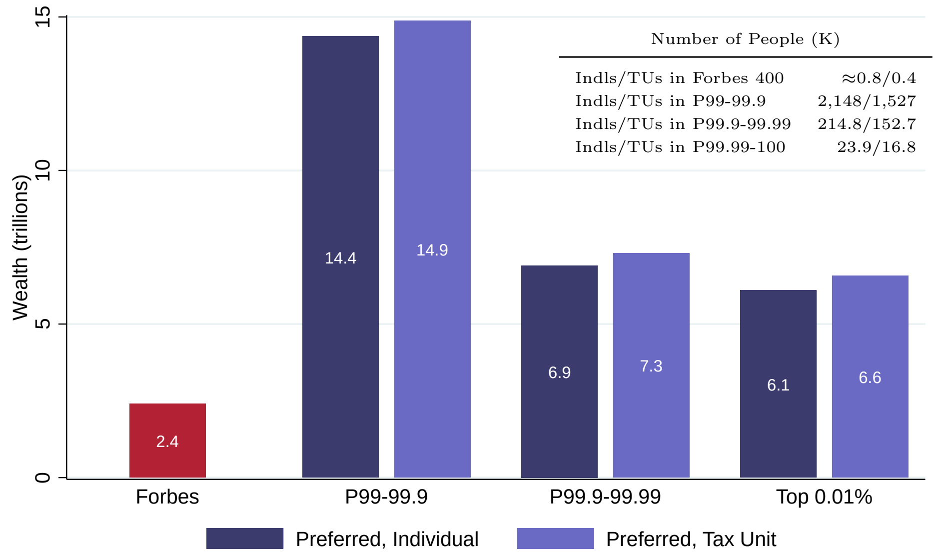


B. Evolution of Housing Capitalization Factors in California



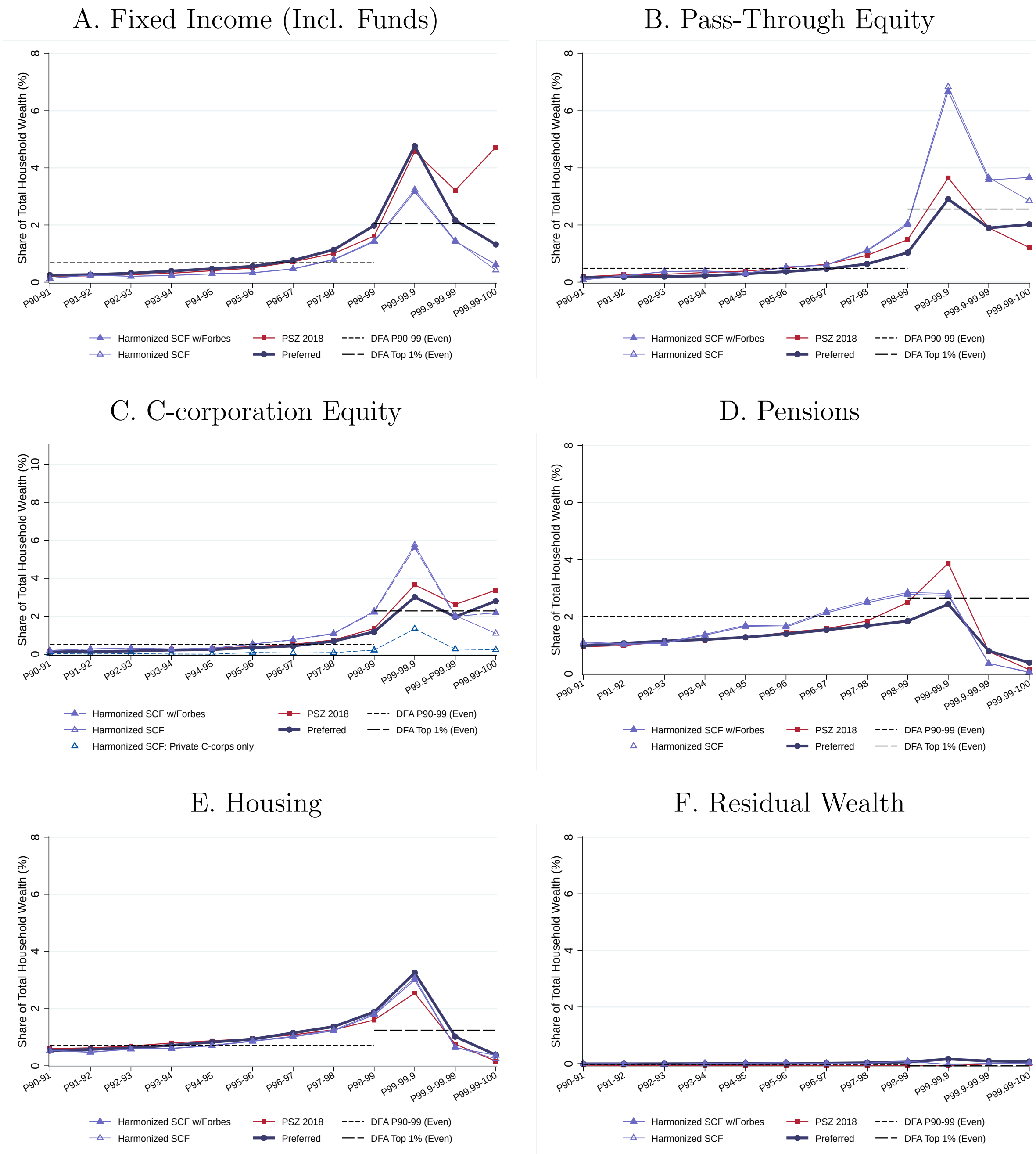
Notes: Panel A provides a map of state property tax rates from ATTOM. Panel B shows how the housing asset capitalization factor, equal to the reciprocal of the state property tax rate, has evolved in California versus an equal returns benchmark pooling all states.

Figure 11: Size of Different Top Wealth Groups



Notes: This figure compares Forbes 400 wealth to aggregate wealth according to our preferred specification for telescoping subgroups of the top 1%: P99-99.9, P99.9-99.99, and the top 0.01% in 2016. The figure reports counts of individuals or tax units in each group.

Figure 12: Wealth Composition in the United States

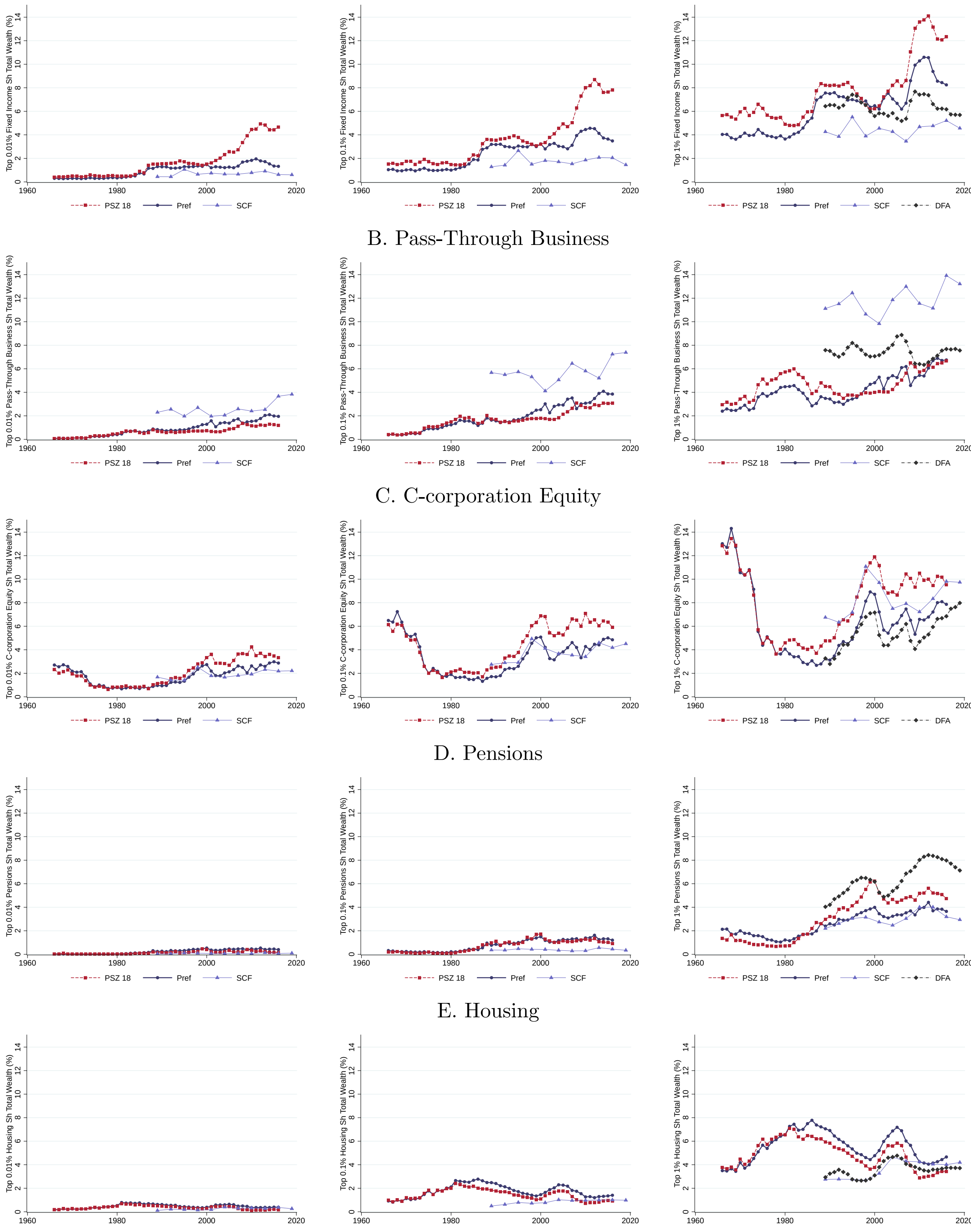


Notes: This figure plots the level and allocation of wealth across asset classes among the top 10% in 2016. We group individuals into percentile bins and further divide the top 1% into P99- 99.9, P99.9-99.99, and the top 0.01%. Each plot shows the share of total household wealth accruing to that group in a particular asset class. We compare our preferred estimates to the equal-returns approach with aggregates and definitions following Piketty, Saez and Zucman (2018) and the harmonized SCF with and without Forbes. Horizontal dashed lines plot analogous figures for the DFA top 1% and P90-99 series split evenly across groups. The DFA series are at the household level, while the other series are at the individual level.

Figure 13: Portfolio Components over Time

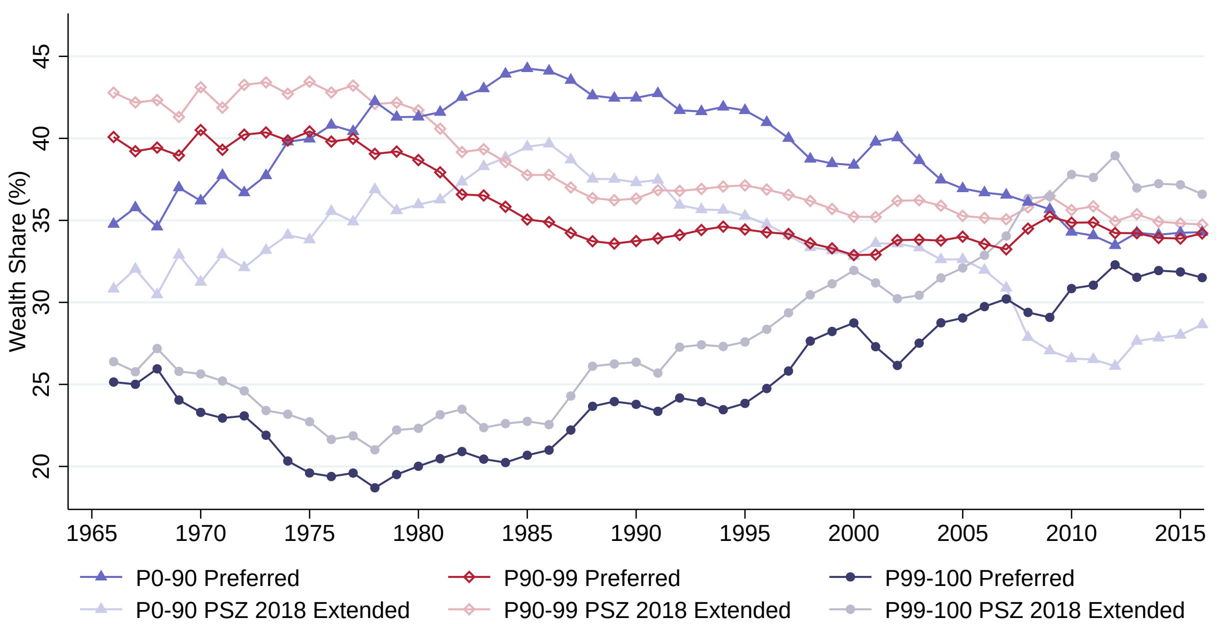
A. Fixed Income

Top 0.01% | Top 0.1% | Top 1%



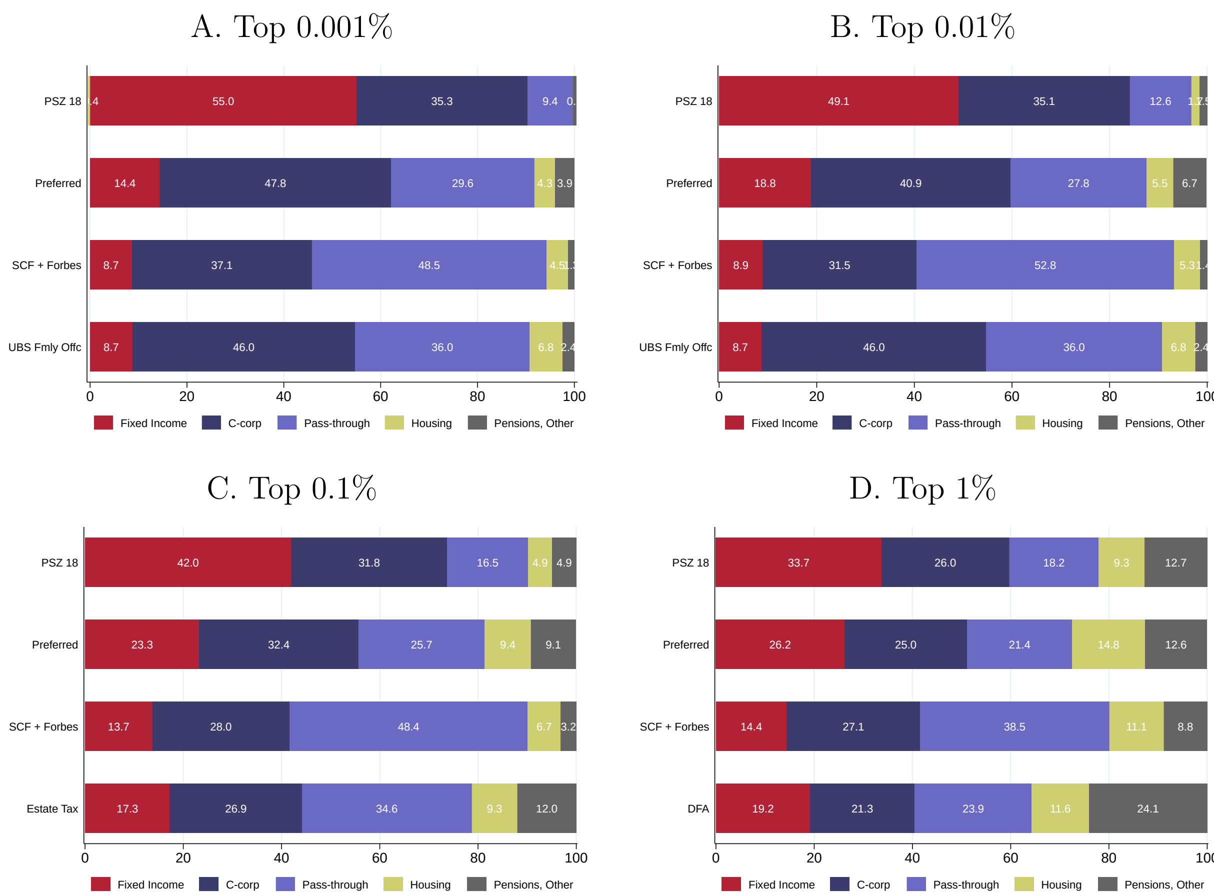
Notes: This figure plots time series versions of Figure 12 for the five major asset classes for the top 0.01%, top 0.1%, and top 1% in our series, the PSZ equal-returns series, the harmonized SCF with Forbes, and the DFA. Appendix Figures A.18 and A.20 present analogous figures with portfolio shares and inflation-adjusted component levels, respectively.

Figure 14: Wealth Concentration by Group under Different Approaches



Notes: This figure plots the share of total household wealth for different wealth groups, including the bottom 90%, P90-99, and the top 1% under our preferred approach and the PSZ equal-returns approach. Each series defines rankings using that approach's respective wealth estimates. Appendix Figure A.21 plots analogous series defined at the tax unit level along with estimates from the DFA.

Figure 15: Top Wealth Composition in 2016 across Specifications and Data Sets

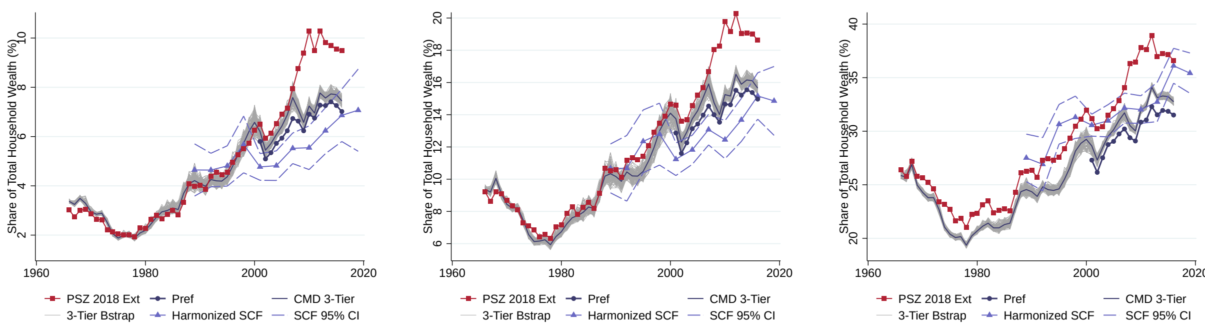


Notes: This figure presents top portfolio shares in 2016 estimated under equal returns assumptions with aggregates and definitions from Piketty, Saez and Zucman (2018) and our preferred assumptions, and as calculated from the harmonized SCF with Forbes, the Distributional Financial Accounts, estate tax returns, and the UBS Family Office Survey. See Appendix C, D, and E for detailed definitions. Estate Tax uses mortality-adjusted estate tax data from the SOI estate tax sample file and only include the top 0.1% of estates implied by sampling and mortality rates. Forbes data are partitioned into portfolio components using hand-collected publicly available data on business ownership for 2016 (see Appendix I) as well as portfolio share data for non-business wealth from the SCF for the top 0.01%.

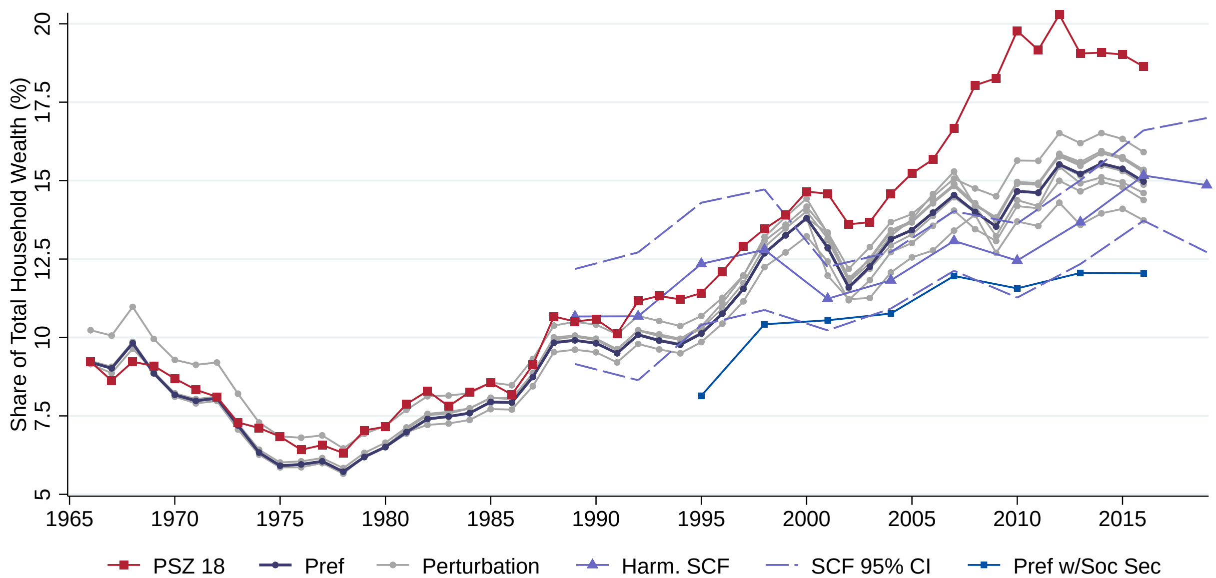
Figure 16: Top Share of Wealth under Alternative Specifications

A. Bootstrapping Fixed Income and C-corporation Parameters

Top 0.01% Top 0.1% Top 1%



B. Perturbations of Preferred Specification for Top 0.1%



Notes: Panel A of this figure plots top wealth shares under uncertainty for different series from Figure 1B. For our capitalized series, we simulate fixed income and C-corporation wealth estimates using the sampling distribution of interest rates and weight on dividends estimated under classical minimum distance. We then combine these estimates with other asset classes to define new top wealth groups and present the 95% band of top wealth shares using this procedure. We also plot the information-return based series for 2001–2016. For the SCF, we sample SCF households using the replicate weights and following the procedure in Bricker, Henriques, Krimmel and Sabelhaus (2016). We treat the Forbes 400 share of household wealth as a constant and add this amount to the series. PSZ 18 series are plotted as in Figure 1. Panel B also plots series that result from perturbing the preferred specification to include alternatives for each asset class (from Figures 5C, 8C, 8D, 9C, and A.15), such as using the CMD 3-tier approach for fixed income, using a weight of $\alpha = .75$ on dividends, different labor and liquidity adjustments for private business, and excluding unfunded DB pensions. The "Pref w/ Soc Sec" series is the Sabelhaus and Volz (2019) series from Figure 9C.

Table 1: Predicting Dividend-Generating Assets with Equity Flows in the SCF

	(1)	(2)	(3)	(4)	(5)
	Full sample	Bottom 90%	Top 1%	Top 0.1%	Top 0.01%
Capital gains	1.042	1.067	0.845	0.736	0.318
	(0.011)	(0.014)	(0.027)	(0.041)	(0.083)
Dividends	15.763	15.554	14.022	11.892	14.985
	(0.054)	(0.057)	(0.134)	(0.187)	(0.410)
Implied α	0.938	0.936	0.943	0.942	0.979
	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)
N (unweighted)	441,260	374,866	66,394	31,234	9,391

Notes: This table reports the relative informativeness of dividends and capital gains for estimating dividend-generating wealth within the SCF pooling over all individuals and years and for subgroups of the wealth distribution. We estimate regressions of the form:

$$\text{Dividend Assets}_i = \beta_1 \text{Dividends}_i + \beta_2 \text{Capital gains}_i + \gamma_t + \epsilon_i.$$

Standard errors are in parentheses. Implied α is the ratio of β_1 to the sum of the coefficients. All regressions split married couples to imitate our equal-split tax data (see Appendix D) and use SCF survey weights. Column 1 estimates the regression among all SCF participants 1989-2019. Columns 2-5 estimate the regression among subgroups of the wealth distribution using our preferred SCF wealth definition.

Table 2: Thresholds and Average Wealth in Top Wealth Groups (2016)

Wealth group	Count	Pref. Threshold	Average wealth		Wealth share	
			Preferred	PSZ 2018 Ext.	Preferred	PSZ 2018 Ext.
Panel A. Top wealth groups						
Full population	238,657,000		$364,000	$317,000	100.0%	100.0%
Top 10%	23,866,100	$717,000	$2,392,000	$2,259,000	65.7%	71.3%
Top 1%	2,386,700	$3,730,000	$11,469,000	$11,584,000	31.5%	36.6%
Top 0.1%	238,700	$17,800,000	$54,491,000	$59,005,000	15.0%	18.6%
Top 0.01%	23,900	$84,300,000	$255,397,000	$300,580,000	7.0%	9.5%
Panel B. Intermediate wealth groups						
Bottom 90%	214,790,900		$139,000	$101,000	34.3%	28.7%
Top 10-1%	21,479,400	$717,000	$1,383,000	$1,223,000	34.2%	34.7%
Top 1-0.1%	2,148,000	$3,730,000	$6,688,000	$6,317,000	16.5%	18.0%
Top 0.1-0.01%	214,800	$17,800,000	$32,160,000	$32,189,000	8.0%	9.2%

Notes: This table provides summary statistics on the distribution of wealth across individuals in 2016. Average wealth and wealth shares are calculated under our preferred specification and following the equal-returns capitalization approach in Saez and Zucman (2016) applied at the individual level using the definitions and aggregates in Piketty, Saez and Zucman (2018).

Table 3: Portfolio Shares in Top Wealth Groups (2016)

Wealth group	Fixed Income	C-corporation Equity	Pass-through Business	Housing	Pensions	Other
Panel A. Top wealth groups						
Full population	17.3%	12.5%	13.3%	21.2%	37.5%	-1.8%
Top 10%	21.9%	17.4%	15.7%	20.2%	24.1%	0.7%
Top 1%	26.2%	25.0%	21.4%	14.8%	11.6%	1.0%
Top 0.1%	23.3%	32.4%	25.7%	9.4%	8.0%	1.1%
Top 0.01%	18.8%	40.9%	27.8%	5.5%	5.7%	1.0%
Panel B. Intermediate wealth groups						
Bottom 90%	8.5%	3.1%	8.6%	23.2%	63.2%	-6.6%
Top 10-1%	17.9%	10.5%	10.4%	25.2%	35.7%	0.3%
Top 1-0.1%	28.8%	18.2%	17.6%	19.7%	14.8%	1.0%
Top 0.1-0.01%	27.2%	24.9%	23.8%	12.8%	10.1%	1.2%

Notes: This table shows 2016 portfolio shares of fixed income, C-corporation equity, pass-through business, housing, pension wealth, and other wealth according to our preferred estimates for top groups and intermediate wealth groups.