TOP WEALTH IN AMERICA: NEW ESTIMATES UNDER HETEROGENEOUS RETURNS*

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This article uses administrative tax data to estimate top wealth in the United States. We assemble new data that link 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 3.5 times higher than the average. We value the population of U.S. firms using firm-level characteristics and apportion this wealth using firm-owner links. 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 that build upon the methods of Saez and Zucman (2016a). From 1989 to 2016, the top 1%, 0.1%, and 0.01% wealth shares increased by 6.6, 4.6, and 2.9 percentage points, respectively, to 33.7%, 15.7%, and 7.1%. Overall, although we estimate a large degree of return heterogeneity, accounting for this heterogeneity does not change the fundamental story for top wealth shares and their growth—wealth inequality is high and has risen substantially over recent decades. *JEL Codes:* D31, E01, E21, N32.

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I. Introduction

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 on the quality of top wealth estimates. Measuring the concentration of wealth also matters for economic analysis of growth, savings, and capital accumulation.

A central approach to estimate wealth is to scale up, or "capitalize," income observed on tax returns (Giffen 1913; Stewart 1939; Saez and Zucman 2016a). This approach estimates wealth W_i of individual i as a function of income y_i using the relationship, $W_i = \beta y_i$, where β is the capitalization factor. In the case of a bond, β is $\frac{1}{r}$ where r is the interest rate.

Mapping income flows to wealth, however, is challenging. Returns can vary across individuals and increase with wealth (Bach, Calvet, and Sodini 2020; Fagereng et al. 2020). Moreover, in the low interest rate environment of the mid-2000s and postrecession period, small differences in returns δ can lead to large differences in capitalization factors $\left(\frac{1}{r+\delta}\right)$ and thus wealth estimates (Kopczuk 2015; Fagereng et al. 2016). Bach, Calvet, and Sodini (2020) find that heterogeneity in returns explains most of the historical increase in top wealth shares in Sweden. Campbell, Ramadorai, and Ranish (2019) reach a similar conclusion studying stock portfolios in India. Despite this emerging evidence on the importance of return heterogeneity, there is limited evidence on the degree of return heterogeneity in the United States and its consequences for estimates of top wealth levels and their dynamics.

This article uses administrative tax data to estimate top wealth in the United States. We assemble new data that link people to their sources of capital income and develop new methods to estimate the degree of return heterogeneity within asset classes. We value the population of pass-through firms using firm-level characteristics and apportion this wealth using firm-owner links. 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 that build on the pioneering methods of Saez and Zucman (2016a) (SZ) and Piketty, Saez, and Zucman (2018) (PSZ).

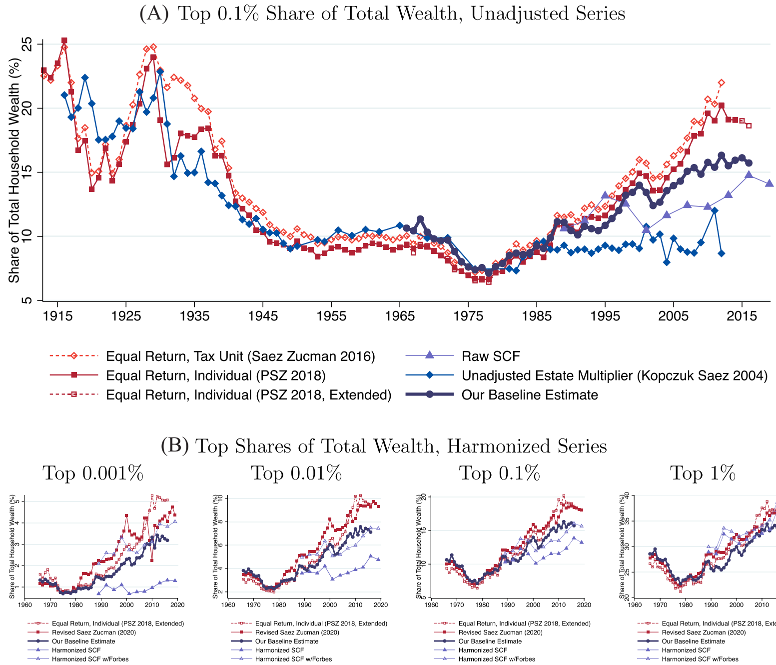

FIGURE I

Wealth Concentration in the United States

This figure plots the share of total household wealth for different wealth groups. Panel A graphs our baseline specification for the top 0.1% share of net household wealth, along with analogous series from Piketty, Saez, and Zucman (2018) (PSZ), Piketty, Saez, and Zucman (2017), Saez and Zucman (2016a), Kopczuk and Saez (2004) (retrieved from and updated in Saez and Zucman (2016b)), and the SCF. Panel B compares our baseline estimates to PSZ, the revised series in Saez and Zucman (2020) (SZ20), and the harmonized SCF with and without Forbes for the top 0.001%, 0.01%, 0.1%, and 1% share of net household wealth. To aid comparison across methodologies, our baseline series exactly matches the aggregates in SZ20 derived from the Financial Accounts. The SZ20 series are based on their October 2020 release, https://gabriel-zucman.eu/usdina/ (accesssed January 2022).

Overall, although we estimate a large degree of return heterogeneity, accounting for this heterogeneity does not change the fundamental story for top wealth shares and their growth—wealth inequality is high and has risen substantially over recent decades. Figure I, Panel A shows that in the past two decades, our baseline top 0.1% wealth share estimates hover between the raw Survey of Consumer Finance (SCF) and the benchmark series in

SZ and PSZ. Figure I, Panel B telescopes into the top 1% wealth share and compares our baseline to alternative capitalization approaches and a harmonized SCF series that aligns aggregates and includes the Forbes 400. Across all approaches, top wealth shares have steadily risen since the 1980s.[1]

In terms of top portfolios, we find that accounting for estimated return heterogeneity makes a difference. First, relative to an equal-returns approach, we find a larger role for pass-through business wealth and a smaller role for fixed-income wealth. Second, the fixed-income portfolio share falls and the equity share rises with wealth at the top. 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 53% of top 0.001% wealth, and pass-through business accounts for 22%. In contrast, pensions and housing account for almost all wealth of the bottom 90%. Third, we find that the fixed-income portfolio share at the very top remained relatively stable, whereas under equal returns, the fixed-income portfolio share increased substantially since 2000.

These findings reflect several methodological innovations. For fixed-income wealth, we contribute two innovations. First, 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. These 3.2 billion source-owner observations allow us to disaggregate taxable interest income into subcomponents. This disaggregation reveals that rich people 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). These data reveal a striking amount of return heterogeneity across wealth groups, with the top 0.01% group receiving returns that are 3.5 times average returns. In 2016, our return estimates increase from nearly 1% in the bottom 99.9% to 1.6% for P99.9–99.99 to 3.8% for the top 0.01%.

1. From 1989 to 2016, the top 1%, 0.1%, 0.01%, and 0.001% wealth shares in our baseline series increased by 6.6, 4.6, 2.9, and 1.7 percentage points, respectively, to 33.7%, 15.7%, 7.1%, and 3.2%. In the PSZ series, wealth shares increased by 10.0, 7.9, 5.4, and 3.1 percentage points to 36.6%, 18.6%, 9.5%, and 4.6%. In recent follow-on work, Saez and Zucman (2020) take a different approach from ours to incorporating heterogeneity; in their series, wealth shares increased by 7.7, 6.3, 4.1, and 1.8 percentage points to 36.3%, 18.4%, 9.3%, and 4.1%.

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% (std. err. = 0.7%) for the top 0.1% group and 1.4% (std. err. = 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.

We also contribute new valuation methods and estimates of pass-through business wealth, which plays a key role in top wealth and tax policy (Bricker, Moore, and Volz 2021). We build linked firm-owner data and industry-specific valuation multiples from public markets to estimate and apportion 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 et al. (2019) (SYZZ) and liquidity discounts of private firms. We find that two-thirds of pass-through wealth is held by the top 1% of the wealth distribution, and accounting for return heterogeneity doubles the portfolio share in pass-through business at the very top. Returns to pass-through business rise sharply with business income, but decline for those at the top of the wealth distribution. We also find that 17% of total pass-through business wealth accrues to those with losses in terms of pass-through income.

For C-corporation equity, we develop a method for using both dividends and realized capital gains to estimate C-corporation equity wealth. 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 that upper-tail wealth ratios are best predicted using dividends, and 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. We provide supplemental series to quantify the potential importance of this concern using external estimates of top equity wealth.

For pension wealth, we develop a new approach to capitalize an age-group-specific combination of wages and pension distributions. This approach allows us to incorporate heterogeneity due to life cycle patterns in pension wealth and associated income flows. Although less important for top wealth, pension wealth accounts for 63% of wealth for the bottom 90% and 36% for the P90–99 group.[2]

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 vary by ± 1 percentage point. We also present a broader perturbation analysis that incorporates model uncertainty and alternative aggregate wealth category estimates. Supplemental series quantify the effects of alternative approaches to estimating aggregate private business wealth, defining pension wealth, incorporating Forbes estimates, and accounting for the unrealized capital gains of non-dividend-generating equity.

Prior work explores how allowing for some interest rate heterogeneity affects capitalized wealth shares in recent years. Bricker et al. (2016) (BHKS) show that assigning the top 1% a higher interest rate 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, Bricker, Henriques, and Hansen (2018) (BHH) show that adjusting for top 1% heterogeneity in interest rates narrows most of the gap between the SCF and the

2. Although we do not account for the value of unfunded defined benefit pension wealth or Social Security in our baseline, 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 2019a; Catherine, Miller, and Sarin 2020).

capitalization approach for the top 1% and about one-third of the gap for the top 0.1%.[3] SZ also consider robustness analysis that assigns top groups higher interest rates based on estimates from estate tax data.

Our approach has several advantages relative to other ways of measuring interest rate heterogeneity. First, past work (e.g., SZ, BHKS, BHH) has likely 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 nonqualified 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 return in 2016 in the SCF for the top 0.1% wealth group from 2.3% (std. err. = 0.4%) to 3.9% (std. err. = 1.0%). The same issue affects interest rates measured using estate tax records linked to income tax data. Moreover, in the SCF 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 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 measure return heterogeneity with population data, our estimates are much more precise than those derived from either the SCF (due to sampling error) or the estate tax (due to

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), in Section III.C and Online Appendix R.

5. BHH primarily focus on the top 1% and do not attempt to measure interest rates further up the distribution. We find considerable portfolio heterogeneity that contributes to quantitatively relevant return heterogeneity within the top 1%. Accounting 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%.

volatility from mortality rates and small sample sizes). Last, our risk-exposure approach permits us to generate standard errors for characterizing uncertainty in returns and wealth estimates.

There are several benefits from our new bottom-up, micro-tax-data-based method for valuing private business. It allows for industry and firm-size heterogeneity in mapping flows to stocks, including heterogeneity in financial and human capital components of pass-through business income. Second, we incorporate new data on firm characteristics, which enables more accurate valuations of firms with negative taxable income despite having significant assets, such as in the real estate sector. A meaningful share of total pass-through business wealth accrues to those with negative business income, and these losses are often claimed by the rich. Third, it provides an alternative bottom-up estimate of pass-through business wealth. Independent estimates that are not tied to the Financial Accounts or self-reports help triangulate the true value of a primary source of top wealth and income. Fourth, it provides estimates of rates of return for U.S. pass-through businesses and their owners, which are valuable independently of the main focus of the article. Finally, this method mirrors how practitioners value private business, reduces sampling uncertainty, and sheds light on the nature of private business wealth and returns—key determinants of optimal capital tax policy (Guvenen et al. 2019; Gaillard and Wangner 2021).

II. Data

II.A. Our Data Sources

Aggregate wealth data come from the U.S. Financial Accounts (USFA) 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 come from the IRS Statistics of Income (SOI) stratified random samples for 1965 to 2016. These data provide the core inputs for our wealth estimates. To aid comparison, our baseline series exactly matches the USFA-derived aggregates in Saez and Zucman (2020) (SZ20).[6]

6. In Section VII, we present supplemental series that depart from these aggregates, which may aid future research. For instance, one supplemental series uses a bottom-up estimate of pass-through business wealth, another expands our definition of pension wealth, and a third augments our series with Forbes.

We compare our estimates to other series, including the SCF for 1989–2019, supplemented with the Forbes 400, and the estate tax series from Kopczuk and Saez (2004), updated to 2016. We separately aggregate mortality-rate-adjusted micro 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 USFA categories, providing a useful bridge between the SCF and the aggregate series in the capitalization approach.

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 III 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; Board of Governors of the Federal Reserve System) 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, four-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 in a supplemental series.

Third, for C-corporation equity, we use data from the IRS Sales of Capital Assets files and population-level information returns (Forms 1065-K1 and 1099-B) 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, in a supplemental pension series, we add estimates of unfunded defined benefit pension wealth from Sabelhaus and Volz (2019a) and Sabelhaus and Volz (2019b) to the SCF. Data on aggregate Social Security wealth come 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 indices from CoreLogic, and state-by-year property tax revenues and population from the Census of States.

II.B. 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 in tax units, whereas the SCF unit of observation is the household. Second, the SCF does not include estimates of funded defined-benefit pension wealth, so we supplement SCF data with the Sabelhaus and Volz (2019a) estimates. Third, because there is no flow concept on tax returns that corresponds to nonfinancial 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. We present SCF series with and without Forbes.[7] We define private business using the SCF questions that cover private C- and S-corporations, as well as noncorporate private business (see Online Appendix D for definitions).

7. Online Appendix Figure A.1 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. Saez and Zucman (2019) make some but not all of these adjustments.

II.C. Defining and Updating Macroeconomic Wealth Components

Our Financial Accounts aggregates draw from SZ, updated through 2014 in PSZ, and updated through 2016 by us. In our baseline series, we make a few modifications to align components based on subsequent research. First, as in SZ20, we remove fixed-income mutual funds from the class of aggregates that generate taxable interest. These funds pay nonqualified dividends, not interest. Second, we reassign debt secured by commercial real estate from housing to noncorporate business (Mian, Straub, and Sufi 2020). Third, to separate C-corporation wealth from S-corporation wealth in the Financial Accounts and the division between sole proprietor and partnership wealth, we adopt the updated aggregates for each pass-through component from SZ20. Relative to SZ, PSZ, and our supplemental bottom-up estimates, these updated aggregates increase the share of combined proprietor and partnership wealth allocated to partnerships. Finally, unlike SZ20, we do not assign residual wealth in the Financial Accounts to fixed income, leaving it to be allocated in proportion to total wealth.

Online Appendices C, D, and E provide detailed definitions for each wealth component in the tax data, the SCF, and the DFA, respectively. Online Appendix F provides the sources for aggregate wealth components. Online Appendix G describes the level, composition, and evolution of aggregate wealth and capital income. Online Appendix H gives sources for other data used in this article.

III. Fixed Income

III.A. 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 three reasons. First, taxable interest income is a broad bucket that comprises many different categories of assets delivering fixed income to owners. 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. Especially in the low interest rate environment of the mid-2000s and postrecession period, small differences in returns δ are quantitatively first order in terms of capitalization factors $\left(\frac{1}{r+\delta}\right)$ (Kopczuk 2015; Fagereng et al. 2016).

Second, 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 nonqualified dividends, not interest.[8] 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.

Third, 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 II, 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, non-money-market fixed-income mutual funds, and other fixed-income assets. Among fixed-income assets, high net worth households hold 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 wealth in liquid assets.

III.B. 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 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 classify payments reported on Form 1099-INT into

8. The term “nonqualified” implies that these dividends do not benefit from lower tax rates reserved for most dividend payments on equity claims.

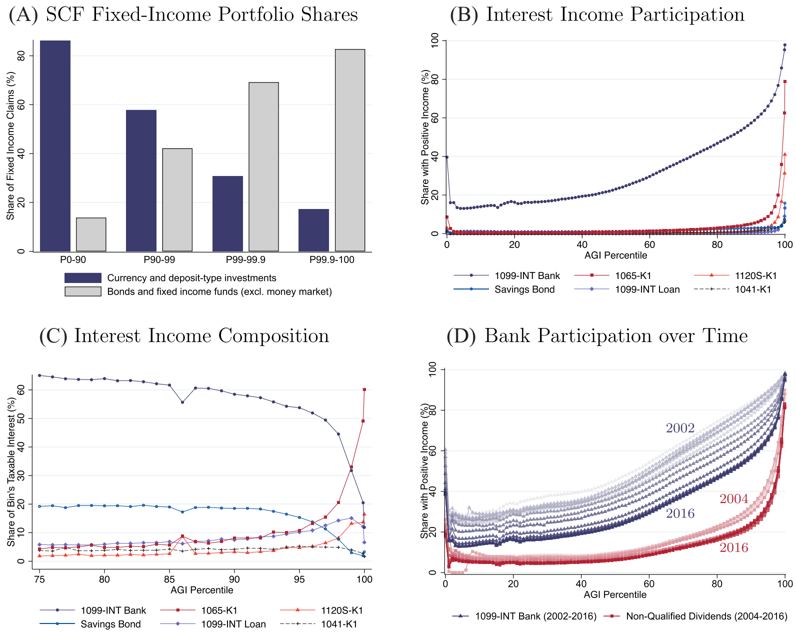

FIGURE II

Fixed-Income Portfolio Heterogeneity across Groups

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%, P99–99.9, 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, P99.9–99.99, 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.

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.

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 nonqualified dividends, which includes payments from money market and fixed-income mutual funds. Online Appendix Figure A.2 plots aggregate flows for each source over time. Interest income flows on information returns account for 80%–90% of aggregate taxable interest.[9] 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%.

Figure II, Panels B–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. Second, in contrast to broad participation in banks, only top taxpayers receive interest income from pass-throughs, 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. This trend coincides with a dramatic increase in taxable interest income concentration (Online Appendix Figure A.3B). 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

9. 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 et al. 2016).

consistent with rising taxable interest concentration.[10] 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. We use these flow data to estimate individual-level returns and capitalized fixed-income wealth.

III.C. *Using Tax Data to Measure Return Heterogeneity*

1. *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 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

10. Unlike for bank deposits, we do not see a sharp decline in participation in nonqualified 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.

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 dividends, capital gains, and interest, but total assets are not reported in sufficient detail to allow us to isolate the bonds. We 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. Online Appendix I discusses the representativeness of these fixed-income funds and the distribution and evolution of these boutique interest rates.

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 noncurrent 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 unable to use tax data to estimate returns. For deposits, we compute group-specific capitalization factors with groups partitioned by noninterest wealth into deciles from P0 to P90, percentiles from P90 to P99, and P99–P99.9 and top 0.1%. We use SCF data to estimate the share of total bank deposits for each group, then use these shares to allocate aggregate USFA deposits to these groups in the tax data. We define group-specific bank interest rates as the group-level ratio of taxable interest from banks on information returns to deposits. These interest rates deliver capitalization factors for estimating bank deposits 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 people typically receive higher interest rates on bank deposits (see Fagereng et al. 2020 for evidence from Norway). Moreover, wealthy people 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. 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.[11]

We estimate returns for savings bonds using SCF data and following a similar approach to our approach for private loans.[12] In the case of fixed-income mutual funds, we assign wealth in proportion to individual-level nonqualified dividends from individual tax returns (Form 1040), thus assuming equal returns within this segment of assets.

Figure III, Panel A 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 noninterest wealth.[13] Business loan rates are 4.5%. Nonqualified dividend rates are 2.2%. Savings bond rates are 5.3%.[14] 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

11. 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 nondeposit assets, as well as the measurement issues at the bottom discussed in note 10.

12. 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 U.S. Treasury. We use these savings bond rates to generate yearly capitalization factors for capitalizing savings bond interest.

13. This convexity is consistent with evidence from Norway, which shows an average premium in returns for safe assets of roughly 1% for top wealth groups relative to the median (Fagereng et al. 2020, figure 2B).

14. 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.

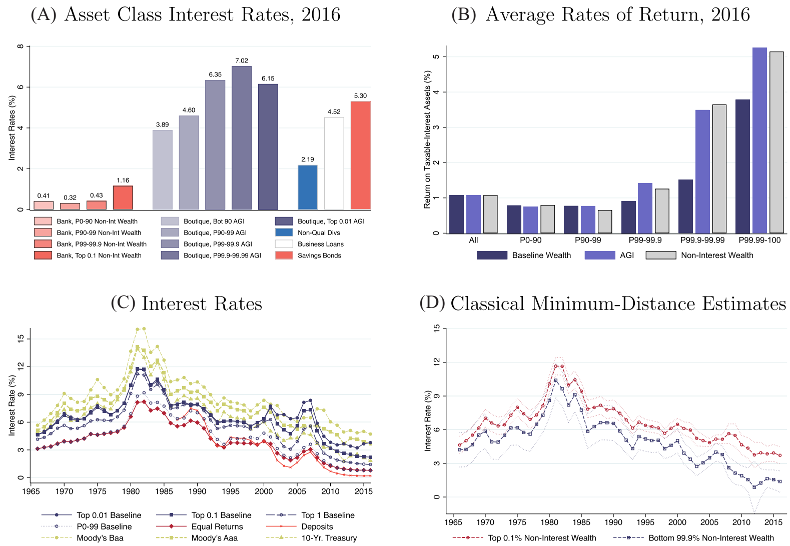

FIGURE III

Fixed-Income Rates of Return Vary across Wealth and Income Groups

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 baseline wealth, AGI, and noninterest wealth. Panel C plots the baseline 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 noninterest wealth. Equal Returns plots $\bar{r}_{fix}$, in which aggregate fixed-income wealth includes taxable-interest-generating assets, nonqualified dividend–generating fixed income and money market assets, and miscellaneous wealth. 10-yr. Treasury, Moody's Aaa, and Moody's Baa refer to 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 noninterest wealth.

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 sources, even during the low interest rate period.

2. *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 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 noninterest wealth distribution receives a capitalization factor of 312 ($= \frac{1}{0.0032}$), whereas \$1 of boutique interest for the top P99.9–99.99 of the AGI distribution receives a capitalization factor of 14 ($= \frac{1}{0.0702}$). This step generates an amount of assets for each source at the individual level.[15]

Second, to match the total amount to the USFA, we scale fixed-income assets in proportion to fixed-income assets from the capitalization of information returns.[16] One reason our bottom-up aggregate fixed-income wealth may not match the USFA 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 USFA household fixed-income aggregate is itself a residual, the USFA includes a broader portion of fixed-income assets than when measured directly via tax returns. In robustness analysis, we present estimates that scale the USFA totals for fixed-income wealth to match the SCF.

Figure III, Panel B 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 0.79% for P0–90 to 0.77% for P90–99 to 0.91% for P99–99.9 to 1.52% for P99.9–99.99 to 3.79% for P99.99–100. Rates of return that rank by AGI or by noninterest wealth display moderately greater heterogeneity in absolute terms though the differences are similar in relative

15. 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 II, Panel B 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.

16. For example, in 2016, aggregate capitalized fixed-income assets equals \$9.28T and aggregate fixed-income assets in the USFA 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 USFA total.

terms. Overall, these data reveal a striking amount of return heterogeneity with the P99.99–100 wealth groups receiving returns that are 3.5 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 III, Panel C shows the time series of rates of return for top and bottom 99% groups ranked by baseline wealth. We compare these rates to the equal-returns rate and to various capital market rates: the deposit rate from Savov, the 10-year U.S. 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. Since 2000, the bottom 99% rate tracks the deposit rate closely, exceeding it by around 0.6 percentage points in the low interest rate period. The equal-returns yield, which fell from 8.2% in 1982 to 0.8% in 2016, equals the bottom 99% rate but is below the top 1% and top 0.1% rates. The top 1% rate tracks the 10-year U.S. Treasury rate although is slightly lower since the Great Recession. The top 0.1% rate hovers between the 10-year U.S. Treasury and the Aaa rate, moving toward the 10-year rate in the last few years of the sample. In our series, the top 0.01% rate is below the riskier Baa corporate bond rate in almost all years and is roughly equal to the Aaa rate in 2016.

3. *Are These Top Return Estimates Realistic?* Our boutique interest rates are considerably higher than deposit or Treasury market rates. Are these reasonable? Online Appendix J presents supporting evidence that the answer is yes.

We provide three types of evidence. First, looking at what these rates imply for aggregate quantities, our approach generates aggregate boutique asset estimates that align with the relevant components in the USFA and the SCF. Second, a word cloud analysis of boutique fund names reveals that many of these funds invest in subordinate securities in private equity and real estate transactions, mezzanine and distressed debt, mortgage servicing rights, foreign bonds, and so on, which carry considerably more credit risk than investments in government securities or bank deposits. Third, data on fixed-income portfolios from family office surveys, conversations with wealth managers and fixed-income fund managers, and public disclosures from high-wealth politicians all point toward substantial exposure to risky credit.

Together, these data confirm that wealthy people 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.

4. *Using Risk Exposure to Estimate Return Heterogeneity.* We complement the information returns series, which is available from 2001 to 2016, with a return series that uses the covariance structure of interest rates, assets, and returns 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 returns approach. Online Appendix K describes the model setup, estimation, and inference. Consistent with the information returns approach, we find that the top wealth group has much stronger exposure to credit risk.

Figure III, Panel D 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%.[17] The confidence interval

17. Online Appendix Figure A.4 shows that 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.

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 USFA aggregate for fixed income assets (see Online Appendix L for details).

Despite the instability of bottom rates in recent years, these estimates remain useful for quantifying return heterogeneity. Figure IV, Panel A presents estimates and standard errors of a key ratio of the top rate relative to the equal-returns rate, $\frac{r_{1t}}{\bar{r}_t}$. In recent years, the ratio's value is around 3.5 for the top 0.1% of the noninterest wealth distribution. Moreover, we can reject the null 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. The ratio for our baseline top 0.01% of the wealth distribution also increases sharply in recent years to a level of 3.5.[18]

Figure IV, Panel B illustrates the capitalization factors, $\beta_t = \frac{1}{r_t}$, 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 reflects a rate of return that includes all fixed-income assets, including non-interest-generating mutual funds, as well as residual wealth in the numerator of the capitalization factor. It results in a capitalization factor of 126 in 2016.[19] 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 Moody's Aaa factor ranged from 11 to 15. Our baseline top 0.01% estimates using information returns (or minimum distance for the top 0.1%

18. 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 III, Panel B, the 2016 return ranked by wealth for the top group is 75% ($= \frac{3.8\%}{5.1\%}$) of the return ranked by noninterest wealth). In other words, using this ratio of 2.1 for the top 0.1% ranked by wealth corresponds to 2.8 ranked by noninterest wealth.

19. The benchmark SZ and PSZ approach is equivalent to the equal-returns series except with money market mutual funds allocated along with C-corporation wealth. This approach results in a capitalization factor of 113. In Section VII, we present a supplemental series which shows that the results following this approach are very close to the equal-returns series.

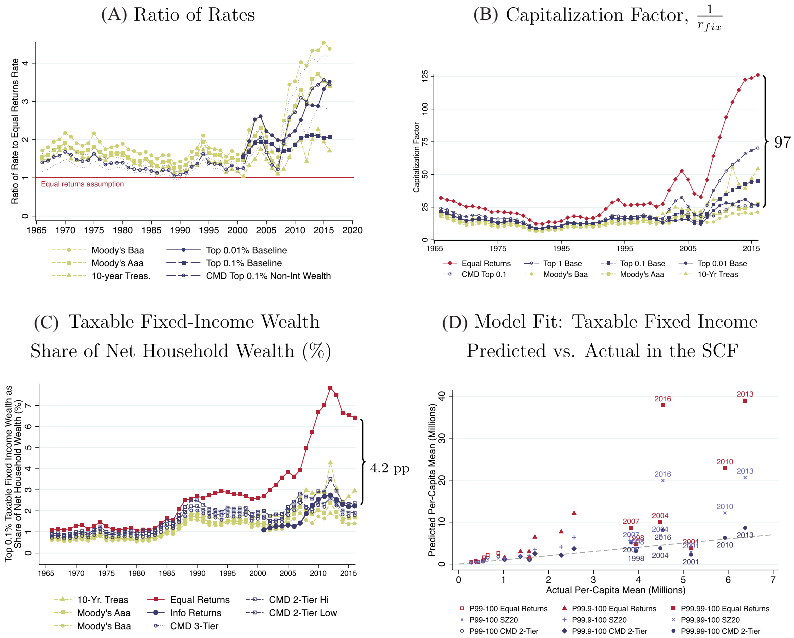

FIGURE IV

Alternative Capitalization Factors for Fixed-Income Wealth

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, $\frac{r_{1t}}{\bar{r}_t}$, which summarizes the degree of heterogeneity. We plot this ratio for different wealth groups ranked by baseline 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, that is, the reciprocal of the interest rates from Figure III, Panel C. We add a series based on the top 0.1% non-interest-wealth CMD estimates from Figure III, Panel D. Panel C shows top 0.1% fixed-income wealth (including funds that generate nonqualified dividends) relative to total household wealth when using different capitalization approaches for the top group under wealth ranks from our baseline definition. 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 noninterest wealth. 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 wealth groups for a given year using equal-returns capitalization factors, the heterogeneous-returns approach in Saez and Zucman (2020), and the two-group CMD approach. We define SCF fixed-income wealth to exclude funds that do not generate taxable interest.

of noninterest wealth), with a value of 26 (and 27) in 2016, fall between that implied by the Treasury series and the Baa. Our baseline top 0.1% factor tracks the Treasury-implied factor over time, and the top 1% factor exceeds it in recent years.

Figure IV, Panel C shows the effect 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 baseline wealth to isolate the role of capitalization assumptions. The equal-returns factor delivers an estimate in 2016 of 6.4% of household wealth. Alternative factors deliver lower estimates, including 2.9% for the 10-year Treasury, 2.2% under our baseline approach, and 1.7% and 1.4% when using the Aaa and Baa rates, respectively.[20] With the equal-returns 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 then surges dramatically starting in 2000 to a peak of 7.8% of total household wealth in 2012. Top estimates using other factors show a much attenuated rise since 2000.

Figure IV, Panel D compares actual taxable-interest-generating fixed-income wealth in the SCF to predicted fixed-income wealth using the equal-returns approach versus the two-tier CMD approach.[21] Predicted fixed-income wealth under equal-returns exceeds SCF wealth with a prediction error that increases sharply with actual fixed-income wealth.[22]

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

20. 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 noninterest wealth. We then allocate the residual for capitalizing non-top-1% interest income. As an alternative robustness analysis, we present a supplemental series in Section VII that haircuts the information returns–based boutique rate by using the smaller of the lower bound (i.e., 5th percentile) of the minimum-distance estimates and the boutique rate.

21. 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.

22. In 2016, the average top 1% household in the SCF has $0.9M of actual fixed income wealth, whereas the equal return 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 equal return estimates are $12.1M and $37.9M, with corresponding prediction errors of 465% and 842%.

rates from other data sources. In robustness analyses, SZ present results that scale down fixed-income assets for those at the top using either the 10-year U.S. Treasury rate or estate tax data.[23] BHKS also consider a top 0.1% capitalization factor chosen to match the 10-year U.S. Treasury rate.[24] BHH use the 10-year U.S. 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.

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, 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.[25] 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.[26]

23. 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 U.S. Treasury bond rate for the top 1% (ranked in terms of adjusted gross income less capital gains).

24. 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.

25. SZ20 also observe that bond mutual funds should be capitalized using nonqualified dividends, not interest, and revise the PSZ capitalization method accordingly. We confirmed this issue when talking to practitioners during the first revision of this article. To estimate interest rates in the SCF, SZ20 remove an estimate of interest generated by boutique-style investments from the numerator. Two limitations of this method are (i) boutique sources are hard to identify in the SCF, and (ii) they account for the bulk of top taxable interest flows in tax data.

26. Online Appendix Figure A.5 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. This uncertainty reflects the

Online Appendix Figure A.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. Removing these assets from the denominator increases the 2016 rate of return for the top 0.1% wealth group from 2.3% (std. err. = 0.4%) to 3.9% (std. err. = 1.0%). The implied ratio of this rate of return to the equal-returns rate from Figure IV, Panel A increases from 2.2 (std. err. = 0.4) to 3.7 (std. err. = 0.9), slightly above that from our information return and minimum-distance estimates. The effects of this refinement increase within the top 1%, which reflects greater exposure to non-interest-generating funds at the very top.[27]

IV. Pass-Through Equity

IV.A. *Challenges in Estimating Pass-Through Equity Wealth*

Estimating pass-through equity wealth, which accounts for the bulk of private business wealth, is challenging for five 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 in the USFA. This difference, which amounts to 60% of national income in recent years,

small underlying sample: in 2016, there are approximately 700 estates with $20M of net worth in the matched-income-estate-tax data, and their collective interest income is $117M, an order of magnitude smaller than the amount of interest income we use for matched fixed-income partnerships. Online Appendix R4 discusses other limitations of using the estate tax data.

27. 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.

likely reflects a combination of factors, including self-reported valuations versus market valuations, liquidity adjustments, and missing data in the USFA.[28]

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 that the value of the underlying businesses are negative or 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—affects estimates 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 et al. 2020). As a result, capitalizing flows in tax data may understate total pass-through business wealth.

IV.B. Estimating Pass-Through Equity Using Firm Characteristics

We estimate pass-through equity wealth using linked firm-owner data to address these challenges. Pass-through wealth includes equity wealth associated with formal pass-throughs (i.e.,

28. Based on conversations with economists who produce the USFA, 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 two-digit sector level, which may understate firm value in the asset-light service sector firms that predominate among S-corporations. Second, noncorporate 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 four-digit industries in our data. Fourth, closely held C-corporations with less than $1–$2B in revenues are not included because of data limitations.

S-corporations and partnerships) and informal pass-throughs (i.e., sole proprietorships). We use an industry-specific approach for formal pass-throughs, but we do not have industry data for sole proprietorships, so we use a simple capitalization approach for this category of wealth. In our baseline series, we scale our estimates to align the components of pass-through wealth to match those in SZ20. In supplemental series, we provide estimates without scaling.

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.[29] For firms with profits below \$50M, modified EBITD equals interest plus depreciation plus 25% of profits, which reflects the non-human-capital contribution of profits estimated in SYZZ. For firms with profits above \$50M, modified EBITD equals interest plus depreciation plus 100% of profits. This hybrid approach reflects the idea that recharacterized wages are less relevant for the largest pass-throughs (Smith et al. 2022).

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:

$$\hat{W}_{it}^{pthru} = 0.9 \times \sum_{j(i)} \frac{1}{3}\Big(\beta_t^{sale,k(j)} \times y_{ijt}^{sale} + \beta_t^{asset,k(j)} \times y_{ijt}^{asset} + \beta_t^{ebitd,k(j)} \times y_{ijt}^{ebitd}\Big), \tag{1}$$

where $j(i)$ indicates that person i owns firm j, $k(j)$ denotes NAICS four-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 NAICS four-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

29. We exclude firms with zero profits. These firms are primarily finance and real estate partnerships that distribute income as dividends, interest, and rents, which we capitalize elsewhere.

data or outlier multiples are assigned the market aggregate multiple for that factor.[30]

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). Online Appendix M details this calculation.

Consider applying equation (1) to a typical top-owned pass-through firm: auto dealers (NAICS 4411) in S-corporation form. In 2016, auto dealers have \$620B, \$179B, and \$8.32B dollars of sales, assets, and modified EBITD, respectively, and the corresponding multiples are 0.3, 0.56, and 6.36. We 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 \$102B in 2016. Note our method accounts for the low profit margins in this industry (i.e., $\frac{\$8.32B}{\$620B} = 1.3\%$) 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.[31]

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 effects 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 person,

30. Equity values equal the price of common stock (PRCC_C) times the number of common shares outstanding (CSHO). We use 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, as it is not appropriate for public C-corporations.

31. 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.

we estimate proprietors' equity by scaling this flow by a common capitalization factor: $\bar{\beta}_t^{sole} = \frac{W_t^{sole+part}}{\sum_i (y_{it}^{sole} + y_{it}^{part})}$, 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 from the USFA, which does not split sole proprietors and partnerships. We then scale estimated propretors' equity to match the aggregate in SZ20. Finally, for a supplemental robustness series, we estimate aggregate missing formal pass-through wealth.[32]

IV.C. Pass-Through Business Wealth Estimates

Figure V, Panel A plots unscaled aggregate pass-through wealth 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 with analogous measures from the USFA 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 the equal-returns approach for S-corporation income.

Our unscaled aggregates fall in between the USFA 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 87% of national income, approximately halfway between the SCF and USFA aggregates. Our fully adjusted series is 20 percentage points lower relative to national income, but still exceeds the USFA total, which we use in the baseline to match the SZ20 aggregates.

Figure V, Panels B and C quantify return heterogeneity across industries and individuals, respectively. To compute returns for a given group, we divide aggregate industry profits

32. This series starts 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 equals \$856B and \$191B, respectively.

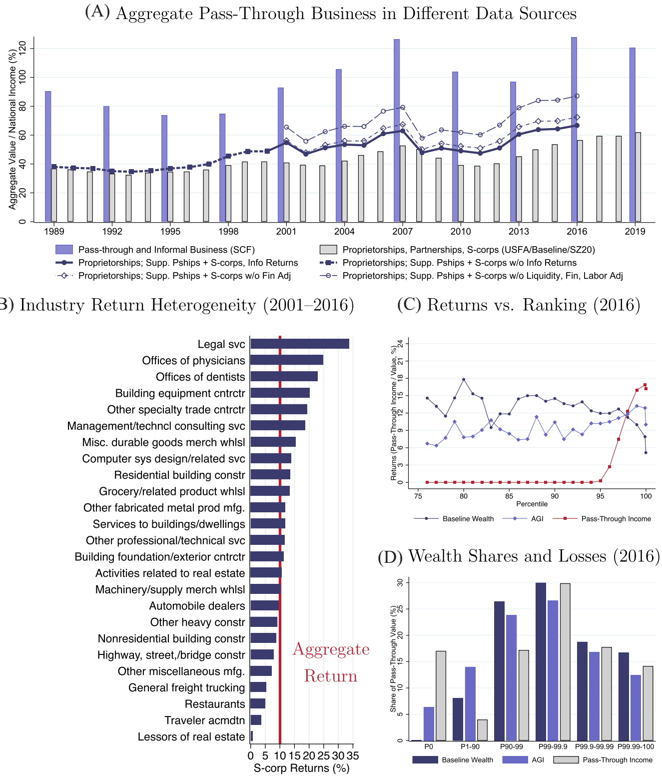

FIGURE V

Aggregate Pass-Through Equity and Unequal Returns across Groups

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 Saez and Zucman (2020) (SZ20) based on the U.S. Financial Accounts, which combines noncorporate 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 bottom-up series—which adjusts for liquidity discounts, labor income characterized as profits, and removes pure financial partnerships—and two unadjusted series. Prior to 2001, our alternative approach follows the capitalization approach with Financial Accounts aggregates, as in Piketty, Saez, and Zucman (2018) and Saez and Zucman (2020), but adds missing pass-through business wealth. Panels B and C quantify return heterogeneity across industries and individuals, respectively. Returns equal aggregate unadjusted 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 baseline 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.

before tax by our estimate of group-specific wealth.[33] Figure V, Panel B plots these returns for the 30 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 nonhuman 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.[34]

Figure V, Panel C 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.[35]

33. 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.

34. To provide more texture on which industries contribute to top pass-through wealth, Online Appendix Table B.1 presents characteristics for the largest 30 four-digit industries. The largest five industries are lessors of real estate (5311, \$530B), other financial investment activity (5239, \$279B), restaurants (7225, \$261B), management of holding companies (5511, \$259B), and other professional and technical services (5419, \$220B). 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.

35. This decreasing pattern contrasts with return heterogeneity when we rank individuals by pass-through income. Moving from lower to higher ranks, returns are sharply increasing in the case of pass-through income. This fact reflects the

Figure V, Panel D 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, 17% of pass-through wealth accrues to those with losses (P0) in terms of pass-through income. Approaches that only capitalize positive business income do not assign substantial business wealth to these individuals. Second, ranking by baseline wealth estimates increases pass-through wealth concentration at the top relative to ranking by business income or AGI. This fact indicates that 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 more than one-third accrues to the top 0.1%.

1. *Comparison to the SCF and SZ.* The SCF uses respondents' self-reported estimated value of the business. However, as we detail in Online Appendix R1, there are a few reasons to believe these values are overstated. First, SCF-implied valuation ratios rival or substantially exceed public company valuations.[36] 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% (Online Appendix Table B.5). Second, these valuations are inconsistent with evidence on liquidity discounts for private targets in large firm acquisitions (Online Appendix M), 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

prevalence of human-capital-rich entrepreneurs in asset-light industries at the top of the income distribution (SYZZ). In addition, Online Appendix Table B.2 presents summary statistics on average returns to private business wealth for the population of pass-through businesses and their owners.

36. For example, Online 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 versus 16.3) and cost basis (8 and 9.5 versus either 3 or 6.5 depending on whether the measure of cost basis in Compustat is book equity or net capital).

values such as housing (Feiveson and Sabelhaus 2019; Gallin et al. 2021). Finally, even taking respondents' values as given, a wide range of total private business values is supported by the data, which reflect the relatively small number of top business owners in the sample and how the concentration of business wealth amplifies sampling uncertainty.

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.[37] Three differences deserve note. First, this approach does not account for 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, including when these firms have significant assets (e.g., real estate). Third, it relies on the USFA aggregates for the value of private business. Our bottom-up approach provides a novel estimate of this aggregate.

V. C-Corporation Equity, Pensions, and Housing Wealth

We summarize our approach to modeling return heterogeneity for C-corporation equity, pensions, and housing, the details for which are presented in Online Appendices N, O, and P, respectively.

For C-corporation equity, we develop a method for using both dividends and realized capital gains to estimate C-corporation equity wealth. 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 capitalized equity wealth model. The results strongly support placing substantially more weight on dividends when capitalizing flows to estimate C-corporation wealth. Moreover, they suggest that the degree of heterogeneity across wealth groups in mapping flows to stocks is relatively unimportant for this asset class. We therefore capitalize a composite flow that applies a weight of 0.9 to dividends and 0.1 to realized capital gains.

37. For proprietors' equity, SZ20 use a similar methodology with a refined approach for splitting aggregate sole proprietors from partnerships. They apply heterogeneous labor and capital shares for partnership income based on the size of the partnership, which is similar to our hybrid labor adjustment approach.

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. We provide supplemental series to quantify the potential importance of this concern using external estimates of top equity wealth. Due to their relative size—Forbes individuals collectively account for 3.1% 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. Online Appendices Q and R3 provide additional discussion of Forbes.

Both pensions and housing are relatively small at the top of the wealth distribution. Given our baseline estimates do not depart from the aggregates in PSZ or SZ20, accounting for heterogeneity therefore affects the distribution of these wealth components across people but matters less for top wealth.

For pension wealth, we capitalize an age-group specific combination of wages and pension distributions. This approach allows us to incorporate heterogeneity due to life cycle patterns in pension wealth and associated income flows. Although less important for top wealth, pension wealth accounts for 63% of wealth for the bottom 90% and 36% for the P90–99 group. Our baseline uses the USFA aggregates excluding unfunded defined benefit plans. We then present two supplemental series: one that adds unfunded defined benefit pension wealth and another that adds Social Security wealth.

For housing wealth, we allow effective property tax rates to vary across U.S. states, yielding heterogeneous capitalization factors for mapping property tax deductions to estimated housing assets. To derive capitalization factors for each state over time, we draw on state- and property-level information on effective property tax rates, property tax assessments, house price indices, property tax revenues, and local demographics. Tax rate heterogeneity matters mostly for the geographic distribution of housing wealth and its 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.

VI. Adding It Up: New Top Wealth Estimates

VI.A. The Level of Top Wealth

Table I shows the number of people 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 under three approaches: (i) our baseline, (ii) equal returns, and (iii) SZ20 (i.e., "Revised SZ").[38] The baseline and equal-returns estimates are reported based on their respective ranks. By construction, all series allocate the same aggregate wealth.

Panel A focuses on top wealth groups. The full population includes 239 million people whose average wealth is \$320K in 2016. The top 1% includes 2.4 million individuals with wealth of at least \$3.5M and average wealth equal to 34 times average wealth in the full population. This group's share of total wealth is 33.7% under our baseline approach, compared with 38.9% under equal returns and 36.3% in SZ20. Similarly, for the top 0.1%, who have wealth exceeding \$17.2M, our estimates reduce the share from 20.4% under equal returns to 15.7%. The SZ20 estimates lie roughly in between these estimates at 18.4%. Thus, the combined effect of accounting for estimated heterogeneity, estimating private business values, and other adjustments has a modest effect on the estimated concentration of top wealth. Although the difference between equal returns and the baseline increases in the very top group, these differences only represent a few percentage points of overall wealth.

Panel B focuses on intermediate wealth groups. The bottom 90%, who collectively hold 31.4% of wealth, are allocated 4.8 percentage points more wealth than under equal returns. The P90–99 class, a group with more than \$617K but less than \$3.5M in baseline wealth, hold 34.9% of total wealth, on par with the bottom 90% and top 1%.

Online Appendix Figure A.7 compares Forbes 400 wealth to our estimates for subgroups at the top.[39] The wealth threshold to

38. October 2020 release, accessed at https://gabriel-zucman.eu/usdina/ in January 2022.

39. We do not incorporate Forbes estimates in our baseline estimates for several reasons. First, Forbes only knows something about the wealth of people who cooperate with it and tell the truth, and some types of wealth like private business are hard to value, especially without official data on firm characteristics like revenues and EBITD. Second, evidence from Raub, Johnson, and Newcomb (2010) and Moretti and Wilson (2020) suggests estate tax collections are substantially

TABLE I

THRESHOLDS AND AVERAGE WEALTH IN TOP WEALTH GROUPS (2016)

			Average wealth			Wealth share (%)		
Wealth group	Count	Baseline Threshold	Baseline	Equal Returns	Revised SZ	Baseline	Equal Returns	Revised SZ
Panel A: Top wealth groups								
Full population	238,657,000		\$320,000	\$320,000	\$320,000	100.0	100.0	100.0
Top 10%	23,866,300	\$617,000	\$2,193,000	\$2,345,000	\$2,346,000	68.6	73.4	73.4
Top 1%	2,386,600	\$3,520,000	\$10,774,000	\$12,434,000	\$11,594,000	33.7	38.9	36.3
Top 0.1%	238,700	\$17,200,000	\$50,263,000	\$65,094,000	\$58,873,000	15.7	20.4	18.4
Top 0.01%	23,800	\$77,800,000	\$227,687,000	\$337,295,000	\$296,765,000	7.1	10.5	9.3
Top 0.001%	2,400	\$362,825,000	\$1,024,956,000	\$1,631,821,000	\$1,309,734,000	3.2	5.1	4.1
Panel B: Intermediate wealth groups								
Bottom 90%	214,790,700		\$112,000	\$95,000	\$95,000	31.4	26.6	26.6
Top 10–1%	21,479,700	\$617,000	\$1,240,000	\$1,224,000	\$1,318,000	34.9	34.4	37.1
Top 1–0.1%	2,147,900	\$3,520,000	\$6,385,000	\$6,586,000	\$6,339,000	18.0	18.5	17.8
Top 0.1–0.01%	214,900	\$17,200,000	\$30,573,000	\$34,876,000	\$32,473,000	8.6	9.8	9.1
Top 0.01–0.001%	21,500	\$77,800,000	\$139,622,000	\$194,299,000	\$184,874,000	3.9	5.5	5.2

Notes. This table provides summary statistics on the distribution of wealth across individuals in 2016. Capitalized average wealth and wealth shares are calculated under our baseline specification and equal returns. We compare these estimates to those in Saez and Zucman (2020). By construction, all three series have the same aggregate wealth component definitions.

be in the top 0.001% in 2016 is $363M for individuals and $548M for tax units. The Forbes 400 have considerable wealth ($2.4T in 2016), but the total wealth of the P99–99.9 and P99.9–99.99 groups exceeds this amount by factors of 5.8 and 2.8, respectively. Our top 0.001% group of 2.4K adults holds $2.5T of wealth, slightly above the Forbes total. If we take Forbes at face value, this figure suggests that our top 0.001% estimate may be too low. However, each member listed in the Forbes 400 usually corresponds to more than one adult, which complicates comparisons with our baseline individual-level estimates. The average Forbes individual in 2019 is 67 years old and has 2.6 children. The many adult children of Forbes individuals may also be represented in Forbes.[40] Adding the 400 Forbes billionaires, their spouses, and their adult children plus spouses amounts to 2,370 people who are possibly represented in Forbes.[41] Thus, the number of adults whose wealth is represented in the Forbes 400 estimate of $2.4T might be close to the number in our top 0.001% group. In Section VII, we present supplemental series that take alternative approaches to incorporating Forbes estimates into our wealth series.[42]

smaller than implied by Forbes wealth estimates for Forbes individuals. Third, the number of wealth holders for each Forbes entry is larger than one, but estimating the number of adults is difficult to do precisely. Comparing probated wealth against Rich List wealth in the United Kingdom, Alvaredo, Atkinson, and Morelli (2018) found that if wealth holders are treated as individuals, that would suggest a Pareto parameter of 4.7 in recent years, which is about twice as high as in their baseline population. We thank Daniel Waldenstrom for this helpful insight.

40. Conversations with journalists who have worked on the Forbes estimates confirm this point. The Camden Family Office Report suggests it is common to move shares of companies to kids from an early age: “Families with private wealth in excess of USD 150 million are ideal candidates for establishing a single family office structure. While it is not uncommon for first-generation entrepreneurs to establish a family office, family offices often support families with more complexity in terms of number of households and generations.”

41. Based on marriage rates by age of those with high incomes (Online Appendix Table B.8), there are around 360 Forbes spouses. Based on Forbes 400 data on age and number of kids as well as dependent-claiming rates by age of those with high income, around 880 of the 1,051 children of Forbes are adults. Many of these adult children are also married. Assuming children are 30 years younger than their parents and applying marriage rates by age gives another 730 adults, amounting to 2,370 Forbes adults overall (Online Appendix Table B.9).

42. Replacing the top 800 capitalized people (which are the top 400 capitalized tax units split equally) with Forbes estimates raises the baseline top 0.01% wealth level from $5.43T to $6.16T. Table III and Online Appendix Figure A.8 show the effects on top wealth shares. Online Appendix R3 provides additional discussion.

TABLE II
PORTFOLIO SHARES IN TOP WEALTH GROUPS (2016)

Wealth group	Portfolio shares (baseline) (%)					
	Fixed income	C-corporation equity	Pass-through business	Housing	Pensions	Other
Panel A: Top wealth groups						
Full population	19.7	14.1	11.9	24.1	34.4	– 4.2
Top 10%	24.1	18.9	14.4	22.0	20.1	0.4
Top 1%	28.2	26.2	19.9	15.5	9.1	1.1
Top 0.1%	26.0	34.0	22.9	9.7	6.1	1.3
Top 0.01%	21.6	43.9	23.3	5.9	3.9	1.4
Top 0.001%	18.9	52.7	21.8	3.4	1.8	1.4
Panel B: Intermediate wealth groups						
Bottom 90%	10.1	3.5	6.5	28.6	65.7	– 14.4
Top 10–1%	20.3	11.9	9.0	28.4	30.8	– 0.2
Top 1–0.1%	30.0	19.4	17.4	20.5	11.7	1.0
Top 0.1–0.01%	29.7	25.8	22.5	12.8	7.8	1.3
Top 0.01–0.001%	23.7	36.8	24.5	8.0	5.6	1.3

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 baseline estimates for top groups and intermediate wealth groups.

VI.B. The Composition of Top Wealth

Table II, Panels A and B show the wealth composition in 2016 for each wealth group in our baseline approach. Pass-through business, C-corporation equity, and fixed income account for 23%, 34%, and 26% 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 53% of top 0.001% wealth, but pass-through business looms large at 22%. In contrast, the wealth composition for the bottom 90% is 66% pensions and 29% in housing. The portfolios of the P90–99 are more balanced, with almost equal shares from fixed income (20%), C-corporation plus pass-through equity (21%), housing (28%), and a larger role for pensions (31%).

Figure VI 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 baseline estimates to the equal-returns approach and the harmonized SCF with Forbes.

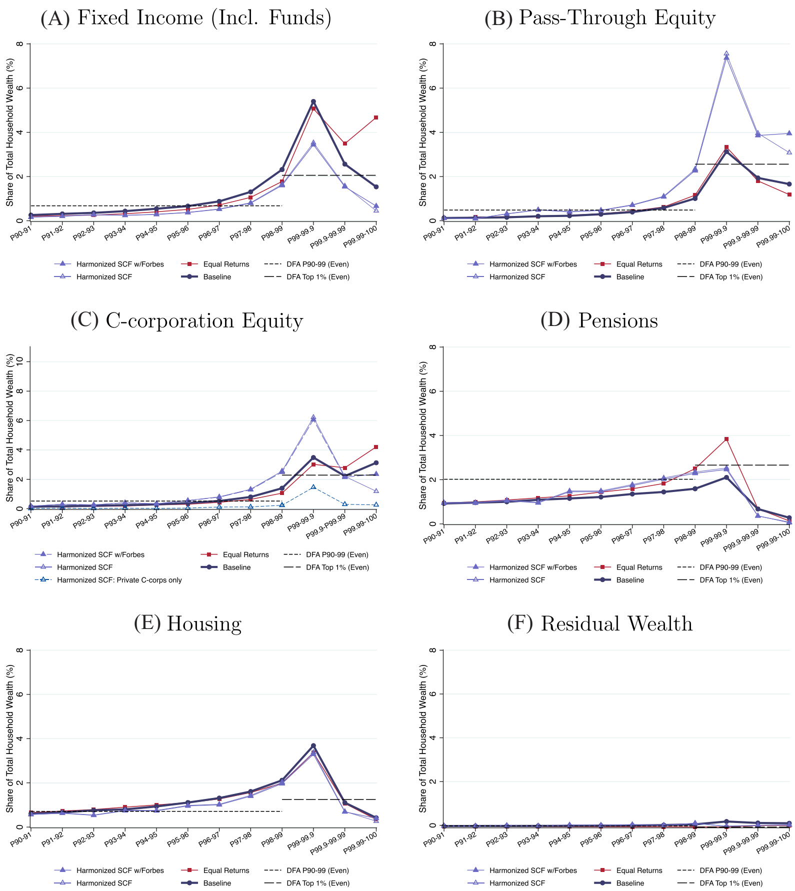

FIGURE VI

Wealth Composition in the United States

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 baseline estimates to the equal-returns approach 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.

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 7.1% of total household wealth in our series, of which 1.5 percentage points, 1.7 percentage points, 3.1 percentage points, and 0.8 percentage points are due to fixed income, pass-through business, public equity, and other categories, respectively. The largest difference between our series and the equal-returns series is fixed income, for which the equal-returns approach estimates that fixed-income assets of the top 0.01% account for 4.7% of total U.S. household wealth. This difference is partially offset by our pass-through business estimate. 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 top 0.01% holds more wealth than the P99–99.9 and P99.9–99.99 groups despite representing one-hundredth and one-tenth 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 with our baseline series, pass-through business in the SCF for the P99–99.9, P99.9–99.99, and top 0.01% groups respectively account for 4.3, 2.0, and 2.2 percentage points of the gap in top 1% shares. 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.

Figure VII compares top portfolio shares in our baseline 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 baseline estimates to the equal return series. 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 DFA portfolio shares.[43]

43. Our series and the SCF series use equal split, individual-level definitions for groups and the estate tax returns cover single decedents, while the unit of

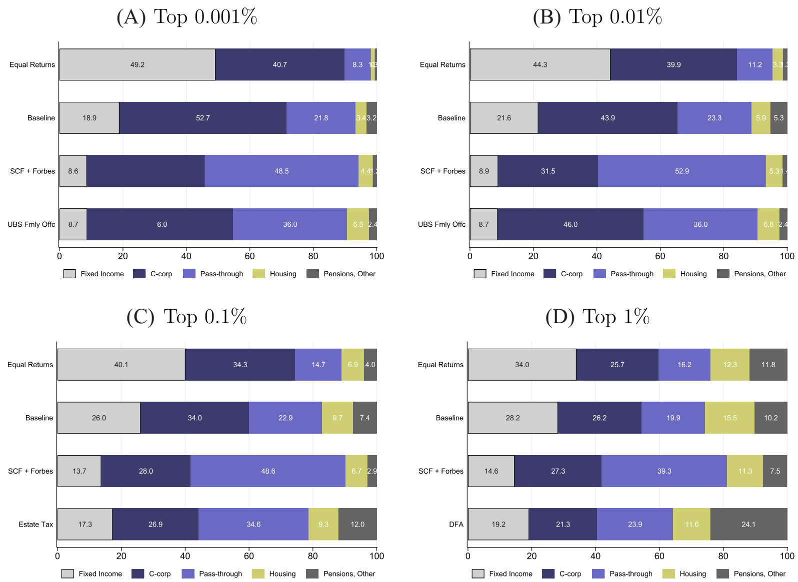

FIGURE VII

Top Wealth Composition in 2016 across Specifications and Data Sets

This figure presents top portfolio shares in 2016 estimated under equal-returns and our baseline assumptions, and as calculated from the harmonized SCF with Forbes, the Distributional Financial Accounts (DFA), estate tax returns, and the UBS Family Office Survey. See Online Appendices C, D, and E for detailed definitions. Estate Tax uses mortality-adjusted estate tax data from the SOI estate tax sample file and only includes 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 Online Appendix Q) as well as portfolio share data for nonbusiness wealth from the SCF for the top 0.01%.

Figure VII, Panel A presents portfolio shares for the top 0.001% across different series. Our baseline fixed-income portfolio share (19%) is 2.6 times smaller than that in the equal return series (49%). This shift is offset by C-corporation equity and pass-through business wealth, which increase from 41% to 53% and from 8% to 22%, respectively. The results are similarly stark for the top 0.01% (Figure VII, Panel B) and top 0.1% (Figure VII, Panel C), with fixed-income shares in our specification falling from 44% to 22% and from 40% to 26%, respectively. For the top

observation is the household for the DFA and the family office for UBS. This distinction affects portfolio shares much less than wealth levels and top shares.

1% (Figure VII, Panel D), differences in portfolio composition go in the same directions but are smaller. However, housing plays a larger role in our series at 16% relative to 12% under equal returns, reflecting the importance of top 1% individuals who live in low property tax states like California. Our baseline shares are closer to the SCF than the equal-returns series, especially for fixed income. Pass-through business wealth is larger in the SCF (approximately half for the top 0.1% and above) versus 20% to 25% 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 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.[44]

VI.C. The Growth of Top Wealth

Figure I plots our baseline estimates from 1966 to 2016 for the top 0.001%, 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 7.1% in 1978, then steadily rises to 15.7% in 2016. From 1978 to 2016, the PSZ top 0.1% series grew from 6.3% to 18.6%, and the SZ20 series grew from 7.1% to 18.4%. Thus, all approaches agree that the top 0.1% share increased by around 10 percentage points, give or take a few points, since the late 1970s nadir. Focusing on the 1989–2016 period, the top 0.1% share grew 4.3 percentage points in the SCF, 7.9 percentage points in PSZ, 6.3 percentage points in SZ20, and 4.6 percentage points in our series.

44. Scandinavian administrative data also show small contributions of fixed income and large roles of equity and especially private business at the top (Bach, Calvet, and Sodini 2020; Fagereng et al. 2020).

For the top 1%, these approaches reflect similar growth. Since 2000, the SCF top 1% share hovers between the PSZ and SZ20 series and our baseline, but shows a sharper increase between 2013 and 2016 that appears to have partly reversed in the 2019 survey. For groups in the top 0.1%, our series are somewhat below PSZ and SZ20 in terms of recent levels but display similar growth, especially compared to SZ20. For all these top groups, our series closely track the harmonized SCF with Forbes in recent years.

Figure VIII plots time series versions of Figure VI for the five major asset classes for the top 0.01%, top 0.1%, and top 1% in our series, the equal-returns series, and the harmonized SCF including Forbes. The figure displays 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.[45]

In the equal returns top 0.1% series, which rises by 4.9 percentage points between 2001 and 2016, fixed-income wealth, C-corporation wealth, pass-through business, and the residual categories account for 4.3, 0.3, 1.0, and −0.7 percentage points, respectively. In our baseline series, which rises by 2.3 percentage points, these components respectively account for 1.0, 0.8, 0.8, and −0.3 percentage points. Thus, the largest difference between these 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%.[46]

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. Whereas the value of pass-through business rises in both capitalized specifications from 1989 to 2016, the SCF trend is

45. 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. Online Appendix Figure A.10 shows top 1% levels for each component in capitalized estimates at the tax unit level compared with the DFA. The takeaways in terms of comparability across data sets are unchanged.

46. Online Appendix Figure A.13 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 pass-through business is more important.

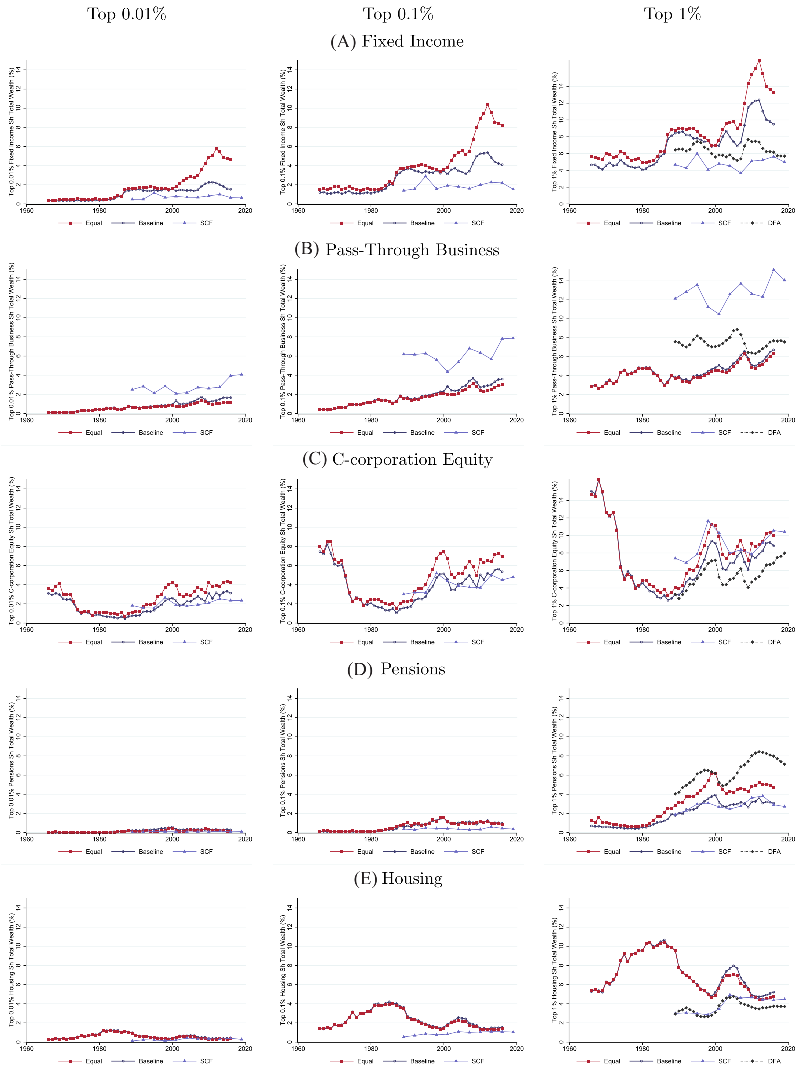

FIGURE VIII

Portfolio Components over Time

This figure plots time-series versions of Figure VI for the five major asset classes for the top 0.01%, top 0.1%, and top 1% in our baseline series, the equal-returns series, the harmonized SCF with Forbes, and the DFA. Online Appendix Figures A.11 and A.12 present analogous figures with portfolio shares and inflation-adjusted component levels, respectively.

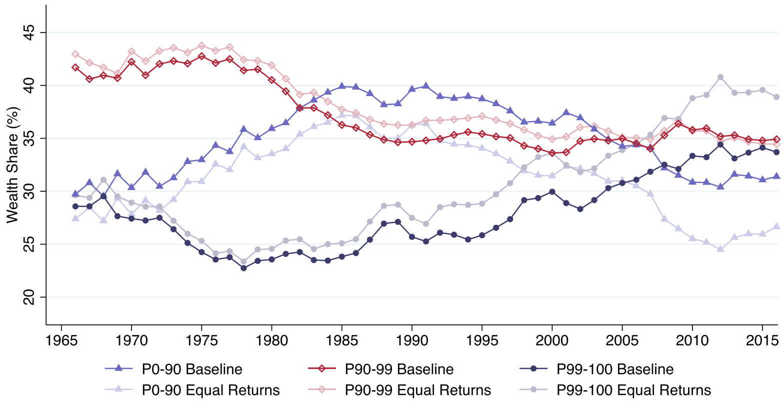

FIGURE IX

Wealth Concentration by Group under Different Approaches

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 baseline approach and the equal-returns approach. Each series defines rankings using that approach's respective wealth estimates. Online Appendix Figure A.14 plots analogous series defined at the tax unit level along with estimates from the DFA.

flatter, fluctuating around 12% of total household wealth for the top 1%. The DFA series, which maps SCF shares onto Financial Accounts aggregates, shows a similar stability around 8% of total household wealth. Housing volatility appears more important for the top 1% than for groups further in the right tail, and as a result, the 1980s housing cycle affects the earlier trend for both capitalized specifications.

Figure IX plots top 1%, P90–99, and P0–90 wealth shares over this time period under both our baseline and the equal return approaches. The difference in growth between these 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 6.4 to 4.8 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. Average wealth of the bottom 90% increased modestly by 8% from 2001 to 2016 (from $104K to $112K in 2016 dollars), whereas average wealth for P90–99 and the top 1% rose by 32% and 50% (from $0.9M to $1.2M and from $7.2M to $10.8M), respectively.

VII. Robustness and Comparison with Other Approaches

VII.A. Characterizing Parameter and Model Uncertainty

We first account 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.[47] We then combine these estimates with the baseline estimates of other asset classes, which do not vary across draws, to define new top wealth groups. We present the 95% band.

Figure X, Panel A plots top share series and compares them to our baseline series and the equal-returns series. For the top 0.01% and top 0.1%, our baseline 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 baseline series is closer to the lower bound of the SCF confidence interval, and the equal-returns series is well above it for most of the 2000s, other than the 2016 estimate.

Figure X, Panel B plots the consequences of changing other modeling assumptions that govern wealth component estimates.

47. We take draws for these parameters from a normal distribution with the respective means and variances using estimates in Online Appendix Tables B.10 and K.2. For each draw b, we form an estimate of r_{1t}^{b} using equation (10) 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_i^{b}, 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. For the SCF, we sample SCF households using the replicate weights and following the procedure in BHKS to generate confidence bands for top shares.

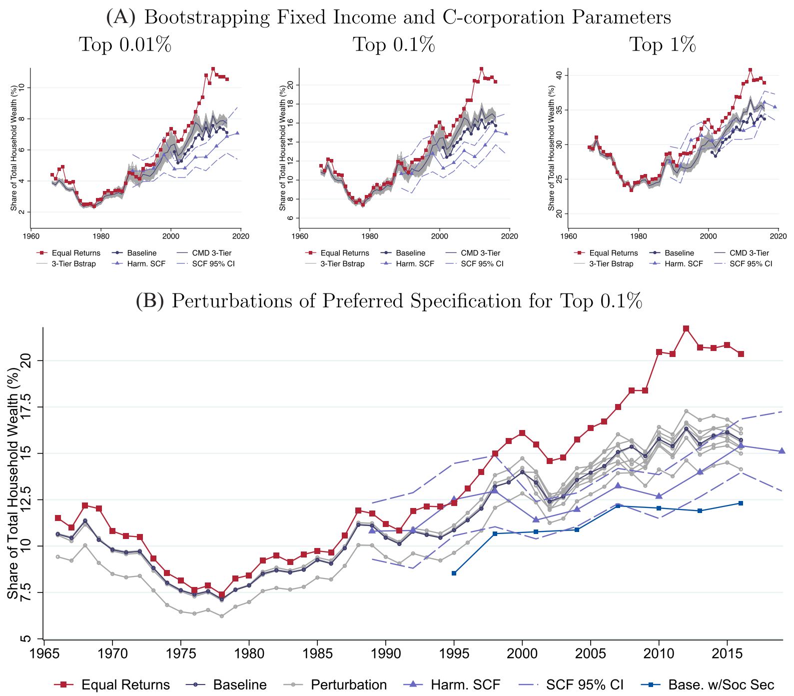

FIGURE X

Top Share of Wealth under Alternative Specifications

Panel A of this figure plots top wealth shares under uncertainty for the top 1%, top 0.1%, and top 0.01%. 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 et al. (2016). We treat the Forbes 400 share of household wealth as a constant and add this amount to the series. The Equal Returns series follow the equal-returns approach for each asset class. Panel B plots series that result from perturbing the baseline specification to include alternatives for each asset class (from Figure IV Panel C and Online Appendix Figures A.9, A.25C, and A.28C), such as using the CMD three-tier approach for fixed income, using a weight of $\alpha = 0.75$ on dividends, different labor and liquidity adjustments for private business, and including unfunded DB pensions. The “Pref w/ Soc Sec” series is the Sabelhaus and Volz (2019b) series from Online Appendix Figure A.28C.

It combines series from Figure IV, Panel C and Online Appendix Figures A.9, A.25C, and A.28C and shows the implications for top 0.1% wealth shares.[48] We fix the ranks to isolate the role of each change. Perturbing our baseline specification results in moderate differences in top 0.1% series that fall within the 95% confidence interval of the SCF in 2016.

VII.B. Reconciling with Other Approaches

Online Appendix R compares our estimates and approaches to those from the SCF, SZ, PSZ, DFA, estate tax data, and Forbes. There are two main sources of difference between our top wealth shares and the harmonized SCF.[49] First, as noted already, 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 USFA aggregates closes all of the gap for our top 1% estimates (Online Appendix Figures A.15 and A.16). 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 USFA relative to the SCF contributes to higher portfolio shares in fixed income in our series (Online Appendix Figures A.17 and A.18). 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.

Table III compares our benchmark series with various alternatives: equal returns, SZ20, PSZ, and several others that use alternative aggregates as well as methods to incorporate Forbes estimates and fixed-income approaches. For each series, we provide top wealth shares in 2016, growth in top shares, top portfolio shares in 2016, and growth in top portfolio shares. We emphasize three points. First, our results are robust to reasonable perturbations in the top boutique rate—using a lower bound adds less than half a percentage point to top wealth shares. Second, different approaches to incorporating Forbes—which add less than a percentage point to top shares—lead to the same

48. These perturbations include using the CMD three-tier approach for fixed income instead of information returns after 2001, using a weight of $\alpha = 0.75$ on dividends, different labor and liquidity adjustments for private business, and including unfunded DB pensions.

49. Differences between capitalized series and the raw SCF have been addressed previously by SZ; BHKS; BHH; SZ20; Henriques and Hsu (2014); Bricker, Hansen, and Volz (2019); and SV. Moreover, concerns about response bias are addressed in BHKS, suggesting this cannot account for differences across methods.

TABLE III

SUMMARY OF SUPPLEMENTAL WEALTH SERIES

	Population		Top wealth share (%)				Per capita wealth ($M)			
	Agg ($T)	Per Cap ($K)	1%	0.1%	0.01%	0.001%	1%	0.1%	0.01%	0.001%
Panel A: Top wealth share and per capita wealth in 2016										
Benchmark series										
1. Baseline	76.3	319.7	33.7	15.7	7.1	3.2	10.8	50.3	227.7	1,025.0
2. Equal returns	76.3	319.7	38.9	20.4	10.5	5.1	12.4	65.1	337.3	1,631.8
3. Revised Saez Zucman (2020)	76.3	319.7	36.3	18.4	9.3	4.1	11.6	58.9	296.8	1,309.7
4. Piketty Saez Zucman (2018)	75.6	316.7	36.6	18.6	9.5	4.6	11.6	59.0	300.6	1,450.9
Alternative aggregates										
5. Spec #1 with unscaled pass-through	76.9	322.1	32.9	15.3	6.9	3.1	10.6	49.2	222.2	1,001.7
6. Spec #5 with missing pass-through	77.9	326.6	32.9	15.3	6.9	3.1	10.7	49.8	225.0	1,014.7
7. Spec #6 with unfunded pensions	84.3	353.3	31.1	14.3	6.4	2.9	11.0	50.5	227.1	1,018.6
8. Spec #7 with debt adjustments	85.9	360.1	30.5	14.0	6.3	2.8	11.0	50.5	227.1	1,018.4
9. Spec #8 with no student debt	87.3	366.0	30.0	13.8	6.2	2.8	11.0	50.5	227.1	1,018.2
Forbes Augmentation										
10. Spec #1 with BHV reweighting	76.6	321.0	34.0	16.2	7.6	3.7	10.9	51.9	244.9	1,196.1
11. Spec #1 with replace top 400	76.9	322.1	34.3	16.5	8.0	4.1	11.1	53.2	258.4	1,341.8
12. Spec #6 with BHV reweighting	78.2	327.9	33.3	15.7	7.4	3.6	10.9	51.5	242.7	1,187.5
13. Spec #8 with BHV reweighting	86.2	361.4	30.8	14.5	6.8	3.3	11.1	52.2	244.7	1,192.6
Robustness series										
14. Spec #2 with bond split	76.3	319.7	39.0	20.5	10.6	5.1	12.5	65.5	339.7	1,635.3
15. Spec #1 with low boutique	76.3	319.7	34.0	16.0	7.3	3.3	10.9	51.3	234.7	1,066.1
16. Spec #8 with low boutique	85.9	360.1	30.8	14.3	6.5	2.9	11.1	51.6	234.3	1,058.8
17. Spec #13 with low boutique	86.2	361.4	31.0	14.7	6.9	3.3	11.2	53.1	250.0	1,216.1

TABLE III
CONTINUED

	Top 0.1% since				Top 0.01% since				Top 0.001% since			
	1966	1978	1989	2001	1966	1978	1989	2001	1966	1978	1989	2001
Panel B: Growth in top wealth shares through 2016 (percentage points)												
Benchmark series												
1. Baseline	5.1	8.6	4.6	2.3	3.3	4.8	2.9	1.2	1.9	2.5	1.7	0.9
2. Equal returns	8.8	13.0	8.6	4.9	6.1	8.2	6.1	3.4	3.5	4.3	3.5	2.1
3. Revised Saez Zucman (2020)	8.4	11.3	6.3	2.9	5.8	6.9	4.1	1.6	2.9	3.4	1.8	0.5
4. Piketty Saez Zucman (2018)	9.3	12.2	7.9	3.9	6.4	7.5	5.4	2.9	3.5	3.9	3.1	1.9
Alternative aggregates												
5. Spec #1 with unscaled pass-through	4.6	8.1	4.3	2.0	3.1	4.6	2.8	1.1	1.8	2.4	1.7	0.8
6. Spec #5 with missing pass-through	4.6	8.1	4.3	2.0	3.1	4.6	2.8	1.1	1.8	2.4	1.6	0.9
7. Spec #6 with unfunded pensions	4.8	8.0	4.0	1.6	3.0	4.4	2.5	0.9	1.7	2.2	1.5	0.7
8. Spec #7 with debt adjustments	4.7	7.8	3.9	1.6	3.0	4.3	2.5	0.9	1.7	2.2	1.5	0.7
9. Spec #8 with no student debt	4.5	7.6	3.7	1.5	2.9	4.3	2.4	0.9	1.6	2.2	1.4	0.7
	1966	1982	1989	2001	1966	1982	1989	2001	1966	1982	1989	2001
Forbes augmentation												
10. Spec #1 with reweighting		7.3	4.7	2.4		4.5	3.1	1.3		2.6	1.9	0.9
11. Spec #1 with replace top 400		7.5	4.9	2.3		4.7	3.3	1.3		2.8	2.1	0.9
12. Spec #6 with reweighting		6.8	4.4	2.1		4.2	2.9	1.2		2.5	1.8	0.9
13. Spec #8 with reweighting		6.5	4.0	1.7		4.0	2.6	1.0		2.3	1.6	0.8
	1966	1978	1989	2001	1966	1978	1989	2001	1966	1978	1989	2001
Robustness series												
14. Spec #2 with bond split	9.0	13.1	8.4	4.0	6.2	8.3	6.0	2.9	3.5	4.3	3.5	1.8
15. Spec #1 with low boutique	5.4	8.9	4.9	2.5	3.5	5.1	3.2	1.4	2.0	2.6	1.9	0.9
16. Spec #8 with low boutique	4.9	8.1	4.2	1.8	3.2	4.5	2.7	1.1	1.8	2.3	1.6	0.8
	1966	1982	1989	2001	1966	1982	1989	2001	1966	1982	1989	2001
17. Spec #13 with low boutique		6.7	4.3	1.9		4.1	2.8	1.1		2.3	1.7	0.8

TABLE III
CONTINUED

	Top 0.1%			Top 0.01%			Top 0.001%		
	Fix	Pthru	C-corp	Fix	Pthru	C-corp	Fix	Pthru	C-corp
Panel C: Top portfolio shares in 2016 (%)									
Benchmark series									
1. Baseline	26.0	22.9	34.0	21.6	23.3	43.9	18.9	21.8	52.7
2. Equal returns	40.1	14.7	34.3	44.3	11.2	39.9	49.2	8.3	40.7
3. Revised Saez Zucman (2020)	28.0			28.4					
4. Piketty Saez Zucman (2018)	44.5	16.5	29.7	51.0	12.9	32.9	56.6	9.7	32.9
Alternative aggregates									
5. Spec #1 with unscaled pass-through	26.8	20.9	34.8	22.0	21.6	44.9	19.4	19.7	54.1
6. Spec #5 with missing pass-through	26.5	21.9	34.3	21.7	22.6	44.3	19.2	20.8	53.4
7. Spec #6 with unfunded pensions	25.9	21.6	33.8	21.4	22.4	44.2	19.0	20.7	53.1
8. Spec #7 with debt adjustments	25.9	21.6	33.8	21.5	22.4	44.2	19.0	20.7	53.1
9. Spec #8 with no student debt	25.9	21.6	33.8	21.5	22.4	44.2	19.0	20.7	53.1
Forbes augmentation									
10. Spec #1 with reweighting	25.0	24.5	33.6	19.5	26.7	42.6	14.9	29.0	49.0
11. Spec #1 with replace top 400	24.0	26.1	33.2	17.6	29.8	41.5	11.6	34.7	46.3
12. Spec #6 with reweighting	25.4	23.7	33.9	19.6	26.3	42.9	15.0	28.4	49.4
13. Spec #8 with reweighting	24.8	23.4	33.4	19.4	26.1	42.7	14.9	28.3	49.2
Robustness series									
14. Spec #2 with bond split	35.7	14.6	38.9	38.9	11.1	45.5	43.0	8.2	47.0
15. Spec #1 with low boutique	27.2	22.6	33.4	24.2	22.7	42.5	22.8	21.0	50.4
16. Spec #8 with low boutique	27.0	21.3	33.3	24.0	21.8	42.8	22.9	20.0	50.8
17. Spec #13 with low boutique	25.8	23.1	32.9	21.3	25.5	41.8	17.3	27.8	47.8

TABLE III

CONTINUED

	Top 0.1%			Top 0.01%			Top 0.001%		
	Fix	Pthru	C-corp	Fix	Pthru	C-corp	Fix	Pthru	C-corp
Panel D: Growth in top portfolio shares 2001–2016 (percentage points)									
Benchmark series									
1. Baseline	2.7	1.8	0.1	−1.7	0.3	4.4	−6.1	1.6	7.4
2. Equal returns	15.2	1.5	−8.9	19.2	0.9	−15.2	25.1	0.9	−22.9
3. Revised Saez Zucman (2020)	1.2			3.3					
4. Piketty Saez Zucman (2018)	18.0	2.9	−6.1	23.0	1.6	−9.1	28.4	0.9	−12.1
Alternative aggregates									
5. Spec #1 with unscaled pass-through	3.3	0.7	0.5	−1.4	−0.9	5.2	−6.2	1.9	7.5
6. Spec #5 with missing pass-through	3.6	−0.4	1.0	−1.0	−1.9	5.7	−5.8	0.8	8.0
7. Spec #6 with unfunded pensions	3.4	−0.4	1.0	−1.0	−1.9	6.0	−5.7	0.8	8.2
8. Spec #7 with debt adjustments	3.4	−0.3	1.0	−1.0	−1.9	6.1	−5.7	0.8	8.2
9. Spec #8 with no student debt	3.4	−0.3	1.0	−1.0	−1.9	6.1	−5.7	0.8	8.2
Forbes augmentation									
10. Spec #1 with reweighting	2.4	2.1	−0.3	−2.1	1.0	3.2	−5.7	2.3	4.6
11. Spec #1 with replace top 400	2.1	2.5	−0.7	−2.6	2.1	2.1	−6.3	4.0	2.4
12. Spec #6 with reweighting	3.2	0.0	0.6	−1.5	−1.1	4.5	−5.6	1.4	5.4
13. Spec #8 with reweighting	3.0	0.1	0.6	−1.4	−1.0	4.8	−5.5	1.5	5.4
Robustness series									
14. Spec #2 with bond split	16.5	2.5	−12.3	20.6	1.9	−18.7	26.8	1.9	−26.2
15. Spec #1 with low boutique	3.3	1.7	−0.2	0.0	−0.1	3.4	−3.3	0.9	5.8
16. Spec #8 with low boutique	3.9	−0.5	0.7	0.7	−2.3	5.1	−3.1	0.3	6.6
17. Spec #13 with low boutique	3.4	−0.1	0.4	−0.1	−1.5	4.1	−3.8	1.1	4.3

TABLE III
CONTINUED

Notes. This table compares our benchmark series with a number of alternatives: equal returns, SZ20 ("Revised Saez Zucman"), and PSZ. We then present supplemental series that use alternative aggregates. "Unscaled Pass-Through" replaces the Financial Accounts aggregates from SZ20 with unscaled aggregates from our bottom-up partnership and S-corporation approach and uses a combined partnership-plus-sole-proprietorship capitalization factor for proprietors' income (following PSZ). "Missing Pass-Through" adds estimates of missing S-corporation and partnership wealth using underreported income estimates from Auten and Splinter (2019). "Unfunded Pensions" adds unfunded defined benefit pension wealth to our pension model following Sabelhaus and Volz (2019a). "Debt Adjustments" removes vehicle debt and scales credit card balances to exclude convenience-use credit. "No Student Debt" removes student debt from the nonmortgage debt total. We also present alternative approaches for incorporating Forbes estimates. "BHV Blending" follows Bricker, Hansen and Volz (2019) by blending Forbes observations into the tax data and adjusting sampling weights to account for overlap. "Replace Top 400" replaces the richest 800 individuals with the Forbes 400 after equally splitting wealth. For non-pass-through wealth components, we then scale non-Forbes aggregates to ensure the total matches the Financial Accounts. We also present a robustness series ("Bond Split") that follows the equal-returns approach of SZ and PSZ by separately allocating money market mutual funds in proportion to dividends and bond mutual funds in proportion to taxable interest. Last, we present robustness series ("Low Boutique") that set the boutique interest rate in our information-returns approach to the minimum of either the estimated boutique rate or the 5%-confidence-level top-0.1% interest rate in our CMD-based approach (equal to 3% in 2016). For each of these series, we provide top wealth shares and levels in 2016 (Panel A), growth in top portfolio shares in 2016 (Panel B), top shares from different base periods through 2016 (Panel C), and growth in top portfolio shares from 2001 to 2016 (Panel D). In Panel B we present growth through 2016 starting in various reference years: the first year of our series (1966), the nadir of top wealth shares (1978), the first year of the SCF (1989), and the first year for our information-returns approach for pass-through and fixed income. Forbes-augmented series begin in 1982, the first year for which we have Forbes data.

conclusions as our baseline. Third, changing the aggregates for pass-throughs and unfunded DB pensions modestly reduces top shares, but does not change the fundamental story that top wealth is concentrated and has been increasing in recent decades.

VIII. Conclusion

This article combines administrative tax data and new methods to provide estimates of wealth concentration and composition in the United States. In our baseline series, the top 0.1% share of wealth has increased since its nadir in the late 1970s from 7.1% to 15.7%. We find the growth in top shares broadly accords with the trends in other leading capitalization series (Piketty, Saez, and Zucman 2018; Saez and Zucman 2020) and the SCF. Overall, although we estimate a large degree of return heterogeneity, accounting for this heterogeneity does not change the fundamental story for top wealth shares and their growth—wealth inequality is high and has risen substantially over recent decades.

Our estimates have implications for inequality, capital tax policy, and savings behavior. We find a large role at the top for pass-through business and C-corporation wealth, low and stable concentration of fixed-income wealth, and equity concentration that rises sharply with wealth—these facts all point to a central role for entrepreneurs and other stockholders. In the case of entrepreneurs, understanding the causes of entrepreneurial wealth accumulation is a natural direction for future research. In the case of stockholders, understanding the role of trends in asset prices, both public and private, is another important question.

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. We find a large role for illiquid wealth categories where valuations are more contentious than for stocks and bonds, which implies higher administrative burdens for proposals to tax wealth or unrealized capital gains.

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. 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 et al. 2019). Indeed, if recent asset price changes reflect a transition from a high interest rate environment to a low one, then extrapolating the trend in wealth concentration to measure the capital tax base may not be justified (Cochrane 2020). Third, if wealth growth depends more on asset price growth, the magnitude of unrealized capital gains and corresponding potential tax revenue from taxing these gains is 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 et al. 2022).

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 et al. 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 inequality can improve our understanding of its drivers. 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 forthcoming; 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.

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Supplementary Material

An Online Appendix for this article can be found at *Quarterly Journal of Economics* online.

Data Availability

Code replicating the tables and figures in this article can be found in Smith, Zidar, and Zwick (2022) in the Harvard Dataverse, https://doi.org/10.7910/DVN/JKFYMJ.

References

Alvaredo, Facundo, Anthony B. Atkinson, and Salvatore Morelli, "Top Wealth Shares in the UK Over More than a Century," *Journal of Public Economics*, 162 (2018), 26–47. https://doi.org/10.1016/j.jpubeco.2018.02.008

Atkeson, Andrew, and Magnus Irie, "Understanding 100 Years of the Evolution of Top Wealth Shares in the U.S.: What Is the Role of Family Firms?" NBER Working Paper no. 27465, 2020. https://doi.org/10.3386/w27465

Atkinson, Anthony Barnes, and Joseph E. Stiglitz, "The Design of Tax Structure: Direct versus Indirect Taxation," *Journal of Public Economics*, 6 (1976), 55–75. https://doi.org/10.1016/0047-2727(76)90041-4

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

Bach, Laurent, Laurent E. Calvet, and Paolo Sodini, "Rich Pickings? Risk, Return, and Skill in Household Wealth," *American Economic Review*, 110 (2020), 2703–2747. https://doi.org/10.1257/aer.20170666

Bhandari, Anmol, and Ellen R. McGrattan, "Sweat Equity in US Private Business," *Quarterly Journal of Economics*, 136 (2021), 727–781. https://doi.org/10.1093/qje/qjaa041

Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Quoted on an Investment Basis [GS5], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GS5.

Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis [DGS10], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10.

Bricker, Jesse, Peter Hansen, and Alice Henriques Volz, "Wealth Concentration in the US after Augmenting the Upper Tail of the Survey of Consumer Finances," *Economics Letters*, 184 (2019), 108659. https://doi.org/10.1016/j.econlet.2019.108659

Bricker, Jesse, Alice Henriques, and Peter Hansen, "How Much Has Wealth Concentration Grown in the United States? A Re-Examination of Data from 2001–2013," Finance and Economics Discussion Series 2018–024, Board of Governors of the Federal Reserve System, 2018. https://doi.org/10.17016/FEDS.2018.024

Bricker, Jesse, Alice Henriques, Jacob Krimmel, and John Sabelhaus, "Measuring Income and Wealth at the Top Using Administrative and Survey Data," *Brookings Papers on Economic Activity*, 2016 (2016), 261–331. http://dx.doi.org/10.17016/FEDS.2015.030

Bricker, Jesse, Kevin B. Moore, and Alice Henriques Volz, "Private Business Wealth and Rates of Return in the US," Society for the Study of Economic Inequality working paper, 2021. http://www.ecineq.org/wp-content/uploads/papers_EcineqLSE/EcineqLSE-218.pdf

Campbell, John Y., Tarun Ramadorai, and Benjamin Ranish, "Do the Rich Get Richer in the Stock Market? Evidence from India," *American Economic Review: Insights*, 1 (2019), 225–240. http://dx.doi.org/10.1257/aeri.20180158

Catherine, Sylvain, Max Miller, and Natasha Sarin, "Social Security and Trends in Inequality," Jacobs Levy Equity Management Center for Quantitative Financial Research Paper, 2020. http://dx.doi.org/10.2139/ssrn.3546668

Cochrane, John, "Wealth and Taxes," *Cato Institute, Tax and Budget Bulletin*, 86 (2020). https://ssrn.com/abstract=3567365
Cooper, Michael, John McClelland, James Pearce, Richard Prisinzano, Joseph Sullivan, Danny Yagan, Owen Zidar, and Eric Zwick, "Business in the United States: Who Owns It, and How Much Tax Do They Pay?," *Tax Policy and the Economy*, 30 (2016), 91–128. https://doi.org/10.1086/685594
Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "The Deposits Channel of Monetary Policy," *Quarterly Journal of Economics*, 132 (2017), 1819–1876. https://doi.org/10.1093/qje/qjx019
Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri, "Heterogeneity in Returns to Wealth and the Measurement of Wealth Inequality," *American Economic Review Papers & Proceedings*, 106 (2016), 651–655. https://doi.org/10.1257/aer.p20161022
———, "Heterogeneity and Persistence in Returns to Wealth," *Econometrica*, 88 (2020), 115–170. https://doi.org/10.3982/ECTA14835
Fagereng, Andreas, Martin Blomhoff Holm, Benjamin Moll, and Gisle Natvik, "Saving Behavior across the Wealth Distribution: The Importance of Capital Gains," NBER Working Paper, 2019. https://doi.org/10.3386/w26588
Feiveson, Laura J., and John Sabelhaus, "Lifecycle Patterns of Saving and Wealth Accumulation," Finance and Economics Discussion Series 2019-010, Board of Governors of the Federal Reserve System, 2019. https://doi.org/10.17016/FEDS.2019.010r1
Gaillard, Alexandre, and Philipp Wangner, "Wealth, Returns, and Taxation: A Tale of Two Dependencies," available at SSRN 3966130, 2021. http://dx.doi.org/10.2139/ssrn.3966130
Gallin, Joshua, Raven Molloy, Eric Nielsen, Paul Smith, and Kamila Sommer, "Measuring Aggregate Housing Wealth: New Insights from Machine Learning," *Journal of Housing Economics*, 51 (2021), 101734. https://doi.org/10.1016/j.jhe.2020.101734
Giffen, Robert, *Statistics* (London: Macmillan, 1913).
Gomez, Matthieu, "Decomposing the Growth of Top Wealth Shares," *Econometrica*, forthcoming.
Guvenen, Fatih, Gueorgui Kambourov, Burhanettin Kuruscu, Sergio Ocampo-Diaz, and Daphne Chen, "Use It or Lose It: Efficiency Gains from Wealth Taxation," NBER Working Paper, 2019. http://dx.doi.org/10.3386/w26284
Guyton, John, Patrick Langetieg, Daniel Reck, Max Risch, and Gabriel Zucman, *Tax Evasion by the Wealthy: Measurement and Implications* (Chicago: University of Chicago Press, 2020).
Henriques, Alice M., and Joanne W. Hsu, "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, Dale W. Jorgenson, J. Steven Landefeld, and Paul Schreyer, eds. (Chicago: University of Chicago Press, 2014), 245–274.
Koeplin, John, Atulya Sarin, and Alan C. Shapiro, "The Private Company Discount," *Journal of Applied Corporate Finance*, 12 (2000), 94–101. https://doi.org/10.1111/j.1745-6622.2000.tb00022.x
Kopczuk, Wojciech, "What Do We Know about the Evolution of Top Wealth Shares in the United States?," *Journal of Economic Perspectives*, 29 (2015), 47–66. http://dx.doi.org/10.1257/jep.29.1.47
Kopczuk, Wojciech, and Emmanuel Saez, "Top Wealth Shares in the United States: 1916–2000: Evidence from Estate Tax Returns," *National Tax Journal*, 57 (2004), 445–488. https://doi.org/10.17310/ntj.2004.2S.05
Mazur, Mark J., and Alan H. Plumley, "Understanding the Tax Gap," *National Tax Journal*, 60 (2007), 569–576. https://doi.org/10.17310/ntj.2007.3.14
Mian, Atif R., Ludwig Straub, and Amir Sufi, "The Saving Glut of the Rich," NBER Working Paper no. 26941, 2020.
Moretti, Enrico, and Daniel J. Wilson, "Taxing Billionaires: Estate Taxes and the Geographical Location of the Ultra-Wealthy," NBER Working Paper, 2020. https://doi.org/10.3386/w26387

Officer, Micah S., “The Price of Corporate Liquidity: Acquisition Discounts for Unlisted Targets,” *Journal of Financial Economics*, 83 (2007), 571–598. https://doi.org/10.1016/j.jfineco.2006.01.004
Piketty, Thomas, *Capital in the 21st Century* (Cambridge, MA: Harvard University Press, 2014).
Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman, Replication data for: “Distributional National Accounts: Methods and Estimates for the United States,” Harvard Dataverse, 2017, https://doi.org/10.7910/DVN/SLXCUJ
Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman, “Distributional National Accounts: Methods and Estimates for the United States,” *Quarterly Journal of Economics*, 133 (2018), 553–609. https://doi.org/10.1093/qje/qjx043
Raub, Brian, Barry Johnson, and Joseph Newcomb, “A Comparison of Wealth Estimates for America’s Wealthiest Decedents Using Tax Data and Data from the Forbes 400,” in *National Tax Association Proceedings, 103rd Annual Conference on Taxation*, 103 (2010), 128–135. http://www.jstor.org/stable/prancotamamnta.103.128
Sabelhaus, John, and Alice Henriques Volz, “Are Disappearing Employer Pensions Contributing to Rising Wealth Inequality?” Technical report, Board of Governors of the Federal Reserve System (US) (2019a). https://doi.org/10.17016/2380-7172.2308
———, Replication Data for: “Are Disappearing Employer Pensions Contributing to Rising Wealth Inequality?” Technical report, Board of Governors of the Federal Reserve System (US) (2019b).
———, “Social Security Wealth, Inequality, and Lifecycle Saving,” in *Measuring Distribution and Mobility of Income and Wealth,* Raj Chetty, John N. Friedman, Janet C. Gornick, Barry Johnson, and Arthur Kennickell, eds. (Chicago: University of Chicago Press, 2020).
Saez, Emmanuel, “The Desirability of Commodity Taxation under Non-Linear Income Taxation and Heterogeneous Tastes,” *Journal of Public Economics*, 83 (2002), 217–230. https://doi.org/10.1016/S0047-2727(00)00159-6
Saez, Emmanuel, and Gabriel Zucman, “Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data,” *Quarterly Journal of Economics*, 131 (2016a), 519–578. https://doi.org/10.1093/qje/qjw004
———, “Replication Data for: Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data,” (2016b). https://gabriel-zucman.eu/uswealth/
———, “Progressive Wealth Taxation,” *Brookings Papers on Economic Activity* (Fall 2019), 437–533.
———, “Trends in US Income and Wealth Inequality: Revising after the Revisionists,” NBER Working Paper no. 27921, 2020. https://doi.org/10.3386/w27921
Sarin, Natasha, Lawrence H. Summers, Owen M. Zidar, and Eric Zwick, “Rethinking How We Score Capital Gains Tax Reform,” *Tax Policy and The Economy*, 36 (2022), 1–33. https://www.journals.uchicago.edu/doi/10.1086/718949
Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick, “Capitalists in the Twenty-First Century,” *Quarterly Journal of Economics*, 134 (2019), 1675–1745. https://doi.org/10.1093/qje/qjz020
———, “The Rise of Pass-Throughs and the Decline of the Labor Share,” *American Economic Review: Insights*, 4 (2022), 323–340. https://doi.org/10.1257/aeri.20210268
Smith, Matthew, Owen Zidar, and Eric Zwick, “Replication Data for: ‘Top Wealth in America: New Estimates under Heterogeneous Returns’,” (2022), Harvard Dataverse, https://doi.org/10.7910/DVN/JKFYMJ.
Stewart, Charles, “Income Capitalization as a Method of Estimating the Distribution of Wealth By Size Groups,” in *Studies in Income and Wealth,* vol. 3 (Cambridge, MA: NBER, 1939), 95–146.
U.S. Bureau of Economic Analysis, National income [A032RC1A027NBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A032RC1A027NBEA.