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

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Abstract

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

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

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

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

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

¹SZ identify three factors that account for differences between their estimates and the SCF—the unit of observation, inclusion of the Forbes 400, and differences in household balance sheet aggregates—but find that adjusting for these factors leaves a residual gap. SZ attribute the residual gap to the possibility of sampling errors and underreporting, but Bricker, Henriques, Krimmel and Sabelhaus (2016) present compelling evidence that suggests the SCF sampling process does a good job of identifying and adjusting for differential response rates at the top of the distribution. As for the estate tax, Saez and Zucman (2019a) find that adjusting for mortality rate differentials can increase the trend in the estate tax series, though there is still uncertainty about this adjustment in the time series and estimates are sensitive to a small number of underlying observations and low mortality rates. Despite this progress in reconciling differences, several issues remain, which we describe and address using new data and methods.
This paper uses administrative tax data to estimate top wealth in the United States. We assemble new data that links people to their sources of capital income and develop new methods to estimate the degree of return heterogeneity within asset classes. We combine this new data on fixed income and pass-through business returns with refined estimates of C-corporation equity, housing, and pension wealth to deliver new capitalized wealth estimates. Our approach—which builds on SZ and Piketty, Saez and Zucman (2018) (PSZ) as well as Bricker, Henriques and Hansen (2018) (BHH)—reduces bias because wealth and rates of return are correlated. We provide new wealth estimates, new evidence on the rates of return, and a systematic analysis of the issues most consequential for capitalization.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

\(^4\) We discuss the relationship between our work and contemporaneous and subsequent work, including SZ, PSZ, BHKS, BHH, and Saez and Zucman (2020b), in Appendix L. The revisions in Saez and Zucman (2020b) result in a similar top 0.1% share compared to the SZ series (Appendix Figure A.1), partly because they account for a smaller degree of return heterogeneity than we find for fixed income (Figure 5A).
return in 2016 in the SCF for the top 0.1% wealth group from 2.3% (s.e.=0.4%) to 3.9% (s.e.=1.0%). The same issue affects interest rates measured using estate tax records linked to income tax data. Moreover, in the SCF data and estate tax data, it is not possible to isolate the boutique funds that we find are key for generating the bulk of interest income for those at the very top in recent years. Consequently, disaggregating and separately capitalizing these flows is not possible in these other data sets. In contrast, our data permit us to characterize and incorporate heterogeneity across fixed income sources and further into the top tail. Second, our ability to isolate these flows allows us to shed light on why different groups earn such different returns. Third, because we are measuring return heterogeneity with population data, our estimates are substantially more precise than those derived from either the SCF due to sampling error or the estate tax due to volatility from mortality rates and small sample sizes. Last, our risk-exposure approach permits us to generate standard errors for characterizing uncertainty in rates of return and capitalized wealth estimates.

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

1 Data

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

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

BHH primarily focus on the top 1% and do not attempt to measure interest rates further up the distribution. We show that there is considerable portfolio heterogeneity that contributes to quantitatively relevant return heterogeneity within the top 1%. Failing to account for this heterogeneity within the top 1% matters for accurate measurement of top wealth and we find that much of the difference is in the top 0.1% and top 0.01%.
We use numerous data sources to estimate wealth and validate our estimates for each asset class. First, for fixed income, we assemble novel source-owner linked data for the population of interest income recipients. These sources include large financial institutions, pass-throughs (partnerships and S-corporations), trusts, private loans to businesses, and savings bonds. We draw from a range of firm-level data, including balance sheet information on assets and income statement information on interest payments, to determine interest rates paid for each source. Section 3 describes these data in detail.

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

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

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

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

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

**Harmonized SCF.** We make several adjustments to the SCF to ensure comparability. First, our approach defines the relevant observation at the individual level based on equal splits within tax units, whereas the SCF unit of observation is the household. Second, the
SCF does not include estimates of defined benefit pension wealth, so we supplement SCF data with the Sabelhaus and Volz (2019) estimates. Third, as there is no flow concept on tax returns that corresponds to non-financial wealth, such as vehicles, jewelry, or art, our approach does not attempt to allocate these assets. Fourth, the SCF excludes the Forbes 400 from the sampling frame for privacy reasons.

Appendix Figure A.2 shows the importance of applying each adjustment and how the final series compares to our preferred approach for both the top 1% and top 0.1%. The most quantitatively important adjustments for the SCF shares are changes to the unit of observation, the inclusion of defined benefit pension wealth, and inclusion of the Forbes 400.6

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

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

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

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6Specifically, going from household-level to an individual-level wealth concept materially reduces the top 1% and top 0.1% shares, as does adding defined benefit pension wealth because most of this wealth accrues to the bottom 99%. Adding the Forbes 400 and ranking the SCF using effective tax unit ranks (which increases the number of SCF households in the top groups) increases top shares. Saez and Zucman (2019a) make some but not all of these adjustments to the SCF.
Higher S-corporation aggregates reduce C-corporation aggregates. Retaining comprehensive pension estimates increases total wealth and mostly affects pensioners outside the top. We show the effect of these updates in the perturbation analysis and when presenting results for specific asset classes.

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

2 Aggregate Wealth and Capital Income Components

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

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

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

7We also depart from SZ and follow PSZ in focusing on individual-level estimates rather than tax unit-level estimates, which helps account for evolving household structure over time and across the income distribution.
8We include unfunded DB pensions for consistency with and similar reasons as BHKS, BHH, and DFA.
Pension growth largely reflects the transition from defined benefit to defined contribution plans and the growth of defined contribution plans after policy reforms in the early 1980s. Both aggregate housing and equity components mirror the rise and fall of asset prices associated with the stock market boom in the late 1990s and the housing boom and bust in the mid-2000s. Fixed income wealth has grown the least, though it has increased since its low point at 44% of national income in 2000 to a level last seen in the early 1990s.

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

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

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

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

3.1 Challenges in Capitalizing Interest Income

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

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

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

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

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

11 The term “non-qualified” implies that these dividends do not benefit from lower tax rates reserved for most dividend payments on equity claims.
3.2 New Data on Fixed Income Components

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

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

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

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

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

Second, in contrast to broad participation in banks, only top taxpayers receive interest income. This gap likely results from three forces. First, for small dollar payments, banks are not required to issue information returns but individuals may still report that income. Second, loans between individuals or issued by foreign entities do not trigger an information reporting requirement (see IRS Regulations Section 1.6049-5). Third, there may be some “line switching” in which income with similar tax treatment (such as real estate income) is reported in the interest box on the individual’s Form 1040. This issue does not affect pass-through bottom-up estimates since the information returns are complete Cooper, McClelland, Pearce, Prisinzano, Sullivan, Yagan, Zidar and Zwick (2016).
income from partnerships, S-corporations, private loans, and trusts. Participation rates in these boutique sources rise sharply within the top decile, reaching 80% for the top 0.01%.

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

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

3.3 Using Tax Data to Measure Return Heterogeneity

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

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

\(^{13}\)Unlike for bank deposits, we do not see a sharp decline in participation in non-qualified-dividend-paying assets. In addition, as highlighted by BHKS, banks are not required to issue information returns when the income falls below $10. The decline in deposit rates since 2000 likely increased the share of accounts subject to this measurement issue; consistent with this idea, we find the number of information returns issued by banks falls from 238 million in 2001 to 126 million in 2016. In contrast to this participation trend, the share of respondents in the SCF reporting bank deposits remained stable over this time period.
partnership’s Form 1065 business tax return.

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

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

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

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

14One potential concern with this approach is that total assets reported by these partnerships may be mismeasured, perhaps because they do not affect the firms’ tax bill or because these firms have non-fixed-income assets that do not generate income. Such classical measurement error is less consequential for boutique assets because the means are well above zero.
Bank interest flows represent a combination of true deposits and these other sources, the relative importance of which varies along the wealth distribution. Ultimately, our approach allows us to estimate heterogeneous returns within fixed income assets at banks.\footnote{In our preferred estimates, bank deposit shares are somewhat more concentrated relative to the SCF shares. For example, the SCF top-1% deposit share is 24%, whereas our top-1% deposit share is 43%. This fact suggests our approach may be conservative relative to the true underlying heterogeneity in bank returns. It also reflects the fact that bank interest flows represent both deposit and non-deposit assets, as well as the measurement issues at the bottom discussed in footnote 13.}

We estimate returns for savings bonds using SCF data and following a similar approach to our approach for private loans.\footnote{Specifically, we restrict the SCF sample to individuals for whom savings bonds make up more than 95% of their taxable-interest-generating assets. We estimate returns for this sample using the ratio of aggregate SCF interest to SCF taxable-interest-generating assets and SCF sampling weights. To interpolate rates for years between SCF sampling years, we use coefficients from a regression of the SCF savings bond rate on the 10-year US Treasury. We use these savings bond rates to generate yearly capitalization factors for capitalizing savings bond interest.} In the case of fixed income mutual funds, we assign wealth in proportion to individual-level non-qualified dividends from individual tax returns (Form 1040), thus assuming equal returns within this segment of assets.

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

**Individual-Level Rates of Return.** The combination of interest rate heterogeneity across sources and greater exposure at the top to higher yielding fixed income assets results in substantial heterogeneity in rates of return across wealth groups. To quantify the
degree of return heterogeneity across groups, we take the following steps. First, we use these different rates to capitalize the interest flows received from each source and by AGI group. For example, $1 of bank interest for the bottom 90% of the non-interest wealth distribution receives a capitalization factor of $312 (=1/0.0032), whereas $1 of boutique interest for the top P99.9-99.99 of the AGI distribution receives a capitalization factor of $14 (=1/0.0702). This step generates an amount of assets for each source at the individual level.\(^{18}\)

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

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

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

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

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

\(^{20}\)Unlike for pass-through business, we adhere to the Financial Accounts totals because the valuations in the Financial Accounts for marketable securities are more certain.
US Treasury rate, and the Moody’s Aaa and Baa corporate bond rates. All interest rates reached a peak in the 1980s during the Volcker tightening and have been falling since then. In the years since 2000, the bottom-99% rate tracks the deposit rate closely, exceeding it by approximately 0.8% in the low-interest-rate period. The equal-returns yield, which fell from 9.5% in 1982 to 1.1% in 2016, exceeds the bottom-99% but is below the top-1% and top 0.1% rates. The top-1% rate tracks the 10-year US Treasury rate although is slightly lower since the Great Recession. The top-0.1% rate hovers between the 10-year US Treasury and the Aaa rate, moving toward the 10-year rate in the last few years of the sample. In our series, top-0.01% rate is below the riskier Baa corporate bond rate in almost all years and is slightly below the Aaa rate in 2016.

Are These Top Return Estimates Realistic? Our boutique interest rates are considerably higher than deposit or Treasury market rates. Are these reasonable? One way to approach this question is by looking at what these rates imply for aggregate quantities. The top 0.1% boutique rates in Figure 4A of 6–7% in 2016 correspond to $16B in taxable interest flows from boutique sources, which implies aggregate boutique assets for this group of $230–270B, equal to approximately 2% of top-0.1% wealth. This category of assets is not separately identified in the SCF; according to experts at the Federal Reserve Board, it is most likely to appear in the category of “Other Managed Assets.” For the top 0.1% in the SCF in 2016, this category amounts to $620B, which includes both fixed income and non-fixed income holdings. Alternately, one can look at aggregate holdings of debt securities by the hedge fund sector in Financial Accounts Table B.101.f, which includes holdings by both individuals and non-individual investors such as pensions and endowments. In 2016, these holdings equal $670B in 2016. Thus, our approach appears to generate reasonable aggregates compared to external sources.\footnote{In contrast, capitalizing these boutique interest flows using the equal-returns rate delivers aggregates of $1.5–2T, which appears much too large relative to these external sources. This total even exceeds aggregate non-bond liabilities of the non-financial corporate sector ($1.1T in 2016), which provides a benchmark for the amount of non-traditional fixed income assets that may be held in boutique partnerships.}

As another way to assess the plausibility of these rates, Appendix Table B.1 presents additional evidence that boutique funds invest in riskier assets.\footnote{We group all 18,758 fixed income partnerships identified in 2016 and then assign each fund to one of many groups based on common words used in the fund’s name. To preserve taxpayer confidentiality, the table only contains words that would not identify particular entities and restricts to those words that appear in more than 50 fund names. Categories with the highest asset-weighted interest rates use terms like MEZZANINE (6.62%), OFFSHORE (6.00%), DEBT (6.27%), HOLDCO (5.19%), CREDIT (4.99%), etc.} Many of these funds appear to invest in subordinate securities in private equity and real estate transactions, mezzanine and distressed debt, mortgage servicing rights, foreign bonds, etc., which carry considerably more credit risk than investments in government securities or bank deposits.
Appendix Table B.2 compares the interest rate distributions for boutique funds and private loans to that for different groups of corporate bonds. We collect corporate bond data from the Thomson Reuters eMaxx database merged to the WRDS Bond Returns database and report the distributions of yield-to-maturity at market values for bonds sorted into Moody’s credit rating groups. The partnership and private loan interest rate distributions are quite similar to each other and overlap with corporate bond distributions for bonds with mid-tier and lower credit ratings. The most speculative corporate bonds appear to have higher yields on average than the loans and boutique funds. Overall, the table suggests our estimates from the tax data are indeed reasonable if we think of these partnerships as holding fixed income assets with substantial underlying credit risk.

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

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

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

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

24 To be clear, no IRS data were used to collect this information. Data were downloaded from OpenSecrets. org. Similar data are available at https://www.taxnotes.com/presidential-tax-returns.
tax returns and other financial information during presidential runs are Carly Fiorina, Tom Steyer, and Mitt Romney. On her 2013 tax return, Fiorina reported $446,458 in taxable interest. Steyer reported $11,963,299 in 2016. Romney reported $3,012,775 in 2011.

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

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

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

3.4 Using Risk Exposure to Estimate Return Heterogeneity

We complement the information-returns based series, which is available from 2001-2016, with a return series that uses the covariance structure of interest rates, assets, and returns...
to estimate risk exposure to credit and interest rate risk for different groups. We use this risk-exposure approach to estimate returns in the years when the information returns are not available and as a validation of the information-return approach.

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

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

\[
\begin{align*}
\ln y_{1t} &= \ln r_{1t} + \ln a_{1t} \\
\ln y_{2t} &= \ln r_{2t} + \ln a_{2t} \\
\ln a_{t}^{\text{total}} &= s_1^a \ln a_{1t} + (1 - s_1^a) \ln a_{2t} \\
\ln r_{1t}^I &= \pi_1^I \ln r_{1t} + \pi_2^I \ln r_{2t} \\
\ln r_{Ct} &= \pi_1^C \ln r_{1t} + \pi_2^C \ln r_{2t}.
\end{align*}
\]

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

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

The model implies restrictions on elements of mean \( \mu \) and covariance matrix \( \Sigma \), where

\(^{26}\)Using other group definitions requires updating the flows that each group collectively receives (i.e., \( y_{1t}, y_{2t} \)). To construct our three-tier estimate, we implement this procedure with 1 representing the top 0.1% of the non-fixed-income-wealth distribution, then run the same steps a second time with group 1 representing the top 1% of the non-fixed-income-wealth distribution, and then use the formulas in Appendix H.3 to construct estimates for the top 0.1%, P99-99.9, and bottom 99% from these results (see Appendix H.2 for step-by-step details).
\(\mu\) is the 5 \times 1 vector of means of the five-equation system:

\[
\mu = \begin{bmatrix}
\mu_{r1} + \mu_{a1} \\
\mu_{r2} + \mu_{a2} \\
\pi_1^c \mu_{r1} + \pi_2^c \mu_{r2} \\
\pi_1^I \mu_{r1} + \pi_2^I \mu_{r2} \\
s_1^a \mu_{a1} + (1 - s_1^a) \mu_{a2}
\end{bmatrix}, \tag{6}
\]

where \(\mu_x\) denotes the mean of \(\ln x_t\). For example, the mean of equation (1), which describes the average log fixed income of group 1 (\(\ln y_{1t}\)), is equal to that group’s average log rate of return plus the average log assets (i.e., \(\mu_{r1} + \mu_{a1}\)). The covariance matrix is:

\[
\Sigma = \begin{bmatrix}
\text{Var}(\ln y_{1t}) & \cdots & \cdots & \cdots & \cdots \\
\text{Cov}(\ln y_{2t}, \ln y_{1t}) & \text{Var}(\ln y_{2t}) & \cdots & \cdots & \cdots \\
\text{Cov}(\ln a_{t1}, \ln y_{1t}) & \text{Cov}(\ln a_{t1}, \ln y_{2t}) & \text{Var}(\ln a_{t1}) & \cdots & \cdots \\
\text{Cov}(\ln r_{1t}^C, \ln y_{1t}) & \text{Cov}(\ln r_{1t}^C, \ln y_{2t}) & \text{Cov}(\ln r_{1t}^C, \ln a_{t1}) & \text{Var}(\ln r_{1t}^C) & \cdots \\
\end{bmatrix}.
\tag{7}
\]

We use the elements from \(\mu\) and \(\Sigma\) to define a 20 \times 1 moment vector \(m(\theta)\) and a 19 \times 1 parameter vector \(\theta\):

\[
m(\theta) = \begin{bmatrix}
\mu, \Sigma_{11}, \Sigma_{21}, \Sigma_{31}, \Sigma_{41}, \Sigma_{51}, \Sigma_{12}, \Sigma_{22}, \Sigma_{32}, \Sigma_{42}, \Sigma_{52}, \Sigma_{13}, \Sigma_{23}, \Sigma_{33}, \Sigma_{43}, \Sigma_{53}, \Sigma_{14}, \Sigma_{24}, \Sigma_{34}, \Sigma_{44}, \Sigma_{54}, \Sigma_{55}
\end{bmatrix}^	op, \tag{8}
\]

\[
\theta = \begin{bmatrix}
\mu_{r1}, \mu_{r2}, \mu_{a1}, \mu_{a2}, \sigma_{r1}^2, \sigma_{r2}^2, \sigma_{a1}^2, \sigma_{a2}^2, c_{r1}, c_{r2}, c_{a1}, c_{a2}, c_{r1,a2}, c_{r2,a1}, c_{r2,a2}, s_1^a, \pi_1^c, \pi_1^I, \pi_2^c, \pi_2^I, s_1^a
\end{bmatrix}^	op.
\tag{9}
\]

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

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

\footnote{For example, \(\Sigma_{42} = \text{Cov}(\ln r_{1t}^C, \ln y_{2t}) = \pi_1^c c_{r1}, r_{2t} + \pi_1^I c_{r1}, a_{2t} + \pi_2^c \sigma_{r2}^2 + \pi_2^I c_{r2}, a_{2t}\), where \(c_{r1}, r_{2t}\) is the covariance of returns for group 1 and 2, \(c_{r1}, a_{2t}\) is the covariance of returns for group 1 and assets for group 2, \(\sigma_{r2}^2\) is the variance of returns \(\ln r_{2t}\), and \(c_{r2}, a_{2t}\) is the covariance of returns and assets for group 2. Solving for \(\pi_2^c = \frac{\Sigma_{42} - \pi_1^c c_{r1}, r_{2t} + \pi_1^I c_{r1}, a_{2t}}{\sigma_{r2}^2} + \pi_2^I c_{r2}, a_{2t}\) helps provide some intuition for how this parameter can be identified. A bigger covariance between group 2’s income and aggregate interest rate risk (i.e., \(\Sigma_{42}\)) indicates that \(\pi_2^c\) is larger. Appendix H.1 provides all of the explicit expressions of covariance moments in terms of parameters and additional discussion of how parameters can be identified.}
and model moments:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} [\hat{m} - m(\theta)]'[\hat{m} - m(\theta)],$$

(8)

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

We focus on estimating the risk exposure parameters of each group (i.e., \(\pi_{1}^{I}, \pi_{2}^{I}, \pi_{1}^{C}, \pi_{2}^{C}\)) and calibrate the other parameters to their corresponding SCF values. Appendix Table H.1 lists the calibrated parameter values. Although we use the SCF to calibrate some of these parameters, this approach only uses tax data to measure income flows over time, so the resulting estimates directly reflect patterns in the tax data.\(^{29}\)

Under regularity conditions, the vector of estimated moments will have a standard normal distribution with \(\sqrt{T}(\hat{m} - m) \rightarrow N(0, V)\). Applying Hansen (1982), we have \(\sqrt{T}(\hat{\theta} - \theta) \rightarrow N(0, \Delta)\) where \(\Delta = (G'G)^{-1}G'VG(G'G)^{-1}\) and \(G = \frac{\partial m(\theta)}{\partial \theta}\). We estimate \(\hat{V}\) via block bootstrap.\(^{30}\)

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

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

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

\(^{29}\)Specifically, the SCF calibrated values only affect step 3 in the estimation steps enumerated in Appendix H.2. The empirical moments in step 2 do not depend on the SCF.

\(^{30}\)In particular, we sample with replacement \((y_{1t}, y_{2t}, a_{t}^{\text{total}}, r_{t}^{I}, r_{t}^{C})\) with overlapping blocks of length 3 (based on the rule of thumb \(T^{3} = (2016 - 1989)^{3} \approx 3, \) where \(T\) is the number of years in the sample).
ables and parameters:

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

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

We can exponentiate these expressions and plug in estimates of \(\hat{\theta}\) to obtain the estimates of \(r_{1t}\) and \(r_{2t}\). We find the top wealth group has much stronger exposure to credit risk.\(^{31}\)

This finding is consistent with the information-return-based result that those at the top have higher exposure to boutique investment funds and lower exposure to bank deposits and savings bonds in their fixed income portfolios.

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

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

Despite the instability of bottom rates in recent years, we can still use these estimates to quantify the extent of return heterogeneity. Figure 5A presents the point estimates and standard errors of a key ratio of the top rate relative to the equal-returns rate, \(\frac{\bar{r}_t}{\bar{r}_t}\). This ratio summarizes the degree of heterogeneity, which is a key aspect of the debate about capitalizing top interest rates (e.g., Saez and Zucman (2020a) Figure 7). In recent years, the ratio’s value is around 3.5 for the top 0.1% of the non-interest wealth distribution. Moreover, we can reject the null hypothesis that the top group earned the equal-returns rate. The confidence interval for this key ratio of top-to-average returns ranges from 2.8 to 4.3 in 2016. Therefore, prior approaches that assign the top group the average rate of return will overstate top returns by 180% to 330% in 2016, thereby substantially overstating top fixed income assets. Our

\(^{31}\) Appendix Table H.2 reports the parameter estimates of the \(\pi\) terms as well as the coefficients in equation (9) and (10). For example, \(\frac{\pi_2^C}{\pi_1^C - \pi_2^C} = 0.05\) (s.e. = 0.14). The resulting expressions are \(\ln \hat{r}_{1t} = 0.05 \ln r_t^I + 0.84 \ln r_t^C\) and \(\ln \hat{r}_{2t} = 0.82 \ln r_t^I + 0.06 \ln r_t^C\).

\(^{32}\) Appendix Figure A.8 shows the average rates of return in 2016 when applying our preferred classical minimum distance (CMD) approach closely match those under our preferred information-returns approach.
estimates also reject the Saez and Zucman (2020b) approach, which assumes the top group’s return exceeds the equal-returns rate by a factor of only 1.4. Figure 5A shows that the ratio for our preferred top 0.01% of the wealth distribution also increases sharply in recent years to a similar level of 3.3 as the minimum distance estimate.33

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

The equal-returns series used in PSZ reflects a rate of return that includes non-interest-generating fixed income assets (namely mutual funds) and residual wealth in the numerator of the capitalization factor. It results in a capitalization factor of 124 in 2016. Removing these funds and using the latest vintage of Financial Accounts aggregates delivers an equal-returns factor of 95 in 2016. The Aaa and Treasury series imply factors of $\frac{1}{\text{1.84%}} = 27$ and $\frac{1}{\text{1.83%}} = 54$, respectively. When interest rates were further from zero in the 1990s, the equal-returns factor ranged from 14 to 25, whereas the more conservative Moody’s Aaa factor ranged from 11 to 15. Our preferred top-0.01% estimates using information returns (or minimum distance for the top-0.1% of non-interest wealth) fall between that implied by the Treasury series and the Baa, with a value of 29 (and 27) in 2016. Our preferred top-0.1% factor tracks the Treasury-implied factor over time, and the top 1% factor exceeds it in recent years. Both are still much smaller than the equal-returns factor.

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

With the PSZ factor, top 0.1% fixed income wealth hovers between 1% and 3% of total household wealth between 1965 and 2000, rising modestly from the 1980s into the 1990s, but

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

34For the 10-year Treasury, Aaa, and Baa series, we use the respective interest rate to capitalize interest income for the top 1% ranked in terms of non-interest wealth. We then allocate the residual for capitalizing non-top-1% interest income.
then surges dramatically starting in 2000 to a peak of 6.3% of total household wealth in 2012. Top estimates using other factors show a significantly attenuated rise since 2000. Overall, the 4.1(=5.9-1.8) percentage point difference in the PSZ and preferred series accounts for a substantial portion of the gap between estimates shown in Figure 1.

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

3.5 Comparison to Prior Estimates of Return Heterogeneity

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

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,

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

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

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

38 The previous version of our paper followed these approaches and generalized the two-tier approach by assigning three different rates: the Aaa for the top 0.1% in terms of interest income, the 10-year US Treasury rate for the next 0.9%, and a residual rate that ensured the aggregates matched the Financial Accounts.
in the SCF data and estate tax data, it is not possible to isolate the boutique funds that we find are key for generating the bulk of interest income for those at the very top in recent years. The second is an imperfect mapping from the SCF and estate tax wealth data to the corresponding income flows. Specifically, the interest rates estimated in these papers include money market and fixed income mutual funds that do not pay taxable interest, thus downward biasing the estimated interest rates and the degree of return heterogeneity. Third, interest rates at the top in the SCF and estate tax data are imprecise due to sampling uncertainty, volatility from mortality rates, and small sample sizes.39

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

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

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

40Saez and Zucman (2020b) also recognize this issue with the interest rate definition based on the SCF. Their approach is to remove an estimate of interest generated by boutique-style investments from the numerator, because such assets are hard to isolate in the SCF. This approach is uninformative about the relevant drivers of interest rate heterogeneity for those at the top, as our information returns data show that boutique sources account for the bulk of top taxable interest flows in tax data.
using our preferred definition has a similarly wide confidence interval, which nevertheless continues to reject both 1 and 1.4.

4 Pass-Through Equity

4.1 Challenges in Estimating Pass-Through Equity Wealth

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

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

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

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

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41 Based on conversations with economists who produce the Financial Accounts, closely-held business is likely understated in the accounts for several reasons. First, S-corporation equity is estimated using ratios of market value of equity to book value of assets at the 2-digit sector level, which may understate firm value in the asset-light service sector firms that predominate among S-corporations. Second, non-corporate business equity is estimated using a mix of market values for real estate and fixed income assets and book values for other assets, which may understate the value of these firms. Third, financial partnerships are not currently included in the accounts, which are among the largest 4-digit industries in our data. Fourth, closely held C-corporations with less than $1-2B in revenues are not included because of data limitations.
zero. Indeed, many privately-held real estate, hotels, and restaurant firms can generate such large taxable losses that the owners’ AGI becomes negative even though these owners have considerable wealth in these assets. As a result, using profits alone to estimate business wealth—whether these profits appear on the individual tax return or on the business tax return—paints a biased picture of the level and distribution of private business wealth.

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

4.2 Estimating Pass-Through Equity using Firm Characteristics

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

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

\[
\hat{W}_{i}^{\text{pthru}} = 0.9 \times \frac{1}{3} \sum_{j(i)} \left( \beta_{t}^{\text{sale},k(j)} \times y_{ijt}^{\text{sale}} + \beta_{t}^{\text{asset},k(j)} \times y_{ijt}^{\text{asset}} + \beta_{t}^{\text{ebid},k(j)} \times y_{ijt}^{\text{ebid}} \right),
\]

(11)

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

\(^{42}\)For firms with zero profits, we use a \( 1/N \) weight to apportion firm characteristics across owners.

\(^{43}\)We consider a 50% profit parameter in a robustness exercise, which reflects the bottom of the 95% confidence interval from both equal-weighted and profit-weighted owner-death estimates in SYZZ (see their Appendix Table J.9, columns (1) and (4)).
NAICS 4-digit industries using data from Compustat:

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

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

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

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

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

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

\[ \bar{\beta}_t^{sole} = \frac{W_t^{sole+part}}{\sum_i (y_{itt}^{sole} + y_{itt}^{part})}, \]

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

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

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

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

4.3 Pass-Through Business Wealth Estimates

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

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

$^{46}$Approximately $20B of the proprietor flows are royalty flows and estate and trust flows earned from pass-through business.
Figures 7B and 7C quantify return heterogeneity across industries and individuals, respectively. To compute returns for a given group, we divide aggregate industry profits before tax by our estimate of group-specific wealth.\textsuperscript{47} Figure 7B plots these returns for the thirty largest industries in aggregate S-corporation wealth and compares them to the aggregate S-corporation return. High return industries tend to be the industries in which we think the primary input is human capital, broadly defined, rather than non-human capital, including architects, engineers, lawyers, and doctors (SYZZ). This fact implies that these industries will have lower valuations compared to an equal-returns approach that does not adjust profits for recharacterized labor income. Conversely, pass-through owners with significant fixed capital (e.g., real estate) should be capitalized more because of low relative returns.

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

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

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

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

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

\textsuperscript{49}This decreasing pattern contrasts with return heterogeneity when we rank individuals by AGI or pass-through income. Moving from lower to higher ranks, returns are weakly increasing in the case of AGI and sharply increasing in the case of pass-through income. This fact reflects the prevalence of human-capital-rich entrepreneurs in asset-light industries at the top of the income distribution (SYZZ). In addition, Appendix Table B.7 presents summary statistics on average returns to private business wealth for the population of pass- through businesses and their owners from 2001 to 2016. For S-corporations, mean unweighted and value-weighted returns are 11.26\% and 9.88\%, respectively. For partnerships, mean unweighted and value-weighted returns are 4.16\% and 6.12\%, respectively.
business wealth to these individuals. Second, ranking by preferred wealth estimates increases pass-through wealth concentration at the top relative to ranking by business income or AGI. This fact indicates those with losses collectively account for significant wealth at the top of the wealth distribution, which is captured by our approach. Third, private business wealth is exceptionally concentrated: when ranked by overall wealth, two-thirds of pass-through business wealth accrues to the top 1% and 40% accrues to the top 0.1%.

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

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

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

5.1 Challenges in Capitalizing C-corporation Equity Flows

Dividends and capital gains both provide information about C-corporation ownership. However, mapping these flows to an estimate of C-corporation wealth involves several challenges. First, unlike fixed income and pass-through business wealth, we cannot link most C-corporations to their owners. Dividend payments are reported on information returns, but not all firms pay dividends. In addition, dividends on stock held through brokerage accounts appear as paid by intermediaries and do not reveal the underlying ownership.51

Second, while dividends derive exclusively from C-corporation ownership, realized capital gains do not.52 Figure 8A presents the capital gains composition from the SOI Sale of Capital Assets study files for the years 1997 to 2012. While sale of corporate stock is one of the largest categories, it accounts for only 20% to 30% of total realized capital gains, whereas pass-through gains is the largest category. While pass-through gains might represent the sale of corporate stock as well, they likely also reflect sales in other categories and “carried interest” compensation to investment managers. The latter is an important source of income for general partners in hedge funds, venture capital, and private equity. We estimate that general partner distributed gains range from 15% to 35% of top 0.1% capital gains in recent years, or $50B to $100B per year between 2012 and 2016.53 This result gives a reason why capital gains may provide inaccurate information about stock ownership, because carried interest does not map to current or future ownership of C-corporation stock.

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

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

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

53 Appendix Figure A.13 presents evidence supporting our estimate. We first validate that SOCA capital gains closely track the SOI realized capital gains in our capitalized income estimates. We then show that the pass-through component of SOCA gains is large relative to SOI realized gains and the gains derived from different information return databases are comparable in magnitude and time series. General partners consistently receive 20% of all distributed gains and 60% of all distributed ordinary income, which strongly supports our approach to identifying active managers.
of their assets in a single year.\textsuperscript{54} Thus, realized capital gains, when observed, may provide inaccurate information about the underlying distribution of wealth. This issue likely matters more in recent years as the rich own substantial stock wealth, and the tax preference for capital gains versus dividends has fluctuated over time generally in favor of capital gains.

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

\section*{5.2 Capitalizing Dividends and Realized Capital Gains}

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

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

$$ a_{it}^C(\alpha_i) = \beta_{it}^C(\alpha_i) \times (\alpha_i y_{it}^D + (1 - \alpha_i) y_{it}^G) $$

$$ s_{it}^C(\alpha_i) = \frac{a_{it}^C(\alpha_i)}{\sum_i a_{it}^C(\alpha_i)}, $$

where $a_{it}^C(\alpha_i)$ is C-corporation equity wealth of group $i$ in year $t$ and $(\alpha_i y_{it}^D + (1 - \alpha_i) y_{it}^G)$ is an $\alpha_i$-weighted average of group $i$’s dividend income $y_{it}^D$ and capital gains $y_{it}^G$. The capitalization factor $\beta_{it}^C(\alpha_i) = \frac{a_{it}^C(\alpha_i)}{(\alpha_i y_{it}^D + (1 - \alpha_i) y_{it}^G)}$ scales up this composite flow and depends on $\alpha_i$, which governs the magnitude of the total income flow $(\alpha_i y_{it}^D + (1 - \alpha_i) y_{it}^G)$ for group $i$. Group $i$’s share of C-corporation equity wealth is $s_{it}^C$.

\textsuperscript{54}Appendix Figure A.14 uses panel data from the population of individual tax returns to compare the year-over-year persistence of realized capital gains to that for other sources of income. For those in the top 1\% of realized gains in year $t$, the average rank in year $t + 1$ is the 75th percentile. In contrast, dividends, interest, wages, and adjusted gross income are much more persistent over time, with the top 1\% having average rank of 99th, 97th, 97th, and 96th percentile, respectively, in the next year. This fact helps explain why dividends are a better predictor than realized capital gains for stock holdings in the SCF.
Minimum Distance Estimation using Equity Wealth Shares. For each group $i$, we find $\alpha_i$ that minimizes the distance between actual and model-based shares of C-corporation equity wealth:

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

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

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

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

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

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

Results. Figure 8B presents results from the share-based approach using group-level data to estimate $\alpha_i$. We present separate estimates for P0-90, P90-99, P99-99.9, P99.9-99.99, and for the top 0.01%. The error-minimizing weight on dividends $\hat{\alpha}_i$ for all groups is very close to 0.9. Except for the top 0.01%, we can precisely estimate this parameter and reject the hypothesis that $\alpha_i = 0.5$, which is the approach taken in SZ and PSZ.
Table 1 presents results from the regression-based approach using household-level data. We find C-corporation wealth is much more strongly related to dividends than realized capital gains in the full sample and for all subgroups. Interpreted through the lens of our model, the estimated $\alpha$s range between 0.94 to 0.98, with the weight on dividends increasing as we move up the wealth distribution. These household-level regressions deliver more precision than the share-based approach, but at the cost of using household-level wealth as the estimand of interest rather than C-corporation wealth shares.

Both approaches strongly support placing substantially more weight on dividends when capitalizing flows to estimate C-corporation wealth. Moreover, they both suggest the degree of heterogeneity in mapping flows to stocks is relatively unimportant for this asset class. Because there appears to be little heterogeneity across groups, we adopt a wealth-weighted average of parameter estimates to set $\alpha_i$ equal to 0.9 in our baseline capitalization. The resulting capitalization factor $\beta^C_t(0.9) = \frac{\sum_i a^C_0}{\sum_i (0.9 y^D_{it} + 0.1 y^G_{it})}$ is the ratio of aggregate C-corporation wealth from the Financial Accounts to the aggregate composite flow of 0.9 times dividends plus 0.1 times capital gains for each year.

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

Compared to SZ and PSZ, our approach reduces the weight on realized capital gains. Instead of a weight of 0.9 on dividends and 0.1 on realized capital gains, PSZ sum both flows, which is equivalent to using weights of 0.5. Note that because aggregate realized capital gains are much larger than dividends—in 2016, total realized gains are $614B versus $254B for dividends (Figure 2)—the relative contribution of capital gains to estimating C-corporation equity wealth exceeds 50% when setting $\alpha = 0.5$. The $\alpha = 0.5$ assumption in the PSZ approach yields an important source of dividend income for those at very top, analogous to results in Fig 8. Figure A.11 shows that heterogeneity in yields appears relatively small.

55Figure A.10 shows that partnerships are an important source of dividend income for those at very top, analogous to results in Fig 8. Figure A.11 shows that heterogeneity in yields appears relatively small.
56The top 0.01% accounts for 6.8% of C-corporation equity wealth in 2016 in the SCF.
57Scholz (1992); Kawano (2014) test the dividend clientele hypothesis (Miller and Modigliani, 1961; Miller, 1977; Auerbach and King, 1983; Auerbach, 1983; Poterba, 2002) and find that high-income households reduce their exposure to dividend-yielding equities for tax reasons. This finding suggests that relying exclusively on dividend payments may not be optimal because it might underweight these high-income households.
58SZ and PSZ also apply “mixed” method for ranking. See Appendix L.2 for details.
series yields an estimate of 6.3% of household wealth for the top 0.1% with our preferred ranks in 2016. The \( \alpha = 0.5 \) assumption using updated aggregates and definitions in the equal-return series yields 5.8%, whereas our preferred series yields 4.9% and dividends only gives 4.5%. The difference between our preferred approach and the PSZ approach amounts to 1.4 (=6.3-4.9) percentage points of overall household wealth accruing to the top 0.1%.

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

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

### 6 Pension Wealth

#### 6.1 Challenges in Estimating Pension Wealth

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

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

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

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

6.2 Capitalizing Wages and Pension Income

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

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

\[
\beta_{t}^{pen,wage,a} = \frac{\sum_{i \in a} \gamma_{a} W_{it}^{pen}}{\sum_{i \in a} y_{it}^{wage}}, \quad \beta_{t}^{pen,pen,a} = \frac{\sum_{i \in a} \gamma_{a} W_{it}^{pen}}{\sum_{i \in a} y_{it}^{pen}},
\]

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

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

\(^{60}\)We construct $\gamma_{a}$ using the mean $\gamma_{at}$ in the SCF from 1989 to 2016. Our measure of pension wealth is
age-group-specific convex combination of capitalized wages and capitalized pension income:

\[
\hat{W}_{it}^{\text{penw}} = \theta_{\text{penw},a} \left( \beta_t^{\text{penw,wage,a}} \times y_{it}^{\text{wage}} \right) + (1 - \theta_{\text{penw},a}) \left( \beta_t^{\text{penw,pen,a}} \times (y_{it}^{\text{pen}}) \right),
\]

where \( \theta_{\text{penw},a} \) is the weight on capitalized wages and \((1 - \theta_{\text{penw},a})\) is the weight on capitalized pension income for age group \( a \). Younger individuals have more weight put on wages and older individuals have more on pensions. In particular, \( \theta_{\text{penw},a} \) is 0.92, 0.83, 0.36, and 0.07 for those younger than 45, 45 to 59, 60 to 74, and above 75, respectively. In 2016, this approach results in the following formula for estimated pension wealth using the defined-benefit-augmented SCF:

\[
\hat{W}_{i,2016}^{\text{pen,SZZ}} = \begin{cases} 
0.92 \left( 1.3 \times y_{i,2016}^{\text{wage}} \right) + (1 - 0.92) \left( 132.4 \times (y_{i,2016}^{\text{pen}}) \right) & \text{if } \text{age} < 45 \\
0.83 \left( 4.3 \times y_{i,2016}^{\text{wage}} \right) + (1 - 0.83) \left( 94.8 \times (y_{i,2016}^{\text{pen}}) \right) & 45 \leq \text{age} < 60 \\
0.36 \left( 10.6 \times y_{i,2016}^{\text{wage}} \right) + (1 - 0.36) \left( 23.5 \times (y_{i,2016}^{\text{pen}}) \right) & 60 \leq \text{age} < 74 \\
0.07 \left( 27.1 \times y_{i,2016}^{\text{wage}} \right) + (1 - 0.07) \left( 7.2 \times (y_{i,2016}^{\text{pen}}) \right) & \text{otherwise}
\end{cases}.
\]

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

Figure 9C considers the effect on top shares of integrating estimates of Social Security wealth from Catherine, Miller and Sarin (2020) (CMS) and Sabelhaus and Volz (2019) (SV). Were we to include this wealth in our household aggregate, the top 0.1% share in 2016 would fall by thirty percent, and the growth in the top 0.1% share would fall by sixty percent. The generosity of social insurance can therefore materially affect wealth concentration measures. We obtain these weights from regressions of pension wealth in the SCF on capitalized wages and capitalized pensions. We set the weight equal to the coefficient on capitalized wages divided by the sum of coefficients. The ratio of coefficients is fairly stable over time when we estimate the regression each year.

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

7.1 Challenges in Estimating Housing Wealth using Tax Data

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

7.2 Capitalization with Unequal Property Tax Rates

We use each individual’s flow of property tax and mortgage interest deductions to estimate housing wealth. This component of wealth does not include rental real estate.\(^{64}\)

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

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

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

\(^{64}\) Most rental housing is likely included in private business wealth. We estimate informal rental housing wealth by capitalizing rental income payments under equal-returns following SZ.
year $t$. We then apply an equal-returns capitalization factor to estimate mortgage debt. For non-itemizers, we assign average housing asset and mortgage values from the SCF for demographic groups $g$ (i.e., income decile $\times$ married $\times$ old). Net housing wealth is given by assets less liabilities, each defined as:

$$
\hat{A}_{it} = \begin{cases} 
\beta_{it}^{tax} y_{it} & \text{if itemizer} \\
\hat{A}_{it}^{hou,SCF} & \text{otherwise, } i \in g 
\end{cases}
$$

and

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

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

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

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

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

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

8 Adding It Up: New Top Wealth Estimates

8.1 The Level of Top Wealth

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

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

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

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

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66Section L.2 discusses differences between our preferred approach and the PSZ equal-returns approach in more detail and component-by-component.
average: these groups respectively contain 1.5 million and 150 thousand tax units, whereas Forbes represents only 400. Our top 0.01% group contains $6.6T of wealth, which includes the impact of blending Forbes into our data.\(^67\)

### 8.2 The Composition of Top Wealth

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

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

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

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

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\(^67\) Without blending, this group would have $6.1T. Replacing the top 400 capitalized tax units with Forbes estimates gives $7.0T. We show the effects of these alternatives on top wealth shares in Figure 8D. With a Pareto parameter of 1.4, the amount of wealth between the Forbes 2016 cutoff of $1.7B and $124M is \([{(1700/124)}^{(1.4-1)} - 1] = 182\%\) of the wealth above $1.7B in Forbes, which is $2.4T. Thus, under the Pareto approximation and taking the Forbes estimate as given, the collective wealth of those with wealth above $124M is $2.4T \times (2.82) = $6.8T. Appendix L.3 provides additional discussion.
top 0.01% holds more wealth than the P99-99.9 and P99.9-99.99 groups despite representing 1/100th and 1/10th the number of individuals, respectively.

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

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

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

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

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

8.3 The Growth of Top Wealth

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

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

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

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

Evidence from administrative data in Scandinavia also shows small contributions of fixed income and large roles of equity and especially private business at the top (Fagereng, Guiso, Malacrino and Pistaferri, 2020; Bach, Calvet and Sodini, 2020).
when different updates occur (1980s for pension and housing, 2001 for pass-through and fixed income with information-returns) and the corresponding effects, and how policy and macroeconomic conditions affect the concentration and composition of wealth. For the top 1%, we include estimates from the DFA for comparison.$^{70}$

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

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

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

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

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

$^{71}$Appendix Figure A.22 decomposes the 1989–2016 growth in concentration by asset class for the top 0.01%, top 0.1%, and top 1%. For both periods, fixed income accounts for a small share of the growth, whereas private business is more important.
percentage points. Overall, wealth is still concentrated: the top 1% holds nearly as much wealth as either the bottom 90% or the “P90-99” class.

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

9 Robustness and Comparison with Other Approaches

9.1 Characterizing Parameter and Model Uncertainty

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

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

\(^{72}\)In particular, we take draws for these parameters from a normal distribution with the respective means and variances using estimates in Appendix Table H.2 and Table 1. For each draw \( b \), we form an estimate of \( \hat{r}_t^{b} \) using equation 9 and then follow the procedure described in the main text for forming estimates for P99-99.9 and everyone else for fixed income. Similarly, for each draw \( b \), we form an estimate of \( \hat{\alpha}_i^b \), 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.
compares them to our preferred series and the PSZ 2018 series. For the top 0.01% and top 0.1%, our preferred series tracks the upper confidence interval of the SCF. Although there is parameter uncertainty for fixed income and equity estimates, this uncertainty is less important for differences across estimates than modeling assumptions about the degree of heterogeneity and the weight on capital gains. For the top 1%, our preferred series is closer to the lower bound of the SCF confidence interval, and the PSZ 2018 series is well above it for most of the 2000s other than the 2016 estimate.

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

9.2 Reconciling Our Estimates with Other Sources

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

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

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

74 Many of the possible differences between our series and the raw SCF have been addressed by previous work, including SZ, BHKS, BHH, and SV and Henriques and Hsu (2014); Bricker, Hansen and Volz (2019b); Saez and Zucman (2020b). Moreover, concerns about response bias are addressed in BHKS, suggesting this cannot account for differences across methods.
tenure or public-sector employment status, characteristics that SV find are important for matching pension wealth in addition to age and income.

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

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

10 Conclusion

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

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

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

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

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

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

We highlight a few avenues for future research. First, there are many ways to improve these wealth estimates and incorporate further refinements, such as the impact of tax avoidance and evasion (Guyton, Langetieg, Reck, Risch and Zucman, 2020), better measures of pension wealth and the accuracy of the Forbes 400, and social insurance programs such as Medicare and Social Security. Second, we hope our estimates for wealth and income inequality can improve our understanding of the drivers of inequality. For example, our estimates provide inputs to investigating how much of wealth is inherited and the relative importance of family firms versus self-made entrepreneurs (Gomez, 2019; Atkeson and Irie, 2020). Third, these estimates can be linked with estate tax data to estimate behavioral responses to capital taxation and inform policy design and enforcement.
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Figure 1: Wealth Concentration in the United States

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

B. Top Shares of Total Wealth, Harmonized Series

Notes: This figure plots the share of total household wealth for different wealth groups. Panel A graphs our preferred specification for the top 0.1% share of net household wealth, along with analogous series from Piketty, Saez and Zucman (2018), Saez and Zucman (2016), Kopczuk and Saez (2004) (retrieved from and updated in the appendix of Saez and Zucman (2016)), and the SCF. Panel B compares our preferred estimates to the PSZ equal-returns approach and the harmonized SCF with Forbes series for the top 0.01%, 0.1%, and 1% share of net household wealth.
Figure 2: Aggregate Household Wealth and Fiscal Income Components

A. Components of Aggregate Household Wealth

![Graph A: Components of Aggregate Household Wealth]

B. Components of Aggregate Fiscal Capital Income

![Graph B: Components of Aggregate Fiscal Capital Income]

Notes: This figure plots the main components of aggregate national household wealth and fiscal capital income. Panel A plots net household wealth components relative to national income. Fixed income assets include taxable bonds, municipal bonds, currencies, and deposits. C-corporation wealth includes public and private C-corporations. Pass-through business includes S-corporation equity and non-corporate equities in sole proprietorships and partnerships. Housing denotes housing wealth net of mortgages. For pass-through business, the “SZ 2020” version follows the definitions in Saez and Zucman (2020b) for pass-through business wealth based on the Financial Accounts. We plot two pension series, one which includes funded and unfunded defined benefit (DB) wealth and one which only includes funded DB wealth. Panel B graphs the ratio of components of fiscal income relative to national income.
Figure 3: Fixed Income Portfolio Heterogeneity across Groups

A. SCF Fixed Income Portfolio Shares

B. Interest Income Participation

C. Interest Income Composition

D. Bank Participation over Time

Notes: This figure uses SCF and tax data to document portfolio heterogeneity along the wealth distribution in the nature of interest-bearing assets. Panel A uses the 2016 SCF to decompose fixed income holdings into two broad categories: liquid assets, including currency, deposits, and money market funds; and less liquid assets, including bonds and non-money-market fixed income mutual funds. We present portfolio shares separately for the top 0.1%, P99-P99.9, P90-99, and for the bottom 90% of respondents, ranked in terms of preferred SCF net worth. Panels B–D use population-level tax data to present participation rates and interest income composition in 2016 and bank participation rates over time, with taxpayers grouped in adjusted gross income (AGI) percentiles. We partition the top 1% into three groups: P99-99.9, P99.9-P99.99, and the top 0.01%. We classify fixed income payments based on the information return on which interest income appears, further classifying payments reported on Form 1099-INT into three categories: bank payments (total payees > 10), loan payments (total payees < 10), and savings bond payments.
Figure 4: Fixed Income Rates of Return Vary across Wealth and Income Groups

A. Asset Class Interest Rates, 2016

B. Average Rates of Return, 2016

C. Interest Rates

D. Classical Minimum Distance Estimates

Notes: This figure provides evidence on fixed income portfolio returns for different groups. Panel A presents interest rates by source for 2016, which serve as inputs into our information-return capitalization approach. Panel B plots the returns to taxable-interest-generating fixed income assets by percentile of preferred wealth, AGI, and non-interest wealth. Panel C plots different the preferred rate-of-return series from Panel B by year. Prior to 2001, these series use the three-tier classical minimum distance (CMD) estimates for return heterogeneity by non-interest wealth. Equal returns plots $\bar{r}_{fix}$ following the capitalization approach in Piketty, Saez and Zucman (2018) with updated aggregates that exclude fixed income assets that generate non-qualified dividends and miscellaneous wealth. 10-Yr. Treasury, Moody’s Aaa, and Moody’s Baa refer are capital market yields for Treasuries and different categories of investment-grade corporate bonds. Deposits are the bank deposit rate from Drechsler, Savov and Schnabl (2017). Panel D plots estimated interest rates and 95% confidence intervals from the two-group CMD estimates with individuals ranked by non-interest wealth.
Figure 5: Alternative Capitalization Factors for Fixed Income Wealth

A. Ratio of Rates

B. Capitalization Factor, $1/r_{fix}$

C. Taxable Fixed Income Wealth Share of Net Household Wealth (%)

D. Model Fit: Taxable Fixed Income Predicted vs. Actual in the SCF

Notes: This figure compares capitalization factors under alternative assumptions of average returns to taxable-interest-generating fixed income wealth. Panel A presents the point estimates and standard errors of a key ratio of the top rate relative to the equal-returns rate, $r_{1t}/r_{t}$, which summarizes the degree of heterogeneity. We plot this ratio for different wealth groups ranked by preferred wealth, for the top 0.1% non-interest-wealth group estimated via classical minimum distance (CMD), and for different capital market interest rates. Panel B plots capitalization factors, i.e., the reciprocal of the interest rates from Figure 4C. We add a series that uses the fixed income wealth definition and aggregates from Piketty, Saez and Zucman (2018) and a series based on the top 0.1% non-interest-wealth CMD estimates from Figure 4D. Panel C shows top 0.1% fixed income wealth (including funds that generate non-qualifying dividends) relative to total household wealth when using different capitalization approaches for the top group under wealth ranks from our preferred definition. As in Panel B, the PSZ 2018 series uses aggregates and definitions from Piketty, Saez and Zucman (2018), while the Equal Returns series updates aggregates and definitions. CMD 3-Tier refers to our preferred minimum distance approach. CMD 2-Tier Upper and 2-Tier Lower use the two-group approach and respectively apply the 95% upper and lower confidence interval for capitalizing top wealth. The capital market rate series apply these rates to the top 1% ranked by taxable interest. Panel D plots predicted versus actual SCF wealth using data on flows and stocks from the SCF. Predictions take flows as an input and produce estimates of fixed income wealth. The dashed line plots the 45-degree line. Points on the graphs show predicted wealth for different income groups for a given year using capitalization factors from Piketty, Saez and Zucman (2018) with unupdated and updated (i.e., Equal Returns) definitions and aggregates, from Saez and Zucman (2020b), and from applying the two-group CMD approach. We define SCF fixed income wealth to exclude funds that do not generate taxable interest.
Figure 6: Interest Rates in the SCF for Taxable-Interest-Generating Assets

A. Interest Rates

B. Ratio of SCF Top Rate to Equal Returns Rate

Notes: This figure plots top interest rates and return ratios under uncertainty for the SCF. We sample SCF households using the replicate weights and following the procedure in Bricker, Henriques, Krimmel and Sabelhaus (2016). We report both our preferred definition, which removes non-interest-generating assets (i.e., fixed income mutual funds and money market funds, which pay non-qualified dividends) from the denominator of the interest rate, as well as the definition from Bricker, Henriques and Hansen (2018). The denominator of the return ratio is the equal-returns rate from Figure 5A.
Figure 7: Aggregate Pass-Through Equity and Unequal Returns across Groups

A. Aggregate Pass-Through Business in Different Data Sources


C. Returns vs. Ranking (2016)

D. Wealth Shares and Losses (2016)

Notes: This figure documents differences in the aggregate value of private businesses across data sources and heterogeneity in effective returns on pass-through equity. Panel A compares aggregate pass-through business values from the Survey of Consumer Finances (SCF) to an analogous concept from the capitalization approach based on the US Financial Accounts, which combines non-corporate business wealth with S-corporation equity wealth. The panel also plots estimates of pass-through business wealth using our valuations for S-corporations and partnerships and our estimate for missing pass-through business wealth. We plot both our preferred series, which adjusts for liquidity discounts and labor income characterized as profits, and an unadjusted series. Prior to 2001, our approach follows the capitalization approach with Financial Accounts aggregates, as in Piketty, Saez and Zucman (2018) and Saez and Zucman (2020b), but adds missing pass-through business wealth. Panels B and C quantify return heterogeneity across industries and individuals, respectively. Returns equal aggregate industry profits before tax divided by our estimate of group-specific wealth. Panel D plots the share of pass-through business wealth in 2016 for groups ranked by wealth, AGI, and pass-through income. We divide the P0-90 group into a P0 and a P1-90 group to isolate those with losses and significant business wealth.
Figure 8: Dividends are More Informative than Realized Gains for Inferring Stock Wealth

A. Realized Gains Composition (SOI Aggregates, 1997–2012)

B. Weight on Dividends by Net Worth

C. C-corporation Wealth

D. Forbes Adjustments

Notes: This figure presents evidence supporting our approach to inferring stock wealth from dividends and realized capital gains, and considers the impact of augmenting capitalization estimates with Forbes 400 data. Panel A decomposes realized capital gains by component using IRS statistics of income aggregates from 1997-2012. Panel B uses minimum distance to estimate the optimal weight on dividends versus capital gains for different wealth groups in the SCF. Panel C is analogous to Figure 5C. We plot C-corporation equity estimates given different weights on dividends and realized capital gains, and applying the equal returns approach (0.5 weight on both dividends and capital gains) using updated aggregates and definitions and the unupdated series following Piketty, Saez and Zucman (2018). Panel D presents three alternative approaches that combine Forbes data with our capitalized estimates for the top 1%, top 0.1%, and top 0.01% in 2016. The first “Replace” replaces the richest 400 in our data with the Forbes 400. The second “Pref, BHV 2019” follows Bricker, Hansen and Volz (2019b) by blending the Forbes data into the tax sample and adjusting sampling weights to account for overlap. The third “BHV 2019+” adds an estimate of non-dividend-generating C-corporation wealth from Appendix L.3 to our preferred, BHV blending approach.
Figure 9: Using Wages and Pension Distributions to Infer Pension Wealth

A. The Life Cycle of Pension Wealth vs. Wage and Pension Income

B. Flow-Stock Relationships for Pension Wealth Vary with Age

C. Top 0.1% Share with Social Security

Notes: This figure explores the relative informativeness of wages and pension income for inferring pension wealth for different age groups. Panel A plots 1989–2016 data from the SCF on the life cycle of pension wealth, wage income, and pension income. Pension wealth is the defined-benefit-augmented SCF from Sabelhaus and Volz (2019). The dashed lines plot average pension wealth for that age group. Panel B plots the ratio of wage income or pension income to pension wealth for the full population, those under 45, those aged 45-59, those aged 60-64, and those over 75. Panel C plots our preferred top 0.1% wealth share and a modified series that includes total Social Security wealth in the denominator and top 0.1% Social Security wealth in the numerator (the latter of which is close to zero relative to total wealth). Social Security data come from Catherine, Miller and Sarin (2020) (CMS) and Sabelhaus and Volz (2019) (SHV).
Figure 10: Regional Variation in the Returns to Housing Assets

A. Geographic Variation in Property Tax Rates

B. Evolution of Housing Capitalization Factors in California

Notes: Panel A provides a map of state property tax rates from ATTOM. Panel B shows how the housing asset capitalization factor, equal to the reciprocal of the state property tax rate, has evolved in California versus an equal returns benchmark pooling all states.
Figure 11: Size of Different Top Wealth Groups

<table>
<thead>
<tr>
<th>Wealth (trillions)</th>
<th>Number of People (K)</th>
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<tr>
<td>Forbes</td>
<td>2.4</td>
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<tr>
<td>P99-99.9</td>
<td>14.4</td>
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<tr>
<td>P99.9-99.99</td>
<td>14.9</td>
</tr>
<tr>
<td>Top 0.01%</td>
<td></td>
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</tbody>
</table>

**Indls/TUs in Forbes 400**: ≈0.8/0.4
**Indls/TUs in P99-99.9**: 2,148/1,527
**Indls/TUs in P99.9-99.99**: 214.8/152.7
**Indls/TUs in P99.99-100**: 23.9/16.8

Notes: This figure compares Forbes 400 wealth to aggregate wealth according to our preferred specification for telescoping subgroups of the top 1%: P99-99.9, P99.9-99.99, and the top 0.01% in 2016. The figure reports counts of individuals or tax units in each group.
Figure 12: Wealth Composition in the United States

A. Fixed Income (Incl. Funds)  
B. Pass-Through Equity

C. C-corporation Equity  
D. Pensions

E. Housing  
F. Residual Wealth

Notes: This figure plots the level and allocation of wealth across asset classes among the top 10% in 2016. We group individuals into percentile bins and further divide the top 1% into P99-99.9, P99.9-99.99, and the top 0.01%. Each plot shows the share of total household wealth accruing to that group in a particular asset class. We compare our preferred estimates to the equal-returns approach with aggregates and definitions following Piketty, Saez and Zucman (2018) and the harmonized SCF with and without Forbes. Horizontal dashed lines plot analogous figures for the DFA top 1% and P90-99 series split evenly across groups. The DFA series are at the household level, while the other series are at the individual level.
Figure 13: Portfolio Components over Time

A. Fixed Income

Top 0.01%

Top 0.1%

Top 1%

B. Pass-Through Business

C. C-corporation Equity

D. Pensions

E. Housing

Notes: This figure plots time series versions of Figure 12 for the five major asset classes for the top 0.01%, top 0.1%, and top 1% in our series, the PSZ equal-returns series, the harmonized SCF with Forbes, and the DFA. Appendix Figures A.18 and A.20 present analogous figures with portfolio shares and inflation-adjusted component levels, respectively.
Figure 14: Wealth Concentration by Group under Different Approaches

Notes: This figure plots the share of total household wealth for different wealth groups, including the bottom 90%, P90-99, and the top 1% under our preferred approach and the PSZ equal-returns approach. Each series defines rankings using that approach’s respective wealth estimates. Appendix Figure A.21 plots analogous series defined at the tax unit level along with estimates from the DFA.
Figure 15: Top Wealth Composition in 2016 across Specifications and Data Sets

A. Top 0.001%

B. Top 0.01%

C. Top 0.1%

D. Top 1%

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

Figure 16: Top Share of Wealth under Alternative Specifications

A. Bootstrapping Fixed Income and C-corporation Parameters

B. Perturbations of Preferred Specification for Top 0.1%

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

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<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td></td>
<td>Full sample</td>
<td>Bottom 90%</td>
<td>Top 1%</td>
<td>Top 0.1%</td>
<td>Top 0.01%</td>
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<tr>
<td>Capital gains</td>
<td>1.042</td>
<td>1.067</td>
<td>0.845</td>
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<td>0.318</td>
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<td>(0.011)</td>
<td>(0.014)</td>
<td>(0.027)</td>
<td>(0.041)</td>
<td>(0.083)</td>
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<tr>
<td>Dividends</td>
<td>15.763</td>
<td>15.554</td>
<td>14.022</td>
<td>11.892</td>
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<td>(0.054)</td>
<td>(0.057)</td>
<td>(0.134)</td>
<td>(0.187)</td>
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<td>Implied $\alpha$</td>
<td>0.938</td>
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<td>0.979</td>
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<td>(0.002)</td>
<td>(0.003)</td>
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<td>$N$ (unweighted)</td>
<td>441,260</td>
<td>374,866</td>
<td>66,394</td>
<td>31,234</td>
<td>9,391</td>
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</table>

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

$$\text{Dividend Assets}_{it} = \beta_1 \text{Dividends}_{it} + \beta_2 \text{Capital gains}_{it} + \gamma_t + \epsilon_{it}.$$  

Standard errors are in parentheses. Implied $\alpha$ is the ratio of $\beta_1$ to the sum of the coefficients. All regressions split married couples to imitate our equal-split tax data (see Appendix D) and use SCF survey weights. Column 1 estimates the regression among all SCF participants 1989-2019. Columns 2-5 estimate the regression among subgroups of the wealth distribution using our preferred SCF wealth definition.
Table 2: Thresholds and Average Wealth in Top Wealth Groups (2016)

<table>
<thead>
<tr>
<th>Wealth group</th>
<th>Count</th>
<th>Pref. Threshold</th>
<th>Average wealth</th>
<th>Wealth share</th>
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</thead>
<tbody>
<tr>
<td>Panel A. Top wealth groups</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Full population</td>
<td>238,657,000</td>
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<td>$364,000</td>
<td>$317,000</td>
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<tr>
<td>Top 10%</td>
<td>23,866,100</td>
<td>$717,000</td>
<td>$2,392,000</td>
<td>$2,259,000</td>
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<tr>
<td>Top 1%</td>
<td>2,386,700</td>
<td>$3,730,000</td>
<td>$11,469,000</td>
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<tr>
<td>Top 0.1%</td>
<td>238,700</td>
<td>$17,800,000</td>
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<tr>
<td>Top 0.01%</td>
<td>23,900</td>
<td>$84,300,000</td>
<td>$255,397,000</td>
<td>$300,580,000</td>
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<tr>
<td>Panel B. Intermediate wealth groups</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Bottom 90%</td>
<td>214,790,900</td>
<td></td>
<td>$139,000</td>
<td>$101,000</td>
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<tr>
<td>Top 10-1%</td>
<td>21,479,400</td>
<td>$717,000</td>
<td>$1,383,000</td>
<td>$1,223,000</td>
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<tr>
<td>Top 1-0.1%</td>
<td>2,148,000</td>
<td>$3,730,000</td>
<td>$6,688,000</td>
<td>$6,317,000</td>
</tr>
<tr>
<td>Top 0.1-0.01%</td>
<td>214,800</td>
<td>$17,800,000</td>
<td>$32,160,000</td>
<td>$32,189,000</td>
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</table>

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

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

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

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

Sections C, D, and E describe the construction of variables in the tax data, the SCF, and the DFA, respectively. Section G gives sources for other data used in this paper. Section F describes the construction of aggregate parameters by portfolio category.

Section H details the classical minimum distance (CMD) procedure, including covariance expressions, the estimation steps, and the derivation of formulas for three-tier CMD fixed income wealth estimates. Section J describes how we estimate liquidity discounts for private business valuation. Section I describes the Forbes 400 portfolio data construction. Section K describes how we construct the panel of state-year capitalization factors for housing values.

Section L provides supplementary discussion of how our approach and results compares to SZ and PSZ (Section L.2), Forbes 400 (Section L.3), and estate tax data (Section L.4). Section M provides a detailed comparison of capitalization formula for estimating fixed income wealth.
A Appendix Figures

Figure A.1: Preferred Estimates and Updated SZ Estimates (Tax Units)

Notes: This figure plots top 0.1% wealth shares from our preferred tax-unit series and compares them to SZ and the updated series in Saez and Zucman (2020b) (as of September 2020, accessed in August 2021).
### Figure A.2: Top Shares of Wealth in the SCF Before and After Adjustments

#### A. Top 1%

<table>
<thead>
<tr>
<th>Year</th>
<th>Raw SCF</th>
<th>Incl. DB</th>
<th>Incl. F400</th>
<th>TU adj.</th>
<th>ES adj.</th>
<th>All adj. ES</th>
<th>All adj. TU</th>
<th>Preferred ES</th>
<th>Preferred TU</th>
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#### B. Top 0.1%

<table>
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<tr>
<th>Year</th>
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<th>Incl. DB</th>
<th>Incl. F400</th>
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<th>ES adj.</th>
<th>All adj. ES</th>
<th>All adj. TU</th>
<th>Preferred ES</th>
<th>Preferred TU</th>
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</table>

#### C. Progressive adjustments with tax unit ranks

##### Top 1%, 2016

- +4.55
- -5.75
- +0.46
- +1.47

##### Top 0.1%, 2016

- +1.96
- -2.35
- +0.10
- +2.01

#### D. Progressive adjustments with equal split ranks

##### Top 1%, 2016

- +1.75
- +2.67
- -5.30
- +0.40
- +1.54

##### Top 0.1%, 2016

- -0.92
- +1.05
- -2.08
- +0.07
- +2.05

**Notes:** The Raw SCF specification ranks by and uses the net worth bulletin concept directly from the SCF. To obtain tax unit ranks in the SCF, we follow Saez and Zucman (2019) in computing the number of households with wealth greater than each SCF observation, dividing this quantity by the number of US tax units in that year, and subtracting this quantity from one. To obtain equal split ranks in the SCF, we duplicate observations for which the respondent is married and halve net worth, then compute the number of individuals with wealth greater than each observation, divide this quantity by the number of US equal split individuals, and subtract this quantity from one. This procedure first converts household wealth into equal split wealth as we do in the tax data, and then adjusts the threshold to match the number of observations in the tax data. Defined benefit wealth adjustments rank by and use defined benefit wealth from Sabelhaus and Volz (2019). Panels A and B show baseline and final adjusted series, as well as series adjusted exclusively for DB wealth, tax unit rankings, and Forbes 400 wealth. Adjustments in panels C and D are successive. All Adjustments series in panels A and B are top shares after applying all adjustments from panels C and D.
Figure A.3: Components of Aggregate Household Wealth (1912-2016)

Notes: This figure extends the series shown in Figure 2A back to 1912. Wealth data is from Piketty, Saez and Zucman (2018), which draws from the US Financial Accounts (1945-2016) as well as Goldsmith, Brady, and Mendershausen (1956), Wolff (1989) and Kopczuk and Saez (2004) prior to 1945. National income data is from NIPA from 1929-onwards, and Kuznets (1941) and King (1930) before that.

Figure A.4: Components of Aggregate Household Wealth (1965-2016), PSZ18 versus SZ20

Notes: This figure compares aggregates derived from the Financial Accounts in Piketty, Saez and Zucman (2018) to those in the updated series with updated definitions in Saez and Zucman (2020b).
Figure A.5: Concentration of Fiscal Income Components (Ranked by Component)

A. Taxable Interest

B. Property Tax

C. Dividends

D. Capital Gains

E. S-corporation + Partnership

F. Sole Proprietorship

G. Wage

H. Pension Income

Notes: This figure describes the top share of fiscal income of different types. Panel A plots the evolution of top shares of interest income. Panel B, C, D, E, F, G, and H provide analogous series for property taxes, dividends, realized capital gains, S-corporation plus partnership income, sole proprietorship income, wages, and pension income, respectively. Ranks are for each component. For example, Panel A Top 10% plots the share of taxable interest income that goes to those in the top 10% of the taxable interest income distribution each year.
Figure A.6: Aggregate Taxable Interest Flows from Information Returns

A. Taxable Interest & Non-Qual Dividends

B. Total Info Flows Relative to Taxable Interest

C. Sources Relative to Taxable Interest

D. Sources Relative to Total Info Flows

Notes: This figure plots aggregate flows for each source of taxable interest identified in information returns plus non-qualified dividends over time. Panel A plots in nominal dollars each source from information returns (Form 1099-INT for banks, savings bonds, and private loans; Form 1065-K1 for partnerships; Form 1120S-K1 for S-corporations; Form 1041 for trusts) along with aggregate taxable interest and non-qualified dividends from individual tax returns (Form 1040). Panel B plots aggregate information return interest relative to aggregate taxable interest. Panel C plots the ratio of each source of information return interest relative to aggregate taxable interest. Panel D plots the share of each source of information return interest relative to aggregate information return interest.
Figure A.7: Interest Rates in Estate Tax Data under Uncertainty

Notes: This figure plots top interest rates under uncertainty for estate tax data. We bootstrap draws from the estate tax sample using SOI sample weights combined with age- and capital-income-specific mortality rates. We compute interest rates using our preferred definition, which attempts to remove fixed income funds from the fixed income asset definition.

Figure A.8: Average Rates of Return in Info Returns and CMD 3-Tier Approaches, 2016

Notes: This figure compares the average rates of return in 2016 under our preferred information-returns approach to those from our preferred classical minimum distance (CMD) approach. Both series plot the returns to taxable-interest-generating fixed income assets. In the CMD 3-Tier series, groups are ranked using total wealth including fixed income wealth estimated via the CMD approach. The preferred series is defined as in Figure 4B.
Figure A.9: Business in the SCF under Uncertainty

A. Pass-Throughs

Top 0.1%  P99-99.9  Top 1%

B. Pass-Throughs and Private C-corporations

Top 0.1%  P99-99.9  Top 1%

C. Public and Private C-corporations

Top 0.1%  P99-99.9  Top 1%

Notes: This figure plots private business (Panels A and B) and C-corporation equity (Panel C) as a share of total wealth for different top groups in the SCF under uncertainty. We sample SCF households using the replicate weights and following the procedure in Bricker, Henriques, Krimmel and Sabelhaus (2016).
Figure A.10: Equity Portfolio Heterogeneity across Groups

A. Dividend Participation

B. Capital Gains Participation

C. Dividend Composition

D. Capital Gains Composition

Notes: This figure documents portfolio heterogeneity along the wealth distribution in the nature of equity income-generating assets. Panels A and B are analogous to Figure 3B but for dividend income and realized capital gains, respectively. Panels C and D are similarly analogous to Figure 3C. Private 1099-DIV payers have fewer than 100 recipients, public 1099-DIV payers have 100 or more recipients and fewer than 10000 recipients, and brokers have more than 10,000 recipients. Form 1099-B reports capital gains and basis amounts at the asset level for certain assets. Other categories are defined as for Figure 3.
Figure A.11: Interest Rate and Dividend Yield Heterogeneity for Partnerships (2016)

Notes: This figure shows that interest rate heterogeneity is more important at the top for fixed income partnerships than dividend yield heterogeneity is for equity partnerships. We use data from information returns for fixed income partnerships and equity partnerships matched to the population of individual tax returns in 2016. For each series, we restrict the population of partnerships to those for which more than 99% of all income distributed to partners is either taxable interest or equity income (including dividends and capital gains). We estimate yields at the partnership level as a ratio of interest or dividend income to total assets reported by the partnership. For each individual, we use these yields to capitalize interest or dividend flows received and then construct a wealth-weighted average interest rate or yield for respective groups of individuals ranked by AGI.
Figure A.12: Public Company Share of Corporate Activity

A. Public Share of C-corp Activity

B. Public Share of C+S-corp Activity

Notes: This figure uses the SOI corporate sample to divide corporate activity between non-public companies and public companies, defined as having shares listed on a public stock exchange such that the company’s financial disclosures are available in the Compustat database. Panel A restricts to C-corporations. Panel B includes S-corporations.
Figure A.13: Identifying Carried Interest Compensation among Realized Capital Gains

A. SOI’s SOCA Totals Track the SOI Sample Capital Gains

B. Pass-Through Share of Gains Tracks 1065 K-1 Gains

C. General Partners Receive 20% of Distributed Gains

D. General Partner Gains versus Total and Top Capital Gains

Notes: This figure presents evidence supporting our attempt to estimate the share of top realized capital gains that reflects carried interest compensation for financial services general partners (e.g., hedge fund, venture capital, private equity managers). We combine the realized capital gains flows used in our capitalized income estimates with data from SOI’s Sale of Capital Assets (SOCA) study and information returns from different IRS databases. Fund managers are identified via the General Partner checkbox on information returns available in the e-file database.
Figure A.14: Persistence of Realized Capital Gains and Other Income Flows

A. Top 1% Dividends

B. Top 10% Dividends

C. Top 1% Interest

D. Top 10% Interest

E. Top 1% Adjusted Gross Income

F. Top 10% Adjusted Gross Income

G. Top 1% Wage Income

H. Top 10% Wage Income

Notes: This figure uses the population of individual tax returns to evaluate year-over-year persistence of different income flows. For each year from 1996 to 2015, we construct the flow rank for an individual or joint filer in that year and the next year. We plot the average next-year ranks within percentiles for the top 10% and within 1000-tiles for the top 1%, pooled over all years in the data set. We compare the rank-rank correlation for realized capital gains to that for dividends, interest, adjusted gross income, and wages.
Figure A.15: Comparing Approaches for Other Asset Classes

A. Pass-Through

B. Housing

C. Pension

D. Munis, Currency, Debt, Other

Notes: This figure shows the consequences of different approaches for pass-through business, housing, pensions, and other categories in Panels A, B, C, and D, respectively. It complements Figures 5C and 8C, which report series for taxable fixed income assets and C-corporation equity, respectively. The PSZ 2018 and Equal Returns series show the impact of differences in aggregates (e.g., the aggregate updates described in Section 1). All graphs rank by preferred wealth to isolate the impact of different wealth models. Panel A shows that going from the PSZ 2018 to updated aggregates in the equal return series lowers top 0.1% wealth. Our preferred approach, however, increases the contribution of pass-through business wealth to top 0.1% shares from around 2 with equal returns to around 3.5%, which exceeds the PSZ 2018 estimates by about a percentage point in 2016. We also report a series that excludes pass-through businesses in finance industries, which distribute no ordinary income, as some of this wealth likely appears elsewhere in our capitalized estimates. Panels B and D show that the aggregate updates between PSZ 2018 and equal returns are more minor in terms of the impact on the top, though Panel D shows larger amounts of municipal bonds, currency, and other in the equal returns series, mostly due to miscellaneous wealth no longer being allocated along with taxable fixed income wealth.
Figure A.16: Social Security Aggregates Relative to National Income

Notes: This figure shows aggregate wealth as a share of US national income under our preferred capitalized specification with and without Social Security wealth as estimated by Catherine, Miller and Sarin (2020) and Sabelhaus and Volz (2020).

Figure A.17: Validating Housing Capitalization Approach

A. Housing Assets Values Match

Financial Accounts

B. State Property Tax Rates Match ACS

Notes: This figure shows two validation exercises for our housing capitalization approach. Panel A compares the aggregate value of housing wealth using two alternative capitalization methods: using owner and renter-occupied wealth allocated to match Financial Accounts, and using CoreLogic and Housing Price Index assessments. Panel B scatters our preferred property tax rate measure (the inverse of our housing capitalization factors) against ACS property tax rates from US Census years from Fajgelbaum, Morales, Suárez Serrato and Zidar (2019).
Figure A.18: Portfolio Composition over Time

A. Fixed Income

Top 0.01%

Top 0.1%

Top 1%

B. C-corporation Equity

C. Pass-Through Business

D. Pensions

E. Housing

Notes: This figure presents analogous series to Figure 13 with portfolio shares for each group relative to the group's respective total wealth.
Figure A.19: Portfolio Totals at the Top of the Wealth Distribution

A. Top 0.01%

B. Top 0.1%

C. Top 1% equal-split individuals

D. Top 10% equal-split individuals

E. Top 1% tax units

D. Top 10% tax units

Notes: This figure shows portfolio totals in 2016 among top wealth groups for both equal-split individuals and tax unit definitions. SCF and DFA portfolio delineations are described in Appendix D and E, respectively.
Figure A.20: Portfolio Components in Levels over Time

A. Fixed Income

B. C-corporation Equity

C. Pass-Through Business

D. Pensions

E. Housing

Notes: This figure presents analogous series to Figure 13 with inflation-adjusted component levels for each group.
Figure A.21: Wealth Concentration by Group under Different Approaches (Tax Units)

Notes: This figure plots analogous series to Figure 14 defined at the tax unit level, which enables comparison to estimates from the DFA.
Figure A.22: Change in Top Wealth Shares by Component: 1989-2016

A. Top 1%

B. Top 0.1%

C. Top 0.01%

Notes: This figure decomposes the growth of the top 1%, 0.1%, and top 0.01% share of aggregate wealth by portfolio category under alternative capitalizations, as well as in the harmonized SCF with Forbes. Portfolio category bars are differences between 2016 and 1989 values in the series from Figure 13. Total top share changes are differences between 2016 and 1989 values in Figure 1B.
Figure A.23: Top Wealth Shares vs. Capitalized Income Shares in SCF

A. Replicating Figure IV.B. of Saez and Zucman (2016)

B. Actual vs. Capitalized Fixed Income

C. Actual vs. Capitalized Business Income

Notes: This figure plots the fraction of wealth (excluding housing and pensions) held by the top 10%, 1%, and 0.1% in the SCF using actual SCF wealth and capitalized income wealth. We exclude housing and pensions to exactly replicate Figure IV.B. of Saez and Zucman (2016). Panel A replicates Figure IV.B and plots two series. The solid line plots actual SCF wealth, while the dashed line plots SCF capitalized income. The composition of a given income group differs across the two measures as each group is defined using each series’ own ranking. For example, the share of wealth held by households that are in the top 10% of actual SCF wealth (excluding housing and pensions) are plotted in the solid blue series in Panel A, whereas the dashed series corresponds to a different group of top 10% households who have top 10% wealth based on ranking households using a wealth measure from capitalizing SCF income by category. Panel B and C show that the similarity in shares in Panel A masks substantial differences in actual versus capitalized wealth by category. Panel B shows that plotting the shares of fixed income wealth using the same overall wealth rankings as panel A reveals that the capitalized series overstates fixed income wealth concentration relative to the actual. In contrast, Panel C shows that capitalized private business income understates actual private business wealth concentration in the SCF.
Figure A.24: Top Share of Wealth with SCF Private Business Scaled to Match USFA

### A. Scaling Pass-Through Business

#### Top 0.01%

#### Top 0.1%

#### Top 1%

### B. Scaling Pass-Throughs and Private C-corporations

#### Top 0.01%

#### Top 0.1%

#### Top 1%

### C. Scaling Sole Proprietorships and Partnerships

#### Top 0.01%

#### Top 0.1%

#### Top 1%

**Notes:** This figure considers the impact on top wealth shares in the SCF of scaling private business in the SCF to match Financial Accounts totals. Panel A shows the effect of scaling down pass-through business assets. Panel B shows the effect of scaling down all private business, which includes pass-through business and private C-corporations. Panel C scales down non-corporate pass-through business only.
Figure A.25: Top Portfolio Shares with SCF Private Business Scaled to Match USFA

A. Fixed Income

B. C-corporation Equity

C. Pass-Through Business

Notes: This figure considers the impact of the adjustments in Appendix Figure A.25 for top portfolio shares in the SCF.
Figure A.26: Top Share of Wealth with SCF Fixed Income Scaled to Match USFA

A. Scaling All Fixed Income

B. Scaling Taxable-Interest-Generating Fixed Income

Notes: This figure considers the impact on top wealth shares in the SCF of scaling fixed income assets in the SCF to match Financial Accounts totals. Panel A shows the effect of scaling up all fixed income assets, including those that do not generate taxable interest. Panel B shows the effect of scaling down only fixed income assets that generate taxable interest.
Figure A.27: Top Portfolio Shares with SCF Fixed Income Scaled to Match USFA

A. Fixed Income

B. C-corporation Equity

C. Pass-Through Business

Notes: This figure considers the impact of the adjustments in Appendix Figure A.27 for top portfolio shares in the SCF.
Figure A.28: Top 0.1% Wealth Shares using Estate Tax Data

Notes: This figure plots top 0.1% wealth shares in estate tax data under four different approaches. First, Preferred Estate Tax uses estate tax data with our mortality rates, as defined in Section L.4. Second, SZ (2019) estate tax replication uses our implementation of Saez and Zucman (2019a)'s methodology for updating mortality differentials. Third, SZ (2019) estate tax facsimile plots a copied series from their published figure, which differs from the replication series because it smooths estimates across years. For example, there is a data point in 2010, although the estate tax was temporarily abolished that year. Fourth, KS (2004) updated follows the approach in Kopczuk and Saez (2004b), updated in Saez and Zucman (2016) and then by us through 2016. Prior to 1995, we use the Kopczuk and Saez (2004b) estate tax series from the appendix in Saez and Zucman (2016). The figure also shows top 0.1% wealth shares in our preferred capitalized series and under equal returns.
Figure A.29: Sensitivity of Age Group Wealth Shares to Mortality Rates in Top 0.1%

Notes: This figure plots the wealth shares of age groups within the top 0.1% of the wealth distribution in estate tax data. For example, a value of 2% for age group 51-55 means that those individuals in this age group collectively hold 2% of total household wealth. It also shows the change in estimated wealth share resulting from a 0.1 percentage point increase in mortality rates for each age group. Specifically, the bottom series is our estate tax wealth share estimate minus the “perturbed” estimate. For example, a value of 0.5% for the group 51-55 would indicate that if we raised the mortality rate by 0.001 for everyone in the age group, the estimated wealth share would drop by 0.5% of total household wealth. The two series are the mean across years from 1998 to 2016.
### Table B.1: Interest Rates for Fixed Income Partnerships Grouped by Common Words (2016)

<table>
<thead>
<tr>
<th>Fund Name</th>
<th>Token</th>
<th>Number of Funds</th>
<th>Rate, Unweighted Mean</th>
<th>Std. Dev.</th>
<th>Rate, Weighted Mean</th>
<th>Std. Dev.</th>
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<tbody>
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<td>FUND</td>
<td>2095</td>
<td>4.77</td>
<td>4.81</td>
<td>2.40</td>
<td>3.24</td>
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<td>PARTNERS</td>
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<td>2.79</td>
<td>3.21</td>
<td>3.21</td>
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<td>INVESTMENT</td>
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<td>INVESTMENTS</td>
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<td>4.56</td>
<td>4.14</td>
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<td>CAPITAL</td>
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<td>HOLDING</td>
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<td>4.28</td>
<td>5.12</td>
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<td>HOLDINGS</td>
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<td>4.98</td>
<td>4.92</td>
<td>4.28</td>
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<td>5.22</td>
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<td>2.69</td>
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<td>VENTURE</td>
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</table>

**Notes:** This table presents additional evidence that boutique funds invest in riskier assets. We group all 18,758 fixed income partnerships identified in 2016 and then assign each fund to one of many groups based on common words used in the fund’s name. To preserve taxpayer confidentiality, the table only contains words that would not identify particular entities and restricts to those words that appear in more than 50 fund names.
Table B.2: Interest Rates for Fixed Income Partnerships, Private Loans, and Corporate Bonds (2016)

<table>
<thead>
<tr>
<th></th>
<th>Mean (%)</th>
<th>Std. Dev. (%)</th>
<th>P5 (%)</th>
<th>P25 (%)</th>
<th>P50 (%)</th>
<th>P75 (%)</th>
<th>P95 (%)</th>
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<td><strong>Fixed Income Partnerships, Tax Data</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>All</td>
<td>4.9</td>
<td>4.8</td>
<td>0.3</td>
<td>1.3</td>
<td>3.8</td>
<td>6.8</td>
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<td><strong>Private Loans, Tax Data</strong></td>
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<tr>
<td>All</td>
<td>4.5</td>
<td>4.2</td>
<td>0.5</td>
<td>1.9</td>
<td>3.7</td>
<td>6.0</td>
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<td><strong>Corporate Bonds with Moody’s Ratings</strong></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Prime (AAA, N = 91)</td>
<td>2.8</td>
<td>1.0</td>
<td>1.3</td>
<td>1.8</td>
<td>3.0</td>
<td>3.8</td>
<td>4.3</td>
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<tr>
<td>High (AA1-AA3, N = 564)</td>
<td>2.8</td>
<td>1.0</td>
<td>1.4</td>
<td>1.9</td>
<td>2.6</td>
<td>3.8</td>
<td>4.3</td>
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<td>Upper Medium (A1-A3, N = 2,183)</td>
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<td>1.0</td>
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<td>1.8</td>
<td>2.7</td>
<td>3.6</td>
<td>4.5</td>
<td>5.6</td>
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<tr>
<td>Speculative (BA1-BA3, N = 698)</td>
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<td>1.4</td>
<td>2.5</td>
<td>3.8</td>
<td>4.7</td>
<td>5.5</td>
<td>7.0</td>
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<tr>
<td>Highly Speculative (B1-B3, N = 565)</td>
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<td>1.8</td>
<td>3.5</td>
<td>5.1</td>
<td>5.9</td>
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<td>9.7</td>
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<tr>
<td>Substantial Risks (CAA1-CAA3, N = 172)</td>
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<td>5.8</td>
<td>7.3</td>
<td>8.6</td>
<td>11.3</td>
<td>14.6</td>
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<tr>
<td>Extremely Speculative (CA, N = 14)</td>
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<td>7.4</td>
<td>11.9</td>
<td>12.6</td>
<td>14.8</td>
<td>15.6</td>
</tr>
</tbody>
</table>

*Notes:* This table presents statistics on average interest rates for fixed income partnerships and private loans, as measured in administrative tax data, and for different categories of corporate bonds. 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. 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. For private loans we construct a firm-level interest rate as the sum of taxable interest reported on all information returns issued by the firm divided by the sum of mortgages, loans from shareholders, and other non-current liabilities reported on the firm’s tax return (Form 1120 or 1120S, Schedule L). We restrict the sample to firms that issue fewer than 10 information returns to individuals and where total interest on information returns approximately matches the firm’s total interest payments (Form 1120 or 1120S, Line 13). To preserve taxpayer anonymity, quantiles at percentile P are means centered around P plus or minus 1 percent. Corporate bond data come from Thomson Reuters eMaxx database, which contain asset holdings for fixed income mutual funds and other institutional investors, and from the Bond Returns database in Wharton Research Data Services, which contains data on bond yields and credit ratings. The table contains yield-to-maturity information for 7,470 bonds rated by Moody’s and held by fixed income funds in the eMaxx data in 2016Q4.
Table B.3: Characteristics of top-owned businesses in the SCF (2016)

<table>
<thead>
<tr>
<th></th>
<th>P99-99.9 wealth</th>
<th>Top 0.1% wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. dev.</td>
</tr>
<tr>
<td>Share (%) own any business</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>Number of businesses owned</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Actively managed</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Non-actively managed</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

**Active Business #1**

|                                |       |           |      |      |      |      |       |           |      |      |      |
| Share (%) own 1+ actively-mgd bus. | 54    | 72       |      |      |      |      |       |           |      |      |      |
| Gross sales                     |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 80,638| 635,722   | 2,500| 0    | 10,000,000| 176,027| 689,162| 22,500| 0     | 17,577,640|
| Respondents’ share              | 5,786 | 15,310    | 1,166| 0    | 262,500  | 63,626  | 192,566| 10,516| 0     | 4,394,410 |
| Net income (profits)            |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 8,827 | 49,547    | 300  | -1,000| 1,250,000| 25,998  | 107,652| 4,700  | -1,000| 3,000,000|
| Respondents’ share              | 612   | 1,391     | 160  | -1,000| 21,000   | 5,467   | 16,683 | 1,650  | -1,000| 990,000   |
| Market value                    |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 27,163| 80,101    | 6,429| 0    | 1,000,000| 101,665| 283,144| 30,030| 0     | 4,592,000|
| Respondents’ share              | 5,650 | 5,810     | 4,000| 0    | 30,000   | 40,694  | 85,080 | 18,890| 0     | 1,375,350|
| Cost basis                      |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 11,913| 46,205    | 1,500| 0    | 640,000  | 22,430  | 104,951| 4,706  | 0     | 2,500,000|
| Respondents’ share              | 1,986 | 4,184     | 500  | 0    | 45,000   | 16,011  | 38,060 | 700   | 0     | 391,340   |
| Total employment                | 207   | 782       | 10   | 1    | 5,000    | 868     | 40     | 1     | 5,000   |      |

**Active Business #2**

|                                |       |           |      |      |      |      |       |           |      |      |      |
| Share (%) own 2+ actively-mgd bus. | 20    | 41       |      |      |      |      |       |           |      |      |      |
| Gross sales                     |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 3,862 | 15,668    | 454  | 0    | 400,000  | 12,666  | 49,506 | 2,000  | 0     | 1,080,340|
| Respondents’ share              | 1,648 | 12,926    | 290  | 0    | 400,000  | 4,567   | 16,011 | 700   | 0     | 378,602   |
| Net income (profits)            |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 560   | 3,115     | 50   | -325 | 36,460   | 2,042   | 16,639 | 450   | -1,000| 423,580   |
| Respondents’ share              | 143   | 375       | 30   | -325 | 3,900    | 512     | 1,214  | 180   | -920  | 43,838    |
| Market value                    |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 4,575 | 7,208     | 2,400| 0    | 48,000   | 47,357  | 145,419| 9,440  | 0     | 2,000,000|
| Respondents’ share              | 2,053 | 2,246     | 1,300| 0    | 26,410   | 8,185   | 18,481| 5,000  | 0     | 300,830   |
| Cost basis                      |       |           |      |      |      |      |       |           |      |      |      |
| Total                           | 2,124 | 3,907     | 1,000| 0    | 32,000   | 27,219  | 100,824| 3,000  | 0     | 1,549,143|
| Respondents’ share              | 1,089 | 1,820     | 350  | 0    | 19,800   | 3,681   | 7,958  | 1,600  | 0     | 119,110   |
| Total employment                | 29    | 71        | 3    | 1    | 600      | 71      | 194   | 10    | 1     | 5,000    |      |

**Active Businesses #3 and Beyond**

|                                |       |           |      |      |      |      |       |           |      |      |      |
| Share (%) own 3+ actively-mgd bus. | 11    | 24       |      |      |      |      |       |           |      |      |      |
| Net income rcvd by respondents  | 281   | 475       | 30   | -650 | 2,660   | 1,021   | 3,532  | 367   | -500  | 52,080    |
| Market value respondents’ share | 3,515 | 5,080     | 1,420| 0    | 20,000   | 15,009  | 40,126 | 7,410  | 0     | 922,110   |
| Cost basis respondents’ share   | 1,362 | 2,566     | 250  | 0    | 15,000   | 6,306   | 16,658 | 4,800  | 0     | 270,160   |

**Non-actively managed businesses**

|                                |       |           |      |      |      |      |       |           |      |      |      |
| Share (%) own non-actively mgd bus. | 22    | 43       |      |      |      |      |       |           |      |      |      |
| Net income rcvd by respondents  | 109   | 348       | 30   | -195 | 5,861   | 789    | 2,659  | 92    | -100  | 57,290    |
| Market value respondents’ share | 2,038 | 3,395     | 583  | 20   | 33,260  | 14,829  | 47,381 | 2,815  | 0     | 901,941   |
| Cost basis respondents’ share   | 581   | 1,154     | 250  | 0    | 12,000   | 5,413   | 22,199 | 671   | 0     | 486,190   |

**Notes:** This table describes privately-held businesses owned by households at the top of the wealth distribution in the SCF, ranked by our preferred SCF wealth concept. Rows entitled share “Share (%) own n+ actively-mgd business” are the share of individuals reporting any ownership stake in n or more businesses. Active businesses #1 and #2 are the two actively-managed businesses that respondents identify as their largest and next-largest actively-managed businesses. For these businesses, “total” net income, gross sales, market value, and cost basis correspond to the whole business, whereas “respondents’ share” represent respondents’ shares only. “Number of businesses owned” is the sum of actively-managed and non-actively managed businesses owned.
### Table B.4: Valuation multiples for top-owned businesses in the SCF vs. Compustat (2016)

#### A. Top-Owned Businesses in the SCF

<table>
<thead>
<tr>
<th></th>
<th>P99-99.9 wealth</th>
<th>Top 0.1% wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. dev.</td>
</tr>
<tr>
<td><strong>Active Business #1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value</td>
<td>2.6</td>
<td>2.0</td>
</tr>
<tr>
<td>Sales</td>
<td>22.6</td>
<td>19.2</td>
</tr>
<tr>
<td>Profits</td>
<td>8.0</td>
<td>8.0</td>
</tr>
<tr>
<td>Cost basis</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Active Business #2</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value</td>
<td>2.8</td>
<td>2.0</td>
</tr>
<tr>
<td>Sales</td>
<td>24.5</td>
<td>20.2</td>
</tr>
<tr>
<td>Profits</td>
<td>5.8</td>
<td>7.2</td>
</tr>
<tr>
<td>Cost basis</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Active Businesses #3 and Beyond</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value</td>
<td>27.8</td>
<td>19.9</td>
</tr>
<tr>
<td>Profits</td>
<td>5.8</td>
<td>6.4</td>
</tr>
<tr>
<td>Cost basis</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Non-actively managed businesses</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value</td>
<td>31.8</td>
<td>20.0</td>
</tr>
<tr>
<td>Profits</td>
<td>5.5</td>
<td>7.0</td>
</tr>
<tr>
<td>Cost basis</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### B. Compustat

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market value</td>
<td>1.8</td>
<td>1.3</td>
<td>0.2</td>
<td>0.7</td>
<td>1.5</td>
<td>2.7</td>
<td>4.4</td>
</tr>
<tr>
<td>Sales</td>
<td>16.3</td>
<td>9.3</td>
<td>5.2</td>
<td>10.2</td>
<td>14.2</td>
<td>19.9</td>
<td>37.1</td>
</tr>
<tr>
<td>Pretax Income</td>
<td>3.0</td>
<td>2.8</td>
<td>0.7</td>
<td>1.3</td>
<td>2.0</td>
<td>3.5</td>
<td>8.6</td>
</tr>
<tr>
<td>Book Equity</td>
<td>6.5</td>
<td>5.4</td>
<td>0.5</td>
<td>1.7</td>
<td>4.9</td>
<td>10.3</td>
<td>17.5</td>
</tr>
</tbody>
</table>

**Notes:** This table compares valuation distributions for the private businesses in the SCF versus those in Compustat. Panel A shows valuation multiples for private businesses owned by households at the top of the wealth distribution in the SCF, ranked by our preferred wealth concept. Multiples are calculated using market values, net income, gross sales, and cost basis measures shown in Appendix Table B.3, and adjust for partial ownership of the businesses. All multiples are bottom-censored at zero. Consistent with our private business valuation inputs, sales multiples are top-censored at 5, cost basis multiples are top-censored at 20, and net income multiples are top-censored at 50. Panel B shows valuation multiples for approximately analogous concepts in Compustat. Because there is no cost-basis concept in Compustat, we report multiples relative to the book value of equity and the net value of property, plants, and equipment.
Table B.5: Valuation multiples for top 1%-owned businesses in the SCF: detail (2016)

<table>
<thead>
<tr>
<th>Total sales under 1M</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P50</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share top 1%-owned lgst actively-mngd bus. value</td>
<td>8.53</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value Sales</td>
<td>3.81</td>
<td>1.82</td>
<td>0.49</td>
<td>5.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Market value Profits</td>
<td>28.46</td>
<td>20.35</td>
<td>0.00</td>
<td>50.00</td>
<td>50.00</td>
</tr>
<tr>
<td>Market value Cost basis</td>
<td>7.43</td>
<td>8.21</td>
<td>0.74</td>
<td>2.24</td>
<td>20.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total sales from 1M to 10M</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P50</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share top 1%-owned lgst actively-mngd bus. value</td>
<td>28.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value Sales</td>
<td>3.03</td>
<td>1.76</td>
<td>0.50</td>
<td>2.90</td>
<td>5.00</td>
</tr>
<tr>
<td>Market value Profits</td>
<td>25.99</td>
<td>18.60</td>
<td>0.67</td>
<td>22.22</td>
<td>50.00</td>
</tr>
<tr>
<td>Market value Cost basis</td>
<td>9.25</td>
<td>8.13</td>
<td>1.00</td>
<td>5.00</td>
<td>20.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total sales from 10M to 50M</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P50</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share top 1%-owned lgst actively-mngd bus. value</td>
<td>27.73</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value Sales</td>
<td>1.26</td>
<td>1.24</td>
<td>0.22</td>
<td>0.83</td>
<td>5.00</td>
</tr>
<tr>
<td>Market value Profits</td>
<td>14.19</td>
<td>13.28</td>
<td>0.05</td>
<td>8.89</td>
<td>50.00</td>
</tr>
<tr>
<td>Market value Cost basis</td>
<td>7.91</td>
<td>7.60</td>
<td>0.83</td>
<td>3.16</td>
<td>20.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total sales from 50M to 100M</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P50</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share top 1%-owned lgst actively-mngd bus. value</td>
<td>4.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value Sales</td>
<td>0.68</td>
<td>0.79</td>
<td>0.00</td>
<td>0.47</td>
<td>2.18</td>
</tr>
<tr>
<td>Market value Profits</td>
<td>11.69</td>
<td>16.27</td>
<td>1.00</td>
<td>5.33</td>
<td>50.00</td>
</tr>
<tr>
<td>Market value Cost basis</td>
<td>6.36</td>
<td>7.58</td>
<td>0.80</td>
<td>1.81</td>
<td>20.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total sales greater than 100M</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>P5</th>
<th>P50</th>
<th>P95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share top 1%-owned lgst actively-mngd bus. value</td>
<td>30.69</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market value Sales</td>
<td>0.76</td>
<td>0.67</td>
<td>0.00</td>
<td>0.55</td>
<td>1.40</td>
</tr>
<tr>
<td>Market value Profits</td>
<td>9.31</td>
<td>12.78</td>
<td>0.00</td>
<td>6.32</td>
<td>50.00</td>
</tr>
<tr>
<td>Market value Cost basis</td>
<td>7.66</td>
<td>7.95</td>
<td>0.80</td>
<td>2.33</td>
<td>20.00</td>
</tr>
</tbody>
</table>

Notes: This table shows valuation multiples among the single largest actively-managed businesses owned by households in the top 1% of the SCF wealth distribution, conditional on these households owning at least one actively-managed business. We bin businesses by their total gross sales, reported in question X3131. We calculate “Share top 1%-owned largest actively-managed business value” as each bin’s share of total private business wealth in the table; for example, firms with between 1M and 10M in sales account for 28.12% of the total wealth across all size bins.
Table B.6: Industrial Composition of Pass-through Firm Value (2016)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Industry (NAICS)</th>
<th>S&amp;P Value ($B)</th>
<th>Returns (%)</th>
<th>Value/Firm ($M)</th>
<th>Value/Owner ($M)</th>
<th>S Value</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Other financial investment activity (5239)</td>
<td>1,043.8</td>
<td>2.6</td>
<td>4.1</td>
<td>0.5</td>
<td>52.8</td>
<td>991.0</td>
</tr>
<tr>
<td>2</td>
<td>Lessors of real estate (5311)</td>
<td>530.3</td>
<td>0.3</td>
<td>0.4</td>
<td>0.2</td>
<td>57.3</td>
<td>473.0</td>
</tr>
<tr>
<td>3</td>
<td>Restaurants (7225)</td>
<td>260.7</td>
<td>3.9</td>
<td>1.2</td>
<td>0.7</td>
<td>179.0</td>
<td>81.7</td>
</tr>
<tr>
<td>4</td>
<td>Management/holding cos (5511)</td>
<td>243.8</td>
<td>4.9</td>
<td>4.4</td>
<td>0.3</td>
<td>151.0</td>
<td>92.8</td>
</tr>
<tr>
<td>5</td>
<td>Other professional/technical svc (5419)</td>
<td>216.4</td>
<td>7.8</td>
<td>0.9</td>
<td>0.6</td>
<td>162.0</td>
<td>54.4</td>
</tr>
<tr>
<td>6</td>
<td>Activities related to real estate (5313)</td>
<td>201.3</td>
<td>4.8</td>
<td>0.4</td>
<td>0.1</td>
<td>47.3</td>
<td>154.0</td>
</tr>
<tr>
<td>7</td>
<td>Other specialty trade cntrctr (2389)</td>
<td>157.8</td>
<td>9.9</td>
<td>0.9</td>
<td>0.7</td>
<td>140.0</td>
<td>17.8</td>
</tr>
<tr>
<td>8</td>
<td>Legal svc (5411)</td>
<td>140.5</td>
<td>36.4</td>
<td>1.3</td>
<td>0.7</td>
<td>43.0</td>
<td>97.5</td>
</tr>
<tr>
<td>9</td>
<td>Other investment pools/funds (5259)</td>
<td>120.1</td>
<td>1.4</td>
<td>2.2</td>
<td>0.2</td>
<td>5.1</td>
<td>115.0</td>
</tr>
<tr>
<td>10</td>
<td>Offices of physicians (6211)</td>
<td>104.8</td>
<td>21.2</td>
<td>1.0</td>
<td>0.6</td>
<td>75.9</td>
<td>28.9</td>
</tr>
<tr>
<td>11</td>
<td>Computer sys design/related svc (5415)</td>
<td>89.0</td>
<td>10.2</td>
<td>0.7</td>
<td>0.5</td>
<td>74.3</td>
<td>14.7</td>
</tr>
<tr>
<td>12</td>
<td>Automobile dealers (4411)</td>
<td>88.8</td>
<td>8.2</td>
<td>2.3</td>
<td>1.5</td>
<td>75.0</td>
<td>13.8</td>
</tr>
<tr>
<td>13</td>
<td>Misc. durable goods merch whlsl (4239)</td>
<td>86.5</td>
<td>6.8</td>
<td>1.6</td>
<td>1.1</td>
<td>73.8</td>
<td>12.7</td>
</tr>
<tr>
<td>14</td>
<td>Accounting/bookkeeping svc (5412)</td>
<td>81.3</td>
<td>13.2</td>
<td>1.0</td>
<td>0.7</td>
<td>34.1</td>
<td>47.2</td>
</tr>
<tr>
<td>15</td>
<td>Traveler acmdtn (7211)</td>
<td>77.1</td>
<td>3.6</td>
<td>1.5</td>
<td>0.5</td>
<td>30.4</td>
<td>46.7</td>
</tr>
<tr>
<td>16</td>
<td>Nonresidential building constr (2362)</td>
<td>70.5</td>
<td>11.1</td>
<td>1.7</td>
<td>1.1</td>
<td>59.4</td>
<td>11.1</td>
</tr>
<tr>
<td>17</td>
<td>Building foundation/exterior cntrctr (2381)</td>
<td>69.5</td>
<td>10.4</td>
<td>0.6</td>
<td>0.5</td>
<td>61.8</td>
<td>7.7</td>
</tr>
<tr>
<td>18</td>
<td>Oil/gas extraction (2111)</td>
<td>60.0</td>
<td>1.4</td>
<td>1.3</td>
<td>0.1</td>
<td>21.4</td>
<td>38.6</td>
</tr>
<tr>
<td>19</td>
<td>General freight trucking (4841)</td>
<td>59.3</td>
<td>5.5</td>
<td>0.6</td>
<td>0.5</td>
<td>50.9</td>
<td>8.4</td>
</tr>
<tr>
<td>20</td>
<td>Residential building constr (2361)</td>
<td>57.8</td>
<td>15.2</td>
<td>0.3</td>
<td>0.2</td>
<td>42.6</td>
<td>15.2</td>
</tr>
<tr>
<td>21</td>
<td>Building equipment cntrctr (2382)</td>
<td>57.0</td>
<td>18.2</td>
<td>0.5</td>
<td>0.4</td>
<td>52.6</td>
<td>4.4</td>
</tr>
<tr>
<td>22</td>
<td>Other miscellaneous store retailers (4539)</td>
<td>51.6</td>
<td>5.7</td>
<td>0.8</td>
<td>0.6</td>
<td>43.1</td>
<td>8.5</td>
</tr>
<tr>
<td>23</td>
<td>Other motor vehicle dealers (4412)</td>
<td>50.2</td>
<td>3.2</td>
<td>4.2</td>
<td>2.8</td>
<td>43.0</td>
<td>7.2</td>
</tr>
<tr>
<td>24</td>
<td>Other miscellaneous mfg. (3399)</td>
<td>49.3</td>
<td>9.0</td>
<td>1.5</td>
<td>0.7</td>
<td>40.1</td>
<td>9.2</td>
</tr>
<tr>
<td>25</td>
<td>Security contracts broker (5231)</td>
<td>48.8</td>
<td>2.9</td>
<td>3.2</td>
<td>0.2</td>
<td>8.5</td>
<td>40.3</td>
</tr>
<tr>
<td>26</td>
<td>Depository credit intrmd (5221)</td>
<td>47.2</td>
<td>3.1</td>
<td>26.7</td>
<td>1.8</td>
<td>46.6</td>
<td>0.6</td>
</tr>
<tr>
<td>27</td>
<td>Offices of dentists (6212)</td>
<td>46.9</td>
<td>18.8</td>
<td>0.7</td>
<td>0.6</td>
<td>43.0</td>
<td>3.9</td>
</tr>
<tr>
<td>28</td>
<td>Nondepository credit intrmd (5222)</td>
<td>46.8</td>
<td>6.0</td>
<td>2.1</td>
<td>0.7</td>
<td>32.1</td>
<td>14.7</td>
</tr>
<tr>
<td>29</td>
<td>Insurance agencies/brokerages (5242)</td>
<td>44.2</td>
<td>20.0</td>
<td>0.5</td>
<td>0.4</td>
<td>36.6</td>
<td>7.6</td>
</tr>
<tr>
<td>30</td>
<td>Other fabricated metal prod mfg. (3329)</td>
<td>43.0</td>
<td>9.9</td>
<td>2.4</td>
<td>1.4</td>
<td>38.5</td>
<td>4.5</td>
</tr>
<tr>
<td></td>
<td>Aggregate</td>
<td>6,327.6</td>
<td>7.6</td>
<td>0.8</td>
<td>0.3</td>
<td>3,389.3</td>
<td>2,938.2</td>
</tr>
</tbody>
</table>

Notes: This table presents statistics on the value of all pass-through businesses by 4-digit industry in 2016. The rows are sorted by the level of total pass-through value for S-corporations and partnerships. For this table, we are using population-level information returns and business tax returns to generate values, so the totals do not exactly match those in our main wealth estimates, which are based on the SOI individual sample. Returns are estimated as the ratio of ordinary income to pass-through business value according to our preferred specification.
Table B.7: Implied Rates of Return for Pass-Through Business (2001–2016)

<table>
<thead>
<tr>
<th></th>
<th>Mean (%)</th>
<th>Std. Dev. (%)</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>P10 (%)</th>
<th>P50 (%)</th>
<th>P90 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>S-corporations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unweighted</td>
<td>11.26</td>
<td>30.58</td>
<td>-0.13</td>
<td>4.46</td>
<td>-20.05</td>
<td>7.67</td>
<td>51.09</td>
</tr>
<tr>
<td>Value-weighted</td>
<td>9.88</td>
<td>17.69</td>
<td>0.92</td>
<td>8.27</td>
<td>-2.98</td>
<td>5.87</td>
<td>30.85</td>
</tr>
<tr>
<td><strong>Partnerships</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unweighted</td>
<td>4.16</td>
<td>24.66</td>
<td>0.57</td>
<td>7.29</td>
<td>-11.55</td>
<td>0.00</td>
<td>34.47</td>
</tr>
<tr>
<td>Value-weighted</td>
<td>6.12</td>
<td>17.77</td>
<td>1.74</td>
<td>9.54</td>
<td>-2.48</td>
<td>0.00</td>
<td>27.86</td>
</tr>
</tbody>
</table>

Notes: This table presents statistics on average returns to private business wealth for the population of pass-through businesses and their owners from 2001 to 2016. We first construct returns at the owner-firm-year level as the ratio of ordinary business income to pass-through value according to our preferred specification. We then compute mean returns at the owner-level using pass-through value as weights. Finally, we compute value-weighted and unweighted distributions of owner-level returns for S-corporations and partnerships. To preserve taxpayer anonymity, quantiles at percentile P are means centered around P plus or minus 0.5 percent.
Table B.8: Total Housing Wealth under Heterogeneous Property Tax Capitalization (2016)

<table>
<thead>
<tr>
<th>State</th>
<th>2016 Housing Wealth</th>
<th>2016 Housing Wealth (cont.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Assets (B)</td>
<td>Wealth (B)</td>
</tr>
<tr>
<td>AK</td>
<td>48.24</td>
<td>10.81</td>
</tr>
<tr>
<td>AL</td>
<td>213.45</td>
<td>82.63</td>
</tr>
<tr>
<td>AR</td>
<td>128.70</td>
<td>53.68</td>
</tr>
<tr>
<td>AZ</td>
<td>504.59</td>
<td>250.45</td>
</tr>
<tr>
<td>CA</td>
<td>7757.94</td>
<td>5090.96</td>
</tr>
<tr>
<td>CO</td>
<td>631.84</td>
<td>343.28</td>
</tr>
<tr>
<td>CT</td>
<td>354.59</td>
<td>175.32</td>
</tr>
<tr>
<td>DC</td>
<td>54.69</td>
<td>11.68</td>
</tr>
<tr>
<td>DE</td>
<td>72.14</td>
<td>36.45</td>
</tr>
<tr>
<td>FL</td>
<td>1977.42</td>
<td>1293.72</td>
</tr>
<tr>
<td>GA</td>
<td>589.29</td>
<td>264.57</td>
</tr>
<tr>
<td>HI</td>
<td>202.28</td>
<td>105.95</td>
</tr>
<tr>
<td>IA</td>
<td>188.53</td>
<td>101.53</td>
</tr>
<tr>
<td>ID</td>
<td>88.61</td>
<td>30.05</td>
</tr>
<tr>
<td>IL</td>
<td>962.20</td>
<td>479.84</td>
</tr>
<tr>
<td>IN</td>
<td>323.62</td>
<td>165.88</td>
</tr>
<tr>
<td>KS</td>
<td>147.26</td>
<td>66.29</td>
</tr>
<tr>
<td>KY</td>
<td>173.36</td>
<td>62.09</td>
</tr>
<tr>
<td>LA</td>
<td>221.89</td>
<td>92.31</td>
</tr>
<tr>
<td>MA</td>
<td>891.79</td>
<td>509.38</td>
</tr>
<tr>
<td>MD</td>
<td>679.01</td>
<td>339.53</td>
</tr>
<tr>
<td>ME</td>
<td>96.87</td>
<td>47.13</td>
</tr>
<tr>
<td>MI</td>
<td>555.84</td>
<td>287.42</td>
</tr>
<tr>
<td>MN</td>
<td>446.01</td>
<td>213.51</td>
</tr>
<tr>
<td>MO</td>
<td>328.48</td>
<td>162.29</td>
</tr>
<tr>
<td>MS</td>
<td>85.79</td>
<td>30.16</td>
</tr>
<tr>
<td>MT</td>
<td>66.67</td>
<td>21.01</td>
</tr>
</tbody>
</table>

Notes: This table summarizes total housing assets and wealth under heterogeneous property tax capitalization. Asset and wealth totals are measured in billions of 2016 dollars; per capita measures are in thousands of 2016 dollars.
Table B.9: Changes in Piketty, Saez, and Zucman (2018) relative to our preferred specification by asset class

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Top 1%</td>
<td>Top 0.1%</td>
</tr>
<tr>
<td>Panel A. Taxable fixed income</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>Heterogeneous returns, PSZ aggregate</td>
<td>32.7</td>
<td>14.8</td>
</tr>
<tr>
<td>4.</td>
<td>Equal returns, SZZ aggregate</td>
<td>36.8</td>
<td>19.1</td>
</tr>
<tr>
<td>5.</td>
<td>Heterogeneous returns, SZZ aggregate</td>
<td>32.6</td>
<td>15.0</td>
</tr>
<tr>
<td>6.</td>
<td>Heterogeneous returns SZZ agg., reranked</td>
<td>33.8</td>
<td>15.8</td>
</tr>
</tbody>
</table>

Panel B. C-corporation equity

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>90% weight on dividends, PSZ aggregate</td>
<td>36.2</td>
<td>18.2</td>
</tr>
<tr>
<td>4.</td>
<td>Equal weight on divs &amp; KGs, SZZ aggregate</td>
<td>37.8</td>
<td>19.9</td>
</tr>
<tr>
<td>5.</td>
<td>90% weight on dividends, SZZ aggregate</td>
<td>36.0</td>
<td>18.0</td>
</tr>
<tr>
<td>6.</td>
<td>90% weight on dividends SZZ agg., reranked</td>
<td>36.3</td>
<td>18.3</td>
</tr>
<tr>
<td>7.</td>
<td>Blend in Forbes 400, reranked</td>
<td>36.2</td>
<td>18.2</td>
</tr>
</tbody>
</table>

Panel C. Formal pass-through business

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>SZZ methodology scaled to PSZ total</td>
<td>38.1</td>
<td>20.5</td>
</tr>
<tr>
<td>4.</td>
<td>SZZ methodology scaled to SZZ total</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>5.</td>
<td>SZZ methodology</td>
<td>38.0</td>
<td>20.4</td>
</tr>
<tr>
<td>6.</td>
<td>SZZ methodology, reranked</td>
<td>38.8</td>
<td>21.1</td>
</tr>
<tr>
<td>7.</td>
<td>Blend in Forbes 400, reranked</td>
<td>38.5</td>
<td>20.6</td>
</tr>
</tbody>
</table>

Panel D. Pensions

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>Age profile capitalization, PSZ aggregate</td>
<td>36.7</td>
<td>20.4</td>
</tr>
<tr>
<td>4.</td>
<td>PSZ pension build, SZZ aggregate</td>
<td>36.2</td>
<td>18.8</td>
</tr>
<tr>
<td>5.</td>
<td>Age profile capitalization, SZZ aggregate</td>
<td>34.6</td>
<td>19.1</td>
</tr>
<tr>
<td>6.</td>
<td>Age profile capitalization SZZ agg., reranked</td>
<td>35.6</td>
<td>19.3</td>
</tr>
</tbody>
</table>

Panel E. Owner-occupied housing assets

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>Geographic heterogeneity, PSZ aggregate</td>
<td>38.2</td>
<td>20.2</td>
</tr>
<tr>
<td>4.</td>
<td>Equal returns, SZZ aggregate</td>
<td>38.6</td>
<td>20.5</td>
</tr>
<tr>
<td>5.</td>
<td>Geographic heterogeneity, SZZ aggregate</td>
<td>37.8</td>
<td>19.9</td>
</tr>
<tr>
<td>6.</td>
<td>Geographic heterogeneity SZZ agg., reranked</td>
<td>37.9</td>
<td>20.0</td>
</tr>
</tbody>
</table>

Panel F. Mutual funds

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>Allocate according to non-qualified dividends</td>
<td>38.3</td>
<td>20.3</td>
</tr>
<tr>
<td>4.</td>
<td>Allocate according to non-qualified dividends, reranked</td>
<td>38.4</td>
<td>20.4</td>
</tr>
</tbody>
</table>

Panel G. Miscellaneous wealth

<table>
<thead>
<tr>
<th>Panel</th>
<th>Asset Class</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2.</td>
<td>PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3.</td>
<td>Allocate in proportion to other wealth</td>
<td>38.0</td>
<td>20.1</td>
</tr>
<tr>
<td>4.</td>
<td>Allocate in proportion to other wealth, reranked</td>
<td>38.0</td>
<td>20.1</td>
</tr>
</tbody>
</table>

Notes: This table shows effects of perturbing capitalization approaches relative to PSZ 2018 on wealth shares and portfolio composition by asset class and wealth groups. PSZ 2018’s “mixed method,” is the ranking PSZ use when presenting their baseline wealth shares, which does not include capital gains in equity capitalization when ranking individuals into wealth groups, but does put equal weight on dividends and capital gains when calculating top shares. Rows labelled “PSZ 2018 reranked without mixed method...” undoes this choice, ranking and calculating wealth shares using the same wealth concept, which we do when presenting non-replicated wealth shares throughout the paper. Rows reranked “after asset class refinements” are ranked by Wealth^{PSZ18} − a^{PSZ18} + a^{SZZ} for a ∈ {Taxable fixed income, C-corporation equity,..., Mortgages for tenant-occupied housing}. We describe substantive updates to capitalization methodology in asset class-specific sections, and describe updates to aggregate wealth categories in Appendix F.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top 1%</td>
<td>Top 0.1%</td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Allocate in proportion to other wealth</td>
<td>38.0</td>
<td>20.1</td>
</tr>
<tr>
<td>4. Allocate in proportion to other wealth, reranked</td>
<td>38.0</td>
<td>20.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel I. Other refinements</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top 1%</td>
<td>Top 0.1%</td>
</tr>
<tr>
<td><strong>Sole proprietorships</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Update aggregate</td>
<td>38.6</td>
<td>20.5</td>
</tr>
<tr>
<td>4. Update agg., reranked</td>
<td>38.6</td>
<td>20.5</td>
</tr>
<tr>
<td><strong>Mortgages for owner-occupied housing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Update aggregate</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>4. Update agg., reranked</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td><strong>Non-mortgage debt</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Update aggregate</td>
<td>37.4</td>
<td>19.8</td>
</tr>
<tr>
<td>4. Update agg., reranked</td>
<td>37.4</td>
<td>19.8</td>
</tr>
<tr>
<td><strong>Currency</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Update aggregate</td>
<td>38.2</td>
<td>20.2</td>
</tr>
<tr>
<td>4. Update agg., reranked</td>
<td>38.2</td>
<td>20.2</td>
</tr>
<tr>
<td><strong>Non-taxable fixed claims</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
<td>20.2</td>
</tr>
<tr>
<td>3. Update aggregate</td>
<td>38.4</td>
<td>20.3</td>
</tr>
<tr>
<td>4. Update agg., reranked</td>
<td>38.5</td>
<td>20.3</td>
</tr>
<tr>
<td><strong>Tenant-occupied housing assets</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. PSZ 2018</td>
<td>36.6</td>
<td>18.6</td>
</tr>
<tr>
<td>2. PSZ 2018, reranked without mixed method</td>
<td>38.1</td>
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<td>3. Update aggregate</td>
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<td><strong>Mortgages for tenant-occupied housing</strong></td>
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*Notes:* This table is part two of Table B.9.
Table B.10: Changes in preferred specification relative to PSZ by asset class

<table>
<thead>
<tr>
<th>Panel</th>
<th>Taxable fixed income</th>
<th>Wealth shares in 2016</th>
<th>Portfolio shares in 2016</th>
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<tr>
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<td>16.9</td>
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<td>C-corporation equity</td>
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Notes: This table is similar to Table B.9, but considers changes starting from our preferred specification rather than from the PSZ specification.
Table B.10 (cont.): Changes in preferred specification by asset class

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<tr>
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<td>4. Update agg., reranked</td>
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<td><strong>Mortgages for tenant-occupied housing</strong></td>
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Notes: This table is part two of Table B.10.
Notes on changes relative to Piketty, Saez, and Zucman (2018) by asset class:

- Every panel:
  - “PSZ 2018 (mixed method)” is PSZ 2018’s preferred specification. PSZ ignore capital gains and capitalize equity solely based on dividends “when ranking individuals into wealth groups,” but take capital gains into account “when computing top shares” (SZ 2016 page 534, section III.B.2).

A.1, B.1, ..., G.1 “PSZ 2018 reranked with dividends and KGs capitalization” ranks individuals by the net worth concept that PSZ 2018 use to calculate top wealth shares, a concept that, unlike the ranking concept in the “mixed method,” fully capitalizes capital gains. In other words, this step undoes PSZ’s “mixed method.”

- Panel A: Taxable fixed income
  A.2 Allocate PSZ 2018 stale stock concept, which includes fixed income mutual funds, using information returns to account for heterogeneity by interest income composition and AGI rank.
  A.3 Preferred taxable fixed claims concept: Allocate updated (smaller) stock concept, which excludes fixed income mutual funds, using information returns to account for heterogeneity by interest income composition and AGI rank.
  A.4 Reranks after refining taxable fixed claims capitalization, so that ranking concept is wealth concept from A.1 minus PSZ 2018 taxable fixed claims plus preferred taxable fixed claims (e.g. A.3) concept.
  A.5 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. A.1) concept, but rerank after refinements to fixed income (same ranking as in A.4).

- Panel B: C-corporation equity
  B.2 Allocate PSZ 2018 stale stock concept, which is constructed using coarser S-corporation equity and IRA equities concepts (both subtracted off from a total “Corporate equity” concept in the Financial Accounts) and includes a portion of money market fund shares. Use a composite flow of 90% dividends, 10% capital gains.\textsuperscript{76}
  B.3 Preferred C-corporation equity concept: capitalized updated C-corporation aggregate, which excludes any money market fund shares and subtracts off refined estimates of total S-corporation equity and IRA equities holdings from total equity, using composite flow of 90% dividend and 10% KGs.
  B.4 Reranks after refining C-corp. equity capitalization, so that ranking concept is wealth concept from B.1 minus PSZ 2018 C-corp equity plus preferred C-corp equity (e.g. B.3) concept.

\textsuperscript{76}Capitalization factor is \( \beta_{\text{C-corp}} = \frac{\text{Aggregate C-corporation wealth}}{0.9 \times \text{Aggregate dividends} + 0.1 \times \text{Aggregate KGs}} \), applied at the individual level to a flow of \( 0.9 \times \text{Dividends}_i + 0.1 \times \text{KGs}_i \).
B.5 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. B.1) concept, but rerank after refinements to C-corp equity (same ranking as in B.4).

• Panel C: Formal pass-through business (e.g. S-corporations and partnerships)

C.2 Use our preferred multiples-based valuation, implementing a 75% “human capitalists”’ reduction in profits and a 10% liquidity discount, but scale S-corporation and partnership assets so that aggregate valuations match PSZ 2018 S-corporation and partnership aggregates, respectively.

C.3 Preferred formal pass-through concept: Use our preferred multiples-based valuation, implementing a 75% “human capitalists”’ reduction in profits and a 10% liquidity discount, untethering aggregates from PSZ 2018.

C.4 Reranks after refining formal pass-through capitalization, so that ranking concept is wealth concept from C.1 minus PSZ 2018 plus preferred (e.g. C.3) concept.

C.5 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. C.1) concept, but rerank after refinements to formal pass-through business (same ranking as in C.4).

• Panel D: Pensions

D.2 Allocate PSZ 2018 pension wealth, which comprises IRA holdings, life insurance reserves, defined contribution pensions, and the funded portion of defined benefit pensions, using our age group-variant wage and pension income flows methodology.

D.3 Use preferred capitalization methodology (as in D.2) to allocate updated version of PSZ 2018 pension wealth, which uses a more recent Financial Accounts release than PSZ (2016Q2 → 2020Q2) but does not make any substantive modifications.

D.4 Preferred pensions concept: Use preferred capitalization modification to allocate updated pension aggregate, which is PSZ 2018 pension wealth plus unfunded DB pension assets.

D.5 Reranks after refining formal pass-through capitalization, so that ranking concept is wealth concept from D.1 minus PSZ 2018 plus preferred (e.g. D.4) concept.

D.6 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. D.1) concept, but rerank after refinements to formal pass-through business (same ranking as in D.5).

• Panel E: Mutual funds (note: PSZ 2018 lumps money market and bond mutual funds in with taxable fixed income and C-corporation equity), so unlike other asset classes there is no PSZ 2018 version of this aggregate).

E.2 Preferred mutual funds concept: Allocate aggregate taxable bonds and loans held through mutual funds according to non-qualified dividends, following SZ 2020.
E.3 Reranks after allocating mutual funds separately from taxable fixed claims and equity, so that ranking concept is wealth concept from E.1 minus PSZ 2018 plus preferred (e.g. D.4) concept.

E.4 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. D.1) concept, but rerank after separate capitalization of taxable bonds and loans held in mutual funds (same ranking as in D.5).

• Panel F: Owner-occupied housing assets

F.2 Allocate PSZ 2018 housing stock concept, which is conceptually identical to latest aggregate but whose underlying Financial Account series were subject to quantitatively significant updates, using state property tax rates.

F.3 Preferred owner-occupied housing assets concept: allocate updated housing stock concept (conceptually identical to PSZ 2018 aggregate but underlying Financial Account series subject to significant updates) using state property tax rates.

F.4 Reranks after refining formal pass-through capitalization, so that ranking concept is wealth concept from F.1 minus PSZ 2018 plus preferred (e.g. F.3) concept.

F.5 Reranking only: Calculates top shares using PSZ 18’s preferred wealth (e.g. F.1) concept, but rerank after refinements to formal pass-through business (same ranking as in F.4).

• Panel G: Other refinements describes refinements to asset classes for which we do not change capitalization methodology relative to PSZ 2018, but only update stock concepts. For all categories except “Mortgages for owner-occupied housing,” the updated aggregates represent conceptually important changes:

  – Sole proprietorships The stock concept we use for capitalization is in fact total equity in non-corporate business minus tenant-occupied real estate net of mortgages. This includes sole proprietorships but also partnerships, because the Financial Accounts does not disaggregate partnership and sole prop. equity. The PSZ 2018 vintage uses a more expansive concept for mortgages associated with rental properties, resulting in a larger estimate of business assets than in the updated vintage.

  – Non-mortgage debt Relative to the PSZ 2018 and SZ 2020 version of this concept, we make two modifications for conceptual consistency. First, we remove auto loans from the non-mortgage debt concept, as these loans secure durables whose values neither we nor PSZ are trying to capture through capitalization. Second, we scale down credit card debt to the level reported in the SCF. As discussed in Batty et al. 2020 “The Distributional Financial Accounts of the United States” appendix A, the Financial Accounts measure of credit card debt includes “convenience use” balances on credit cards, e.g. credit card debt that is paid off at the end of each month, whereas the corresponding SCF measure comprises only rotating balances.

  – Currency In the PSZ 2018 vintage, SZ do not subtract off cash and non-interest bearing deposits of non-profits from their currency totals, leading them to slightly
overstate the amount of cash and non-interest bearing deposits held by households. This is fixed in updated aggregates.

- **Non-taxable fixed claims** In both updated and PSZ 2018 aggregates, SZ sum the same concepts for “munis directly held,” “Munis held through mutual funds,” and “Money market fund shares invested in munis;” however, in updated aggregates, SZ use a ready-made series to estimate government securities held by non-profits, and do not subtract off a concept for municipal bonds held by IRAs, making the updated concept larger than the PSZ 2018 concept.

- **Tenant-occupied housing assets** In both updated and PSZ 2018 aggregates, SZ construct this concept as the value of tenant-occupied properties net of mortgages associated with those properties; however, in the Revisionists vintage, SZ use a narrower definition of these mortgages (see note on sole proprietorships above), driving up their estimate of the value of tenant-occupied properties net of mortgages.

- **Mortgages for tenant-occupied housing assets** In PSZ 2018, SZ used “Nonfinancial noncorporate business; total mortgages; liability” (Financial Accounts series FL113165005). This concept encompassed not only mortgages for single- and multi-family tenant-occupied dwellings, but also farms and commercial mortgages. SZ Revisionists construct this concept, which we use, as the sum of mortgages associated with “one-to-four family dwellings,” “multifamily dwellings,” and farms.
Figure B.1: Summary of Changes Relative to PSZ 2018

A. Changes in Top Shares relative to PSZ by Category

-4 -3 -2 -1 0 1
Percentage Points of Total Household Wealth

Fixed Income C-Corporations Pass-Through Pensions Housing + Rental Other

B. Decomposing Top Share Differences in Absolute Value by Category

<table>
<thead>
<tr>
<th>Category</th>
<th>Top 1%</th>
<th>Top 0.1%</th>
<th>Top 0.01%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Income</td>
<td>42.4</td>
<td>51.7</td>
<td>54.2</td>
</tr>
<tr>
<td>C-Corporations</td>
<td>18.2</td>
<td>22.8</td>
<td>20.3</td>
</tr>
<tr>
<td>Pass-Through</td>
<td>11.1</td>
<td>12.6</td>
<td>10.2</td>
</tr>
<tr>
<td>Pensions</td>
<td>25.3</td>
<td>10.3</td>
<td>8.5</td>
</tr>
<tr>
<td>Housing + Rental</td>
<td>2.0</td>
<td>2.3</td>
<td>5.1</td>
</tr>
<tr>
<td>Other</td>
<td>1.0</td>
<td>1.1</td>
<td>1.7</td>
</tr>
</tbody>
</table>

Notes: This exhibit plots the total change in top shares between our preferred approach and PSZ 2018 by asset class for different wealth groups in Table B.9. The specific change is calculated as the difference between line 2 and the second to last line in each asset class. For example, for the top 0.1%, the difference between line 2 and line 6 values of 20.2 and 15.8 is 4.4 percentage points for fixed income. For the category fixed income, we sum the change in Panel A, F, non-mortgage debt, currency, and non-taxable fixed income claims. For pass-throughs, we sum Panel C, H, and sole proprietorships. For housing and rental, we sum Panel E with Mortgages for owner-occupied housing, Tenant-occupied housing assets, and Mortgages for tenant-occupied housing. Other is panel G. Panel B decomposes the sum of the absolute value of these differences into contributions from each category.
C Portfolio Category Definitions in Tax Data

C.1 Overall wealth

This section provides portfolio definitions in our preferred capitalized series. For some portfolio categories, our capitalization methodology changes over time due to issues with data availability in earlier years. Below is a brief discussion of these categories.

At a high level, the wealth concept we use is

\[
\text{Net worth} = \text{Currency} + \text{Taxable interest-generating fixed claims} + \text{Tax-exempt interest-generating fixed claims} \\
+ \text{Bonds and loans held in mutual funds} + \text{C-corporation equity} + \text{Pass-through business} \\
+ \text{Pensions} + \text{Housing net of mortgages} + \text{Non-mortgage debt} + \text{Miscellaneous wealth} + \text{Forbes wealth}
\]

2016 example = $1.0T + $9.3T + $2.3T + $2.3T + $10.3T + $11.2T + $32.6T + $18.4T - $2.6T + $1.0T + $1.2T = $86.9T

C.2 Wealth categories

Currency = currency

2016 example = $1.0T


Taxable interest-generating fixed claims = \begin{cases} 
\text{taxbond_info} & \text{if year} \geq 2001 \\
\text{taxbond_cmd_3tier} & \text{if year} < 2001 \end{cases}

2016 example = $9.3T

where taxbond_info capitalizes interest income by using Financial Accounts, SCF, and tax data to generate and apply source specific (e.g. banks, business loans, deposits) capitalization factors. To calculate taxbond_cmd_3tier, we use the covariance structure of interest rates, assets, and returns to estimate risk exposure to credit and interest rate risk for different groups. We then use this risk-exposure approach to estimate returns.
Tax-exempt interest-generating fixed claims = muni

\[ muni_{2016 \text{ example}} = 2.3T \]


Bonds and loans held in mutual funds = taxbond_muf

\[ \text{taxbond}_{2016 \text{ example}} = 2.3T \]

where \textit{taxbond} \textit{muf} allocates aggregate bonds and loans held in mutual funds using the SZ (2020) aggregate in proportion to non-qualified dividends from 2003-onward, and proportionally to financial wealth (defined as the sum of taxable interest-generating fixed claims, tax-exempt interest-generating fixed claims, and C-corporation equity) beforehand.

C-corporation equity = ccorw_9010

\[ \text{ccorw}_{2016 \text{ example}} = 10.3T \]

where \textit{ccorw} \textit{9010} capitalizes a composite flow made up of 90% dividends and 10% capital gains using updated aggregates from SZ (2020).

Pass-through business = \(\begin{cases} \text{solepropw} + \text{s.value.avg.ebitda.red} + \text{p.value.avg.ebitda.red} + \text{missing.scorp} + \text{missing.pship} & \text{if year} \geq 2001 \\ \text{solepropw} + \text{scorw} + \text{partw} + \text{missing.scorp} + \text{missing.pship} & \text{if year} < 2001 \end{cases}\)

\[ \text{2016 example} = 3.2T + 3.8T + 3.1T + 0.2T + 0.9T = 11.2T \]

where \textit{solepropw}, \textit{partw}, and \textit{scorw} use PSZ (2018) capitalization methodology and updated aggregates from SZ (2020), \textit{s.value.avg.ebitda.red} and \textit{p.value.avg.ebitda.red} use our multiples-based valuation, and \textit{missing.scorp} and \textit{missing.pship} allocate missing pass-through wealth to
individuals in proportion to other wealth.

\[
Pensions = \begin{cases} 
penw_{szz \text{ scaled}} & \text{if year } \geq 1980 \\
szz\cdot penw_{\text{pre1980}} & \text{if year } < 1980 
\end{cases}
\]

\[
\text{2016 example } = \$32.6T
\]

where \(penw_{szz \text{ scaled}}\) determines pension wealth by capitalizing wage and pension income using age- and source-specific capitalization factors. Pension wealth is then scaled to match the updated aggregate from SZ (2020) plus an estimate of the value of unfunded defined benefit entitlements from Sabelhaus and Volz (2019). For \(szz\cdot penw_{\text{pre1980}}\), we allocate 60% of pension wealth in proportion to wage income and the other 40% in proportion to pension income. As with \(penw_{szz \text{ scaled}}\), we use the updated aggregate from SZ (2020) and add in unfunded defined benefit entitlements.

\[
\text{Housing net of mortgages} = \begin{cases} 
\text{ownerhome}_{szz} + \text{rentalhome} + \text{ownermort} + \text{rentalmort} & \text{if year } \geq 1980 \\
\text{ownerhome}_{\text{ini}} + \text{rentalhome} + \text{ownermort}_{\text{ini}} + \text{rentalmort} & \text{if year } < 1980 
\end{cases}
\]

\[
\text{2016 example } = \$23.6T + \$6.2T - \$9.6T - \$1.8T = \$18.4T
\]

where \(\text{ownerhome}_{\text{ini}}\) and \(\text{ownermort}_{\text{ini}}\) use PSZ (2018) capitalization methodology and PSZ (2018) aggregates; \(\text{rentalhome}, \text{ownermort},\) and \(\text{rentalmort}\) use PSZ (2018) capitalization model with updated aggregates from SZ (2020); and \(\text{ownerhome}_{szz}\) capitalizes owner-occupied housing values using heterogeneous property tax rates and updated aggregates from SZ (2020).

\[
\text{Non-mortgage debt} = \text{nonmort}
\]

\[
\text{2016 example } = -\$2.6T
\]

where \(\text{nonmort}\) uses PSZ (2018) capitalization methodology and updated aggregates from SZ (2020).

\[
\text{Miscellaneous wealth} = \text{miscw}_{\text{hweal}}
\]

\[
\text{2016 example } = \$1.0B
\]

where \(\text{miscw}_{\text{hweal}}\) allocates financial assets not classified elsewhere in proportion to other wealth.
Forbes wealth = \begin{cases} 
\text{forbes400\_wealth} & \text{if } \text{year} \geq 1982 \\
0 & \text{if } \text{year} < 1982 
\end{cases}

\begin{align*}
\text{2016 example} &= $1.2T
\end{align*}

where \text{forbes400\_wealth} blends the Forbes 400 with tax data following BHV (2019). Forbes wealth is allocated to portfolio categories according to the portfolio shares of the top 0.01% in the SCF. We also present Forbes results in terms of tax units (as opposed to our baseline individual-level approach in Figure 11) which shows $2.4T, which is the initial value before constructing the equal-split individual-level series.
D Portfolio Category Definitions in the SCF

This section describes our portfolio category definitions in the SCF. For definitions of variables in the SCF Bulletin extract data (henceforth “bulletin concepts”), see the SCF’s page “SAS macro - Variable Definitions (TXT),” which is available here: https://www.federalreserve.gov/econres/files/bulletin.macro.txt. All figures are in current dollars.

D.1 Portfolio components not defined in SCF Bulletin extract data

D.1.1 Overview

We make two major departures from bulletin concepts when measuring aggregate wealth and portfolio composition:

1. Add defined benefit pensions We use estimates from Sabelhaus and Volz (2019) (SHV) and use them to allocate an aggregate defined benefits concept which matches the sum of funded and unfunded defined benefit assets according to Financial Accounts definitions in Saez and Zucman (2020b).

2. Disaggregate bulletin concepts to allocate assets and liabilities across portfolio categories We disaggregate the following bulletin concepts at the level of the SCF observation (henceforth “at the micro-level”):

   (a) bus: Disaggregate into private C-corporation (privccorw) and pass-through (pthrubus) components.

   (b) oresre: Break out mortgages issued by surveyed households (mortgageassets) to allocate to taxable interest-generating fixed claims.

   (c) othfin: Break out cash (cash) to allocate to currency, and private loans (privloans) to allocate to taxable interest-generating fixed claims.

   (d) othnfin: Break out durables (durables), which we exclude from our preferred net worth concept.

   (e) trusts: Split trusts into portions invested in equity (trusts_equity) and proportions invested in “other;” further allocate the “other” component into taxable interest-generating fixed claims (trusts_intttaxw), tax-exempt fixed claims (trusts_intexmw), and bonds and loans held in mutual funds (trusts_mmbondfund).

D.1.2 Add defined benefit pensions

We use SHV’s defined benefit pension allocation methodology to use a different aggregate concept than they allocate in their paper. The aggregate concept SHV 2020 allocate is “Households and nonprofit organizations; defined benefit and annuity pension entitlements; asset” (series code FL153050045).

Because the SCF includes a direct measure of annuities, and because the questions SHV use to calculate future payments pertain only to defined

benefit pensions and not annuities, we choose a less expansive Financial Accounts concept, namely “Defined benefit pension funds; pension entitlements (total liabilities)” (series code FL594190045 https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL594190045&t=). This series is the aggregate defined benefit pension wealth concept in Saez and Zucman (2020b) (see appendix sheet “DataWealth” column BR), though SZ allocate only the funded portion.

In practice, we merge on defined benefit pensions variables from SHV and calculate our preferred measure as:

\[
\text{Defined benefit pensions} \equiv \text{Tot_pen}_db = (\text{currec_pv}_dbamt_rtot + \text{currec_pv}_dbamt_stot + \text{future_pv}_dbamt_rtot + \text{future_pv}_dbamt_stot + \text{curjob_pv}_dbamt_rtot + \text{curjob_pv}_dbamt_stot) \times \text{Defined benefit pension funds; pension entitlements (total liabilities)}
\]

\[\text{2016 example} = (\$5.6T + \$1.7T + \$334B + \$96B + \$6.75T + \$3.2T) \times 83.75\% = \$14.8T\]

D.1.3 Disaggregate bulletin concepts to allocate assets and liabilities across portfolio categories

We disaggregate private business (bus) in two steps. First, we separately calculate the market values of survey participants’ largest three (before 2010) or two (from 2010 onward) actively-managed businesses. Second, we use actively-managed business organizational form questions X3119, X3219, X3319 (before 2010), and organizational form-specific non-actively managed business questions to allocate shares in respondents’ largest actively-managed businesses and all non-actively managed businesses across C-corporation and pass-through categories. Finally, we calculate the C-corporation share of identifiable private business equity and allocate the remainder (actively-managed businesses smaller than the second- or third-largest business) proportionally across organizational forms. In 2016, the calculation at the micro-level is:

\[\text{Actvly-mgd. bus. 1 mkt. val.} = \max(0, X3129) + \max(0, X3124) - \max(0, X3126) \times (X3127 = 5) + \max(0, X3121) \times \text{inlist}(X3122, 1, 6)\]

\[\text{Actvly-mgd. bus. 2 mkt. val.} = \max(0, X3229) + \max(0, X3224) - \max(0, X3226) \times (X3227 = 5) + \max(0, X3221) \times \text{inlist}(X3222, 1, 6)\]

\[\text{Private C-corp. (prelim.)} = \text{Actvly-mgd. bus. 1 mkt. val.} \times (X3119 = 4) + \text{Actvly-mgd. bus. 2 mkt. val.} \times (X3219 = 4) + \max(0, X3420)\]

\[\text{Pass-through (prelim.)} = \text{bus} - \text{Private C-corp. (prelim.)} - \max(0, X3335)\]

\[\text{Private C-corp. } \equiv \text{privccorw} = \text{Private C-corp. (prelim.)} + \frac{\text{Private C-corp. (prelim.)}}{\text{Private C-corp. (prelim.)} + \text{Pass-through (prelim.)}} \times \max(0, X3335)\]

\[\text{Pass-through (prelim.)} \equiv \text{pthrubus} = \text{Pass-through (prelim.)} + \left(1 - \frac{\text{Private C-corp. (prelim.)}}{\text{Private C-corp. (prelim.)} + \text{Pass-through (prelim.)}}\right) \times \max(0, X3335)\]

We calculate mortgages issued by surveyed households as:

\[\text{Mortgage assets } \equiv \text{mortgageassets} = \begin{cases} \max(X1405, X1409) + \max(X1505, X1509) + \max(0, X1619) & \text{if year } \leq 2010 \\ \max(X1306, X1310) + \max(X1325, X1329) + \max(0, X1339) & \text{if year } > 2010 \end{cases}\]
We calculate cash as:

\[
\text{Cash} \equiv \text{cash} = X_{4022} \times (X_{4020} = 63) + X_{4026} \times (X_{4024} = 63) + X_{4030} \times (X_{4028} = 63)
\]

where \( X_{4022}, X_{4026}, \) and \( X_{4030} \) are the values of respondents’ most valuable, second most valuable, and third most valuable miscellaneous assets, and a code of 63 for \( X_{4020}, X_{4024}, \) and \( X_{4028} \) indicates that the aforementioned assets are “Cash not elsewhere classified.”

We calculate private loans as

\[
\text{Private loans} \equiv \text{privloans} = X_{4022} \times \text{inlist}(X_{4020}, 61, 62) + X_{4026} \times \text{inlist}(X_{4024}, 61, 62) + X_{4030} \times \text{inlist}(X_{4028}, 61, 62)
\]

where codes 61 and 62 indicate that miscellaneous assets 1, 2, and 3 are “Loans to friends/relatives” and “Other loans/debts owed to [respondent],” respectively.

We calculate durables as

\[
\text{Durables} \equiv \text{durables} = X_{4022} \times \text{inlist}(X_{4020}, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76) + X_{4026} \times \text{inlist}(X_{4024}, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76) + X_{4030} \times \text{inlist}(X_{4028}, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76)
\]

where codes 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, and 76 indicate that miscellaneous assets 1, 2, and 3 are “Jewelry; gem stones (incl. antique);” “Cars (antique or classic);” “Antiques; furniture;” “Art objects; paintings, sculpture, textile art, ceramic art, photographs;” “(Rare) books;” “Coin collections;” “Stamp collections;” “Guns;” “China; figurines; crystal/glassware;” “Musical instruments;” “Oriental rugs;” “Furs;” “Other collections, incl. baseball cards, records, wine;” “Computer;” and “Equipment/tools, NEC,” respectively.

We disaggregate trusts (\text{trusts}) in two steps:

1. We split \text{trusts} into the portion invested in equities and the portion invested in other assets, following the SZ 2020 assumption that this share is 50% before 2004.

2. We allocate the “other assets” portion across three fixed claims categories: taxable interest-generating fixed claims, tax-exempt fixed claims (e.g. municipal bonds); and bonds and loans held in mutual funds. For individuals with non-zero assets in the three aforementioned fixed claims categories, we allocate in proportion to their (non-trust) assets across these categories. For individuals with zero assets in the three categories, we allocate in proportion to aggregate allocation.

In practice, step 1 is:

\[
\text{Share trusts invested in equity} = \begin{cases} 
(X_{6591} = 1) + \text{inlist}(X_{6591}, 3, 30) \times \max(0, X_{6592})/10,000 & \text{if year} \geq 2004 \\
0.5 & \text{if year} < 2004 
\end{cases}
\]

\[
\text{Trusts invested in equity} \equiv \text{trusts\_equity} = \text{Sh. trusts inv. in equ.} \times \text{trusts}
\]

\[
\text{Trusts not invested in equity} = \text{trusts} - \text{trusts\_equity}
\]
and step 2 is:

Non-trust txble int.-gen. fixed claims = saving + cds + mmda + call + savbnd + (bond − notxbnd) + privloans + mortgageassets

Non-trust tax-exempt fixed claims = notxbnd + tfbmutf

Non-trust fix mut. funds = (0.5 × comutf) + (0.5 × omutf) + gbmutf + obmutf + mmmf

Trusts inv. in txble int.-gen. fixed claims =

\[
\text{trusts} \times \text{Non-trust txble int.-gen. fixed claims}
\]

Trusts inv. in tax-exempt fixed claims =

\[
\text{trusts} \times \text{Non-trust tax-exempt fixed claims}
\]

Trusts inv. in fix mut. funds =

\[
\text{trusts} \times \text{Non-trust fix mut. fds}
\]

D.2 Main wealth categories

In our harmonized SCF series, aggregate wealth is:

\[
\text{Net worth} = \text{networth} + \text{tot pen db} - (\text{vehic} - \text{veh inst}) - \text{durables}
\]

\[
\begin{align*}
2016 \text{ example} &= $86.9T + $14.8T - ($2.7T - $733B) - $501B = $99.2T
\end{align*}
\]

where networth, vehic, and veh_inst are bulletin concepts representing total wealth, vehicles, and vehicle loans respectively, and tot_pen_db and durables are defined as in section D.1. We refer to the networth bulletin concept as “raw SCF” wealth.

Below is a mutually exclusive and collectively exhaustive categorization of the assets in our preferred net worth concept. We often refer to the sum of currency; taxable interest-generating fixed claims; tax-exempt fixed claims; and bonds and loans held in mutuals funds as “fixed income,” though we only use taxable interest-generating fixed claims to calculate interest rates.

\[
\text{Currency} = \text{checking} + \text{cash} + \text{prepaid}
\]

\[
\begin{align*}
2016 \text{ example} &= $1.17T + $6B + $8B - $1.18T
\end{align*}
\]

where checking and prepaid are bulletin concepts representing checking accounts (excl. money market) and prepaid cards, respectively, and cash is defined as in section D.1.

\[
\text{Taxable interest-generating fixed claims} = \text{saving} + \text{cds} + \text{mmda} + \text{call} + \text{savbnd} + (\text{bond} − \text{notxbnd}) + \text{privloans} + \text{mortgageassets} + \text{trusts inttaxw}
\]

\[
\begin{align*}
2016 \text{ example} &= $2.0T + $620B + $1.1T + $350B + $104B + ($1.2T - $781B) + $0 + $319B \\
&+ $968B = 5.9T
\end{align*}
\]
where saving, cds, mmda, call, savbnd, bond, and notxbnd are bulletin concepts representing savings accounts; certificates of deposit; money market deposit accounts; call accounts; savings bonds; bonds; and tax-exempt bonds, respectively, and privloans, mortgageassets, and trusts_inttaxw are defined as in section D.1.

\[
\text{tax-exempt fixed claims} = \text{notxbnd} + \text{tfbmutf} + \text{trusts_intexmw}
\]

\[
\begin{align*}
2016 \text{ example} &= 781B + 1.3T + 222B = 2.3T
\end{align*}
\]

where notxbnd and tfbmutf are bulletin concepts representing tax-exempt bonds and tax-free bond mutual funds, and trusts_intexmw is defined as in section D.1.

\[
\text{Bonds and loans held in mutual funds} = (0.5 \times \text{comutf}) + (0.5 \times \text{omutf}) + \text{gbmutf} + \text{obmutf} + \text{mmmf} + \text{trusts_mmbondfund}
\]

\[
\begin{align*}
2016 \text{ example} &= 378B + 505B + 276B + 404B + 318B + 163B = 2.0T
\end{align*}
\]

where comutf, omutf, gbmutf, obmutf, and mmmf are bulletin concepts representing combination mutual funds; other mutual funds; government bond mutual funds; other bond mutual funds; and money market mutual funds, respectively, and trusts_mmbondfund is defined as in section D.1.

\[
\text{C-corporation equity} = \text{stocks} + \text{privccorw} + \text{stmutf} + (0.5 \times \text{comutf}) + (0.5 \times \text{omutf}) + \text{trusts_equity}
\]

\[
\begin{align*}
2016 \text{ example} &= 5.7T + 2.6T + 5.9T + 378B + 505B + 1.0T + = 16.1T
\end{align*}
\]

where stocks, stmutf, comutf, and omutf are bulletin concepts representing directly-held stocks, stock mutual funds, combination mutual funds, and other mutual funds, respectively, and privccorw and trusts_equity are defined as in section D.1.

\[
\text{Pass-through business} = \text{pthrubus} + \text{nnresre}
\]

\[
\begin{align*}
2016 \text{ example} &= 16.8T + 3.7T = 20.5T
\end{align*}
\]

where nnresre is the bulletin concept representing net equity in non-residential real estate and pthrbus is defined as in section D.1.

\[
\text{Pensions} = \text{annuit} + \text{cashli} + \text{retqliq} + \text{tot_pen_db}
\]

\[
\begin{align*}
2016 \text{ example} &= 876B + 914B + 15.0T + 14.8T = 31.6T
\end{align*}
\]

where annuit, cashli, and retqliq are bulletin concepts representing annuities, cash value of whole life insurance, and quasi-liquid retirement accounts (including individual and employer-sponsored account-type pensions), and tot_pen_db is as defined in section D.1.
Housing = houses + (oresre − mortgageassets) + mrthel + resdbt

$^{2016\ example} = 24.2T + (6.3T − 31.9B) + 8.3T + 1.1T = 20.7T$

where houses, oresre, mrthel, and resdbt are SCF bulletin concepts representing primary residence; residential property excluding primary residence (e.g. vacation homes); debt secured by primary residence; and debt secured by other residential property, respectively, and mortgageassets is as defined in section D.1.

Non-mortgage debt = −othloc − ccbal − edn_inst − oth_inst − odeb

$^{2016\ example} = −127B − 316B − 962B − 280B − 176B = −1.9T$

where othloc, ccbal, edn_inst, oth_inst, and odeb are all bulletin concepts representing other lines of credit not secured by residential real estate; credit card balances; education loans; other installment loans; and other debt (e.g. loans against pensions or life insurance, margin loans).

Other = (othfin − cash − privloans) + (othnfin − durables)

$^{2016\ example} = (659B − 6B − 0) + (559B − 501B) = 710B$

where othfin and othnfin are bulletin concepts representing other miscellaneous financial and non-financial assets, respectively, and cash, privloans, and durables are all as defined in section D.1.
E Portfolio Category Definitions in the Distributional Financial Accounts

This section describes how we construct portfolio categories in the Distributional Financial Accounts (DFA). We draw heavily from Batty, Bricker, Briggs, Holmquist, Hume McIntosh, Moore, Nielsen, Reber, Shatto, Sommer, Sweeney and Henriques Volz (2019) Appendix A though we reconcile portfolio definitions to harmonize with our reorganization of the SCF and the Financial Accounts.

For the DFA Bulletin data, see the Federal Reserve’s page “DFA: Distributional Financial Accounts” at https://www.federalreserve.gov/releases/z1/dataviz/dfa/index.html. We use the file dfa-networth-levels.csv, retrieved via https://www.federalreserve.gov/releases/z1/dataviz/download/zips/dfa.zip on February 16, 2021. All figures are annual averages over quarters in current dollars.

E.1 Portfolio components not defined in unprocessed DFA data

E.1.1 Overview

We make four major departures from the portfolio classification in the unprocessed data, all of which amount to disaggregating ready-made DFA portfolio concepts:

1. Classify IRAs as pension entitlements, rather than according to their underlying assets Table B.101.h of the Financial Accounts of the United States—the basis for the DFA’s portfolio delineations—allocates IRAs to portfolio categories (e.g., corporate equities and mutual funds; corporate and foreign bonds) according to their underlying investments. In contrast, the SCF and the Saez Zucman (2016; 2020) reorganization of the Financial Accounts both allocate IRAs to a “pensions” category. According to Batty et al. (2020), the portfolio categories “Time deposits and short-term investments;” “Money market fund shares;” “US government and municipal securities;” “Corporate and foreign bonds;” and “Corporate equities and mutual funds” all contain IRAs.

2. Disaggregate “Corporate equities and mutual funds” into public C-corporations (including held through mutual funds); privately C-corporations; S-corporations; mutual funds invested in taxable fixed income (bonds and loans held in mutual funds); and mutual funds invested in tax-exempt fixed income.

3. Disaggregate “Money market fund shares” into money market deposit accounts, which generate interest for tax purposes, and money market mutual funds, which generate dividends for tax purposes.

4. Disaggregate “US government and municipal securities” into US government bonds, which generate taxable interest, and municipal securities, which generate tax-exempt interest.

We use essentially the same process to conduct each of these adjustments:

(a) Using our processed SCF micro-file, create concepts which resemble as closely as possible all DFA concepts (including aggregate wealth), closely following the reconciliation instructions in Batty et al. (2020) Appendix A.

(b) Rank SCF units by DFA-reconciled net worth concept, and group into the groups used in the DFA: bottom 50%, next 40%, next 9%, top 1%.

(c) Calculate total assets and liabilities by DFA-reconciled wealth group within DFA-reconciled portfolio categories, as well as their SCF constituent concepts.

(d) Calculate wealth group-specific component shares of the DFA-analog SCF concept we want to disaggregate using its constituent concepts.
For step (a), we construct DFA-analog concepts in the SCF as:

\[
\begin{align*}
\text{Real estate}_{\text{SCF}} &= \text{houses} + \text{oresre} \\
\text{Consumer durables}_{\text{SCF}} &= \text{vehic} + \text{durables} \\
\text{Time deposits and short-term investments}_{\text{SCF}} &= \text{saving} + \text{cds} \\
\text{Money market fund shares}_{\text{SCF}} &= \text{mmda} + \text{mmmf} \\
\text{US government and municipal securities}_{\text{SCF}} &= \text{notxbnd} + \text{gvtbnd} \\
\text{Other loans and advances}_{\text{SCF}} &= \text{call} + \text{privloans} \\
\text{Corporate equities and mutual funds}_{\text{SCF}} &= \text{ccorw} + \text{fixmutf} + 0.5 \times (\text{privccorw}_\text{costbasis} - \text{privccorw}) \\
&\quad+ 0.5 \times (\text{scorw} + \text{scorw}_\text{costbasis}) - \text{mmmf} + \text{tfbmutf} \\
\text{Pension entitlements}_{\text{SCF}} &= \text{retqliq} - \text{irakh} + \text{tot pen db} \\
\text{Equity in non-corporate business}_{\text{SCF}} &= 0.5 \times (\text{pthrubus}_\text{costbasis} + \text{nnresre} - \text{scorw}_\text{costbasis}) + 0.5 \times (\text{pthru} - \text{scorw}) \\
\text{Home mortgages (liability)}_{\text{SCF}} &= \text{mrthel} + \text{resdbt} \\
\text{Consumer credit}_{\text{SCF}} &= \text{install} + \text{ccbal} \\
\text{Checkable deposits and currency}_{\text{SCF}} &= \text{currency} \\
\text{Corporate and foreign bonds}_{\text{SCF}} &= \text{obnd} \\
\text{Mortgages (asset)}_{\text{SCF}} &= \text{mortgageassets} \\
\text{Depository institution loans n.e.c.}_{\text{SCF}} &= \text{othloc} \\
\text{Other loans and advances}_{\text{SCF}} &= \text{odebt}
\end{align*}
\]

where all concepts but \text{privccorw}_\text{costbasis}, \text{scorw}_\text{costbasis}, and \text{pthrubus}_\text{costbasis} are defined in Appendix D, and the cost basis concepts are analogs to \text{privccorw}, \text{scorw}, and \text{pthrubus} concepts defined therein, constructed using cost basis questions.\textsuperscript{78}

Then the DFA-reconciled net worth concept is the sum of these, plus the \text{irakh} concept which is distributed in the DFA according to its underlying assets. Step (b) entails ranking and grouping by this net worth concept. Step (c) entails collapsing to yield group-specific totals of the concepts enumerated above, as well as their SCF constituent components (e.g., \text{houses}, \text{oresre}, and so on).

Finally, in step (d) we use our SCF constructions to split apart ready-made DFA concepts into our preferred concepts, calculating shares by wealth group to carry out adjustments 1 – 4. Because the SCF is only available triennially and our preferred DFA measures are annual averages of the raw file’s quarterly measures, we interpolate linearly after calculating shares in SCF years to cover the DFA’s full time range.

\textsuperscript{78}These are full file questions X3130, X3230, X3330, and X3336 for actively-managed businesses, and X3409, X3413, X3453 (after 2007) or X3425 (until 2007), X3417, X3421, and X3429 for non-actively managed businesses.
E.1.2 Classify IRAs as pension entitlements, rather than according to their underlying assets

To split out IRAs from asset classes which contain them, we first calculate total assets containing IRAs in the SCF for each group \( g \in \{ \text{Bot 50\%}, \text{Next 40\%}, \text{Next 9\%}, \text{Top 1\%} \} \):

\[
\text{Total IRA-containing assets}_{SCF,g} = \text{irakh}_{g} + \text{Time deposits and short-term investments}_{SCF,g} \\
+ \text{Money market fund shares}_{SCF,g} + \text{US government and municipal securities}_{SCF,g} \\
+ \text{Corporate and foreign bonds}_{SCF,g} + \text{Corporate equities and mutual funds}_{SCF,g}
\]

Then, for each constituent asset class of Total IRA-containing assets\(_{SCF,g}\), we calculate its share in Total IRA-containing assets\(_{SCF,g}\):

\[
\text{IRA sh. assets incl. IRAs}_{SCF,g} = \frac{\text{irakh}_{g}}{\text{Total IRA-containing assets}_{SCF,g}}
\]

\[
\text{Time depsts & short-term inv. sh. assets incl. IRAs}_{SCF,g} = \frac{\text{Time deposits and short-term investments}_{SCF,g}}{\text{Total IRA-containing assets}_{SCF,g}}
\]

\[
\vdots
\]

\[
\text{Corp. equ. & mut. funds sh. assets incl. IRAs}_{SCF,g} = \frac{\text{Time deposits and short-term investments}_{SCF,g}}{\text{Total IRA-containing assets}_{SCF,g}}
\]

Then, we calculate Total IRA-containing assets\(_{DFA,g}\) as we computed it for the SCF:

\[
\text{Total IRA-containing assets}_{DFA,g} = \text{Time deposits and short-term investments}_{DFA,g} + \text{Money market fund shares}_{DFA,g} \\
+ \text{US government and municipal securities}_{DFA,g} + \text{Corporate and foreign bonds}_{DFA,g} \\
+ \text{Corporate equities and mutual funds}_{DFA,g}
\]
and finally apply the shares we calculated in the SCF to yield a DFA IRA measure, and IRA-free measures of Time deposits and short-term investments, US governmet and municipal securities, etc.

\[ \text{IRAs}_{\text{DFA}, g} = \text{peniraw}_{\text{DFA}} = \text{IRA sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

Time depsts & short-term inv. excl. IRAs\[ \text{timdepshttrtm}_{\text{excl,iras}} = \text{Time depsts & short-term inv. sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

Money market fund shares excl. IRAs\[ \text{mnymrktfundshares}_{\text{excl,iras}} = \text{Money mkt. fund shares sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

US govt. & muni. scties excl. IRAs\[ \text{usgovsecmunishares}_{\text{excl,iras}} = \text{US govt. & muni. scties sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

Corp. & frgn. bnds excl. IRAs\[ \text{corpfrgnbnd}_{\text{excl,iras}} = \text{Corp. & frgn. bnds sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

Corp. equ. & mut. funds excl. IRAs\[ \text{corpequmutf}_{\text{excl,iras}} = \text{Corp. equ. & mut. funds sh. assets incl.} \text{ IRAs}_{\text{SCF}, g} \times \text{Total IRA-containing assets}_{\text{DFA}, g} \]

**E.1.3 Disaggregate “Corporate equities and mutual funds”**

For each constituent asset class of Corporate equities and mutual funds_{SCF} – public equities (including held through mutual funds); private C-corporations; S-corporations; mutual funds invested in taxable fixed claims; and mutual funds invested in tax-exempt fixed claims – we calculate component shares in the SCF for each group \( g \in \{ \text{Bot 50\%, Next 40\%, Next 9\%, Top 1\%} \} : \)

\[ \text{Public equities sh. corp. equi. & mut. funds}_{\text{SCF}, g} = \frac{\text{stocks}_{g} + \text{trusts}_{g} + \text{stmutf}_{g} + (0.5 \times \text{comutf}_{g}) + (0.5 \times \text{omutf}_{g})}{\text{Corporate equities and mutual funds}_{\text{SCF}, g}} \]

\[ \text{Private C-corp. sh. corp. equi. & mut. funds}_{\text{SCF}, g} = \frac{0.5 \times (\text{privccorw}_{g} + \text{privccorw}_{g} \times \text{costbasis})}{\text{Corporate equities and mutual funds}_{\text{SCF}, g}} \]

\[ \text{S-corp. sh. corp. equi. & mut. funds}_{\text{SCF}, g} = \frac{0.5 \times (\text{scorw}_{g} + \text{scorw}_{g} \times \text{costbasis}_{g})}{\text{Corporate equities and mutual funds}_{\text{SCF}, g}} \]

Mut. fds. in taxble fxed clms sh. corp. equi. & mut. funds_{\text{SCF}, g} = \frac{0.5 \times \text{comutf}_{g} + \text{gmutuf}_{g} + \text{omutf}_{g} + 0.5 \times \text{omutf}_{g} + \text{trusts}_{g} \times \text{mmbondfund}_{g} + \text{tfbmutf}_{g}}{\text{Corporate equities and mutual funds}_{\text{SCF}, g}} \]

Mut. fds. in tx-exmpt fxed clms sh. corp. equi. & mut. funds_{\text{SCF}, g} =
Then we apply the shares above to Corp. equ. & mut. funds excl. IRAs\(_{DFA,g}\) (see subsection E.1.2), which delivers disaggregated concepts:

\[
\text{Public equities}^{DFA, g} \equiv 
\text{pubccorp}_{dfa} = \text{Public equities sh. corp. equ. & mut. funds}_{SCF, g} \times \text{Corp. equ. & mut. funds excl. IRAs}_{DFA,g}
\]

\[
\text{Private C-corp.}^{DFA, g} \equiv 
\text{privccorp}_{dfa} = \text{Private C-corp. sh. corp. equ. & mut. funds}_{SCF, g} \times \text{Corp. equ. & mut. funds excl. IRAs}_{DFA,g}
\]

\[
\text{S-corp.}^{DFA, g} \equiv 
\text{scorp}_{dfa} = \text{S-corp. sh. corp. equ. & mut. funds}_{SCF, g} \times \text{Corp. equ. & mut. funds excl. IRAs}_{DFA,g}
\]

\[
\text{Mut. fnds. in txble fxd clms}^{DFA, g} \equiv 
\text{inttaxmutf}_{dfa} = \text{Mut. fnds. in txble fxd clms sh. corp. equ. & mut. funds}_{SCF, g} \times \text{Corp. equ. & mut. funds excl. IRAs}_{DFA,g}
\]

\[
\text{Mut. fnds. in tx-exmpt fxd clms}^{DFA, g} \equiv 
\text{intexmmutf}_{dfa} = \text{Mut. fnds. in tx-exmpt fxd clms sh. corp. equ. & mut. funds}_{SCF, g} \times \text{Corp. equ. & mut. funds excl. IRAs}_{DFA,g}
\]

### E.1.4 Disaggregate “Money market fund shares”

For the two constituent asset classes in Money market fund shares\(_{SCF}\), money market mutual funds and money market deposit accounts, we calculate component shares in the SCF for each group \(g \in \{\text{Bot 50%}, \text{Next 40%}, \text{Next 9%}, \text{Top 1}\%\}:

\[
\text{Mny mkt mut. funds sh. mny mkt fund shares}_{SCF, g} = \frac{\text{mmm}_{g}}{\text{Money market fund shares}_{SCF, g}}
\]

\[
\text{Mny mkt dpst acct sh. mny mkt fund shares}_{SCF, g} = \frac{\text{mmda}_{g}}{\text{Money market fund shares}_{SCF, g}}
\]

Then we apply the shares above to Money market fund shares excl. IRAs\(_{DFA,g}\) (see subsection E.1.2), which delivers disaggregated concepts:

\[
\text{Money market mutual funds}^{DFA, g} \equiv 
\text{mmm}_{dfa} = \text{Mny mkt mut. funds sh. mny mkt fund shares}_{SCF, g} \times \text{Money market fund shares excl. IRAs}_{DFA,g}
\]

\[
\text{Money market deposit account}^{DFA, g} \equiv 
\text{mmda}_{dfa} = \text{Mny mkt dpst acct sh. mny mkt fund shares}_{SCF, g} \times \text{Money market fund shares excl. IRAs}_{DFA,g}
\]
E.1.5 Disaggregate “US government and municipal securities”

For the two constituent asset classes in US government and municipal securities_{SCF}, US government securities and municipal bonds, we calculate component shares in the SCF for each group \( g \in \{ \text{Bot 50\%}, \text{Next 40\%}, \text{Next 9\%}, \text{Top 1\%} \} \):

\[
\begin{align*}
\text{US govt scties sh. US govt & muni. scties}_{SCF, g} &= \frac{\text{govtbind}_{g}}{\text{US government and municipal securities}_{SCF}} \\
\text{Munis sh. US govt & muni. scties}_{SCF, g} &= \frac{\text{notxbnd}_{g}}{\text{US government and municipal securities}_{SCF}}
\end{align*}
\]

Then we apply the shares above to US govt. & muni. scties excl. IRAs_{DFA, g} (see subsection E.1.2), which delivers disaggregated concepts:

\[
\begin{align*}
\text{US govt securities}_{DFA, g} &= \text{govtbind}_{DFA, g} = \text{US govt scties sh. US govt & muni. scties}_{SCF, g} \times \text{US govt. & muni. scties excl. IRAs}_{DFA, g} \\
\text{Municipal bonds}_{DFA, g} &= \text{notxbnd}_{DFA, g} = \text{Munis sh. US govt & muni. scties}_{SCF, g} \times \text{US govt. & muni. scties excl. IRAs}_{DFA, g}
\end{align*}
\]

E.2 Main portfolio categories

In our preferred DFA series, aggregate wealth is:

\[
\text{Net worth} = \text{networth} - \text{consumerdurables}
\]

\[
\text{2016 example} = $89.0T - $5.1T = $83.9T
\]

where both \( \text{networth} \) and \( \text{consumerdurables} \) are ready-made DFA concepts representing aggregate household wealth (as in Financial Accounts of the United States table B.101.h) and consumer durable goods.\(^79\)

Below is a mutually exclusive and collectively exhaustive categorization of the assets in our preferred net worth concept. We often refer to the sum of currency; taxable interest-generating fixed claims; tax-exempt fixed claims; and bonds and loans held in mutuals funds as “fixed income,” though we only use taxable interest-generating fixed claims to calculate interest rates to make the numerator and denominators consistent with each other.

\[
\text{Currency} = \text{checkabledepostsandcurrency}
\]

\[
\text{2016 example} = 1.0T
\]

where \( \text{checkabledepostsandcurrency} \) is a ready-made DFA concept representing checkable deposits and currency.

\(^{79}\)Because the unprocessed DFA data are aggregates by group (e.g., total \( \text{networth} \) for the bottom 50\%, the next 40\%, and so on) as opposed to micro-level data, we are unable to rerank after constructing our preferred total wealth measure.
Taxable interest-generating fixed claims = otherloansandadvancesassets + mortgages + timdepshrttrm_excl_iras + mmda_dfa + corpfrgnbnd_excl_iras + govtbnd_dfa

\[ 2016 \text{ example} = \$843B + \$94B + \$6.1T + \$864B + \$732B + \$532B = \$9.2T \]

where otherloansandadvancesassets and mortgages are ready-made DFA concepts representing other loans and advances (cash accounts at brokers and dealers) and mortgages held as assets by households, and timdepshrttrm_excl_iras, mmda_dfa, corpfrgnbnd_excl_iras, and govtbnd_dfa are all defined as in section E.1.

Tax-exempt fixed claims = notxbind_dfa + intexmmutf_dfa

\[ 2016 \text{ example} = \$1.9T + \$581B = \$2.4T \]

where notxbind_dfa and intexmmutf_dfa are both defined as in section E.1.

Bonds and loans held in mutual funds = inttaxmutf_dfa + mmmf_dfa

\[ 2016 \text{ example} = \$984B + \$183B = \$1.2T \]

where inttaxmutf_dfa and mmmf_dfa are both defined as in section E.1.

C-corporation equity = pubccorp_dfa + privccorp_dfa

\[ 2016 \text{ example} = \$5.4T + \$927B + \$4.8T = \$11.1T \]

where pubccorp_dfa and privccorp_dfa are both defined as in section E.1.

Pass-through business = equityinnoncorporatebusiness + scorp_dfa

\[ 2016 \text{ example} = \$10.0T + \$1.9T = \$11.9T \]

where equityinnoncorporatebusiness is a ready-made DFA concept representing equity in non-corporate business and scorp_dfa is defined as in section E.1.
\[
\text{Pensions} = \text{lifeinsurancereserves} + \text{pensionentitlements} + \text{peniraw_dfa}
\]

2016 example = $1.6T + $24.0T + $9.9T = $35.5T

where \text{lifeinsurancereserves} and \text{pensionentitlements} are ready-made DFA concepts representing life insurance reserves and pension entitlements (excluding DC pensions), and \text{peniraw_dfa} is defined as in section E.1.

\[
\text{Housing} = \text{realestate} - \text{homemortgages}
\]

2016 example = $24.3T - $9.6T = $14.7T

where \text{realestate} and \text{homemortgages} are ready-made DFA concepts representing real estate and home mortgages (liabilities).

\[
\text{Non-mortgage debt} = -\text{otherloansandadvancesliabilities} - \text{depositoryinstitutionsloansnec} - \text{deferredandunpaidlifeinsurancep} - \text{consumercredit}
\]

2016 example = $438T - $225T - $33T - $3.5T = $4.2T

where \text{otherloansandadvancesliabilities}, \text{depositoryinstitutionsloansnec}, \text{deferredandunpaidlifeinsurancep}, and \text{consumercredit} are all ready-made DFA concepts representing other loans and advances (liabilities, including margin accounts at broker-dealers and loans against life insurance policies); depository institution loans not elsewhere classified; deferred and unpaid life insurance premiums; and consumer credit.

\[
\text{Other} = \text{miscellaneousassets}
\]

2016 example = $1.1T

where \text{miscellaneousassets} is a ready-made DFA concept representing miscellaneous assets, which Batty et al. (2020) explain consist of “receivables due from property-casualty insurance companies, the value of other policies from life insurance companies [...] , and government-sponsored retiree health care fund reserves.”
F Sources for Aggregate Parameters

This section describes how we define and derive our aggregate parameter values, which result from reconstructing and extending the “parameters.xlsx” file in Saez and Zucman (2020b). This parameters file is from the October 2020 version of their paper, and can be retrieved from http://gabriel-zucman.eu/usdina/ as of July 22, 2021.\textsuperscript{80}

F.1 Unprocessed inputs

We use data from the following primary sources:

1. **Financial Accounts of the United States** (henceforth USFA): we use the 2020Q3 USFA release, updating very slightly relative to SZ 2020 who use the 2020Q2 release. It is sufficient to pull from the following tables: L.108, L.117, L.121, L.122, L.218, L.219, L.221, L.223, L.227, B.101, B.101n, B.101e, B.104, and the Flow of Funds Matrix (CSV file is all\_sectors\_levels\_a.csv).

2. **Investment Company Institute** (henceforth ICI): we use data from table 19 of the ICI publication “The US Retirement Market, Third Quarter 2020.” SZ 2020 use a previous vintage of these data, but values are the same for all relevant years.

We follow SZ 2016, PSZ 2018, and SZ 2020 in taking midyear averages of these series, so that our 2016 value is the average of 2015Q4 and 2016Q4 values in the raw data.

We also use two SZ (2020) series as direct inputs:

- **Correction factor for directly held munis before 2004**: SZ 2020 note that:
  
  The FRB missed a lot of households-held munis in its Flow of Funds before 2004; this has recently been revised but the official series is not corrected prior to 2004, so there’s a big jump in 2004 that needs to be corrected, see e.g.,: http://blogs.reuters.com/muniland/2011/12/09/found-800-billion-in-municipal-bonds/. Note that by construction our correction does not affect net household wealth, because we compute "other assets" as the residual of the FRB household wealth series and the sum of components.

  We apply a correction factor from column AB of SZ’s DataWealth sheet in order to obtain a full count of municipal bond wealth from 1993-2004. This correction only affects the tax-exempt bonds concept in TB1, or ttintexmw concept in the “parameters.xlsx” file.

- **S corp profits (micro files), firms with positive profits only**: The Financial Accounts series giving the total value of S-corporation equity only extends back to 1996. To fill in values from 1966-1996, SZ capitalize S-corporation profits for firms with positive profits based on 1996-2011 average returns to equity.\textsuperscript{81} Their description of the column in DataWealth (EL) alludes to micro files, and indeed from 2014 onward they write that the “S corp profits...” concept is the aggregate scorpinc in “small files.” However, the provenance of their pre-2014 data points is unclear: it does not match the scorpinc in the sheet “TotalIRSIncome.” To follow their S-corporation equity calculations, we copy this column from the DataWealth sheet.

\textsuperscript{80}Click on “Stata programs to construct distributional national accounts micro-files” to download a folder called “PSZ2020Programs.”

\textsuperscript{81}They assume zero profits (and consequently zero S-corporation equity) before 1966.
F.2 Changes relative to PSZ 2018

SZ 2020 update their aggregate wealth series relative to PSZ 2018. As discussed in Section 1, we generally follow SZ 2020’s aggregates construction, but make the following additional adjustments:

1. **Add unfunded defined benefit pensions assets** to “Assets of defined benefit and defined contributions pensions plans,” because defined benefit pensions plan beneficiaries have a legally enforceable right to their benefits regardless of their plan’s funding status.

2. **Exclude vehicle loans** from “Non-mortgage debt” because the assets they secure are non-capitalizable (durables) and therefore excluded from the total assets concept we allocate.

3. **Scale down credit card balances** within “Non-mortgage debt” to match aggregate credit card balances from the SCF, because the USFA credit card balances measure reflects convenience use (e.g., credit card balances paid off at the end of each billing period) in addition to revolving balances (e.g., credit card debt on which debtors pay interest).

Note also that SZ 2020’s revised aggregates make several important changes relative to PSZ 2018, including:

- Segregating bonds and loans held in mutual funds from other taxable bonds, deposits and loans, as the former pay non-qualified dividends and the latter pay taxable interest.
- Allocating miscellaneous wealth proportionally to other wealth instead of to interest.
- Reassign debt secured by commercial real estate from housing to non-corporate business.

F.3 Constructing portfolio categories: summary

We transform aggregates from the sources described in subsection F.1 to construct wealth categories that are roughly consistent with the 2008 System of National Accounts (United Nations, 2009). Here we list and summarize construction of our preferred portfolio categories:

- **Owner-occupied gross housing**: Direct from Financial Accounts series “Households; owner-occupied real estate including vacant land and mobile homes at market value” table B.101 line 4.

- **Tenant-occupied gross housing**: Direct from Financial Accounts series “Nonfinancial non-corporate business; residential real estate at market value” table B.104 line 4.

- **Equity: Other than S-corporations**: Financial Accounts Corporate equities and mutual fund shares minus the sum of corporate equities and mutual funds shares held by non-profit organizations; IRAs invested in equities; and S-corporation equity.

- **Equity: S-corporations**: From 1996-onward, direct from Financial Accounts series “All domestic sectors; closely held S corporation corporate equities; liability” L.223 line 31; beforehand, capitalized based on average 1996-2011 return to equity.

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82The wealth delineations in previous vintages of SZ/PSZ aggregates were exactly in line with the 2008 SNA; see http://gabriel-zucman.eu/files/PSZ2018DataAppendix.pdf for the PSZ 2018 data appendix.
• Taxable bonds, deposits, and loans (excl. held through funds): Sum of time and savings deposits; foreign deposits; Treasury and agency-backed securities directly held; and corporate and foreign bonds directly held, after subtracting off assets in each of these categories held by non-profit organizations. Also subtract off IRAs invested in taxable fixed claims other than bonds and loans in mutual funds or money market funds. Finally, add loans and security credits.

• Tax-exempt bonds: Municipal bonds directly held minus government securities held by non-profits, plus municipal bonds held by mutual funds and money market fund shares invested in munis.\(^{83}\)

• Non-interest bearing deposits and currency: Checkable deposits and currency held by household and non-profits, minus cash and non-interest bearing deposits held by non-profits.

• Business assets: Proprietors’ equity in noncorporate business held by households and non-profits (B.101 line 28) minus noncorporate business invested in residential real estate net of mortgages, including mortgages on multifamily dwellings and farms.

• Assets of defined benefit and contribution pensions plans: Defined benefit plans assets plus defined contribution assets.

• Life insurance: Life insurance reserves and pension entitlements.

• Individual Retirement accounts: IRA assets excluding assets held by life insurance companies.

• Mortgages: Owner-occupied dwellings: Direct from Financial Accounts series “Households and nonprofit organizations; one-to-four-family residential mortgages; liability” B.101 line 33.

• Mortgages: Residential real estate (tenant-occupied): Nonfinancial noncorporate business: mortgages on one-to-four-family residential dwellings, multifamily dwellings, and farms.

• Non-mortgage debt: Consumer credit and depository institution loans not elsewhere classified minus auto loans, scaling credit card balances down to level of SCF credit card balances.\(^{84}\)

• Other assets: Residual after subtracting corporate equities, money market fund shares, debt securities, time and savings deposits, private foreign deposits, checkable deposits and currency, proprietors’ equity in noncorporate business, mutual fund shares, life insurance reserves, pension entitlements, and loans (asset) from total financial assets held by households and nonprofits.

• Taxable bonds and loans held through funds: Bonds (other than municipal bonds) held by mutual funds plus money market fund shares (except invested in munis) minus money market fund shares held by IRAs.

---

\(^{83}\)These latter series are included here and not in “taxable bonds and loans held through funds” because municipal bonds pay tax-exempt interest even when held through funds.

\(^{84}\)The auto loans concept we subtract off from consumer credit is series FL153166400 “Households and nonprofit organizations; consumer credit, automobile loans; liability.” The credit card balances concept we scale down is series FL153166100 “Households and nonprofit organizations; revolving consumer credit; liability,” which we scale to match the aggregate ccbal SCF bulletin concept.
F.4 Constructing portfolio categories

These wealth aggregates—besides the modifications described in section F.2 items 1, 2, and 3—are documented in SZ 2020 via a set of excel sheets in the appendix document “PSZ2020AppendixTablesI(Aggreg).xlsx,” downloaded via [https://gabriel-zucman.eu/files/PSZ2020AppendixTablesI(Aggreg).xlsx](https://gabriel-zucman.eu/files/PSZ2020AppendixTablesI(Aggreg).xlsx) on January 21, 2021. The relevant sheets are:

1. **ima_raw**: Contains series pulled directly from the 2020Q2 release of the Integrated Macroeconomic Accounts and USFA.
2. **DataWealth**: Primarily wealth aggregates and liabilities calculated or pulled directly from ima_raw sheet with more informative formatting.
3. **TSB5**: Breakdown of interest-bearing assets by type of income generated; draws primarily from DataWealth and auxiliary aggregates from the Investment Company Institute (see bullet 2 in subsection F.1).
G  Other Data Sources

In addition to administrative tax data, SCF data, and DFA data, we also use several other series in our analysis:


- **Interest rates on deposits** from Drechsler, Savov and Schnabl (2017) data, retrieved from correspondence with authors on October 15th, 2019.

- **Interest rates on corporate bonds** from Thomson Reuters eMaxx merged to the WRDS Bond Returns database.

- **Kopczuk and Saez (2004a) estate tax series shown in figure 1** retrieved from Saez and Zucman (2016) “Other Estimates” appendix tables.


H Minimum Distance Appendix

H.1 Covariance expressions and Identifying Risk-Exposure Parameters

The covariance terms from equation (7) in terms of parameters are:

\[
\begin{align*}
\Sigma_{11} &= \sigma_{r_1}^2 + \sigma_{a_1}^2 + 2c_{r_1,a_1} \\
\Sigma_{21} &= c_{r_1,r_2} + c_{r_1,a_2} + c_{r_2,a_1} + c_{a_1,a_2} \\
\Sigma_{31} &= s_1^a c_{r_1,a_1} + s_1^a \sigma_{a_1}^2 + (1 - s_1^a) c_{r_1,a_2} + (1 - s_1^a) c_{a_1,a_2} \\
\Sigma_{41} &= \pi_1^I \sigma_{r_1}^2 + \pi_1^I c_{r_1,a_1} + \pi_2^I c_{r_1,r_2} + \pi_2^I c_{r_2,a_1} \\
\Sigma_{51} &= \pi_1^C \sigma_{r_1}^2 + \pi_1^C c_{r_1,a_1} + \pi_2^C c_{r_1,r_2} + \pi_2^C c_{r_2,a_1} \\
\Sigma_{22} &= \sigma_{r_2}^2 + \sigma_{a_2}^2 + 2c_{r_2,a_2} \\
\Sigma_{32} &= s_1^a c_{r_2,a_1} + s_1^a c_{a_1,a_2} + (1 - s_1^a) c_{r_2,a_2} + (1 - s_1^a) \sigma_{a_2}^2 \\
\Sigma_{42} &= \pi_1^I c_{r_1,r_2} + \pi_1^I c_{r_1,a_2} + \pi_2^I \sigma_{r_2}^2 + \pi_2^I c_{r_2,a_2} \\
\Sigma_{52} &= \pi_1^C c_{r_1,r_2} + \pi_1^C c_{r_1,a_2} + \pi_2^C \sigma_{r_2}^2 + \pi_2^C c_{r_2,a_2} \\
\Sigma_{33} &= (s_1^a)^2 \sigma_{a_1}^2 + (1 - s_1^a)^2 \sigma_{a_2}^2 + 2(s_1^a)(1 - s_1^a) c_{a_1,a_2} \\
\Sigma_{43} &= \pi_1^I s_1^a c_{r_1,a_1} + \pi_1^I (1 - s_1^a) c_{r_1,a_2} + \pi_2^I s_1^a c_{r_2,a_1} + \pi_2^I (1 - s_1^a) c_{r_2,a_2} \\
\Sigma_{53} &= \pi_1^C s_1^a c_{r_1,a_1} + \pi_1^C (1 - s_1^a) c_{r_1,a_2} + \pi_2^C s_1^a c_{r_2,a_1} + \pi_2^C (1 - s_1^a) c_{r_2,a_2} \\
\Sigma_{44} &= (\pi_1^I)^2 \sigma_{r_1}^2 + (\pi_2^I)^2 \sigma_{r_2}^2 + 2\pi_1^I \pi_2^I c_{r_1,r_2} \\
\Sigma_{54} &= \pi_1^I \pi_1^C \sigma_{r_1}^2 + (\pi_1^I \pi_2^C + \pi_2^I \pi_1^C) c_{r_1,r_2} + \pi_2^I \pi_2^C \sigma_{r_2}^2 \\
\Sigma_{55} &= (\pi_1^C)^2 \sigma_{r_1}^2 + (\pi_2^C)^2 \sigma_{r_2}^2 + 2\pi_1^C \pi_2^C c_{r_1,r_2}
\end{align*}
\]

We can combine subsets of the moments to illustrate how key parameters can be identified. Note that the full over-id system estimates (see equation (8)) uses additional information from other moments to estimate these risk-exposure parameters. Nonetheless, it is useful to consider one way in which these parameters can be identified in terms of moments and other calibrated parameters, and observe that the full-system estimates are similar to these just-identified estimates.

Identifying \(\pi_1^I\) and \(\pi_2^I\): Start with row 4 of equation (6), i.e., \(\mu_{r,t} = \pi_1^I \mu_{r_1} + \pi_2^I \mu_{r_2}\), and the expression for \(\Sigma_{42}\) in equation (25).

\[
\begin{bmatrix}
\mu_{r,t} \\
\Sigma_{42}
\end{bmatrix} =
\begin{bmatrix}
\pi_1^I \mu_{r_1} + \pi_2^I \mu_{r_2} \\
\pi_1^I c_{r_1,r_2} + \pi_1^I c_{r_1,a_2} + \pi_2^I \sigma_{r_2}^2 + \pi_2^I c_{r_2,a_2}
\end{bmatrix}
\]

Apply Cramer's Rule
Identifying $\pi^C$ and $\pi^G$:

Start with row 5 of equation (6), i.e., $\mu_r = \pi^C \mu_r + \pi^G \mu_r$, and the expression for $\Sigma_{52}$ in equation (26).

$$\begin{bmatrix} \mu_r \\ \Sigma_{52} \end{bmatrix} = \begin{bmatrix} \pi^C \mu_r + \pi^G \mu_r \\ \pi^C c_{r_1,r_2} + \pi^G c_{r_1,a_2} + \pi^G \sigma^2 \end{bmatrix}$$ (36)

Apply Cramer's Rule

$$\pi^C_1 = \frac{D \pi^C_1}{D} = \frac{\begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix} - \begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix}}{\begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix} - \begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix}} = \frac{(\mu_r)(\sigma^2 - (\mu_r)(\Sigma_{52})}{(\mu_r)(\sigma^2 - (\mu_r)(\Sigma_{52})}$$ (37)

Empirically, $\pi^C_1 = \frac{(2.11)(0.325 - 0.123) - (1.165)(0.13)}{(1.694)(0.325 - 0.123) - (1.165)(0.113 - 0.045)} \approx 1.04.$

$$\pi^C_2 = \frac{D \pi^C_2}{D} = \frac{\begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix} - \begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix}}{\begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix} - \begin{vmatrix} \mu_r \\ \Sigma_{52} \end{vmatrix}} = \frac{(\mu_r)(\Sigma_{52}) - (\mu_r)(\Sigma_{52})}{(\mu_r)(\Sigma_{52}) - (\mu_r)(\Sigma_{52})}$$ (38)

$$\pi^C_2 = \frac{(1.694)(0.13) - (2.11)(0.113 - 0.045)}{(1.694)(0.325 - 0.123) - (1.165)(0.113 - 0.045)} \approx 0.29.$$

**Key point:** Overall, these just-identified estimates of parameters are close to the full (over-identified) system estimates in Table H.2.
H.2 Steps to implement CMD

We estimate interest rates using CMD using the following steps:

1. Input annual panel data of tax data aggregates of income flows by group, aggregate fixed income assets, and interest rates for credit risk and interest rate risk (i.e., \((y_{1t}, y_{2t}, a_{t}^{\text{total}}, r_{I}^{t}, r_{C}^{t})\)), where \(y_{1t}\) is the aggregate fixed income of the top 0.1% of the non-interest wealth distribution and \(y_{2t}\) is the aggregate fixed income of the bottom 99.9%.

2. Compute \(\hat{\mathbf{m}}\) using the data \((y_{1t}, y_{2t}, a_{t}^{\text{total}}, r_{I}^{t}, r_{C}^{t})\). That is, compute the empirical mean and covariance matrix:

\[
\hat{\mathbf{m}} = \begin{bmatrix}
\hat{\mu}_{y1}, & \hat{\mu}_{y2}, & \hat{\mu}_{a_{t}^{\text{total}}}, & \hat{\mu}_{r_{I}}, & \hat{\mu}_{r_{C}}, & \hat{\Sigma}_{11}, & \hat{\Sigma}_{21}, & \hat{\Sigma}_{31}, & \hat{\Sigma}_{41}, & \hat{\Sigma}_{51}, & \hat{\Sigma}_{22}, & \hat{\Sigma}_{32}, & \hat{\Sigma}_{42}, & \hat{\Sigma}_{52}, & \hat{\Sigma}_{33}, & \hat{\Sigma}_{43}, & \hat{\Sigma}_{53}, & \hat{\Sigma}_{44}, & \hat{\Sigma}_{54}, & \hat{\Sigma}_{55}
\end{bmatrix}.
\]

These moments measure how aggregate interest income for different groups (i.e., \(y_{1t}, y_{2t}\)), as well as aggregate asset values (i.e., \(a_{t}^{\text{total}}\)), vary and covary with interest rate risk \(r_{I}^{t}\) and credit risk \(r_{C}^{t}\) in the data from 1989 to 2016.

3. Compute calibrated parameter values from SCF.

(a) We construct an annual dataset of fixed income assets and returns \((a_{1t}, a_{2t}, r_{1t}, r_{2t})\) in the SCF from 1989-2016. We define fixed income assets and returns as in section D.

(b) We compute the analogous moments using this dataset. For example, we take the mean of log assets of group 1 to compute \(\mu_{a_{1}}\).

(c) For the top share parameter \(s_{t}^{a}\), we use the average over the full sample.
4. Compute the model moments \( \mathbf{m}(\theta) \), where

\[
\mathbf{m}(\theta) = \begin{pmatrix}
\mu_{r_1} + \mu_{a_1} \\
\mu_{r_2} + \mu_{a_2} \\
s^0_{1a_1} \mu_{a_1} + (1 - s^0_{1a_1}) \mu_{a_2} \\
\pi^1_{a} \mu_{a_1} + \pi^2_{a} \mu_{r_1} \\
\pi^1_{a} \mu_{r_1} + \pi^2_{a} \mu_{r_2} \\
\sigma^2_{r_1} + \sigma^2_{a_1} + 2c_{r_1,a_1} \\
s^0_{1} c_{r_1,a_1} + s^0_{1} \sigma^2_{a_1} + (1 - s^0_{1}) c_{r_1,a_2} + (1 - s^0_{1}) c_{a_1,a_2} \\
\pi^1_{a} \sigma^2_{r_1} + \pi^1_{a} \sigma^2_{a_1} + \pi^2_{a} \sigma^2_{r_2} + \pi^2_{a} \sigma^2_{r_1,a_1} + \pi^1_{a} \sigma^2_{r_1,a_2} + \pi^2_{a} \sigma^2_{r_2,a_1} + \pi^2_{a} \sigma^2_{r_2,a_2} \\
\sigma^2_{r_2} + s^0_{1} c_{r_2,a_1} + s^0_{1} c_{a_1,a_2} + (1 - s^0_{1}) c_{r_2,a_2} + (1 - s^0_{1}) \sigma^2_{a_2} \\
\pi^1_{a} \sigma^2_{r_1} + \pi^1_{a} \sigma^2_{a_1} + \pi^2_{a} \sigma^2_{r_2} + \pi^2_{a} \sigma^2_{r_1,a_1} + \pi^1_{a} \sigma^2_{r_1,a_2} + \pi^2_{a} \sigma^2_{r_2,a_1} + \pi^2_{a} \sigma^2_{r_2,a_2} \\
(s^0_{1})^2 \sigma^2_{a_1} + (1 - s^0_{1})^2 \sigma^2_{a_2} + 2(s^0_{1})(1 - s^0_{1}) c_{a_1,a_2} \\
\pi^1_{a} \sigma^2_{r_1} + \pi^1_{a} \sigma^2_{a_1} + \pi^2_{a} \sigma^2_{r_2} + \pi^2_{a} \sigma^2_{r_1,a_1} + \pi^1_{a} \sigma^2_{r_1,a_2} + \pi^2_{a} \sigma^2_{r_2,a_1} + \pi^2_{a} \sigma^2_{r_2,a_2} \\
(\pi^1_{a})^2 \sigma^2_{r_1} + \pi^1_{a} \sigma^2_{r_2} + \pi^2_{a} \sigma^2_{r_1,a_1} + \pi^2_{a} \sigma^2_{r_1,a_2} + \pi^2_{a} \sigma^2_{r_2,a_1} + \pi^2_{a} \sigma^2_{r_2,a_2} \\
(\pi^1_{a})^2 \sigma^2_{r_1} + \pi^1_{a} \sigma^2_{r_2} + \pi^2_{a} \sigma^2_{r_1,a_1} + \pi^2_{a} \sigma^2_{r_1,a_2} + \pi^2_{a} \sigma^2_{r_2,a_1} + \pi^2_{a} \sigma^2_{r_2,a_2} \\
\end{pmatrix}
\]

(39)

Calibrating values listed in Appendix Table H.1 for each parameter besides the risk parameters of interest results in expressions in which the risk parameters (i.e., \( \pi^1_{a}, \pi^2_{a}, \pi^C_{1}, \pi^C_{2} \)) are the only unknowns.

5. Find the parameter values (i.e., \( \pi^1_{a}, \pi^2_{a}, \pi^C_{1}, \pi^C_{2} \)) that minimize the distance between the empirical moments described in step 2 and the model models described in the previous step. This results in estimates of the risk parameters (i.e., \( \hat{\pi}^1_{a}, \hat{\pi}^2_{a}, \hat{\pi}^C_{1}, \hat{\pi}^C_{2} \)).

6. Plug in estimated parameter values into equation 9 and 10 to solve for top 0.1% and bottom 99.9% interest rates on fixed income, i.e.,

\[
\ln r^1_{1t} = \frac{\hat{\pi}^2_{a} C}{\pi^1_{a} \hat{\pi}^C_{1} - \pi^2_{a} \hat{\pi}^C_{1}} \ln r^1_{1t} - \frac{\hat{\pi}^1_{a} C}{\pi^2_{a} \hat{\pi}^C_{1} - \pi^1_{a} \hat{\pi}^C_{1}} \ln r^2_{1t} \\
\ln r^2_{1t} = \frac{\hat{\pi}^1_{a} C}{\pi^1_{a} \hat{\pi}^C_{1} - \pi^2_{a} \hat{\pi}^C_{1}} \ln r^1_{1t} + \frac{\hat{\pi}^1_{a} C}{\pi^2_{a} \hat{\pi}^C_{1} - \pi^1_{a} \hat{\pi}^C_{1}} \ln r^2_{1t}.
\]

(40)

(41)

Exponentiate these expressions to obtain the estimates of \( \hat{r}^1_{1t} \) and \( \hat{r}^2_{1t} \), which are available since 1965 using annual data on interest rate risk \( r^1_{1t} \), which is the US Treasury 5 year rate, and credit risk \( r^2_{1t} \), which is the Baa index.

7. Overall, this procedure produces estimates of \( \hat{r}^{top}_{1t} \) and \( \hat{r}^{99.9}_{2t} \) given data on aggregate income flows for each group (i.e., \( y^{top}_{1t}, y^{99.9}_{2t} \)) as well as calibrated parameter values in the SCF that are calculated for the analogous group (e.g., the top 0.1% of non-
interest income wealth). We then repeat steps 1-6, but with group 1 defined as the top 1% of the non-interest wealth distribution (instead of the top 0.1%), use the appropriate aggregate income flows for the top 1% in the tax data (i.e., \((y^t_{11}, y^t_{099})\)), and use calibrated parameter values in the SCF corresponding to the top 1% of the non-interest wealth distribution in the SCF (rather than the values in Appendix Table H.1 which are based on defining the top group as the top 0.1% of the non-interest wealth distribution in the SCF). Executing these steps results in estimates \(\hat{r}^t_{1t} \) and \(\hat{r}^t_{2t} \).

8. We then compute the three-tier CMD estimates as follows:

\[
\hat{r}^{CMD,three-tier}_t = \begin{cases} 
\hat{r}^{p99-99.9}_t = \frac{\hat{r}^{t01}_t}{\hat{r}^{t11}_t} & \text{if non-interest wealth rank} \geq 99.9 \\
\hat{r}^{p99-99.9}_t = \hat{r}^{t01}_t \times \left( \frac{y^{t11}_t - y^{t01}_t}{y^{t11}_t - r^{t01}_t} \right) & \text{if } 99.9 > \text{Non-interest wealth rank} \geq 99.99 \\
\hat{r}^{00-99}_t = \frac{a^{total,fix}_t - \sum_{i\in top1} a^{fix}_t}{\sum_{i\in top1} y^{fix}_t} & \text{otherwise}
\end{cases}
\]

where the P99-99.9 expression is derived in the Appendix H.3.

### H.3 Computing three-tier estimates

This section shows how we solve for \(\hat{r}^{p99-99.9} \) given income flows for the top 0.1 and top 1 (i.e., \(y^{t01}_t \) and \(y^{t11}_t \)), and returns for the top 0.1 and top 1 (i.e., \(r^{t01}_t \) and \(r^{t11}_t \)).

- \(y^{t01}_t \) is fixed income for top 0.1 of non-interest wealth (niw)
- \(y^{t11}_t \) is fixed income for top 1 of niw
- \(y^{p99-99.9}_t = y^{t11}_t - y^{t01}_t \) is fixed income for P99-99.9 of niw
- \(r^{t01}_t \) is return on fixed income for top 0.1 of niw
- \(r^{t11}_t \) is return fixed income for top 1 of niw
- \(r^{p99-99.9}_t \) is return fixed income for P99-99.9 of niw
- \(a^{t01}_t \) is fixed income wealth for top 0.1 of niw
- \(a^{t11}_t \) is fixed income wealth for top 1 of niw
- \(a^{p99-99.9}_t = a^{t11}_t - a^{t01}_t \) is fixed income wealth for P99-99.9 of niw
We can express the returns on fixed income for the P99-99.9 as the ratio of their aggregate income flow to their assets, and make the following substitutions:

\( r_{p99-99.9}^{99-99.9} = \frac{y_{p99-99.9}}{a_{p99-99.9}} \)  
(43)

\( r_{p99-99.9}^{99-99.9} = \frac{y_{11}^{1} - y_{10.1}^{1}}{a_{11}^{1} - a_{10.1}^{1}} \)  
(44)

\( r_{p99-99.9}^{99-99.9} = \frac{y_{11}^{1} - y_{10.1}^{1}}{\frac{y_{11}^{1}}{r_{11}^{1}} - \frac{y_{10.1}^{1}}{r_{10.1}^{1}}} \)  
(45)

\( r_{p99-99.9}^{99-99.9} = \frac{r_{11}^{1} y_{11} - y_{10.1}^{1}}{r_{11}^{1} y_{11}^{1} - y_{11}^{0.1}} \)  
(46)

\( r_{p99-99.9}^{99-99.9} = r_{11}^{1} \times \left( \frac{y_{11}^{1} - y_{10.1}^{1}}{y_{11}^{1} - \frac{r_{11}^{1}}{r_{10.1}^{1}} y_{10.1}^{1}} \right) \)  
(47)

Scaling factor less than one when \( \frac{r_{11}^{1}}{r_{10.1}^{1}} < 1 \)

This expression shows that \( r_{p99-99.9}^{99-99.9} \), which is the interest rate for p99-99.9, is the top 1% rate \( r_{11}^{1} \) multiplied by a scaling factor term that is less than one when the top 0.1% gets higher returns than the top 1% (because, in that case, the fraction \( \frac{r_{11}^{1}}{r_{10.1}^{1}} < 1 \)).
Table H.1: Classical minimum distance calibrated parameters

<table>
<thead>
<tr>
<th>Moment</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{r_1}$</td>
<td>1.694</td>
</tr>
<tr>
<td>$\mu_{r_2}$</td>
<td>1.165</td>
</tr>
<tr>
<td>$\mu_{a_1}$</td>
<td>-1.068</td>
</tr>
<tr>
<td>$\mu_{a_2}$</td>
<td>1.409</td>
</tr>
<tr>
<td>$\sigma^2_{r_1}$</td>
<td>0.086</td>
</tr>
<tr>
<td>$\sigma^2_{r_2}$</td>
<td>0.325</td>
</tr>
<tr>
<td>$\sigma^2_{a_1}$</td>
<td>0.073</td>
</tr>
<tr>
<td>$\sigma^2_{a_2}$</td>
<td>0.064</td>
</tr>
<tr>
<td>$c_{r_1,r_2}$</td>
<td>0.113</td>
</tr>
<tr>
<td>$c_{r_1,a_1}$</td>
<td>-0.066</td>
</tr>
<tr>
<td>$c_{r_1,a_2}$</td>
<td>-0.045</td>
</tr>
<tr>
<td>$c_{r_2,a_1}$</td>
<td>-0.136</td>
</tr>
<tr>
<td>$c_{r_2,a_2}$</td>
<td>-0.123</td>
</tr>
<tr>
<td>$c_{a_1,a_2}$</td>
<td>0.057</td>
</tr>
<tr>
<td>$\sigma^a_{1}$</td>
<td>0.078</td>
</tr>
</tbody>
</table>

Notes: This table shows moments calibrated in the SCF for the top 0.1% and bottom 99.9% of the non-interest wealth distribution. Non-interest wealth is our preferred net worth concept (excluding durables net of auto loans, including defined benefit pensions) minus our measure of taxable fixed claims. We log all quantities before using them in the model, so that $\mu_{r_1}$ is the average logged interest rate of the top 0.1% of the non-interest wealth distribution, $\mu_{r_2}$ is the averaged logged interest rate of the bottom 99.9%, and so on. Assets $a_1$ and $a_2$, like other dollar-denominated CMD inputs, are scaled into trillions and adjusted to 2019 dollars before being logged.

Table H.2: Classical minimum distance parameters

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^f_1$</td>
<td>-0.08</td>
<td>(0.23)</td>
</tr>
<tr>
<td>$\pi^f_2$</td>
<td>1.22</td>
<td>(0.26)</td>
</tr>
<tr>
<td>$\pi^C_1$</td>
<td>1.20</td>
<td>(0.08)</td>
</tr>
<tr>
<td>$\pi^C_2$</td>
<td>-0.07</td>
<td>(0.10)</td>
</tr>
</tbody>
</table>

Notes: This table shows parameters from our classical minimum distance fixed income exercise when estimating taxable fixed interest return heterogeneity across the top 0.1% and bottom 99.9% of the non-interest wealth distribution. Non-interest wealth is total capitalized wealth except for assets generating taxable interest.
I Treatment of Forbes 400 in 2016

This section describes how we use public data on the Forbes 400 in 2016 to assign Forbes 400 wealth to portfolio categories. De-identified administrative tax data were not used for any of our analysis of the Forbes 400.

I.1 Primary source of equity wealth

I.1.1 Public and private companies

We start with an individual-level data file on the Forbes 400 in 2016.\textsuperscript{85} In this file, each observation has a \texttt{source} and \texttt{titlecompany} variable which describes the primary source of each individual’s wealth. We combine these variables with publicly available information regarding the listed company to assign an individual’s equity wealth as deriving either from a public or private company. Our strategy is as follows:

1. If the individual’s primary source of wealth is one company (according to the \texttt{source} and \texttt{titlecompany} variables), we check if this company is public or private (either now or while it was active).

2. Otherwise, if the individual accumulated their wealth at more than one company according to the \texttt{source} and \texttt{titlecompany} variables, then:

   - If these companies were all public or all private, then we designate the individual as primarily public-equity-rich or private-business-rich accordingly.

   - If these companies were not all of the same type, then we determine whether the private or public companies were their main source of wealth, and note judgment calls below in subsection I.2.1.

I.2 Allocating wealth to portfolio categories to complement SCF

Our general strategy for allocating Forbes 400 wealth for non-equity components is based on portfolio shares from the top 0.1% of the wealth distribution in the SCF. We then allow Forbes 400 shares of public equity and private business to vary depending on whether we designate individuals as primarily private-business-rich or public-equity-rich.

To be specific, we allocate Forbes 400 wealth to portfolio categories as follows:

1. For Forbes 400 individuals whom we designate as primarily public-equity-rich, we allocate 81% of their wealth (the combined portfolio share of private business and public equity among SCF top 0.1% wealth-holders) to public equity.

2. For Forbes 400 individuals whom we designate as primarily private-business-rich, we allocate 81% of their wealth to private business.

\textsuperscript{85}We retrieve the data file \texttt{forbes\_20112018\_bdays.dta} from the website https://github.com/BITSS/opa-wealthtax/blob/master/rawdata\_forbes\_20112018\_bdays.dta, which was linked to on Saez and Zucman’s website http://wealthtaxsimulator.org/ under the link labeled “Source code here.”
3. For every individual in the 2016 Forbes 400, we allocate wealth to fixed income, housing, pensions, and other assets according to the portfolio shares for those components of the top 0.1% of the SCF wealth distribution in 2016.

This allocation results in the following portfolio shares for the Forbes 400 in 2016: 42.3% public equity, 38.8% private business, 0.7% pensions, 10.2% fixed income, 4.6% housing, and 3.3% other assets.

I.2.1 Public/private company judgment calls

- No. 34 - Elon Musk - Tesla is public but other sources of wealth e.g. X.com, Zip2, SpaceX (all private). Assigned public.
- No. 44 - Dustin Markovitz - co-founder of Facebook (public) and Asana (private). Assigned public.
- No. 50 - Jan Koum - Whatsapp initially private but bought by Facebook (public). Assigned public.
- No. 114 & No. 115 - Santo Domingo family - much of fortune from Bavaria Brewery, which was sold in 2005 and again in 2016 and is now part of Anheuser Busch/InBev (public). Difficult to ascertain whether Bavaria Brewery was public; holding company is Santo Domingo Group (private). Assigned private.
- No. 118 - Sumner Redstone - majority owner of National Amusements theater chain (private) but through NA are majority shareholders of ViacomCBS (public). Assigned public.
- No. 132 - Karen Pritzker - Marmon Holdings (private) and Hyatt hotels (public). Assigned public.
- No. 146 - H Ross Perot Sr - EDS and Perot Systems both public until 2009 when they were bought. Assigned public.
- No. 147 - James Jannard - Oakley went public in 1995, then bought by Luxottica Group in 2007; Red Digital Camera is private. Assigned public.
- No. 155 - Walter Scott Jr - former CEO of Peter Kiewit Sons’ Incorporated (private), but was also chairman of Level 3 Communications (public). Assigned private.
- No. 189 - Steven Udvar-Hazy - Former Chairman and CEO of ILFC until 2010 (private at that point); now CEO of Air Lease Corporation (public). Assigned public.
• No. 191 & 193 - Anthony & JB Pritzker - similar to Karen Pritzker; also managing partner of Pritzker Group (private). Assigned public.

• No. 192 - Roger Wang - chairman of Golden Eagle International Group (private) but also founder and main shareholder of Golden Eagle Retail Group, which went public in 2006. Assigned public.

• No. 216 - David Rockefeller Sr - Complex portfolio. Assigned private.

• No. 234 - Wilbur Ross Jr - was part of Rothschild & Co (public) for a while. Founded WL Ross & Co which (private). Assigned private.

• No. 244 - Ken Langone - Home Depot main source of wealth. Assigned public.

• No. 250 - A Jerrold Perenchio - chairman and CEO of Univision while it was public. But also lots of other businesses, several of which private. Assigned public.

• No. 258 - Steve Wynn - Mirage Resorts was private; sold in 2000, then started Wynn Resorts, which went public in 2002. Assigned public.

• No. 303 - Bill Gross - PIMCO acquired by Allianz SE in 2000; Janus Capital Group, where he worked from 2014, was public. Assigned private.

• No. 315 - Thomas Siebel - Siebel Systems was a publicly traded company 1996-2006; c3.ai is private as is his holding company First Virtual Group. Assigned public.

• No. 317 - Noam Gottesman - GLG partners IPO in 2007, bought by Man group in 2010. TOMS capital is private. Assigned private.

• No. 348 - Dan Snyder - bought Snyder Communications in 1996 and sold in 2000; then bought Washington Redskins. Assigned private since the football team is not publicly traded.

• No. 378 - Amy Wyss - Synthes primary source of wealth, which was public from 1996 until Johnson & Johnson bought it in 2012. Assigned public.

• No. 380 - Phillip T (Terry) Ragon - InterSystems, his firm, is not publicly traded. Assigned private.

• No. 390 - Vincent Viola - many businesses, some public. Assigned public.

• No. 419 - Rocco Commisso - founder and CEO of MediaCom, which was public until Commisso bought it in 2011, now private. Assigned private.

• No. 423 - Ernest Garcia II - largest shareholder of Carvana (public as of 2017) and owns and runs DriveTime Automotive (private). Assigned private.

• No. 425 - H Ross Perot Jr - Perot Systems was public until 2009. Hillwood private; Perot holdings private. Assigned public.

• No. 451 - Chris Larsen - Founded Prosper (private), Ripple (public) and e-Loan (which was public). Assigned public.
I.3 Non-Dividend-Generating Public Equity Wealth in Forbes

This section describes how we estimate non-dividend generating C-corporation wealth. To decompose Forbes 400 public equity wealth into dividend-generating and non-dividend-generating subcomponents, we take the following steps. First, we allocate Forbes wealth into public or private equity versus other asset classes using the shares described in section I.2. In 2016, this step results in 81% of Forbes wealth (which amounts to $1.94 T) being classified as either public or private business wealth. Second, we decompose this wealth into public equity wealth and private business wealth. In 2016, we find that our assignments imply that 51% (=1.2395/( 1.1579+1.2395)) of this $1.94T is public equity. This public equity wealth in Forbes amounts to $1T. Third, we divide public equity owners into those whose companies received dividends or not in 2016. For example, for Bill Gates, who is ranked 1 in 2016, we can check whether Microsoft paid a dividend in 2016. From https://www.nasdaq.com/market-activity/stocks/msft/dividend-history, we see that MSFT did pay a dividend. For Bezos, who is number 2 in 2016, we see that Amazon did not. Section I.3.1 enumerates some of our dividend-recipient classifications. Of the top 400 individuals in Forbes, 68 out of 159 public equity owners did not receive dividends, 91 out of 159 did receive dividends, and the other 241 individuals were private business owners. Of the top 50 ranked individuals in Forbes, 13 out of 29 public equity owners did not receive dividends, 16 out of 29 did receive dividends, and the other 21 individuals were private business owners. The total Forbes wealth of the 68 individuals who primarily own public firms and whose companies did not pay dividends represent 44% (=547.5B/(547.5B + 697B)) of the total wealth of Forbes 400 individuals who primarily own public firms. Thus, we can take the estimate of $1T of Forbes wealth from public equity and decompose it into $440B for public companies that didn’t pay dividends in 2016 and $560B for public companies that did pay dividends.

I.3.1 Dividend Recipient Classification Judgment Calls

We have assigned no dividends whenever the dividend history of the individual’s main business was unavailable.

- Number 54 – Pierre Omidyar – eBay started paying dividends after 2016. Assigned no dividends.
- Number 58 – Eli Broad – Kaufman and Broad’s dividend history unavailable on most websites including NASDAQ but few claimed that they did pay dividends. Assigned no dividends.

Of the top 50 ranked individuals in Forbes, 13 out of 29 public equity owners did not receive dividends, 16 out of 29 did receive dividends, and the other 21 individuals were private business owners. To be clear, “receiving dividends” means that the company the individual owns (e.g., Microsoft) did pay dividends in 2016 according to publicly available data.

The total Forbes wealth of the 13 individuals in the top 50 who primarily own public firms and whose companies did not pay dividends represent 47% (=373B/(373B + 428B)) of the total wealth of Forbes 50 individuals who primarily own public firms.

• Number 132 – Karen Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018 and to Marmon Group which has been held by Berkshire Hathaway group since 2013. And their dividend history is unavailable. Assigned no dividends.

• Number 140 – Phillip Frost – Owns stock in several firms and dividend history is unavailable for all his major investments. Assigned no dividends.

• Number 146 – H Ross Perot Sr – Founded two firms: EDS was acquired by General Motors in 1984 and Perot Systems was acquired by Dell in 2009. Assigned no dividends.

• Number 147 – James Jannard – Sold firm Oakley Inc. to Luxottica in 2007. Assigned no dividends.

• Number 150 – Reid Hoffman – Sold Linkedin to Microsoft in 2016 and Microsoft paid dividends in 2016. Assigned dividends received.

• Number 191 – Anthony Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

• Number 193 – JB Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

• Number 197 – David Filo – Yahoo acquired by Verizon Media in 2016 and Verizon Media paid dividends. Assigned dividends received.


• Number 214 – Thomas Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

• Number 223 – Romesh T. Wadhwani – The dividend history of his firm Symphony Technology Group is unclear. Assigned no dividends.

• Number 244 – Ken Langone – Has been on the board of several firms including General Electric which paid dividends. Assigned dividends received.

• Number 250 – A Jerrold Perenchio – Sold his firm Univision in 2007. Assigned no dividends.


• Number 268 – William Wrigley Jr – Wrigley company was acquired by the private firm MARS Inc in 2016. Assigned no dividends.
- Number 297 – Jean (Gigi) Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

- Number 304 – Penny Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. She is however on the board of Microsoft and Microsoft does pay dividends. Assigned dividends received.


- Number 316 – John Pritzker – Heir to Hyatt Hotels. Also built two roads hospitality which was later acquired by Hyatt in 2018. Neither paid dividend. Assigned no dividends.

- Number 331 – Jerry Yang – Co-founded Yahoo which was acquired by Verizon Media in 2016 and Verizon Media paid dividends. Assigned dividends received.

- Number 366 – James Clark – Owns stock in multiple companies, some of which like Apple pay dividends. Assigned dividends received.

- Number 371 – Kavitark Ram Shriram – His venture capital firm (Sherpalo Ventures) is not publicly traded and alphabet (aka google) does not pay dividends. Assigned no dividends.


- Number 386 – Jennifer Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

- Number 394 – Linda Pritzker – Heir to Hyatt Hotels which started paying dividends after 2018. Assigned no dividends.

- Number 400 – Christopher Cline – Sold his stake in his coal mining firm, Foresight Energy, in 2015. Assigned no dividends.

This appendix explains our replication of Koeplin, Sarin and Shapiro (2000) (henceforth KSS), which studies whether the value of private companies reflects an illiquidity discount. This appendix also discusses our extension of their analysis to include data after 1998.

J.1 Creating a Transactions Sample

To construct the sample, we first identify all acquisitions of US companies on Thomson One (formerly on SDC Platinum) between 1984 and 2019. KSS restrict the sample to those acquisitions where necessary financial historical data were available. We take this restriction to mean that KSS drop all transactions which have a missing value for any of the variables they use. We also follow KSS in dropping transactions of financial and public utility firms. Ultimately, our sample consists of 167 private firm transactions from 1984-2019, and 113 private firm transactions from 1984-1998. Our sample is somewhat larger than that of KSS, which consists of 84 transactions over the period 1984-1998.

We then endeavor to compare each private firm transaction to a comparable public company acquisition. We do so according to the following algorithm:

1. For each private firm transaction, we attempt to identify an acquisition of a public company in the same year and in the same 4-digit industry.

2. If there was more than one such comparable acquired public company, we use the public company closest in sales to the private company in question.

3. If there was no public company transaction in the same year and same 4-digit industry, we attempt to find a comparable transaction in the same year and 3-digit industry.

4. If this is also unsuccessful, we repeat the above step for the same 2-digit and then 1-digit industry.

This matching strategy matches some private company transactions to the same public company transaction.

J.2 Calculating the Discount

KSS focus on four multiples:

- EBIT multiple: Ratio of enterprise value to EBIT. EBIT is defined as earnings before interest income, interest expense, non-operating income, taxes and minority interest for the last 12 months ending on the date of the most current financial information prior to the announcement of the transaction.

- EBITDA multiple: Ratio of enterprise value to EBITDA. EBITDA is defined as earnings before interest, taxes, depreciation and amortization for the last 12 months ending on the date of the most current financial information prior to the transaction.
• Book multiple: Ratio of enterprise value to book value. Book value is defined, as in KSS, as short-term debt + long-term debt + shareholders’ equity as of the date of the most current financial information prior to the announcement of the transaction.

• Sales multiple: Ratio of enterprise value to net sales. Net sales is defined as revenue after taking into account returned goods and allowances for price reductions for the last 12 months ending on the date of the most recent financial information prior to the announcement of the transaction. If net sales are not available, total revenues are used instead.

Tables J.1 and J.2 present mean and median multiples for two sample periods, 1984-2019 and 1984-1998, respectively. Specifically, following KSS, we:

1. Calculate the mean (median) multiple for all private companies and for all public companies

2. Calculate the private company discount from the mean (median) multiple of the private target companies and the comparable mean (median) multiple of the public target companies.

The discount column is calculated from the group means or medians using the following formula:

$$\text{Private company discount} = 1 - \frac{\text{Private company multiple}}{\text{Public company multiple}}$$  \hspace{1cm} (48)

### J.3 Results

Overall, our estimates are similar to KSS once we restrict the sample to earlier years. In later years, the private company discount appears to have fallen somewhat.

Focusing on the full sample results, means and medians differ substantially. Because the median is more robust to outliers, we prefer median-based measures. Observing the median, we see evidence of a private company discount associated with EBITDA multiples on the order of 6% to 9%, though we cannot rule out a discount of zero. This discount estimate is smaller than that of KSS, which was around 12%. Based on this evidence, we use 10% as an approximate liquidity discount for pass-through firms.
Table J.1: Private Company Discounts of Sample Transactions 1984-2019

<table>
<thead>
<tr>
<th></th>
<th>Private Targets</th>
<th>Public Targets</th>
<th>Discount</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>Enterprise Value/EBIT</td>
<td>20.67</td>
<td>12.71</td>
<td>51.74</td>
</tr>
<tr>
<td>Enterprise Value/EBITDA</td>
<td>10.86</td>
<td>8.87</td>
<td>11.62</td>
</tr>
<tr>
<td>Enterprise Value/Book Value</td>
<td>3.50</td>
<td>2.45</td>
<td>2.56</td>
</tr>
<tr>
<td>Enterprise Value/Sales</td>
<td>4.62</td>
<td>1.13</td>
<td>1.99</td>
</tr>
</tbody>
</table>

Notes: This table presents mean and median multiples for the sample period 1984-2019. Discounts are computed following equation 48. We test whether the private company discounts we measure for means are distinct from zero using a t-test on the equality of means for the private and public company multiples. We test whether the private company discounts we measure for medians are distinct from zero using a t-test on the equality of medians for the private and public company multiples.

Table J.2: Private Company Discounts of Sample Transactions 1984-1998

<table>
<thead>
<tr>
<th></th>
<th>Private Targets</th>
<th>Public Targets</th>
<th>Discount</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>Enterprise Value/EBIT</td>
<td>17.45</td>
<td>12.07</td>
<td>24.17</td>
</tr>
<tr>
<td>Enterprise Value/EBITDA</td>
<td>10.45</td>
<td>8.19</td>
<td>11.93</td>
</tr>
<tr>
<td>Enterprise Value/Book Value</td>
<td>3.64</td>
<td>2.43</td>
<td>2.67</td>
</tr>
<tr>
<td>Enterprise Value/Sales</td>
<td>1.50</td>
<td>1.12</td>
<td>2.05</td>
</tr>
</tbody>
</table>

Notes: This table is the same as table J.1, except it uses only transactions from 1984 to 1998, following KSS.
K State-Year Housing Capitalization Factors

To derive capitalization factors based on unequal property tax rates over time, we combine state-level data from four sources: (1) effective property tax rate data from ATTOM, (2) property tax assessor data from 2012 from DataQuick, (3) CoreLogic state-level house price indexes, and (4) state-level property tax revenues and population from the US Census of States. For itemizers, we estimate housing assets at the person-level using the formula,

$$\hat{A}_{ht}^{huit} = \beta_{st}^{ptax} y_{it}^{ptax} = \frac{1}{r_s^t} \times y_{it}^{ptax},$$  \hfill (49)

where $r_s^t$ is the effective state-level property tax rate in year $t$ and $y_{it}^{ptax}$ is the observed flow of property tax deductions. To estimate $r_s^t$, we separately estimate the numerator—state-level property tax revenues—and denominator—state-level housing asset values—each year.

State-level property tax revenues $\tilde{R}_t^S$ are given by,

$$\tilde{R}_t^S = R_{Census,t}^S \times \theta_{R,2012}$$  \hfill (50)

where $R_{Census,t}^S$ is state-level property tax revenues from the Census of States, and $\theta_{R,2012}$ equals $R_{DataQuick,2012}^S / R_{Census,2012}^S$ is a time-invariant factor equaling 0.64 used to scale down Census revenues to remove commercial property taxes from the Census figures. We use 2012 as a baseline year because, for this year, we have the assessed property tax amounts from DataQuick.

State-level housing asset values are then given by,

$$\tilde{W}_t^S = \tilde{W}_{2012}^S \times \frac{p_{CoreLogic,t}^{CoreLogic}}{p_{CoreLogic,2012}^{CoreLogic}} \times \frac{pop_t^S}{pop_{2012}^S},$$  \hfill (51)

where $\tilde{W}_{2012}^S$ equals $(1/r_s^{ATTOM}) \times R_{DataQuick,2012}^S$ and provides an estimate in 2012 of property values underlying assessed tax amounts, $p_{CoreLogic,t}^{CoreLogic}$ is the state-level CoreLogic house price index based on a repeat-sales methodology, and $pop_t^S$ is state-level population from the Census. We use population to proxy for the number of households and hence housing units. Adjusting the value of housing for growth in housing units allows us to apply the price index to the approximately correct underlying stock of housing units. Finally, we estimate the state-level property tax rate over time as

$$r_t^S = \frac{\tilde{R}_t^S}{\tilde{W}_t^S}.$$  \hfill (52)

We validate this approach in two ways. First, we compare the cross-sectional property tax rates from ATTOM to those based on the Census. Second, we compare aggregate real estate values to the US Financial Accounts. Both match our estimates reasonably well (Appendix Figure A.17).
L Additional Discussion Comparing Our Approach to Alternatives

L.1 SCF

Many of the possible differences between our series and the raw SCF have been addressed by previous work, including Henriques and Hsu (2014); Saez and Zucman (2016); Bricker, Henriques, Krimmel and Sabelhaus (2016); Bricker, Henriques and Hansen (2018); Sabelhaus and Volz (2019); Bricker, Hansen and Volz (2019b); Saez and Zucman (2020b). We have incorporated these lessons into our analysis and discuss them in Section 1 when discussing how we adjust the SCF. Moreover, concerns about the sampling process and response bias are addressed with compelling evidence in Bricker, Henriques, Krimmel and Sabelhaus (2016), suggesting this cannot account for differences across methods. In this section, we focus on the remaining discrepancies.\(^8\)

Our preferred series closely fits the most comparable equal-split SCF series that makes all adjustments, trending similarly and matching the levels for the top 0.01% and top 0.1% (Figure 1). For the top 1%, there are level differences ranging between 1 and 7 percentage points of total household wealth, with the gap narrowing in the 2000s and then opening again in 2016. On average the level difference is about 3 percentage points.

What are the likely sources of the difference between our top 1% series and the SCF?

**Private Business.** 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. Appendix Figure A.24 shows that scaling the aggregate private business values to match Financial Account totals results in a very similar level and trend for the top 1% SCF series. It also aligns the portfolio shares (Appendix Figure A.25). These findings align with those in Bricker, Henriques, Krimmel and Sabelhaus (2016) and Bricker, Henriques and Hansen (2018), who show that scaling private business to match Financial Accounts aggregates closes some of the gap between capitalized estimates and the SCF. This force also explains why the DFA measures of top 1% shares are closer to ours.\(^9\)

The SCF uses respondents’ self-reported estimated value of the business.\(^9\) The accuracy of this approach for estimating aggregates depends on who responds, the number of respondents sampled, and whether the answer reflects market values or some other concept. Response rates to the SCF decline at the top, but BHKS present compelling evidence that those sampled are representative of the population along many relevant dimensions.

\(^8\)Bricker and Volz (2020) updates the findings in BHH and compares them to other estimates. Since it follows the BHH method, the issues that we raise about SCF interest rates apply to BV as well.

\(^9\)Note the DFA units are at the household level, so require additional adjustment for comparison to ours. Appendix Figure A.19 presents levels of different wealth components for top groups comparing our tax unit series to the DFA series.

\(^9\)In particular, they answer the question, “What is the net worth of (your share of) this business?” and, if the person doesn’t know, then they answer the question, “What could you sell it for?” for each business. (questions X3129 for business 1, X3229 for business 2, and X3335 for remaining businesses). Bhandari, Birinci, McGrattan and See (2019) provide a critique of reported responses to private business questions in the SCF. However, some argue some of these critiques are based on a misreading of survey questions.
However, sampling uncertainty remains nontrivial. Even taking respondents’ values as given, a wide range of total private business values is supported by the data, which reflects the relatively small number of top business owners in the sample and how the concentration of business wealth amplifies sampling uncertainty.

Beyond sampling uncertainty, there are a few reasons to believe SCF respondents are reporting values that might reflect their reservation prices rather than the prices they would receive if they actually sold the business. First, we compare median and average valuation ratios for SCF respondent businesses to public market equivalents. Appendix Table B.3 presents summary statistics and Appendix Tables B.4 and B.5 provide multiples overall and for specific wealth groups, respectively. We measure ratios relative to revenues, cost basis (a proxy for the book value of assets), and profits, and report statistics for those in the P99-99.9 and top 0.1% in SCF net worth who are active business owners (54% and 72% of these groups, respectively). Across metrics, SCF-implied valuation ratios rival or substantially exceed public company valuations. For example, Appendix Table B.4 shows that the average market value to sales ratio in the SCF is 2.6 and 2.5 for those in the P99-99.9 and top 0.1% of net worth, which is much higher than the market to sales ratio of 1.8 in Compustat. Similar valuation premia appear for ratios relative to profits (22.6 and 18.2 vs. 16.3) and cost basis (8 and 9.5 vs. either 3 or 6.5 depending on whether the measure of cost basis in Compustat is book equity or net capital). These facts also contrast with evidence we present on liquidity discounts for private targets in large firm acquisitions (Appendix J), evidence on private market sales data for mid-market firms (Bhandari and McGrattan, 2021), and the literature estimating private firm sales discounts (Officer, 2007), all of which point toward considerable private firm discounts.91

Second, SCF respondents appear to report high values for other assets without readily available market values. For example, respondents report higher housing values relative to market values based on house price indices and hedonic models based on comparable transactions (Gallin, Molloy, Nielsen, Smith and Sommer, 2021; Feiveson and Sabelhaus, 2019; Batty, Bricker, Briggs, Holmquist, Hume McIntosh, Moore, Nielsen, Reber, Shatto, Sommer, Sweeney and Henriques Volz, 2019). On average, aggregate housing values in the SCF exceed those in the Financial Accounts by 15-40%.92 It is worth noting that, in comparison to illiquid and more heterogeneous private businesses, housing is an asset class for which respondents are more likely to have better comparable transactions with more available public information about the market price of their house.

There are several benefits from our bottom-up, tax-data-based approach. Our estimates use firm-level performance data from business tax returns and detailed industry information from the population of private pass-through firms, combined with market-based valuation multiples and an empirically appropriate liquidity discount. There is substantial value from independent estimates that are not tied to the Financial Accounts or self-reports. They help triangulate the true value of a primary source of top wealth and income and enable an estimate of the returns to private business wealth across individuals and industries. Our approach sheds more light on the nature of private business valuation, reduces sampling uncertainty, and points toward potential drivers of differences across data sets.

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91 See Bhandari and McGrattan (2021) Appendix Table A.9.
92 There are also methodological differences between the SCF and Financial Accounts.
Fixed Income. A second difference between our results and those based on the SCF concerns the share of top wealth held in fixed income. While our estimates for fixed income portfolio shares are well below the PSZ series, our shares exceed those for the adjusted SCF, the estate tax series, and the UBS family office data. A key potential driver of this force is the large aggregate level of deposits in the Financial Accounts relative to the SCF. For example, in 2016, the Financial Accounts total for time deposits and short term investments is $8.7T whereas the SCF total is only $4.1T (Batty, Bricker, Briggs, Holniquist, Hume McIntosh, Moore, Nielsen, Reber, Shatto, Sommer, Sweeney and Henriques Volz, 2019). Because the Financial Accounts household sector is a residual that includes hedge funds, the aggregate may be too big. Since we allocate this Financial Accounts total, if this amount includes deposits not held by individuals or is otherwise too large, we will assign too much fixed income wealth overall and to those with interest income from financial institutions. Consistent with this idea, the DFA series for the top 1% shows a higher concentration of fixed income assets than in the SCF (Figure 13).

Other categories. 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. Our housing aggregates follow the Financial Accounts. According to Gallin, Molloy, Nielsen, Smith and Sommer (2021), housing wealth in the accounts is between 10 and 20% below the total for housing wealth in the SCF and in the American Community Survey, with an especially wide gap during the housing bust. Overall, the SCF totals appear less cyclical than those in the Financial Accounts. Together, these differences imply that homeowners in the bottom 99% have more housing wealth in the SCF than in our estimates.

Regarding pensions, the SCF-derived numbers augmented by Sabelhaus and Volz (2019) (SV) show more pension wealth in the P90-99 group than we estimate, whereas our model predicts relatively more wealth in the bottom 90 and in the right tail. Estimating pension wealth via capitalization is challenging because we do not have information about worker tenure or public-sector employment status, characteristics that SV find are important for matching pension wealth in addition to age and income. These considerations are less important at the very top because pension wealth is a small share of total top wealth. However, incorporating more data to improve the assignment of pension wealth at the bottom is a worthy goal for future work.

These discrepancies between the SCF and Financial Accounts have been highlighted in prior work. In addition to the papers mentioned above, Henriques and Hsu (2014) provide an overview and comparison of methods for the Flow of Funds (now the Financial Accounts) versus the SCF. They focus on differences between series in terms of aggregate wealth and describe likely drivers of these differences. They find the gap between net worth levels in the SCF and the Financial Accounts is largely due to a combination of higher values of private business and owner-occupied housing in the SCF, as well as larger values of consumer credit in the Financial Accounts.93 Bricker, Henriques, Krimmel and Sabelhaus (2016) also

93Regarding the latter, we follow Henriques and Hsu (2014) in adjusting aggregate Financial Accounts consumer credit to better reflect credit card debt instead of current balances. However, we do not adjust housing or private business to align with the SCF in order to develop estimates that more closely align with market values rather than self-reports.
highlight the gap in housing wealth between the SCF and the Financial Accounts in their reconciliation analysis.

The Distributional Financial Accounts map all categories of the SCF onto the aggregates of the Financial Accounts. The goal of this exercise is to enable higher frequency estimates of the wealth distribution consistent with valuation methods used in the Accounts. Key aggregate adjustments include reducing the value of private business wealth, both in corporate and non-corporate firms, and reducing the value of real estate relative to SCF aggregates. In addition, because the Financial Accounts include defined benefit pensions, the DFA aggregates exceed SCF aggregates for combined pension wealth. Because it combines several of the aggregate adjustments described above, the DFA top shares are closer than the SCF top shares to ours.

Overall, the SCF is a crucial input into the wealth inequality debate. It allows researchers using income tax data to say more than we otherwise could, provides a benchmark for inequality research, contains detailed portfolio information that is unavailable in other data sets, and enables analysis by characteristics (such as race) that cannot be studied elsewhere. It is also the only U.S. data set that contains independent estimates for the joint distribution of wealth and income with meaningful representation at the top. Understanding the likely source of differences between our series and the SCF helps identify key issues for future research. Ultimately, we view the SCF as a complementary resource to our data for learning about the wealth distribution. Among respondents, the SCF collects valuable information on debt, non-taxed items, and the joint distribution between stocks and flows, which we use to evaluate the fit of our empirical model.

At the same time, the SCF is of course too small of a sample for some things. First, while it is possible to estimate top shares for groups within the top 1%, the underlying number of observations becomes small, resulting in uncertainty due to sampling error (Bricker, Henriques and Hansen, 2018; Bricker, Hansen and Volz, 2019b). Second, the data collected on private business in the SCF have limited detail in terms of firm characteristics, which could help shed light on the nature of this wealth and on its value. Our approach uses firm-level performance data and detailed industry information from the population of private pass-through firms, combined with market-based valuation multiples and an empirically appropriate liquidity discount. Third, it is difficult to characterize the underlying assets in the portfolios of the wealthy because of the complexity of their portfolios and uncertainty about how certain assets are classified by respondents. For example, the majority of interest income generated at the top comes from partnerships that might be classified in one of several ways on the SCF survey. Consequently, measuring the risk profile of wealthy portfolios and the return for different asset classes is not feasible without making strong assumptions. Fourth, estimates of wealth inequality at the geographic level are not possible, again due to the sample size.

L.2 SZ (2016) and PSZ (2018)

We start by comparing our preferred estimates to those in SZ and PSZ, which adopts the equal-returns approach for capitalizing income to estimate wealth within asset class.
L.2.1 Fixed income under equal returns

The two main differences in fixed income approaches are (1) the degree of heterogeneity in returns and (2) the aggregate amount of fixed income in different vintages of papers (i.e., in SZ, PSZ, SZ 2020).

The headline results in SZ and PSZ assume no heterogeneity in fixed income returns. However, as we noted in the introduction, SZ 2016 do include some robustness series that assume modestly higher rates at the top. For example, they present a two-tier model that assigns some a capitalization factor that is based on the US 10-year treasury rate:

$$\beta_{fix,UST}^t = \begin{cases} 
\beta_{fix,UST,bot}^t & \text{if original wealth rank } \geq 99 \\
\beta_{fix,UST,bot}^t \times \frac{y_{fix}^t}{\hat{a}_{fix,UST}^t} & \text{otherwise}
\end{cases}$$

(53)

where $$y_{fix}^t$$ is taxable interest income, $$\hat{a}_{total,fix}^t$$ is total household fixed income assets from the Financial Accounts, $$\hat{a}_{fix}^t$$ is the fixed income wealth estimate, and original wealth is $$\hat{a}_{fix}^t + \sum_k \hat{a}_k^t$$ where $$k$$ are the other types of wealth. Note that the baseline equal-return fixed income wealth estimate $$\hat{a}_{fix}^t$$ is used to determine the wealth rank. While the UST10 approach improves model fit relative to the equal-returns approach (Figure 5D), it underperforms our estimates by overstating estimated wealth, especially for the top 0.1% and top 0.01%.

SZ 2016 also present a robustness series that uses a top rate from estate tax data. This series follows the same approach but replaces $$r_{fix,UST}^t$$ with $$r_{fix,estate}^t$$ for the top group, although this rate isn’t weighted and has several other limitations.

94 The headline approach to estimate fixed income is: $$\hat{a}_{fix}^t = \beta_{fix}^t \times y_{fix}^t$$, where $$\beta_{fix}^t = \frac{1}{r_{fix,UST}^t}$$ is the equal-return interest rate, $$y_{fix}^t$$ is taxable interest income, and $$\hat{a}_{total,fix}^t$$ is total household fixed income assets from the Financial Accounts.

95 Saez and Zucman (2020a) cite Bricker, Henriques and Hansen’s (2018) estimated rate of return as partial motivation for applying a lower rate like the UST10 rate. However, Bricker, Henriques and Hansen (2018) focus on the top 1%, not the top 0.1%, and the rate of return for the top 1% ranked by net worth, not by interest income.

96 Appendix Figure A.23 uses a test similar to Saez and Zucman (2016) to show that capitalizing top fixed income in the SCF overstates actual SCF top fixed income wealth and its growth. However, our analysis of heterogeneity in SCF fixed income yields different results. We investigated the sources of difference. Appendix Figure A.23 replicates Figure IV.B. of Saez and Zucman (2016), which they use to test the capitalization approach within the SCF. We first successfully replicate their figure in panel A. Panel B shows that capitalizing fixed income within the SCF, however, results in overstated fixed income concentration, but Panel C shows this overstatement is masked by understated private business wealth concentration. Moreover, this exercise does not hold the ranks fixed when comparing actual to capitalized wealth. In addition, it applies SCF-based capitalization factors, which are smaller than the factors used in the tax data due to lower aggregates in the SCF. Our analysis in Appendix Figure A.23 holds ranks fixed and uses the tax-based capitalization factors.

97 For the estate tax returns, we also apply inverse mortality rates, which is needed to estimate rates of return for the living. Saez and Zucman (2016) advocate applying this approach “one should weight matched estate-income observation by the inverse of the mortality rate conditional on age, gender, and wealth. We
estimate has a denominator that includes too many assets—specifically, fixed income and money market mutual funds—which are more prevalent at the top, which biases the rate down. There is also considerable uncertainty due to small samples in the estate tax data.\footnote{Indeed, SZ 2016 cite this limitation as well: “We retain our baseline top 0.1% wealth share estimate because only a few hundred non-married individuals die with estates above $20 million each year. As a result, there is likely significant noise in the annual series, making it difficult to make a precise and systematic inference of the true interest premium at the top.” (p. 550)} Moreover, in the SCF data and estate tax data, it is not possible to isolate the boutique funds that we show generate 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.

Our estimates from information returns and from the minimum distance approach find substantially more heterogeneity in returns (Figure 5), and thus allocate much less fixed income wealth to the top. The basis for our approach, which is described in Section 3, are (i) data from billions of information tax returns, (ii) estimates from a risk exposure model, (iii) substantial corroborating evidence on top returns from PIMCO, family office surveys, and public disclosures of wealthy politicians. We also provide several reasons why past estimates using returns in the estate tax data and SCF are likely biased downward. Figure 6 provides updated SCF estimates of top rates and ratios of top rates to average rates.

A second source of difference is the update in aggregates described in Section 1. Removing categories that do not generate taxable fixed income flows and making other updates to aggregates in SZ (2020) result in smaller capitalization factors for fixed income. Figure 5B shows that assuming no heterogeneity with the updated fixed income aggregates results in capitalization factors in 2016 of around 100, whereas the no heterogeneity ones using the PSZ 2018 aggregates result in capitalization factors that were about 25% larger. Figure 5C shows the consequences for estimated top 0.1% wealth shares (holding ranks fixed using our preferred measure).\footnote{The latest SZ (2020) approach uses these updated aggregates but a substantially smaller degree of heterogeneity than what we find using information returns and CMD estimates (Figure 5A). Appendix M provides the specific formulas for SZ 2020 fixed income.}

Another source of difference in fixed income estimates concerns the ranking of individuals. We find that 20% of aggregate private business wealth is held by those who report losses. The SZ approach will rank rich private business holders, who can own businesses with very large assets and revenues, much lower than we do in the wealth distribution, resulting in different people getting smaller fixed income capitalization factors when accounting for heterogeneous returns on fixed income.

Figure 5C shows the consequences of different aggregates (compare the PSZ 2018 with old aggregates to equal returns with updated aggregates) and methods for estimating the degree of return heterogeneity on the top 0.1% wealth shares.

\subsection*{L.2.2 Public equity with more weight on capital gains}

For estimating C-corporation equity, the key difference between our approach and Saez and Zucman (2016) and PSZ is that we reduce the relative weight on realized capital gains. Instead of a weight of 0.9 on dividends and 0.1 on realized capital gains, Saez and Zucman leave this difficult task to future research.” (p. 549)
(2016) sum both flows, which is equivalent to using weights of 0.5. Note that because aggregate realized capital gains are much larger than dividends—in 2016, total realized gains are $614B versus $254B for dividends—the relative contribution of capital gains to estimating C-corporation equity wealth exceeds 50%. A second difference is that we apply updated SZ 2020 aggregates as described in Section 1. A third difference is that we do not use SZ's mixed method approach that "ignores capital gains when ranking individuals into wealth groups but are taken into account when computing top shares. To determine a family's ranking in the wealth distribution, dividends are multiplied by 54 for 2000, and to compute top shares both dividends and capital gains are multiplied by 10." (p. 534). In other words, the weight on dividends is 1 when ranking units, but .5 when computing top shares, with the other .5 being applied to capital gains. Another difference relative to SZ and PSZ is that we incorporate Forbes wealth into our estimates of both C-corporation and private business wealth. Figure 8C shows the consequences of different aggregates (compare the PSZ 2018 with old aggregates to equal returns with SZ 2020 C-corporation equity aggregates) and weights on dividends and capital gains for top 0.1% wealth shares.

SZ and PSZ address the potential bias from overweighting capital gains through applying a “mixed” method, which defines ranks separately from wealth estimates. They motivate this approach by arguing that, relative to alternatives, the ranks are not biased by lumpy realizations and the method “uses all the available information” but do not provide direct evidence supporting the \( \alpha = 0.5 \) assumption for estimating C-corporation wealth. Their primary defense of this approach is that “it does not affect the results much” in terms of overall top wealth shares. Although these assumptions are indeed less important for top shares than adjusting for heterogeneous returns in fixed income, moving from their mixed approach to our \( \alpha = 0.1 \) approach matters; for example, it has a larger effect than augmenting our series with Forbes. By providing statistical tests of alternative models using SCF data on both stocks and flows, our approach uses the data to discipline these assumptions.

L.2.3 Pass-through Equity, Housing, and Pensions

For pass-through business, Saez and Zucman (2016) apply one equal-returns capitalization factor for the sum of positive proprietorship and positive partnership income and a separate equal-returns capitalization factor for positive S-corporation income. Three differences deserve note. First, relative to ours, this approach misses industry heterogeneity in the mapping of flows to stocks, including heterogeneity in financial and human capital components of pass-through business income. Second, it estimates wealth of zero for firms that generate

\footnote{Note that in SZ (2020), this mixed method is no longer used. Instead for both rankings and shares, SZ (2020) put .5 weight on dividends and .5 weight on a smoothed measure of capital gains, which equals “the capital gains realized on average by the tax unit and it’s closest 20 neighbors in terms of wealth (estimated by capitalizing equity solely with dividends).” SZ (2020) now only use qualified dividends starting in 2003. \footnote{SZ (2020) adjust equity wealth to match the amount of billionaire wealth implied by Forbes, although they appear to allocate all of this wealth to C-corporation equity rather than allocating some to pass-through business (which section I shows is nearly as large as a share of Forbes wealth in 2016). “Between 1982 and 2005, we adjust the equity wealth of the top 400 so that total top 400 wealth matches Forbes (reducing equity wealth proportionally in the rest of the distribution) [...] Starting in 2006 we implement the same correction but for a group slightly larger than the top 400, namely billionaires (estimated using the Forbes 400 and Pareto-interpolation techniques).”}}
zero or negative taxable income despite having significant assets, such as in the real estate sector. We estimate that 20% of total pass-through business wealth accrues to those with negative business income and that these losses are often claimed by rich individuals. Third, SZ and PSZ rely on the Financial Accounts aggregates for the value of private business, which may be understated due to incomplete source data as discussed in Section 7.

For pensions, SZ apply a convex combination of a capitalized function of wages and capitalized pension income.\footnote{The function is $y_{it}^{wagetop60} = \begin{cases} y_{it}^{wage} - \text{median}(y_{it}^{wage}) & \text{if } P_{it}^{wage} \geq .5 \\ 0 & \text{if } P_{it}^{wage} < .5 \end{cases}$. The goal is to correct for relatively low pension wealth among those with below median wages. They apply a weight of 0.4 for the wage-based estimate and 0.6 for the pension-income-based estimate.} First, relative to ours, this approach does not account for the significant life-cycle pattern for pension wealth. We use age-specific capitalization factors and weights on wages versus pension income to fit this pattern. Second, we incorporate external estimates for the distribution of defined benefit pension wealth, which improves estimates especially for the bottom 90%.\footnote{Saez and Zucman (2016) construct their model to target the top 10% share of defined contribution and funded defined benefit wealth in the cross section and over time (see their footnote 24). They invite the use of new data to improve the allocation across the wealth distribution.} Third, as noted by Auten and Splinter (2019), Saez and Zucman (2016) include nontaxable pension rollovers in their measure of pension income, which tends to overstate the concentration of pension wealth because rollovers are stock rather than flow measures and disproportionately accrue to the top. In contrast, we only use taxable pension distributions to estimate pension wealth. Last, we present new estimates in auxiliary series that augment pension wealth with various estimates of Social Security wealth.

For housing, we follow a similar approach to Saez and Zucman (2016), except they apply an equal-returns capitalization factor in a given year for mapping property tax deductions to housing assets. That approach ignores quantitatively relevant cross-state differences in property taxes and regional house price dynamics.

Figure A.15 shows the consequences of different approaches for pass-through business, housing, pensions, and other categories in Panels A, B, C, and D, respectively. The PSZ 2018 and equal returns series show the impact of differences in aggregates (e.g., the SZ 2020 aggregate updates mentioned in Section 1, as well as the bottom-up pass-through estimates). Figure A.15A shows that going from the PSZ series to updated aggregates in the equal return series lowers top 0.1% wealth. Our preferred approach, however, increases the contribution of pass-through business wealth to top 0.1% shares from around 2% with equal returns to around 3.5%, which exceeds the PSZ estimates by about a percentage point in 2016. Panels B and D show that the aggregate updates between PSZ and equal returns are more minor in terms of the impact on the top, though panel D shows larger amounts of munis, currency, and other in the equal returns series and our preferred series than the PSZ series. This difference reflects the fact that SZ and PSZ allocate residual wealth as a component of fixed income.

The concentration of fiscal income flows also helps illustrate why different approaches can deliver different capitalization estimates. Figure A.5 shows how the concentration of fiscal income flows has evolved. Each series shows the share of fiscal income for each category accruing to the top 10%, top 1%, top 0.1%, and top 0.01%, where the ranks are defined
using the respective fiscal income flow distribution. Figure A.5A shows that concentration has risen dramatically for interest income. The top 1% received approximately 30% of all taxable interest income from 1965 to 1985. This share started climbing steadily to above 40% in the 1990s, to above 50% in the mid-2000s, and then rapidly rose after 2009 to nearly 80%. Under the equal returns assumption, this growth in interest income concentration implies spectacular growth in the concentration of fixed income wealth.

Figures A.5B-H show that the evolution of other capital income components has been less dramatic over time. Property tax payments are much less concentrated than the other components, reflecting the broad holdings of owner-occupied real estate across people. Top 1% shares have hovered around 20% since the late 1980s. For C-corporation equity wealth, the extent of concentration depends on the measure being used. Concentration is higher for capital gains than dividends, though both are very concentrated. The top 1% dividend share exceeded 70% in the late 1960s, hovered around 60% from 1980 to 2000, and recovered to around 70% since the early 2000s. Top 1% capital gains, in contrast, started near 80% and have fluctuated between 80 and 100% since 2000. As shown in Figure 2B, the aggregate capital gains series is also more volatile than the other series, reflecting the accumulation of past gains and losses and the importance of timing decisions for realization. Income concentration among S-corporations and partnerships is higher than for C-corporation dividends and has been stable over time. Proprietorship income is less concentrated.

As pensions have grown in popularity and breadth over time and the population has aged, the concentration of pension income has fallen from the top 1% receiving 60% of income in 1966 to just 20% in 2016. Wage income shows a modest increase in concentration relative to other components.

L.3 Forbes 400

An important limitation of capitalizing equity flows is that it may miss some of the richest Americans, for whom the majority of capital gains are unrealized. Several top Forbes individuals have their wealth concentrated in public firms, some of which do not pay dividends (e.g., Warren Buffett and Berkshire Hathaway, Mark Zuckerberg and Facebook, and Jeff Bezos and Amazon). Others do (e.g., Bill Gates and Microsoft, Larry Ellison and Oracle, the Waltons and Walmart, Phil Knight and Nike). In section I.3, we find that the majority of people who are primarily public equity rich in Forbes own companies that paid dividends in 2016. We find that 56% of the collective wealth of Forbes individuals who are primarily public equity rich owned companies that paid dividends in 2016. Nonetheless, our capitalization approach relies on observable fiscal capital income, so would miss non-dividend-generating C-corporation wealth.104

104S-corporation income concentration is somewhat higher than in Cooper, McClelland, Pearce, Prisinzano, Sullivan, Yagan, Zidar and Zwick (2016) because we rank by flow component rather than total fiscal income. 105Saez and Zucman (2020a) note that our approach underestimates wealth for those like Bezos who realize a small portion of capital gains. “According to SEC Form 4 public records, in 2016 Jeff Bezos sold around 2 million Amazon stocks at a price of around $700, resulting in up to 1.4 billion in capital gains. In the SZZ methodology, the implied equity wealth is $1.4 billion = $5.6 billion. That same year, Bezos's stake in Amazon was valued at around $60 billion.” (p.8–9). However, this issue is equally relevant for the approach in SZ and PSZ. The capitalization factor for $\alpha = .5$ in 2016 is 26, so Bezos's estimated wealth in the SZ capitalization approach is 13 times $1.4B = 18.2 billion. Rather than illustrating that our approach is dramatically inferior to SZ's, the example shows that no approach to capitalization will get Bezos close
To address concerns that our approach may miss Forbes wealth, we augment our capitalized estimates with Forbes data. Figure 8D presents three alternative approaches that combine Forbes data with our capitalized estimates for the top 1%, top 0.1% and top 0.01% in 2016. The first bar presents our estimates without augmentation. The second bar replaces the richest 400 in our data with the Forbes 400. Note this approach may be suboptimal because our estimates of private business wealth are arguably more accurate than the self-reported and hard-to-verify private business valuations in Forbes. The third bar follows Bricker, Hansen and Volz (2019a) (BHV). In particular, we add the Forbes 400 members and adjust the sampling weights to account for overlap between capitalized estimates and the additional observations from Forbes. For comparison, we include the equal-returns estimates from PSZ. Finally, we also present a bar that uses a bottom-up estimate of missing C-corporation wealth associated with non-dividend-generating firms that augments our primary approach of BHV. Our preferred estimates include the Forbes-augmented series using the BHV method.

Different approaches to incorporating the Forbes data have only a modest effect on our overall top share estimates. The key reason why this is the case is that, while those in the Forbes list are very wealthy, their collective wealth only accounts for 2.8% of total household wealth. Given that more than half of these individuals derive most of their wealth from private business, our estimates likely incorporate a substantial portion of the collective wealth in Forbes. In addition, among those who are primarily C-corporation rich, 68 of 159 owned companies that did not pay dividends in 2016, whereas 91 of 159 owned companies that did pay dividends. Overall, we estimate that owners of private businesses or dividend-paying public companies account for 77% of collective Forbes wealth in 2016.

As noted above, while some individuals at the very top own non-dividend paying companies, several receive substantial dividend income, for whom we are able to allocate C-corporation wealth appropriately. In section I.3, we estimate that non-dividend-generating C-corporation owners in Forbes collectively have around $440B in C-corporation equity wealth in 2016. Since the BHV approach effectively averages Forbes estimates with tax data estimates when bins overlap, this $440B amounts to $220B (=0.5 × $440B) of missing C-corporation equity wealth in our baseline estimates that use BHV blending (assuming that our tax data approach assigns these units zero wealth). This $220B estimate amounts to 9.2% of overall Forbes wealth and 0.26 percentage points of overall household wealth. In other words, if we added an additional $220B for potentially missing non-dividend-generating C-corporation equity wealth in top shares, our top 0.1% share estimate would increase from 15.0% to 15.26% in the main equal-split, individual-level series.

There are several reasons why the Forbes wealth estimates are uncertain. First, when Raub, Johnson and Newcomb (2010) link the Forbes 400 data to the estate tax data, they only find about half of that wealth in the administrative data. It’s hard to determine how

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106 The total Forbes wealth of the 68 individuals who primarily own public firms and whose companies did not pay dividends represent 44% (=547.5B/ (547.5B + 697B)) of the total wealth of Forbes 400 individuals who primarily own public firms.
much of this gap is due to tax avoidance and evasion, which are also likely quite substantial. Second, given the publicity associated with placing onto the Forbes list, it is possible that individuals exaggerate their wealth (Kopczuk, 2015). There are several well-known cases of substantially exaggerated private business values in the Forbes list. Third, many of the Forbes 400, those in the Bloomberg billionaires list, or top 400 units in the SCF have substantial shares of wealth in private firms, which are difficult to value. One contribution of our approach is that our private firm values are based on firm-level administrative data and capital market valuation multiples, which are likely more accurate than estimates based on harder to verify self-reported estimates.

**Forbes comparisons.** We can compare estimates from different approaches to the Forbes data. Saez and Zucman (2019b) fit a Pareto distribution to estimate the number of billionaires and their collective wealth using Forbes data (see footnote 3 in Saez and Zucman (2019b)).

In terms of top wealth shares, the Forbes-based Pareto parameter of 1.4 in 2016 implies top 0.01%, top 0.1%, and top 1% shares in 2016 of 3.8%, 7.3%, and 14.1%, respectively. Top shares from our preferred series in terms of tax units (3.6%, 7.6%, and 16.1%) line up fairly closely with these Forbes-400-implied top shares. In terms of dollars, a Pareto parameter of 1.4 implies that those making above $590M, which is the threshold for being in the top 0.001%, collectively hold $3.6T in wealth. Our estimate in Figure 8D for this group estimates that their collective wealth is $3.1T. This difference is sensitive to the Pareto parameter, which is somewhat uncertain as it varies depending on the cutoff of the 400th person and depends on distributional assumptions. It also depends on the accuracy of the Forbes $2.4T estimate in 2016.

Given the importance of pass-through business wealth—which represents around one trillion dollars in Forbes wealth in 2016—and the uncertainty in the Forbes estimates, our preferred approach is to use the blending approach of BHV rather than replace the top 400 capitalized estimate with the Forbes data. Many of these tax units may be in the data already and it is not clear that the accuracy of top wealth shares would improve. Instead, we think it is best to describe what we do and provide a number of alternative approaches.

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108 Indeed the Bloomberg list has an accuracy rating system that reflects these difficulties: [here](https://www.bloomberg.com/billionaires/methodology/)

109 On the other hand, Forbes also misses some billionaires, since people above the Forbes 400 threshold but who do not appear in Forbes have been sampled by the SCF (Batty et al., 2020, Appendix E).

110 Given the 2016 estimate of the Pareto parameter of $a = 1.4$, and the assumption that top wealth is Pareto distributed, the top $p$ percentile’s share of wealth in 2016 is $\left(\frac{p}{100}\right)^{1.4-1}$. Without blending, the top 0.001% tax unit group would have $2.66T. Replacing the top 400 capitalized tax units with the Forbes 400 estimates would result in an estimate of $3.53T. Augmenting our preferred approach by adding the estimate of non-dividend-generating C-corporation equity yields an estimate of $3.36T. With a Pareto parameter of 1.4, the amount of wealth between the Forbes 2016 cutoff of $1.7B and $590M is $\left[\frac{1700}{590}\right]^{(1.4-1)} - 1 = 52\%$ of the wealth above $1.7B in Forbes, which is $2.4T. Thus, the collective wealth of those with wealth above $590M is $2.4T \times 1.52 = 3.6T$. 

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to help readers understand the potential magnitudes of different adjustments to account for Forbes wealth.

### L.4 Estate Tax

There are several limitations to the estate tax series for understanding levels and trends of wealth inequality. Comparing estimates using estate tax data requires scaling up observed wealth by an estimate of the underlying sampling rate, which is the decedent’s unobserved mortality rate. Only those with sufficiently high wealth face the estate tax, and mortality rates are likely correlated with wealth and may be trending over time.

We consider alternative approaches for estimating mortality rate differentials across wealth groups and over time and the effect on top wealth share estimates based on estate tax data. To address this problem, Kopczuk and Saez (2004b) (KS) begin with population mortality rates produced by the Social Security Administration. Lacking time-varying mortality rates by wealth, KS apply time-fixed mortality differentials for white college graduates by age and gender from Brown, Liebman and Pollet (2002). Saez and Zucman (2019a) (SZ) argue that mortality differentials are understated in the KS series, and that mortality differentials have increased over time. SZ update and apply the KS series through 2012, and then apply new mortality rate differentials for the top 1 percent by household income. Specifically, SZ construct mortality differentials by age and gender using 2012-2014 mortality rates by household income percentile from Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016) (CSALSTBC). SZ then linearly extrapolate between the KS differential in 1980 and the top income differential in 2012.

These differentials have several weaknesses. First, individuals are ranked based on household income at age 61 or lower, which necessitates an age threshold of 76 in the CSALSTBC data. Because these data do not include mortality rates for those over 76, SZ impute via extrapolation the mortality differentials for this group—which comprises the majority of estate tax filers. Second, SZ calculate the mortality differential using only three years of mortality data, 2012 to 2014, so mortality rate trends and thus trends in estimated wealth concentration depend on an assumed underlying trend. To address these concerns, and to examine the sensitivity of estate tax-based wealth estimates, we estimate new mortality rates for the top 1% using two measures of household income, using 1- and 2-year lagged income, and employing two smoothing techniques, for ages 30 to 90 and for years 1998 to 2017.

Appendix Figure A.28 compares the original KS approach, which we have updated to 2016, to the SZ approach, and to the approach using our mortality statistics.\(^{112}\) Consistent

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\(^{112}\) The new mortality rates for years 2001-2014 are generally similar to those of Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). Mortality rates constructed using household capital income (AGI plus tax exempt interest less wages) are slightly higher on average for both genders than mortality rates constructed using income including wages.

\(^{113}\) For comparison, we focus on mortality rates constructed using income definitions which most closely match the CSALSTBC estimates. Specifically, we rank individuals by household adjusted gross income plus tax-exempt interest measured two years prior. CSALSTBC use the same definition of income, measured two years prior, or at age 61, whichever is earlier. To more closely approximate the smooth relationship between mortality rates and age in the baseline mortality rates produced by the Social Security Administration, we use five-year moving averages across age. For example, the estimated mortality rate at age 90 is an average of point estimates for those aged 88 to 92.
with SZ, our estate tax series shows a higher level of wealth concentration relative to the KS approach. However, we find that the mortality differential across the income distribution was already substantial in 1998 and has increased only slightly over subsequent years. As a result, our estate tax series shows only modest growth in wealth concentration, compared to the SZ series which relies on linearly increasing mortality differentials through 2012. The level of top 0.1% wealth concentration estimated in the new estate tax series is 13.7% in 2016.

Little is known about mortality rate trends by wealth group. Moreover, because mortality rates for younger people are fairly low and there are many high wealth individuals in their 50s, small differences in assumed mortality rates can lead to significant differences in estimated wealth.\footnote{Appendix Figure A.29 shows the sensitivity of wealth share estimates to small differences in assumed mortality rates by age. Wealth share estimates are 8.8 times more sensitive to a 0.1 percentage point increase in mortality rates for those aged 51 to 55 compared to those aged 71 to 75.} Thus, considerable uncertainty remains inherent to this approach.

We note a few additional limitations of the estate tax series. First, widespread use of estate tax planning services, avoidance behavior, and the possibility of evasion imply that the amount of wealth observed may be too low relative to the truth. Second, the threshold for filing estate tax returns has increased substantially over time from less than $1M in 2000 to more than $5M in 2016, so estimating wealth shares for groups below these thresholds is impossible. A third weakness for estate tax data involves adding defined benefit pensions. Annuity pension wealth is not included in the estate tax base, therefore we can only estimate top wealth shares excluding this category.

As with the SCF, a key use of the estate tax data is for cross-validating the flow-stock relationship among sampled individuals, especially to measure the interest rate of the wealthy. Unfortunately, the same ambiguities in defining the denominator of interest-bearing assets affect estate tax data, which collect information on boutique funds and dividend-generating fixed income funds in categories that are hard to isolate. Given these definitional issues and the sampling-uncertainty challenges mentioned above, the estate tax data do not permit sufficiently precise measurement of interest rate heterogeneity along the wealth distribution.\footnote{SZ (2016) also cite sampling issues with the estate tax data in choosing not to rely on this source to measure interest rate heterogeneity: “We retain our baseline top 0.1% wealth share estimate because only a few hundred non-married individuals die with estates above $20 million each year. As a result, there is likely significant noise in the annual series, making it difficult to make a precise and systematic inference of the true interest premium at the top.” (p.550)} Appendix Figure A.7 provides estimates of interest rates by different groups. We bootstrap draws from the estate tax sample using SOI sample weights combined with age- and capital-income-specific mortality rates. We compute interest rates using our preferred definition, which attempts to remove fixed income funds from the fixed income asset definition. It illustrates the wide range of the confidence intervals and the sensitivity to mortality events.

The estate tax data do provide useful information about portfolio composition for these individuals. Equity wealth is the most important category for top wealth shares in the estate tax. Private business wealth plays a significant role despite well-known issues associated with valuation of such assets in estates. Fixed income portfolio shares in estate tax data closely resemble those in our preferred series.
M Comparing Fixed Income Capitalization Formulae

This appendix compares the capitalization formulae of different approaches by SZZ and SZ.

1. SZZ 1965-2000 (Classical Minimum Distance Two-Tier)
   - $y_{it}^{fix}$ is taxable interest income
   - $a_{total,fix}^t$ is total household fixed income assets
   - $r_{t}^{fix,CMD,top}$ is the estimated interest rate for the top 0.1% of those in the non-interest wealth distribution; non-top gets implied residual that rationalizes aggregates
     
     \[
     \beta_{t}^{fix,CMD} = \begin{cases} 
     \beta_{t}^{fix,CMD,top} = \frac{1}{r_{t}^{fix,CMD,top}} & \text{if non-interest wealth rank} \geq 99.9 \\
     \beta_{t}^{fix,CMD,bot} = \frac{a_{total,fix}^t - \sum_{i \in \text{top}} \hat{a}_{it}^{fix}}{\sum_{i \in \text{top}} y_{it}^{fix}} & \text{otherwise} 
     \end{cases}
     \]
     
     \[
     \hat{a}_{it}^{fix,CMD} = \begin{cases} 
     \beta_{t}^{fix,CMD,top} \times y_{it}^{fix} & \text{if non-interest wealth rank} \geq 99.9 \\
     \beta_{t}^{fix,CMD,bot} \times y_{it}^{fix} & \text{otherwise} 
     \end{cases}
     \]

2. SZZ 1965-2000 (Classical Minimum Distance Three-Tier)
   - $y_{it}^{fix}$ is taxable interest income
   - $a_{total,fix}^t$ is total household fixed income assets
   - $r_{t}^{fix,CMD,p99.9-100}$ is the estimated interest rate for the top 0.1% of those in the non-interest wealth distribution, $r_{t}^{fix,CMD,p99-99.9}$ is the estimated interest rate for the P99-99.9 in the non-interest wealth distribution (see equation 42 and section H.3 for derivation details), and the P0-P99 group gets implied residual that rationalizes aggregates
     
     \[
     \beta_{t}^{fix,CMD} = \begin{cases} 
     \beta_{t}^{fix,CMD,p99.9-100} = \frac{1}{r_{t}^{fix,CMD,p99.9-100}} & \text{if non-interest wealth rank} \geq 99.9 \\
     \beta_{t}^{fix,CMD,p99-99.9} = \frac{1}{r_{t}^{fix,CMD,p99-99.9}} & \text{if 99.9} > \text{Non-interest wealth rank} \geq 99.99 \\
     \beta_{t}^{fix,CMD,bot} = a_{total,fix}^t - \sum_{i \in \text{top1}} \hat{a}_{it}^{fix} & \sum_{i \in \text{top1}} y_{it}^{fix} & \text{otherwise} 
     \end{cases}
     \]
     
     \[
     \hat{a}_{it}^{fix,CMD} = \begin{cases} 
     \beta_{t}^{fix,CMD,p99.9-100} \times y_{it}^{fix} & \text{if non-interest wealth rank} \geq 99.9 \\
     \beta_{t}^{fix,CMD,p99-99.9} \times y_{it}^{fix} & \text{if 99.9} > \text{Non-interest wealth rank} \geq 99.99 \\
     \beta_{t}^{fix,CMD,bot} \times y_{it}^{fix} & \text{otherwise} 
     \end{cases}
     \]

3. SZZ 2001-2016 (Information Returns)
   - $y_{it}^{fix,k}$ is taxable interest income of type $k \in \{\text{deposits, bonds, loans, boutique}\}$ where boutique means interest income on form 1065-K1, 1120S-K1, and 1041-K1
   - $a_{total,fix}^t$ is total household fixed income assets
     
     (a) Boutique fixed income assets
     
     - $r_{t}^{fix,boutique,Top0.01}$ is the estimated rate of return on boutique fixed income assets for those in the top 0.01 percentile of the AGI distribution
- $r_{fix, boutique, P99.9−99.99}^t$ is the estimated rate of return on boutique fixed income assets for those in the P99.9-99.99 percentile of the AGI distribution.
- $r_{fix, boutique, P99−99.9}^t$ is the estimated rate of return on boutique fixed income assets for those in the P99-99.9 percentile of the AGI distribution.
- $r_{fix, boutique, P90−99}^t$ is the estimated rate of return on boutique fixed income assets for those in the P90-99 percentile of the AGI distribution.
- $r_{fix, boutique, B90}^t$ is the estimated rate of return on boutique fixed income assets for those in the bottom 90 percentile of the AGI distribution.

$$
\hat{\alpha}_{fix, boutique, it} = \begin{cases} 
\beta_{fix, boutique, Top0.01}^t &= \frac{1}{r_{fix, boutique, Top0.01}^t} \quad \text{if AGI rank} \geq 99.99 \\
\beta_{fix, boutique, P99.9−99.99}^t &= \frac{1}{r_{fix, boutique, P99.9−99.99}^t} \quad \text{if} \ 99.9 > \text{AGI rank} \geq 99.99 \\
\beta_{fix, boutique, P99−99.9}^t &= \frac{1}{r_{fix, boutique, P99−99.9}^t} \quad \text{if} \ 99 > \text{AGI rank} \geq 99 \\
\beta_{fix, boutique, P90−99}^t &= \frac{1}{r_{fix, boutique, P90−99}^t} \quad \text{if} \ 99 > \text{AGI rank} \geq 90 \\
\beta_{fix, boutique, B90}^t &= \frac{1}{r_{fix, boutique, B90}^t} \quad \text{if} \ 90 > \text{AGI rank} \\
\end{cases}
$$

(b) Business Loans
- $y_{fix, loan, it}^t$ is taxable interest income from portfolio of loans to other businesses.
- $r_{fix, loan, it}^t$ is the estimated interest rate on business loans.
- $\beta_{fix, loan, it}^t = \frac{1}{r_{fix, loan, it}^t}$ is the capitalization factor.
- $\hat{\alpha}_{fix, loan, it}^t = \beta_{fix, loan, it}^t \times y_{fix, loan, it}^t$ is the fixed income wealth estimate for loan assets.

(c) Deposits
- $y_{fix, deposits, it}^t$ is taxable interest income from deposits.
- $\alpha_{total, fix, deposits, it}^t$ is total household deposits from the Financial Accounts.
- $s_{fix, deposits, g}^t$ is group $g$’s share of total deposits in the SCF. Groups are ranked in terms of the non-interest wealth distribution.
- $r_{fix, deposits, g}^t = \frac{\sum_{i \in g} y_{fix, deposits, it}^t \times \alpha_{total, fix, deposits, it}^t}{s_{fix, deposits, g}^t \times \alpha_{total, fix, deposits, it}^t}$ is the estimated interest rate on deposits for group $g$, where $g \in \{P0 − 90, P90 − 99, P99 − 99.9, P99.9 − 99.99, Top0.01\}$.
\[ \beta_{t}^{\text{fix,deposits}} = \begin{cases} \frac{1}{r_{t}^{\text{fix,deposits,Top0.01}}} & \text{if non-int with rank } \geq 99.99 \\ \frac{1}{r_{t}^{\text{fix,deposits,p99.9-99.99}}} & \text{if } 99.9 > \text{rank} \geq 99.99 \\ \frac{1}{r_{t}^{\text{fix,deposits,p99-99.99}}} & \text{if } 99 > \text{rank} \geq 99 \\ \frac{1}{r_{t}^{\text{fix,deposits,p90-99}}} & \text{if } 90 > \text{rank} \geq 99 \\ \frac{1}{r_{t}^{\text{fix,deposits,p0-90}}} & \text{otherwise} \end{cases} \]

\[ \hat{\alpha}_{it}^{\text{fix,deposits}} = \beta_{t}^{\text{fix,deposits}} \times y_{it}^{\text{fix,deposits}} \] is the fixed income wealth estimate for deposits

(d) Savings Bonds
- \( y_{it}^{\text{fix,bonds}} \) is taxable interest income from savings bonds
- \( r_{t}^{\text{fix,bonds}} \) is the estimated interest rate on savings bonds based on the SCF and coefficients from projecting the SCF on the Treasury rate
- \( \beta_{t}^{\text{fix,bonds}} = \frac{1}{r_{t}^{\text{fix,bonds}}} \) is the capitalization factor
- \( \hat{\alpha}_{it}^{\text{fix,bonds}} = \beta_{t}^{\text{fix,bonds}} \times y_{it}^{\text{fix,bonds}} \) is the fixed income wealth estimate for savings bonds

(e) Fixed Income Mutual Funds
- \( y_{it}^{\text{non-qual-divs}} \) is taxable non-qualified dividend income
- \( a_{it}^{\text{total,fix,mutual}} \) is total household fixed income assets in the form of [fixed income mutual funds]
- \( r_{t}^{\text{fix,mutual}} = \sum y_{it}^{\text{non-qual-divs}} / a_{it}^{\text{total,fix,mutual}} \) is the estimated interest rate on fixed income mutual funds
- \( \beta_{t}^{\text{fix,mutual}} = \frac{1}{r_{t}^{\text{fix,mutual}}} \) is the capitalization factor
- \( \hat{\alpha}_{it}^{\text{fix,mutual}} = \beta_{t}^{\text{fix,mutual}} \times y_{it}^{\text{non-qual-divs}} \) is the fixed income wealth estimate for fixed income mutual funds

\[ \hat{\alpha}_{it}^{\text{fix,info}} = \frac{\hat{\alpha}_{it}^{\text{fix,boutique}} + \hat{\alpha}_{it}^{\text{fix,loan}} + \hat{\alpha}_{it}^{\text{fix,deposits}} + \hat{\alpha}_{it}^{\text{fix,bonds}} + \hat{\alpha}_{it}^{\text{fix,mutual}}}{\sum \hat{\alpha}_{it}^{\text{fix,boutique}} + \hat{\alpha}_{it}^{\text{fix,loan}} + \hat{\alpha}_{it}^{\text{fix,deposits}} + \hat{\alpha}_{it}^{\text{fix,bonds}} + \hat{\alpha}_{it}^{\text{fix,mutual}}} \times a_{t}^{\text{total,fix}}. \]

4. SZ 2016 (baseline)
- \( y_{it}^{\text{fix}} \) is taxable interest income
- \( a_{t}^{\text{total,fix}} \) is total household fixed income assets
- \( r_{t}^{\text{fix}} = \sum y_{it}^{\text{fix}} / a_{t}^{\text{total,fix}} \) is the equal-return interest rate
- \( \beta_{t}^{\text{fix}} = \frac{1}{r_{t}^{\text{fix}}} = a_{t}^{\text{total,fix}} / \sum y_{it}^{\text{fix}} \) is the capitalization factor for all
- \( \hat{\alpha}_{it}^{\text{fix}} = \beta_{t}^{\text{fix}} \times y_{it}^{\text{fix}} \) is the fixed income wealth estimate

---

\(^{116}\) This approach is for the full sample, i.e., for 1965-2016.

\(^{117}\) To match the total amount to the financial accounts (\( a_{t}^{\text{total,fix}} \)), we scale fixed income assets in proportion to fixed income assets from the capitalization of information returns (i.e., \( \hat{\alpha}_{it}^{\text{fix,boutique}} + \hat{\alpha}_{it}^{\text{fix,loan}} + \hat{\alpha}_{it}^{\text{fix,deposits}} + \hat{\alpha}_{it}^{\text{fix,bonds}} + \hat{\alpha}_{it}^{\text{fix,mutual}} \)).
5. SZ 2016 (robustness appendix)

- $y_{it}^{fix}$ is taxable interest income
- $a_{it}^{total, fix}$ is total household fixed income assets
- $r_{it}^{fix, UST}$ is the ten year US Treasury rate; non-top gets implied residual that rationalizes aggregates.\(^{118}\)

\[
\beta_t^{fix, UST} = \begin{cases} 
\beta_t^{fix, UST, top} = \frac{1}{r_t^{fix, UST}} & \text{if original wealth rank } \geq 99 \\
\beta_t^{fix, UST, bot} = \frac{a_t^{total, fix} - \sum_{i \in \text{top}} \hat{a}_{it}^{fix}}{\sum_{i \in \text{top}} y_{it}^{fix}} & \text{otherwise}
\end{cases}
\]

\[
\hat{a}_{it}^{fix, UST} = \begin{cases} 
\beta_t^{fix, UST, top} \times y_{it}^{fix} & \text{if original wealth rank } \geq 99 \\
\beta_t^{fix, UST, bot} \times y_{it}^{fix} & \text{otherwise}
\end{cases}
\]

6. SZ Revising Revisionists (2020)

- $y_{it}^{fix}$ is taxable interest income
- $a_{it}^{total, fix, SZ2020}$ is total household fixed income assets, updated to remove fixed income assets that generate dividends for tax purposes (taxable bonds and loans held through mutual funds, including money market funds)

\[
r_t^{fix, SZ2020} \equiv \frac{\sum y_{it}^{fix}}{a_{it}^{total, fix, SZ2020}} \text{ is the equal-return interest rate}
\]

\[
r_t^{fix, top, SZ2020} = \begin{cases} 
1.15 \times r_t^{fix, SZ2020} & \text{if } t \in \{2003, 2004, ..., 2007\} \text{ and original wealth rank } \geq 99 \\
1.4 \times r_t^{fix, SZ2020} & \text{if } t \geq 2008 \text{ and original wealth rank } \geq 99
\end{cases}
\]

\[
\beta_t^{fix, SZ2020} = \begin{cases} 
\beta_t^{fix, top, SZ2020} = \frac{1}{r_t^{fix, top, SZ2020}} & \text{if original wealth rank } \geq 99 \\
\beta_t^{fix, bot, SZ2020} = \frac{a_t^{total, fix, SZ2020} - \sum_{i \in \text{top}} \hat{a}_{it}^{fix, SZ2020}}{\sum_{i \in \text{top}} y_{it}^{fix}} & \text{otherwise}
\end{cases}
\]

\[
\hat{a}_{it}^{fix, SZ2020} = \begin{cases} 
\beta_t^{fix, top, SZ2020} \times y_{it}^{fix} & \text{if original wealth rank } \geq 99 \\
\beta_t^{fix, bot, SZ2020} \times y_{it}^{fix} & \text{otherwise}
\end{cases}
\]

\(^{118}\)Note that SZ 2016 also present a series that uses a top rate from estate tax data. This series follows the same approach but replaces $r_t^{fix, UST}$ with $r_t^{fix, estate}$ for the top group.

\(^{119}\)Where original wealth is $a_{it}^{fix} + \sum_k a_{ik}^{k}$ where $k$ are the other types of wealth, i.e., the baseline equal-return fixed income wealth estimate $\hat{a}_{it}^{fix}$ is used to determine the wealth rank.

\(^{120}\)Where original wealth is $a_{it}^{fix} + \sum_k a_{ik}^{k}$ where $k$ are the other types of wealth, i.e., the baseline equal-return fixed income wealth estimate $\hat{a}_{it}^{fix}$ is used to determine the wealth rank.