Top Wealth in America
New Estimates under Heterogeneous Returns

by Matthew Smith, Owen Zidar, and Eric Zwick

Online Appendix

1. Sections A and B provide appendix figures and tables, respectively.

2. Sections C, D, and E describe the construction of variables in the tax data, the SCF, and the DFA, respectively.

3. Section F describes the construction of aggregate parameters by portfolio category.

4. Section G describes the level, composition, and evolution of aggregate wealth and capital income.

5. Section H gives sources for other data used in this paper.

6. Section I discusses the representativeness of the fixed income partnerships we use to estimate the boutique interest rates. Section J presents supporting evidence that these boutique interest rates are quantitatively reasonable.

7. Section K describes 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.

8. Section L provides a detailed comparison of capitalization formula for estimating fixed income wealth.

9. Section M describes how we estimate liquidity discounts for private business valuation.

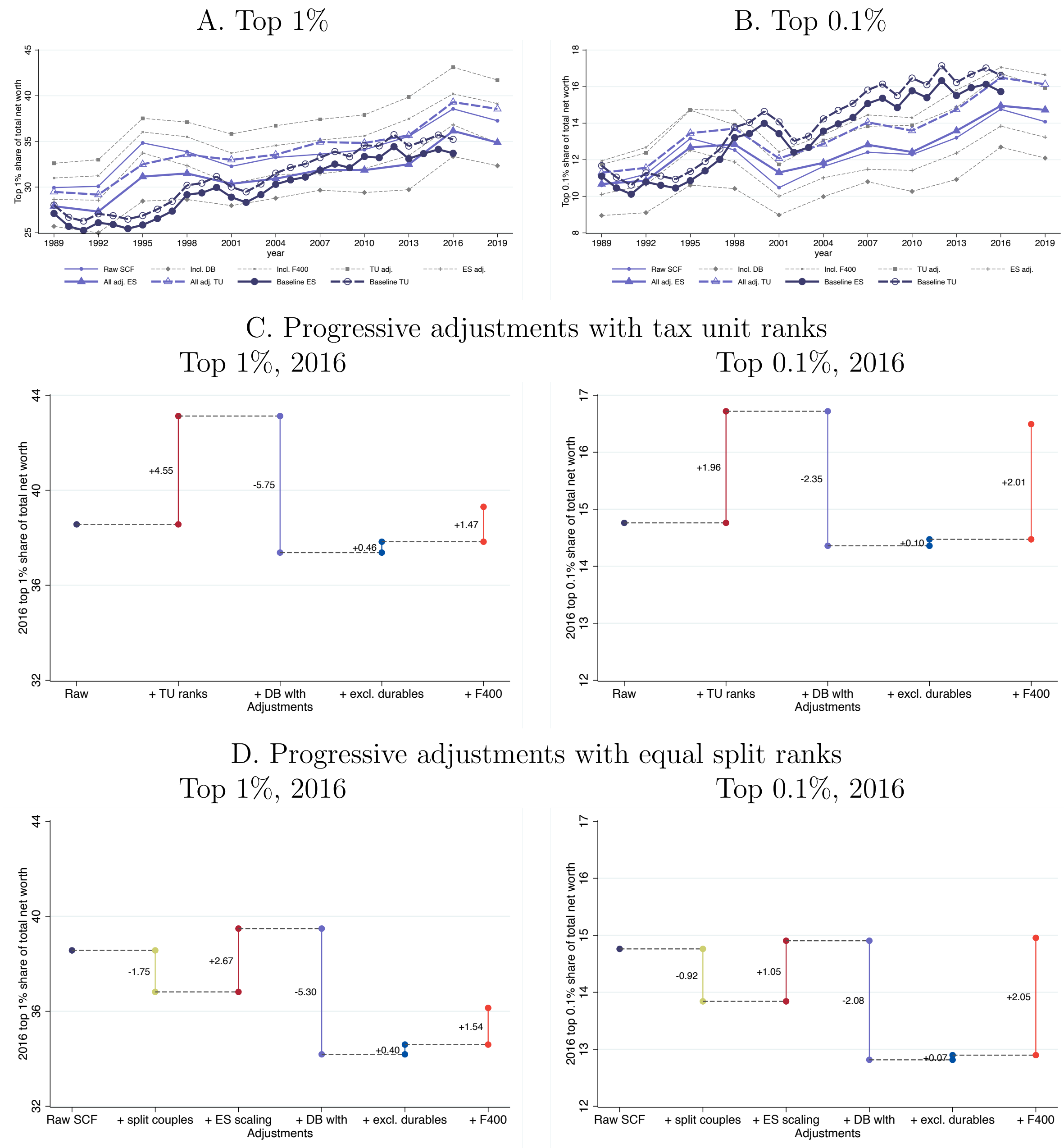
10. Sections N, O, and P discuss how we estimate C-corporation equity wealth, pension wealth, and housing wealth, respectively.

11. Section Q describes the Forbes 400 portfolio data construction.

12. Section R provides supplementary discussion of how our approach and results compare to the SCF (Section R.1); SZ, PSZ, and SZ20 (Section R.2); the Forbes 400 (Section R.3); and estate tax data (Section R.4).

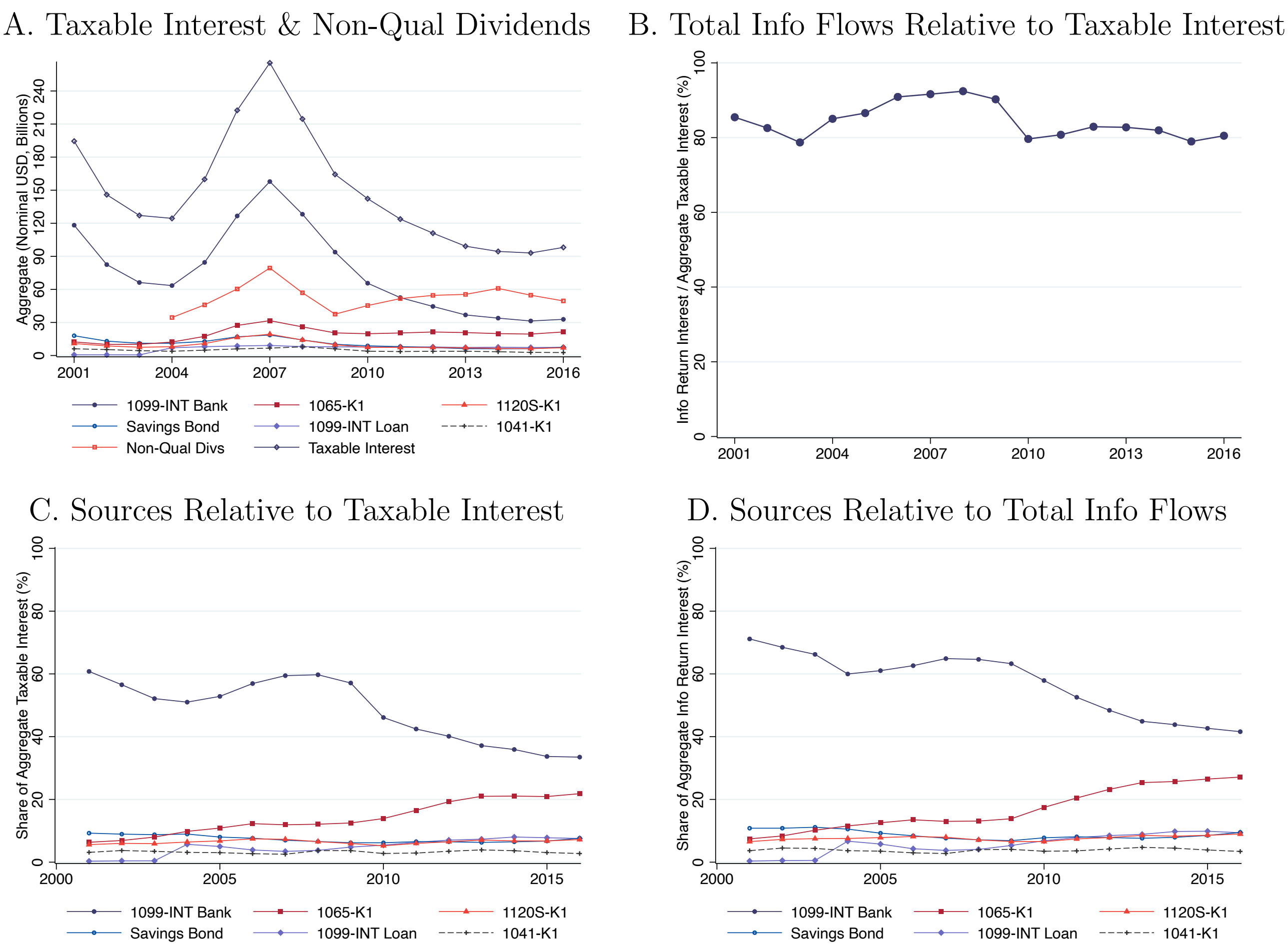
A Appendix Figures

Figure A.1: Top Shares of Wealth in the SCF Before and After Adjustments



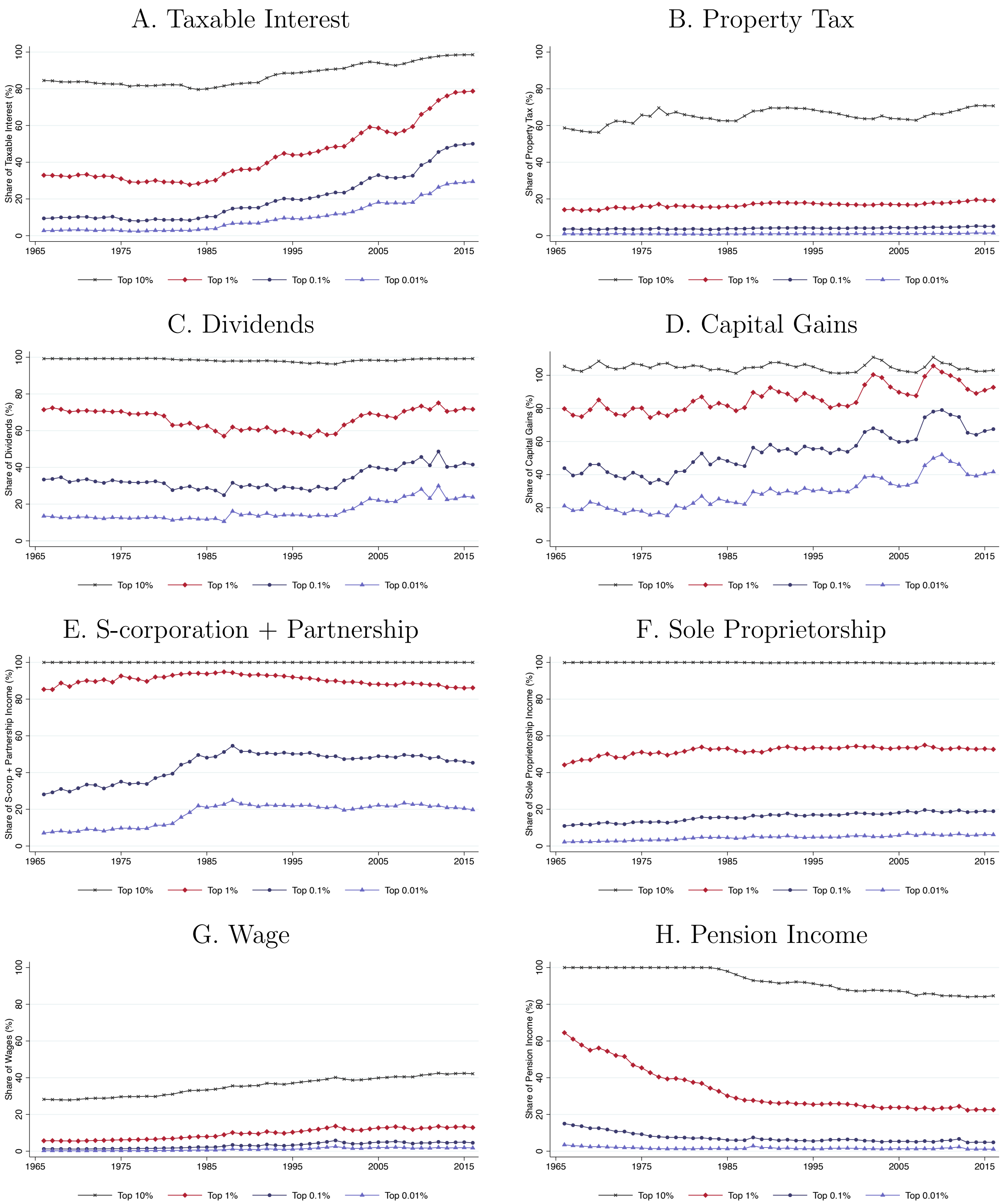
Notes: The Raw SCF specification ranks by and uses the net worth bulletin concept directly from the SCF. To obtain tax unit ranks in the SCF, we follow Saez and Zucman (2019) in computing the number of households with wealth greater than each SCF observation, dividing this quantity by the number of US 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.2: Aggregate Taxable Interest Flows from Information Returns



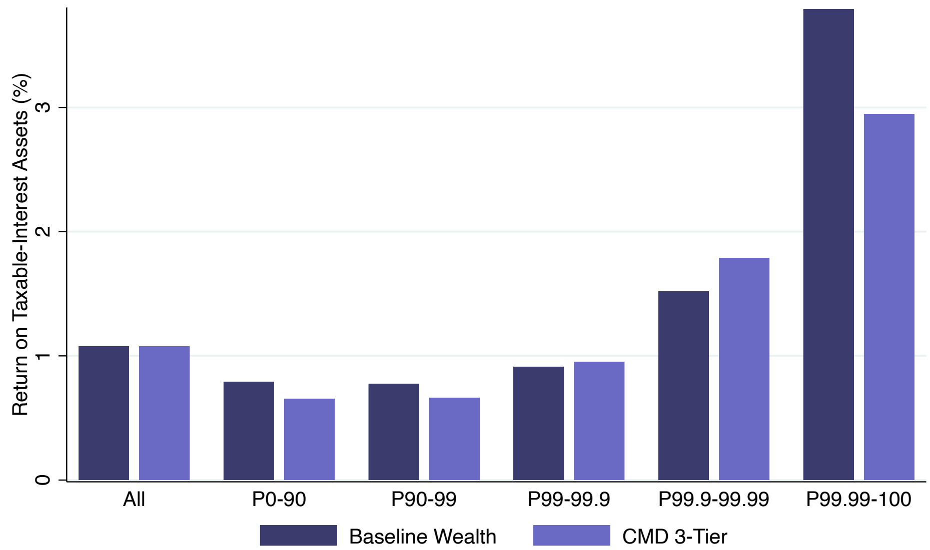
Notes: This figure plots aggregate flows for each source of taxable interest identified in information returns plus non-qualified dividends over time. Panel A plots in nominal dollars each source from information returns (Form 1099-INT for banks, savings bonds, and private loans; Form 1065-K1 for partnerships; 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.3: Concentration of Fiscal Income Components (Ranked by Component)



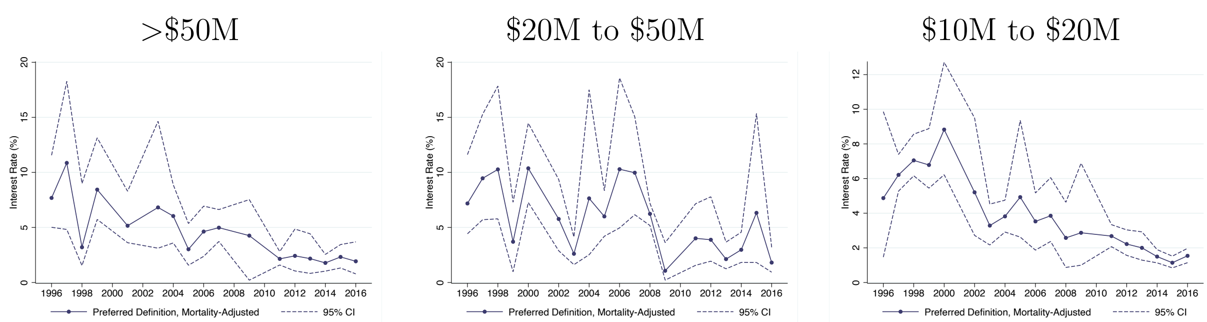
Notes: This figure describes the top share of fiscal income of different types. Panel A plots the evolution of top shares of interest income. Panel B, C, D, E, F, G, and H provide analogous series for property taxes, dividends, realized capital gains, S-corporation plus partnership income, sole proprietorship 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.4: 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 information-returns approach to those from our 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 baseline series is defined as in Figure 3B.

Figure A.5: Interest Rates in Estate Tax Data under Uncertainty

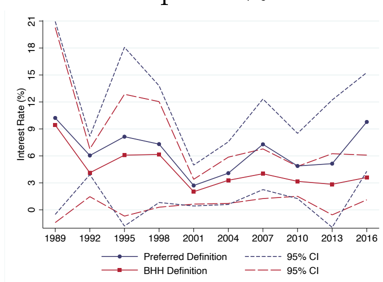


Notes: This figure plots top interest rates under uncertainty for estate tax data. We bootstrap draws from the estate tax sample using SOI sample weights combined with age- and capital-income-specific mortality rates. We compute interest rates using our preferred definition, which attempts to remove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

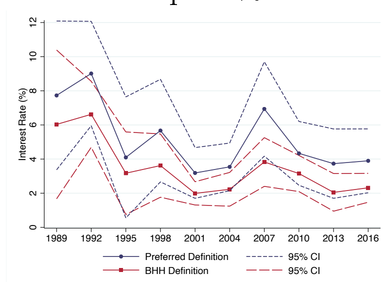
Figure A.6: Interest Rates in the SCF for Taxable-Interest-Generating Assets

A. Interest Rates

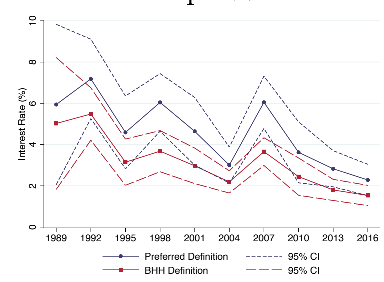
Top 0.01%



Top 0.1%

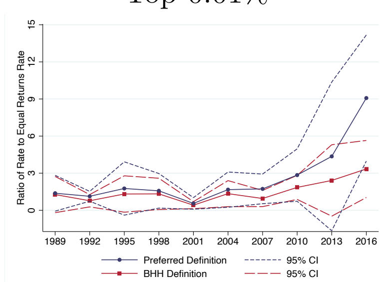


Top 1%

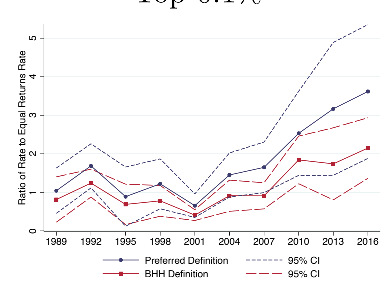


B. Ratio of SCF Top Rate to Equal Returns Rate

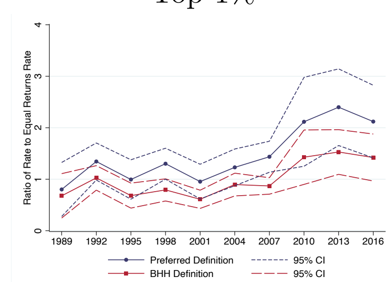
Top 0.01%



Top 0.1%

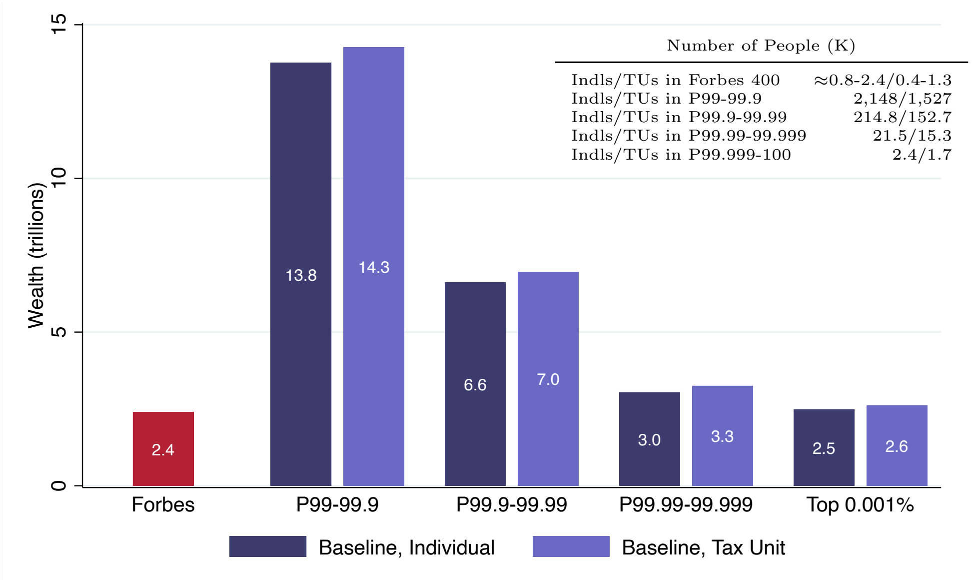


Top 1%



Notes: This figure plots top interest rates and return ratios under uncertainty for the SCF. We sample SCF households using the replicate weights and following the procedure in Bricker et al. (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 4A.

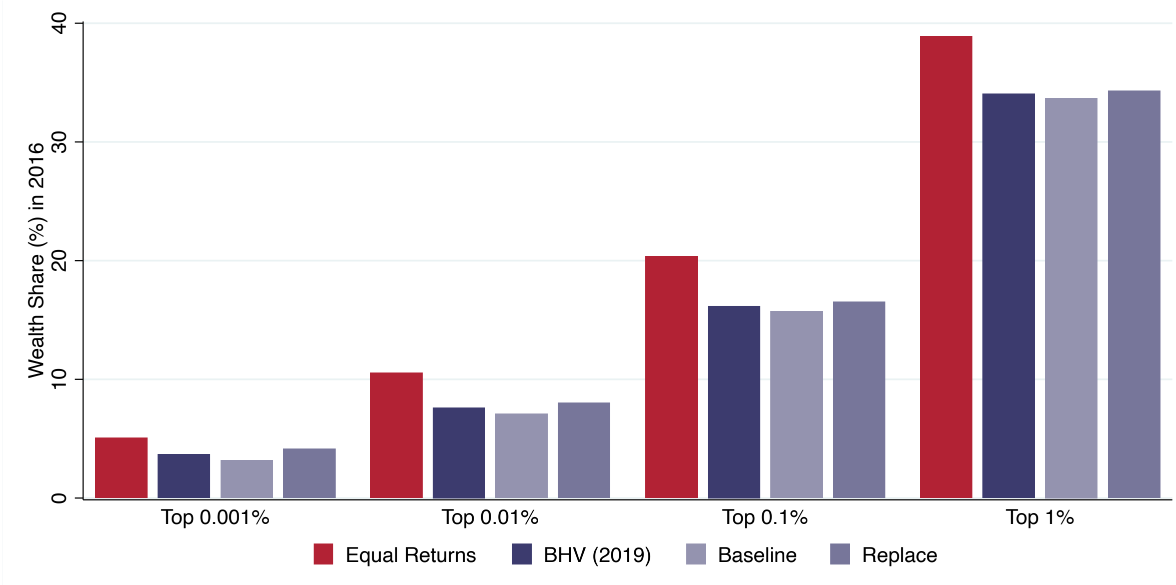
Figure A.7: Size of Different Top Wealth Groups (Baseline)



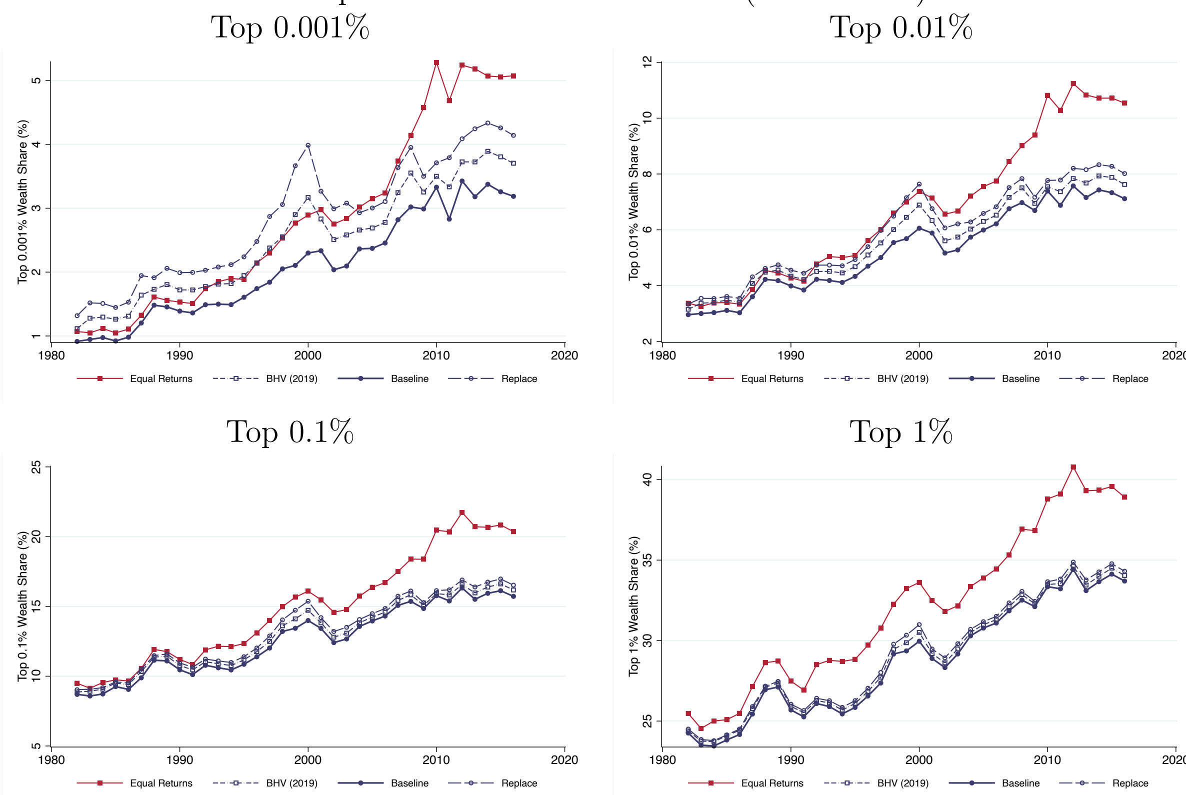
Notes: This figure compares Forbes 400 wealth to aggregate wealth according to our baseline specification for telescoping subgroups of the top 1%: P99-99.9, P99.9-99.99, P99.99-99.999, and the top 0.001% in 2016. The figure reports counts of individuals or tax units in each group. There is considerable uncertainty regarding the number of individuals and tax units that are represented in Forbes. The lower-end-of-the-range estimate assumes each observation in Forbes represents one tax unit and two individuals. For the higher-end estimate, we add the 400 Forbes billionaires, their spouses, and their adult children plus spouses, which amounts to 2,370 individuals who may be represented in Forbes (see Section 5 and footnote 41 for a discussion and Appendix Table B.9 for detailed calculations). For the number of tax units, we add the 400 Forbes individuals plus their approximately 880 adult children to obtain the 1.3K estimate.

Figure A.8: Adding Forbes to Capitalized Estimates

A. Equal Returns vs. Alternatives (2016)

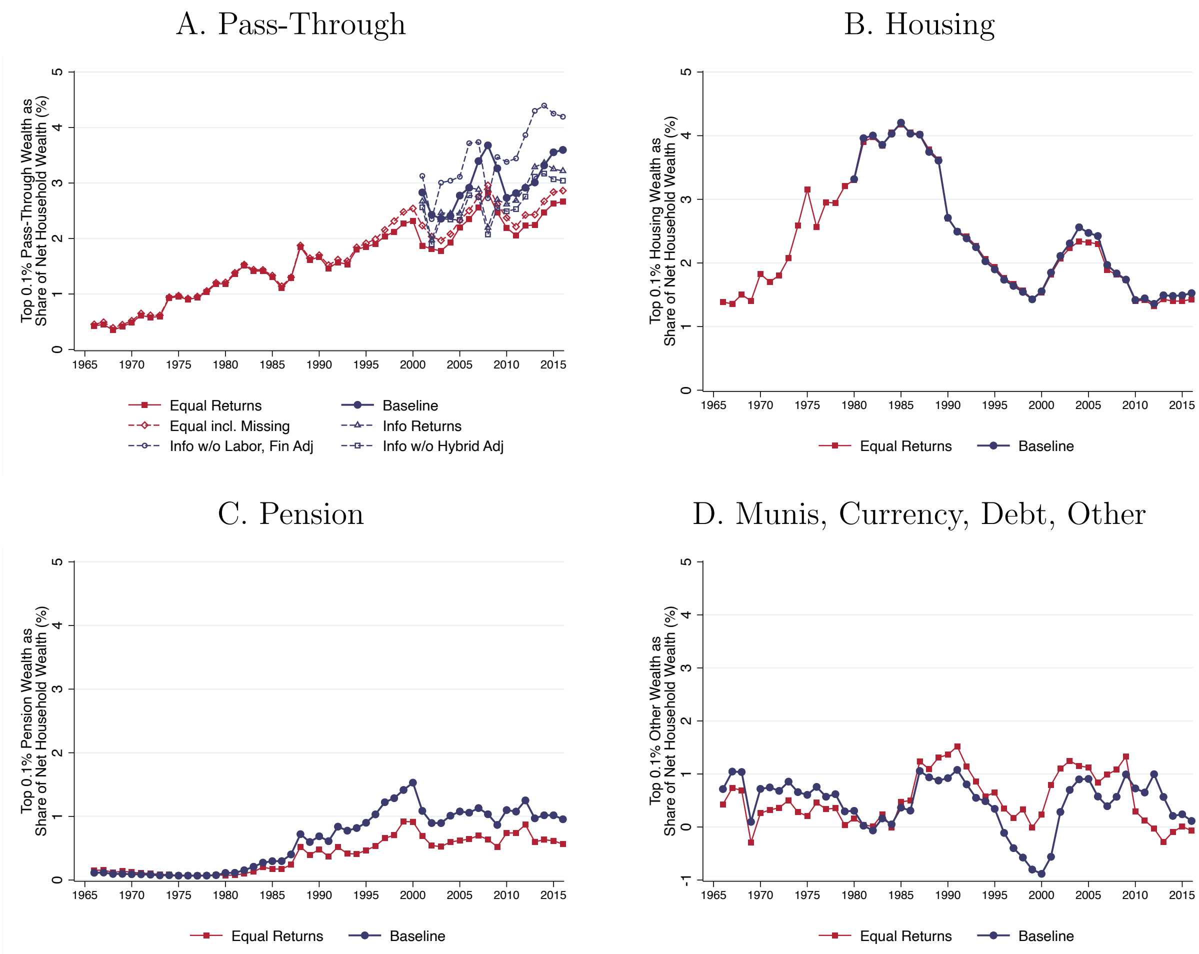


B. Equal Returns vs. Alternatives (Time Series)



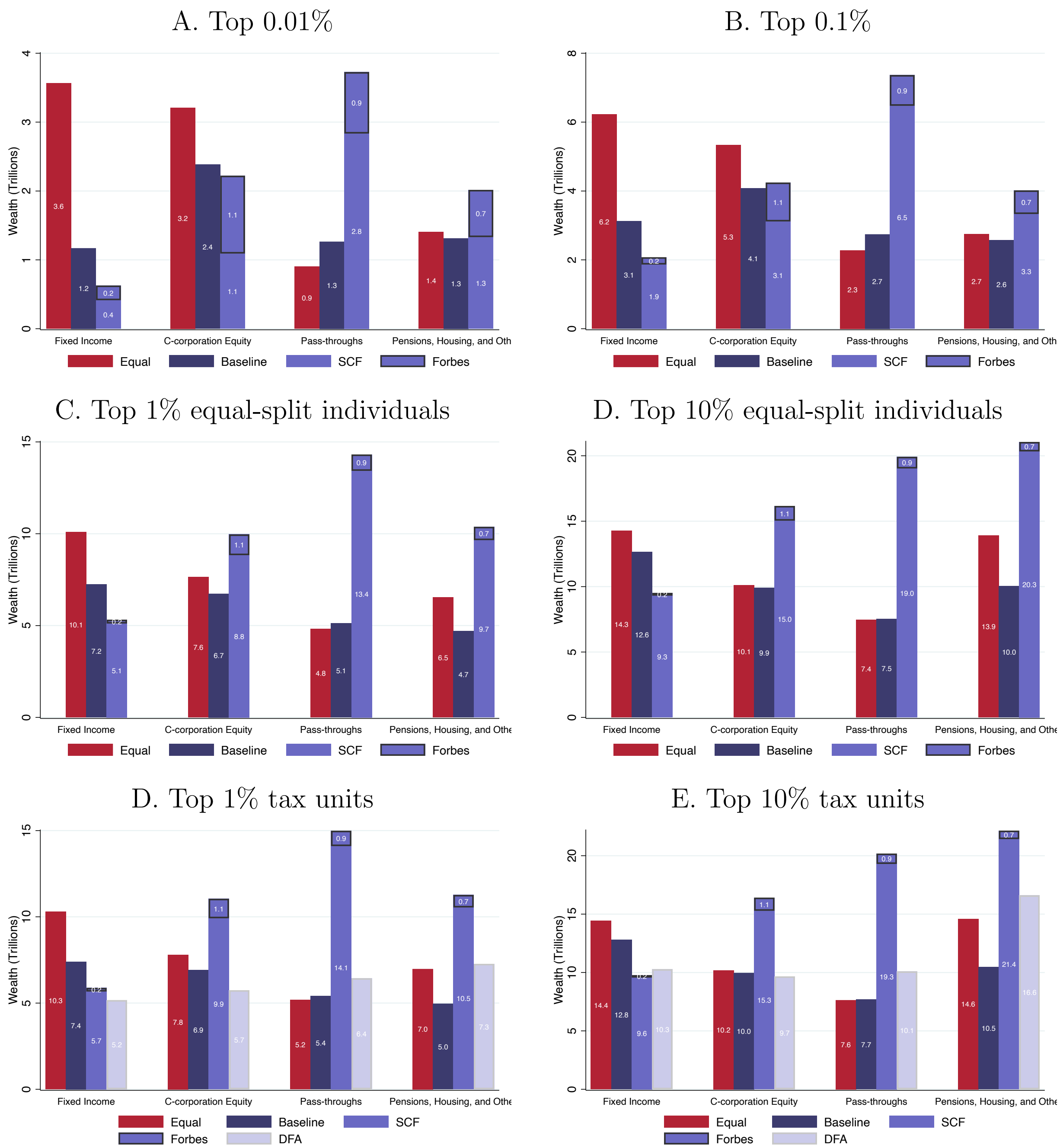
Notes: This figure compares alternative approaches for incorporating Forbes estimates. “BHV (2019)” follows Bricker, Hansen and Volz (2019) by blending Forbes observations into the tax data and adjusting sampling weights to account for overlap. “Replace” replaces the richest 800 individuals with the Forbes 400 after equally splitting wealth. For non-pass-through wealth components, we then scale non-Forbes aggregates to ensure the total matches the Financial Accounts.

Figure A.9: Comparing Approaches for Other Asset Classes (Top 0.1%)



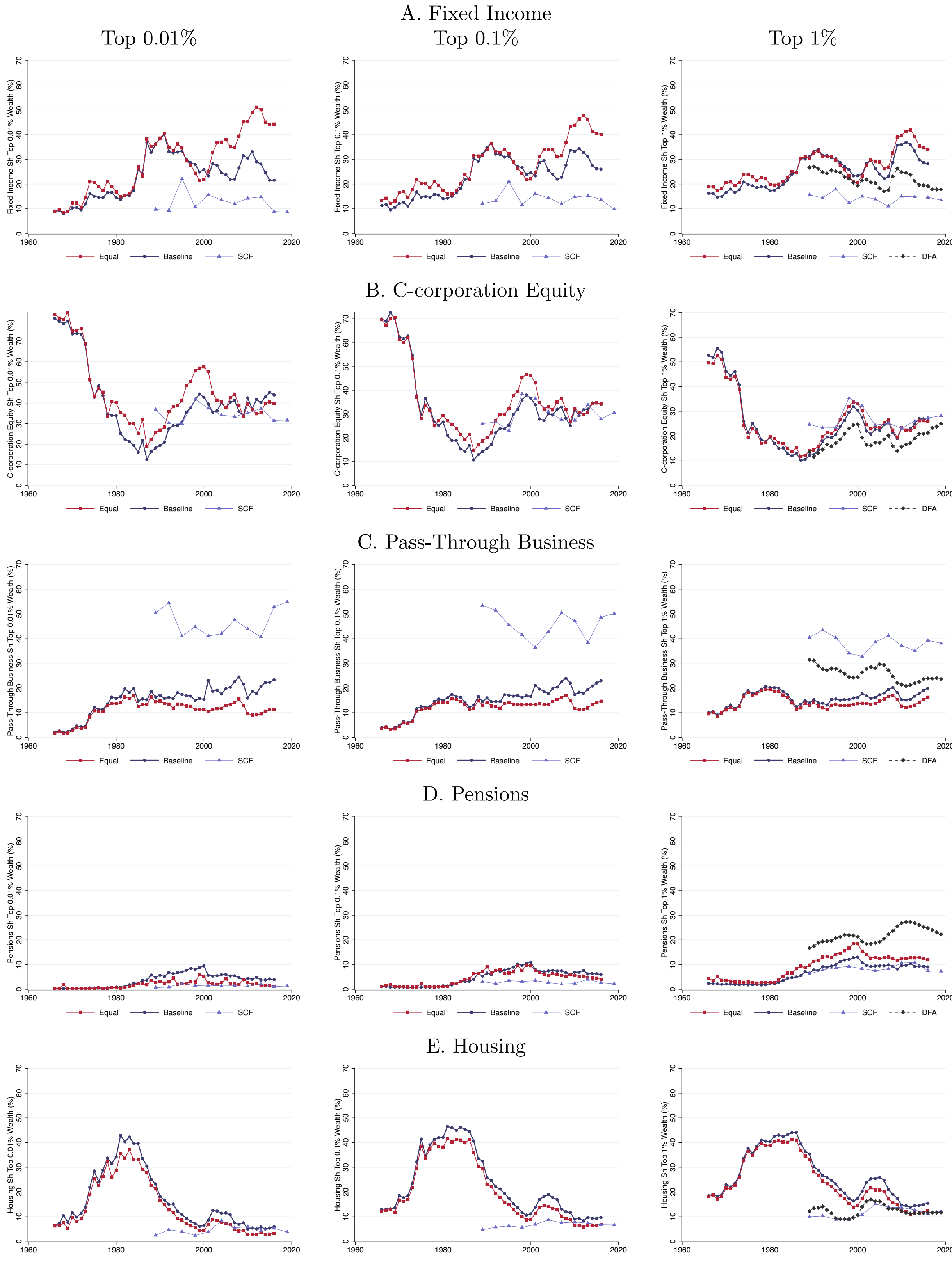
Notes: This figure shows the consequences of different approaches for pass-through business, housing, pensions, and other categories in Panels A, B, C, and D, respectively. It complements Figures 4C and A.25C, which report series for taxable fixed income assets and C-corporation equity, respectively. All graphs rank by baseline wealth to isolate the impact of different wealth models. Panel A shows that going from the Equal Returns series to our baseline approach increases the contribution of pass-through business wealth to top 0.1% shares. In our baseline, we scale our bottom-up estimates to match the aggregates in Saez and Zucman (2020*b*) for S-corporations, partnerships, and sole proprietorships; here, Info Returns reports an unscaled estimate. Our baseline approach excludes pass-through businesses in pure finance firms (which do not distribute ordinary income), as this wealth likely appears elsewhere in our capitalized estimates. We report a series that includes these firms and removes our "hybrid" adjustment for recharacterized wages, as well as one that applies the labor adjustment to pass-throughs with greater than $50 million in profits (which are unadjusted in our baseline approach). Panels B and D show that the differences between equal returns and our baseline are more minor in terms of the impact on the top. Our approach to pensions increases top 0.1% shares because we supplement wages with recharacterized pass-through income in our pension wealth estimates.

Figure A.10: Portfolio Totals at the Top of the Wealth Distribution



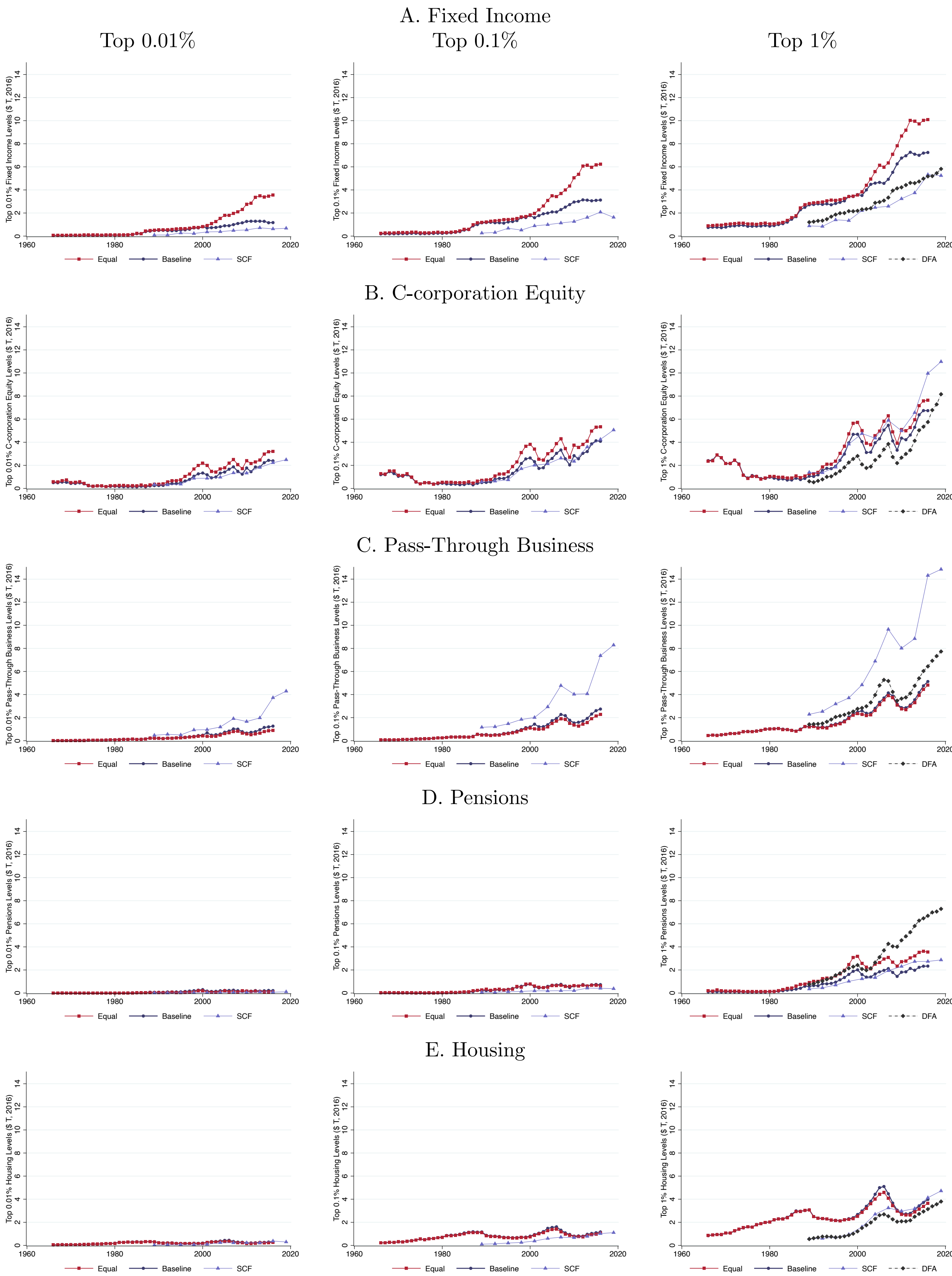
Notes: This figure shows portfolio totals in 2016 among top wealth groups for both equal-split individuals and tax unit definitions. A key difference between the SCF and capitalization series is the aggregate valuation of pass-through business and private C-corporations. For example, our baseline series scales bottom-up pass-through estimates to match aggregates based on the Financial Accounts in SZ20, whereas the SCF values reflect respondent self-reported valuations. A key difference between the DFA and other series is the DFA includes unfunded defined benefit pension wealth. SCF and DFA portfolio definitions are described further in Appendix D and E, respectively.

Figure A.11: Portfolio Composition over Time



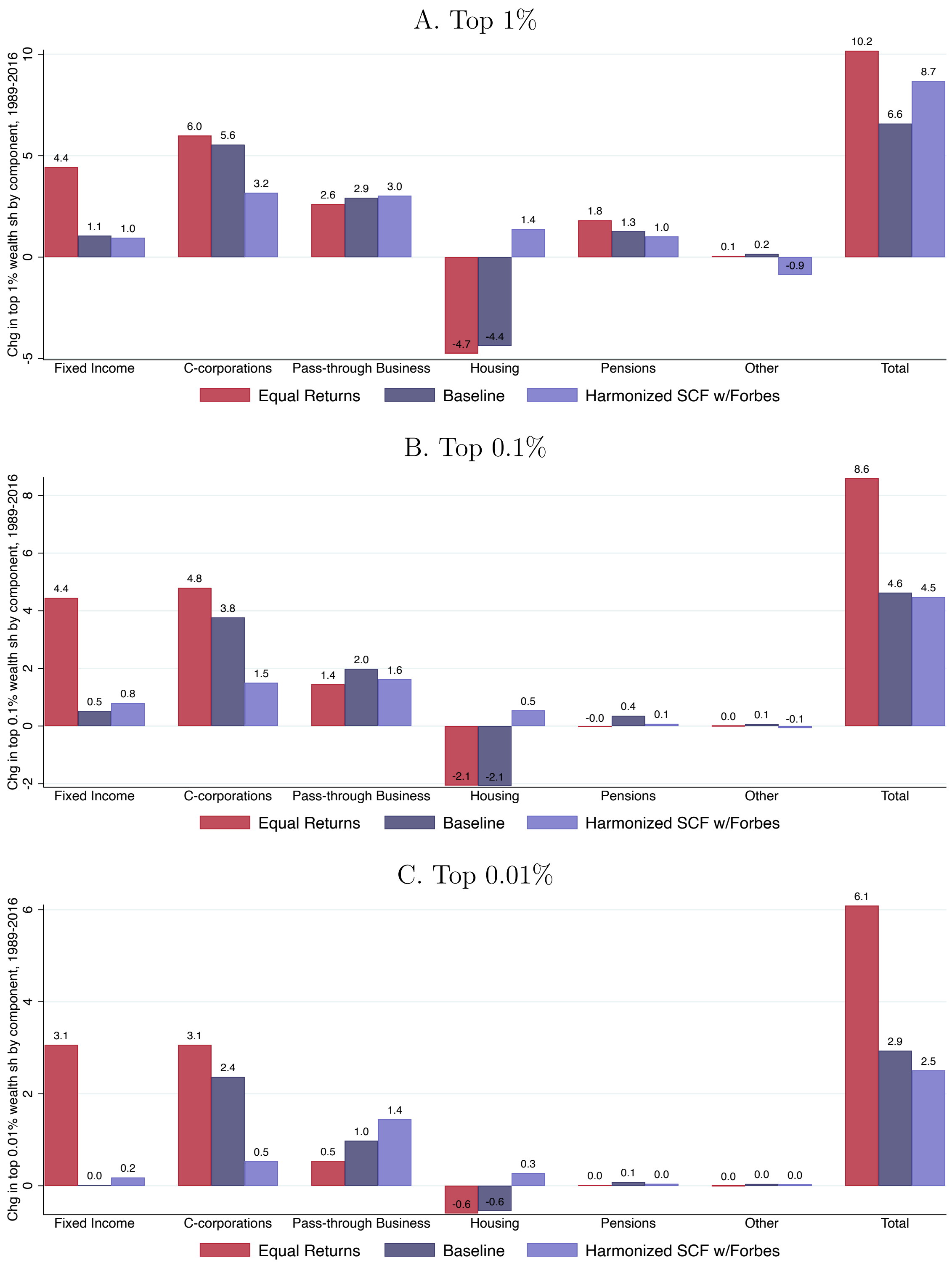
Notes: This figure presents analogous series to Figure 8 with portfolio shares for each group relative to the group's respective total wealth.

Figure A.12: Portfolio Components in Levels over Time



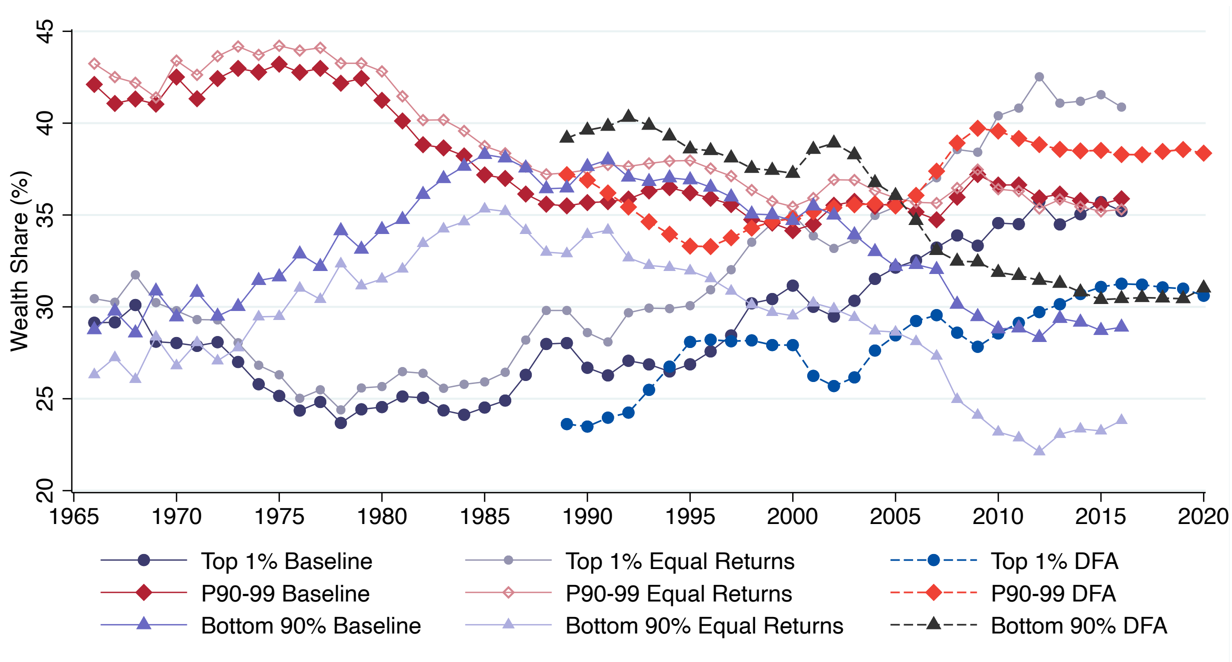
Notes: This figure presents analogous series to Figure 8 with inflation-adjusted component levels for each group.

Figure A.13: Change in Top Wealth Shares by Component: 1989-2016



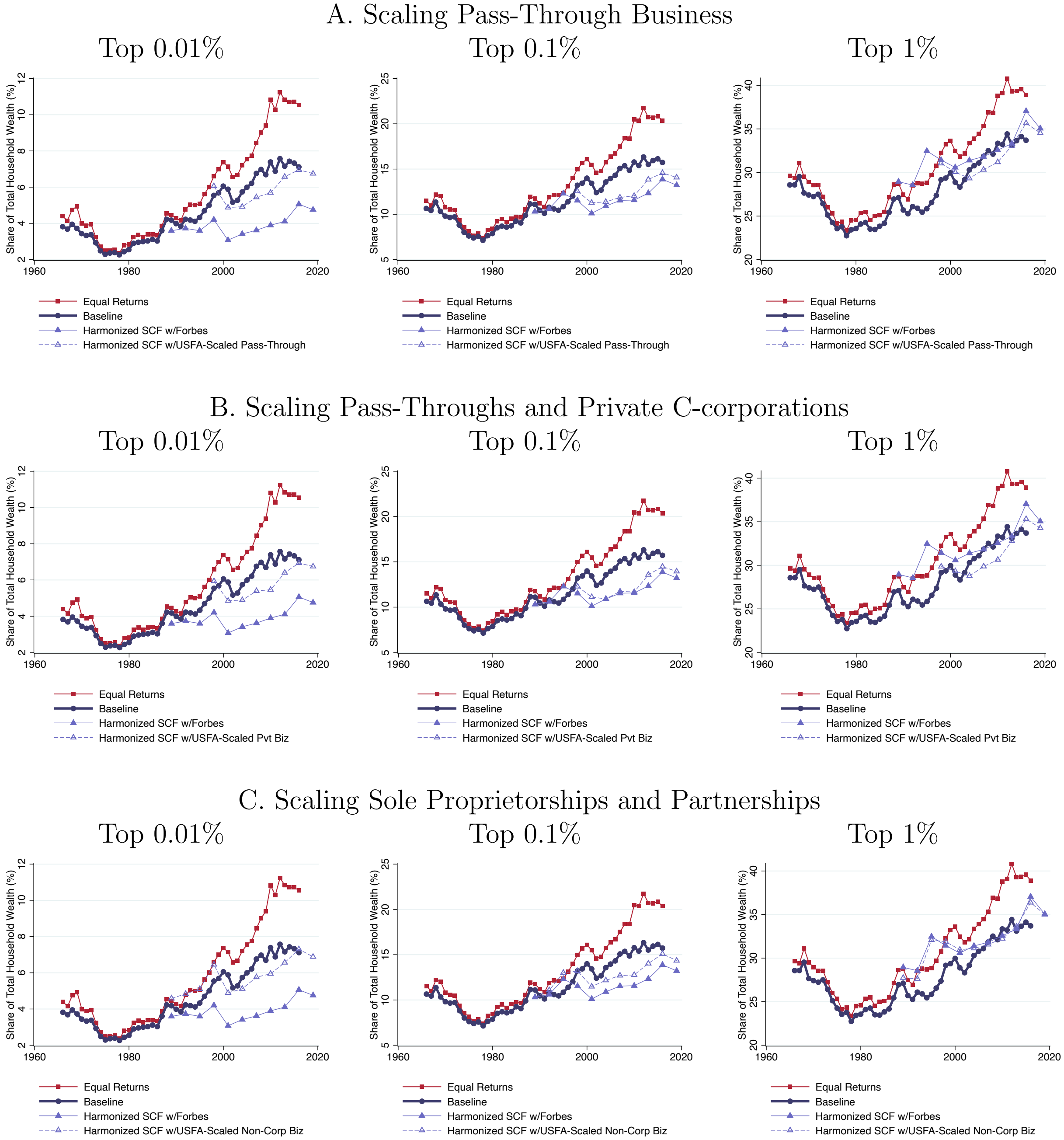
Notes: This figure decomposes the growth of the top 1%, 0.1%, and top 0.01% share of aggregate wealth by portfolio category under alternative capitalizations, as well as in the harmonized SCF with Forbes. Portfolio category bars are differences between 2016 and 1989 values in the series from Figure 8. Total top share changes are differences between 2016 and 1989 values in Figure 1B.

Figure A.14: Wealth Concentration by Group under Different Approaches (Tax Units)



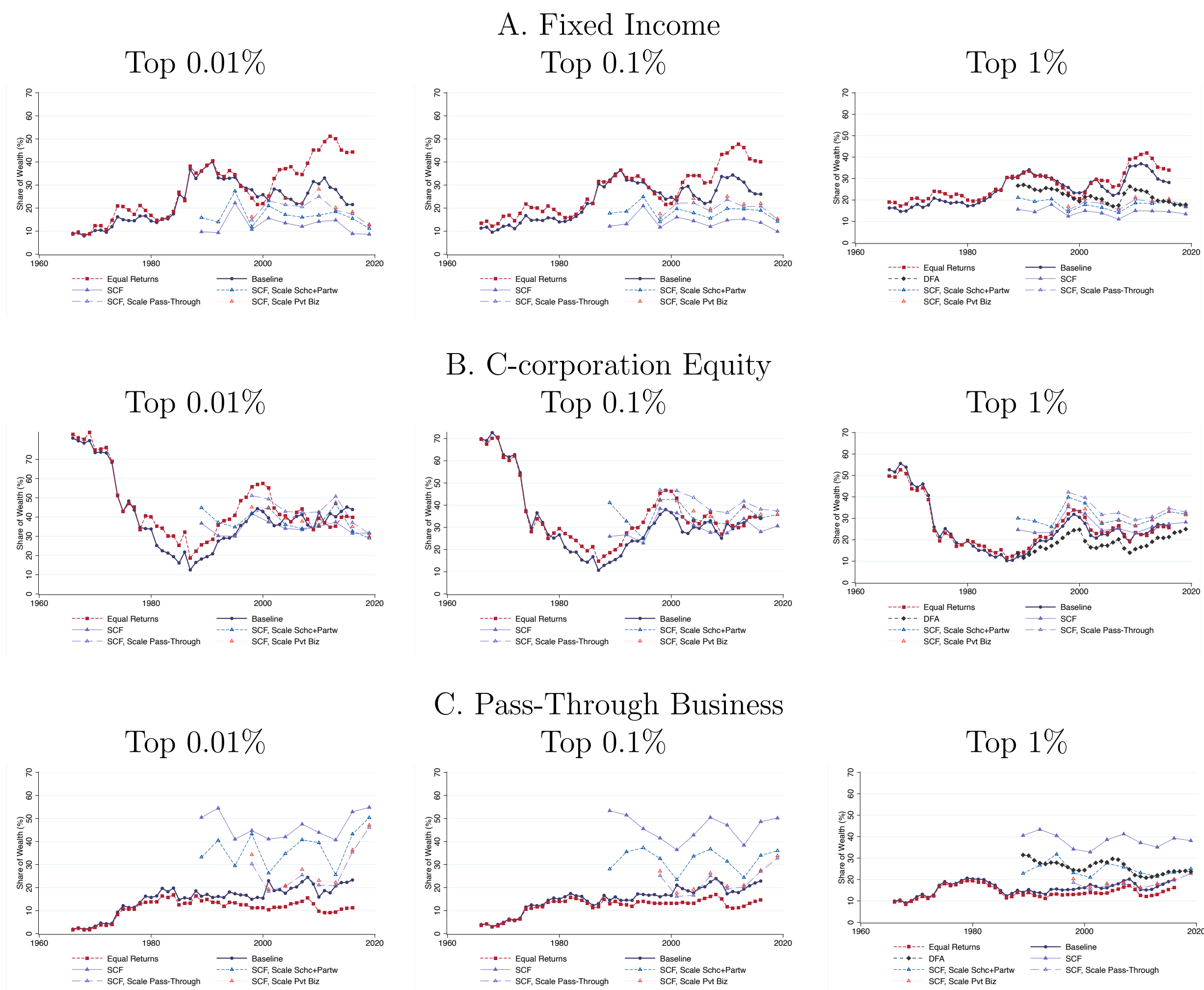
Notes: This figure plots analogous series to Figure 9 defined at the tax unit level, which enables comparison to estimates from the DFA. A key difference between the DFA and capitalization series is the DFA includes unfunded defined benefit pension wealth.

Figure A.15: Top Share of Wealth with SCF Private Business Scaled to Match USFA



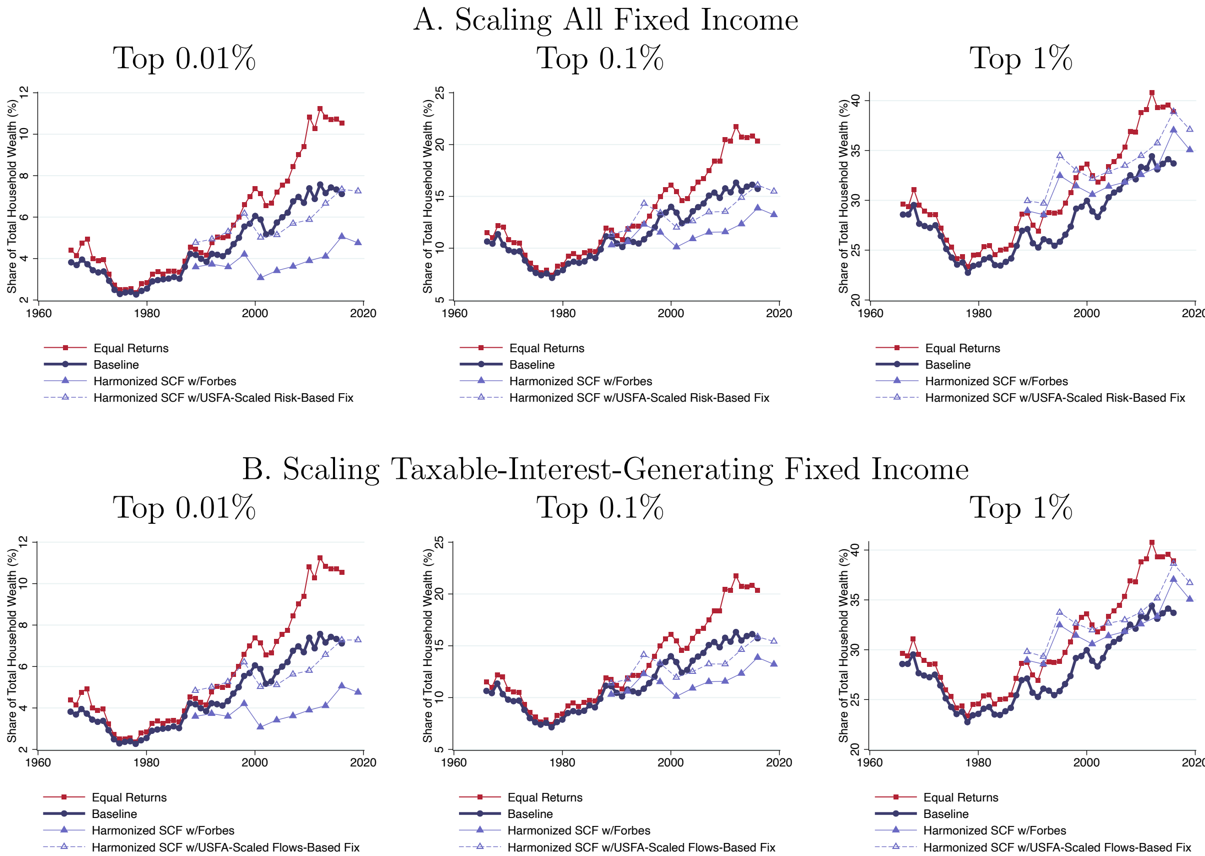
Notes: This figure considers the impact on top wealth shares in the SCF of scaling private business in the SCF to match Financial Accounts totals. Panel A shows the effect of scaling down pass-through business assets. Panel B shows the effect of scaling down all private business, which includes pass-through business and private C-corporations. Panel C scales down non-corporate pass-through business only.

Figure A.16: Top Portfolio Shares with SCF Private Business Scaled to Match USFA



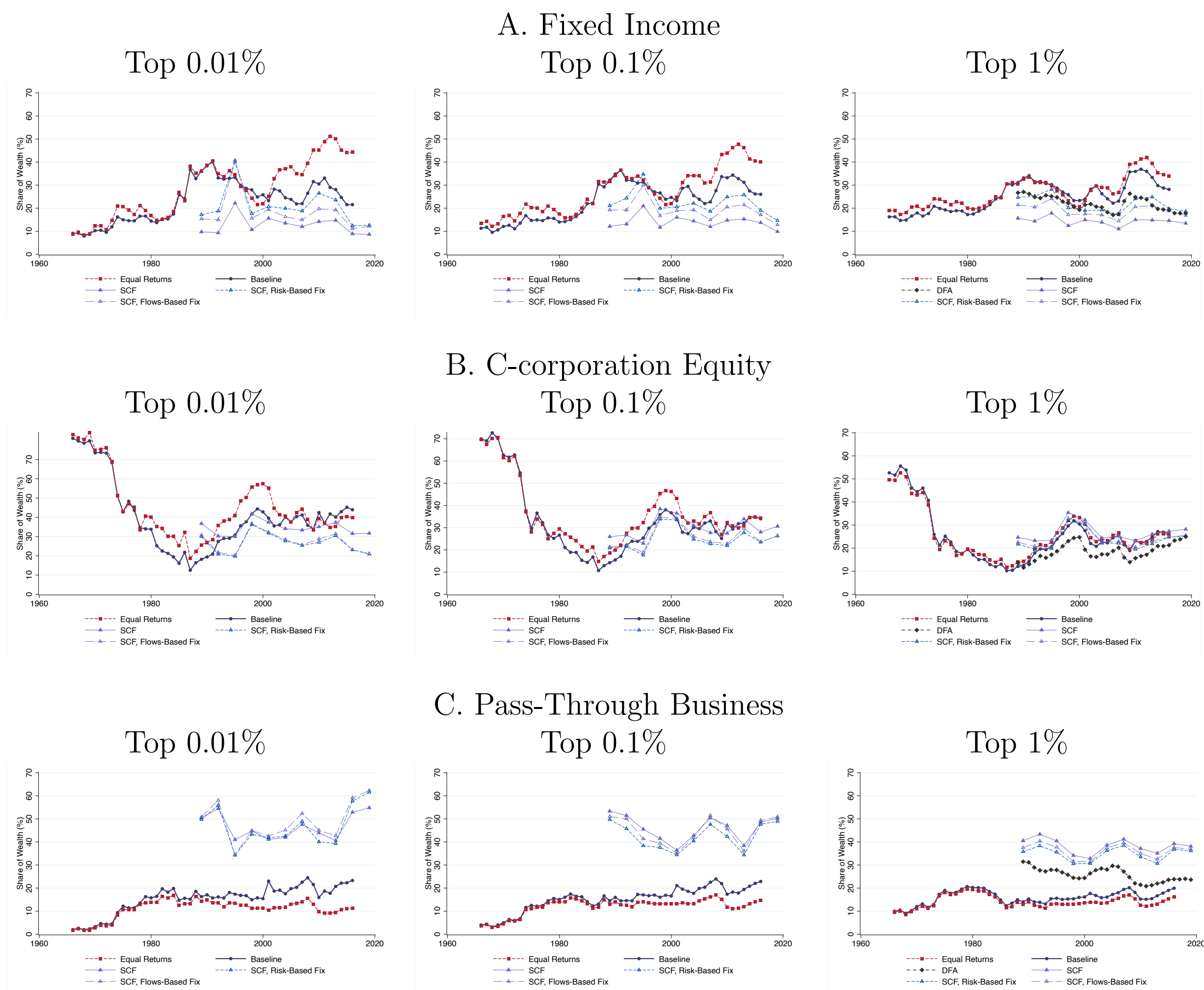
Notes: This figure considers the impact of the adjustments in Appendix Figure A.15 for top portfolio shares in the SCF.

Figure A.17: Top Share of Wealth with SCF Fixed Income Scaled to Match USFA



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.

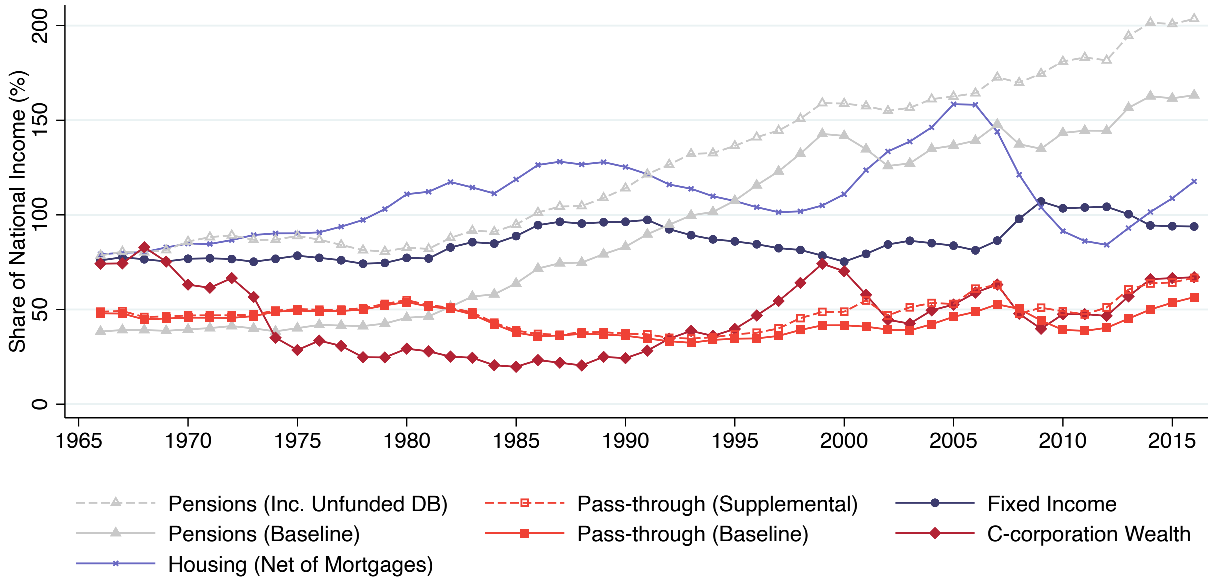
Figure A.18: Top Portfolio Shares with SCF Fixed Income Scaled to Match USFA



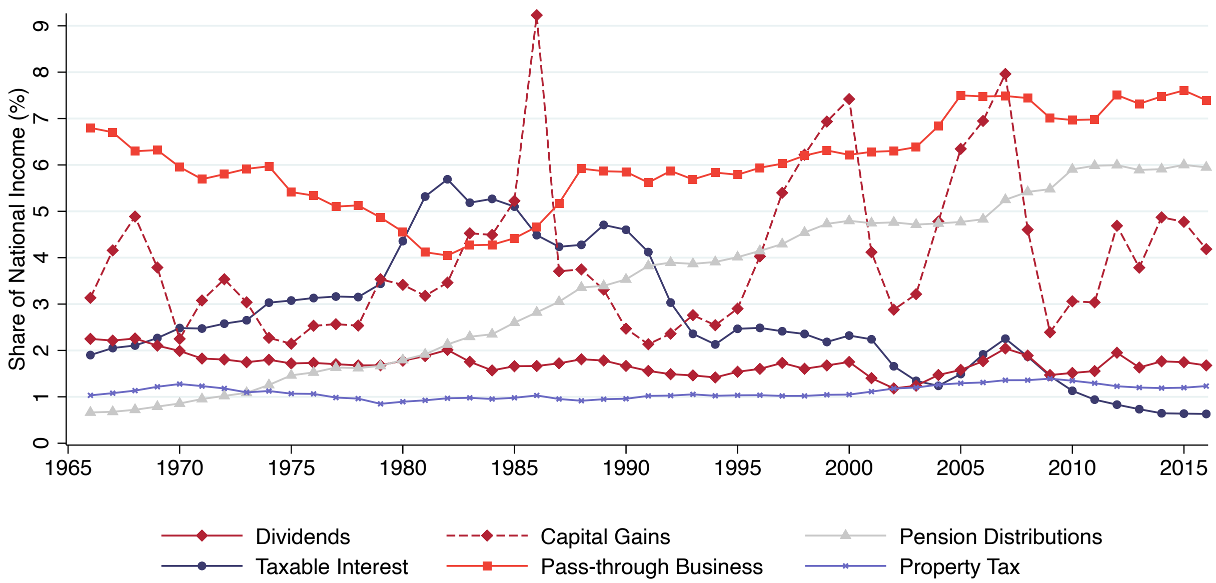
Notes: This figure considers the impact of the adjustments in Appendix Figure A.17 for top portfolio shares in the SCF.

Figure A.19: Aggregate Household Wealth and Fiscal Income Components

A. Components of Aggregate Household Wealth

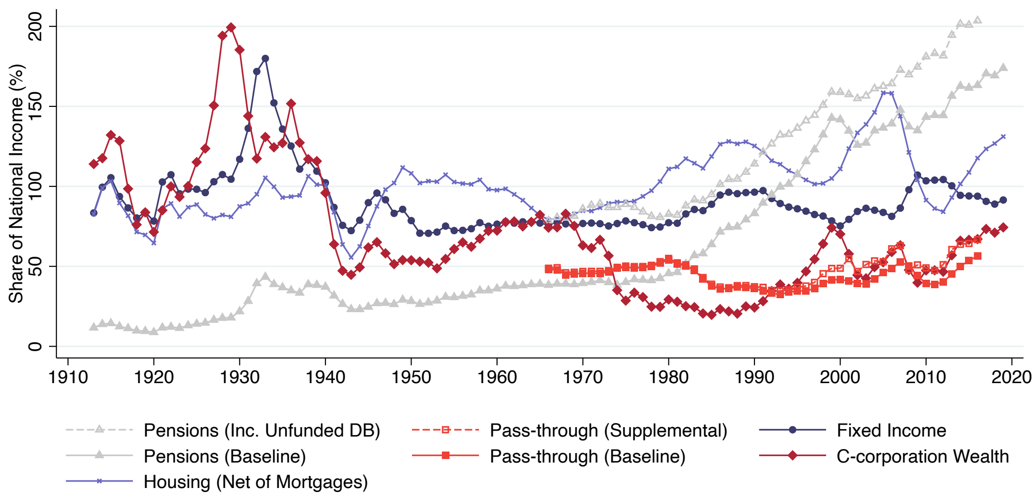


B. Components of Aggregate Fiscal Capital Income



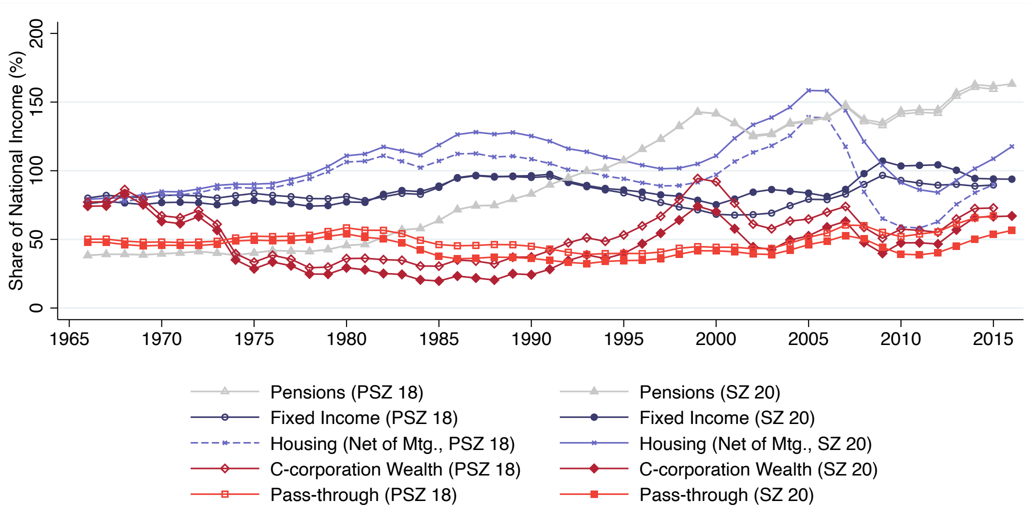
Notes: This figure plots the main components of aggregate national household wealth and fiscal capital income. Panel A plots net household wealth components relative to national income. Fixed income assets include taxable bonds, municipal bonds, currencies, and deposits. C-corporation wealth includes public and private C-corporations. Pass-through business includes S-corporation equity and non-corporate equities in sole proprietorships and partnerships. Housing denotes housing wealth net of mortgages. For pass-through business, the "Baseline" version follows the definitions in Saez and Zucman (2020*b*) (SZ20) for pass-through business wealth based on the Financial Accounts. The "Supplemental" version replaces the Financial Accounts aggregates with our bottom-up estimates for S-corporation and partnership wealth and missing pass-through wealth. We plot two pension series, one which includes funded and unfunded defined benefit (DB) wealth and a "Baseline" which only includes funded DB wealth, as in SZ20. Panel B graphs the ratio of components of fiscal income relative to national income.

Figure A.20: Components of Aggregate Household Wealth (1912-2016)



Notes: This figure extends the series shown in Figure A.19A 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 Kopzcuk and Saez (2004) prior to 1945. National income data is from NIPA from 1929-onwards, and Kuznets (1941) and King (1930) before that.

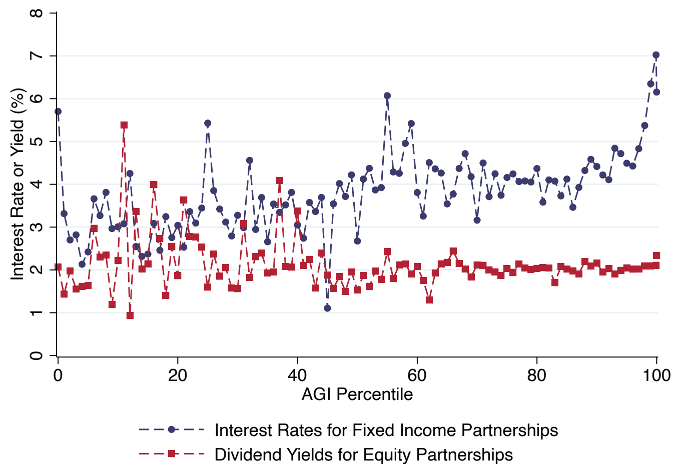
Figure A.21: Components of Aggregate Household Wealth (1965-2016), PSZ versus SZ20



Notes: This figure compares aggregates derived from the Financial Accounts in Piketty, Saez and Zucman (2018) to those in the updated series in Saez and Zucman (2020*b*).

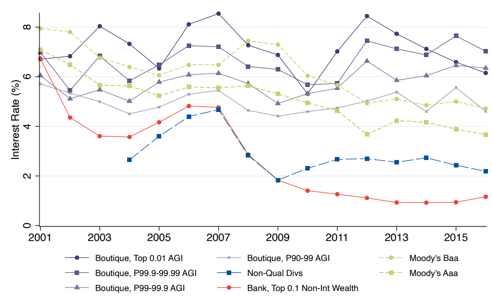
Figure A.22: Supplementary Facts on Heterogeneous Returns in Fixed Income

A. Interest Rate and Dividend Yield Heterogeneity for Partnerships (2016)

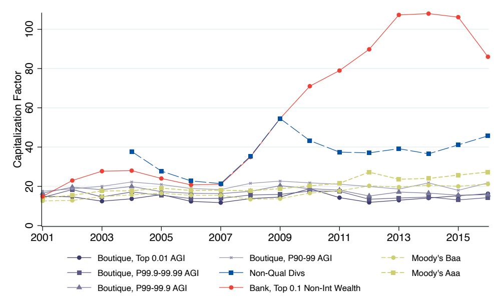


B. Interest Rate and Fixed Income Capitalization Factor Heterogeneity (2001–16)

Interest Rates

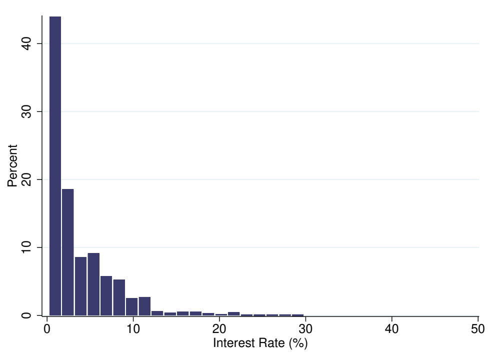


Capitalization Factors

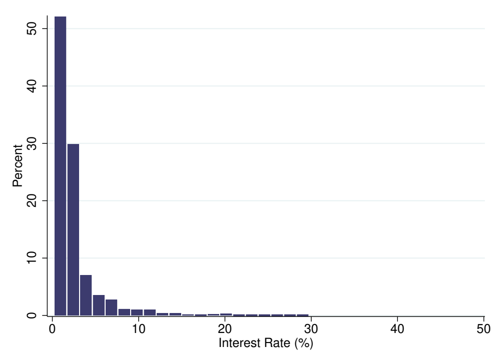


C. Histograms of Fixed Income Partnership Interest Rates (2016)

Has Individual Partners

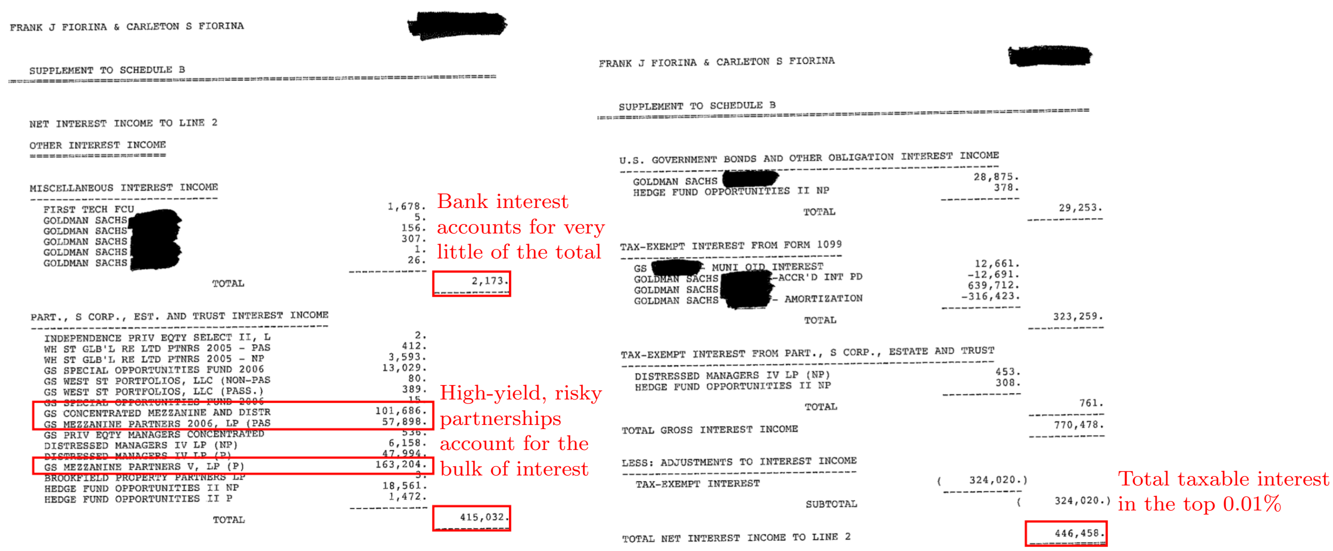


No Individual Partners



Notes: This figure presents supplementary facts on heterogeneous returns within the set of fixed income assets. Panel A 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. Panel B presents time series and implied capitalization factors for the various interest rates in Figure 3A. Panel C presents an asset-weighted histogram of interest rates for fixed income partnerships, divided into those for which we identify at least one individual partner and those for which all partners are non-individuals (e.g., other partnerships, non-profits, corporations, foreigners).

Figure A.23: Annotated Public Tax Disclosures from Carleton Fiorina



FRANK J FIORINA & CARLETON S FIORINA [redacted]

SUPPLEMENT TO SCHEDULE B

NET INTEREST INCOME TO LINE 2

OTHER INTEREST INCOME

MISCELLANEOUS INTEREST INCOME

FIRST TECH FCU	1,678.	
GOLDMAN SACHS [redacted]	5.	
GOLDMAN SACHS	156.	
GOLDMAN SACHS	307.	
GOLDMAN SACHS	1.	
GOLDMAN SACHS	26.	
TOTAL		2,173.

PART., S CORP., EST. AND TRUST INTEREST INCOME

INDEPENDENCE PRIV EQTY SELECT II, L	2.	
WH ST GLB'L RE LTD PTNRS 2005 - PAS	412.	
WH ST GLB'L RE LTD PTNRS 2005 - NP	3,593.	
GS SPECIAL OPPORTUNITIES FUND 2006	13,029.	
GS WEST ST PORTFOLIOS, LLC (NON-PAS	80.	
GS WEST ST PORTFOLIOS, LLC (PASS.)	389.	
GS SPECIAL OPPORTUNITIES FUND 2006	15.	
GS CONCENTRATED MEZZANINE AND DISTR	101,686.	
GS MEZZANINE PARTNERS 2006, LP (PAS	57,898.	
GS PRIV EQTY MANAGERS CONCENTRATED	536.	
DISTRESSED MANAGERS IV LP (NP)	6,158.	
DISTRESSED MANAGERS IV LP (P)	47,994.	
GS MEZZANINE PARTNERS V, LP (P)	163,204.	
BROOKFIELD PROPERTY PARTNERS LP	3.	
HEDGE FUND OPPORTUNITIES II NP	18,561.	
HEDGE FUND OPPORTUNITIES II P	1,472.	
TOTAL		415,032.

FRANK J FIORINA & CARLETON S FIORINA [redacted]

SUPPLEMENT TO SCHEDULE B

U.S. GOVERNMENT BONDS AND OTHER OBLIGATION INTEREST INCOME

GOLDMAN SACHS [redacted]	28,875.	
HEDGE FUND OPPORTUNITIES II NP	378.	
TOTAL		29,253.

TAX-EXEMPT INTEREST FROM FORM 1099

GS [redacted] - MUNI OID INTEREST	12,661.	
GOLDMAN SACHS [redacted] -ACCR'D INT PD	-12,691.	
GOLDMAN SACHS	639,712.	
GOLDMAN SACHS [redacted] - AMORTIZATION	-316,423.	
TOTAL		323,259.

TAX-EXEMPT INTEREST FROM PART., S CORP., ESTATE AND TRUST

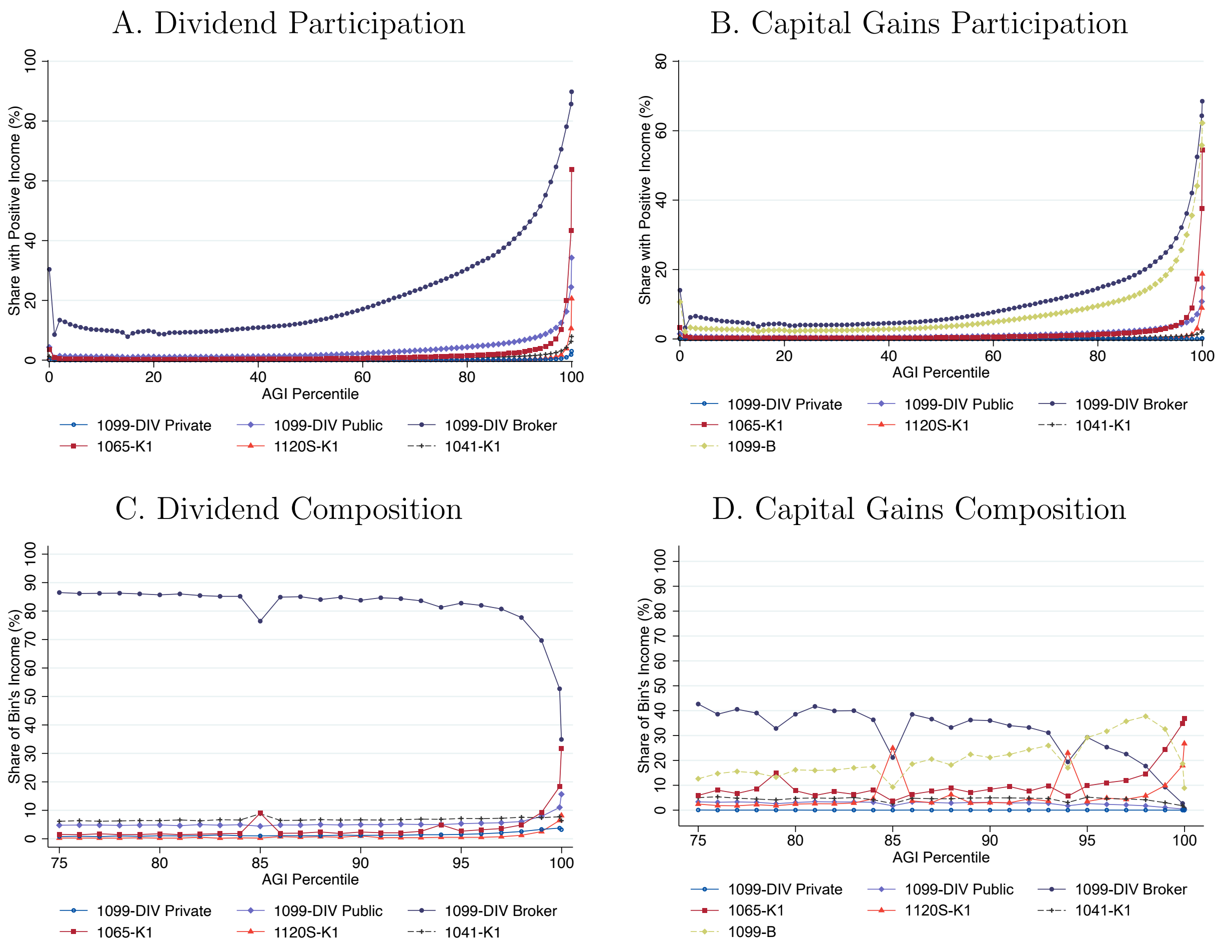
DISTRESSED MANAGERS IV LP (NP)	453.	
HEDGE FUND OPPORTUNITIES II NP	308.	
TOTAL		761.
TOTAL GROSS INTEREST INCOME		770,478.

LESS: ADJUSTMENTS TO INTEREST INCOME

TAX-EXEMPT INTEREST	(324,020.)	
SUBTOTAL		(324,020.)
TOTAL NET INTEREST INCOME TO LINE 2		446,458.

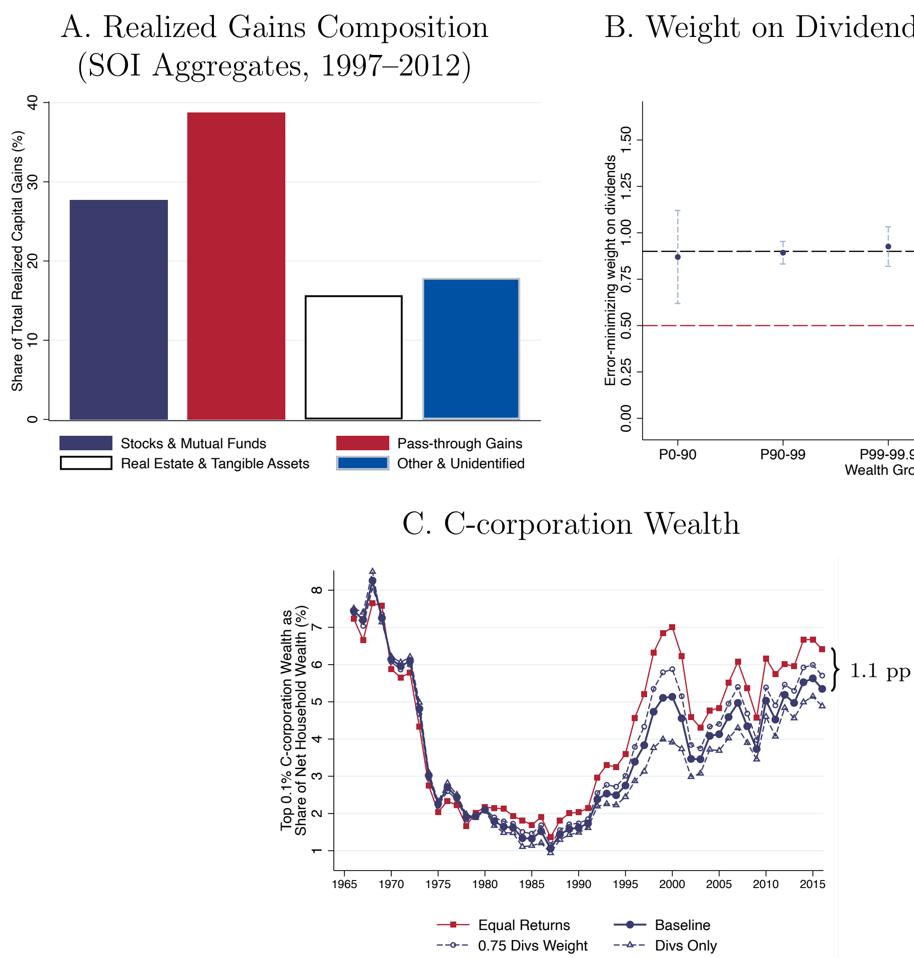
Notes: This figure presents annotated attachments on the fixed income assets that generate taxable interest for a high net worth individual (Carleton Fiorina) who disclosed her tax return when running for public office. No IRS data were used to identify this individual or her tax information.

Figure A.24: Equity Portfolio Heterogeneity across Groups



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 2B but for dividend income and realized capital gains, respectively. Panels C and D are similarly analogous to Figure 2C. 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 2.

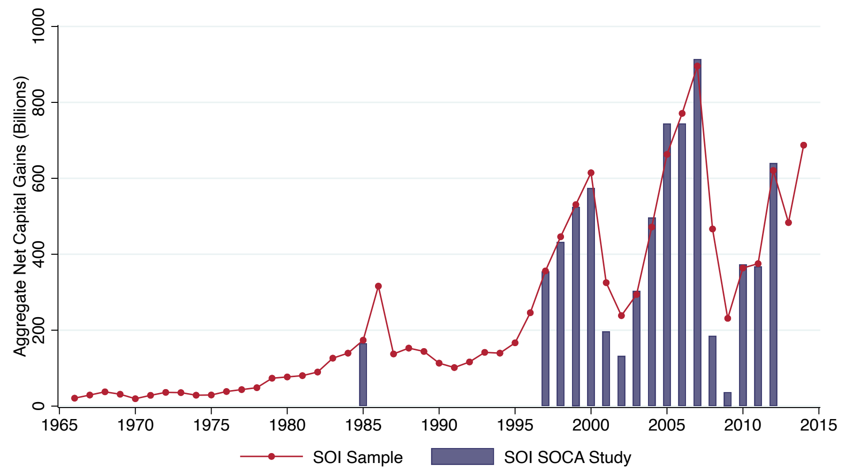
Figure A.25: Dividends are More Informative than Realized Gains for Inferring Stock Wealth



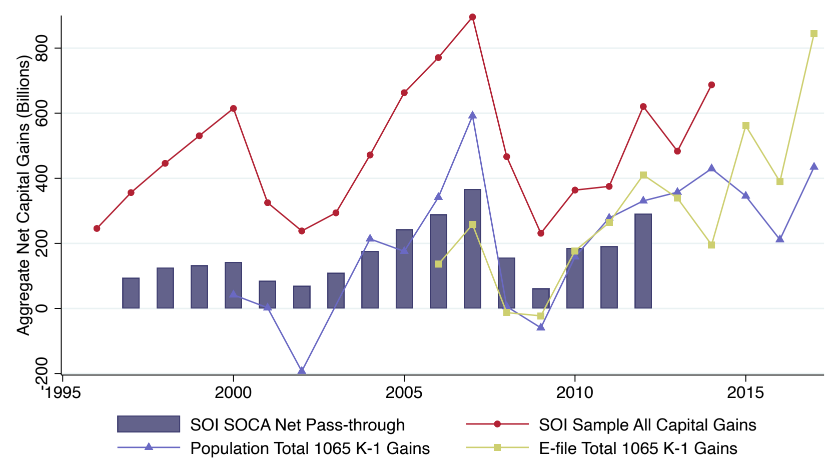
Notes: This figure presents evidence supporting our approach to inferring stock wealth from dividends and realized capital gains. Panel A decomposes realized capital gains by component using IRS statistics of income aggregates from 1997-2012. Panel B uses minimum distance to estimate the optimal weight on dividends versus capital gains for different wealth groups in the SCF. Panel C is analogous to Figure 4C. We plot C-corporation equity estimates given different weights on dividends and realized capital gains. Equal Returns applies equal weight of 0.5 to both dividends and capital gains.

Figure A.26: Identifying Carried Interest Compensation among Realized Capital Gains

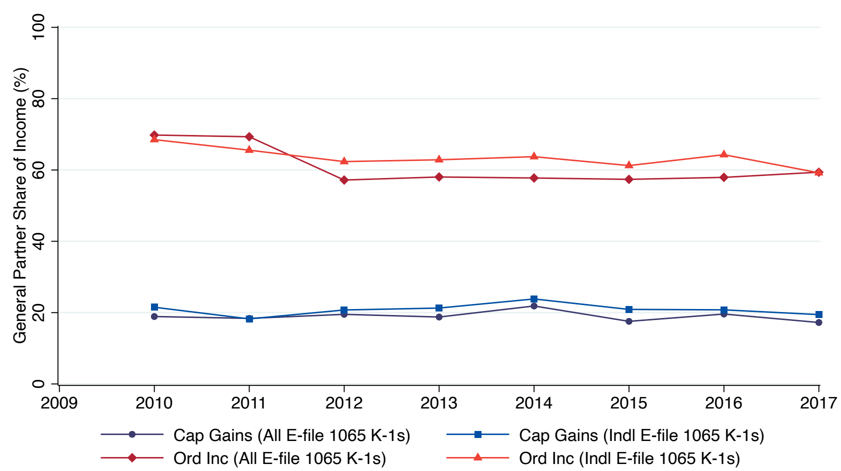
A. SOI's SOCA Totals Track the SOI Sample Capital Gains



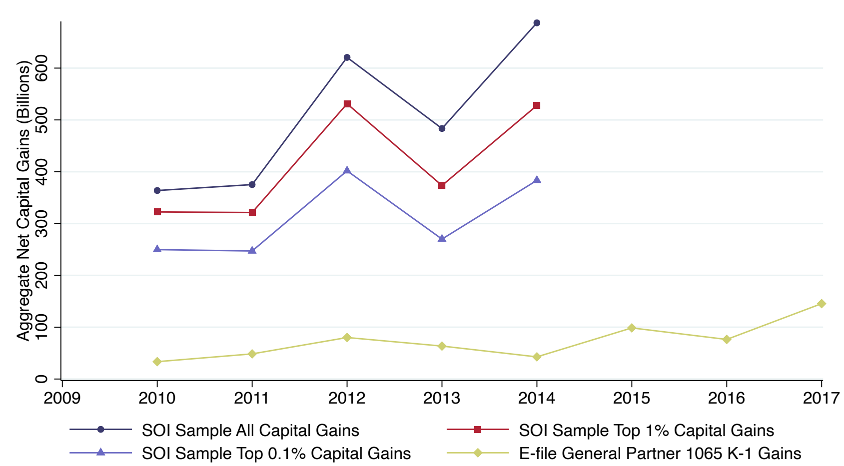
B. Pass-Through Share of Gains Tracks 1065 K-1 Gains



C. General Partners Receive 20% of Distributed Gains

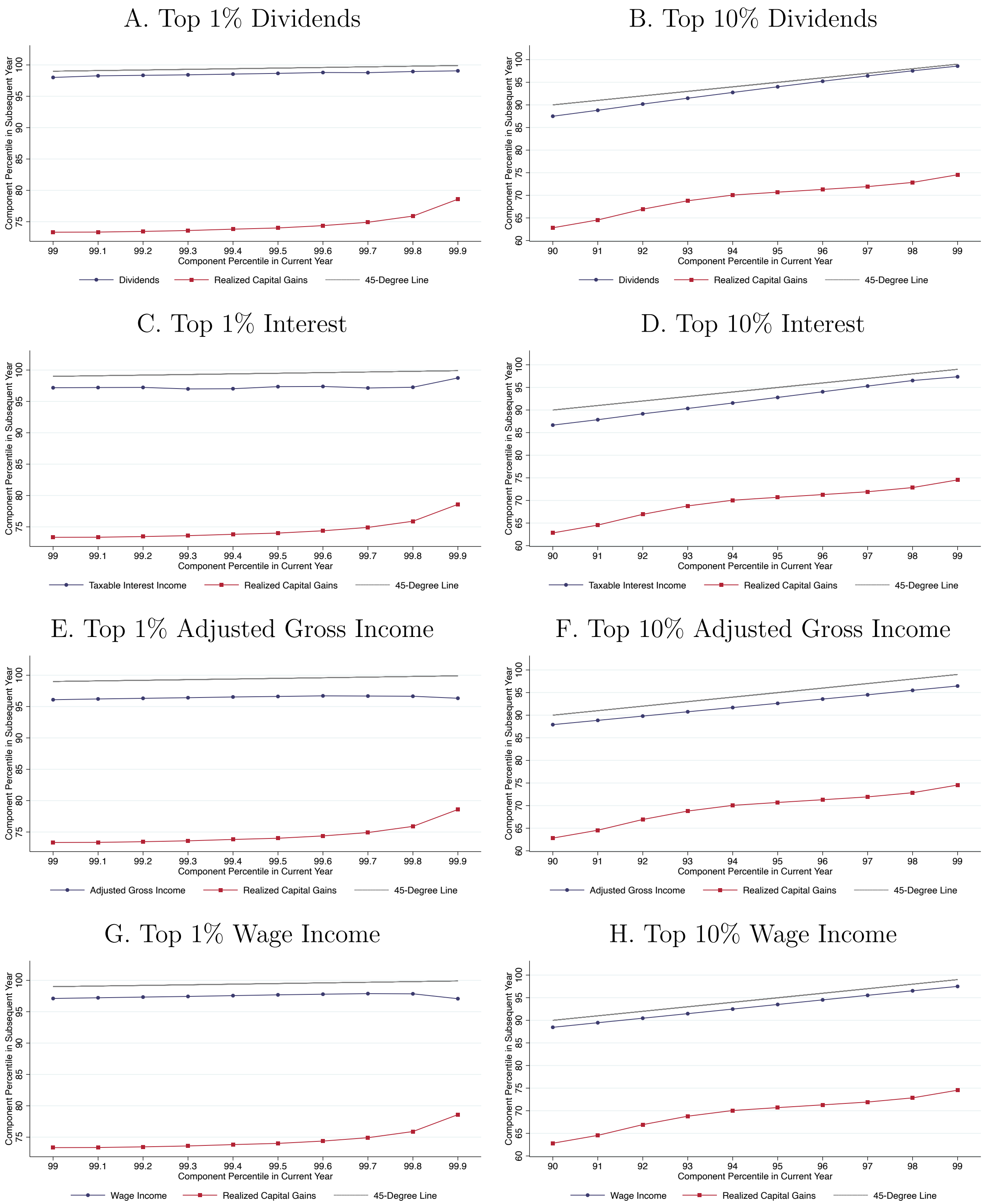


D. General Partner Gains versus Total and Top Capital Gains



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.

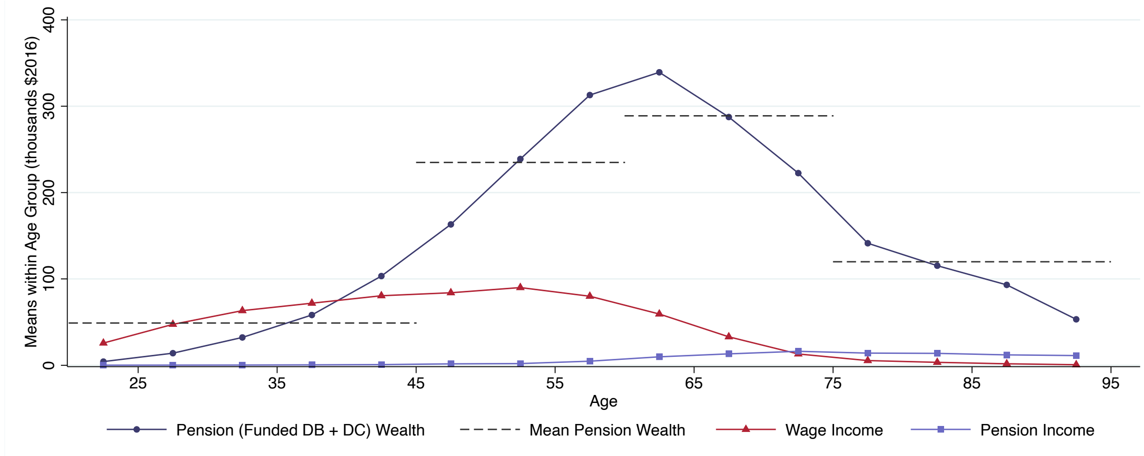
Figure A.27: Persistence of Realized Capital Gains and Other Income Flows



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.28: Using Wages and Pension Distributions to Infer Pension Wealth

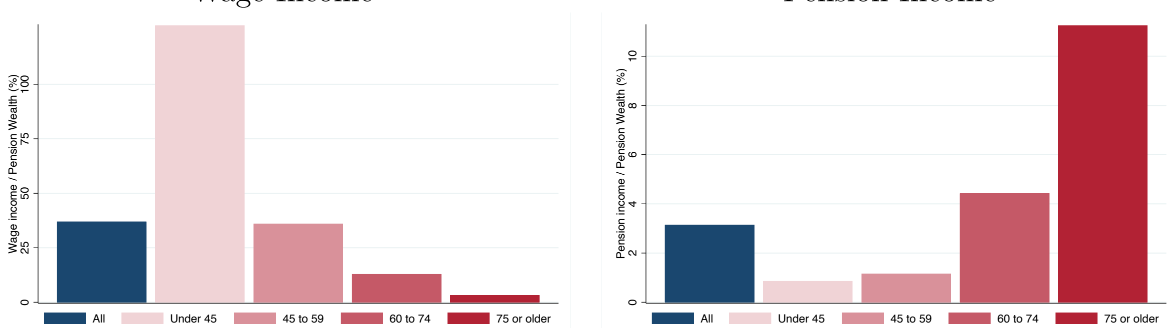
A. The Life Cycle of Pension Wealth vs. Wage and Pension Income



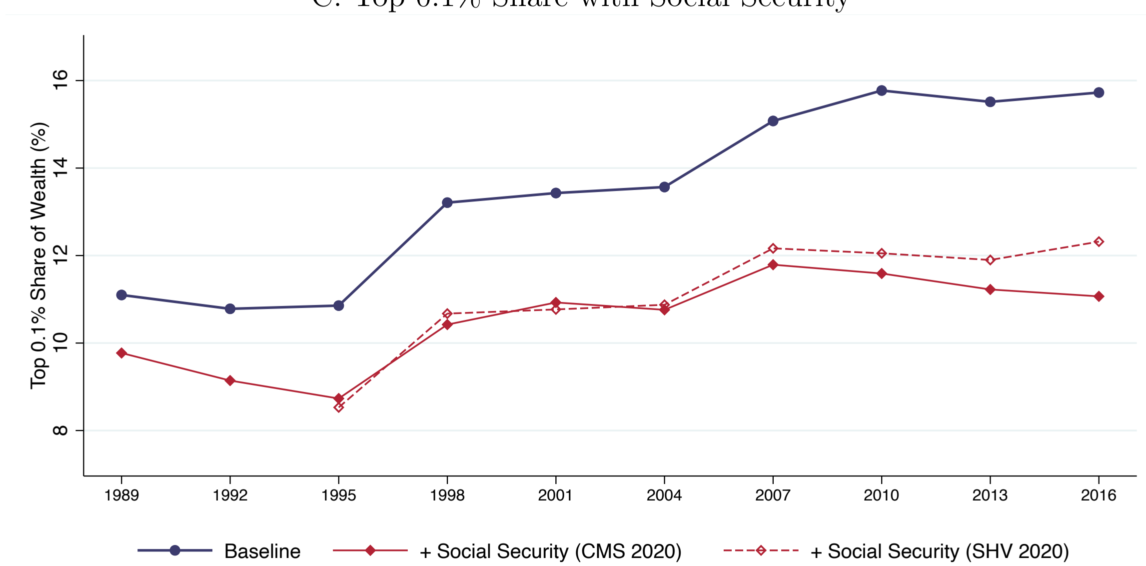
B. Flow-Stock Relationships for Pension Wealth Vary with Age

Wage Income

Pension Income

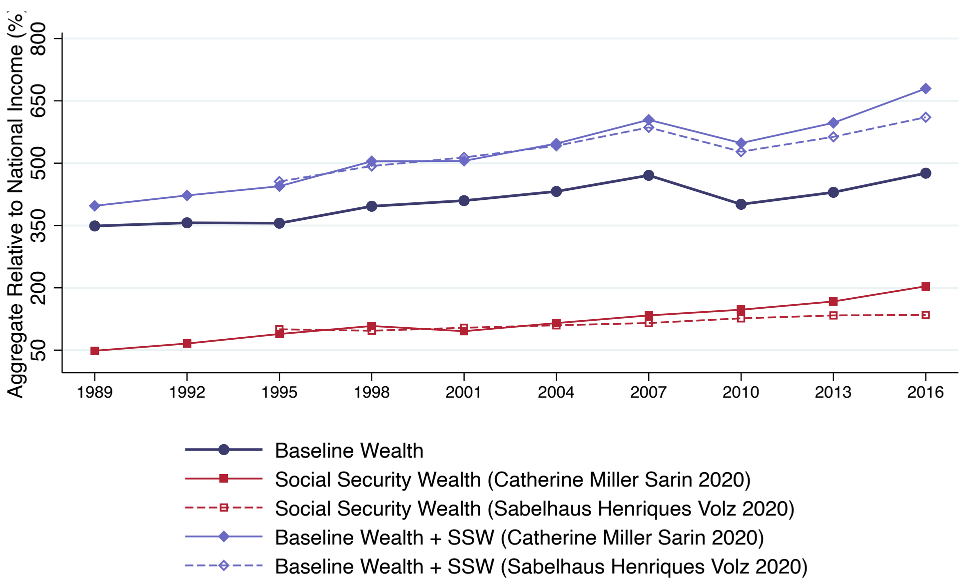


C. Top 0.1% Share with Social Security



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 funded-DB-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).

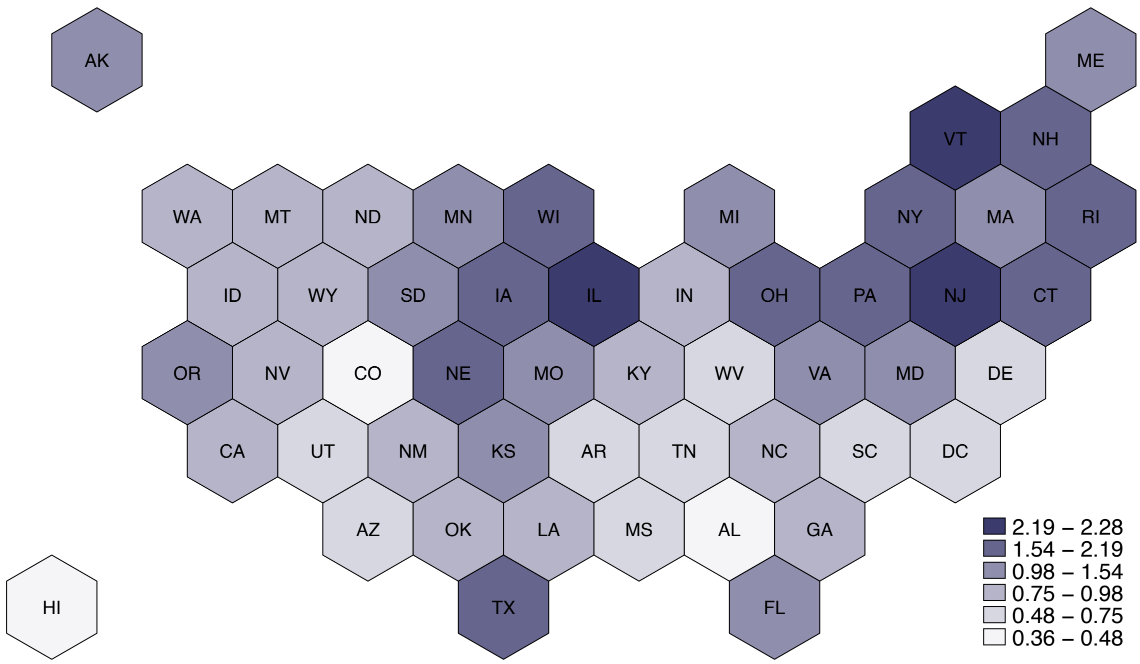
Figure A.29: Social Security Aggregates Relative to National Income



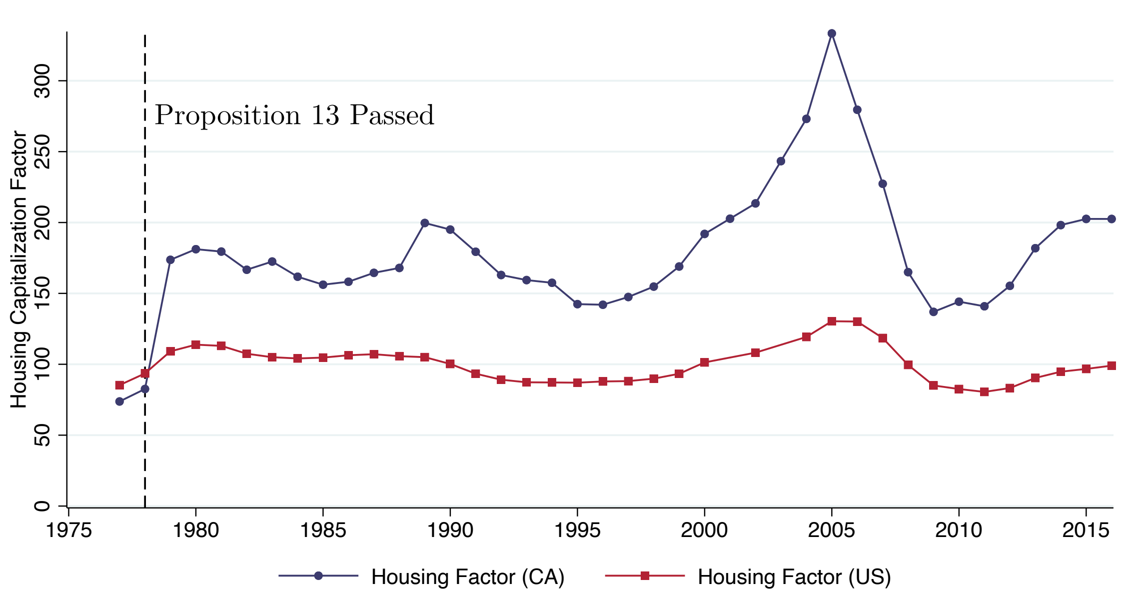
Notes: This figure shows aggregate wealth as a share of US national income under our baseline capitalized specification with and without Social Security wealth as estimated by Catherine, Miller and Sarin (2020) and Sabelhaus and Volz (2020).

Figure A.30: Regional Variation in the Returns to Housing Assets

A. Geographic Variation in Property Tax Rates



B. Evolution of Housing Capitalization Factors in California

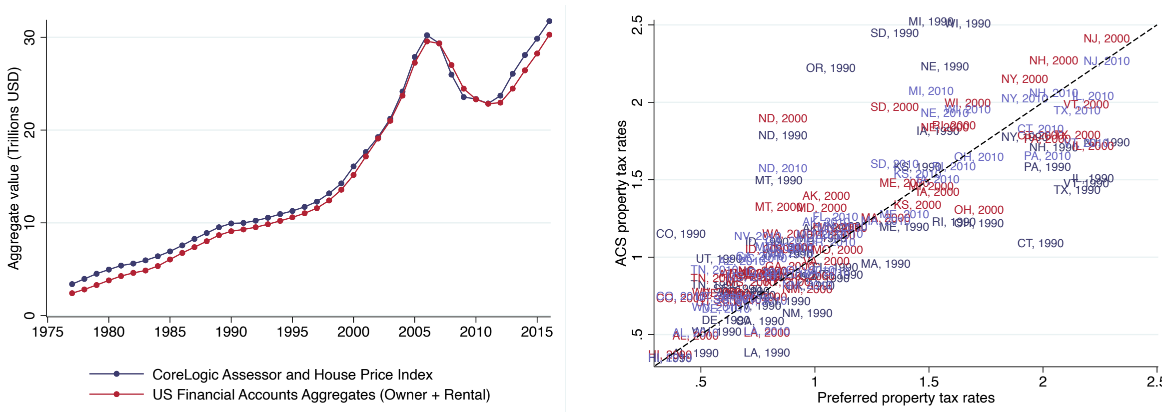


Notes: Panel A provides a map of state property tax rates from ATTOM. Panel B shows how the housing asset capitalization factor, equal to the reciprocal of the state property tax rate, has evolved in California versus an equal returns benchmark pooling all states.

Figure A.31: Validating Housing Capitalization Approach

A. Housing Assets Values Match Financial Accounts

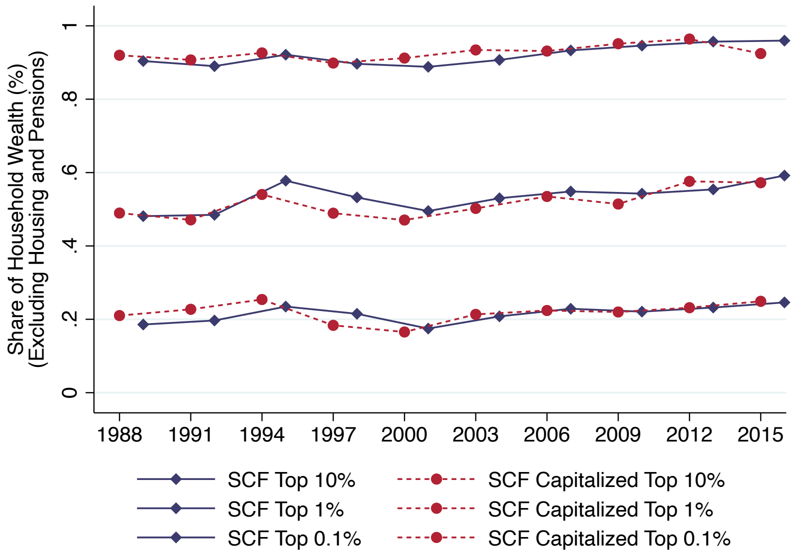
B. State Property Tax Rates Match ACS



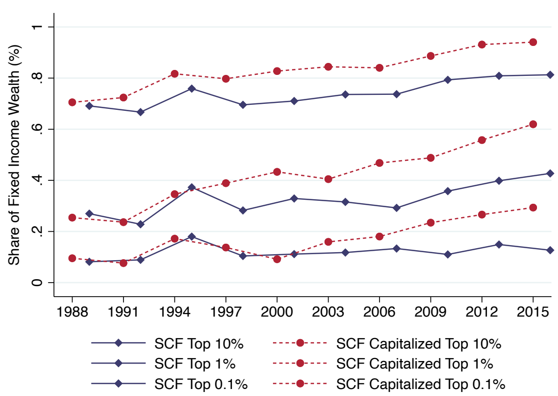
Notes: This figure shows two validation exercises for our housing capitalization approach. Panel A compares the aggregate value of housing wealth using two alternative capitalization methods: using owner and renter-occupied wealth allocated to match Financial Accounts, and using CoreLogic and Housing 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 et al. (2019).

Figure A.32: Top Wealth Shares vs. Capitalized Income Shares in SCF

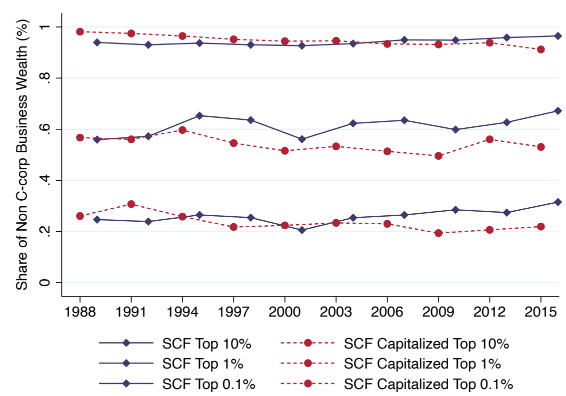
A. Replicating Figure IV.B. of Saez and Zucman (2016)



B. Actual vs. Capitalized Fixed Income

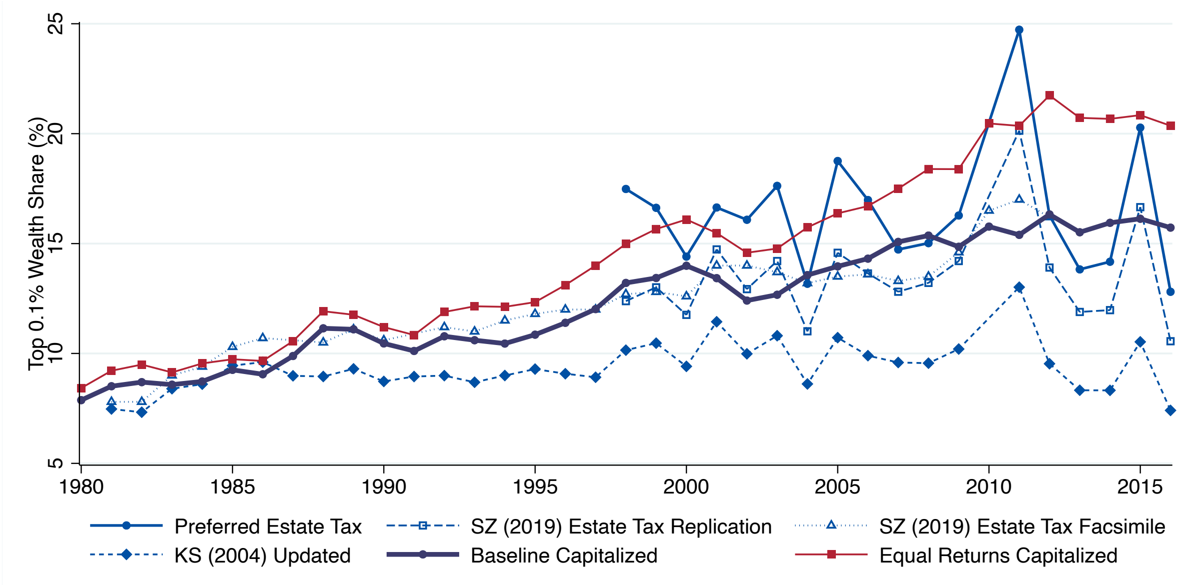


C. Actual vs. Capitalized Business Income



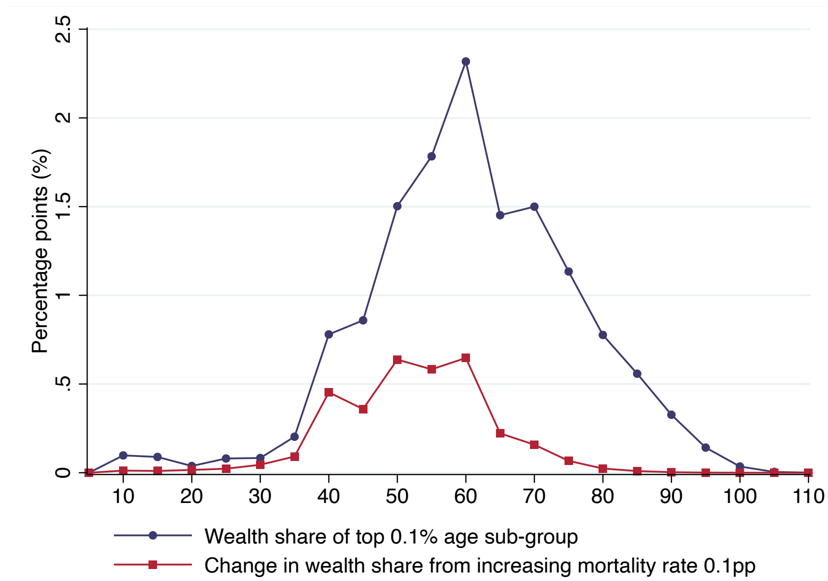
Notes: This figure plots the fraction of wealth (excluding housing and pensions) held by the top 10%, 1%, and 0.1% in the SCF using actual SCF wealth and capitalized income wealth. We exclude housing and pensions to exactly replicate Figure IV.B. of Saez and Zucman (2016). Panel A replicates Figure IV.B 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.33: 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 R.4. Second, SZ (2019) estate tax replication uses our implementation of Saez and Zucman (2019)'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 (2004*a*), updated in Saez and Zucman (2016) and then by us through 2016. Prior to 1995, we use the Kopczuk and Saez (2004*a*) estate tax series from the appendix in Saez and Zucman (2016). The figure also shows top 0.1% wealth shares in our baseline capitalized series and under equal returns.

Figure A.34: Sensitivity of Age Group Wealth Shares to Mortality Rates in Top 0.1%

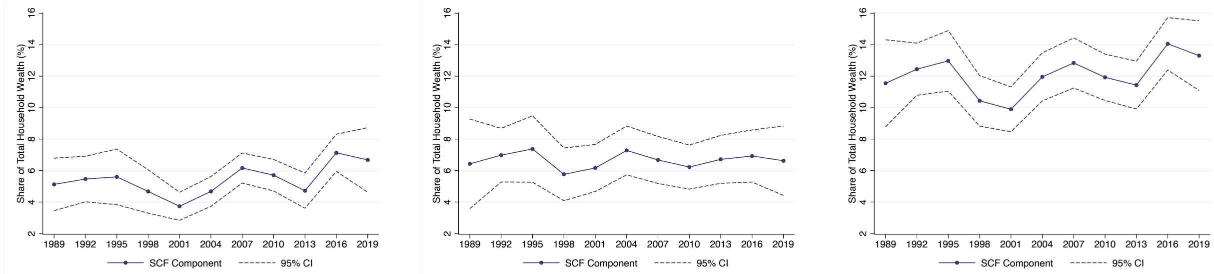


Notes: This figure plots the wealth shares of age groups within the top 0.1% of the wealth distribution in estate tax data. For example, a value of 2% for age group 51-55 means that those individuals in this age group collectively hold 2% of total household wealth. It also shows the change in estimated 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.

Figure A.35: Business in the SCF under Uncertainty

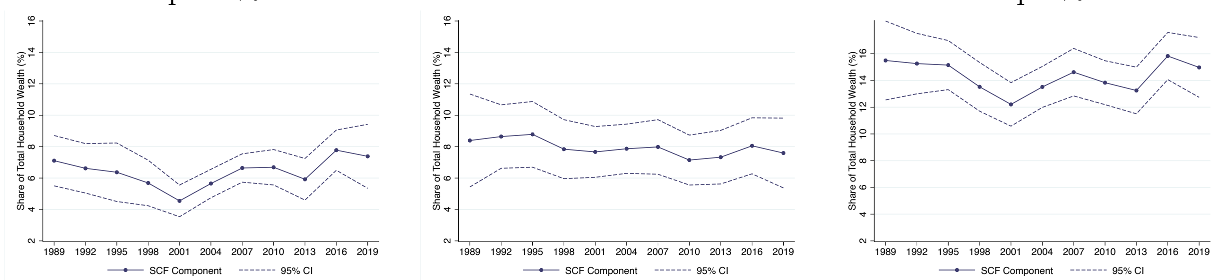
A. Pass-Throughs

Top 0.1% | P99-99.9 | Top 1%



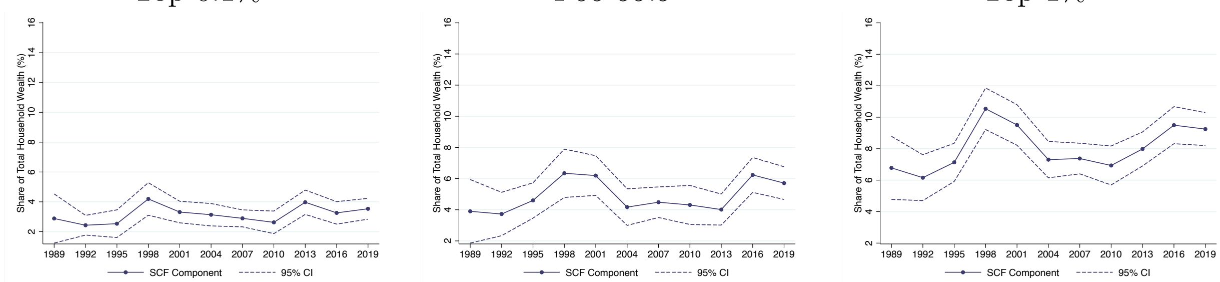
B. Pass-Throughs and Private C-corporations

Top 0.1% | P99-99.9 | Top 1%



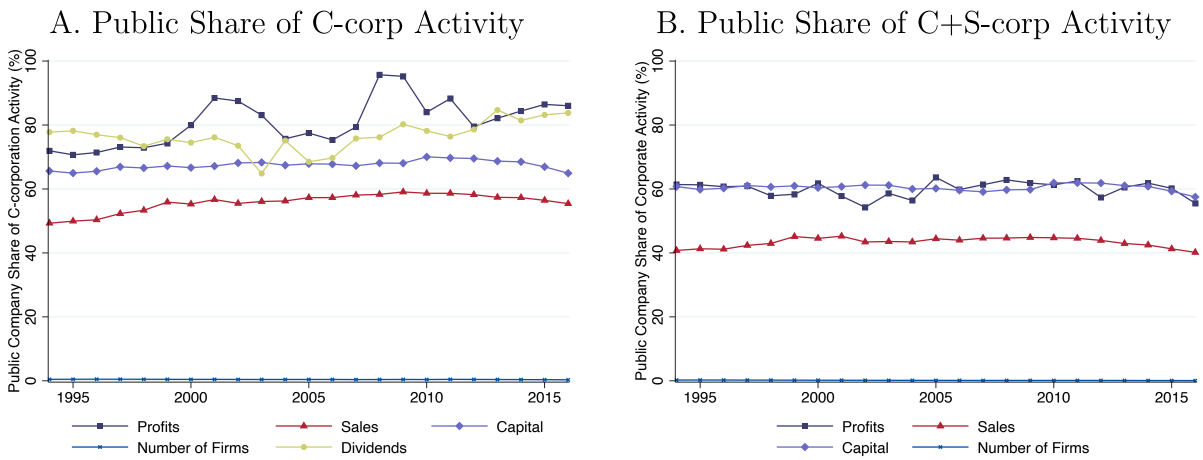
C. Public and Private C-corporations

Top 0.1% | P99-99.9 | Top 1%



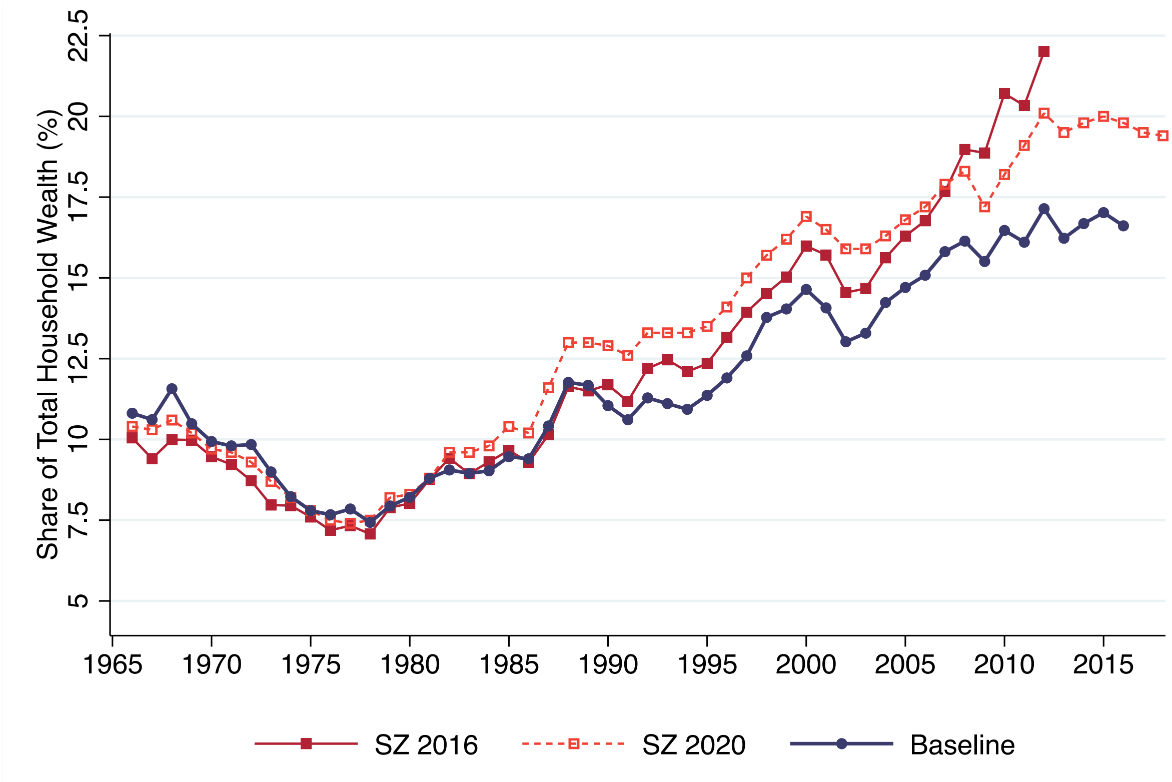
Notes: This figure plots private business (Panels A and B) and C-corporation equity (Panel C) as a share of total wealth for different top groups in the SCF under uncertainty. We sample SCF households using the replicate weights and following the procedure in Bricker et al. (2016).

Figure A.36: Public Company Share of Corporate 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.37: Baseline Estimates and Updated SZ Estimates (Tax Units)



Notes: This figure plots top 0.1% wealth shares from our baseline tax-unit series and compares them to SZ and the updated series in Saez and Zucman (2020*b*) (as of September 2020, accessed in August 2021).

B Appendix Tables

Table B.1: Industrial Composition of Pass-through Firm Value (2016)

Rank	Industry (NAICS)	S + P Value (B$)	Returns (%)	Value/Firm (M$)	Value/Owner (M$)	S Value	P Value
1	Lessors of real estate (5311)	530.3	0.3	0.4	0.2	57.3	473.1
2	Other financial investment actvty (5239)	279.0	9.6	1.1	0.1	57.1	221.9
3	Restaurants (7225)	261.2	3.9	1.2	0.7	179.4	81.9
4	Management/holding cos (5511)	258.7	4.6	4.6	0.3	158.4	100.2
5	Other professional/technical svc (5419)	219.5	7.7	0.9	0.6	162.7	56.8
6	Activities related to real estate (5313)	202.7	4.8	0.4	0.1	47.3	155.3
7	Legal svc (5411)	192.0	26.6	1.8	0.9	43.3	148.7
8	Other specialty trade cntrctr (2389)	158.1	9.9	0.9	0.7	140.3	17.8
9	Offices of physicians (6211)	110.2	20.2	1.0	0.6	76.0	34.2
10	Computer sys design/related svc (5415)	91.8	9.9	0.7	0.5	76.7	15.1
11	Accounting/bookkeeping svc (5412)	91.7	11.7	1.2	0.7	34.1	57.6
12	Misc. durable goods merch whlsl (4239)	91.1	6.5	1.7	1.1	78.0	13.2
13	Automobile dealers (4411)	88.8	8.2	2.3	1.5	75.1	13.8
14	Traveler acmdtn (7211)	77.4	3.5	1.5	0.5	30.7	46.7
15	Nonresidential building constr (2362)	72.3	10.9	1.8	1.1	60.7	11.6
16	Building foundation/exterior cntrctr (2381)	69.4	10.4	0.6	0.5	61.8	7.7
17	Oil/gas extraction (2111)	65.8	1.3	1.5	0.1	22.8	43.0
18	General freight trucking (4841)	59.2	5.5	0.6	0.5	50.9	8.4
19	Residential building constr (2361)	58.0	15.1	0.3	0.2	42.7	15.3
20	Other information svc (5191)	57.7	9.6	2.1	1.1	47.7	10.1
21	Building equipment cntrctr (2382)	57.2	18.2	0.5	0.4	52.8	4.4
22	Other miscellaneous store retailers (4539)	51.9	5.7	0.8	0.6	43.4	8.5
23	Other motor vehicle dealers (4412)	50.7	3.2	4.2	2.8	43.5	7.2
24	Other miscellaneous mfg. (3399)	49.7	8.9	1.5	0.7	40.5	9.2
25	Nondepository credit intrmd (5222)	48.2	5.8	2.1	0.7	33.5	14.7
26	Security contracts broker (5231)	48.2	3.0	3.1	0.2	8.5	39.7
27	Depository credit intrmd (5221)	47.4	3.1	26.8	1.8	46.8	0.6
28	Offices of dentists (6212)	46.9	18.8	0.7	0.6	43.0	3.9
29	Insurance agencies/brokerages (5242)	44.4	20.0	0.5	0.4	36.6	7.7
30	Other fabricated metal prod mfg. (3329)	43.7	9.7	2.5	1.4	38.9	4.8
	Aggregate	5,620.9	8.5	0.8	0.3	3,453.2	2,167.6

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.2: Implied Rates of Return for Pass-Through Business (2001–2016)

	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	P10 (%)	P50 (%)	P90 (%)
S-corporations							
Unweighted	11.39	30.61	-0.14	4.46	-20.01	7.84	51.25
Value-weighted	9.95	17.29	0.86	8.47	-2.81	6.22	30.07
Partnerships							
Unweighted	4.32	25.82	0.46	6.70	-14.27	0.00	36.04
Value-weighted	8.47	19.04	1.01	7.56	-4.22	1.38	31.37

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 pass-through valuation methodology (without scaling to match the USFA-derived SZ20 values). 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.3: Characteristics of top-owned businesses in the SCF (2016)

	P99-99.9 wealth					Top 0.1% wealth				
	Mean	Std. dev.	P50	Min.	Max	Mean	Std. dev.	P50	Min.	Max
Share (%) own any business	64					88				
Number of businesses owned	2	3	1	0	26	5	6	2	0	30
Actively managed	1	2	1	0	25	3	5	1	0	25
Non-actively managed	1	2	0	0	25	2	5	0	0	25
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	22,590	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	10,226	25,881	2,000	0	391,340
Total employment	207	782	10	1	5,000	370	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

	P99-99.9 wealth					Top 0.1% wealth				
	Mean	Std. dev.	P5	P50	P95	Mean	Std. dev.	P5	P50	P95
Active Business #1										
$\frac{\text{Market value}}{\text{Sales}}$	2.6	2.0	0.2	2.0	5.0	2.5	2.0	0.0	1.7	5.0
$\frac{\text{Market value}}{\text{Profits}}$	22.6	19.2	0.0	17.0	50.0	18.2	16.6	0.0	11.6	50.0
$\frac{\text{Market value}}{\text{Cost basis}}$	8.0	8.0	0.8	3.0	20.0	9.5	8.5	0.9	6.0	20.0
Active Business #2										
$\frac{\text{Market value}}{\text{Sales}}$	2.8	2.0	0.3	2.4	5.0	2.7	2.0	0.2	1.6	5.0
$\frac{\text{Market value}}{\text{Profits}}$	24.5	20.2	0.0	20.0	50.0	22.2	19.2	0.0	15.8	50.0
$\frac{\text{Market value}}{\text{Cost basis}}$	5.8	7.2	0.3	1.6	20.0	5.6	7.0	0.2	2.0	20.0
Active Businesses #3 and Beyond										
$\frac{\text{Market value}}{\text{Profits}}$	27.8	19.9	0.7	17.3	50.0	27.8	18.2	0.0	17.3	50.0
$\frac{\text{Market value}}{\text{Cost basis}}$	5.8	6.4	0.8	1.9	20.0	5.8	7.1	0.7	1.9	20.0
Non-actively managed businesses										
$\frac{\text{Market value}}{\text{Profits}}$	31.8	20.0	2.2	50.0	50.0	31.6	18.3	5.3	40.0	50.0
$\frac{\text{Market value}}{\text{Cost basis}}$	5.5	7.0	0.5	2.0	20.0	4.8	6.3	1.0	2.0	20.0

B. Compustat

	Mean	Std. dev.	P5	P25	P50	P75	P95
$\frac{\text{Market value}}{\text{Sales}}$	1.8	1.3	0.2	0.7	1.5	2.7	4.4
$\frac{\text{Market value}}{\text{Pretax Income}}$	16.3	9.3	5.2	10.2	14.2	19.9	37.1
$\frac{\text{Market value}}{\text{Book Equity}}$	3.0	2.8	0.7	1.3	2.0	3.5	8.6
$\frac{\text{Market value}}{\text{Net Capital}}$	6.5	5.4	0.5	1.7	4.9	10.3	17.5

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)

	Mean	Std. dev.	P5	P50	P95
Total sales under 1M					
Share top 1%-owned lgst actively-mngd bus. value	8.53				
$\frac{\text{Market value}}{\text{Sales}}$	3.81	1.82	0.49	5.00	5.00
$\frac{\text{Market value}}{\text{Profits}}$	28.46	20.35	0.00	25.00	50.00
$\frac{\text{Market value}}{\text{Cost basis}}$	7.43	8.21	0.74	2.24	20.00
Total sales from 1M to 10M					
Share top 1%-owned lgst actively-mngd bus. value	28.12				
$\frac{\text{Market value}}{\text{Sales}}$	3.03	1.76	0.50	2.90	5.00
$\frac{\text{Market value}}{\text{Profits}}$	25.99	18.60	0.67	22.22	50.00
$\frac{\text{Market value}}{\text{Cost basis}}$	9.25	8.13	1.00	5.00	20.00
Total sales from 10M to 50M					
Share top 1%-owned lgst actively-mngd bus. value	27.73				
$\frac{\text{Market value}}{\text{Sales}}$	1.26	1.24	0.22	0.83	5.00
$\frac{\text{Market value}}{\text{Profits}}$	14.19	13.28	0.05	8.89	50.00
$\frac{\text{Market value}}{\text{Cost basis}}$	7.91	7.60	0.83	3.16	20.00
Total sales from 50M to 100M					
Share top 1%-owned lgst actively-mngd bus. value	4.93				
$\frac{\text{Market value}}{\text{Sales}}$	0.68	0.79	0.00	0.47	2.18
$\frac{\text{Market value}}{\text{Profits}}$	11.69	16.27	1.00	5.33	50.00
$\frac{\text{Market value}}{\text{Cost basis}}$	6.36	7.58	0.80	1.81	20.00
Total sales greater than 100M					
Share top 1%-owned lgst actively-mngd bus. value	30.69				
$\frac{\text{Market value}}{\text{Sales}}$	0.76	0.67	0.00	0.55	1.40
$\frac{\text{Market value}}{\text{Profits}}$	9.31	12.78	0.00	6.32	50.00
$\frac{\text{Market value}}{\text{Cost basis}}$	7.66	7.95	0.80	2.33	20.00

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: Interest Rates for Fixed Income Partnerships Grouped by Common Words (2016)

Fund Name Token	Number of Funds	Rate, Unweighted		Rate, Weighted	
		Mean	Std. Dev.	Mean	Std. Dev.
FUND	2095	4.77	4.81	2.40	3.24
PARTNERS	1830	4.56	4.69	2.79	3.23
INVESTMENT	1616	4.93	4.72	1.39	2.64
INVESTMENTS	1040	4.93	4.56	4.14	3.74
CAPITAL	1020	5.06	5.52	3.55	3.34
HOLDING	1005	5.01	4.88	4.28	5.12
HOLDINGS	883	4.98	4.92	4.28	5.22
PARTNERSHIP	726	3.79	3.69	2.70	2.46
US	723	4.40	4.39	1.36	2.08
FAMILY	699	3.56	3.69	2.69	2.80
PROPERTIES	575	4.60	3.58	3.20	3.05
INVESTORS	487	5.91	5.58	4.36	4.13
VENTURE	474	3.63	4.62	2.18	3.76
REAL	413	5.35	4.03	5.01	3.50
CDE	410	2.01	1.45	2.04	1.44
SUB	409	2.50	2.66	4.43	2.99
GROUP	385	5.40	4.84	3.67	3.03
SERIES	374	4.51	4.24	3.33	2.46
FUNDING	359	7.35	5.23	4.71	3.66
ASSOCIATES	344	5.25	5.16	5.11	5.57
LAND	335	4.25	3.86	3.30	2.15
VENTURES	290	3.24	4.35	1.47	2.32
DEVELOPMENT	252	3.64	3.98	2.40	2.12
NEW	251	3.39	3.61	2.54	2.72
COMPANY	244	4.51	4.21	1.62	2.53
LOAN	232	5.94	4.56	3.68	3.21
CREDIT	227	6.73	6.23	4.99	4.60
LENDER	227	7.23	5.32	5.77	4.58
REALTY	222	5.42	3.89	4.22	2.46
ENTERPRISES	207	4.70	4.42	2.88	3.36
ESTATE	206	5.20	4.24	5.19	3.78
MARKET	194	2.44	2.47	2.01	1.95
MANAGEMENT	192	4.31	5.86	0.67	0.87
MEZZ	179	8.54	4.47	7.63	4.35
SUB-CDE	174	2.03	1.62	2.02	1.61
PTR	166	4.83	2.95	2.93	2.49
OPPORTUNITIES	164	5.38	4.77	4.80	3.51
AIV	158	5.49	5.13	4.93	4.88
FINANCE	157	5.93	4.75	3.49	3.39
FINANCIAL	153	6.01	5.11	2.33	2.92

Fund Name Token	Number of Funds	Rate, Unweighted		Rate, Weighted	
		Mean	Std. Dev.	Mean	Std. Dev.
DEBT	152	7.65	4.93	6.27	4.56
MASTER	147	3.15	4.33	1.65	1.49
EQUITY	141	4.40	4.99	2.95	3.70
LENDING	139	7.41	5.65	4.14	4.14
ENERGY	133	5.57	6.18	4.48	4.17
SUBSIDIARY	122	2.78	2.91	4.76	4.01
INCOME	109	7.00	5.27	2.89	4.40
MEZZANINE	104	7.84	4.63	6.62	3.64
OPPORTUNITY	102	3.79	4.67	2.60	3.96
COMMUNITY	101	2.53	2.32	3.73	3.53
MORTGAGE	101	6.66	4.99	4.93	4.54
TRUST	100	4.19	4.25	1.92	1.95
ASSET	96	5.85	5.87	2.94	2.99
GLOBAL	91	3.89	5.24	1.81	0.80
ENHANCED	90	2.39	2.56	2.08	2.26
PRIVATE	90	4.17	4.79	3.01	2.78
MARKETS	89	2.48	2.21	4.07	1.97
PROPERTY	87	5.25	4.94	2.53	3.96
NOTE	85	7.13	5.61	3.85	2.82
FEEDER	83	4.46	4.76	3.88	2.61
HOLDCO	81	7.70	6.14	5.19	3.91
AVENUE	80	5.97	4.43	6.17	3.29
LENDERS	69	7.46	4.94	5.57	2.54
SPECIAL	67	5.91	4.68	4.71	3.80
CENTER	67	4.46	3.08	7.71	3.89
OFFSHORE	64	7.30	6.35	6.00	5.72
CO-INVESTMENT	61	5.08	4.45	5.66	4.60
NMTC	58	2.52	2.93	2.35	2.16
SERVICES	54	5.58	6.02	1.78	1.82
FINANCING	54	6.85	5.09	7.43	3.37
INFRASTRUCTURE	53	4.96	2.72	4.70	2.91
STRATEGIC	53	4.96	4.47	3.97	3.04
APARTMENTS	52	5.48	4.61	4.29	5.98

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. See Appendix I for discussion of representativeness of these data and more information about the closely held fixed income funds excluded from this table.

Table B.7: Interest Rates for Fixed Income Partnerships, Private Loans, and Corporate Bonds (2016)

	Mean (%)	Std. Dev. (%)	P5 (%)	P25 (%)	P50 (%)	P75 (%)	P95 (%)
Fixed Income Partnerships, Tax Data							
All	4.9	4.8	0.3	1.3	3.8	6.8	14.5
Private Loans, Tax Data							
All	4.5	4.2	0.5	1.9	3.7	6	10.8
Corporate Bonds with Moody's Ratings							
Prime (AAA, $N = 91$)	2.8	1.0	1.3	1.8	3.0	3.8	4.3
High (AA1-AA3, $N = 564$)	2.8	1.0	1.4	1.9	2.6	3.8	4.3
Upper Medium (A1-A3, $N = 2,183$)	3.0	1.0	1.5	2.2	3.0	4.0	4.5
Lower Medium (BAA1-BAA3, $N = 3,183$)	3.6	1.2	1.8	2.7	3.6	4.5	5.6
Speculative (BA1-BA3, $N = 698$)	4.7	1.4	2.5	3.8	4.7	5.5	7.0
Highly Speculative (B1-B3, $N = 565$)	6.1	1.8	3.5	5.1	5.9	7.0	9.7
Substantial Risks (CAA1-CAA3, $N = 172$)	9.3	2.8	5.8	7.3	8.6	11.3	14.6
Extremely Speculative (CA, $N = 14$)	12.7	2.5	7.4	11.9	12.6	14.8	15.6

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.8: Share of High-Income People with Dependents and Spouses by Age

Age	**Share with Dependents**	**Share Married**
23	6%	19%
24	6%	22%
25	13%	24%
26	15%	30%
27	19%	37%
28	24%	46%
29	27%	51%
30	32%	61%
31	40%	67%
32	45%	70%
33	55%	77%
34	63%	81%
35	68%	84%
36	75%	87%
37	77%	88%
38	81%	89%
39	83%	91%
40	84%	91%
41	85%	92%
42	85%	92%
43	85%	92%
44	85%	93%
45	86%	93%
46	85%	93%
47	85%	93%
48	84%	93%
49	82%	93%
50	80%	92%
51	78%	92%
52	73%	91%
53	69%	92%
54	64%	91%
55	59%	91%
56	52%	91%
57	46%	90%
58	40%	90%
59	33%	90%
60	28%	89%
61	24%	89%
62	19%	89%
63	16%	89%
64	13%	89%
65	11%	89%
66	10%	89%
67	8%	89%
68	7%	89%
69	7%	89%
70	5%	89%
71	4%	89%
72	4%	89%
73	4%	89%
74	3%	89%
75	3%	89%
76	2%	89%
77	2%	89%
78	2%	89%
79	2%	89%
80	2%	89%
81	1%	89%
82	1%	89%
83	1%	89%
84	1%	89%

Notes: This table provides the share of high-income individuals who claim dependents and spouses for individuals by age. The data are from the most recently available data in the US Treasury databank—2015. By high-income, we mean those whose adjusted-gross income exceeds $1,000,000 in absolute value.

Table B.9: Estimating the Number of Adults For Each Forbes Observation Using Public Forbes Data and Table B.8 Shares

Rank (1)	**Name** (2)	**Net Worth ($B)** (3)	**Age** (4)	**# of Kids** (5)	**"And Family"** (6)	**Prob. of Spouse** (7)	**Prob. of Dep.** (8)	**Exp. # of Adult Kid** (9)	**Mean Age of Adult Kid** (10)	**Prob. Adult Kid Single** (11)	**Exp. # of Adult Spouse** (12)	**Exp. # of Adult Kid & Spouse** (13)	**Total Adults** (14)
	Mean	11.1	67.2	2.6	0.1	0.9	0.2	2.2	37.2	0.3	1.8	4.0	5.9
	Median	5.5	67.0	3.0	0.0	0.9	0.1	2.0	37.0	0.1	1.7	3.7	5.6
	Max	201.0	96.0	14.0	1.0	0.9	0.9	13.5	66.0	1.0	12.5	25.9	27.8
	Min	2.9	29.0	0.0	0.0	0.5	0.0	0.0	-1.0	0.0	0.0	0.0	1.5
	Total	4,456		1,051	30	358		877			729	1,606	2,364
1	Jeff Bezos	201	58	4	0	90%	40%	2.4	28	54%	1.1	3.5	5.4
2	Elon Musk	190.5	50	6	0	92%	80%	1.2	20	89%	0.1	1.3	3.3
3	Mark Zuckerberg	134.5	37	2	0	88%	77%	0.5	7	100%	0.0	0.5	2.3
4	Bill Gates	134	66	3	0	89%	10%	2.7	36	13%	2.4	5.1	7.0
5	Larry Page	123	48	1	0	93%	84%	0.2	18	95%	0.0	0.2	2.1
6	Sergey Brin	118.5	48	3	0	93%	84%	0.5	18	95%	0.0	0.5	2.4
7	Larry Ellison	117.3	77	4	0	89%	2%	3.9	47	7%	3.6	7.6	9.5
8	Warren Buffett	102	91	3	0	89%	1%	3.0	61	11%	2.7	5.6	7.5
9	Steve Ballmer	96.5	65	3	0	89%	11%	2.7	35	16%	2.2	4.9	6.8
10	Michael Bloomberg	70	80	2	0	89%	2%	2.0	50	8%	1.8	3.8	5.7
11	Jim Walton	68.8	73	4	0	89%	4%	3.9	43	8%	3.6	7.4	9.3
12	Alice Walton	67.9	72	0	0	89%	4%	0.0	42	8%	0.0	0.0	1.9
13	Rob Walton	67.6	77	3	0	89%	2%	2.9	47	7%	2.7	5.7	7.6
14	Phil Knight & Fam	59.9	83	3	1	89%	1%	3.0	53	8%	2.7	5.7	7.6
15	MacKenzie Scott	58.5	51	4	0	92%	78%	0.9	21	87%	0.1	1.0	2.9
16	Charles Koch	51	86	2	0	89%	1%	2.0	56	9%	1.8	3.8	5.7
17	Julia Koch & Fam	51	59	3	1	90%	33%	2.0	29	49%	1.0	3.0	4.9
18	Michael Dell	50.1	56	4	0	91%	52%	1.9	26	70%	0.6	2.5	4.4
19	Stephen Schwarzman	37.4	75	3	0	89%	3%	2.9	45	7%	2.7	5.6	7.5
20	Len Blavatnik	36.7	64	4	0	89%	13%	3.5	34	19%	2.8	6.3	8.1
21	Jacqueline Mars	31.8	82	3	0	89%	1%	3.0	52	9%	2.7	5.7	7.6
22	John Mars	31.8	86	3	0	89%	1%	3.0	56	9%	2.7	5.7	7.6
23	Daniel Gilbert	30.9	60	5	0	89%	28%	3.6	30	39%	2.2	5.8	7.7
24	Miriam Adelson	30.4	76	5	0	89%	2%	4.9	46	7%	4.6	9.5	11.4
25	Leonard Lauder	28.9	88	2	0	89%	1%	2.0	58	10%	1.8	3.8	5.6
26	Pierre Omidyar	25.3	54	3	0	91%	64%	1.1	24	78%	0.2	1.3	3.2
27	Abigail Johnson	25.2	60	2	0	89%	28%	1.4	30	39%	0.9	2.3	4.2
28	Jim Simons	24.4	83	3	0	89%	1%	3.0	53	8%	2.7	5.7	7.6
29	Dustin Moskovitz	24.1	37	0	0	88%	77%	0.0	7	100%	0.0	0.0	1.9
30	Eric Schmidt	23.9	66	2	0	89%	10%	1.8	36	13%	1.6	3.4	5.3
31	Rupert Murdoch & Fam	23	90	6	1	89%	1%	5.9	60	11%	5.3	11.2	13.1
32	Sam Bankman-Fried	22.5	29	0	0	51%	27%	0.0	-1	0%	0.0	0.0	1.5
33	Laurene Powell Jobs & Fam	22.1	58	3	1	90%	40%	1.8	28	54%	0.8	2.6	4.5
34	Jensen Huang	21.3	59	2	0	90%	33%	1.3	29	49%	0.7	2.0	3.9
35	Thomas Frist, Jr. & Fam	20.8	83	3	1	89%	1%	3.0	53	8%	2.7	5.7	7.6
36	Ray Dalio	20	72	4	0	89%	4%	3.8	42	8%	3.5	7.4	9.3
37	Thomas Peterffy	20	77	3	0	89%	2%	2.9	47	7%	2.7	5.7	7.6
38	Robert Pera	19	43	0	0	92%	85%	0.0	13	100%	0.0	0.0	1.9
39	Ernest Garcia, II.	18.8	64	1	0	89%	13%	0.9	34	19%	0.7	1.6	3.5
40	Donald Newhouse	18.1	92	3	0	89%	1%	3.0	62	11%	2.7	5.6	7.5
41	Lukas Walton	17.2	35	1	0	84%	68%	0.3	5	100%	0.0	0.3	2.2
42	Hank & Doug Meijer	16.9	70	4	1	89%	5%	3.8	40	9%	3.5	7.3	9.2
43	Carl Icahn	16.6	86	2	0	89%	1%	2.0	56	9%	1.8	3.8	5.7
44	John Menard, Jr.	16.6	82	6	0	89%	1%	5.9	52	9%	5.4	11.4	13.3
45	Jay Chaudhry	16.3	62	3	0	89%	19%	2.4	32	30%	1.7	4.1	6.0
46	Donald Bren	16.2	89	7	0	89%	1%	6.9	59	10%	6.2	13.1	15.0
47	Ken Griffin	16.1	53	3	0	92%	69%	0.9	23	81%	0.2	1.1	3.0
48	Steve Cohen	16	65	7	0	89%	11%	6.2	35	16%	5.2	11.4	13.3
49	David Tepper	15.8	64	3	0	89%	13%	2.6	34	19%	2.1	4.7	6.6
50	David Duffield	15.5	81	10	0	89%	1%	9.9	51	8%	9.1	19.0	20.9

Rank (1)	Name (2)	Net Worth ($B) (3)	Age (4)	# of Kids (5)	& Family (6)	Prob. of Spouse (7)	Prob. of Dep. (8)	Exp. # of Adult Kid (9)	Mean Age of Adult Kid (10)	Prob. Adult Kid Single (11)	Exp. # of Adult Spouse (12)	Exp. # of Adult Kid & Spouse (13)	Total Adults (14)
51	John Doerr	15.2	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
52	Bobby Murphy	15.2	33	0	0	77%	55%	0.0	3	100%	0.0	0.0	1.8
53	Jack Dorsey	14.9	45	0	0	93%	86%	0.0	15	100%	0.0	0.0	1.9
54	Eric Yuan & Fam	14.5	52	3	1	91%	73%	0.8	22	84%	0.1	0.9	2.8
55	Evan Spiegel	13.8	31	2	0	67%	40%	1.2	1	100%	0.0	1.2	2.9
56	Charles Ergen	13	68	5	0	89%	7%	4.6	38	11%	4.1	8.8	10.7
57	Brian Chesky	12.5	40	0	0	91%	84%	0.0	10	100%	0.0	0.0	1.9
58	Jeff Yass	12	63	4	0	89%	16%	3.4	33	23%	2.6	5.9	7.8
59	Li Ge	11.6	55	0	0	91%	59%	0.0	25	76%	0.0	0.0	1.9
60	Brian Armstrong	11.5	39	0	0	91%	83%	0.0	9	100%	0.0	0.0	1.9
61	Edward Johnson, III.	11.5	91	3	0	89%	1%	3.0	61	11%	2.7	5.6	7.5
62	Charles Schwab	11.5	84	5	0	89%	1%	5.0	54	9%	4.5	9.5	11.4
63	Harold Hamm & Fam	11.4	76	5	1	89%	2%	4.9	46	7%	4.6	9.5	11.4
64	Diane Hendricks	11	74	7	0	89%	3%	6.8	44	7%	6.3	13.0	14.9
65	Jan Koum	10.9	45	0	0	93%	86%	0.0	15	100%	0.0	0.0	1.9
66	Philip Anschutz	10.8	82	3	0	89%	1%	3.0	52	9%	2.7	5.7	7.6
67	Carl Cook	10.8	59	1	0	90%	33%	0.7	29	49%	0.3	1.0	2.9
68	Joe Gebbia	10.8	40	0	0	91%	84%	0.0	10	100%	0.0	0.0	1.9
69	Gordon Moore	10.8	93	2	0	89%	1%	2.0	63	11%	1.8	3.7	5.6
70	Stanley Kroenke	10.7	74	2	0	89%	3%	1.9	44	7%	1.8	3.7	5.6
71	Israel Englander	10.5	73	3	0	89%	4%	2.9	43	8%	2.7	5.6	7.5
72	David Geffen	10.5	79	0	0	89%	2%	0.0	49	7%	0.0	0.0	1.9
73	Chase Coleman, III.	10.3	46	4	0	93%	85%	0.6	16	100%	0.0	0.6	2.5
74	Marc Benioff	10.2	57	2	0	90%	46%	1.1	27	63%	0.4	1.5	3.4
75	Steven Rales	10.1	70	3	0	89%	5%	2.8	40	9%	2.6	5.4	7.3
76	Nathan Blecharczyk	10	38	2	0	89%	81%	0.4	8	100%	0.0	0.4	2.3
77	George Kaiser	10	79	3	0	89%	2%	2.9	49	7%	2.7	5.7	7.6
78	Andrew Beal	9.9	69	6	0	89%	7%	5.6	39	9%	5.1	10.7	12.6
79	Leon Black	9.9	70	4	0	89%	5%	3.8	40	9%	3.5	7.3	9.2
80	Jim Kennedy	9.7	74	3	0	89%	3%	2.9	44	7%	2.7	5.6	7.5
81	Blair Parry-Okeden	9.7	71	2	0	89%	4%	1.9	41	8%	1.8	3.7	5.6
82	Paul Xiaoming Lee & Fam	9.5	64	0	1	89%	13%	0.0	34	19%	0.0	0.0	1.9
83	Ernest Garcia, III.	9.3	39	0	0	91%	83%	0.0	9	100%	0.0	0.0	1.9
84	Ann Walton Kroenke	9.3	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
85	Tom & Judy Love	9.3	84	4	1	89%	1%	4.0	54	9%	3.6	7.6	9.5
86	Jerry Jones	9.1	79	3	0	89%	2%	2.9	49	7%	2.7	5.7	7.6
87	Bernard Marcus	9.1	92	3	0	89%	1%	3.0	62	11%	2.7	5.6	7.5
88	George Roberts	9	78	3	0	89%	2%	2.9	48	7%	2.7	5.6	7.5
89	Patrick Soon-Shiong	8.9	69	2	0	89%	7%	1.9	39	9%	1.7	3.6	5.5
90	James Goodnight	8.8	79	3	0	89%	2%	2.9	49	7%	2.7	5.7	7.6
91	Herbert Kohler, Jr. & Fam	8.8	83	3	1	89%	1%	3.0	53	8%	2.7	5.7	7.6
92	Vinod Khosla	8.6	67	4	0	89%	8%	3.7	37	12%	3.2	6.9	8.8
93	George Soros	8.6	91	5	0	89%	1%	5.0	61	11%	4.4	9.4	11.3
94	Shahid Khan	8.5	71	2	0	89%	4%	1.9	41	8%	1.8	3.7	5.6
95	Henry Kravis	8.5	78	2	0	89%	2%	2.0	48	7%	1.8	3.8	5.7
96	Nancy Walton Laurie	8.5	70	1	0	89%	5%	0.9	40	9%	0.9	1.8	3.7
97	Lin Bin	8.5	54	3	0	91%	64%	1.1	24	78%	0.2	1.3	3.2
98	Rocco Commisso	8.4	72	2	0	89%	4%	1.9	42	8%	1.8	3.7	5.6
99	Jack Dangermond	8.4	76	0	0	89%	2%	0.0	46	7%	0.0	0.0	1.9
100	David Green & Fam	8.4	80	3	1	89%	2%	2.9	50	8%	2.7	5.7	7.5

Rank	Name	Net Worth ($B)	Age	# of Kids	& Family	Prob. of Spouse	Prob. of Dep.	Exp. # of Adult Kid	Mean Age of Adult Kid	Prob. Adult Kid Single	Exp. # of Adult Spouse	Exp. # of Adult Kid & Spouse	Total Adults
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
101	John Malone	8.4	80	2	0	89%	2%	2.0	50	8%	1.8	3.8	5.7
102	Mat Ishbia	8.3	42	3	0	92%	85%	0.4	12	100%	0.0	0.4	2.4
103	Robert Kraft	8.3	80	4	0	89%	2%	3.9	50	8%	3.6	7.5	9.4
104	Stephen Ross	8.3	81	4	0	89%	1%	4.0	51	8%	3.7	7.6	9.5
105	Christy Walton	8.3	73	1	0	89%	4%	1.0	43	8%	0.9	1.9	3.7
106	Pauline MacMillan Keinath	8.2	88	4	0	89%	1%	4.0	58	10%	3.5	7.5	9.4
107	Douglas Leone	8.1	64	4	0	89%	13%	3.5	34	19%	2.8	6.3	8.1
108	Tamara Gustavson	8	60	2	0	89%	28%	1.4	30	39%	0.9	2.3	4.2
109	Marijke Mars	8	57	0	0	90%	46%	0.0	27	63%	0.0	0.0	1.9
110	Pamela Mars	8	61	3	0	89%	24%	2.3	31	33%	1.5	3.8	5.7
111	Valerie Mars	8	63	2	0	89%	16%	1.7	33	23%	1.3	3.0	4.9
112	Victoria Mars	8	65	4	0	89%	11%	3.6	35	16%	3.0	6.5	8.4
113	Stewart & Lynda Resnick	8	85	5	1	89%	1%	5.0	55	9%	4.5	9.5	11.4
114	Michael Rubin	8	49	1	0	93%	82%	0.2	19	92%	0.0	0.2	2.1
115	Reinhold Schmieding	7.8	67	2	0	89%	8%	1.8	37	12%	1.6	3.4	5.3
116	Ronald Wanek	7.6	80	3	0	89%	2%	2.9	50	8%	2.7	5.7	7.5
117	Mitchell Rales	7.5	65	2	0	89%	11%	1.8	35	16%	1.5	3.3	5.2
118	David Shaw	7.5	70	3	0	89%	5%	2.8	40	9%	2.6	5.4	7.3
119	Ronda Stryker	7.5	67	3	0	89%	8%	2.7	37	12%	2.4	5.2	7.0
120	Jonathan Gray	7.4	52	4	0	91%	73%	1.1	22	84%	0.2	1.2	3.2
121	Patrick Ryan	7.4	84	3	0	89%	1%	3.0	54	9%	2.7	5.7	7.6
122	Tim Sweeney	7.4	51	0	0	92%	78%	0.0	21	87%	0.0	0.0	1.9
123	Paul Tudor Jones, II.	7.3	67	4	0	89%	8%	3.7	37	12%	3.2	6.9	8.8
124	Arthur Blank	7.2	79	6	0	89%	2%	5.9	49	7%	5.4	11.3	13.2
125	Edward Johnson, IV.	7.2	57	2	0	90%	46%	1.1	27	63%	0.4	1.5	3.4
126	George Lucas	7.2	77	4	0	89%	2%	3.9	47	7%	3.6	7.6	9.5
127	Michael Moritz	7.2	67	2	0	89%	8%	1.8	37	12%	1.6	3.4	5.3
128	Richard Kinder	7.1	77	1	0	89%	2%	1.0	47	7%	0.9	1.9	3.8
129	Jane Lauder	7.1	49	2	0	93%	82%	0.4	19	92%	0.0	0.4	2.3
130	Ralph Lauren	7.1	82	3	0	89%	1%	3.0	52	9%	2.7	5.7	7.6
131	Christopher Reyes	7.1	68	4	0	89%	7%	3.7	38	11%	3.3	7.0	8.9
132	Jude Reyes	7.1	66	3	0	89%	10%	2.7	36	13%	2.4	5.1	7.0
133	Ken Xie	7	59	1	0	90%	33%	0.7	29	49%	0.3	1.0	2.9
134	Jim Davis & Fam	6.9	78	2	1	89%	2%	2.0	48	7%	1.8	3.8	5.7
135	John Morris	6.9	73	4	0	89%	4%	3.9	43	8%	3.6	7.4	9.3
136	Sun Hongbin	6.9	59	2	0	90%	33%	1.3	29	49%	0.7	2.0	3.9
137	Anthony Wood	6.9	56	3	0	91%	52%	1.4	26	70%	0.4	1.9	3.8
138	Stanley Druckenmiller	6.8	68	3	0	89%	7%	2.8	38	11%	2.5	5.3	7.1
139	Jeff Skoll	6.8	57	0	0	90%	46%	0.0	27	63%	0.0	0.0	1.9
140	Dennis Washington	6.8	87	2	0	89%	1%	2.0	57	10%	1.8	3.8	5.7
141	Micky Arison	6.7	72	2	0	89%	4%	1.9	42	8%	1.8	3.7	5.6
142	Michael Kim	6.7	58	2	0	90%	40%	1.2	28	54%	0.6	1.8	3.7
143	Robert F. Smith	6.7	59	7	0	90%	33%	4.7	29	49%	2.4	7.1	9.0
144	David Sun	6.7	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
145	John Tu	6.7	80	2	0	89%	2%	2.0	50	8%	1.8	3.8	5.7
146	Henry Samueli	6.6	67	3	0	89%	8%	2.7	37	12%	2.4	5.2	7.0
147	Judy Faulkner	6.5	78	3	0	89%	2%	2.9	48	7%	2.7	5.6	7.5
148	Philippe Laffont	6.5	54	0	0	91%	64%	0.0	24	78%	0.0	0.0	1.9
149	John Overdeck	6.5	52	3	0	91%	73%	0.8	22	84%	0.1	0.9	2.8
150	David Siegel	6.5	60	0	0	89%	28%	0.0	30	39%	0.0	0.0	1.9

Rank	Name	Net Worth ($B)	Age	# of Kids	& Family	Prob. of Spouse	Prob. of Dep.	Exp. # of Adult Kid	Mean Age of Adult Kid	Prob. Adult Kid Single	Exp. # of Adult Spouse	Exp. # of Adult Kid & Spouse	Total Adults
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
151	Neil Bluhm	6.4	84	3	0	89%	1%	3.0	54	9%	2.7	5.7	7.6
152	James Chambers	6.4	64	2	0	89%	13%	1.7	34	19%	1.4	3.1	5.0
153	Ken Fisher	6.4	71	3	0	89%	4%	2.9	41	8%	2.6	5.5	7.4
154	Katharine Rayner	6.4	77	0	0	89%	2%	0.0	47	7%	0.0	0.0	1.9
155	Harry Stine	6.4	80	4	0	89%	2%	3.9	50	8%	3.6	7.5	9.4
156	Margaretta Taylor	6.4	79	1	0	89%	2%	1.0	49	7%	0.9	1.9	3.8
157	Meg Whitman	6.4	65	2	0	89%	11%	1.8	35	16%	1.5	3.3	5.2
158	Orlando Bravo	6.3	51	3	0	92%	78%	0.7	21	87%	0.1	0.8	2.7
159	Tilman Fertitta	6.3	64	4	0	89%	13%	3.5	34	19%	2.8	6.3	8.1
160	Melinda French Gates	6.3	57	3	0	90%	46%	1.6	27	63%	0.6	2.2	4.1
161	Dannine Avara	6.2	57	0	0	90%	46%	0.0	27	63%	0.0	0.0	1.9
162	Scott Duncan	6.2	39	0	0	91%	83%	0.0	9	100%	0.0	0.0	1.9
163	Milane Frantz	6.2	52	0	0	91%	73%	0.0	22	84%	0.0	0.0	1.9
164	Bruce Kovner	6.2	76	3	0	89%	2%	2.9	46	7%	2.7	5.7	7.6
165	Antony Ressler	6.2	60	3	0	89%	28%	2.2	30	39%	1.3	3.5	5.4
166	Leonard Stern	6.2	83	3	0	89%	1%	3.0	53	8%	2.7	5.7	7.6
167	Randa Duncan Williams	6.2	60	1	0	89%	28%	0.7	30	39%	0.4	1.2	3.0
168	Elizabeth Johnson	6.1	58	0	0	90%	40%	0.0	28	54%	0.0	0.0	1.9
169	Edward Roski, Jr.	6.1	83	3	0	89%	1%	3.0	53	8%	2.7	5.7	7.6
170	Charles Simonyi	6.1	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
171	John A. Sobrato & Fam	6.1	82	3	1	89%	1%	3.0	52	9%	2.7	5.7	7.6
172	Chris Larsen	6	61	2	0	89%	24%	1.5	31	33%	1.0	2.5	4.4
173	Joe Mansueto	6	65	3	0	89%	11%	2.7	35	16%	2.2	4.9	6.8
174	Isaac Perlmutter	6	79	0	0	89%	2%	0.0	49	7%	0.0	0.0	1.9
175	Sam Zell	6	80	3	0	89%	2%	2.9	50	8%	2.7	5.7	7.5
176	John Brown	5.9	87	2	0	89%	1%	2.0	57	10%	1.8	3.8	5.7
177	Scott Cook	5.9	69	3	0	89%	7%	2.8	39	9%	2.5	5.3	7.2
178	Tom Gores	5.9	57	3	0	90%	46%	1.6	27	63%	0.6	2.2	4.1
179	Ken Langone	5.9	86	3	0	89%	1%	3.0	56	9%	2.7	5.7	7.6
180	Timothy Springer	5.9	73	0	0	89%	4%	0.0	43	8%	0.0	0.0	1.9
181	Les Wexner & Fam	5.9	84	4	1	89%	1%	4.0	54	9%	3.6	7.6	9.5
182	Peter Gassner	5.8	56	2	0	91%	52%	1.0	26	70%	0.3	1.2	3.2
183	Min Kao & Fam	5.8	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
184	Henry Nicholas, III.	5.8	62	3	0	89%	19%	2.4	32	30%	1.7	4.1	6.0
185	Gary Rollins	5.8	77	4	0	89%	2%	3.9	47	7%	3.6	7.6	9.5
186	Fred Smith	5.8	77	10	0	89%	2%	9.8	47	7%	9.1	18.9	20.8
187	David Steward	5.8	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
188	Stephen Bisciotti	5.7	61	2	0	89%	24%	1.5	31	33%	1.0	2.5	4.4
189	Joshua Harris	5.7	57	5	0	90%	46%	2.7	27	63%	1.0	3.7	5.6
190	Reed Hastings	5.7	61	2	0	89%	24%	1.5	31	33%	1.0	2.5	4.4
191	Ray Lee Hunt	5.7	78	5	0	89%	2%	4.9	48	7%	4.5	9.4	11.3
192	Terrence Pegula	5.7	70	5	0	89%	5%	4.7	40	9%	4.3	9.1	11.0
193	Karen Pritzker	5.7	64	4	0	89%	13%	3.5	34	19%	2.8	6.3	8.1
194	Alan Trefler	5.7	65	0	0	89%	11%	0.0	35	16%	0.0	0.0	1.9
195	David Baszucki	5.6	59	4	0	90%	33%	2.7	29	49%	1.4	4.1	6.0
196	Charles Dolan & Fam	5.6	95	6	1	89%	1%	5.9	65	11%	5.3	11.2	13.1
197	Dagmar Dolby & Fam	5.6	80	2	0	89%	2%	2.0	50	8%	1.8	3.8	5.7
198	Charles B. Johnson	5.6	89	6	0	89%	1%	5.9	59	10%	5.3	11.3	13.2
199	Eric Smidt	5.6	62	0	0	89%	19%	0.0	32	30%	0.0	0.0	1.9
200	Bubba Cathy	5.5	67	6	0	89%	8%	5.5	37	12%	4.8	10.3	12.2

Rank (1)	Name (2)	Net Worth ($B) (3)	Age (4)	# of Kids (5)	& Family (6)	Prob. of Spouse (7)	Prob. of Dep. (8)	Exp. # of Adult Kid (9)	Mean Age of Adult Kid (10)	Prob. Adult Kid Single (11)	Exp. # of Adult Spouse (12)	Exp. # of Adult Kid & Spouse (13)	Total Adults (14)
201	Don Cathy	5.5	68	2	0	89%	7%	1.9	38	11%	1.7	3.5	5.4
202	Trudy Cathy White	5.5	65	4	0	89%	11%	3.6	35	16%	3.0	6.5	8.4
203	Don Hankey	5.5	78	4	0	89%	2%	3.9	48	7%	3.6	7.5	9.4
204	Mark Walter	5.4	61	1	0	89%	24%	0.8	31	33%	0.5	1.3	3.2
205	Ronald Lauder	5.3	77	2	0	89%	2%	2.0	47	7%	1.8	3.8	5.7
206	Barry Diller	5.2	79	0	0	89%	2%	0.0	49	7%	0.0	0.0	1.9
207	Bam Kim	5.2	43	1	0	92%	85%	0.1	13	100%	0.0	0.1	2.1
208	Gwendolyn Sontheim Meyer	5.2	59	2	0	90%	33%	1.3	29	49%	0.7	2.0	3.9
209	Jeff Tangney	5.1	49	3	0	93%	82%	0.5	19	92%	0.0	0.6	2.5
210	Jeff Greene	5.1	66	3	0	89%	10%	2.7	36	13%	2.4	5.1	7.0
211	Tom Golisano	5.1	79	2	0	89%	2%	2.0	49	7%	1.8	3.8	5.7
212	Daniel Ziff	5	50	1	0	92%	80%	0.2	20	89%	0.0	0.2	2.1
213	Robert Ziff	5	55	2	0	91%	59%	0.8	25	76%	0.2	1.0	2.9
214	Dirk Ziff	5	57	2	0	90%	46%	1.1	27	63%	0.4	1.5	3.4
215	Mark Shoen	5	70	1	0	89%	5%	0.9	40	9%	0.9	1.8	3.7
216	Scott Schleifer	5	44	0	0	93%	85%	0.0	14	100%	0.0	0.0	1.9
217	Howard Schultz	5	68	2	0	89%	7%	1.9	38	11%	1.7	3.5	5.4
218	Dan Kurzius	5	49	2	0	93%	82%	0.4	19	92%	0.0	0.4	2.3
219	Ben Chestnut	5	47	2	0	93%	85%	0.3	17	97%	0.0	0.3	2.2
220	Robert Bass	5	73	4	0	89%	4%	3.9	43	8%	3.6	7.4	9.3
221	Noubar Afeyan	5	59	4	0	90%	33%	2.7	29	49%	1.4	4.1	6.0
222	Robert Rich, Jr.	4.9	80	4	0	89%	2%	3.9	50	8%	3.6	7.5	9.4
223	Robert Langer	4.9	73	3	0	89%	4%	2.9	43	8%	2.7	5.6	7.5
224	Mark Stevens	4.8	61	3	0	89%	24%	2.3	31	33%	1.5	3.8	5.7
225	Richard Schulze	4.8	80	10	0	89%	2%	9.8	50	8%	9.0	18.8	20.7
226	Jeff Rothschild	4.8	66	3	0	89%	10%	2.7	36	13%	2.4	5.1	7.0
227	Julian Robertson, Jr.	4.8	89	3	0	89%	1%	3.0	59	10%	2.7	5.6	7.5
228	Bert Beveridge	4.8	59	3	0	90%	33%	2.0	29	49%	1.0	3.0	4.9
229	Todd Wanek	4.7	57	2	0	90%	46%	1.1	27	63%	0.4	1.5	3.4
230	Marc Rowan	4.7	59	0	0	90%	33%	0.0	29	49%	0.0	0.0	1.9
231	Matthew Prince	4.7	46	0	0	93%	85%	0.0	16	100%	0.0	0.0	1.9
232	Igor Olenicoff	4.7	79	2	0	89%	2%	2.0	49	7%	1.8	3.8	5.7
233	Marianne Liebman	4.7	68	2	0	89%	7%	1.9	38	11%	1.7	3.5	5.4
234	Ted Lerner & Fam	4.7	96	3	1	89%	1%	3.0	66	11%	2.7	5.6	7.5
235	William Lauder	4.7	61	3	0	89%	24%	2.3	31	33%	1.5	3.8	5.7
236	Rupert Johnson, Jr.	4.7	81	0	0	89%	1%	0.0	51	8%	0.0	0.0	1.9
237	James Cargill, II.	4.7	72	2	0	89%	4%	1.9	42	8%	1.8	3.7	5.6
238	Austen Cargill, II.	4.7	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
239	Robert Brackman	4.7	80	1	0	89%	2%	1.0	50	8%	0.9	1.9	3.8
240	Ron Baron	4.6	78	2	0	89%	2%	2.0	48	7%	1.8	3.8	5.7
241	Daniel D'Aniello	4.6	75	2	0	89%	3%	1.9	45	7%	1.8	3.7	5.6
242	Jim Davis	4.6	61	2	0	89%	24%	1.5	31	33%	1.0	2.5	4.4
243	Jeffrey Hildebrand	4.6	62	3	0	89%	19%	2.4	32	30%	1.7	4.1	6.0
244	Sami Mnaymneh	4.6	60	0	0	89%	28%	0.0	30	39%	0.0	0.0	1.9
245	Jon Stryker	4.6	63	2	0	89%	16%	1.7	33	23%	1.3	3.0	4.9
246	Tony Tamer	4.6	64	4	0	89%	13%	3.5	34	19%	2.8	6.3	8.1
247	David Bonderman	4.5	79	5	0	89%	2%	4.9	49	7%	4.5	9.4	11.3
248	Mark Cuban	4.5	63	3	0	89%	16%	2.5	33	23%	1.9	4.4	6.3
249	Gary Friedman	4.5	64	2	0	89%	13%	1.7	34	19%	1.4	3.1	5.0
250	Thomas Pritzker	4.5	71	3	0	89%	4%	2.9	41	8%	2.6	5.5	7.4

Rank (1)	Name (2)	Net Worth ($B) (3)	Age (4)	# of Kids (5)	& Family (6)	Prob. of Spouse (7)	Prob. of Dep. (8)	Exp. # of Adult Kid (9)	Mean Age of Adult Kid (10)	Prob. Adult Kid Single (11)	Exp. # of Adult Spouse (12)	Exp. # of Adult Kid & Spouse (13)	Total Adults (14)
251	Trevor Rees-Jones	4.5	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
252	Barry Sternlicht	4.5	61	3	0	89%	24%	2.3	31	33%	1.5	3.8	5.7
253	Dan Friedkin	4.4	56	4	0	91%	52%	1.9	26	70%	0.6	2.5	4.4
254	Rakesh Gangwal	4.4	68	1	0	89%	7%	0.9	38	11%	0.8	1.8	3.6
255	Jeff T. Green	4.4	44	3	0	93%	85%	0.4	14	100%	0.0	0.4	2.4
256	Johnelle Hunt	4.4	90	2	0	89%	1%	2.0	60	11%	1.8	3.7	5.6
257	Marian Ilitch	4.4	89	7	0	89%	1%	6.9	59	10%	6.2	13.1	15.0
258	Aerin Lauder	4.4	51	2	0	92%	78%	0.4	21	87%	0.1	0.5	2.4
259	John Sall	4.4	73	4	0	89%	4%	3.9	43	8%	3.6	7.4	9.3
260	Joe Shoen	4.4	72	3	0	89%	4%	2.9	42	8%	2.7	5.5	7.4
261	Rick Caruso	4.3	63	4	0	89%	16%	3.4	33	23%	2.6	5.9	7.8
262	Daniel Och	4.3	61	3	0	89%	24%	2.3	31	33%	1.5	3.8	5.7
263	Robert Rowling	4.3	68	2	0	89%	7%	1.9	38	11%	1.7	3.5	5.4
264	David Rubenstein	4.3	72	3	0	89%	4%	2.9	42	8%	2.7	5.5	7.4
265	Paul Singer	4.3	77	2	0	89%	2%	2.0	47	7%	1.8	3.8	5.7
266	Ty Warner	4.3	77	0	0	89%	2%	0.0	47	7%	0.0	0.0	1.9
267	Cameron Winklevoss	4.3	40	0	0	91%	84%	0.0	10	100%	0.0	0.0	1.9
268	Tyler Winklevoss	4.3	40	0	0	91%	84%	0.0	10	100%	0.0	0.0	1.9
269	Jim McKelvey	4.2	56	2	0	91%	52%	1.0	26	70%	0.3	1.2	3.2
270	Janice McNair	4.2	85	4	0	89%	1%	4.0	55	9%	3.6	7.6	9.5
271	Walter Scott, Jr. & Fam	4.2	90	6	1	89%	1%	5.9	60	11%	5.3	11.2	13.1
272	Lynsi Snyder	4.2	39	4	0	91%	83%	0.7	9	100%	0.0	0.7	2.6
273	Margot Birmingham Perot	4.1	88	5	0	89%	1%	5.0	58	10%	4.4	9.4	11.3
274	Thai Lee	4.1	63	2	0	89%	16%	1.7	33	23%	1.3	3.0	4.9
275	Eric Lefkofsky	4.1	52	3	0	91%	73%	0.8	22	84%	0.1	0.9	2.8
276	J. Joe Ricketts & Fam	4.1	80	4	1	89%	2%	3.9	50	8%	3.6	7.5	9.4
277	Thomas Siebel	4.1	69	4	0	89%	7%	3.7	39	9%	3.4	7.1	9.0
278	Peter Thiel	4.1	54	2	0	91%	64%	0.7	24	78%	0.2	0.9	2.8
279	Steven Udvar-Hazy	4.1	75	4	0	89%	3%	3.9	45	7%	3.6	7.5	9.4
280	Russ Weiner	4.1	51	0	0	92%	78%	0.0	21	87%	0.0	0.0	1.9
281	William Conway, Jr.	4	72	1	0	89%	4%	1.0	42	8%	0.9	1.8	3.7
282	George Kurtz	4	51	2	0	92%	78%	0.4	21	87%	0.1	0.5	2.4
283	Daniel Loeb	4	60	3	0	89%	28%	2.2	30	39%	1.3	3.5	5.4
284	Ramzi Musallam	4	53	0	0	92%	69%	0.0	23	81%	0.0	0.0	1.9
285	John Paulson	4	66	2	0	89%	10%	1.8	36	13%	1.6	3.4	5.3
286	Dan Snyder	4	57	3	0	90%	46%	1.6	27	63%	0.6	2.2	4.1
287	Don Vultaggio & Fam	4	69	2	1	89%	7%	1.9	39	9%	1.7	3.6	5.5
288	Denise York & Fam	4	71	4	1	89%	4%	3.8	41	8%	3.5	7.4	9.2
289	Nick Caporella	3.9	86	4	0	89%	1%	4.0	56	9%	3.6	7.5	9.4
290	Amos Hostetter, Jr.	3.9	85	3	0	89%	1%	3.0	55	9%	2.7	5.7	7.6
291	Richard LeFrak & Fam	3.9	76	2	1	89%	2%	2.0	46	7%	1.8	3.8	5.7
292	Pablo Legorreta	3.9	58	2	0	90%	40%	1.2	28	54%	0.6	1.8	3.7
293	Stepehn Mandel, Jr.	3.9	65	3	0	89%	11%	2.7	35	16%	2.2	4.9	6.8
294	Gabel Newell	3.9	59	2	0	90%	33%	1.3	29	49%	0.7	2.0	3.9
295	Jean (Gigi) Pritzker	3.9	59	3	0	90%	33%	2.0	29	49%	1.0	3.0	4.9
296	Donald Sterling	3.9	87	3	0	89%	1%	3.0	57	10%	2.7	5.6	7.5
297	Kelcy Warren	3.9	66	1	0	89%	10%	0.9	36	13%	0.8	1.7	3.6
298	Herbert Wertheim	3.9	82	2	0	89%	1%	2.0	52	9%	1.8	3.8	5.7
299	Michael Xie	3.9	53	0	0	92%	69%	0.0	23	81%	0.0	0.0	1.9
300	Gayle Benson	3.8	75	0	0	89%	3%	0.0	45	7%	0.0	0.0	1.9

Rank (1)	Name (2)	Net Worth ($B) (3)	Age (4)	# of Kids (5)	& Family (6)	Prob. of Spouse (7)	Prob. of Dep. (8)	Exp. # of Adult Kid (9)	Mean Age of Adult Kid (10)	Prob. Adult Kid Single (11)	Exp. # of Adult Spouse (12)	Exp. # of Adult Kid & Spouse (13)	Total Adults (14)
301	James Clark	3.8	77	4	0	89%	2%	3.9	47	7%	3.6	7.6	9.5
302	Hao Hong	3.8	66	0	0	89%	10%	0.0	36	13%	0.0	0.0	1.9
303	Brad Jacobs	3.8	65	4	0	89%	11%	3.6	35	16%	3.0	6.5	8.4
304	Peter Kellogg	3.8	79	3	0	89%	2%	2.9	49	7%	2.7	5.7	7.6
305	Michael Milken	3.8	75	3	0	89%	3%	2.9	45	7%	2.7	5.6	7.5
306	Chad Richison	3.8	51	4	0	92%	78%	0.9	21	87%	0.1	1.0	2.9
307	Steven Sarowitz	3.8	56	0	0	91%	52%	0.0	26	70%	0.0	0.0	1.9
308	Bernard Saul, II.	3.8	89	5	0	89%	1%	5.0	59	10%	4.4	9.4	11.3
309	Wang Roger	3.8	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
310	John Catsimatidis	3.7	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
311	Jimmy Haslam	3.7	67	3	0	89%	8%	2.7	37	12%	2.4	5.2	7.0
312	Martha Ingram & Fam	3.7	86	4	1	89%	1%	4.0	56	9%	3.6	7.5	9.4
313	Anthony Pritzker	3.7	61	6	0	89%	24%	4.6	31	33%	3.0	7.6	9.5
314	Ira Rennert	3.7	87	3	0	89%	1%	3.0	57	10%	2.7	5.6	7.5
315	Steven Spielberg	3.7	75	7	0	89%	3%	6.8	45	7%	6.3	13.1	15.0
316	Kenneth Tuchman	3.7	62	2	0	89%	19%	1.6	32	30%	1.1	2.7	4.6
317	Scott Waterson	3.7	66	5	0	89%	10%	4.5	36	13%	3.9	8.4	10.3
318	Charles Cohen	3.6	70	4	0	89%	5%	3.8	40	9%	3.5	7.3	9.2
319	David Filo	3.6	55	1	0	91%	59%	0.4	25	76%	0.1	0.5	2.4
320	John Henry	3.6	72	2	0	89%	4%	1.9	42	8%	1.8	3.7	5.6
321	H. Fisk Johnson	3.6	63	1	0	89%	16%	0.8	33	23%	0.6	1.5	3.4
322	S. Curtis Johnson	3.6	66	4	0	89%	10%	3.6	36	13%	3.1	6.8	8.7
323	Helen Johnson-Leipold	3.6	65	5	0	89%	11%	4.4	35	16%	3.7	8.1	10.0
324	Mary Alice Dorrance Malone	3.6	72	2	0	89%	4%	1.9	42	8%	1.8	3.7	5.6
325	Winifred J. Marquart	3.6	62	4	0	89%	19%	3.2	32	30%	2.3	5.5	7.4
326	Arturo Moreno	3.6	75	3	0	89%	3%	2.9	45	7%	2.7	5.6	7.5
327	Jay Paul	3.6	74	0	0	89%	3%	0.0	44	7%	0.0	0.0	1.9
328	J.B. Pritzker	3.6	57	2	0	90%	46%	1.1	27	63%	0.4	1.5	3.4
329	Rodger Riney & Fam	3.6	76	3	1	89%	2%	2.9	46	7%	2.7	5.7	7.6
330	Thomas Secunda	3.6	67	2	0	89%	8%	1.8	37	12%	1.6	3.4	5.3
331	Jerry Speyer	3.6	81	4	0	89%	1%	4.0	51	8%	3.7	7.6	9.5
332	Vincent Viola	3.6	66	3	0	89%	10%	2.7	36	13%	2.4	5.1	7.0
333	Fred Ehrsam	3.5	33	0	0	77%	55%	0.0	3	100%	0.0	0.0	1.8
334	Archie Aldis Emmerson & Fam	3.5	92	3	1	89%	1%	3.0	62	11%	2.7	5.6	7.5
335	James Irsay	3.5	62	3	0	89%	19%	2.4	32	30%	1.7	4.1	6.0
336	Jeffrey Lurie	3.5	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
337	Lynn Schusterman	3.5	83	3	0	89%	1%	3.0	53	8%	2.7	5.7	7.6
338	Romesh Wadhwani	3.5	74	1	0	89%	3%	1.0	44	7%	0.9	1.9	3.8
339	William Wrigley, Jr.	3.5	58	4	0	90%	40%	2.4	28	54%	1.1	3.5	5.4
340	Steve Conine	3.4	49	3	0	93%	82%	0.5	19	92%	0.0	0.6	2.5
341	Behdad Eghbali	3.4	45	0	0	93%	86%	0.0	15	100%	0.0	0.0	1.9
342	Jose E. Feliciano	3.4	48	0	0	93%	84%	0.0	18	95%	0.0	0.0	1.9
343	Thomas Hagen	3.4	86	2	0	89%	1%	2.0	56	9%	1.8	3.8	5.7
344	Jim Kavanaugh	3.4	59	3	0	90%	33%	2.0	29	49%	1.0	3.0	4.9
345	Steven Klinsky	3.4	65	0	0	89%	11%	0.0	35	16%	0.0	0.0	1.9
346	Frank Laukien	3.4	62	1	0	89%	19%	0.8	32	30%	0.6	1.4	3.3
347	John Middleton	3.4	66	2	0	89%	10%	1.8	36	13%	1.6	3.4	5.3
348	Bob Parsons	3.4	71	1	0	89%	4%	1.0	41	8%	0.9	1.8	3.7
349	Richard Sands	3.4	70	2	0	89%	5%	1.9	40	9%	1.7	3.6	5.5
350	Robert Sands	3.4	63	2	0	89%	16%	1.7	33	23%	1.3	3.0	4.9

Rank	Name	Net Worth ($B)	Age	# of Kids	& Family	Prob. of Spouse	Prob. of Dep.	Exp. # of Adult Kid	Mean Age of Adult Kid	Prob. Adult Kid Single	Exp. # of Adult Spouse	Exp. # of Adult Kid & Spouse	Total Adults
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
351	T. Denny Sanford	3.4	86	2	0	89%	1%	2.0	56	9%	1.8	3.8	5.7
352	RJ Scaringe	3.4	39	3	0	91%	83%	0.5	9	100%	0.0	0.5	2.4
353	Niraj Shah	3.4	47	2	0	93%	85%	0.3	17	97%	0.0	0.3	2.2
354	Herb Simon	3.4	87	8	0	89%	1%	7.9	57	10%	7.1	15.1	16.9
355	Pat Stryker	3.4	65	3	0	89%	11%	2.7	35	16%	2.2	4.9	6.8
356	Thomas Tull	3.4	51	3	0	92%	78%	0.7	21	87%	0.1	0.8	2.7
357	Jerry Yang	3.4	53	2	0	92%	69%	0.6	23	81%	0.1	0.7	2.7
358	John Arnold	3.3	47	2	0	93%	85%	0.3	17	97%	0.0	0.3	2.2
359	Bill Austin	3.3	79	0	0	89%	2%	0.0	49	7%	0.0	0.0	1.9
360	James Leprino	3.3	84	2	0	89%	1%	2.0	54	9%	1.8	3.8	5.7
361	Ben Silbermann	3.3	39	2	0	91%	83%	0.3	9	100%	0.0	0.3	2.3
362	Steve Wynn	3.3	80	2	0	89%	2%	2.0	50	8%	1.8	3.8	5.7
363	Aneel Bhusri	3.2	56	2	0	91%	52%	1.0	26	70%	0.3	1.2	3.2
364	Robert Hale, Jr.	3.2	55	0	0	91%	59%	0.0	25	76%	0.0	0.0	1.9
365	Gail Miller	3.2	78	5	0	89%	2%	4.9	48	7%	4.5	9.4	11.3
366	H. Ross Perot, Jr.	3.2	63	4	0	89%	16%	3.4	33	23%	2.6	5.9	7.8
367	Alice Schwartz	3.2	95	2	0	89%	1%	2.0	65	11%	1.8	3.7	5.6
368	William Ackman	3.1	55	3	0	91%	59%	1.2	25	76%	0.3	1.5	3.4
369	David Gottesman	3.1	95	3	0	89%	1%	3.0	65	11%	2.7	5.6	7.5
370	Hamilton James	3.1	70	3	0	89%	5%	2.8	40	9%	2.6	5.4	7.3
371	Penny Pritzker	3.1	62	2	0	89%	19%	1.6	32	30%	1.1	2.7	4.6
372	Haim Saban	3.1	77	4	0	89%	2%	3.9	47	7%	3.6	7.6	9.5
373	Rodney Sacks	3.1	72	0	0	89%	4%	0.0	42	8%	0.0	0.0	1.9
374	Jeff Sutton	3.1	62	5	0	89%	19%	4.0	32	30%	2.8	6.8	8.7
375	Frank VanderSloot	3.1	73	14	0	89%	4%	13.5	43	8%	12.5	25.9	27.8
376	Jon Yarbrough	3.1	64	2	0	89%	13%	1.7	34	19%	1.4	3.1	5.0
377	William Berkley	3	75	3	0	89%	3%	2.9	45	7%	2.7	5.6	7.5
378	Neal Blue & Fam	3	86	1	1	89%	1%	1.0	56	9%	0.9	1.9	3.8
379	Todd Christopher	3	59	0	0	90%	33%	0.0	29	49%	0.0	0.0	1.9
380	J. Tomilson Hill	3	73	2	0	89%	4%	1.9	43	8%	1.8	3.7	5.6
381	Jeremy Jacobs, Sr. & Fam	3	82	6	1	89%	1%	5.9	52	9%	5.4	11.4	13.3
382	Sheldon Lavin	3	89	3	0	89%	1%	3.0	59	10%	2.7	5.6	7.5
383	Alexis Le-Que	3	47	1	0	93%	85%	0.1	17	97%	0.0	0.2	2.1
384	Joseph Liemandt	3	53	0	0	92%	69%	0.0	23	81%	0.0	0.0	1.9
385	Jed McCaleb	3	47	0	0	93%	85%	0.0	17	97%	0.0	0.0	1.9
386	Drayton McLane, Jr.	3	85	2	0	89%	1%	2.0	55	9%	1.8	3.8	5.7
387	Alejandro Santo Domingo	3	45	2	0	93%	86%	0.3	15	100%	0.0	0.3	2.2
388	Mortimer Zuckerman	3	84	2	0	89%	1%	2.0	54	9%	1.8	3.8	5.7
389	Riley Bechtel & Fam	2.9	69	3	1	89%	7%	2.8	39	9%	2.5	5.3	7.2
390	Baiju Bhatt	2.9	37	1	0	88%	77%	0.2	7	100%	0.0	0.2	2.1
391	Jim Breyer	2.9	60	3	0	89%	28%	2.2	30	39%	1.3	3.5	5.4
392	Bennett Dorrance	2.9	76	2	0	89%	2%	2.0	46	7%	1.8	3.8	5.7
393	Joseph Edelman	2.9	66	2	0	89%	10%	1.8	36	13%	1.6	3.4	5.3
394	John Fisher	2.9	60	4	0	89%	28%	2.9	30	39%	1.8	4.6	6.5
395	Jane Goldman	2.9	66	2	0	89%	10%	1.8	36	13%	1.6	3.4	5.3
396	Joseph Grendys	2.9	60	0	0	89%	28%	0.0	30	39%	0.0	0.0	1.9
397	Donald Horton & Fam	2.9	71	2	1	89%	4%	1.9	41	8%	1.8	3.7	5.6
398	W. Herbert Hunt	2.9	92	5	0	89%	1%	5.0	62	11%	4.4	9.4	11.3
399	Paul Sciarra	2.9	41	0	0	92%	85%	0.0	11	100%	0.0	0.0	1.9
400	Warren Stephens	2.9	65	3	0	89%	11%	2.7	35	16%	2.2	4.9	6.8

Notes: This table lists publicly-available Forbes 400 data on wealth rank, name, net worth, age, and number of children in the first five columns, respectively, as of 10/4/2021 (accessed February 21, 2022) from `https://www.forbes.com/forbes-400/` . Column 6 is an indicator for whether the row has "& family" in the name. Column 7 uses the age in Column 4 and the share married from Appendix Table B.8 to estimate the probability of a spouse. Column 8 does the same but for probability of a dependent. Multiplying (1- Column 8) by the number of kids in Column 5 gives the expected number of adult children in Column 9. Column 10 subtracts 30 from Age in Column 4 to estimate the age of adult children. Column 11 uses the age in Column 10 and shares from Appendix Table B.8 to estimate the probability of a spouse. Column 12 multiplies Column 11 by Column 10 to estimate the expected number of adult child spouses. Column 13 adds Col 12 and 9. Column 14 sums one, Column 13, and Column 7 to estimate the total number of adults for that Forbes observation. **De-identified administrative tax data were not used for any of our analysis of the Forbes 400.**

Table B.10: Predicting Dividend-Generating Assets with Equity Flows in the SCF

	(1)	(2)	(3)	(4)	(5)
	Full sample	Botttom 90%	Top 1%	Top 0.1%	Top 0.01%
Capital gains	1.042	1.074	0.844	0.736	0.318
	(0.011)	(0.014)	(0.027)	(0.041)	(0.083)
Dividends	15.763	15.260	14.017	11.907	14.987
	(0.054)	(0.057)	(0.134)	(0.188)	(0.410)
Implied α	0.938	0.934	0.943	0.942	0.979
	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)
N (unweighted)	441,260	374,654	66,606	31,233	9,395

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

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

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

Table B.11: Total Housing Wealth under Heterogeneous Property Tax Capitalization (2016)

	2016 Housing Wealth					2016 Housing Wealth *(cont.)*			
State	Assets (B)	Wealth (B)	Assets / pop (K)	Wealth / pop (K)	State	Assets (B)	Wealth (B)	Assets / pop (K)	Wealth / pop (K)
AK	48.24	10.81	93.22	20.89	MS	85.79	30.16	54.35	19.11
AL	213.45	82.63	77.10	29.85	MT	66.67	21.01	92.69	29.21
AR	128.70	53.68	71.15	29.68	NC	684.60	333.10	111.22	54.12
AZ	504.59	250.45	123.38	61.24	ND	63.00	38.12	123.07	74.46
CA	7757.94	5090.96	318.45	208.97	NE	99.02	51.76	78.60	41.09
CO	631.84	343.28	176.56	95.93	NH	118.22	59.18	128.42	64.28
CT	354.59	175.32	153.99	76.13	NJ	1047.80	591.53	177.46	100.18
DC	54.69	11.68	128.75	27.49	NM	106.22	49.23	91.54	42.42
DE	72.14	36.45	124.09	62.70	NV	267.45	136.53	146.99	75.03
FL	1977.42	1293.72	154.34	100.98	NY	1733.17	909.18	138.35	72.58
GA	589.29	264.57	99.05	44.47	OH	712.48	401.49	95.10	53.59
HI	202.28	105.95	200.78	105.16	OK	185.48	89.27	79.48	38.26
IA	188.53	101.53	93.91	50.57	OR	481.45	281.78	178.46	104.44
ID	88.61	30.05	82.51	27.98	PA	842.05	421.71	98.44	49.30
IL	962.20	479.84	116.74	58.22	RI	95.75	48.38	130.92	66.15
IN	323.62	165.88	77.07	39.51	SC	271.60	123.75	89.75	40.89
KS	147.26	66.29	78.74	35.44	SD	59.00	29.60	92.86	46.59
KY	173.36	62.09	63.63	22.79	TN	444.38	257.54	108.91	63.12
LA	221.89	92.31	82.00	34.11	TX	1632.20	825.68	97.86	49.51
MA	891.79	509.38	192.64	110.03	UT	230.03	108.07	122.17	57.39
MD	679.01	339.53	174.25	87.13	VA	693.24	241.29	129.50	45.07
ME	96.87	47.13	109.97	53.51	VT	38.87	9.25	78.35	18.66
MI	555.84	287.42	86.58	44.77	WA	1125.66	689.21	232.99	142.65
MN	446.01	213.51	117.26	56.14	WI	432.66	242.11	106.35	59.51
MO	328.48	162.29	85.54	42.26	WV	75.71	39.57	73.19	38.26
MS	85.79	30.16	54.35	19.11	WY	34.56	8.64	86.88	21.71
MT	66.67	21.01	92.69	29.21		.	.	.	.

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.

C Portfolio Category Definitions in Tax Data

C.1 Overall wealth

This section provides portfolio definitions in our baseline 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

$$\begin{aligned}
\text{Net worth} &= \text{Currency} + \text{Taxable interest-generating fixed claims} + \text{Tax-exempt interest-generating fixed claims}\\
&\quad + \text{Bonds and loans held in mutual funds} + \text{C-corporation equity} + \text{Pass-through business}\\
&\quad + \text{Pensions} + \text{Housing net of mortgages} + \text{Non-mortgage debt} + \text{Miscellaneous wealth}\\
{}^{\textit{2016 example}} &= \$1.0T + \$9.4T + \$2.3T + \$2.3T + \$10.8T + \$9.0T + \$26.3T + \$18.4T - \$4.3T + \$1.0T \boxed{= \$76.3T}
\end{aligned}$$

C.2 Wealth categories

$$\begin{aligned}
\textbf{Currency} &= \texttt{currency}\\
{}^{\textit{2016 example}} &\boxed{= \$1.0T}
\end{aligned}$$

where `currency` uses PSZ (2018) capitalization methodology and updated aggregates from SZ (2020).

$$\begin{aligned}
\textbf{Taxable interest-generating fixed claims} &= \begin{cases} \texttt{taxbond_info} & \text{if year } \geq 2001 \\ \texttt{taxbond_cmd_3tier} & \text{if year } < 2001 \end{cases}\\
{}^{\textit{2016 example}} &\boxed{= \$9.4T}
\end{aligned}$$

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.

$$\textbf{Tax-exempt interest-generating fixed claims} = \texttt{muni}$$
$$\overset{\textit{2016 example}}{}\boxed{= \$2.3T}$$

where muni uses PSZ (2018) capitalization methodology and updated aggregates from SZ (2020).

$$\textbf{Bonds and loans held in mutual funds} = \texttt{taxbond\_muf}$$
$$\overset{\textit{2016 example}}{}\boxed{= \$2.3T}$$

where taxbond_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.

$$\textbf{C-corporation equity} = \texttt{ccorw\_9010}$$
$$\overset{\textit{2016 example}}{}\boxed{= \$10.8T}$$

where ccorw_9010 capitalizes a composite flow made up of 90% dividends and 10% capital gains using updated aggregates from SZ (2020).

$$\textbf{Pass-through business} = \begin{cases} \texttt{solepropw\_sz20} + \texttt{scorw\_szzhybnof\_scaled} + \texttt{partw\_szzhybnof\_sz20\_scaled} \text{ if year} \geq 2001 \\ \texttt{solepropw\_sz20} + \texttt{scorw\_sz20} + \texttt{partw\_sz20} \text{ if year } < 2001 \end{cases}$$
$$\overset{\textit{2016 example}}{} = \$1.8T + \$3.4T + \$3.8T \boxed{= \$9.0T}$$

where solepropw_sz20, partw_sz20, and scorw_sz20 use PSZ (2018) capitalization methodology and updated aggregates from SZ (2020), scorw_szzhybnof_scaled and partw_szzhybnof_sz20_scaled use our multiples-based valuation and are scaled to match the SZ20 aggregates.

$$\textbf{Pensions} = \begin{cases} \texttt{penw\_szz\_scaled} \text{ if year } \geq 1980 \\ \texttt{szz\_penw\_pre1980} \text{ if year } < 1980 \end{cases}$$
$$\overset{\textit{2016 example}}{}\boxed{= \$26.3T}$$

where `penw_szz_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 funded defined benefit entitlements from Sabelhaus and Volz (2019). For `szz_penw_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_scaled`, we use the updated aggregate from SZ (2020).

$$\textbf{Housing net of mortgages} = \begin{cases} \texttt{ownerhome\_szz} + \texttt{rentalhome} + \texttt{ownermort} + \texttt{rentalmort} & \text{if year } \geq 1980 \\ \texttt{ownerhome\_ini} + \texttt{rentalhome} + \texttt{ownermort\_ini} + \texttt{rentalmort} & \text{if year } < 1980 \end{cases}$$

$$\textit{2016 example} = \$23.6T + \$6.2T - \$9.6T - \$1.8T \boxed{= \$18.4T}$$

where `ownerhome_ini` and `ownermort_ini` use PSZ (2018) capitalization methodology *and* PSZ (2018) aggregates; `rentalhome`, `ownermort`, and `rentalmort` use PSZ (2018) capitalization model with updated aggregates from SZ (2020); and `ownerhome_szz` capitalizes owner-occupied housing values using heterogeneous property tax rates and updated aggregates from SZ (2020).

$$\textbf{Non-mortgage debt} = \texttt{nonmort}$$

$$\textit{2016 example} \boxed{= -\$4.3T}$$

where `nonmort` uses PSZ (2018) capitalization methodology and updated aggregates from SZ (2020).

$$\textbf{Miscellaneous wealth} = \texttt{miscw\_hweal}$$

$$\textit{2016 example} \boxed{= \$1.0B}$$

where `miscw_hweal` allocates financial assets not classified elsewhere in proportion to other wealth.

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

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 funded 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).[1]

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

[1] Here is a link: `https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL153050045&t=`. This is constructed as "Households and nonprofit organizations; pension entitlements; asset" (series code FL153050005 `https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL153050005&t=`, table B.101) minus "Defined contribution pension funds; total financial assets" (series code FL594090055 `https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL594090055&t=`, table L.117).

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 (2020*b*) (see appendix sheet "DataWealth" column BR). Following SZ, we allocate only the funded portion. To quantify funded DB pensions, we use series code FL592000075.

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

$$\begin{aligned}
&\text{Defined benefit pensions} \equiv \\
&\qquad \texttt{tot_pen_db} = \big(\texttt{currec_pv_dbamt_rtot} + \texttt{currec_pv_dbamt_stot} + \texttt{future_pv_dbamt_rtot} \\
&\qquad\qquad + \texttt{future_pv_dbamt_stot} + \texttt{curjob_pv_dbamt_rtot} + \texttt{curjob_pv_dbamt_stot}\big) \\
&\qquad\qquad \times \frac{\text{Funded defined benefit pension funds; pension entitlements (total liabilities)}}{\text{Households and nonprofit organizations; defined benefit and annuity pension entitlements; asset}} \\
&\qquad {}^{\textit{2016 example}} = \big(\$5.6T + \$1.7T + \$334B + \$96B + \$6.75T + \$3.2T\big) \times 47\% \boxed{= \$8.3T}
\end{aligned}$$

Note that all DB pensions (rather than just the funded portion) would represent 83.75% rather than 47% in the formula above, amounting to 14.8T in 2016 rather than 8.3T.

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:

$$\begin{aligned}
\text{Actvly-mgd. bus. 1 mkt. val.} &= \texttt{max}(0, X3129) + \texttt{max}(0, X3124) - \texttt{max}(0, X3126) \times (X3127 = 5) + \texttt{max}(0, X3121) \times \texttt{inlist}(X3122, 1, 6) \\
\text{Actvly-mgd. bus. 2 mkt. val.} &= \texttt{max}(0, X3229) + \texttt{max}(0, X3224) - \texttt{max}(0, X3226) \times (X3227 = 5) + \texttt{max}(0, X3221) \times \texttt{inlist}(X3222, 1, 6) \\
\text{Private C-corp. (prelim.)} &= \text{Actvly-mgd. bus. 1 mkt. val.} \times (X3119 = 4) + \text{Actvly-mgd. bus. 2 mkt. val.} \times (X3219 = 4) + \texttt{max}(0, X3420) \\
\text{Pass-through (prelim.)} &= \texttt{bus} - \text{Private C-corp. (prelim.)} - \texttt{max}(0, X3335) \\
\text{Private C-corp.} \equiv \texttt{privccorw} &= \text{Private C-corp. (prelim.)} + \frac{\text{Private C-corp. (prelim.)}}{\text{Private C-corp. (prelim.)} + \text{Pass-through (prelim.)}} \times \texttt{max}(0, X3335) \\
\text{Pass-through (prelim.)} \equiv \texttt{pthrubus} &= \text{Pass-through (prelim.)} + \left(1 - \frac{\text{Private C-corp. (prelim.)}}{\text{Private C-corp. (prelim.)} + \text{Pass-through (prelim.)}}\right) \times \texttt{max}(0, X3335)
\end{aligned}$$

We calculate mortgages issued by surveyed households as:

$$\text{Mortgage assets} \equiv \texttt{mortgageassets} = \begin{cases} \texttt{max}(X1405, X1409) + \texttt{max}(X1505, X1509) + \texttt{max}(0, X1619) & \text{if year } \leq 2010 \\ \texttt{max}(X1306, X1310) + \texttt{max}(X1325, X1329) + \texttt{max}(0, X1339) & \text{if year } > 2010 \end{cases}$$

We calculate cash as:

$$\text{Cash} \equiv \texttt{cash} = X4022 \times (X4020 = 63) + X4026 \times (X4024 = 63) + X4030 \times (X4028 = 63)$$

where $X4022$, $X4026$, and $X4030$ are the values of respondents' most valuable, second most valuable, and third most valuable miscellaneous assets, and a code of 63 for $X4020$, $X4024$, and $X4028$ indicates that the aforementioned assets are "Cash not elsewhere classified."

We calculate private loans as

$$\text{Private loans} \equiv \texttt{privloans} = X4022 \times \texttt{inlist}(X4020, 61, 62) + X4026 \times \texttt{inlist}(X4024, 61, 62) + X4030 \times \texttt{inlist}(X4028, 61, 62)$$

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

$$\begin{aligned} \text{Durables} \equiv \texttt{durables} = {} & X4022 \times \texttt{inlist}(X4020, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76) \\ & + X4026 \times \texttt{inlist}(X4024, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76) \\ & + X4030 \times \texttt{inlist}(X4028, 10, 11, 12, 13, 14, 15, 16, 17, 20, 21, 23, 24, 25, 75, 76) \end{aligned}$$

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 (`trusts`) in two steps:

1. We split `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:

$$\text{Share trusts invested in equity} = \begin{cases} (X6591 = 1) + \texttt{inlist}(X6591, 3, 30) \times \max(0, X6592)/10,000 \text{ if year } \geq 2004 \\ 0.5 \text{ if year } < 2004 \end{cases}$$

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

$$\text{Trusts not invested in equity} = \texttt{trusts} - \texttt{trusts\_equity}$$

and step 2 is:

$$\text{Non-trust txble int.-gen. fixed claims} = \texttt{saving} + \texttt{cds} + \texttt{mmda} + \texttt{call} + \texttt{savbnd} + (\texttt{bond} - \texttt{notxbnd}) + \texttt{privloans} + \texttt{mortgageassets}$$

$$\text{Non-trust tax-exempt fixed claims} = \texttt{notxbnd} + \texttt{tfbmutf}$$

$$\text{Non-trust fix mut. funds} = (0.5 \times \texttt{comutf}) + (0.5 \times \texttt{omutf}) + \texttt{gbmutf} + \texttt{obmutf} + \texttt{mmmf}$$

$$\text{Trusts inv. in txble int.-gen. fixed claims} = \frac{\texttt{trusts} \times \text{Non-trust txble int.-gen. fixed claims}}{\text{Non-trust non-txble fixed claims} + \text{Non-trust non-txble fixed claims} + \text{Non-trust fix mut. fds}}$$

$$\text{Trusts inv. in tax-exempt fixed claims} = \frac{\texttt{trusts} \times \text{Non-trust tax-exempt fixed claims}}{\text{Non-trust non-txble fixed claims} + \text{Non-trust non-txble fixed claims} + \text{Non-trust fix mut. fds}}$$

$$\text{Trusts inv. in fix mut. funds} = \frac{\texttt{trusts} \times \text{Non-trust bonds \& loans in mut. funds}}{\text{Non-trust non-txble fixed claims} + \text{Non-trust non-txble fixed claims} + \text{Non-trust fix mut. fds}}$$

D.2 Main wealth categories

In our harmonized SCF series, aggregate wealth is:

$$\textbf{Net worth} = \texttt{networth} + \texttt{tot\_pen\_db} - \texttt{vehic} - \texttt{durables}$$

$$\overset{\textit{2016 example}}{=} \$86.9T + \$8.3T - \$2.7T - \$501B \boxed{= \$92.0T}$$

where `networth` and `vehic` are bulletin concepts representing total wealth and vehicles,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.

$$\textbf{Currency} = \texttt{checking} + \texttt{cash} + \texttt{prepaid}$$

$$\overset{\textit{2016 example}}{=} \$1.17T + \$6B + \$8B \boxed{= \$1.18T}$$

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.

$$\textbf{Taxable interest-generating fixed claims} = \texttt{saving} + \texttt{cds} + \texttt{mmda} + \texttt{call} + \texttt{savbnd} + (\texttt{bond} - \texttt{notxbnd}) + \texttt{privloans} + \texttt{mortgageassets} + \texttt{trusts\_inttaxw}$$

$$\overset{\textit{2016 example}}{=} \$2.0T + \$620B + \$1.1T + \$350B + \$104B + (\$1.2T - \$781B) + \$0 + \$319B + \$968B \boxed{= 5.9T}$$

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.

$$\textbf{tax-exempt fixed claims} = \texttt{notxbnd} + \texttt{tfbmutf} + \texttt{trusts\_intexmw}$$

$$\overset{\textit{2016 example}}{=} \$781B + \$1.3T + \$222B \boxed{= \$2.3T}$$

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.

$$\textbf{Bonds and loans held in mutual funds} = (0.5 \times \texttt{comutf}) + (0.5 \times \texttt{omutf}) + \texttt{gbmutf} + \texttt{obmutf} + \texttt{mmmf} + \texttt{trusts\_mmbondfund}$$

$$\overset{\textit{2016 example}}{=} \$378B + \$505B + \$276B + \$404B + \$318B + \$163B \boxed{= \$2.0T}$$

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.

$$\textbf{C-corporation equity} = \texttt{stocks} + \texttt{privccorw} + \texttt{stmutf} + (0.5 \times \texttt{comutf}) + (0.5 \times \texttt{omutf}) + \texttt{trusts\_equity}$$

$$\overset{\textit{2016 example}}{=} \$5.7T + \$2.6T + \$5.9T + 378B + 505B + \$1.0T + \boxed{= \$16.1T}$$

where `stocks`, `stmutf`, `comutf`, and `omutf` are bulletin concepts representing direcly-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.

$$\textbf{Pass-through business} = \texttt{pthrubus} + \texttt{nnresre}$$

$$\overset{\textit{2016 example}}{=} \$16.8T + \$3.7T \boxed{= \$20.5T}$$

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

$$\textbf{Pensions} = \texttt{annuit} + \texttt{cashli} + \texttt{retqliq} + \texttt{tot\_pen\_db}$$
$$^{\textit{2016 example}} = \$876B + \$914B + \$15.0T + \$8.3T \boxed{= \$25.1T}$$

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.

$$\textbf{Housing} = \texttt{houses} + (\texttt{oresre} - \texttt{mortgageassets}) + \texttt{mrthel} + \texttt{resdbt}$$
$$^{\textit{2016 example}} = \$24.2T + (\$6.3T - \$319B) + \$8.3T + \$1.1T \boxed{= \$20.7T}$$

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.

$$\textbf{Non-mortgage debt} = -\texttt{vehic\_inst} - \texttt{othloc} - \texttt{ccbal} - \texttt{edn\_inst} - \texttt{oth\_inst} - \texttt{odebt}$$
$$^{\textit{2016 example}} = -\$733 - \$127B - \$316B - \$962B - \$280B - \$176B \boxed{= -\$2.6T}$$

where `vehic_inst`, `othloc`, `ccbal`, `edn_inst`, `oth_inst`, and `odebt` are all bulletin concepts representing vehicle loans, 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).

$$\textbf{Other} = (\texttt{othfin} - \texttt{cash} - \texttt{privloans}) + (\texttt{othnfin} - \texttt{durables})$$
$$^{\textit{2016 example}} = (\$659B - \$6B - \$0) + (\$559B - \$501B) \boxed{= \$710B}$$

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 et al. (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" `Phttps://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:

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

where all concepts but `privccorw_costbasis`, `scorw_costbasis`, and `pthrubus_costbasis` are defined in Appendix D, and the cost basis concepts are analogs to `privccorw`, `scorw`, and `pthrubus` concepts defined therein, constructed using cost basis questions.[2]

Then the DFA-reconciled net worth concept is the sum of these, plus the `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., `houses`, `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.

[2] 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 $g \in \{\text{Bot } 50\%, \text{Next } 40\%, \text{Next } 9\%, \text{Top } 1\%\}$:

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

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

$$\begin{aligned}
\text{IRA sh. assets incl. IRAs}_{\text{SCF},g} &= \frac{\texttt{irakh}_g}{\text{Total IRA-containing assets}_{\text{SCF},g}} \\
\text{Time depsts \& short-term inv. sh. assets incl. IRAs}_{\text{SCF},g} &= \frac{\text{Time deposits and short-term investments}_{\text{SCF},g}}{\text{Total IRA-containing assets}_{\text{SCF},g}} \\
&\vdots \\
\text{Corp. equ. \& mut. funds sh. assets incl. IRAs}_{\text{SCF},g} &= \frac{\text{Time deposits and short-term investments}_{\text{SCF},g}}{\text{Total IRA-containing assets}_{\text{SCF},g}}
\end{aligned}$$

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

$$\begin{aligned}
\text{Total IRA-containing assets}_{\text{DFA},g} = {} & \text{Time deposits and short-term investments}_{\text{DFA},g} + \text{Money market fund shares}_{\text{DFA},g} \\
& + \text{US government and municipal securities}_{\text{DFA},g} + \text{Corporate and foreign bonds}_{\text{DFA},g} \\
& + \text{Corporate equities and mutual funds}_{\text{DFA},g}
\end{aligned}$$

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 goverment and municipal securities, etc.

$$\begin{aligned}
\text{IRAs}_{\text{DFA},g} &\equiv \texttt{peniraw_dfa} = \text{IRA sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g} \\
\text{Time depsts \& short-term inv. excl. IRAs}_{\text{DFA},g} &\equiv \\
\texttt{timdepshrttrm_excl_iras} &= \text{Time depsts \& short-term inv. sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g} \\
\text{Money market fund shares excl. IRAs}_{\text{DFA},g} &\equiv \\
\texttt{mnymrktfundshares_excl_iras} &= \text{Money mkt. fund shares sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g} \\
\text{US govt. \& muni. scties excl. IRAs}_{\text{DFA},g} &\equiv \\
\texttt{usgovsecmunishares_excl_iras} &= \text{US govt. \& muni. scties sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g} \\
\text{Corp. \& frgn. bnds excl. IRAs}_{\text{DFA},g} &\equiv \\
\texttt{corpfrgnbnd_excl_iras} &= \text{Corp. \& frgn. bnds sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g} \\
\text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g} &\equiv \\
\texttt{corpequmutf_excl_iras} &= \text{Corp. equ. \& mut. funds sh. assets incl. IRAs}_{\text{SCF},g} \times \text{Total IRA-containing assets}_{\text{DFA},g}
\end{aligned}$$

E.1.3 Disaggregate "Corporate equities and mutual funds"

For each constituent asset class of Corporate equities and mutual funds$_{\text{SCF}}$ – 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 $g \in \{\text{Bot } 50\%, \text{Next } 40\%, \text{Next } 9\%, \text{Top } 1\%\}$:

$$\begin{aligned}
\text{Public equities sh. corp. equ. \& mut. funds}_{\text{SCF, }g} &= \frac{\texttt{stocks}_g + \texttt{trusts_equity}_g + \texttt{stmutf}_g + (0.5 \times \texttt{comutf}_g) + (0.5 \times \texttt{omutf}_g}{\text{Corporate equities and mutual funds}_{\text{SCF},g}} \\
\text{Private C-corp. sh. corp. equ. \& mut. funds}_{\text{SCF, }g} &= \frac{0.5 \times (\texttt{privccorw} + \texttt{privccorw_costbasis})}{\text{Corporate equities and mutual funds}_{\text{SCF},g}} \\
\text{S-corp. sh. corp. equ. \& mut. funds}_{\text{SCF, }g} &= \frac{0.5 \times (\texttt{scorw}_g + \texttt{scorw_costbasis}_g)}{\text{Corporate equities and mutual funds}_{\text{SCF},g}} \\
\text{Mut. fnds. in txble fxd clms sh. corp. equ. \& mut. funds}_{\text{SCF},g} &= \frac{0.5 \times \texttt{comutf}_g + \texttt{gbmutf}_g + \texttt{obmutf}_g + 0.5 \times \texttt{omutf}_g + \texttt{trusts_mmbondfund}_g}{\text{Corporate equities and mutual funds}_{\text{SCF},g}} \\
\text{Mut. fnds. in tx-exmpt fxd clms sh. corp. equ. \& mut. funds}_{\text{SCF},g} &= \frac{\texttt{tfbmutf}_g}{\text{Corporate equities and mutual funds}_{\text{SCF},g}}
\end{aligned}$$

Then we apply the shares above to Corp. equ. & mut. funds excl. $\text{IRAs}_{\text{DFA},g}$ (see subsection E.1.2), which delivers disaggregated concepts:

$$\begin{aligned}
\text{Public equities}_{\text{DFA},\ g} &\equiv \\
\texttt{pubccorp_dfa} &= \text{Public equities sh. corp. equ. \& mut. funds}_{\text{SCF},\ g} \times \text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g} \\
\text{Private C-corp.}_{\text{DFA},\ g} &\equiv \\
\texttt{privccorp_dfa} &= \text{Private C-corp. sh. corp. equ. \& mut. funds}_{\text{SCF},\ g} \times \text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g} \\
\text{S-corp.}_{\text{DFA},\ g} &\equiv \\
\texttt{scorp_dfa} &= \text{S-corp. sh. corp. equ. \& mut. funds}_{\text{SCF},\ g} \times \text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g} \\
\text{Mut. fnds. in txble fxd clms}_{\text{DFA},g} &\equiv \\
\texttt{inttaxmutf_dfa} &= \text{Mut. fnds. in txble fxd clms sh. corp. equ. \& mut. funds}_{\text{SCF},g} \\
&\quad \times \text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g} \\
\text{Mut. fnds. in tx-exmpt fxd clms}_{\text{DFA},g} &\equiv \\
\texttt{intexmmutf_dfa} &= \text{Mut. fnds. in tx-exmpt fxd clms sh. corp. equ. \& mut. funds}_{\text{SCF},g} \\
&\quad \times \text{Corp. equ. \& mut. funds excl. IRAs}_{\text{DFA},g}
\end{aligned}$$

E.1.4 Disaggregate "Money market fund shares"

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

$$\begin{aligned}
\text{Mny mkt mut. funds sh. mny mkt fund shares}_{\text{SCF},g} &= \frac{\texttt{mmmf}_g}{\text{Money market fund shares}_{\text{SCF},g}} \\
\text{Mny mkt dpst acct sh. mny mkt fund shares}_{\text{SCF},g} &= \frac{\texttt{mmda}_g}{\text{Money market fund shares}_{\text{SCF},g}}
\end{aligned}$$

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

$$\begin{aligned}
\text{Money market mutual funds}_{\text{DFA},g} &\equiv \\
\texttt{mmmf_dfa} &= \text{Mny mkt mut. funds sh. mny mkt fund shares}_{\text{SCF},g} \times \text{Money market fund shares excl. IRAs}_{\text{DFA},g} \\
\text{Money market deposit account}_{\text{DFA},g} &\equiv \\
\texttt{mmda_dfa} &= \text{Mny mkt dpst acct sh. mny mkt fund shares}_{\text{SCF},g} \times \text{Money market fund shares excl. IRAs}_{\text{DFA},g}
\end{aligned}$$

E.1.5 Disaggregate "US government and municipal securities"

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

$$\text{US govt scties sh. US govt \& muni. scties}_{\text{SCF},g} = \frac{\texttt{govtbnd}_g}{\text{US government and municipal securities}_{\text{SCF}}}$$

$$\text{Munis sh. US govt \& muni. scties}_{\text{SCF},g} = \frac{\texttt{notxbnd}_g}{\text{US government and municipal securities}_{\text{SCF}}}$$

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

$$\begin{aligned}
\text{US govt securities}_{\text{DFA},g} &\equiv \\
\texttt{govtbnd_dfa} &= \text{US govt scties sh. US govt \& muni. scties}_{\text{SCF},g} \times \text{US govt. \& muni. scties excl. IRAs}_{\text{DFA},g} \\
\text{Municipal bonds}_{\text{DFA},g} &\equiv \\
\texttt{notxbnd_dfa} &= \text{Munis sh. US govt \& muni. scties}_{\text{SCF},g} \times \text{US govt. \& muni. scties excl. IRAs}_{\text{DFA},g}
\end{aligned}$$

E.2 Main portfolio categories

In our preferred DFA series, aggregate wealth is:

$$\begin{aligned}
\textbf{Net worth} &= \texttt{networth} - \texttt{consumerdurables} \\
&\overset{\textit{2016 example}}{=} \$89.0T - \$5.1T \boxed{= \$83.9T}
\end{aligned}$$

where both `networth` and `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.[3]

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.

$$\begin{aligned}
\textbf{Currency} &= \texttt{checkabledepostsandcurrency} \\
\textit{2016 example} &\boxed{= 1.0T}
\end{aligned}$$

where `checkabledepostsandcurrency` is a ready-made DFA concept representing checkable deposits and currency.

[3]Because the unprocessed DFA data are aggregates by group (e.g., total `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.

$$\textbf{Taxable interest-generating fixed claims} = \texttt{otherloansandadvancesassets} + \texttt{mortgages} + \texttt{timdepshrttrm\_excl\_iras} + \texttt{mmda\_dfa} + \texttt{corpfrgnbnd\_excl\_iras} + \texttt{govtbnd\_dfa}$$

$$\overset{\textit{2016 example}}{=} \$843B + \$94B + \$6.1T + \$864B + \$732B + \$532B \boxed{= \$9.2T}$$

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.

$$\textbf{Tax-exempt fixed claims} = \texttt{notxbnd\_dfa} + \texttt{intexmmutf\_dfa}$$

$$\overset{\textit{2016 example}}{=} \$1.9T + \$581B \boxed{= \$2.4T}$$

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

$$\textbf{Bonds and loans held in mutual funds} = \texttt{inttaxmutf\_dfa} + \texttt{mmmf\_dfa}$$

$$\overset{\textit{2016 example}}{=} \$984B + \$183B \boxed{\$1.2T}$$

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

$$\textbf{C-corporation equity} = \texttt{pubccorp\_dfa} + \texttt{privccorp\_dfa}$$

$$\overset{\textit{2016 example}}{=} \$5.4T + \$927B + \$4.8T \boxed{= \$11.1T}$$

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

$$\textbf{Pass-through business} = \texttt{equityinnoncorpoatebusiness} + \texttt{scorp\_dfa}$$

$$\overset{\textit{2016 example}}{=} \$10.0T + \$1.9T \boxed{= \$11.9T}$$

where `equityinnoncorpoatebusiness` is a ready-made DFA concept representing equity in non-corporate business and `scorp_dfa` is defined as in section E.1.

$$\textbf{Pensions} = \texttt{lifeinsurancereserves} + \texttt{pensionentitlements} + \texttt{peniraw\_dfa}$$
$$\textit{2016 example} = \$1.6T + \$24.0T + \$9.9T \boxed{= \$35.5T}$$

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

$$\textbf{Housing} = \texttt{realestate} - \texttt{homemortgages}$$
$$\textit{2016 example} = \$24.3T - \$9.6T \boxed{= \$14.7T}$$

where `realestate` and `homemortgages` are ready-made DFA concepts representing real estate and home mortgages (liabilities).

$$\begin{aligned}\textbf{Non-mortgage debt} &= -\texttt{otherloansandadvancesliabilities} - \texttt{depositoryinstitutionsloansnec} \\ &\quad - \texttt{deferredandunpaindlifeinsurancep} - \texttt{consumercredit} \\ \textit{2016 example} &= -\$438T - \$225T - \$33T - \$3.5T \boxed{= -\$4.2T}\end{aligned}$$

where `otherloansandadvancesliabilities`, `depositoryinstitutionsloansnec`, `deferredandunpaindlifeinsurancep`, and `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 unapid life insurance premiums; and consumer credit.

$$\textbf{Other} = \texttt{miscellaneousassets}$$
$$\textit{2016 example} \boxed{= \$1.1T}$$

where `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 (2020*b*). 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.[4]

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.[5] 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.

[4] Click on "Stata programs to construct distributional national accounts micro-files" to download a folder called "PSZ2020Programs."

[5] They assume zero profits (and consequently zero S-corporation equity) before 1966.

F.2 Changes in supplemental series 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 in *supplemental* series. In our baseline series, we follow SZ 2020s aggregates to focus effects on the numerator rather than the denominator of wealth shares.

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.
- Use Financial Accounts series for aggregate S-corporation equity from 1996-forward, instead of an assumed portion of unquoted shares of domestic nonfinancial business. Before 1996, assume 19% return on S-corporation equity and capitalize S-corporation income.

F.3 Constructing portfolio categories for *supplemental* series with different aggregates

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).[6] Here we list and summarize construction of portfolio categories for *supplemental* series:

- **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.

[6] The 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.

- **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.
- **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.[7]
- **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.[8]
- **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.

[7] 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.

[8] 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 for supplemental series—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` 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 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.[9]

Appendix Figure A.19A decomposes aggregate wealth and plots the evolution of five key components relative to national income. By construction, our baseline aggregates match those of SZ20. In 2016, national wealth amounts to 475% of national income. The largest component is pensions, which equals 163% of national income. Housing net of mortgages is the next largest (118%), followed by fixed income assets (94%), C-corporation equity (67%), and pass-through business (57%)—which includes proprietorship, partnership, and S-corporation equity. Combined C-corporation and pass-through business wealth gives 124%. Non-mortgage debt, which includes credit-card balances, debt secured by durable goods and vehicles, student loans, and other loans, amounts to -26% of national wealth.

At the aggregate level, wealth has increased from 301% in 1966 to 475% of national income in 2016. Of that increase, 125 percentage points are from pensions, 39 are from net housing, 18 are from fixed income, 9 from pass-through business, and -7 from C-corporation equity. 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.[10] 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.

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 supplemental 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. Appendix Figure A.19B plots six types of capital income relative to national income from 1966 to 2016. Aggregate

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

[10] We plot an additional measure of pension and pass-through business wealth to compare our measures to those in other work and to explore the aggregate implications of our pass-through estimates. We also plot a pension series that includes the unfunded portion of defined benefit pension wealth. Appendix Figure A.21 compares aggregates derived from the Financial Accounts in PSZ to those in the updated series with updated definitions in SZ20.

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.

H 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 10-year Treasury bonds* from the Board of Governors of the Federal Reserve System. Retrieved from FRED Economic Data via `freduse` using series code DGS10. Archived on January 27th, 2020. Collapsed to yield annual averages.

- *Interest rates on Aaa and Baa bonds* from Moody's. Retrieved from FRED Economic Data via `freduse` using series code AAA and BAA. Retrieved and archived on January 27th, 2020. Collapsed to yield annual averages.

- *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 (2004*b*) estate tax series shown in figure 1* retrieved from Saez and Zucman (2016) "Other Estimates" appendix tables.

- *National income in current dollars* from the Bureau of Economic Analysis. Retrieved from FRED Economic Data via `freduse` using series code A032RC1A027NBEA. Archived on January 27th, 2020. Scaled into billions.

- *State-level GDP in current dollars* from the Bureau of Economic Analysis table SAGDP2. Retrieved from `https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1`. Archived on March 12th, 2020.

- *Statistics of Income (SOI) Corporate Sample* from the Internal Revenue Service (IRS). Stratified random sample of US corporate income tax returns. See Zwick and Mahon (2017) and Yagan (2015) for further discussion.

I Additional Discussion of Boutique Interest Rates

This section discusses three potential concerns about the representativeness of the fixed income partnerships we use to estimate the boutique interest rates in Section 2.

1. What share of pass-through interest comes from our sample of partnerships? The 18,758 fixed income partnerships we use to estimate boutique rates distribute \$31B of interest income in 2016, or approximately 20% of total interest income distributed by partnerships to all types of partners. A subset of these funds distribute income to individuals; this subset distributes \$6B of interest income. For reference, the total amount of pass-through interest on K-1s for individuals is \$21B, \$7B, and \$3B for partnerships, S-corporations, and estates, respectively. Thus, despite their specialized nature, the fixed income funds that we can directly link to individuals account for a meaningful share of total interest.

We suspect two categories of partnerships account for the interest that does not flow through these fixed income funds. One is mixed-strategy funds. If these funds invest in a combination of equity, real estate, and fixed income, it is unclear whether the fixed income assets would be riskier or less risky than the single-strategy funds. The second is tiered partnerships that pool investments in multiple unrelated partnerships. Such structures are commonly used for family offices, who make single-strategy investments on behalf of their owners and distribute the proceeds through a parent partnership. For such structures, the evidence from family office surveys on the most popular fixed income investment strategies can be informative. These surveys suggest risky debt and higher yielding bonds account for the bulk of fixed income investments for family offices.

We believe this data makes a meaningful advance in terms of representativeness compared to past evidence, for example, using estate tax data. In 2016, for the approximately 700 estates with $> \$20M$ of net worth in the matched-income-estate-tax data, the total amount of interest income received is \$117M, an order of magnitude smaller than the amount of interest income we use for matched fixed-income partnerships.

2. How stable and reliable are these boutique interest rates over time? We plot the time series of interest rates and their corresponding capitalization factors in Appendix Figure A.22B. The series are fairly stable over time and do not show a sharp decline during the post-2000 period. This time series therefore contrasts with the trend in the risk-free rate and coincides with an increasing share of interest income for the top groups coming from partnerships. We interpret these facts as reflecting a higher exposure to risky assets in fixed income partnerships, as risk premia have not declined in the same way as risk-free rates over this time. Analogously, our minimum-distance estimates show a shallower decline during this time for the top 0.1% versus the bottom 99.9%. Note also that any noise-induced volatility in this series is not consequential for capitalization factors because the mean rates are sufficiently above zero.

3. How much do boutique interest rates vary in the cross-section of funds? We report an asset-weighted histogram of fixed income fund interest rates for 2016 in Appendix Figure A.22C. We also report a restricted histogram that excludes funds we cannot link to any individuals. Such funds are likely held mostly by institutions and tend to have somewhat lower means, consistent with sorting among taxable and tax-exempt investors. The results show a substantial dispersion in interest rates relative to the approximate mean from Appendix Table B.6.

Note that Appendix Table B.6 only includes funds with strings in their names that are sufficiently common to permit disclosure. These funds might not be representative of the broader set of funds that individuals are investing in. To evaluate this idea, we computed the share of interest income for matched fixed income partnerships based on the number of individual partners. A substantial amount of interest income ($3.5B out of the $6B total) comes from funds with fewer than ten partners. These funds tend to have higher interest rates than those with more partners (on the order of 3-5% vs. 2%, on average, for funds with more than 100 partners or with no individual partners, asset-weighted). Many of these funds have interest rates well above 6%, which corresponds approximately to the 75th percentile in the matched funds sample.

It therefore looks like many fixed-income funds in these data are more specialized in their nature and may reflect closely held investments with relatively few investors. For example, venture debt investments in a venture capital deal typically feature an interest rate of 12-15%.[11] Such investments would have relatively few partners and their names would be deal-specific and so unlikely to enter Appendix Table B.6. The remaining gap between the asset-weighted interest rate for these funds and the top-AGI-group rate likely reflects sorting of high-income individuals into higher-interest-rate funds.

Overall, this additional evidence helps bolster the case for our approach to estimating boutique interest rates. Despite this evidence, we nevertheless agree the accuracy of these interest rates depends on well-reported flows and assets and a representative mapping between interest rates from matched data and unmatched individuals. We cannot perfectly test these assumptions. To address other concerns about this approach, we present supplemental series in Section 6 that do not use these boutique rates when capitalizing interest income flows. These alternatives deliver very similar estimates.

[11] See, e.g., `https://flowcap.com/founders-guide-to-venture-debt/`.

J Are These Top Return Estimates Realistic?

This section presents supporting evidence that the boutique interest rates we estimate from information returns are quantitatively reasonable.

1. Implications for aggregates. 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 3A 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 USFA 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.[12]

2. Riskiness implied by common boutique fund names. Appendix Table B.6 presents additional evidence that boutique funds invest in riskier assets.[13] Many of these funds 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.7 compares the interest rate distributions for boutique funds and private loans to that for different groups of corporate bonds.[14] 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.

3. Data and anecdotal evidence from family offices and wealth managers. 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

[12]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.

[13]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.

[14]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.

and from conversations with wealth managers and fixed income fund managers.[15] 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%.[16]

4. Public disclosures from rich politicans. In addition, we obtained from voluntary public disclosures the detailed tax returns with attachments for high wealth politicians.[17] Three of the wealthier politicians to release their tax returns and other financial information during presidential runs are Carleton 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—Appendix Figure A.23 shows 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 holdings of specialty private equity, venture capital, and other boutique investment funds. Romney's interest income is also 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.[18]

[15] 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.

[16] 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.

[17] *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`.

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

K Minimum Distance Appendix

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.[19] 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 relate fixed income flows, assets, and returns across groups:

$$\begin{aligned} \ln y_{1t} &= \ln r_{1t} + \ln a_{1t} && (1) \\ \ln y_{2t} &= \ln r_{2t} + \ln a_{2t} && (2) \\ \ln a_t^{total} &= s_1^a \ln a_{1t} + (1 - s_1^a) \ln a_{2t} && (3) \\ \ln r_t^I &= \pi_1^I \ln r_{1t} + \pi_2^I \ln r_{2t} && (4) \\ \ln r_t^C &= \pi_1^C \ln r_{1t} + \pi_2^C \ln r_{2t}. && (5) \end{aligned}$$

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 (4) is the log-linearized aggregation constraint that relates total fixed income assets a_t^{total} to the assets of both groups, where s_1^a is group 1's share of assets.

Equations (5) and (6) are reduced-form expressions that result from projecting the effective return of each group onto measures of interest rate risk r_t^I and of credit risk r_t^C on fixed income assets. Intuitively, a structural analogue of this projection for group 1, $r_{1t} = \gamma_1^I r_t^I + \gamma_1^C r_t^C$, resembles a CAPM setup in that their return reflects their factor loadings on two aggregate risk factors. This innovation is inspired by Begenau, Piazzesi and Schneider (2020) who estimate bank risk by projecting the returns of fixed income assets on interest rate risk and credit risk measures. A second innovation is to use the coefficient restrictions implied by the model to estimate the key parameters of interest, $(\pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C)$, which govern each group's risk-exposure and allow us to estimate returns for each group.

The model implies restrictions on elements of mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$, where $\boldsymbol{\mu}$ is the 5×1 vector of means of the five-equation system:

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

where μ_x denotes the mean of $\ln x_t$. For example, the mean of equation (2), which describes the average log fixed income of group 1 ($\ln y_{1t}$), is equal to that group's average log rate of

[19]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 K.3 to construct estimates for the top 0.1%, P99-99.9, and bottom 99% from these results (see Appendix K.2 for step-by-step details).

return plus the average log assets (i.e., $\mu_{r_1} + \mu_{a_1}$). The covariance matrix is:

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

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

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

where the moments are mean and covariance elements of equations (7) and (8). The parameters in $\boldsymbol{\theta}$ are means, variances, and covariances of the four unknowns $(r_{1t}, r_{2t}, a_{1t}, a_{2t})$ the $\boldsymbol{\pi}$ parameters governing each group's risk-exposure, and asset shares (s_1^a).[20]

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

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

where $\hat{\mathbf{m}}$ is the empirical estimate of mean and covariance terms, which are a function of data $(y_{1t}, y_{2t}, a_t^{total}, r_t^I, r_t^C)$. In particular, y_{1t}, y_{2t} are total fixed income flows in the tax data for group 1 and 2, respectively. In our baseline approach, group 1 is defined as individuals whose non-interest wealth ranks in the top 0.1% of the non-interest wealth distribution. Total taxable-interest-generating fixed income assets a_t^{total} are from the Financial Accounts, and r_t^I and r_t^C are the 5-year US Treasury rate and Baa index, which follows the approach of Begenau, Piazzesi and Schneider (2020) who show that these two series span interest rate space well.[21] 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 K.1 lists the calibrated parameter values. Although we use the SCF to calibrate some of these

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

[21]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.

parameters, this approach only uses tax data to measure income flows over time, so the resulting estimates directly reflect patterns in the tax data.[22] Under regularity conditions, the vector of estimated moments will have a standard normal distribution with $\sqrt{T}(\hat{\mathbf{m}} - \mathbf{m}) \rightarrow N(0, \mathbf{V})$. Applying Hansen (1982), we have $\sqrt{T}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \rightarrow N(0, \Delta)$ where $\Delta = (\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'\mathbf{V}\mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}$ and $\mathbf{G} = \frac{\partial \boldsymbol{m(\theta)}}{\partial \boldsymbol{\theta}}$. We estimate $\hat{\mathbf{V}}$ via block bootstrap.[23]

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

Estimates of Return Heterogeneity with Standard Errors. We can rearrange the risk exposure equations (5) and (6) to express each group's returns as a function of observables and parameters:

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

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

We can exponentiate these expressions and plug in estimates of $\hat{\boldsymbol{\theta}}$ to obtain the estimates of r_{1t} and r_{2t}. We find the top wealth group has much stronger exposure to credit risk.[24] 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.

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

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

[24] Appendix Table K.2 reports the parameter estimates of the $\boldsymbol{\pi}$ terms as well as the coefficients in equation (10) and (11). For example, $\frac{\hat{\pi}_2^C}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} = 0.05$ ($s.e. = 0.14$). The resulting expressions are $\ln \hat{r}_{1t} = 0.05 \ln r_t^I + 0.84 \ln r_t^C$ and $\ln \hat{r}_{2t} = 0.82 \ln r_t^I + 0.06 \ln r_t^C$.

K.1 Covariance expressions and Identifying Risk-Exposure Parameters

The covariance terms from equation (8) in terms of parameters are:

$$\Sigma_{11} = \sigma^2_{r_1} + \sigma^2_{a_1} + 2c_{r_1,a_1} \tag{11}$$
$$\Sigma_{21} = c_{r_1,r_2} + c_{r_1,a_2} + c_{r_2,a_1} + c_{a_1,a_2} \tag{12}$$
$$\Sigma_{31} = s^a_1 c_{r_1,a_1} + s^a_1 \sigma^2_{a_1} + (1-s^a_1)c_{r_1,a_2} + (1-s^a_1)c_{a_1,a_2} \tag{13}$$
$$\Sigma_{41} = \pi^I_1 \sigma^2_{r_1} + \pi^I_1 c_{r_1,a_1} + \pi^I_2 c_{r_1,r_2} + \pi^I_2 c_{r_2,a_1} \tag{14}$$
$$\Sigma_{51} = \pi^C_1 \sigma^2_{r_1} + \pi^C_1 c_{r_1,a_1} + \pi^C_2 c_{r_1,r_2} + \pi^C_2 c_{r_2,a_1} \tag{15}$$
$$\Sigma_{22} = \sigma^2_{r_2} + \sigma^2_{a_2} + 2c_{r_2,a_2} \tag{16}$$
$$\Sigma_{32} = s^a_1 c_{r_2,a_1} + s^a_1 c_{a_1,a_2} + (1-s^a_1)c_{r_2,a_2} + (1-s^a_1)\sigma^2_{a_2} \tag{17}$$
$$\Sigma_{42} = \pi^I_1 c_{r_1,r_2} + \pi^I_1 c_{r_1,a_2} + \pi^I_2 \sigma^2_{r_2} + \pi^I_2 c_{r_2,a_2} \tag{18}$$
$$\Sigma_{52} = \pi^C_1 c_{r_1,r_2} + \pi^C_1 c_{r_1,a_2} + \pi^C_2 \sigma^2_{r_2} + \pi^C_2 c_{r_2,a_2} \tag{19}$$
$$\Sigma_{33} = (s^a_1)^2 \sigma^2_{a_1} + (1-s^a_1)^2 \sigma^2_{a_2} + 2(s^a_1)(1-(s^a_1))c_{a_1,a_2} \tag{20}$$
$$\Sigma_{43} = \pi^I_1 s^a_1 c_{r_1,a_1} + \pi^I_1(1-s^a_1)c_{r_1,a_2} + \pi^I_2 s^a_1 c_{r_2,a_1} + \pi^I_2(1-s^a_1)c_{r_2,a_2} \tag{21}$$
$$\Sigma_{53} = \pi^C_1 s^a_1 c_{r_1,a_1} + \pi^C_1(1-s^a_1)c_{r_1,a_2} + \pi^C_2 s^a_1 c_{r_2,a_1} + \pi^C_2(1-s^a_1)c_{r_2,a_2} \tag{22}$$
$$\Sigma_{44} = (\pi^I_1)^2 \sigma^2_{r_1} + (\pi^I_2)^2 \sigma^2_{r_2} + 2\pi^I_1 \pi^I_2 c_{r_1,r_2} \tag{23}$$
$$\Sigma_{54} = \pi^I_1 \pi^C_1 \sigma^2_{r_1} + (\pi^I_1 \pi^C_2 + \pi^I_2 \pi^C_1)c_{r_1,r_2} + \pi^I_2 \pi^C_2 \sigma^2_{r_2} \tag{24}$$
$$\Sigma_{55} = (\pi^C_1)^2 \sigma^2_{r_1} + (\pi^C_2)^2 \sigma^2_{r_2} + 2\pi^C_1 \pi^C_2 c_{r_1,r_2} \tag{25}$$

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 (9)) 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 π^I_1 and π^I_2: Start with row 4 of equation (7), i.e., $\mu_{r^I} = \pi^I_1 \mu_{r_1} + \pi^I_2 \mu_{r_2}$, and the expression for Σ_{42} in equation (19).

$$\begin{bmatrix} \mu_{r^I} \\ \Sigma_{42} \end{bmatrix} = \begin{bmatrix} \pi^I_1 \mu_{r_1} + \pi^I_2 \mu_{r_2} \\ \pi^I_1 c_{r_1,r_2} + \pi^I_1 c_{r_1,a_2} + \pi^I_2 \sigma^2_{r_2} + \pi^I_2 c_{r_2,a_2} \end{bmatrix} \tag{26}$$

Apply Cramer's Rule

$$\pi^I_1 = \frac{D_{\pi^I_1}}{D} = \frac{\begin{vmatrix} \mu_{r^I} & \mu_{r_2} \\ \Sigma_{42} & \sigma^2_{r_2} + c_{r_2,a_2} \end{vmatrix}}{\begin{vmatrix} \mu_{r_1} & \mu_{r_2} \\ c_{r_1,r_2} + c_{r_1,a_2} & \sigma^2_{r_2} + c_{r_2,a_2} \end{vmatrix}} = \frac{(\mu_{r^I})(\sigma^2_{r_2} + c_{r_2,a_2}) - (\mu_{r_2})(\Sigma_{42})}{(\mu_{r_1})(\sigma^2_{r_2} + c_{r_2,a_2}) - (\mu_{r_2})(c_{r_1,r_2} + c_{r_1,a_2})} \tag{27}$$

Empirically, $\pi_1^I = \frac{(1.64)(0.325-0.123)-(1.165)(0.28)}{(1.694)(0.325-0.123)-(1.165)(0.113-0.045)} \approx 0.019.$

$$\pi_2^I = \frac{D_{\pi_2^I}}{D} = \frac{\begin{vmatrix} \mu_{r_1} & \mu_{r^I} \\ c_{r_1,r_2} + c_{r_1,a_2} & \Sigma_{42} \end{vmatrix}}{\begin{vmatrix} \mu_{r_1} & \mu_{r_2} \\ c_{r_1,r_2} + c_{r_1,a_2} & \sigma_{r_2}^2 + c_{r_2,a_2} \end{vmatrix}} = \frac{(\mu_{r_1})(\Sigma_{42}) - (\mu_{r^I})(c_{r_1,r_2} + c_{r_1,a_2})}{(\mu_{r_1})(\sigma_{r_2}^2 + c_{r_2,a_2}) - (\mu_{r_2})(c_{r_1,r_2} + c_{r_1,a_2})} \quad (28)$$

Empirically, $\pi_2^I = \frac{(1.694)(0.28)-(1.64)(0.113-0.045)}{(1.694)(0.325-0.123)-(1.165)(0.113-0.045)} \approx 1.38.$

Identifying π_1^C and π_2^C: Start with row 5 of equation (7), i.e., $\mu_{r^C} = \pi_1^C \mu_{r_1} + \pi_2^C \mu_{r_2}$, and the expression for Σ_{52} in equation (20).

$$\begin{bmatrix} \mu_{r^C} \\ \Sigma_{52} \end{bmatrix} = \begin{bmatrix} \pi_1^C \mu_{r_1} + \pi_2^C \mu_{r_2} \\ \pi_1^C c_{r_1,r_2} + \pi_1^C c_{r_1,a_2} + \pi_2^C \sigma_{r_2}^2 + \pi_2^C c_{r_2,a_2} \end{bmatrix} \quad (29)$$

Apply Cramer's Rule

$$\pi_1^C = \frac{D_{\pi_1^C}}{D} = \frac{\begin{vmatrix} \mu_{r^C} & \mu_{r_2} \\ \Sigma_{52} & \sigma_{r_2}^2 + c_{r_2,a_2} \end{vmatrix}}{\begin{vmatrix} \mu_{r_1} & \mu_{r_2} \\ c_{r_1,r_2} + c_{r_1,a_2} & \sigma_{r_2}^2 + c_{r_2,a_2} \end{vmatrix}} = \frac{(\mu_{r^C})(\sigma_{r_2}^2 + c_{r_2,a_2}) - (\mu_{r_2})(\Sigma_{52})}{(\mu_{r_1})(\sigma_{r_2}^2 + c_{r_2,a_2}) - (\mu_{r_2})(c_{r_1,r_2} + c_{r_1,a_2})} \quad (30)$$

Empirically, $\pi_1^C = \frac{(2.11)(0.325-0.123)-(1.165)(0.13)}{(1.694)(0.325-0.123)-(1.165)(0.113-0.045)} \approx 1.04.$

$$\pi_2^C = \frac{D_{\pi_2^C}}{D} = \frac{\begin{vmatrix} \mu_{r_1} & \mu_{r^C} \\ c_{r_1,r_2} + c_{r_1,a_2} & \Sigma_{52} \end{vmatrix}}{\begin{vmatrix} \mu_{r_1} & \mu_{r_2} \\ c_{r_1,r_2} + c_{r_1,a_2} & \sigma_{r_2}^2 + c_{r_2,a_2} \end{vmatrix}} = \frac{(\mu_{r_1})(\Sigma_{52}) - (\mu_{r^C})(c_{r_1,r_2} + c_{r_1,a_2})}{(\mu_{r_1})(\sigma_{r_2}^2 + c_{r_2,a_2}) - (\mu_{r_2})(c_{r_1,r_2} + c_{r_1,a_2})} \quad (31)$$

$\pi_2^C = \frac{(1.694)(0.13)-(2.11)(0.113-0.045)}{(1.694)(0.325-0.123)-(1.165)(0.113-0.045)} \approx 0.29.$

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

K.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., $(y_{1t}, y_{2t}, a_t^{total}, r_t^I, r_t^C))$, 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 $(y_{1t}, y_{2t}, a_t^{total}, r_t^I, r_t^C)$. That is, compute the empirical mean and covariance matrix:

$$\hat{\mathbf{m}} = [\hat{\mu}_{y1}, \hat{\mu}_{y2}, \hat{\mu}_{a^{total}}, \hat{\mu}_{r^I}, \hat{\mu}_{r^C}, \hat{\Sigma}_{11}, \hat{\Sigma}_{21}, \hat{\Sigma}_{31}, \hat{\Sigma}_{41}, \hat{\Sigma}_{51}, \hat{\Sigma}_{22}, \hat{\Sigma}_{32}, \hat{\Sigma}_{42}, \hat{\Sigma}_{52}, \hat{\Sigma}_{33}, \hat{\Sigma}_{43}, \hat{\Sigma}_{53}, \hat{\Sigma}_{44}, \hat{\Sigma}_{54}, \hat{\Sigma}_{55}].'$$

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^{total}), vary and covary with interest rate risk r_t^I and credit risk (r_t^C) 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 μ_{a1}.

   (c) For the top share parameter s_1^a, we use the average over the full sample.

4. Compute the model moments $\boldsymbol{m(\theta)}$, where

$$\boldsymbol{m(\theta)} = \begin{bmatrix} \mu_{r_1} + \mu_{a_1} \\ \mu_{r_2} + \mu_{a_2} \\ s_1^a \mu_{a_1} + (1 - s_1^a)\,\mu_{a_2} \\ \pi_1^I \mu_{r_1} + \pi_2^I \mu_{r_2} \\ \pi_1^C \mu_{r_1} + \pi_2^C \mu_{r_2} \\ \sigma_{r_1}^2 + \sigma_{a_1}^2 + 2c_{r_1,a_1} \\ c_{r_1,r_2} + c_{r_1,a_2} + c_{r_2,a_1} + c_{a_1,a_2} \\ s_1^a c_{r_1,a_1} + s_1^a \sigma_{a_1}^2 + (1 - s_1^a) c_{r_1,a_2} + (1 - s_1^a) c_{a_1,a_2} \\ \pi_1^I \sigma_{r_1}^2 + \pi_1^I c_{r_1,a_1} + \pi_2^I c_{r_1,r_2} + \pi_2^I c_{r_2,a_1} \\ \pi_1^C \sigma_{r_1}^2 + \pi_1^C c_{r_1,a_1} + \pi_2^C c_{r_1,r_2} + \pi_2^C c_{r_2,a_1} \\ \sigma_{r_2}^2 + \sigma_{a_2}^2 + 2c_{r_2,a_2} \\ s_1^a c_{r_2,a_1} + s_1^a c_{a_1,a_2} + (1 - s_1^a) c_{r_2,a_2} + (1 - s_1^a)\sigma_{a_2}^2 \\ \pi_1^I c_{r_1,r_2} + \pi_1^I c_{r_1,a_2} + \pi_2^I \sigma_{r_2}^2 + \pi_2^I c_{r_2,a_2} \\ \pi_1^C c_{r_1,r_2} + \pi_1^C c_{r_1,a_2} + \pi_2^C \sigma_{r_2}^2 + \pi_2^C c_{r_2,a_2} \\ (s_1^a)^2 \sigma_{a_1}^2 + (1 - s_1^a)^2 \sigma_{a_2}^2 + 2(s_1^a)(1 - (s_1^a)) c_{a_1,a_2} \\ \pi_1^I s_1^a c_{r_1,a_1} + \pi_1^I (1 - s_1^a) c_{r_1,a_2} + \pi_2^I s_1^a c_{r_2,a_1} + \pi_2^I (1 - s_1^a) c_{r_2,a_2} \\ \pi_1^C s_1^a c_{r_1,a_1} + \pi_1^C (1 - s_1^a) c_{r_1,a_2} + \pi_2^C s_1^a c_{r_2,a_1} + \pi_2^C (1 - s_1^a) c_{r_2,a_2} \\ (\pi_1^I)^2 \sigma_{r_1}^2 + (\pi_2^I)^2 \sigma_{r_2}^2 + 2\pi_1^I \pi_2^I c_{r_1,r_2} \\ \pi_1^I \pi_1^C \sigma_{r_1}^2 + (\pi_1^I \pi_2^C + \pi_2^I \pi_1^C) c_{r_1,r_2} + \pi_2^I \pi_2^C \sigma_{r_2}^2 \\ (\pi_1^C)^2 \sigma_{r_1}^2 + (\pi_2^C)^2 \sigma_{r_2}^2 + 2\pi_1^C \pi_2^C c_{r_1,r_2} \end{bmatrix}. \tag{32}$$

   Calibrating values listed in Appendix Table K.1 for each parameter besides the risk parameters of interest results in expressions in which the risk parameters (i.e., $\pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C$) are the only unknowns.

5. Find the parameter values (i.e., $\pi_1^I, \pi_2^I, \pi_1^C, \pi_2^C$) 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., $\hat{\pi}_1^I, \hat{\pi}_2^I, \hat{\pi}_1^C, \hat{\pi}_2^C$).

6. Plug in estimated parameter values into equation 10 and 11 to solve for top 0.1% and bottom 99.9% interest rates on fixed income, i.e.,

$$\ln r_{1t} = \frac{\hat{\pi}_2^C}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} \ln r_t^I - \frac{\hat{\pi}_2^I}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} \ln r_t^C \tag{33}$$

$$\ln r_{2t} = \frac{-\hat{\pi}_1^C}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} \ln r_t^I + \frac{\hat{\pi}_1^I}{\hat{\pi}_1^I \hat{\pi}_2^C - \hat{\pi}_2^I \hat{\pi}_1^C} \ln r_t^C. \tag{34}$$

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

7. Overall, this procedure produces estimates of $\hat{r}_{1t}^{top01}$ and $\hat{r}_{2t}^{bot99.9}$ given data on aggregate income flows for each group (i.e., $(y_{1t}^{top01}, y_{2t}^{bot99.9})$) 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., $(y_{1t}^{top1}, y_{2t}^{bot99})$), 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 K.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 $\hat{r}_{1t}^{top1}$ and $\hat{r}_{2t}^{bot99}$.

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

$$r_t^{CMD,three-tier} = \begin{cases} \hat{r}_t^{p99.9-100} = \hat{r}_{1t}^{top01} & \text{if non-interest wealth rank} \geq 99.9 \\ \hat{r}_t^{p99-99.9} = \hat{r}_{1t}^{top1} \times \left(\frac{y_1^{t1} - y_1^{t0.1}}{y_1^{t1} - \frac{r_1^{t1}}{r_1^{t0.1}} y_1^{t0.1}} \right) & \text{if } 99.9 > \text{Non-interest wealth rank} \geq 99.99 \\ \hat{r}_t^{p0-99} = \frac{a_t^{total,fix} - \sum_{i \in top1} \hat{a}_{it}^{fix}}{\sum_{i \notin top1} y_{it}^{fix}} & \text{otherwise} \end{cases} \tag{35}$$

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

K.3 Computing three-tier estimates

This section shows how we solve for $r^{p99-99.9}$ given income flows for the top 0.1 and top 1 (i.e., $y_1^{t0.1}$ and y_1^{t1}), and returns for the top 0.1 and top 1 (i.e., $r_1^{t0.1}$ and r_1^{t1}).

- $y_1^{t0.1}$ is fixed income for top 0.1 of non-interest wealth (niw)
- y_1^{t1} is fixed income for top 1 of niw
- $y^{p99-99.9} = y_1^{t1} - y_1^{t0.1}$ is fixed income for P99-99.9 of niw

- $r_1^{t0.1}$ is return on fixed income for top 0.1 of niw
- r_1^{t1} is return fixed income for top 1 of niw
- $r^{p99-99.9}$ is return fixed income for P99-99.9 of niw
- $a_1^{t0.1}$ is fixed income wealth for top 0.1 of niw
- a_1^{t1} is fixed income wealth for top 1 of niw
- $a^{p99-99.9} = a_1^{t1} - a_1^{t0.1}$ 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:

$$r^{p99-99.9} = \frac{y^{p99-99.9}}{a^{p99-99.9}} \tag{36}$$

$$r^{p99-99.9} = \frac{y_1^{t1} - y_1^{t0.1}}{a_1^{t1} - a_1^{t0.1}} \tag{37}$$

$$r^{p99-99.9} = \frac{y_1^{t1} - y_1^{t0.1}}{\frac{y_1^{t1}}{r_1^{t1}} - \frac{y_1^{t0.1}}{r_1^{t0.1}}} \tag{38}$$

$$r^{p99-99.9} = \frac{r_1^{t1}}{r_1^{t1}} \frac{y_1^{t1} - y_1^{t0.1}}{\frac{y_1^{t1}}{r_1^{t1}} - \frac{y_1^{t0.1}}{r_1^{t0.1}}} \tag{39}$$

$$r^{p99-99.9} = r_1^{t1} \times \underbrace{\left(\frac{y_1^{t1} - y_1^{t0.1}}{y_1^{t1} - \frac{r_1^{t1}}{r_1^{t0.1}} y_1^{t0.1}} \right)}_{\text{Scaling factor less than one when } \frac{r_1^{t1}}{r_1^{t0.1}} < 1} \tag{40}$$

This expression shows that $r^{p99-99.9}$, which is the interest rate for p99-99.9, is the top 1% rate r_1^{t1} 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 $\frac{r_1^{t1}}{r_1^{t0.1}} < 1$).

Table K.1: Classical minimum distance calibrated parameters

Moment	Value
μ_{r_1}	1.694
μ_{r_2}	1.165
μ_{a_1}	-1.068
μ_{a_2}	1.409
$\sigma^2_{r_1}$	0.086
$\sigma^2_{r_2}$	0.325
$\sigma^2_{a_1}$	0.073
$\sigma^2_{a_2}$	0.064
c_{r_1,r_2}	0.113
c_{r_1,a_1}	-0.066
c_{r_1,a_2}	-0.045
c_{r_2,a_1}	-0.136
c_{r_2,a_2}	-0.123
c_{a_1,a_2}	0.057
s^a_1	0.078

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 μ_{r1} is the average logged interest rate of the top 0.1% of the non-interest wealth distribution, μ_{r2} 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 K.2: Classical minimum distance parameters

	Estimate	*Std. error*
π^I_1	-0.08	(0.23)
π^I_2	1.22	(0.26)
π^C_1	1.20	(0.08)
π^C_2	-0.07	(0.10)
Top 0.1% coefficient on ln r^I_t	0.05	(0.11)
Top 0.1% coefficient on ln r^C_t	0.84	(0.10)
Bottom 99.9% coefficient on ln r^I_t	0.82	(0.28)
Bottom 99.9% coefficient on ln r^C_t	0.06	(0.23)

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.

L 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
   - $a_t^{total,fix}$ 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
   - $\beta_t^{fix,CMD} = \begin{cases} \beta_t^{fix,CMD,top} = \frac{1}{r_t^{fix,CMD,top}} & \text{if non-interest wealth rank} \geq 99.9 \\ \beta_t^{fix,CMD,bot} = \frac{a_t^{total,fix} - \sum_{i \in top} \hat{a}_{it}^{fix}}{\sum_{i \notin top} y_{it}^{fix}} & \text{otherwise} \end{cases}$
   - $\hat{a}_{it}^{fix,CMD} = \begin{cases} \beta_t^{fix,CMD,top} \times y_{it}^{fix} & \text{if non-interest wealth rank} \geq 99.9 \\ \beta_t^{fix,CMD,bot} \times y_{it}^{fix} & \text{otherwise} \end{cases}$

2. SZZ 1965-2000 (Classical Minimum Distance Three-Tier)

   - y_{it}^{fix} is taxable interest income
   - $a_t^{total,fix}$ 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 36 and section K.3 for derivation details), and the P0-P99 group gets implied residual that rationalizes aggregates
   - $\beta_t^{fix,CMD} = \begin{cases} \beta_t^{fix,CMD,p99.9-100} = \frac{1}{r_t^{fix,CMD,p99.9-100}} & \text{if non-interest wealth rank} \geq 99.9 \\ \beta_t^{fix,CMD,p99-99.9} = \frac{1}{r_t^{fix,CMD,p99-99.9}} & \text{if } 99.9 > \text{Non-interest wealth rank} \geq 99.99 \\ \beta_t^{fix,CMD,bot} = \frac{a_t^{total,fix} - \sum_{i \in top1} \hat{a}_{it}^{fix}}{\sum_{i \notin top1} y_{it}^{fix}} & \text{otherwise} \end{cases}$
   - $\hat{a}_{it}^{fix,CMD} = \begin{cases} \beta_t^{fix,CMD,p99.9-100} \times y_{it}^{fix} & \text{if non-interest wealth rank} \geq 99.9 \\ \beta_t^{fix,CMD,p99-99.9} \times y_{it}^{fix} & \text{if } 99.9 > \text{Non-interest wealth rank} \geq 99.99 \\ \beta_t^{fix,CMD,bot} \times y_{it}^{fix} & \text{otherwise} \end{cases}$

3. SZZ 2001-2016 (Information Returns)

   - $y_{it}^{fix,k}$ is taxable interest income of type $k \in$ {deposits, bonds, loans, boutique} where boutique means interest income on form 1065-K1, 1120S-K1, and 1041-K1
   - $a_t^{total,fix}$ 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

- $r_t^{fix,boutique,P99.9-99.99}$ is the estimated rate of return on boutique fixed income assets for those in the P99.9-99.99 percentile of the AGI distribution
- $r_t^{fix,boutique,P99-99.9}$ is the estimated rate of return on boutique fixed income assets for those in the P99-99.9 percentile of the AGI distribution
- $r_t^{fix,boutique,P90-99}$ is the estimated rate of return on boutique fixed income assets for those in the P90-99 percentile of the AGI distribution
- $r_t^{fix,boutique,B90}$ is the estimated rate of return on boutique fixed income assets for those in the bottom 90 percentile of the AGI distribution
- $\beta_t^{fix,boutique} = \begin{cases} \beta_t^{fix,boutique,Top0.01} = \frac{1}{r_t^{fix,boutique,Top0.01}} & \text{if AGI rank} \geq 99.99 \\ \beta_t^{fix,boutique,P99.9-99.99} = \frac{1}{r_t^{fix,boutique,P99.9-99.99}} & \text{if } 99.9 > \text{AGI rank} \geq 99.99 \\ \beta_t^{fix,boutique,P99-99.9} = \frac{1}{r_t^{fix,boutique,P99-99.9}} & \text{if } 99 > \text{AGI rank} \geq 99.9 \\ \beta_t^{fix,boutique,P90-99} = \frac{1}{r_t^{fix,boutique,P90-99}} & \text{if } 99 > \text{AGI rank} \geq 90 \\ \beta_t^{fix,boutique,B90} = \frac{1}{r_t^{fix,boutique,B90}} & \text{if } 90 > \text{AGI rank} \end{cases}$
- $\hat{a}_{it}^{fix,boutique} = \begin{cases} \beta_t^{fix,boutique,Top0.01} \times y_{it}^{fix,boutique} & \text{if AGI rank} \geq 99.99 \\ \beta_t^{fix,boutique,P99.9-99.99} \times y_{it}^{fix,boutique} & \text{if } 99.9 > \text{AGI rank} \geq 99.99 \\ \beta_t^{fix,boutique,P99-99.9} \times y_{it}^{fix,boutique} & \text{if } 99 > \text{AGI rank} \geq 99.9 \\ \beta_t^{fix,boutique,P90-99} \times y_{it}^{fix,boutique} & \text{if } 99 > \text{AGI rank} \geq 90 \\ \beta_t^{fix,boutique,B90} \times y_{it}^{fix,boutique} & \text{if } 90 > \text{AGI rank} \end{cases}$

(b) Business Loans

- $y_{it}^{fix,loan}$ is taxable interest income from portfolio of loans to other businesses
- $r_t^{fix,loan}$ is the estimated interest rate on business loans
- $\beta_t^{fix,loan} = \frac{1}{r_t^{fix,loan}}$ is the capitalization factor
- $\hat{a}_{it}^{fix,loan} = \beta_t^{fix,loan} \times y_{it}^{fix,loan}$ is the fixed income wealth estimate for loan assets

(c) Deposits

- $y_{it}^{fix,deposits}$ is taxable interest income from deposits
- $a_t^{total,fix,deposits}$ is total household deposits from the Financial Accounts
- $s_t^{fix,deposits,g}$ is group g's share of total deposits in the SCF. Groups are ranked in terms of the non-interest wealth distribution.
- $r_t^{fix,deposits,g} = \frac{\sum_{i \in g} y_{it}^{fix,deposits}}{s_t^{fix,deposits,g} \times a_t^{total,fix,deposits}}$ is the estimated interest rate on deposits for group g, where $g \in \{\text{P0}-90, \text{P90}-99, \text{P99}-99.9, \text{P99.9}-99.99, \text{Top0.01}\}$.

– $\beta_t^{fix,deposits} = \begin{cases} \beta_t^{fix,deposits,\text{Top0.01}} = \frac{1}{r_t^{fix,deposits,\text{Top0.01}}} & \text{if non-int wlth rank} \geq 99.99 \\ \beta_t^{fix,deposits,p99.9-99.99} = \frac{1}{r_t^{fix,deposits,p99.9-99.99}} & \text{if } 99.9 > \text{rank} \geq 99.99 \\ \beta_t^{fix,deposits,p99-99.9} = \frac{1}{r_t^{fix,deposits,p99-99.9}} & \text{if } 99 > \text{rank} \geq 99.9 \\ \beta_t^{fix,deposits,p90-99} = \frac{1}{r_t^{fix,deposits,p90-99}} & \text{if } 90 > \text{rank} \geq 99 \\ \beta_t^{fix,deposits,p0-90} = \frac{1}{r_t^{fix,deposits,p0-90}} & \text{otherwise} \end{cases}$

– $\hat{a}_{it}^{fix,deposits} = \beta_t^{fix,deposits} \times y_{it}^{fix,deposits}$ is the fixed income wealth estimate for deposits

(d) Savings Bonds

– $y_{it}^{fix,bonds}$ is taxable interest income from savings bonds

– $r_t^{fix,bonds}$ is the estimated interest rate on savings bonds based on the SCF and coefficients from projecting the SCF on the Treasury rate

– $\beta_t^{fix,bonds} = \frac{1}{r_t^{fix,bonds}}$ is the capitalization factor

– $\hat{a}_{it}^{fix,bonds} = \beta_t^{fix,bonds} \times y_{it}^{fix,bonds}$ is the fixed income wealth estimate for savings bonds

(e) Fixed Income Mutual Funds[25]

– $y_{it}^{non-qual-divs}$ is taxable non-qualified dividend income

– $a_t^{total,fix,mututal}$ is total household fixed income assets in the form of fixed income mutual funds

– $r_t^{fix,mutual} = \frac{\sum_i y_{it}^{non-qual-divs}}{a_t^{total,fix,mututal}}$ is the estimated interest rate on fixed income mutual funds

– $\beta_t^{fix,mutual} = \frac{1}{r_t^{fix,mutual}}$ is the capitalization factor

– $\hat{a}_{it}^{fix,mutual} = \beta_t^{fix,mutual} \times y_{it}^{non-qual-divs}$ is the fixed income wealth estimate for fixed income mutual funds

- $\hat{a}_{it}^{fix,info} = \frac{\hat{a}_{it}^{fix,boutique} + \hat{a}_{it}^{fix,loan} + \hat{a}_{it}^{fix,deposits} + \hat{a}_{it}^{fix,bonds} + \hat{a}_{it}^{fix,mutual}}{\sum_i \hat{a}_{it}^{fix,boutique} + \hat{a}_{it}^{fix,loan} + \hat{a}_{it}^{fix,deposits} + \hat{a}_{it}^{fix,bonds} + \hat{a}_{it}^{fix,mutual}} \times a_t^{total,fix}$.[26]

4. SZ 2016 (baseline)

- y_{it}^{fix} is taxable interest income
- $a_t^{total,fix}$ is total household fixed income assets
- $\bar{r}_t^{fix} \equiv \frac{\sum_i y_{it}^{fix}}{a_t^{total,fix}}$ is the equal-return interest rate
- $\beta_t^{fix} = \frac{1}{\bar{r}_t^{fix}} = \frac{a_t^{total,fix}}{\sum_i y_{it}^{fix}}$ is the capitalization factor for all
- $\hat{a}_{it}^{fix} = \beta_t^{fix} \times y_{it}^{fix}$ is the fixed income wealth estimate

[25] This approach is for the full sample, i.e., for 1965-2016.

[26] To match the total amount to the financial accounts ($a_t^{total,fix}$), we scale fixed income assets in proportion to fixed income assets from the capitalization of information returns (i.e., $\hat{a}_{it}^{fix,boutique} + \hat{a}_{it}^{fix,loan} + \hat{a}_{it}^{fix,deposits} + \hat{a}_{it}^{fix,bonds} + \hat{a}_{it}^{fix,mutual}$).

5. SZ 2016 (robustness appendix)

- y_{it}^{fix} is taxable interest income
- $a_t^{total,fix}$ is total household fixed income assets
- $r_t^{fix,UST}$ is the ten year US Treasury rate; non-top gets implied residual that rationalizes aggregates.[27]
- $\beta_t^{fix,UST} = \begin{cases} \beta_t^{fix,UST,top} = \frac{1}{r_t^{fix,UST}} & \text{if original wealth rank} \geq 99 \\ \beta_t^{fix,UST,bot} = \frac{a_t^{total,fix} - \sum_{i \in top} \hat{a}_{it}^{fix}}{\sum_{i \notin top} y_{it}^{fix}} & \text{otherwise} \end{cases}$
- $\hat{a}_{it}^{fix,UST} = \begin{cases} \beta_t^{fix,UST,top} \times y_{it}^{fix} & \text{if originalwealth rank} \geq 99 \\ \beta_t^{fix,UST,bot} \times y_{it}^{fix} & \text{otherwise} \end{cases}$.[28]

6. SZ Revising Revisionists (2020)

- y_{it}^{fix} is taxable interest income
- $a_t^{total,fix,SZ2020}$ 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)
- $\bar{r}_t^{fix,SZ2020} \equiv \frac{\sum_i y_{it}^{fix}}{a_t^{total,fix,SZ2020}}$ is the equal-return interest rate
- $\bar{r}_t^{fix,top,SZ2020} = \begin{cases} 1.15 \times \bar{r}_t^{fix,SZ2020} & \text{if } t \in \{2003, 2004, ..., 2007\} \text{ and original wealth rank} \geq 99 \\ 1.4 \times \bar{r}_t^{fix,SZ2020} & \text{if } t \geq 2008 \text{ and original wealth rank} \geq 99 \end{cases}$
- $\beta_t^{fix,SZ2020} = \begin{cases} \beta_t^{fix,top,SZ2020} = \frac{1}{r_t^{fix,top,SZ2020}} & \text{if original wealth rank} \geq 99 \\ \beta_t^{fix,bot,SZ2020} = \frac{a_t^{total,fix,SZ2020} - \sum_{i \in top} \hat{a}_{it}^{fix,SZ2020}}{\sum_{i \notin top} y_{it}^{fix}} & \text{otherwise} \end{cases}$
- $\hat{a}_{it}^{fix,SZ2020} = \begin{cases} \beta_t^{fix,top,SZ2020} \times y_{it}^{fix} & \text{if originalwealth rank} \geq 99 \\ \beta_t^{fix,bot,SZ2020} \times y_{it}^{fix} & \text{otherwise} \end{cases}$.[29]

[27] 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.

[28] Where original wealth is $\hat{a}_{it}^{fix} + \sum_k \hat{a}_{it}^k$ 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.

[29] Where original wealth is $\hat{a}_{it}^{fix} + \sum_k \hat{a}_{it}^k$ 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.

M Liquidity Discount: Replication and Extension of Koeplin, Sarin, and Shapiro (2000)

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.

M.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.

M.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 M.1 and M.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:

$$\text{Private company discount} = 1 - \frac{\text{Private company multiple}}{\text{Public company multiple}} \tag{41}$$

M.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 M.1: Private Company Discounts of Sample Transactions 1984-2019

	Private Targets		**Public Targets**		**Discount**	
	Mean	Median	Mean	Median	Mean	Median
Enterprise Value/EBIT	20.67	12.71	51.74	14.52	60.05	12.47
Enterprise Value/EBITDA	10.86	8.87	11.62	9.71	6.54	8.65
Enterprise Value/Book Value	3.50	2.45	2.56	1.98	-36.72***	-23.74
Enterprise Value/Sales	4.62	1.13	1.99	1.15	-132.16	1.74

Notes: This table presents mean and median multiples for the sample period 1984-2019. Discounts are computed following equation 42. 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 M.2: Private Company Discounts of Sample Transactions 1984-1998

	Private Targets		**Public Targets**		**Discount**	
	Mean	Median	Mean	Median	Mean	Median
Enterprise Value/EBIT	17.45	12.07	24.17	14.52	27.80	16.87
Enterprise Value/EBITDA	10.45	8.19	11.93	9.34	12.41	12.31
Enterprise Value/Book Value	3.64	2.43	2.67	2.21	-36.33**	-9.95
Enterprise Value/Sales	1.50	1.12	2.05	1.07	26.83**	-4.67

Notes: This table is the same as table M.1, except it uses only transactions from 1984 to 1998, following KSS.

N C-corporation Equity

N.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.[30]

Second, while dividends derive exclusively from C-corporation ownership, realized capital gains do not.[31] Appendix Figure A.25A 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.[32] This result gives a reason why capital gains may provide limited 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 of their assets in a single year.[33] Thus, realized capital gains, when observed, may provide

[30] Appendix Figure A.24 shows that 1099-DIVs from "broker" payers with greater than 10,000 payees are the 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).

[31] 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.

[32] Appendix Figure A.26 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.

[33] Appendix Figure A.27 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.

limited information about the underlying distribution of wealth. This issue likely matters more in recent years as the rich own substantial stock wealth, and the tax preference for capital gains versus dividends has fluctuated over time generally in favor of capital gains.

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

N.2 Capitalizing Dividends and Realized Capital Gains

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

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

$$a_{it}^C(\alpha_i) = \beta_{it}^C(\alpha_i) \times \left(\alpha_i y_{it}^D + (1-\alpha_i) y_{it}^G\right) \tag{42}$$

$$s_{it}^C(\alpha_i) = \frac{a_{it}^C(\alpha_i)}{\sum_i a_{it}^C(\alpha_i)}, \tag{43}$$

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

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

$$\hat{\alpha}_i = \arg\min_{\alpha_i} \sum_t \left[\hat{s}_{it}^C - s_{it}^C(\alpha_i)\right]^2 \tag{44}$$

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

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

$$a_{nt}^C = \beta^D y_{nt}^D + \beta^G y_{nt}^G + \varepsilon_{nt} \tag{45}$$

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 (43) reveals that $\beta^D = \beta^C \alpha$ and $\beta^G = \beta^C(1-\alpha)$. These two expressions identify α in terms of coefficients: $\alpha = \frac{\beta^D}{\beta^D + \beta^G}$. Intuitively, if there is a common capitalization factor for the composite flow for all groups and if dividends are more related to C-corporation wealth empirically, then minimizing error at the person level requires more weight on dividends.

We can also investigate the degree of heterogeneity in α_i by fitting the model in equation (46) within certain wealth groups. Looking at these subsamples will produce estimates of α_i by group i. In addition, we also can weigh these regressions by wealth to put more focus on minimizing error for those of substantial means.

Results. Appendix Figure A.25B presents results from the share-based approach using group-level data to estimate α_i. We present separate estimates for P0-90, P90-99, P99-99.9, P99.9-99.99, and for the top 0.01%. The error-minimizing weight on dividends $\hat{\alpha}_i$ for all groups is very close to 0.9. Except for the top 0.01%, we can precisely estimate this parameter and reject the hypothesis that $\alpha_i = 0.5$.

Appendix Table B.10 presents results from the regression-based approach using household-level data. We find C-corporation wealth is much more strongly related to dividends than realized capital gains in the full sample and for all subgroups. Interpreted through the lens of our model, the estimated αs range between 0.94 to 0.98, with the weight on dividends increasing as we move up the wealth distribution. These household-level regressions deliver more precision than the share-based approach, but at the cost of using household-level wealth as the estimand of interest rather than C-corporation wealth shares.

Both approaches strongly support placing substantially more weight on dividends when capitalizing flows to estimate C-corporation wealth. Moreover, they both suggest the degree of heterogeneity in mapping flows to stocks is relatively unimportant for this asset class.[34] Because there appears to be little heterogeneity across groups, we adopt a wealth-weighted average of parameter estimates to set α_i equal to 0.9 in our baseline capitalization.[35] The resulting capitalization factor $\beta_t^C(0.9) = \frac{\sum_i a_{it}^C}{\sum_i \left(0.9 y_{it}^D + 0.1 y_{it}^G\right)}$ is the ratio of aggregate C-corporation wealth from the Financial Accounts to the aggregate composite flow of 0.9 times dividends plus 0.1 times capital gains for each year.

[34] Figure A.24 shows that partnerships are an important source of dividend income for those at very top, analogous to results in Fig A.25. Figure A.22 shows that heterogeneity in yields appears relatively small.

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

Appendix Figure A.25C 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.[36] 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.[37] 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 (Appendix Figure A.19)—the relative contribution of capital gains to estimating C-corporation equity wealth exceeds 50% when setting $\alpha = 0.5$.

In a supplemental series, we replace the richest 400 in our capitalized data with the Forbes 400. Due to their relative size—Forbes individuals collectively account for 3.1% of total household wealth in 2016—and overlap with our estimates—owners of private businesses or dividend-paying public companies account for 77% of collective Forbes wealth—we find that incorporating the Forbes data has only a modest effect on our overall top share estimates. Appendix R.3 provides additional discussion.[38]

O Pension Wealth

O.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. Appendix Figure A.28A uses the SCF to plot average wages, pension income, and pension wealth in 2016 dollars, averaging across cohorts from 1989 to 2016. Wage income

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

[37] SZ and PSZ also apply a "mixed" method for ranking. See Appendix R.2 for details.

[38] 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 Q). For non-pass-through wealth components, we then scale non-Forbes aggregates to ensure the total matches the USFA.

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. Appendix Figure A.28B 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 excluding unfunded defined benefit plans. We then present two supplemental series: one that shows the effect of including unfunded defined benefit pension wealth and another that adds Social Security wealth estimates.

O.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 funded defined benefit (DB) pension entitlements based on estimates from Sabelhaus and Volz (2019).[39]

We begin with wages y_{it}^{wage} and pension income y_{it}^{pen} for person i in year t.[40] For each flow, we apply an age-group-specific capitalization factor:

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

where age group $a \in \{< 45, 45 \text{ to } 59, 60 \text{ to } 74, > 75\}$ and γ_a is the ratio of pension wealth per capita within an age group to aggregate pension wealth per capita.[41]

Our estimate is an age-group-specific convex combination of capitalized wages and capi-

[39] We use the ratio of funded to unfunded DB pension entitlements to scale down the DB estimates of Sabelhaus and Volz (2019) so that the DB portion aggregates to the funded DB value in SZ20.

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

[41] We construct γ_a using the mean γ_{at} in the SCF from 1989 to 2016. Our measure of pension wealth is the defined-benefit-augmented SCF from Sabelhaus and Volz (2019).

talized pension income:

$$\hat{W}_{it}^{penw} = \theta^{penw,a} \left(\beta_t^{penw,wage,a} \times y_{it}^{wage}\right) + \left(1 - \theta^{penw,a}\right) \left(\beta_t^{penw,pen,a} \times \left(y_{it}^{pen}\right)\right), \qquad (46)$$

where $\theta^{penw,a}$ is the weight on capitalized wages and $(1 - \theta^{penw,a})$ is the weight on capitalized pension income for age group a. Younger individuals have more weight put on wages and older individuals have more on pensions. In particular, $\theta^{penw,a}$ is 0.94, 0.85, 0.38, and 0.08 for those younger than 45, 45 to 59, 60 to 74, and above 75, respectively.[42]

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

$$\hat{W}_{i,2016}^{pen,SZZ} = \begin{cases} .94\left(1.1 \times y_{i,2016}^{wage}\right) + (1 - .94)\left(112.8 \times \left(y_{i,2016}^{pen}\right)\right) & \text{if } age < 45 \\ .85\left(3.4 \times y_{i,2016}^{wage}\right) + (1 - .85)\left(75.3 \times \left(y_{i,2016}^{pen}\right)\right) & 45 \leq age < 60 \\ .38\left(8.4 \times y_{i,2016}^{wage}\right) + (1 - .38)\left(18.5 \times \left(y_{i,2016}^{pen}\right)\right) & \text{if } 60 \leq age < 74 \\ .08\left(22.0 \times y_{i,2016}^{wage}\right) + (1 - .08)\left(5.9 \times \left(y_{i,2016}^{pen}\right)\right) & \text{otherwise} \end{cases}. \qquad (47)$$

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 A.28C 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).[43] Were we to include this wealth in our household aggregate, the top 0.1% share in 2016 would fall by twenty to thirty percent, and the growth since 1995 in the top 0.1% share would fall by twenty to fifty percent. The generosity of social insurance can therefore materially affect wealth concentration measures.

P Housing

P.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

[42]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.

[43]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.29). 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.

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.[44] Figure A.30A 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.

P.2 State-Year Housing Capitalization Factors

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.[45]

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

For itemizers, we estimate housing assets at the person-level using the formula,

$$\hat{A}_{it}^{hou} = \beta_{st}^{ptax} y_{it}^{ptax} = \frac{1}{r_t^s} \times y_{it}^{ptax}, \tag{48}$$

where r_t^s 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_t^s, 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,

$$\tilde{R}_t^S = R_{Census,t}^S \times \theta_{R,2012} \tag{49}$$

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

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

[45] 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.

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,

$$\tilde{W}_t^S = \tilde{W}_{2012}^S \times \frac{p_{CoreLogic,t}}{p_{CoreLogic,2012}} \times \frac{pop_t^S}{pop_{2012}^S}, \tag{50}$$

where $\tilde{W}_{2012}^S$ equals $(1/r_{ATTOM}^S) \times R_{DataQuick,2012}^S$ and provides an estimate in 2012 of property values underlying assessed tax amounts, $p_{CoreLogic,t}$ 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

$$r_t^S = \frac{\tilde{R}_t^S}{\tilde{W}_t^S}. \tag{51}$$

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.31).

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

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

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

P.3 Capitalization with Unequal Property Tax Rates

Accounting for state-specific capitalization factors is important for estimating the level and geographic distribution of housing assets. Figure A.30B 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 differences 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 issue of fixed income wealth estimated under an equal-returns assumption during low-interest-rate periods.

Figure A.30B 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 SZ except for the estimation of state-year-specific capitalization factors.[46] They apply an equal-returns capitalization factor in a given year for mapping property tax deductions to housing assets. A limitation of this approach is that it does not account for cross-state differences in property taxes and attenuates regional house price dynamics.

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

Q 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.**

Q.1 Primary source of equity wealth

Q.1.1 Public and private companies

We start with an individual-level data file on the Forbes 400 in 2016.[47] In this file, each observation has a `source` and `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 `source` and `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 `source` and `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 Q.2.1.

Q.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.

[47] We retrieve the data file `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.

Q.2.1 Public/private company judgment calls

- No. 20 - Michael Dell - Dell public until 2013 and after 2018. Assigned public.
- 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. 78 - Travis Kalanick - Uber not public until 2019. Assigned private.
- 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. 172 - Helen Johnson-Leipold - inherited S.C. Johnson & Son shares (private). But since 1999, chairman and CEO of Johnson Outdoors (public). Assigned public.
- 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.

Q.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 Q.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 Q.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.[48] 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.[49] 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.

Q.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 55 – Thomas Frist Jr – his health care firm started paying dividends after 2018. 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.

[48]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.

[49]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 82 – Robert Rowling – His firm Trio-Tech International only paid dividends in 2006 and 2008. Assigned no dividends.
- 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 210 – Robert Pera – Ubiquiti Networks started paying dividends after 2019. Assigned no dividends.
- 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 263 – Daniel Och – His hedge fund, Sculptor Capital Management Inc. started paying dividends in 2019. 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 309 – Meg Whitman – eBay started paying dividends in 2019. Assigned no dividends.
- 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 378 – Amy Wyss – Sold medical equipment firm Synthes to J&J in 2012. 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.

R Additional Discussion Comparing Our Approach to Alternatives

R.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 et al. (2016); Bricker, Henriques and Hansen (2018); Sabelhaus and Volz (2019); Bricker, Hansen and Volz (2019); Saez and Zucman (2020*b*). 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 et al. (2016), suggesting this cannot account for differences across methods. In this section, we focus on the remaining discrepancies.[50]

Our baseline 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.15 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.16). These findings align with those in Bricker et al. (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.[51]

The SCF uses respondents' self-reported estimated value of the business.[52] 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. 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

[50] 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.

[51] Note the DFA units are at the household level, so require additional adjustment for comparison to ours. Appendix Figure A.10 presents levels of different wealth components for top groups comparing our tax unit series to the DFA series.

[52] 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 et al. (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.

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 M), evidence on private market sales data for mid-market firms (Bhandari and McGrattan, 2021), and the literature estimating private firm sales discounts (Officer, 2007), all of which point toward considerable private firm discounts.[53]

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 et al., 2021; Feiveson and Sabelhaus, 2019; Batty et al., 2019). On average, aggregate housing values in the SCF exceed those in the Financial Accounts by 15-40%.[54] 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.

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

[53]See Bhandari and McGrattan (2021) Appendix Table A.9.

[54]There are also methodological differences between the SCF and Financial Accounts.

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 et al., 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 8).

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 et al. (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.[55] Bricker et al. (2016) also 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

[55] Regarding 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.

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, 2019). 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.

R.2 SZ (2016) and PSZ (2018)

We start by comparing our estimates to those in SZ and PSZ, which adopt the equal-returns approach for capitalizing income to estimate wealth within asset class.

R.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, SZ20).

The headline results in SZ and PSZ assume no heterogeneity in fixed income returns.[56] However, as we noted in the introduction, SZ do include some robustness series that assume higher rates at the top.[57] For example, they present a two-tier model that assigns some a capitalization factor that is based on the US 10-year treasury rate:

$$\beta_t^{fix,UST} = \begin{cases} \beta_t^{fix,UST,top} = \frac{1}{r_t^{fix,UST}} & \text{if original wealth rank} \geq 99 \\ \beta_t^{fix,UST,bot} = \frac{a_t^{total,fix} - \sum_{i \in top} \hat{a}_{it}^{fix}}{\sum_{i \notin top} y_{it}^{fix}} & \text{otherwise} \end{cases} \tag{52}$$

$$\hat{a}_{it}^{fix,UST} = \begin{cases} \beta_t^{fix,UST,top} \times y_{it}^{fix} & \text{if originalwealth rank} \geq 99 \\ \beta_t^{fix,UST,bot} \times y_{it}^{fix} & \text{otherwise,} \end{cases} \tag{53}$$

where y_{it}^{fix} is taxable interest income, $a_t^{total,fix}$ is total household fixed income assets from the Financial Accounts, $\hat{a}_{it}^{fix}$ is the fixed income wealth estimate, and original wealth is $\hat{a}_{it}^{fix} + \sum_k \hat{a}_{it}^k$ where k are the other types of wealth. Note that the baseline equal-return fixed income wealth estimate $\hat{a}_{it}^{fix}$ is used to determine the wealth rank. While the UST10 approach improves model fit relative to the equal-returns approach, it underperforms our estimates by overstating estimated wealth, especially for the top 0.1% and top 0.01%.[58]

SZ also present a robustness 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, although this rate isn't weighted and has several other limitations.[59] The estate tax rate 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.[60] Moreover, in the

[56] The headline approach to estimate fixed income is: $\hat{a}_{it}^{fix} = \beta_t^{fix} \times y_{it}^{fix}$, where $\beta_t^{fix} = \frac{1}{\bar{r}_t^{fix}} = \frac{a_t^{total,fix}}{\sum_i y_{it}^{fix}}$ is the capitalization factor for all, $\bar{r}_t^{fix} \equiv \frac{\sum_i y_{it}^{fix}}{a_t^{total,fix}}$ is the equal-return interest rate, y_{it}^{fix} is taxable interest income, and $a_t^{total,fix}$ is total household fixed income assets from the Financial Accounts.

[57] Saez and Zucman (2020*a*) 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.

[58] Appendix Figure A.32 uses a test similar to SZ 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.32 replicates Figure IV.B. of SZ, 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.32 holds ranks fixed and uses the tax-based capitalization factors.

[59] For the estate tax returns, we also apply inverse mortality rates, which is needed to estimate rates of return for the living. SZ 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 leave this difficult task to future research." (p. 549)

[60] SZ 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

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 4), and thus allocate less fixed income wealth to the top. The basis for our approach, which is described in Section 2, 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 A.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. PSZ allocate money market mutual funds along with C-corporation wealth in proportion to dividends, which affects the aggregate amount and capitalization factor in the fixed income category. Using the PSZ aggregates and allocation result in capitalization factors that are around 113 in 2016. Table 3 presents a supplemental series that applies equal returns while allocating money market mutual funds in proportion to dividends instead of interest. In comparison, an equal-returns approach that also includes money market mutual funds in the numerator results in a capitalization factor of 125 in 2016. Figure 4C shows the consequences of different capitalization factors for estimated top 0.1% wealth shares (holding ranks fixed using our baseline measure).[61]

Another source of difference in fixed income estimates concerns the ranking of individuals. We find that 17% 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.

R.2.2 Public equity with more weight on capital gains

For estimating C-corporation equity, the key difference between our approach and SZ 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, SZ 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 SZ20 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 [takes them into account] when computing top shares. To determine a family's ranking in the wealth distribution, dividends are multiplied

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)

[61] We use the same aggregates as SZ20, but they assume a smaller degree of heterogeneity than what we find using information returns and CMD estimates (Figure 4A). Appendix L provides the specific formulas for SZ20 fixed income.

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.[62] For our supplemental series that augment the top 400 with Forbes wealth estimates, another difference relative to SZ and PSZ is that our approach effectively incorporates Forbes estimates into our estimates of both C-corporation and private business wealth, which are the largest categories at the very top.[63] Figure A.25C shows the consequences of different weights on dividends and capital gains for top 0.1% wealth shares.

SZ and PSZ undo some of the weight placed on 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. By providing statistical tests of alternative models using SCF data on both stocks and flows, our approach uses the data to discipline these assumptions.

R.2.3 Pass-through Equity, Housing, and Pensions

For pass-through business, 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, relative to ours, this approach does not account for industry or firm-size 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 zero or negative taxable income despite having significant assets, such as in the real estate sector. We estimate that 17% of total pass-through business wealth accrues to those with negative business income and that these losses are often claimed by rich individuals. Third, our micro-data approach delivers independent estimates of the aggregate value of private business, as discussed in Section 5.

For pensions, SZ apply a convex combination of a capitalized function of wages and capitalized pension income.[64] First, relative to ours, this approach does not account for the

[62] Note that in SZ20, this mixed method is no longer used. Instead for both rankings and shares, SZ20 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)." SZ20 now only use qualified dividends starting in 2003.

[63] SZ20 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 Q 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)."

[64] The function is $y_{it}^{wagetop60} = \begin{cases} y_{it}^{wage} - median(y_{it}^{wage}) & \text{if } P_{it}^{wage} \geq .5 \\ 0 & \text{if } P_{it}^{wage} < .5 \end{cases}$. 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.

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 funded defined benefit pension wealth, which improves estimates especially for the bottom 90%.[65] Third, as noted by Auten and Splinter (2019), SZ 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 as well as unfunded defined benefit pensions.

For housing, we follow a similar approach to SZ, except they apply an equal-returns capitalization factor in a given year for mapping property tax deductions to housing assets. That approach does not account for cross-state differences in property taxes and regional house price dynamics.

Figure A.9 shows the consequences of different approaches for pass-through business, housing, pensions, and other categories in Panels A, B, C, and D, respectively. Figure A.9A shows our baseline approach increases the contribution of pass-through business wealth to top 0.1% shares from around 2.5% with equal returns to around 3.5% in 2016. Panels B, C, and D show that equal returns and baseline are pretty similar for housing and residual wealth, but diverge slightly for pensions. The difference for pensions reflects our inclusion of the labor share of pass-through income alongside wages in our pension model.

The concentration of fiscal income flows also helps illustrate why different approaches can deliver different capitalization estimates. Figure A.3 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.3A 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 large growth in the concentration of fixed income wealth.

Figures A.3B-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 A.19B, the aggregate capital gains series is also more volatile than the other series, reflecting the accumulation of

[65] SZ 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.

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.[66] 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.

R.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 Q.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.[67]

To address concerns that our approach may miss Forbes wealth, we provide supplemental series that replaces the richest 400 in our data with the Forbes 400. 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. In addition, there is considerable uncertainty in terms of the number of adults represented in the Forbes wealth estimates (see Section 5 and footnote 41 for a discussion and Appendix Table B.9 for detailed calculations of the expected number of spouses, adult children, and their spouses).

Nonetheless, even under the conservative assumption that Forbes represents 400 tax units (equivalently, 800 equal-split adults), incorporating the Forbes data via top 400 replacement only has 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

[66] S-corporation income concentration is somewhat higher than in Cooper et al. (2016) because we rank by flow component rather than total fiscal income.

[67] Saez and Zucman (2020*a*) 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 4 × \$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. The example shows that neither approach to capitalization will get Bezos close to right. The case of Warren Buffett is even more extreme, with the SZ approach assigning stock wealth equal to just over 2% of his listed stake in Berkshire Hathaway. Moreover, to the extent past attempts to capitalize tax data have delivered top wealth that matches Forbes (as in SZ and PSZ), these estimates have been driven by large amounts of fixed income wealth rather than equity wealth.

accounts for 3.1% 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.[68] 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 Q.3, we estimate that non-dividend-generating C-corporation owners in Forbes collectively have around $440B in C-corporation equity wealth in 2016 or about half a percentage point of total wealth.

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 much of this gap is due to tax avoidance and evasion, which are also likely quite substantial. Recent findings in Moretti and Wilson (2020) on the large difference between statutory and effective estate tax collections from Forbes individuals corroborates this concern. 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.[69] 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.[70] 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.[71] Fourth, the number of wealth holders for each Forbes entry is likely well above one due to spouses and families, but estimating the exact number of adults and their respective wealth is difficult (Appendix Table B.9).

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 both in terms of collective wealth and the number of adults represented, we focus on capitalized estimates in our baseline series and provide alternative approaches to help readers understand the potential magnitudes of different adjustments to account for Forbes wealth.

[68]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.

[69]For example, consider the recent cases of Kylie Jenner `https://www.forbes.com/sites/chasewithorn/2020/05/29/inside-kylie-jennerss-web-of-lies-and-why-shes-no-longer-a-billionaire/?sh=5e71e24225f7` and Wilber Ross `https://www.forbes.com/sites/danalexander/2017/11/07/the-case-of-wilbur-ross-phantom-2-billion/?sh=5402df8f7515`.

[70]The Bloomberg list has an accuracy rating system that reflects these difficulties: `https://www.bloomberg.com/billionaires/methodology/`

[71]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).

R.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 (2004*a*) (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 (2019) (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 et al. (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.[72]

Appendix Figure A.33 compares the original KS approach, which we have updated to 2016, to the SZ approach, and to the approach using our mortality statistics.[73] Consistent 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

[72]The new mortality rates for years 2001-2014 are generally similar to those of Chetty et al. (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.

[73]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.

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.[74] 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. Annuitized 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.[75] Appendix Figure A.5 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 baseline series.

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[74] Appendix Figure A.34 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

[75] 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)

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