

The Distributional Financial Accounts of the United States*

Michael Batty, Jesse Bricker, Joseph Briggs, Sarah Friedman,
Danielle Nemschoff, Eric Nielsen, Kamila Sommer, and Alice Henriques Volz

June 2020

Abstract

This paper describes the construction of the Distributional Financial Accounts (DFA), a dataset containing quarterly estimates of the distribution of U.S. household wealth since 1989. The DFA builds on two existing Federal Reserve Board statistical products — quarterly aggregate measures of household wealth from the Financial Accounts of the United States, and triennial wealth distribution measures from the Survey of Consumer Finances — to incorporate distributional information into a national accounting framework. The DFA complements other sources by generating distributional statistics that are consistent with macro aggregates by providing quarterly data on a timely basis, and by constructing wealth distributions across demographic characteristics. We encourage policymakers, researchers, and other interested parties to use the DFA to better understand issues related to the distribution of U.S. household wealth.

*The analysis and conclusions set forth here are those of the authors and do not indicate concurrence by other members of the research staff, the Board of Governors, or the Federal Reserve System. This project reflects the combined efforts of the Flow of Funds and Microeconomic Survey sections at the Federal Reserve Board. Sarah Reber provided outstanding research assistance. We are grateful to Marco Cagetti, Karen Pence, and Paul Smith for providing outstanding guidance and supervision of this project, as well as numerous edits to this paper's text. We also thank Kevin Moore, Jeff Thompson, Molly Shatto, Elizabeth Holmquist, Susan McIntosh, and Tom Sweeney for work on the DFA project from which this paper derives. In addition, we also thank seminar participants at the Federal Reserve Board and the NBER Conference on Research in Income and Wealth, in particular Bill Gale, for their useful feedback and suggestions.

1 Introduction

There is a growing consensus that wealth inequality in the United States has increased substantially over the last 30 years (Wolff et al. (2012), Piketty (2013), Bricker et al. (2016), Saez and Zucman (2016), Rios-Rull and Kuhn (2016)). This has undermined the ability of aggregate economic statistics to describe of the economic well-being of most Americans. Further, the increase in inequality has implications for other economic and social outcomes. For instance, studies have examined the relationship between the wealth distribution and economic growth (Banerjee and Duflo (2003)), monetary policy transmission (Auclert (2019), Gornemann et al. (2016), Kaplan et al. (2018)), aggregate saving rates (Fagereng et al. (2016)), optimal tax policy (Albanesi (2011), Shourideh (2012)), social mobility (Benhabib et al. (2017)), and even political engagement (Solt (2008)).

This paper introduces the Distributional Financial Accounts (DFA), a new data product that provides quarterly measurement of the distribution of U.S. household wealth from 1989 through the present.¹ The DFA integrates two statistical products produced by the Federal Reserve Board: the Financial Accounts of the United States and the Survey of Consumer Finances (SCF). The Financial Accounts are U.S. national accounts that measure aggregate wealth by economic sector, including households. The SCF collects detailed balance sheets for a sample of U.S. households (including the very wealthy). We construct the DFA in three steps: 1) we build an SCF analog for each component of aggregate household net worth in the Financial Accounts, 2) for each part of the wealth distribution, we interpolate and forecast the SCF analogs between the triennial SCF observations, and 3) we apply the distribution of the (interpolated) SCF analogs to the Financial Accounts aggregates each quarter.

This approach produces a rich and reliable measure of the wealth distribution that we believe is particularly useful for several reasons. First, the DFA exists in a national accounting framework, meaning it is consistent with the Financial Accounts aggregates that have become well-established tools for studying the macro-economy.² Second, it is available

¹The DFA project is part of the Enhanced Financial Accounts (EFAs) initiative, which seeks to expand the scope of the Financial Accounts by adding additional information from other data sources. More information about the EFA initiative, and additional EFA projects, can be found at <https://www.federalreserve.gov/releases/efa/enhanced-financial-accounts.htm>.

²Scholars have often expressed interest in incorporating microeconomic heterogeneity into national accounting frameworks. For example, Carroll (2014) cites the need for distributional national statistics, while the Inter-Agency Group on Economic and Financial Statistics has called on G-20 nations to develop such statistics that are internationally comparable. Other efforts to construct distributional national measures in

quarterly in near real-time (approximately 11 weeks after the quarter close). In contrast, alternative measures of the wealth distribution are available at an annual frequency at best, and typically have a lag of several years. Third, the Financial Accounts definition of wealth is quite comprehensive, including important components such as defined benefit pensions that are not easily measured in other sources. Finally, the SCF’s detailed household-level information reduces the need to rely on strong assumptions to generate distributional statistics, and allows us to study how wealth is related to demographic characteristics.

The paper proceeds as follows. In Section 2, we describe the construction of SCF wealth concepts that are consistent with each component of household net worth in the Financial Accounts. In Section 3, we document how we interpolate and forecast the SCF distributions between SCF observations. In Section 4, we present high-level results, and illustrate how the DFA furthers our understanding the distribution of household wealth. In Section 5, we show our results are robust to key reconciliation assumptions, alternative approaches to interpolation and forecasting, and sampling variability inherent in the SCF. Finally, we summarize in Section 6 the DFA’s key contributions.

2 Reconciling the Financial Accounts and the SCF

The first step in constructing the DFA is reconciling the measurement concepts used in the Financial Accounts and the SCF. Our primary focus is organizing information captured by the SCF in a way that is conceptually compatible with each line on Table B.101.h of the Financial Accounts (the balance sheet that reports the components of the aggregate wealth of U.S. households). That is, we aim to distribute each B.101.h asset and liability using analogous information reported by SCF respondents. As described in more detail below, this is a straightforward process when the baseline concepts are closely aligned between the Financial Accounts and the SCF. However, significant adjustments are necessary in cases when the Financial Accounts concept is captured differently, or not at all, in the SCF. Ultimately, we are able to construct an appropriate match for each B.101.h category either by employing one or more SCF measures, or by constructing an SCF measure from relevant

the United States include early work by King (1915), King (1927), King et al. (1930), Kuznets (1947), and Kuznets and Jenks (1953), more recent efforts by Piketty et al. (2017), and prototype estimates recently released by the Bureau of Economic Analysis (Fixler et al. (2020), Gindelsky (2020) Furlong (2014), Fixler and Johnson (2014), Fixler et al. (2017)).

information recorded in the survey.

Comparing and reconciling the SCF and Financial Accounts has a long history, including Avery et al. (1987), Antoniewicz (1996), Maki et al. (2001), Henriques and Hsu (2014), and Dettling et al. (2015). Generally, these studies find that the aggregated SCF “bulletin” measures of assets and liabilities align reasonably well, but not perfectly, with the Financial Accounts.³ Our approach, though similar in spirit to much of this prior work, extends it in several important ways, thereby producing the most rigorous reconciliation of the SCF and Financial Accounts concepts of household net worth to date. First, prior work has reconciled the SCF (a household survey) with Financial Accounts Table B.101 (which includes nonprofit organizations). We are able to make use of the recently developed Financial Accounts Table B.101.h, which provides a slightly less-detailed breakdown of wealth categories than B.101, but excludes nonprofits.⁴ Second, while prior reconciliations have largely excluded assets and liabilities that are absent or difficult to measure in the SCF (e.g., the value of defined benefit pensions, insurance reserves, and annuities), for the DFA, we distribute these Financial Accounts totals to SCF respondents using other relevant information reported in the survey (e.g. pension benefits received and insurance ownership). In Section 4, we demonstrate how incorporating these assets and liabilities produces a somewhat less skewed distribution of wealth. Finally, we also extend prior reconciliations by relying on a method that re-weights the SCF to incorporate the wealth of the Forbes 400. These individuals are explicitly excluded from the SCF sample due to privacy concerns but contribute materially to the top of the wealth distribution.⁵

B.101.h assets and liabilities fall into three broad categories: 1) those for which there is an SCF analog with no or relatively little adjustment; 2) those for which substantial adjustment and/or investigation is necessary to construct a comparable SCF measure; and 3) those for which there is no analogous valuation in the SCF, but for which there is relevant information provided by SCF respondents that we use to distribute the B.101.h total. While

³The “bulletin” measures refer to the SCF statistics reported in the Federal Reserve Bulletin associated with each data release (for example, see Bricker et al. (2017a)).

⁴However, because it is calculated residually, it includes the holdings of sectors not captured elsewhere, the most significant of which is hedge funds. For more information about Table B.101.h, see “Household and Nonprofit Balance Sheets in the Financial Accounts of the U.S” (Holmquist (2019)). <https://www.federalreserve.gov/econres/notes/feds-notes/household-and-nonprofit-balance-sheets-in-the-financial-accounts-of-the-us-20190104.htm>

⁵See Appendix E for a description of the re-weighting method. The weighting correction is based on ?. For details on the Forbes list of wealthiest families, see <https://www.forbes.com/forbes-400/>.

the distinction between the first and second categories is somewhat subjective, Table 1 shows how we categorize each line of B.101.h. In the remainder of this section, we focus on describing the reconciliation process for large assets and liabilities in categories two and three. The full description of how we reconstruct all nineteen balance sheet lines from Table B.101.h using SCF data is available in Appendix A.

Table 1: B.101.h Assets and Liabilities by Reconciliation Category

<u>Minimal Adjustment</u>	<u>Substantial Adjustment</u>	<u>Indirectly Measured in SCF</u>
Real estate	Corporate equities and mutual funds	Pension entitlements (excluding DC pensions)
Home mortgages (liability)	Equity in noncorporate business	Life insurance
DC pensions (a component of pension entitlements)	Time deposits and short-term investments	Miscellaneous assets
Checkable deposits and currency	Consumer durables	Deferred and unpaid life insurance premiums
Other loans and advances (asset)	US government and municipal securities	
Other loans and advances (liability)	Consumer credit	
Home mortgages (asset)	Money market mutual fund shares	
Depository institution loans not elsewhere classified	Corporate and foreign bonds	

Notes: This categorizes each component of B.101.h into three reconciliation groups: 1) those for which there is an SCF analog with no or relatively little adjustment; 2) those for which substantial adjustment and/or investigation is necessary to construct a comparable SCF measure; and 3) those for which there is no analogous valuation in the SCF, but for which there is relevant information provided by SCF respondents that we use to distribute the B.101h total. Columns are sorted by size.

Pension entitlements (excluding DC Pensions):

DB pensions and annuities make up 60% and 10% of pension entitlements in the Financial Accounts, respectively. These include accrued benefits to be paid in the future from defined benefit (DB) plans, and annuities sold by life insurers directly to individuals.⁶

Unlike DC pensions, the SCF does not directly measure accrued DB assets. Therefore, we utilize information the SCF captures about plan participation and anticipated benefits to distribute the DB component of the B.101.h aggregate. To proceed, we rely on methodology from Sabelhaus and Volz (2019). They break the SCF households who are entitled to DB benefits into those currently receiving pension payments, those expecting future payments from a past job, and those expecting future payments from a current job. The SCF collects the benefit amount for those currently collecting a pension, and the expected timing and amount of future pension benefits from a past job for those who are entitled to but are not yet collecting benefits. This information is used to calculate the present discounted

⁶The defined-benefit component includes total accrued benefits from private-sector, state-and-local government, and federal employment, whether fully funded or not. Notably, it does not include Social Security, which is not currently included in the Financial Accounts. The annuities component also includes annuities held in IRAs. IRA investments in other instruments, such as mutual fund shares, are included in the other asset categories described above.

value of the future income stream for these two groups. Finally, the remaining B.101.h DB assets (obtained residually as the B.101.h DB total net of the present value of future income streams calculated above) are allocated to the SCF respondents who have a plan tied to their current job but are not yet receiving benefits. The primary difference between the DFA and Sabelhaus and Volz (2019) is that a subset of life insurance assets are given the same treatment as DB assets.⁷ We use the respondents’ current wage, years in the plan, and age to determine the allocation.⁸

The economic value of annuities is also not directly collected by the SCF in a manner that is comparable to B.101.h. However, the SCF reports the amount of income received from annuities that are in the payout phase, as well as the cash value of deferred annuities (which differs from the economic value due to surrender penalties and other policy benefits not immediately payable in cash). To reconcile the SCF and B.101.h annuity measures, we capitalize the payout annuity income reported by SCF households into a present value using a set of sample annuity policies (see Appendix A), and then distribute the B.101.h annuity reserves according to the sum of the cash value of deferred annuities and capitalized value of payout annuities reported in the SCF. In Appendix A, we describe similar methods used to distribute life insurance reserves and property and casualty insurance reserves (the latter of which is a component of miscellaneous assets).

Financial assets held through IRAs, trusts, and managed investment accounts:

It is relatively straightforward to assign financial assets directly held by SCF households to the appropriate B.101.h categories (e.g., directly held stocks and mutual funds are assigned to the B.101.h category “corporate equity and mutual fund holdings”). However, we must make additional assumptions to assign financial assets that are held by SCF households indirectly through IRAs, trusts, and managed investment accounts.⁹ For these types of investment vehicles, the SCF asks what percentage of holdings are invested in equities versus interest-bearing assets. Using this percentage, we assign the share of these assets that are invested in equities to “corporate equity and mutual fund holdings.” For the non-equity share, since we

⁷Benefits for workers with current job plans are calculated residually for two primary reasons. First, this allows direct mapping to the Financial Accounts aggregate, the best estimate of DB assets that belong to households. Second, the SCF does not capture the generosity of DB pension plans, which is a crucial parameter required to calculate accrued DB assets.

⁸All DB estimates rely on differential mortality defined by age group, marital status, race, education, and income quantile. See Sabelhaus and Volz (2019) for a more detailed description of the DB imputation methodology.

⁹Defined-contribution retirement accounts are included with pension plans, as described below.

do not directly observe the composition of the interest-bearing assets, we use the Investment Company Institute Fact Book (Collins (2018)) and IRA Database (Holden and Bass (2018)) for the relevant year to estimate the breakdown, assuming each SCF respondent holds a representative portfolio. These adjustments are applied to time deposits and short-term investments, money market mutual fund shares, US government and municipal securities, corporate and foreign bonds, and corporate equities and mutual funds (and are the reason we place these assets in category 2).

Equity in noncorporate business:

This category includes non-publicly traded businesses and real estate owned by households for renting out to others. Notably, closely-held S and C corporations are not included in this category. There are substantial differences in its measurement between the SCF and Financial Accounts. The B.101.h measure is a hybrid of different accounting bases. Real estate (e.g., rental properties), which accounts for approximately 60% of this category, is recorded at market value. In contrast, other nonfinancial assets are recorded at cost basis, based on investment data collected by the BEA. Financial assets and liabilities are recorded at book value from tax data.

In the SCF, rental properties are reported at market value. For other noncorporate business assets, the SCF captures owners' self-reports of both the market value and the cost basis of their businesses. When we compare these two measures to B.101.h, we find (unsurprisingly) that the market-value SCF measure exceeds the B.101.h measure (with an average ratio of approximately 150%), while the cost-basis SCF measure falls below the B.101.h measure (with an average ratio of 70%).¹⁰ To reconcile the SCF and B.101.h, we use the average of the two SCF valuations, which tracks the B.101.h measure quite well empirically. In Section 5, we show our results are robust to this choice, which implies the SCF market and cost basis measures are roughly proportional to each other throughout the wealth distribution.

Corporate equities and mutual funds:

In addition to the indirectly held equities described above, two additional complications exist for the corporate equities and mutual fund category. First, similar to equity in noncorporate business, the value of closely held corporations (S and C corporations) is reported in

¹⁰Despite the level differences between the B.101.h and the two SCF measures, all three series exhibit similar trends over time.

the SCF at both market value and at cost basis. The market and cost basis valuations in the SCF again straddle the Financial Accounts valuation, so we employ the average of the SCF measures in the DFA. Section 5 shows our results are also robust to using either the SCF market or cost-basis valuations.

Second, the SCF’s bulletin measure of mutual funds includes an “other” category that is comprised largely of hedge funds. Hedge funds are not separately recorded in the Financial Accounts, meaning that the assets held by hedge funds are included in the applicable B.101.h categories.¹¹ We use a preliminary estimate of the breakdown of hedge fund assets from a supplemental Financial Accounts table built from data they report through Form PF (in development) to assign the SCF hedge fund assets to the appropriate B.101.h categories.

Consumer durable goods:

This B.101.h category, taken from the BEA’s stock of fixed assets and consumer durable goods, captures many durable assets: automobiles, trucks/motor vehicles, furniture, carpet/rugs, light fixtures, household appliances, audio/video/photo equipment, computers, boats, books, jewelry/watches, health and therapeutic equipment, and luggage, among others.

The SCF asks specifically about cars and other vehicles, which account for about 30% of B.101.h consumer durables. For the remaining assets, the SCF asks “Other than pension assets and other such retirement assets, do you (or anyone in your family living here) have any other substantial assets that I haven’t already recorded...?” If families indicate that they own any such assets, they are queried about the type of the asset and its value. We sum all nonfinancial assets included in responses to this question to obtain our reconciled SCF measure of consumer durable goods.

The SCF reports fewer consumer durables than the Financial Accounts, with the ratio typically around 60%. This occurs in large part because the BEA measure covers essentially any item that has resale value, whereas the SCF focuses on the most substantial assets.¹² To the extent that these significant assets are concentrated among the wealthy, and the

¹¹Ideally, the Financial Accounts would include a sector that shows hedge funds’ holdings of financial assets, and an instrument that represents other sectors’ investments in hedge funds. Due to data limitations we are unable to construct a full hedge fund sector, so most assets held by hedge funds appear directly on the residually-calculated household balance sheet.

¹²While the SCF question offers examples of items that fall into many of the BEA categories, its prompt begins with a list geared towards items that may have considerable value, as opposed to typical household goods: “for example, artwork, precious metals, antiques, oil and gas leases, futures contracts, future proceeds from a lawsuit or estate that is being settled, royalties, or something else?”

regular household goods that the SCF may miss are more equally distributed, applying the SCF distribution to the Financial Accounts total may overstate inequality. To assess the significance of this potential bias, we group the SCF assets into the twenty-eight BEA consumer durable categories with an eye toward understanding how evenly spread these assets might be. We find little systematic evidence that the SCF more severely underreports consumer durable goods that are likely more evenly distributed (such as “window covering” or “sporting equipment”) than it does for items that are more likely concentrated among the wealthy (such as “jewelry and watches” or “pleasure aircraft”). Thus, we conclude there is little reason to believe that consumer durables not reported in the SCF are distributed significantly differently from those that are reported in the SCF.

2.1 Comparing the Reconciled Balance Sheets

After constructing measures that are conceptually aligned, we assess the degree to which the national aggregates implied by the SCF are numerically similar to those from the Financial Accounts. While close empirical matches are ideal, the measurement approaches employed by the two sources are different enough that we aim for similarity in magnitude more so than a precise match.¹³ Table 2 summarizes the results of the SCF-B.101.h reconciliation exercise by showing the ratio of the two measures for each line of Table B.101.h, for each wave of the SCF since 1989. A ratio of 100% would indicate that the two series match exactly, while lower (higher) percentages indicate that the reconciled SCF understates (overstates) the B.101.h total. Note, the B.101.h and reconciled SCF lines for categories not directly measured in the SCF match by construction. For reference, the figure also shows the level of the B.101.h and SCF series in 2016 in billions of dollars.

Overall, we find that the topline numbers (assets, liabilities, and net worth) from our reconciled SCF balance sheet are quite similar to those from B.101.h. For example, in 2016, reconciled SCF assets aggregate to \$113 trillion, compared with \$105 trillion on B.101.h, and reconciled SCF liabilities aggregate to \$12 trillion, versus \$14 trillion on B.101.h. Averaging across SCF waves, aggregate SCF net worth is very close (at 103%) to B.101.h net worth.¹⁴

¹³One difference between the Financial Accounts and the SCF is that the Financial Accounts typically calculate household holdings of each financial asset category residually by subtracting the holdings of every other sector from the total outstanding (due to the lack of comprehensive aggregate data on household assets). In contrast, SCF households directly report the value of their financial assets in their survey responses.

¹⁴While the match is reasonable in all years, the alignment further improves in recent years. For example,

Looking deeper, we find the two data sets also align reasonably well for most, and importantly the largest, underlying asset and liability categories. Further, while there are numerical discrepancies, Section 4 shows that if we distribute the reconciled SCF totals rather than the B.101.h totals, the overall wealth distribution and the trends over time are little changed. This gives us further confidence that combining the SCF and Financial Accounts provides reliable information about the wealth distribution.

3 Constructing Quarterly Distributional Measures from the Reconciled SCF Balance Sheets

Having shown that the SCF can reasonably approximate B.101.h after appropriate adjustments, the second main challenge in constructing the DFA quarterly is that the SCF is fielded triennially. Thus, we must impute and forecast the reconciled SCF balance sheets for quarters where SCF measures are not available. This “temporal disaggregation” problem of imputing higher-frequency data from lower-frequency observations has been well-studied, beginning with the foundational paper Chow and Lin (1971). We apply the Chow-Lin approach (after assessing several subsequent extensions) to interpolate and forecast quarterly data from the reconciled SCF to quarters where it is not observed. In particular, we use the empirical relationship between the SCF, the Financial Accounts, and other macroeconomic data when all three are observed to impute the SCF data in quarters when only the Financial Accounts and macroeconomic data are available. We apply this method to the reconciled SCF assets and liabilities described in the previous section for four wealth groups: the top 1% of the wealth distribution, the next 9% (i.e., 90th-99th percentile), the next 40% (50th-90th percentile), and the bottom 50%.¹⁵ As a final step in constructing the DFA data, we calculate the share of the reconciled SCF total held by each wealth group each quarter, and multiply these shares by the B.101.h total for each asset and liability to produce the DFA.¹⁶

Section 3.1 and Appendix B present the mathematical details of this method. Section 3.2 shows how we implement the Chow-Lin method, and Section 3.3 presents selected results

in 2016 the ratio of SCF to B.101.h assets, liabilities, and net worth are 100%, 84% and 102%.

¹⁵These wealth groups are chosen to provide a more detailed view of household balance sheets at the top of wealth distribution and to facilitate comparison to other data sources and studies.

¹⁶The details of this final step are presented in Appendix C.

Table 2: The Ratio of the Reconciled SCF Household Balance Sheet to B.101.h

	Ratios in SCF Years														Recent Levels (\$ billion)		
	1989	1992	1995	1998	2001	2004	2007	2010	2013	2016	Average	FA 2016Q3	SCF 2016				
Total Assets	97	91	90	97	108	104	102	106	102	107	100	104,972	112,693				
Nonfinancial assets	97	93	92	99	97	106	114	117	115	110	104	29,651	32,603				
Real estate (1)	108	105	102	110	105	114	123	131	127	119	114	24,528	29,238				
Consumer durable goods (2)	60	48	58	58	64	67	63	62	63	66	61	5,123	3,365				
Financial assets	97	91	89	96	113	103	96	101	97	106	99	75,320	80,090				
Checkable deposits and currency	64	44	49	84	131	182	691	224	126	138	173	993	1,367				
Time deposits and short-term investments	60	63	59	65	58	63	51	54	42	47	56	8,725	4,128				
Money market fund shares	82	80	76	59	72	102	71	93	133	128	90	1,446	1,856				
U.S. government and municipal securities	70	53	54	54	107	96	94	72	81	100	78	3,339	3,343				
Corporate and foreign bonds	88	51	26	31	68	61	59	45	63	105	60	1,146	1,199				
Other loans and advances	333	123	185	63	62	43	34	52	71	53	102	835	447				
Mortgages	110	94	91	84	97	97	102	96	177	275	122	92	254				
Corporate equities and mutual fund shares	143	119	120	131	186	141	111	128	111	129	132	20,606	26,517				
Life insurance reserves**	100	100	100	100	100	100	100	100	100	100	100	1,574	1,574				
Pension entitlements (3)	101	101	96	100	100	100	100	100	100	100	100	24,222	24,285				
Equity in noncorporate business (5)	104	91	80	85	98	91	98	129	109	125	101	11,220	13,994				
Miscellaneous assets**	101	101	100	100	101	100	100	100	101	100	101	1,121	1,126				
Total Liabilities	79	81	79	86	82	89	84	88	86	87	84	13,991	12,144				
Home mortgages (5)	81	85	85	93	89	95	87	92	94	94	90	9,710	9,174				
Consumer credit	59	57	55	60	52	59	65	69	59	68	60	3,574	2,414				
Depository institution loans n.e.c.	1897	3134	278	210	470	-3153	216	89	95	36	327	226	82				
Other loans and advances	99	99	99	97	99	99	98	89	98	99	98	448	441				
Deferred and unpaid life insurance premiums	102	102	99	100	99	99	99	98	98	99	100	33	32				
Net worth	100	93	92	99	112	107	106	110	105	111	103	90,981	10,0549				

Notes:

- (1) All types of owner-occupied housing including farm houses and mobile homes, as well as second homes that are not rented, vacant homes for sale, and vacant land. At market value.
- (2) At replacement (current) cost.
- (3) Includes public and private defined benefit and defined contribution pension plans and annuities, including those in IRAs and at life insurance companies. Excludes social security.
- (4) Net worth of nonfinancial noncorporate business and owners' equity in unincorporated security brokers and dealers.
- (5) Includes loans made under home equity lines of credit and home equity loans secured by junior liens.

from our imputations and forecasts that indicate our method provides reliable estimates of the wealth distribution between SCF observations.

3.1 The Chow-Lin Method of Temporal Disaggregation

The Chow-Lin method assumes that the target series Y (in our case, the level of each reconciled SCF balance sheet line) that requires imputation/forecasting comes from a higher-frequency underlying series X . Let B be the matrix which selects the observed elements Y from the underlying series X . In our application, Y is observed every 3 years, while X is quarterly.¹⁷

$$Y = B'X \quad (1)$$

The Chow-Lin method uses higher-frequency indicator series, denoted here by Z , to impute/forecast the underlying series X . It does this by supposing that X and Z have a linear relationship¹⁸

$$X = \beta'Z + u,$$

where the residual vector u is mean zero with covariance matrix $V = \mathbb{E}[uu']$. Linearity combined with Equation 1 implies that

$$Y = B'Z'\beta + B'u. \quad (2)$$

The Chow-Lin method solves the multiple regression model specified by Equations 1 and 2 to obtain an estimate X given observations Y and Z and covariance matrix V . Chow and

¹⁷Formally, we suppose that $Y = [y_1, y_2, \dots, y_m]'$ is observed m times, with $k - 1$ unobserved periods between observations and e periods to extrapolate after the last observation of Y so that $X = [x_1, x_2, \dots, x_n]'$ with observation y_m of Y corresponding to observation $x_{(m-1)k+1}$ of X . The $n \times m$ matrix B can thus be written as

$$B = \begin{bmatrix} \mathbf{1} & \dots & \mathbf{0}_{(m-1)k} \\ \mathbf{0}_{(m-1)k} & \dots & \mathbf{1} \\ \mathbf{0}_e & \dots & \mathbf{0}_e \end{bmatrix}$$

where $\mathbf{1}$ represents a k -dimensional column vector with one as the first element and zero elsewhere, and where $\mathbf{0}_j$ denotes a j -dimensional column vector of zeros.

¹⁸ Z can be expressed as an $n \times q$ matrix $Z = [Z_1, Z_2, \dots, Z_q]$, where each Z_i denotes a separate column vector $Z_i = [z_{i,1}, z_{i,2}, \dots, z_{i,n}]'$ corresponding to the i^{th} indicator series.

Lin (1971) show that a linear unbiased estimate X is given by

$$\hat{X} = Z\hat{\beta} + VB(B'VB)^{-1}[Y - B'Z\hat{\beta}] \quad (3)$$

$$\hat{\beta} = [Z'B(B'VB)^{-1}B'Z]^{-1}Z'B(B'VB)^{-1}Y. \quad (4)$$

Here, $\hat{\beta}$ is a vector obtained from the generalized least squares regression specified in Equation 2 with Y as the dependent variable, $B'Z$ as the dependent variable, and residual covariance matrix $(B'VB)$.

Equation 3 shows that the estimate \hat{X} can be expressed as the sum of two components. The first component, $Z\hat{\beta}$, represents the predicted values of the higher-frequency target series X given the higher-frequency observations of Z , i.e., $\mathbb{E}[X|Z]$. The second component, $VB(B'VB)^{-1}[Y - B'Z\hat{\beta}]$, reflects the estimate of the vector of higher-frequency residuals obtained by distributing the vector of lower-frequency residuals $[Y - B'Z\hat{\beta}]$ across periods where the target series is unobserved. The distributing matrix $VB(B'VB)^{-1}$ is determined by the assumed covariance matrix V . Note that $\hat{X} = Y$ by construction for the periods that Y is observed.

A key input into this method is the assumed error structure of the higher-frequency residuals, represented by V . This covariance matrix is not observed and must be estimated — any consistent estimate for V can then be used to obtain FGLS estimates $\hat{\beta}$ and \hat{X} . We assess three different versions of this FGLS procedure corresponding to different assumption on the higher-frequency residuals. Our first version follows Chow and Lin (1971) and produces estimates under the assumption that these residuals are first-order autocorrelated. Our second and third versions adopt the methods in Fernandez (1981) and Litterman (1983), who characterize solutions for error processes of the form

$$\begin{aligned} u_t &= u_{t-1} + v_t \\ v_t &= \rho v_{t-1} + \eta_t. \end{aligned}$$

In particular, Fernandez (1981) assumes a random walk ($\rho = 0$), while Litterman (1983) generalizes to a random walk, Markov model ($0 < \rho < 1$). Appendix B provides more detail on the estimation of V in the Chow-Lin, Fernandez, and Litterman methods. Section 5 compares these variants of the Chow-Lin method and shows that they all perform relatively

similarly out-of-sample. We therefore adopt the approach from Chow and Lin (1971) as we are unable to reject this method in favor of more sophisticated models.

3.2 Implementation of the Chow-Lin Method

A key decision in the implementation of this method is the choice of the indicator series Z that give information about the reconciled SCF assets and liabilities for each wealth group — the target series — in time periods when the SCF is not observed. Given the relatively few SCF years available for estimating the indicator-target relationships, we parsimoniously choose the indicator series that measure similar quantities to the target series, capture important developments in the overall economy, or predict changes in the distribution of assets and liabilities across economic groups. Specifically, we use the corresponding quarterly B.101.h series in every interpolation because these series and the aggregate reconciled SCF series are closely related by construction, and the B.101.h series is therefore likely to predict asset and liability levels for each wealth group we consider.¹⁹ We also include the S&P 500 stock index for almost all assets and liabilities, since this series is correlated with price changes for most financial assets and since it tracks overall business cycle dynamics.²⁰ Similarly, for financial assets whose values and flows are closely tied to interest rates, we include the federal funds rate as an indicator variable, and for assets and liabilities related to real estate holdings, we include the Federal Housing Finance Agency (FHFA) home price index. We also include the overall debt-to-income ratio from the Financial Accounts as an indicator series for all of the reconciled liability numbers, as this ratio likely correlates differentially with the liabilities of different wealth groups.

In addition, because changes in the distributions of assets and liabilities are often correlated with an individual’s decision about whether to hold an asset or incur a liability, whenever possible we include indicators for participation in related markets. For example, for all housing-related assets and liabilities, we include the home ownership rate calculated from U.S. Census Current Population Survey (CPS). We also include the ratio of B.101.h defined benefit assets to defined contribution assets as an indicator series for pension enti-

¹⁹Indeed, the B.101.h series are frequently the most important drivers of the interpolation/extrapolation estimates, although the small number of SCF years limits our power to compare the relative contributions of the different indicator series.

²⁰We exclude the S&P 500 as an indicator series when estimating corporate equities and mutual funds because it is too highly correlated with the B.101.h series.

tlements, and vehicle and student loans outstanding from the Federal Reserve’s G.19 data release as indicator series for depository loans and consumer credit, respectively. Appendix Table D.2 summarizes which indicator series are used for each asset and liability class on our reconciled household balance sheet.

3.3 Predictions from the Chow-Lin Method

In this section, we present selected imputation and forecast results to highlight the method’s ability to generate plausible estimates of unobserved movements in household balance sheets. We begin by showing that the DFA makes predictions that are both consistent with broader economic conditions at the time and not apparent from the surrounding SCF observations. The corporate equities and mutual funds category, shown in Figure 1(a), is a salient example. Booms and busts in equity markets often occur in between SCF observations (marked with vertical black lines), and the DFA responds intuitively with the holdings of the top 1%, and to a lesser extent the next 9%, rising and falling sharply. These movements are expected given that wealthier households hold larger and riskier corporate equity and mutual fund portfolios. Panel (b) shows that these movements in equity markets generate spikes and troughs in the top 1% overall wealth share at several points between SCF observations, such as the late 1990s equity boom, the bursting of the tech bubble in the early 2000s, and the Great Recession in the late 2000s.

Although this check is informal, it is still quite informative. For example, different wealth groups’ asset and liability holdings will respond differently to changes in indicator series (as each asset and liability category for each group is modeled separately), resulting in estimated fluctuations in asset and liabilities that vary across our four wealth groups. Confirming that the cross-sectional pattern of these fluctuations is consistent with our prior economic knowledge and intuition, therefore, provides a valuable reasonableness check for our imputation and forecast procedure.

While the Chow-Lin predictions for periods between SCF observations cannot be validated against existing data, an alternative is to employ our interpolation/extrapolation method as if a given SCF observation did not exist, and then compare these predictions to the DFA for that period (which are based upon the omitted SCF observation). For example, we compare the 2013q3 DFA wealth shares to those produced by the Chow-Lin method when we omit the 2013 SCF and, instead, interpolate each period between the 2010 and 2016

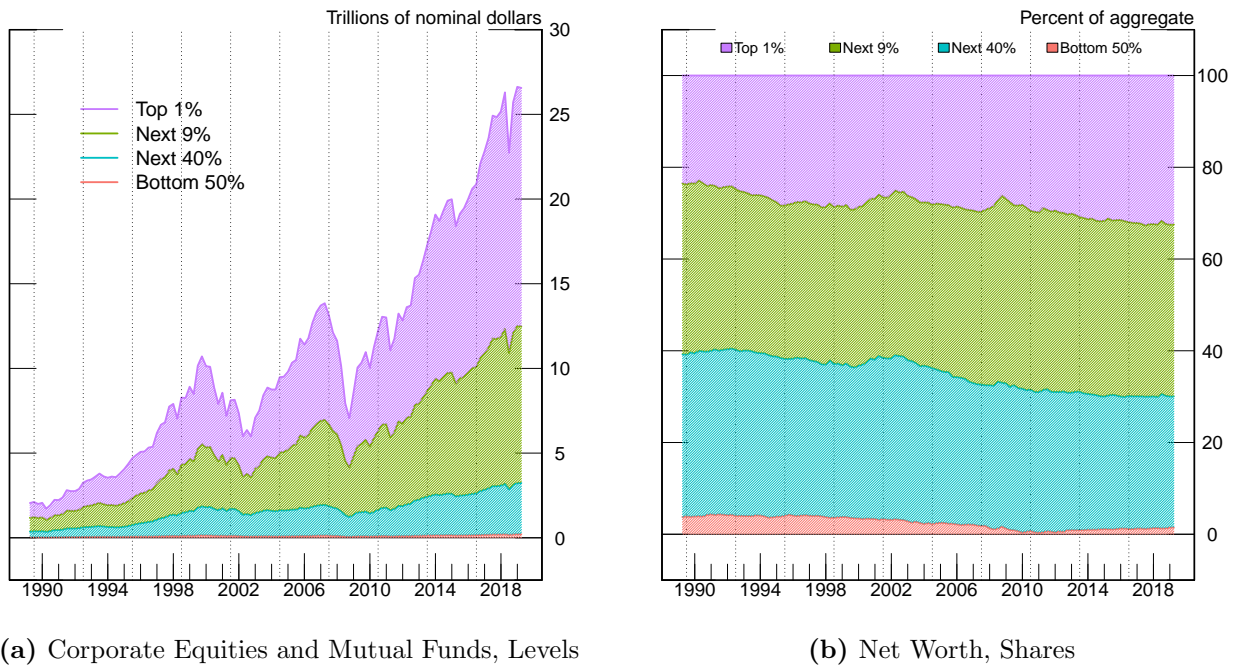


Figure 1: Predicted Corporate Equities/Mutual Funds and Net Worth

SCF waves (which correspond to the 2010q3 and 2016q3 DFA periods). This exercise is considerably more ambitious than the baseline DFA because it interpolates over six years rather than three. Thus, we view it as a useful way to bound the amount of error that we could reasonably expect in the DFA between SCF observations.

Table 3 shows the baseline DFA wealth shares and those from the this “leave-one-out” exercise for each SCF from 2001 through 2016. Overall, the “leave-one-out” Chow-Lin method does an admirable job of replicating the omitted SCF observations. Although there are some modest numerical differences, the exercise does accurately capture important qualitative characteristics of the underlying data such as the top 1% wealth share’s rapid increase before and then dip during the Great Recession and the prolonged decline in the bottom 50% wealth share after the Great Recession. In section 4, we perform similar tests that extrapolate over the Great Recession (assuming SCF releases beyond 2007 are not available) and suggest the DFA could be useful during times of economic turmoil.

Table 3: Deviation from DFA Wealth Distribution

<u>SCF Year</u>	<u>Method</u>	<u>Top 1</u>	<u>Next 9</u>	<u>Next 40</u>	<u>Bottom 50</u>
2001	Excluding this SCF	27.45%	34.60%	34.76%	3.19%
	Baseline	25.95%	35.20%	35.71%	3.14%
2004	Excluding this SCF	27.01%	36.86%	33.52%	2.61%
	Baseline	27.67%	35.80%	34.08%	2.45%
2007	Excluding this SCF	30.67%	37.49%	30.81%	1.03%
	Baseline	29.68%	37.62%	30.80%	1.90%
2010	Excluding this SCF	27.27%	38.62%	33.05%	1.07%
	Baseline	28.79%	39.81%	30.84%	0.56%
2013	Excluding this SCF	31.11%	38.30%	29.97%	0.61%
	Baseline	30.43%	38.52%	30.17%	0.88%
2016	Excluding this SCF	30.65%	38.54%	29.29%	1.52%
	Baseline	31.74%	38.32%	28.70%	1.24%

Notes: This table shows the DFA wealth shares for SCF periods and the wealth share predicted by the Chow-Lin method when that SCF is omitted.

4 The DFA in Action

The DFA breaks down aggregate B.101.h wealth and its components into four wealth percentile groups for the United States as a whole: top 1%, next 9%, the next 40%, and the bottom 50%. The DFA also gives wealth breakdowns along demographic characteristics: income, age, generation (birth cohort), and race. This section presents some high-level takeaways from the DFA, as well as how these data compare to other sources of information on wealth inequality. We also show examples of how the frequency and timeliness of the DFA provide new insights, and we present results split by generation as an application of the available demographic information. The full dataset is available via an interactive visualization tool and for download here: <https://www.federalreserve.gov/releases/efa/efa-distributional-financial-accounts.htm>.

4.1 Headline Results

The DFA shows wealth inequality is high and has grown considerably since 1989. Figure 2 shows the level and share of total net worth for the four wealth percentile groups. The top 10% of the wealth distribution — the purple and green areas together — hold a large and

growing share of U.S. aggregate wealth, while the bottom half (the thin red area) holds a tiny share. While the total net worth of U.S. households has more than quadrupled in nominal terms since 1989 (Panel (a)), this increase has accrued more to the top of the distribution than the bottom (Panel (b)). In 2019, the top 10% of U.S. households controlled more than 70 percent of total household wealth, up from 60 percent in 1989. The share of the top 1% of the wealth distribution increased from 23.5 percent to 32.5 percent over this period. The increase in the wealth share of the top 10% came primarily at the expense of households in the 50th to 90th percentiles of the wealth distribution (blue region), whose share decreased from 35.5 percent to 28.6 percent over this period. In addition, Panel (a) shows that the bottom 50% of the wealth distribution experienced virtually no increase in their nominal net worth over the last 30 years, resulting in a fall in total wealth share from 4 percent in 1989 to just 1.5 percent in 2019.

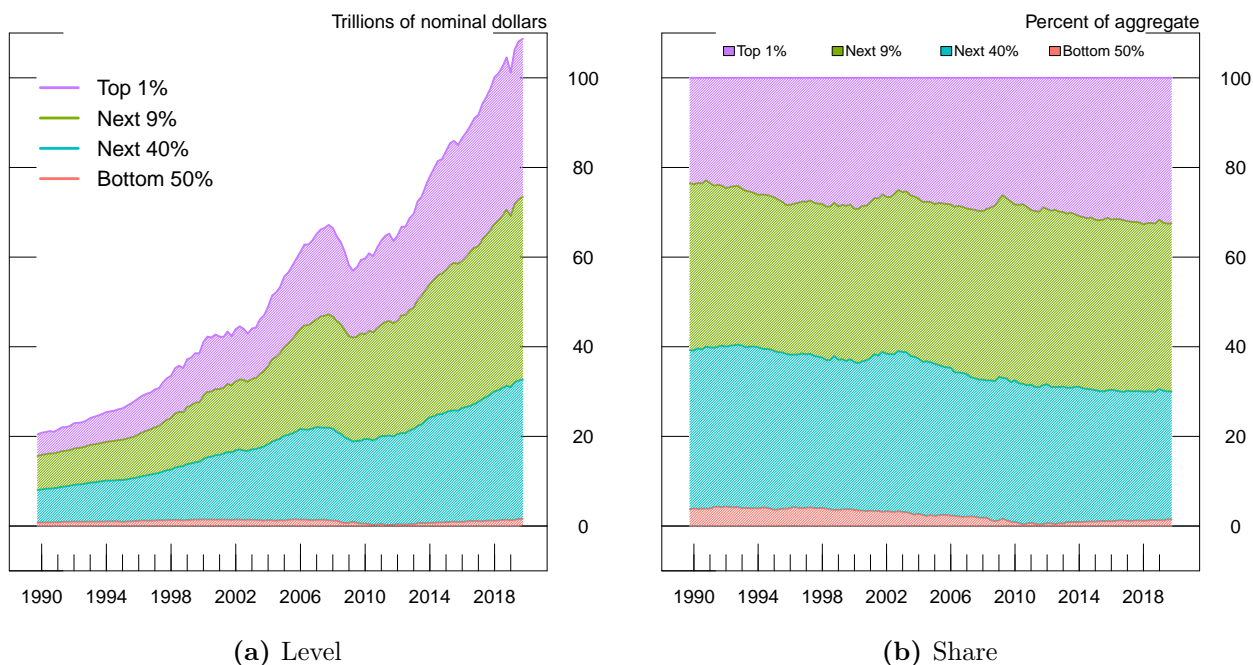


Figure 2: Net Worth by Wealth Percentile Group

The rise in wealth inequality stems primarily from asset accumulation of the top 1% percent, and to a lesser extent the next 9%, as opposed to an accumulation of debt throughout the middle and bottom of the distribution. Figure 3(b) shows the share of assets held by the top 10% of the wealth distribution rose from 55 percent to 64 percent since 1989, with asset shares increasing the most for the top 1% of households. In contrast, figure 3(b) shows that

liabilities have remained much more evenly distributed, on net, since 1989.

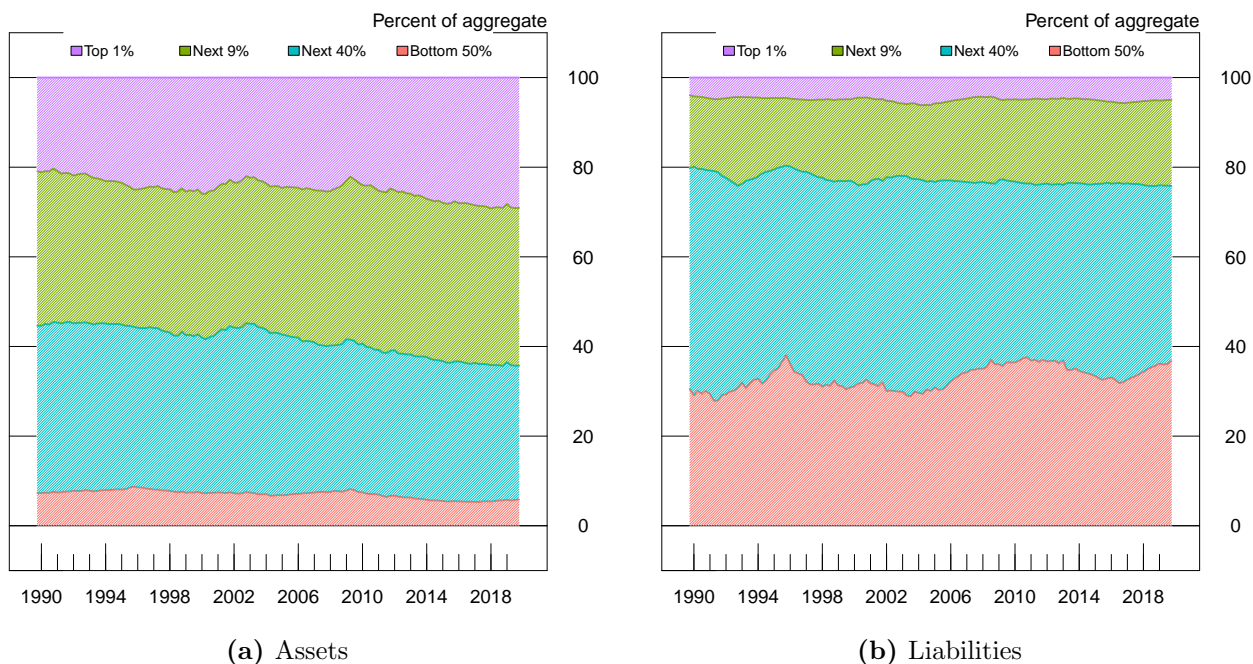


Figure 3: Total Asset and Liability Shares by Wealth Percentile Group

Figure 4(a) and (b) show that business equity is largely held by the top of the distribution. Business equity comprises nearly one-third of all household assets and is the largest driver of the increase in concentration over time. This category includes the value of both corporate and noncorporate business but not equities held through pension funds and annuities (which are included in pension entitlements). The distribution of these assets has long been skewed: in 1989, the richest 10% of households held 82 percent of corporate equity and 80 percent of equity in noncorporate business. Since 1989, the top 10%'s shares of both corporate and noncorporate equity have increased, on net, to 88 percent. Furthermore, only the top 1% has gained share in these assets. The top 1% shares of corporate equities and noncorporate business increased by 10 and 13 percentage points, respectively, while the next 9% fell by 5 percentage points each. As shown in 4(c), pensions are spread more evenly, at least through the top half of the wealth distribution, and have not contributed to the growing share of the top 1 percent. Instead, they are the primary reason the next 9% has shown a small increase in its overall wealth share since 1989, with its share of pension entitlements increasing by 6 percentage points. Real estate (4(d)) is also more evenly distributed and has contributed

more modestly to growing inequality. The top 1% gained 5 percentage points, while the next 9% remained stable, and the bottom 50% actually experienced an increase of nearly 2 percentage points, on net.

4.2 Comparison with Other Distributional Statistics

The high and increasing wealth inequality documented in the DFA is broadly consistent with other studies, but there are also subtle differences that are interesting to explore.²¹ Figure 5 plots our wealth shares along with those from the World Inequality Database (WID) and Smith et al. (2019), which are the most comparable datasets to the DFA.²²

The DFA shows a somewhat more equitable distribution of wealth than the WID and a more gradual increase in inequality over time (Figure 5(a)). Specifically, the wealth share of the top 1% in the WID is consistently several percentage points above that of the DFA, while the reverse is true for each other wealth group. Over time, the top 1% share has grown more quickly in the WID, particularly since 2007. The top 1% is also the only group that experienced sustained growth in the WID, whereas the next 9% in the DFA also gained wealth share for much of the 1990s and 2000s.

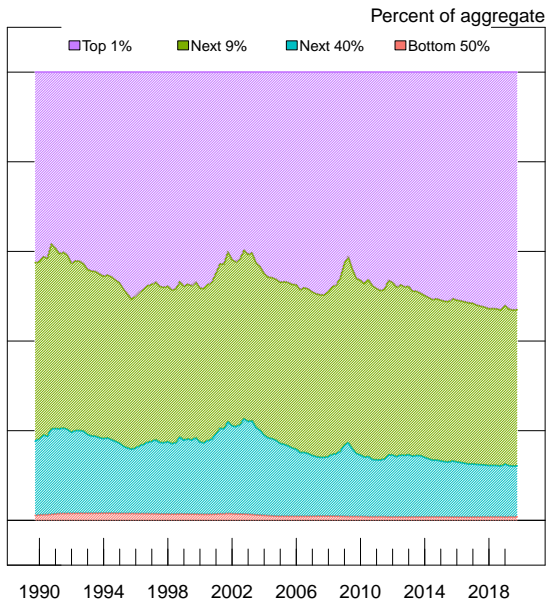
Some of the differences between distributional measures in the DFA and the WID are due to methodology. Both the DFA and WID data distribute aggregate wealth in the Financial Accounts. Unlike the DFA, the WID is based on the distribution of realized income and an assumed relationship between income and components of wealth.²³ As in Saez and Zucman (2016), this relationship is assumed to not vary by wealth, so that realized asset rates of return are the same for wealthy and non-wealthy families.²⁴ As shown in Bricker et al. (2016), these methodological differences account for most of the discrepancy in the concentration measures observed in the WID versus the SCF, and play a particularly large role in the WID's sharper increase in the top 1% wealth share in the years following the Great Recession.

²¹For example, see Wolff et al. (2012), Piketty (2013), Bricker et al. (2016), Saez and Zucman (2016), Rios-Rull and Kuhn (2016), and Smith et al. (2019)

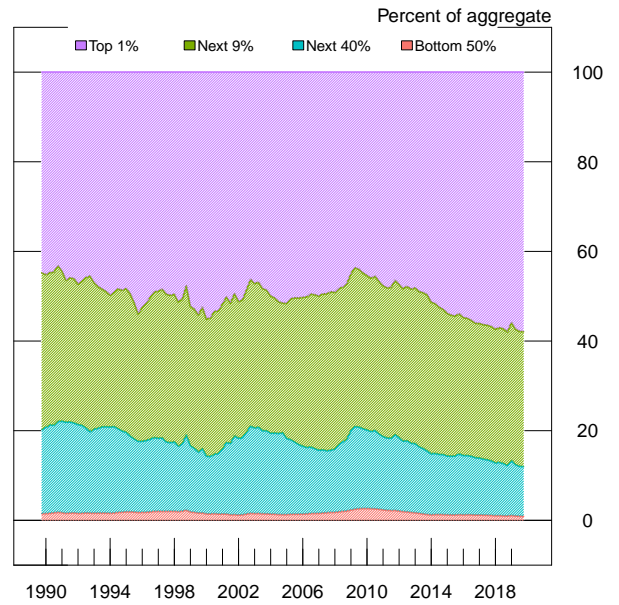
²²The WID is a statistical database focused on measures of income and wealth concentration, funded by a consortium of public and nonprofit institutions. See <https://wid.world/> for more information and Alvaredo et al. (2016) for details on the methodology. The wealth shares available for download through the WID website use individual adults as the unit of observation (in contrast to the SCF and thus the DFA, which is at the household level).

²³Also, the WID results are based on distributing data from Financial Accounts Table B.101, rather than Table B.101.h (as is used in the DFA).

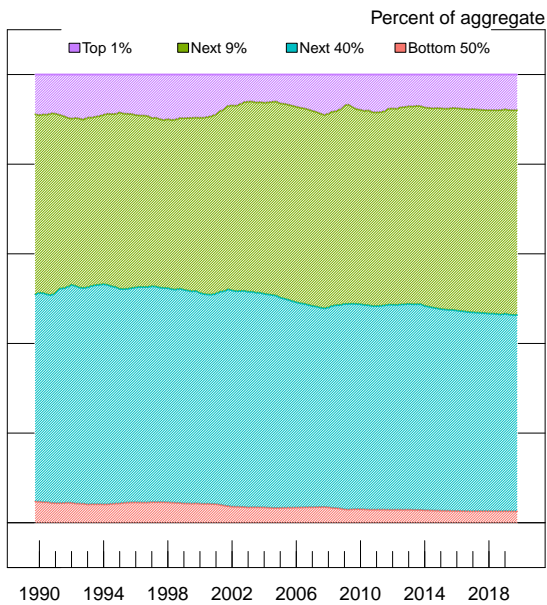
²⁴This method also requires additional assumptions to impute assets and liabilities that do not generate taxable income.



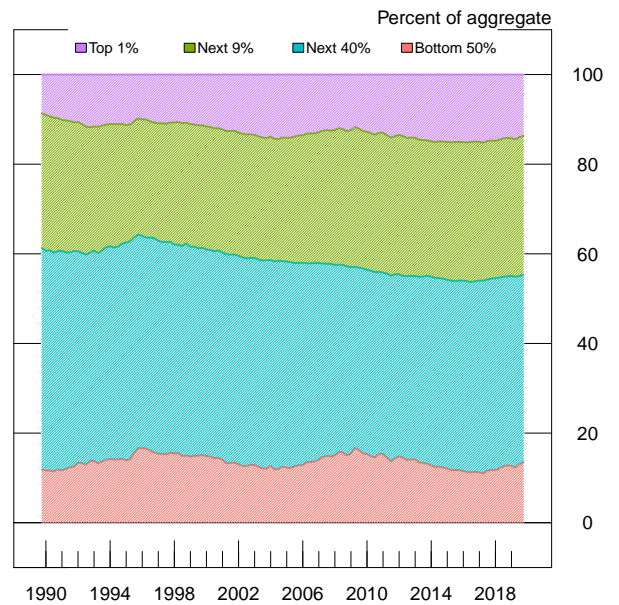
(a) Corporate Equity



(b) Noncorporate Business Equity



(c) Pensions



(d) Real Estate

Figure 4: Pension, Real Estate, Corporate Equity, and Noncorporate Business Equity by Wealth Percentile Group

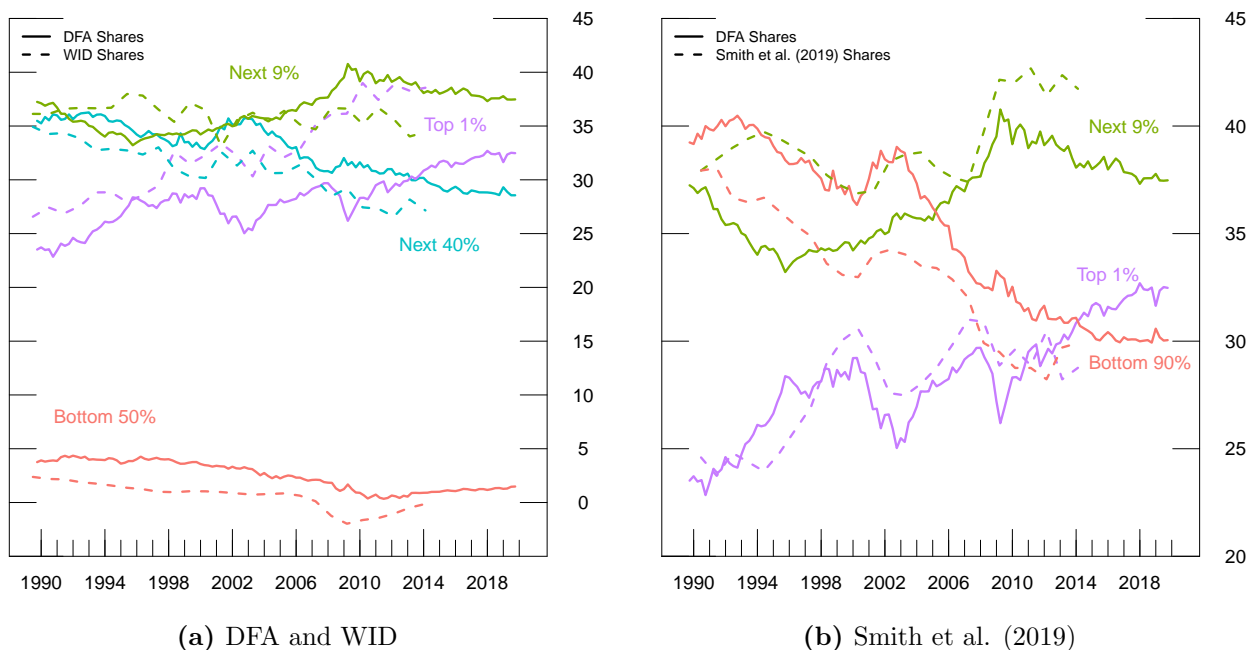


Figure 5: Wealth Shares from the DFA, WID, and Smith et al.

Furthermore, certain asset classes like consumer durables (5% of household wealth) and unfunded defined benefit pensions (6% of household wealth), are omitted from the WID's wealth measure. These are among the more equally distributed assets in the DFA, and their inclusion has a modest overall effect on the distribution of wealth. Still, while the DFA results suggest that the level of wealth concentration among U.S. households is somewhat lower than that shown in the WID, both data sources show a qualitatively similar, increasing trend in wealth concentration (for example, in the share of wealth held by the top 1% in Figure 5(a)).

Recent models have altered assumptions in the WID income capitalization method to allow rates of return on assets to vary by wealth. The model used in Bricker et al. (2018) allows wealthy families to have higher rates of return on interest-bearing assets. The model used in Smith et al. (2019) incorporates this insight, and also places more weight on dividend income, which is more equally distributed than taxable capital gains, to distribute corporate equity wealth.²⁵ In the model preferred by Smith et al. (2019), these assumptions produce a

²⁵These estimates also rely on an improved mapping between real estate taxes and housing wealth, and allow heterogeneous returns in private business equity across industry and business organization. Smith et al. (2019) also deviated from the Financial Accounts by replacing the FA estimate of the value of noncorporate businesses with values of private businesses estimated with Compustat data.

wealth distribution that is less concentrated than the WID, and is quite similar to the DFA (Figure 5(b)).²⁶ In both the DFA and Smith et al. (2019), the top 1% share increases from the low to mid 20s in 1989 to approximately 30% in 2015. The next 9% is relatively flat in the mid to upper 30s over much of the 1990s and early 2000s before increasing around the time of the Great Recession. The bottom 90% share falls consistently over the window, from just below 40% to around 30%.

The SCF itself is also a tool to study wealth inequality. Measures of the wealth distribution derived exclusively from the SCF show somewhat more inequality than the DFA. The most important reason is the inclusion in the DFA of assets and liabilities not directly measured in the SCF (e.g. defined benefit pensions, annuities, and insurance). Appendix D shows a detailed step-wise mapping from the SCF to the DFA. A summarized version is presented below in Table 4.²⁷ Columns (3) and (4) show that these indirectly measured categories are much more equally distributed than those that are directly measured.²⁸ Including these assets and liabilities has a material effect on the overall wealth distribution, lowering the top 1 percent share by nearly two percentage points in the 2010s, increasing the share of the bottom 90, while leaving the next 9 roughly unchanged. It has a particularly large effect for the bottom 50, nearly quintupling their share of total wealth, albeit from a very low starting point. Moreover, the effect of including these imputed categories has grown over time as their share of total net worth has increased from 9.4% in the 1990s, to 10.7% in the 2000s, to 12.4% in the 2010s.²⁹

Another reason the wealth distribution of the DFA differs from that of the SCF is that, as shown in Table 2, even after reconciling the Financial Accounts and SCF conceptually, some categories are larger numerically in the SCF, while others are larger in the Financial Accounts. Column (2) of Table 4 shows what the DFA wealth distribution would be if, rather than using the B.101.h totals, we instead distribute the reconciled SCF balances. Overall, this has a relatively minor effect on the distribution of wealth in each of the time periods, and very little effect on the patterns over time. Thus, we believe that our methodology is

²⁶The data for Figure 5(b) is borrowed with permission from an updated version of Figure 1(b) from Smith et al. (2019).

²⁷See Table D.1

²⁸The indirectly measured categories are DB pensions, annuities, life insurance, miscellaneous assets, other loans and advances, and unpaid life insurance premiums.

²⁹Including certain other assets that are excluded from Table B.101.h, notably Social Security, would presumably have a similarly large effect on the distribution of wealth (see, for example, Feldstein (1974), Deaton et al. (2002), or Love et al. (2009))

robust to the level differences between the Financial Accounts and the SCF.

Table 4: Directly and Indirectly Measured Wealth

<u>Years</u>	<u>Wealth Group</u>	<u>Baseline</u>	<u>SCF Levels</u>	<u>Wealth Breakdown</u>	
				<u>Directly Measured</u>	<u>Indirectly Measured</u>
		<u>(1)</u>	<u>(2)</u>	<u>(3)</u>	<u>(4)</u>
1989-1999	Bottom 50	4.0	4.4	3.5	7.6
	Next 40	35.0	34.8	34.7	38.0
	Next 9	34.8	34.6	34.9	33.6
	Top 1	26.3	26.1	26.9	20.8
2000-2009	Bottom 50	2.4	3.5	1.8	7.3
	Next 40	33.2	32.8	32.0	42.6
	Next 9	36.7	36.2	36.5	35.6
	Top 1	27.7	27.4	30.0	14.6
2010-2019	Bottom 50	1.0	2.1	0.2	5.9
	Next 40	29.7	29.3	28.4	39.6
	Next 9	38.4	37.6	38.8	38.7
	Top 1	31.0	30.9	32.6	15.8

Notes: Table entries indicate the percent share of total wealth for the indicated groups averaged across all quarters in the indicated time periods.

4.3 Insights from Timely, High-Frequency Measures of the Wealth Distribution

A primary advantage of the DFA is that it becomes available several weeks after the quarter close. In contrast, most survey-based data sets that measure the distribution of wealth require lags of at least a year to process the data, and measures using tax data (such as the WID and Smith et al. (2019)) require even longer. These lags limit the ability of users to understand real-time changes in the wealth distribution and how they could relate to policy. For example, Figure 6 shows that since 2014 (the last year the WID is available), the long-term trend of increased concentration at the top has continued in the DFA, with the wealth shares of the top 1% (purple line) rising by nearly 1.5 percentage points. This shift in wealth towards the top of the distribution largely reflects the increased value of business equity over this period. Perhaps surprisingly, the bottom 50% is the other group to gain wealth share over this period as they continue their slow recovery from the Great Recession. Also apparent in Figure 6 are the near-real-time effects of sharp movements in equity markets, such as the decline in late 2018 and recovery in early 2019. The top 1% – whose portfolio

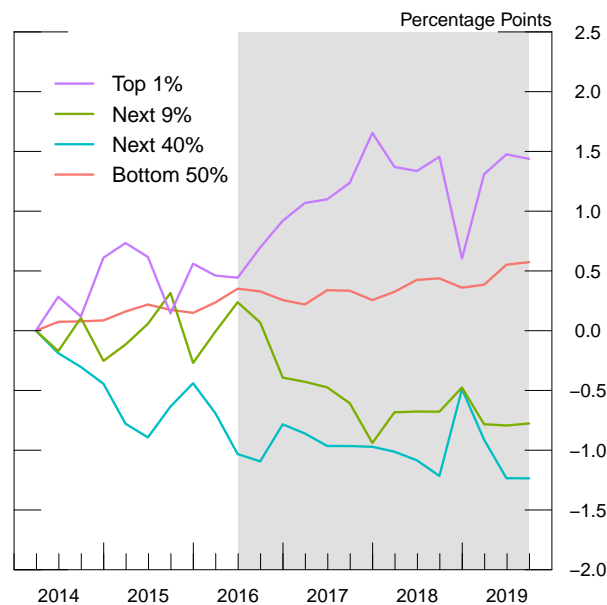


Figure 6: Cumulative Wealth Shares, 2014-Present

Notes: Shaded area represents quarters after 2016, the most recent SCF year. Series shown through 2019Q3, the most recent Financial Accounts release.

is more concentrated in corporate and noncorporate business equity – experienced a sharp 0.8 percentage point decrease in their share of overall wealth. This was mirrored by a sharp increase in the wealth share of households in the 50-90th percentiles, who are much less exposed to business equity risk.

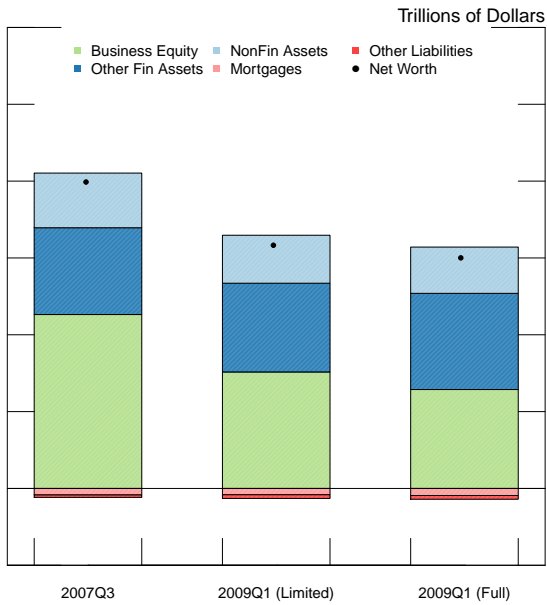
Timely DFA measures could be especially valuable in times of economic turmoil. For example, we know that elevated household leverage played an important role in the Great Recession (Mian et al., 2013), and having a current measure of the distribution of household wealth could support policy-making and analysis in similar situations in the future.³⁰ To test the predictive power of the DFA during changing economic conditions, we simulate how the DFA would have evolved in real time during the Great Recession. To do so, we use data from the SCF only through 2007Q3 (i.e., the last available SCF prior to the Great Recession) and forecast household balance sheets for 2009Q1 using indicator series observations through this quarter (e.g., Financial Accounts and other macroeconomic data through 2009Q1). This provides a pseudo “real-time” forecast of household balance sheets at the trough of the S&P 500 during the Great Recession.

³⁰As noted earlier, the 2009 panel re-interview of the 2007 SCF was commissioned to provide a glimpse of household balance sheets for this reason.

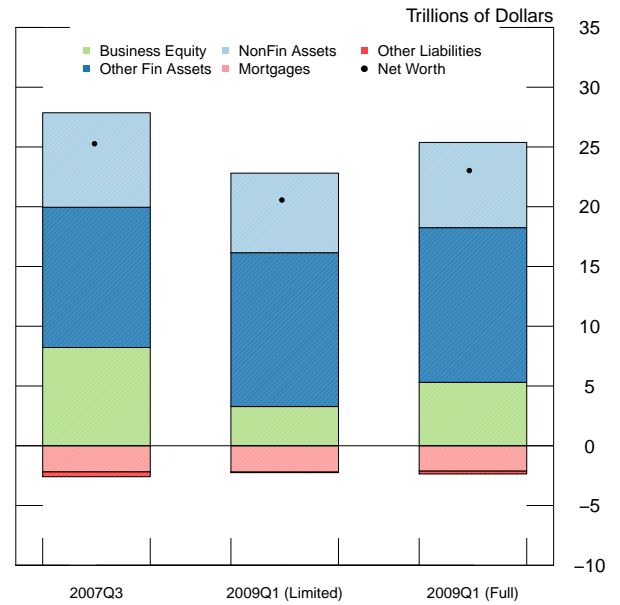
Figure 7 presents results from this exercise for each of our four wealth percentile groups. In each panel, the first bar illustrates the household balance sheet during the quarter of the last pre-recession SCF (2007Q3), the second bar presents our pseudo “real-time” forecast in 2009Q1 based on data available at that time, and the third bar presents the actual household balance sheets estimated from our full data set (i.e., all SCF and Financial Accounts data through 2019Q3). The regions of each bar above the x-axis indicate the level of assets (real estate, other nonfinancial assets, and financial assets), the regions below the x-axis indicate levels of liabilities (mortgages and other liabilities), and the black dots indicate net worth (assets minus liabilities).

For the top 1% of households, comparing the first and second bar in Figure 7(a) shows that our pseudo real-time DFA forecast predicts a significant fall in net worth during the Great Recession. Comparing the asset categories indicated on these two bars, we observe that this decrease in net worth was driven by both a fall in the value of real estate (light blue region) and in the value of financial assets (green region) due to drops in corporate and noncorporate business equity. In contrast, comparing the regions below the x-axis on the first and second bars indicates small changes in the level of liabilities. Comparing the second and third bars in Panel (a) provides a check on the accuracy of our forecast for the top 1%. Although there are some small differences (for example, our forecast underestimates the fall in net worth by about \$1 trillion, or 5% of the pre-recession level), the key qualitative changes in the household balance sheet of the top 1% are confirmed by comparing our pseudo real-time forecast with actual DFA data.

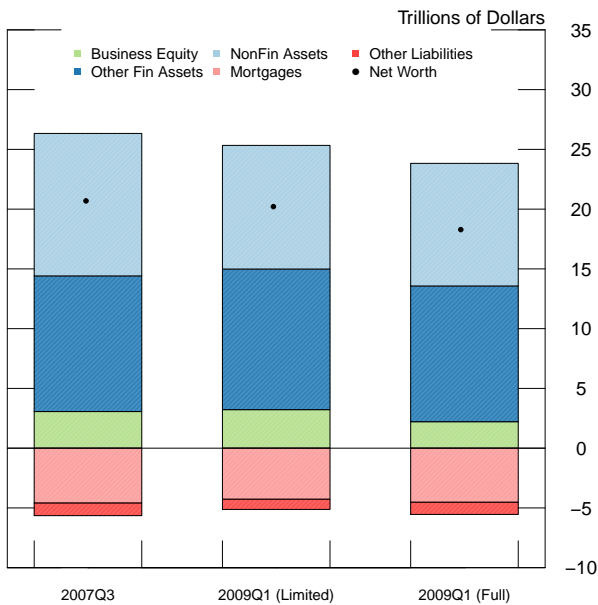
Panels (b)-(d) show that similar patterns hold for households in the next 9%, next 40%, and bottom 50% of the wealth distribution. In each panel, comparing the first and second bars shows that our pseudo real-time forecast predicts a drop in net worth (albeit smaller than for the top 1%) driven by a decrease in the value of real estate holdings. Comparing the second and third bars in each panel shows that our pseudo real-time forecast successfully predicts the qualitative patterns in the actual DFA data, although there are some quantitative differences. For example, our pseudo real-time measures slightly overpredict the decrease in net worth for households in the next 9% and bottom 50% groups (Panels (b) and (d)) and underpredicts the fall in net worth for households in the next 40% group (Panel (c)). Overall, these exercises suggests that the DFA can provide meaningful, real-time insights into the level and composition of wealth across the wealth distribution at economic turning



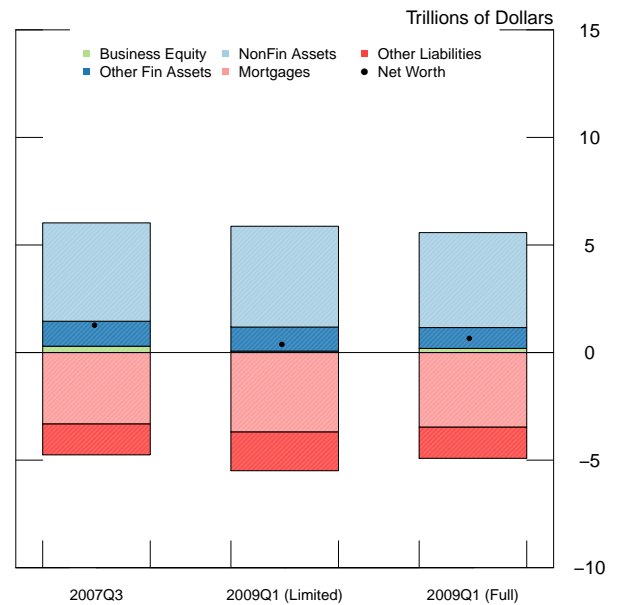
(a) Top 1



(b) Next 9



(c) Next 40



(d) Bottom 50

Figure 7: Household Balance Sheets Across the Wealth Distribution During the Financial Crisis

Notes: The 2007Q3 columns show the DFA balance sheets for 2007Q3 estimated using SCF and Financial Accounts data only through that date. The 2009Q1 (Limited) columns show the extrapolated DFA balance sheets for 2009Q1 using SCF data only through 2007Q3 and Financial Accounts data through 2009Q1. The 2009Q1 columns show the actual DFA balance sheet estimates for 2009Q1 using all available SCF and Financial Accounts data. All panels use the (current) 2018Q4 vintage of the Financial Accounts.

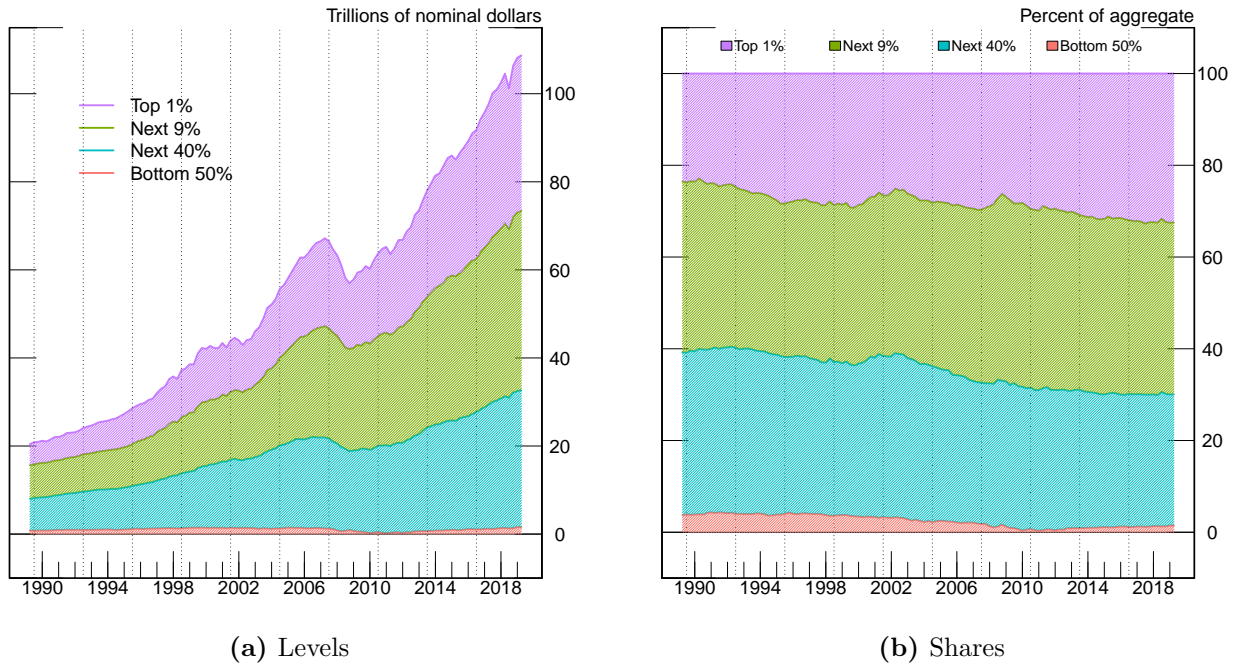


Figure 8: Wealth Levels and Shares in the DFA and SCF

Notes: Vertical lines indicate reconciled SCF observations. Series shown through 2019Q3, the most recent Financial Accounts release.

points.

Another important contribution of the DFA is to provide quarterly observations of the wealth distribution, thus making detailed household balance sheets for different segments of the wealth distribution available across business and credit cycles. Such insights about the evolution of the distribution over business cycles have been limited in existing data sets, as peaks and troughs of asset price and credit cycles often fall between measurements.

The quarterly fluctuations in the wealth distribution captured by the DFA are clearly visible in Figure 8. This figure overlays the DFA levels (Panel (a)) and shares (Panel (b)) with the triennial observations from the reconciled SCF (indicated by the vertical black lines). In Panel (a), we notice a sharp drop in net worth for all wealth percentile groups between 2007Q3 and 2009Q1, with outsized wealth losses for the top 1% of U.S. households (purple region), followed by a recovery that fairly quickly surpassed its 2007 peak. Similar patterns are apparent for the other wealth groups, though with slower and more gradual recoveries. Looking at wealth shares, Panel (b) shows a decrease in the wealth share of the top 1% from 2007Q3 to 2009Q1, followed by a steady increase in wealth share over the subsequent years.

A second illustration of higher-frequency dynamics visible in the DFA is the business cycle between 1998 and 2001. In this case, the net worth of the top 1% of households increased rapidly from 1998 to 1999 but plateaued from 2000-2001 following the burst of the dot-com bubble, a pattern not seen among the other wealth groups. These panels illustrate how the DFA can be used to see higher-frequency detail than is available using the SCF waves.³¹

4.4 Demographics and the Wealth Distribution: Generational Trends

Another contribution of the DFA is the ability to study how wealth is related to a set of demographic characteristics collected from SCF respondents. The DFA currently includes wealth splits by income, education, race, age, and generation (birth cohort). As an application, we explore here generational trends in wealth accumulation. The generation definitions we use are: Silent =born before 1946, Baby Boomer=born 1946-1964, Gen X=born 1965-1980, and Millennial=born 1981-1996. Figure 9(a) shows the evolution of net worth by generation over time. Naturally, generations gain wealth through their adult working years, slowly at first and then more rapidly through middle age. We see the Silent Generation's wealth peak before the Great Recession and then experience very little gain over the next decade. In contrast, Baby Boomers also experience a dip during the Great Recession, but recover by mid-2010. They now have nearly double the wealth of their pre-recession peak and control more wealth than all of the other generations combined (57% of the total). The main driver of the Baby Boomer's notable post-crisis increase in wealth can be seen in panel (b), which shows their large and growing share of corporate and noncorporate equity during the bull market years post-2009.

Of course, the Baby Boomers are a large generation, while the youngest members of the Silent Generation are now in their mid-70s, so their population is shrinking much faster than the other groups. For example, over 50% of households were headed by a member of the Silent Generation at the beginning of our sample, and that number has since fallen steadily to under 15%. Boomers made up slightly over 40% of households until the early 2000s, and have slowly declined to just under 35%. In contrast, Millennials have increased steadily to over 25% of households. Figure 10(a) adjusts for population size to show that the Baby Boomers have caught up to, but not materially surpassed the Silent Generation on a per

³¹The SCF fielded a panel re-interview survey in 2009 of 2007 SCF respondents in order to capture some of the wealth dynamics of the Great Recession. We do not use this data in constructing the DFA.

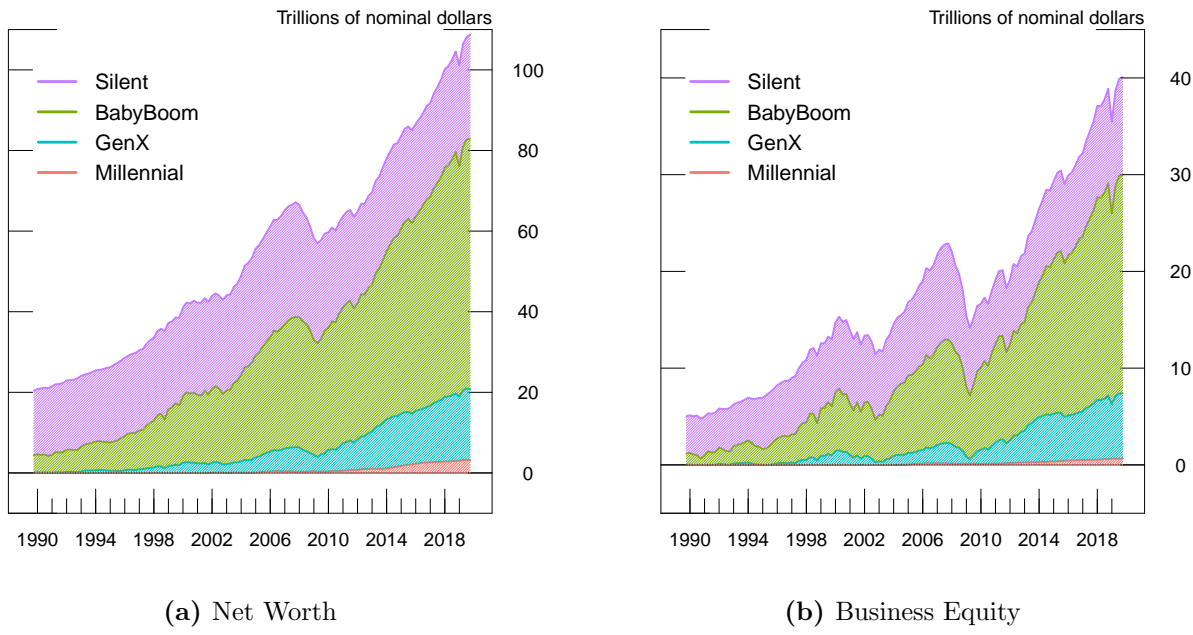


Figure 9: Net Worth and Business Equity Levels by Generation

household basis. The per household wealth gain for Millennials is also muted because the aggregate gains are largely driven by more members of this generation becoming independent heads of households.

Wealth accumulation has a strong life-cycle component, so the generational wealth comparisons in any given calendar year reflect the different ages of the generations to a significant degree. Figure 10(b) presents a more apt comparison of different generations at similar points in their lives. It shows the per household wealth (in 2019 dollars) for each generation at the midpoint of its age range at a given point in time. This comparison reveals that Baby Boomers are well ahead of the pace of the Silent generation. The post-recession bull market that Baby Boomers experienced in their 50s and 60s widened their lead at those ages substantially, but even at the depths of the Great Recession, the average Baby Boomer household was more than \$200,000 richer in real terms than the average Silent household was 20 years earlier. Generation X is largely on pace with the Baby Boomers. Although more often than not, the average wealth of Generation X is slightly below that of Baby Boomers, the only substantial deviations occur when one of the generations is experiencing a strong bull or bear market. For example, Generation X falls behind in the late 30s because they are hit by the Great Recession, and the Baby Boomers pull ahead in the mid-40s as they are

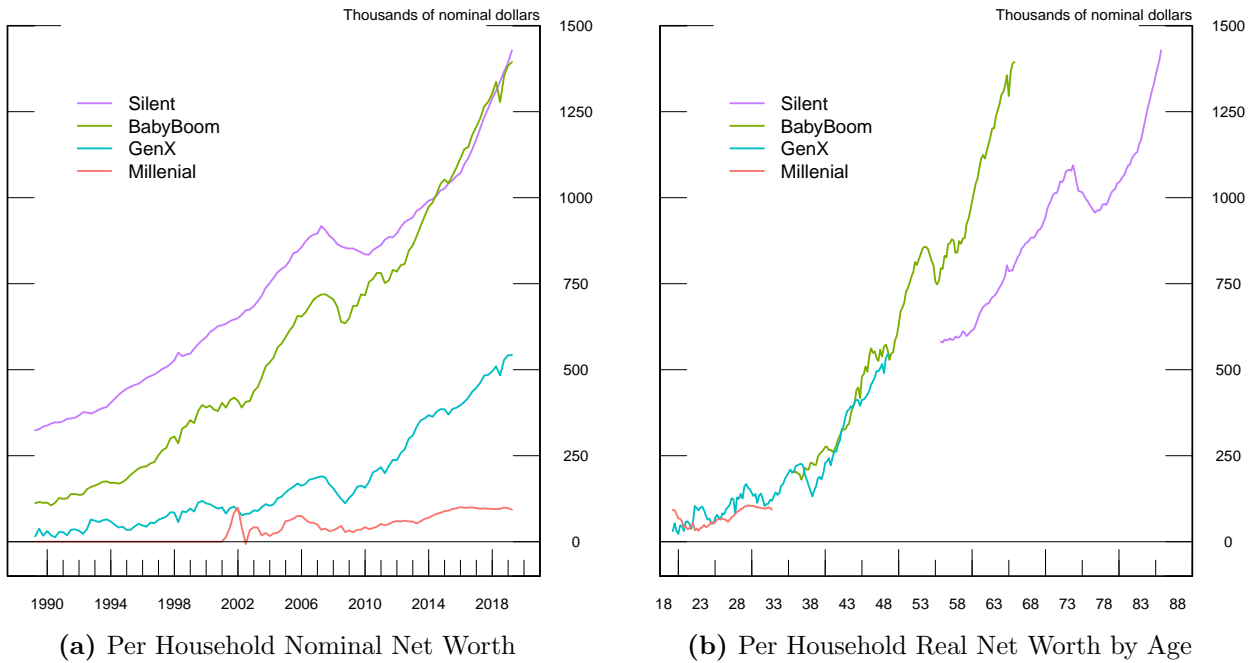


Figure 10: Per Household Net Worth by Generation

riding the tech boom of the late 1990s. In the most recent data for Generation X, the gap with the Baby Boomers is negligible. In contrast, Millennials are more consistently behind Generation X in early adulthood. Over their 20s and early 30s, the net worth of Millennials is an average of nearly \$30,000 (or 27%) below that of Generation X at the same ages. This is consistent with Millennials having struggled to find financial footholds after entering the workforce in the poor labor markets surrounding 9/11 and the Great Recession, which is a narrative that has gained traction in academic work and the popular press (e.g. Rinz (2019), Gale et al. (2020), and Van Dam (2020)).

5 Robustness and Sensitivity Analysis

In this section, we test the sensitivity of our results to alternative assumptions in the data reconciliation step, to sampling variability in the SCF, and to different imputation and forecasting procedures.³²

³²Sampling variability refers to the uncertainty in any sample statistic stemming from the fact that no sample perfectly represents the population from which it is drawn. Because sampling the entire population is infeasible, any survey-based measure will have some sampling variability. As noted above, the SCF intentionally over-samples high-wealth households in order to reduce sampling variability at this end of the

In previous sections, we showed that the asset and liability levels in the Financial Accounts and the SCF are generally comparable, and that distribution of wealth would be quite similar if we instead distributed the reconciled SCF totals. However, at two points in the reconciliation process, we make choices for constructing the SCF analogs that are guided as much by empirical match as they are by conceptual compatibility. These are the valuations of (a) noncorporate business equity and (b) closely held corporate equity (the latter includes S and C corporations and is part of the B.101.h category corporate equity and mutual funds). The SCF records both a subjective market value (i.e. what the respondent says the business could sell for) and the cost basis used for tax valuation for each. In both cases, the Financial Accounts valuation is below the SCF market value, above the SCF cost basis, but close to the average of the two. As a result, the DFA distributes the relevant B.101.h categories based upon an average of the two SCF valuations. Table 5 shows that the results are robust to using either the SCF market value or cost basis. Columns (3) and (4) deviate from the baseline by no more than two tenths of a percentage point, and columns (4) and (5) deviate by no more than one tenth of a percentage point. This implies that while the SCF market and tax valuations differ substantially in level, they are distributed similarly across the survey population, with market value slightly more concentrated than the cost basis value.

We next investigate how precise the results are as a result of sampling variability in the SCF. Because the wealth distribution is known to be highly skewed, the SCF survey design goes to great lengths to oversample wealthy households in order to accurately capture the top of the distribution.³³ Nonetheless, as in any survey, sampling variability is present. To evaluate the impact of SCF sampling variability on the DFA estimates, we bootstrap the SCF balance sheet following the procedure described in Bricker et al. (2017a).

The results are shown in Table 6. While sampling variability is evident, its effects (as measured by the standard errors) are generally modest. Even among the top 1% of households — where sampling concerns are most commonly raised — the standard errors are generally 1% or less in years after 1989.³⁴

As mentioned in section 3, we consider three distinct temporal disaggregation models

distribution.

³³Pure random sampling would lead to relatively few observations at the top of the wealth distribution, which would, combined with increased rates of non-response among high wealth households, increase sampling variability.

³⁴Standard deviations of wealth shares and other balance sheet items are notably larger in 1989 than subsequent years because the 1989 oversample of wealthy households was only about 60% the size of subsequent surveys.

Table 5: Sensitivity of Net Worth Shares to Alternative Balance Sheet Definitions

<u>Years</u>	<u>Wealth Group</u>	<u>Baseline</u>	<u>Closely Held Equity</u>		<u>Non Corporate Business</u>	
			<u>Market Value</u>	<u>Cost Basis</u>	<u>Market Value</u>	<u>Cost Basis</u>
		<u>(1)</u>	<u>(2)</u>	<u>(3)</u>	<u>(4)</u>	<u>(5)</u>
1989-1999	Bottom 50	4.0	3.9	3.9	4.1	3.9
	Next 40	34.9	34.7	35.0	34.9	35.1
	Next 9	34.8	34.7	34.9	34.8	34.9
	Top 1	26.3	26.7	26.2	26.4	26.2
2000-2009	Bottom 50	2.4	2.4	2.4	2.4	2.4
	Next 40	33.2	33.1	33.4	33.3	33.1
	Next 9	36.7	36.6	36.8	36.9	37.3
	Top 1	27.7	27.9	27.5	27.8	27.6
2010-2019	Bottom 50	1.0	1.0	1.0	1.0	1.0
	Next 40	29.7	29.6	29.8	29.7	29.7
	Next 9	38.4	38.3	38.6	38.3	38.5
	Top 1	31.0	31.1	30.7	31.1	30.9

Notes: Table entries indicate the percent share of total wealth for the indicated groups averaged across all quarters in the indicated time periods. Column 2 excludes B101.h balance sheet lines not directly measured in SCF (i.e., life insurance reserves, pension entitlements, miscellaneous assets, and deferred and unpaid life insurance premiums). Column 3 excludes balance sheet lines for which the reconciled SCF and B101.h balance sheet lines differ by more than 25% historically (i.e., corporate and foreign bonds, time and saving deposits, consumer durables, consumer credit, and depository institution loans). Columns 4-6 substitute our baseline real estate and noncorporate business series for the series indicated in the column heading.

that vary based on their assumptions about the error process: Chow Lin (1976), Fernandez (1981), and Litterman (1983). Because there are only 10 observed SCF waves, coefficients for our indicator series, and thus our target series estimates, are unlikely to be statistically distinguishable across models. Nevertheless, below we employ objective criterion to select Chow-Lin as our baseline imputation and forecast model. Reassuringly, these three approaches yield qualitatively similar results.

We construct four different measures of forecast accuracy, all of which compare model predictions made as if we did not have the data from one or more SCF waves to the actual DFA in the time period of the missing SCF. Specifically, we calculate the sum of squared differences between the model prediction and the DFA across the 19 B.101.h wealth categories for each of the four wealth groups. The 2013 forecast uses only the SCF observations from 1989-2010 to predict the 2013Q3 values. In other words, we pretend that our sample ends in 2010, use our method to forecast to 2013, and then compare our forecasts to the actual reconciled SCF totals. The 2016 forecast does the same using the 1989-2013 SCF observations. The 2010 imputation uses the 1989-2007 and 2013-2016 SCF

Table 6: Average Net Worth Shares and Standard Errors from 999 Bootstrap Samples for Each Wealth Group in Selected SCF Years

<u>Year</u>		<u>Wealth Groups</u>			
		<u>Top 1%</u> <u>(1)</u>	<u>Next 9%</u> <u>(2)</u>	<u>Next 40%</u> <u>(3)</u>	<u>Bottom 50%</u> <u>(4)</u>
1989	Share (%)	23.2	37.4	35.7	3.7
	s.e.	1.9	2.3	2.8	0.4
1998	Share (%)	27.4	34.4	34.6	3.6
	s.e.	0.8	0.9	0.8	0.2
2007	Share (%)	29.4	37.7	31.0	1.9
	s.e.	0.9	0.7	0.6	0.2
2016	Share (%)	31.3	38.5	29.0	1.2
	s.e.	0.7	0.7	0.6	0.1

observations to predict the values for 2010Q3, and the 2013 imputation predicts 2013Q3 using the 1989-2010 and 2016 SCF waves. Table 7 presents the results.

The predictions of each model are generally quite similar, and the total-wealth and wealth-by-percentiles total squared errors (TSEs) rarely differ substantially. For reference, the total household net worth that grew from \$62 trillion in 2010, to \$75 in 2013, and \$90 trillion in 2016. With that context, the 2013 forecast errors are very low, about \$4-5 trillion, while the 2016 forecast errors are somewhat larger at \$23-24 trillion. Both the 2013 and 2010 imputation errors are quite modest (\$5-7 trillion). Since none of the candidate methods distinguishes itself, we conclude that the choice of error process is not critical in our application, and we adopt the Chow-Lin method because it performs well and is simple to implement.

6 Conclusion

In this paper, we introduced the Distributional Financial Accounts, a new data set that integrates microdata with a national accounting framework to provide quarterly, timely information on the distribution of U.S. household wealth. These data make several new contributions that we expect will support research on the wealth distribution. For example,

Table 7: Comparison of Candidate Forecasting and Imputation Models

	<u>Sum of Squared Errors (\$ Trillion)</u>		
	Chow-Lin	Fernandez	Litterman
	<u>1</u>	<u>2</u>	<u>3</u>
2013 Forecast	5.2	4.3	4.3
2016 Forecast	24.2	23.0	23.0
2010 Imputation	5.1	6.6	6.9
2013 Imputation	7.0	6.7	6.7

Notes: Each table entry shows the sum of squared errors between the forecast/imputation values calculated excluding the relevant SCF and the values from the DFA that period. The errors are summed across the 19 B.101h wealth categories and the four wealth groups

the DFA comprehensively integrates macroeconomic aggregates with direct observations of detailed household-level balance sheets. With this approach, we find that that wealth concentration has increased in a way that is broadly consistent with prior work, though with a somewhat lower measure of the share of wealth held by the top 1% than in some other studies. Another important contribution is the timeliness of the DFA updates. This provides an ability to look at near-real-time trends in the wealth distribution, which could be useful during times of economic turning points or volatility. In addition, the ability to measure distributional changes at a quarterly frequency allows for study of the relationship between the wealth distribution and business cycle fluctuations. Finally, building from the SCF’s detailed household-level information allows for studying how wealth relates to a range of demographic characteristics.

As part of the Financial Accounts of the U.S., the DFA is intended to contribute to a global conversation about national statistics and the distribution of household wealth. We hope the DFA will become a valuable tool that furthers understanding of the wealth distribution in the United States and around the world. We encourage policymakers, researchers, and other interested parties to explore and use the DFA data, which are now available at <https://www.federalreserve.gov/releases/efa/efa-distributional-financial-accounts.htm>, where

it will be updated on a quarterly basis going forward.

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A Full Reconciliation Methodology

A.1 Reconciliation of Assets

A.1.1 Nonfinancial assets

Real estate (\$24.5 trillion, or 23% of total assets in 2016Q3)

Real estate is the second largest asset category in the Financial Accounts. The reconciled SCF measure of residential real estate differs slightly from the typical “bulletin” SCF measure (Bricker et al. (2017a)) in that it does not include income-producing residential real estate but does include real estate holdings of vacant land. With these adjustments, aggregate real estate measures in the Financial Accounts and SCF align reasonably well until the mid-2000s but diverges somewhat more since. The gap between the two measures was around 10% before the mid-2000s, then increased considerably to 31% by 2010, and has since declined somewhat to about 19%. Important methodological differences drive the divergence between the SCF and Financial Accounts measures of housing wealth measures during the mid-2000s housing cycle. Specifically, the SCF is based upon owner-reported values, whereas the Financial Accounts measure is derived from Zillow’s large-scale automated-valuation model (AVM) that uses property sales and characteristics to estimate values for a substantial fraction of all domestic residential properties.³⁵ Gallin et al. (2018) show that owner self-reports and AVM approaches can diverge notably during housing downturns and recoveries, likely due in part to lags in owner self-reports during market turns.

Consumer durable goods (\$5.1 trillion, or 5% of total assets)

This category, taken from the BEA’s stock of fixed assets and consumer durable goods, captures many durable assets: automobiles, trucks/motor vehicles, furniture, carpet/rugs, light fixtures, household appliances, audio/video/photo equipment, computers, boats, books, jewelry/watches, health and therapeutic equipment, and luggage, among others.

The SCF asks specifically about cars and other vehicles, which account for about 30% of B.101.h consumer durables. For the remaining assets, the SCF asks “Other than pension assets and other such retirement assets, do you (or anyone in your family living here) have any other substantial assets that I haven’t already recorded...?” If families indicate that

³⁵For more information about this measure, see Gallin et al. (2018) and Hall et al. (2018).

they own any such assets, they are queried about the type of the asset and its value. We sum all nonfinancial assets included in responses to this question to obtain our reconciled SCF measure of consumer durable goods.

The SCF reports fewer consumer durables than the Financial Accounts, with the ratio typically around 60%. This occurs in large part because the BEA measure covers essentially any item that has resale value, whereas the SCF focuses on the most substantial assets.³⁶ To the extent that these significant assets are concentrated among the wealthy, and the regular household goods that the SCF may miss are more equally distributed, applying the SCF distribution to the Financial Accounts total may overstate concentration. To assess the significance of this potential bias, we group the SCF assets into the twenty-eight BEA consumer durable categories with an eye toward understanding how evenly distributed across the wealth distribution these assets might be. We find little systematic evidence that the SCF more severely underreports consumer durable goods that are likely more evenly distributed (such as “window covering” or “sporting equipment”) than it does for items that are more likely concentrated among the wealthy (such as “jewelry and watches” or “pleasure aircraft”). Thus, we conclude there is little reason to believe that consumer durables not reported in the SCF are distributed significantly differently from those that are reported in the SCF.

A.1.2 Financial assets

It is relatively straightforward to assign financial assets directly held by SCF households to the appropriate B.101.h categories (e.g., directly held stocks and mutual funds are assigned to the B.101.h category “corporate equity and mutual fund holdings”).³⁷ However, we must make additional assumptions to assign financial assets that are held indirectly through IRAs, trusts, and managed investment accounts.³⁸ For these types of investment vehicles, the SCF asks what percentage of holdings are invested in equities versus interest-bearing assets. Using this percentage, we assign the share of these assets that are invested in equities to “corporate

³⁶While the SCF question offers examples of items that fall into many of the BEA categories, its prompt begins with a list geared towards items that may have considerable value, as opposed to typical household goods: “for example, artwork, precious metals, antiques, oil and gas leases, futures contracts, future proceeds from a lawsuit or estate that is being settled, royalties, or something else?”

³⁷One difference between the Financial Accounts and the SCF is that the Financial Accounts typically calculate household holdings of each financial asset category residually by subtracting the holdings of every other sector from the total outstanding (due to the lack of comprehensive aggregate data on household assets). In contrast, SCF households directly report the value of their financial assets in their survey responses.

³⁸Defined-contribution retirement accounts are included with pension plans, as described below.

equity and mutual fund holdings.” For the non-equity share, since we do not directly observe the composition of the interest-bearing assets, we use the Investment Company Institute Fact Book (Collins (2018)) and IRA Database (Holden and Bass (2018)) for the relevant year to estimate the breakdown, assuming each SCF respondent holds a representative portfolio. Below we describe each financial asset category in detail.³⁹

Checkable deposits and currency (\$993 billion, or 1.0% of total assets)

This category includes checking accounts and physical cash. The SCF total is the sum of all checking accounts (excluding checkable money market-type accounts), cash held by families, the value of prepaid debit cards, and an estimate of deposits in foreign institutions. Although the two measures align well conceptually, they differ empirically, with the SCF consistently below B.101.h in the early years (by an average of 33%), and above B.101.h since 2001 (by an average of more than 155%).⁴⁰

Time deposits and short-term investments (\$8.7 trillion, or 8% of total assets)

This category includes savings accounts, certificates of deposit, money market accounts through banks, and a small amount of foreign deposits. The SCF measure is the sum of savings accounts held at financial institutions, assets held in certificates of deposit, assets held in money market accounts at depository institutions, and a share of assets held in IRA accounts, trusts or managed investment accounts. Again, the measures align well conceptually, but differ empirically. The SCF measure is consistently below the B.101.h measure, historically ranging around 40-60% of the B.101.h total.

Money market fund shares (\$1.4 trillion, or 1.4% of total assets)

The SCF captures direct holdings of money market mutual funds in both checkable and non-checkable accounts at non-depository institutions. The SCF measure of money market mutual funds that are held indirectly through IRAs, trusts, and managed investment accounts are estimated using the imputation approach described above. The relationship between the SCF and B.101.h measures varies across time, with the SCF as much as 50% larger to 27% lower across the years.

³⁹Unless noted otherwise, each category below is calculated residually in the Financial Accounts.

⁴⁰In particular, there is a notable mismatch right before and after the financial crisis due to a significant drop in the B.101.h measure in 2007. We suspect this is due to measurement error in the Financial Accounts, but there also appears to be a long-term trend of checkable deposits and currency growing faster in the SCF than in B.101.h.

US government and municipal securities (\$3.4 trillion, or 3% of total assets)

This category includes Treasury securities, agency- and GSE-backed securities (i.e., securities guaranteed by Ginnie Mae, Fannie Mae, or Freddie Mac), and municipal securities. The SCF records direct holdings of Treasury, GSE, and municipal securities, and we estimate those held indirectly through IRAs, trusts, and managed investment accounts as described above. The SCF total averages 72% of the B.101.h total, and has been fairly stable since 2004.

Corporate and foreign bonds (\$1 trillion, or 1% of total assets)

This is one of the smallest categories of household assets. The SCF captures directly held corporate and foreign bonds through a variable called “other bonds.” This is a catch-all variable after recording government and municipal bonds earlier in the interview. We add these “other bonds” to an imputed measure of corporate and foreign bonds held indirectly through IRAs, trusts, and managed investment accounts (imputed using the approach described above). The SCF total is typically somewhat lower than the B.101.h total, averaging 55%.

Other loans and advances (\$835 billion, or 0.9% of total assets)

This small category includes cash accounts at brokers and dealers. To construct a counterpart in the SCF, we add call accounts to the SCF measure of other unclassified loans, excluding land and mortgage contracts. This reconciled SCF series is fairly close to the B.101.h measure, averaging about 102%.

Mortgage assets (\$92 billion, or 0.1% of total assets)

This tiny category (the smallest of the household asset categories) includes mortgages issued by households (i.e., seller-financed mortgages, including land contracts), as opposed to mortgages owed by households, which are a liability. To construct a comparable measure in the SCF, we sum variables that measure mortgages and other land contracts owed to the respondent. Historically, this reconciled SCF measure averages 122% of the B.101.h measure.

Corporate equities and mutual funds (\$20 trillion, or 20% of total assets)

This is a large asset category for households, behind only pension wealth and real estate among the B.101.h assets.⁴¹ The corresponding SCF measure comprises directly held stocks and mutual funds, and the portion of other investment vehicles that are invested in equi-

⁴¹This category does not include equities and mutual fund shares owned through DC pensions, which are accounted for below in pension entitlements.

ties (such as IRAs, trusts, managed investment accounts, 529 plans, and Health Savings Accounts). In addition to incorporating the indirectly held equities described above, two additional complications exist for the corporate equities and mutual fund category. First, similar to equity in noncorporate business, the value of closely held corporations (S and C corporations) are reported in the SCF at both market value as cost basis. The market and cost-basis valuations in the SCF also straddle the Financial Accounts valuation, and we again employ the average of the SCF measures in the DFA. Section 5 shows our results are also robust to using either the SCF market or cost-basis valuations. Second, the SCF’s bulletin measure of mutual funds includes an “other” category that is comprised largely of hedge funds. Hedge funds are not explicitly captured in the Financial Accounts, meaning that the underlying assets held by hedge funds are included in the applicable B.101h categories. We use a preliminary estimate of the breakdown of hedge fund assets from a supplemental Financial Accounts hedge fund table in development to assign the SCF hedge fund assets to the proper B.101h categories. After these adjustments, the SCF measure is somewhat above the B.101h measure, averaging about 130% historically.

Life insurance reserves (\$1.6 trillion, or 1.5% of total assets)

Since life insurance policies are not traded in a secondary market, insurance companies calculate their policy values using models. These estimates are known as life insurance reserves, and represent the amount insurers are required to hold for future payment of benefits.⁴² Because these reserves are generally not known by policyholders, the SCF does not contain a directly comparable measure. Instead, we use relevant information captured by the SCF to distribute the B.101.h total across SCF households, which means that the gap is zero by construction.

We distribute life insurance reserves as follows. There are two types of life insurance measured in the SCF: term and permanent policies. The SCF records the death benefit of term life insurance policies, and both the death benefit and the cash surrender value of permanent life insurance policies.⁴³ We assume that the death benefit and cash surrender value are generally proportional to the reserve, and that these relationships do not systematically

⁴²The Financial Accounts capture this information from insurers’ statutory financial statements.

⁴³Permanent life insurance policies pay the death benefit whenever the policyholder dies, whereas term insurance policies only pay the benefit if the policyholder dies within a predetermined period (often 5 to 30 years). The death benefit is typically a large multiple of the reserve, whereas the cash surrender value is often significantly below the reserve (due to surrender penalties or other product features that are not immediately redeemable for cash).

vary across the wealth distribution.

The statutory financial statements (with which the B.101.h measure is constructed) report death benefits separately for permanent and term policies, but not the corresponding life insurance reserves. We perform reserve calculations described below for a set of sample insurance policies to estimate the mapping between death benefit and reserves. We then distribute these two estimated B.101.h reserve totals to SCF households according to their SCF-reported death benefits for term policies and surrender values for permanent policies.

To do so, we calculate the reserves by policy year for a set of hypothetical policies with a death benefit of \$1. Permanent insurance is represented by whole life, and term is represented by 5, 10, 15, 20, and 30-year level-premium products. We use the 2017 loaded Commissioner’s Standard Ordinary (CSO) gender-blended composite age-nearest-birthday (ANB) mortality table, and a valuation interest rate of 3.5%. The reserve in each year is the expected present value of future death benefits less the expected present value of future premiums. We calculate a net premium reserve, i.e. the premium rate is set so the reserve is 0 at issue. Figure A.1 shows the results of these calculations for policies issued to a 45 year-old. Products with longer durations build up much larger reserves because the level premiums are above the expected benefits in the early years, and then below them in the later years.

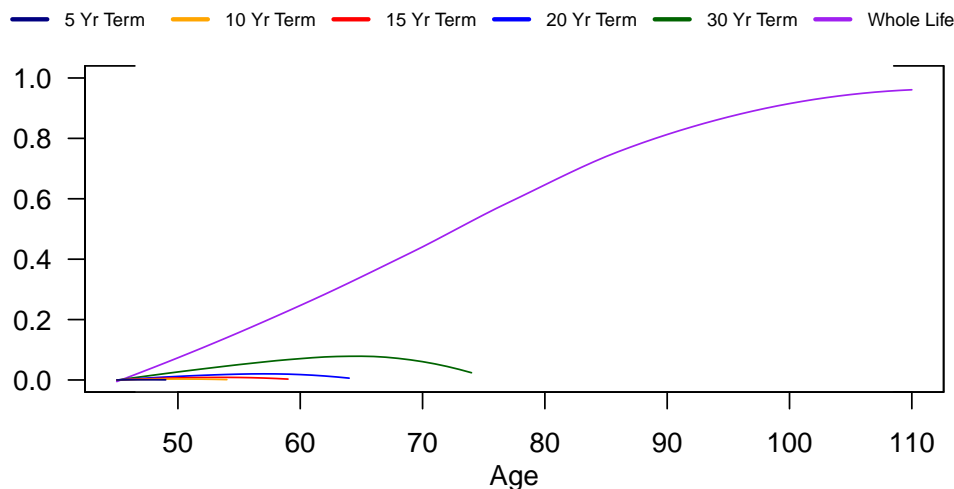


Figure A.1: Life Insurance Reserve per Dollar of Death Benefit for Sample Policies, Issue Age 45

We then calculate a weighted average reserve over the life of each product, with the weight determined by probability the policy is in force each year (assuming the aforementioned mortality rates and a 4% annual surrender rate). We combine the various term insurance

products by assuming the 5, 10, 15, 20, and 30-year products constitute 10%, 25%, 35%, 20%, and 10% of the total, respectively. The resulting numbers for permanent and term insurance represent the relative reserve amounts if each product constituted 50% of the amount in force. We repeat this exercise for policies issued to individuals ages 25 to 65 (at 5-year increments), giving more weight to mid to late middle age where we assume actual policy issuance is concentrated. These calculations imply that permanent insurance would account for approximately 90% of reserves if the in force amounts were split evenly. Finally, we use the actual breakdown of death benefit in force reported each year, which ranges from close to even in the early years of the DFA to approximately 75% term more recently. This results in reserve breakdown estimates that range from 90% permanent at the beginning of our sample to 75% permanent in 2018Q3.

Pension entitlements (\$24.2 trillion, or 23% of total assets)

Pension entitlements make up the largest B.101.h asset category, accounting for nearly a quarter of aggregate household assets. This category includes the balances of defined contribution (DC) pension plans (such as 401(k) and 403(b) plans), accrued benefits to be paid in the future from defined benefit (DB) plans (including those for which life insurance companies have assumed the payment obligation), and annuities sold by life insurers directly to individuals.⁴⁴ These three asset classes account for about 30%, 60%, and 10% of total pension entitlements in the Financial Accounts, respectively.⁴⁵

The SCF captures DC balances in a way that is compatible with the Financial Accounts. The DC aggregates between the two data sources are generally close, with a historical ratio of 97%. However, the SCF does not directly measure accrued DB benefits or annuities.

We utilize information the SCF captures about plan participation and anticipated benefits to distribute the DB component of the B.101.h aggregate across the SCF households. To proceed, we break the SCF households who are entitled to DB benefits into those currently receiving pension payments, those expecting future payments from a past job, and those expecting future payments from a current job. The SCF collects the benefit amount for those currently collecting a pension, and the expected timing and amount of future pension

⁴⁴The annuities component also includes annuities held in IRAs. IRA investments in other instruments, such as mutual fund shares, are included in the other asset categories described above.

⁴⁵The defined-benefit component includes total accrued benefits from private-sector, state-and-local government, and federal employment, whether fully funded or not. Notably, it does not include Social Security, which is not currently included in the Financial Accounts.

benefits from a past job for those who are entitled to a benefit but are not yet collecting benefits. We use this information to calculate the present discounted value of the future income stream for these two groups. Finally, we allocate the remaining B.101.h DB assets (obtained residually as the B.101.h DB total net of the present value of future income streams calculated above) to those SCF respondents who have a plan tied to their current job but are not yet receiving benefits.⁴⁶ We use the respondents' current wage, years in the plan, and age to determine the allocation.⁴⁷

Measures of annuity reserves, like accrued DB pensions, are not directly collected by the SCF in a manner comparable to B.101.h. However, the SCF does report information that can be used to impute the value of annuities for SCF households. Specifically, the SCF reports the amount of income received from annuities that are in the payout phase, as well as the cash value of deferred annuities (which differs from the reserve due to surrender penalties and other policy benefits not immediately payable in cash).⁴⁸ To reconcile the SCF and B.101.h annuity measures, we capitalize the payout annuity income reported by SCF households into a present value using a set of sample annuity policies (see below), and then distribute the B.101.h annuity reserves according to the sum of the cash value of deferred annuities and capitalized value of payout annuities reported in the SCF.

The actuarial calculations supporting the distribution of individual annuity reserves capitalize the SCF-reported periodic payment for payout annuities into an expected present value. We again use the 2017 loaded CSO gender-blended composite ANB mortality table and a valuation interest rate of 3.5%. For each age between 0 and 120, we calculate the present values of \$1 received annually for the life of an individual, and \$1 received annually for the life of the last surviving spouse. We then multiply the annual payout annuity benefits reported by each SCF household by the appropriate annuity factor based upon the age and

⁴⁶Benefits for workers with current job plans are calculated residually for two primary reasons. First, this allows direct mapping to the Financial Accounts aggregate, the best estimate of DB assets that belong to households. Second, the SCF does not capture the generosity of DB pension plans, which is a crucial parameter required to calculate accrued DB assets.

⁴⁷All DB estimates rely on differential mortality defined by age group, marital status, race, education, and income quantile. See Sabelhaus and Volz (2019) for a more detailed description of the DB imputation methodology.

⁴⁸In contrast to traditional annuities, deferred annuities are savings products offered by insurance companies. The account balance of some of these products accumulate at a rate set by the insurer, usually subject to a minimum guarantee determined at the time of sale. Others offer equity market participation, often with some type of embedded return guarantee. These products are called annuities because the policyholder has the option to later annuitize the value of the policy into periodic payments, but exercising this option is not typical.

marital status of the head of household.

Equity in noncorporate business (\$11.2 trillion, or 11% of total assets)

This category includes non-publicly traded businesses and real estate owned by households for renting out to others. There are substantial differences in its measurement between the SCF and Financial Accounts. The B.101.h measure is a hybrid of different accounting bases. Real estate (e.g., rental properties), which accounts for approximately 60% of this category, is recorded at market value. In contrast, other nonfinancial assets are recorded at cost basis, based on investment data collected by the BEA, while financial assets and liabilities are recorded at book value from tax data.

In the SCF, rental properties are reported at market value, as they are in the Financial Accounts. For other noncorporate business assets, the SCF captures owners' self-reports of both the market value and the cost basis of their businesses. When we compare these two measures to B.101.h, we find (unsurprisingly) that the market-value SCF measure exceeds the B.101.h measure (with an average ratio of approximately 150%), while the cost-basis SCF measure falls below the B.101.h measure (with an average ratio of 70%).⁴⁹ To reconcile the SCF and B.101.h, we use the average of the two SCF valuations, because it tracks the B.101.h measure quite well empirically, with an average ratio of 101%, and because, in certain ways, the B.101.h measure does blend the two SCF measures. In Section 5, we test the sensitivity of our results to this choice and find minimal distributional implications because the SCF market and cost basis measures are roughly proportional to each other across most of the wealth distribution.

Miscellaneous assets (\$1.1 trillion, or 1.1% of total assets)

This small category includes receivables due from property-casualty insurance companies, the value of other policies from life insurance companies (excluding reserves for life insurance coverage and annuities — for which we already accounted above), and government-sponsored retiree health care fund reserves. None of these assets are observed in the SCF, so we distribute the B.101.h total to SCF households based upon related data that is captured by the SCF, as described below.

The largest miscellaneous category is receivables from property and casualty insurance (PC) policies, accounting for approximately 50% of miscellaneous assets. These assets arise

⁴⁹Despite the level differences between the B.101.h and the two SCF measures, all three series exhibit similar trends over time.

because households pay in advance for the term of coverage, and can receive a prorated refund upon cancellation. Most PC policies owned by households cover either homes or automobiles. In order to distribute the B.101.h measure of PC insurance receivables across SCF households, we split the amount into auto and home insurance according to the relative premium volume reported by insurers. We then distribute the auto insurance reserves in proportion to SCF reported value of automobiles, and the home insurance reserves in proportion to the SCF reported value of residential real estate.

The value of other life insurer policies includes reserves for accident and health insurance policies, which accounts for approximately 25-30% of miscellaneous assets. This covers a wide array of products, but major categories include long-term care and disability insurance (as opposed to what we more traditionally think of as health insurance). As with life insurance and annuities, the B.101.h values for this component are based upon net present value calculations performed by insurers and reported in statutory financial statements. The SCF contains very little information about ownership or the value of these types of insurance policies. Therefore, we utilize the relationship between ownership of these policies and income in the Health and Retirement Study (HRS) to assign a share of the B.101.h total to each income decile in the SCF.⁵⁰

Other miscellaneous assets arising from life insurers include life insurance claims that have been incurred but not yet paid, which we distribute in proportion to the SCF-reported death benefit of life insurance policies (either term or permanent), and the dividends that insurers owe holders of participating life policies, which we distribute according to the cash surrender value of permanent policies.⁵¹

The final component of miscellaneous assets are reserves for future retirement health benefits given to uniformed service members and postal workers. We distribute these B.101.h assets evenly among SCF respondents who are current and former members of the military

⁵⁰Specifically, we calculate the fraction of total long-term care insurance policies reported in the Health and Retirement Study (a representative panel of Americans over age 50) that are owned by each income decile, and then distribute that same fraction of B.101.h accident and health insurance reserves equally across each SCF household within each income decile. The mismatch in age distribution between the SCF and HRS requires us to assume that the distribution of ownership by income percentiles is invariant to age. This assumption is untestable in existing data sources, but given the small size of this category, it will have negligible effects on our data set.

⁵¹Participating policies are sold by mutual insurers (i.e. insurers that are owned by policyholders). Dividends are the mechanism by which these insurers return profits to the owners. Although we cannot observe in the SCF which life insurance policies are participating, we distribute the dividends over only permanent life policies because it is more common for them to be participating than it is for term policies.

or postal service.

A.2 Reconciliation of Liabilities

Home mortgages (\$9.7 trillion, or 70% of total liabilities)

Home mortgages represent the bulk of household liabilities. In the Financial Accounts, they are derived from measures of residential home mortgage loans as reported by lenders.⁵² In the SCF, households report the remaining balance on their mortgages. Historically, the SCF series tracks quite closely with the B.101.h measure, with an average ratio of 90%.⁵³

Consumer credit (\$3.6 trillion, or 26% of total liabilities)

Consumer credit, which makes up most of the rest of household liabilities, includes credit card, student loan, and vehicle loan balances, as well as other loans extended to consumers. In the Financial Accounts, the data come from the Federal Reserve’s G.19 statistical release.⁵⁴ These data measure outstanding credit extended to individuals for household, family, and other personal expenditures, excluding loans secured by real estate. The total outstanding balance as of the recording date is collected monthly from the holders of the debt.

For student loans, vehicle loans, and other installment loans reported by households during the month of the survey, the SCF measure is conceptually similar to that in the Financial Accounts. In contrast, for credit cards (26% of the B.101.h measure of overall consumer credit in 2016Q3), the SCF measures the revolving balances (i.e., balances carried over to the next month), whereas the Financial Accounts measure includes these revolving balances in addition to “convenience use” that is paid off in full at the end of each month before it begins accruing interest. Convenience use is more common among wealthier households, and its inclusion in the Financial Accounts measure and not the SCF measure may affect our distributional results. However, convenience use accounts for only about 30% of credit card use (or about 7% of the overall B.101.h consumer credit measure) in 2016Q3, suggesting this conceptual difference is unlikely to have significant effect on the overall reconciliation of consumer credit measures across the two data sets.

Overall, the SCF measures are consistently below the B.101.h measures, averaging ap-

⁵²Mortgages on rental properties are included in the calculation of equity in noncorporate businesses.

⁵³Note, the reconciled SCF measure used in the DFA differs from the SCF bulletin measure because the former excludes rental properties.

⁵⁴See <https://www.federalreserve.gov/releases/g19/current/default.htm> for G.19 details.

proximately 50% for credit card debt, 65% for auto and student loans, and 59% overall.⁵⁵ The remaining household liability categories are relatively small, together making up about 5% of B.101.h liabilities.

Depository institution loans not elsewhere classified (\$226 billion, or 1.6% of total liabilities)

This small category includes all depository institution loans to individuals that are not captured above, such as bank overdrafts. These loans are calculated from depository institution regulatory filings, after subtracting loans made to nonprofit organizations. We construct the corresponding measure in the SCF by totaling other lines of credit and loans issued by depository institutions (excluding home equity lines of credit and vehicle loans). The alignment of these two series is generally poor and varies substantially across time, but given that depository loans reflect a small share of overall liabilities, this poor fit is unlikely to affect the wealth distribution overall.

Other loans and advances (\$448 billion, or 3.2% of total liabilities)

Just under two-thirds of this category represents margin accounts at broker-dealers, with most of the rest made up of loans taken against the value of life insurance policies. A small amount represents loans to households from a variety of (mostly housing-related) government programs. The SCF reports the balance of both loans taken against insurance policies and margin loans at stock brokerages. The SCF does not contain information about the various government loans, so we distribute them according to mortgage balance (excluding home equity lines of credit).

Deferred and unpaid life insurance premiums (\$33 billion, or 0.2% of total liabilities)

This tiny category represents amounts payable to insurance companies. Insurers typically allow a period between a premium's due date and when the policy is canceled during which the policyholder keeps the insurance reserve as an asset, but now also has a liability for the premium owed. The SCF does not contain relevant information on unpaid premiums, so we distribute it in the same manner as life insurance reserves (described above).

⁵⁵Some of the difference is due to known measurement differences between the Financial Accounts and SCF, such as the treatment of business credit cards and auto leases. For discussion of measurement of education loans in both the SCF and G.19, see Bricker et al. (2015).

B Estimating Covariance Matrices of the Error Process in the Chow-Lin Methodology

This appendix describes in greater detail how the higher-frequency covariance matrix V is identified in Chow and Lin (1971), Fernandez (1981), and Litterman (1983). Chow and Lin (1971) show how to recover this matrix under two different assumptions about the underlying error process: serial independence and first-order autocorrelation, which is the leading case we pursue in this paper. In particular, they show that if the residuals follow a simple AR(1) process such that

$$u_t = au_{t-1} + \epsilon_t, \tag{5}$$

where the ϵ_t are iid with constant variance σ^2 then

$$V = \begin{bmatrix} 1 & a & a^2 & \dots & a^{n-1} \\ a & 1 & a & \dots & a^{n-2} \\ a^2 & a & 1 & \dots & a^{n-3} \\ \vdots & \dots & \dots & \dots & \vdots \\ a^{3n-1} & \dots & \dots & \dots & 1 \end{bmatrix}$$

$$= A \times \frac{\sigma^2}{1 - a^2}.$$

Substituting Equation 5 into Equations 3 and 4 reveals that a feasible estimate of \hat{X} requires an estimate of a but not σ^2 (the scalar factor $\sigma^2/(1 - a^2)$ cancels in all of the expressions). To estimate a , note that the first order autocorrelation of $[Y - B'Z\hat{\beta}]$ is a^{12} (since SCF data are available every 12 quarters). Iteratively using Equation 5 and Equation 3 and solving for a^{12} by calculating the autocorrelation coefficient of $[Y - B'Z\hat{\beta}]$ until convergence therefore yields a consistent estimate of a , and, by extension, V .

This basic approach has been generalized and extended by several other studies. Notably, Fernandez (1981) and Litterman (1983) characterize solutions for non-stationary error

processes of the form

$$u_t = au_{t-1} + v_t$$

$$v_t = \rho v_{t-1} + \eta_t.$$

Fernandez (1981) assumes $\rho = 0$, while Litterman (1983) assumes $0 < \rho < 1$. In each of these cases, the solution follows the familiar form specified in Equations 3 and 4 with covariance matrix V given by

$$V = [\Delta' H(\rho)' H(\rho) \Delta]^{-1} \times \sigma_\eta^2,$$

where Δ is an $n \times n$ difference matrix with 1 on its diagonal, -1 on its subdiagonal, and zero elsewhere, $H(\rho)$ is an $n \times n$ matrix with 1 on its diagonal, $-\rho$ on its subdiagonal, and zero elsewhere, and σ_η^2 is the variance of the innovations η_t . In particular, Litterman (1983) shows that autoregressive parameter ρ may be estimated by an iterative procedure similar to that proposed in Chow-Lin (1971) using Equations 3 and 4 and the first-order autocorrelation of the first difference of the residuals $[Y - B'Z\hat{\beta}]$.

C Constructing DFA Shares and Levels from Imputed Reconciled SCF Balance Sheets

Following the methodology described in Sections 2 and 3, we produce quarterly measures of the total value of SCF-reconciled assets, liabilities and net worth for households in the top 1%, 90-99%, 50-90%, and bottom 50% of the wealth distribution for all quarters between 1989-present. The final step in producing the DFA is projecting the Financial Accounts data onto the reconciled SCF asset and liability shares. To do so, we define $\gamma_t^{j,p}$ as the level of the asset or liability indexed by balance sheet line j , for wealth quantile group p , in quarter t , and let Γ_t^j denote the corresponding line from the B.101.h balance sheet. Define group p 's asset or liability share of balance sheet line j in quarter t as its share of the total reconciled SCF balance sheet line:

$$\omega_t^{j,p} = \frac{\gamma_t^{j,p}}{\sum_k \gamma_t^{j,k}}$$

To construct the DFA measures of assets and liability levels for each quantile, we multiply these balance sheet shares by the total B.101.h balance sheet line:

$$\bar{\gamma}_t^{j,p} = \Gamma_t^j \omega_t^{j,p}$$

This ensures that the DFA levels of assets and liabilities aggregate to the Financial Accounts household balance sheet table.

For aggregated lines on the household balance sheet (e.g., total assets, total liabilities, net worth, etc.), we aggregate over the calculated DFA balance sheet lines. For example, letting A denote the set of asset lines on the household balance sheet,

$$\begin{aligned} \bar{\gamma}_t^{assets,p} &= \sigma_{j \in A} \bar{\gamma}_t^{j,p} \\ \omega_t^{assets,p} &= \frac{\sum_{j \in A} \gamma_t^{j,p}}{\sum_k \sum_{j \in A} \gamma_t^{j,k}} \end{aligned}$$

Liabilities and liability shares are similarly defined. DFA net worth levels and shares are

defined as

$$\begin{aligned}\bar{\gamma}_t^{NetWorth,p} &= \bar{\gamma}_t^{assets,p} - \bar{\gamma}_t^{liabilities,p} \\ \omega_t^{NetWorth,p} &= \frac{\bar{\gamma}_t^{NetWorth,p}}{\sum_k \bar{\gamma}_t^{NetWorth,k}}.\end{aligned}$$

Because aggregated balance sheet items are constructed from B.101.h balance sheet lines and not reconciled SCF balance sheet lines, the shares of aggregated balance sheet lines for each wealth quantile do not necessarily align with the shares from the SCF.

D Additional Tables and Figures

Table D.1 provides a more detailed description of the differences between the SCF and DFA that are summarized in Table 4. It begins with the wealth distribution from the “bulletin” from the 2016 SCF (Bricker et al., 2017b) and shows the relative importance of including different assets Financial Accounts assets that are not directly measured in the SCF, rescaling assets from the SCF level to the B.101.h level, and making a collection of other minor adjustments. Note, this analysis is based upon a prior vintage of the DFA, and thus is meant to illustrate the significance of each step rather than present an exact mapping from the SCF to the current DFA.

Table D.1: SCF to DFA Steps

	Top 1	Next 9	Next 40	Bottom 50
2016 SCF Bulletin	38.6%	40.1%	20.2%	1.0%
Add DB assets	33.5%	39.6%	25.3%	1.6%
Average cost basis and market value for noncorp bus	32.3%	40.1%	26.0%	1.6%
Add life insurance and annuities	31.6%	40.4%	26.3%	1.7%
Remove SCF misc assets	31.3%	40.2%	26.6%	1.9%
Scale DC assets to FA, include CC convenience use	30.6%	40.6%	27.0%	1.8%
Scale remaining categories to FA levels	30.0%	41.3%	27.6%	1.1%
Add wealth of the Forbes 400	31.6%	40.4%	26.9%	1.1%

Table D.2: Summary of Indicator Series Used in Interpolating and Forecasting Household Balance Sheets

EA Series	S&P 500	FHFA Index	Home Ownership Rate	DB-DC Ratio	Fed Funds Rate	Vehicle Loans	Student Loans	DTI Ratio	NYSE Volume
Real Estate	X	X	X						
Consumer Durable Goods	X		X						
Financial Assets	X		X						
Checkable Deposits and Currency	X				X				X
Time Deposits	X				X				
Money Market Fund Shares	X				X				
US Government and Municipal Securities	X				X				
Corporate and Foreign Bonds	X				X				
Loans	X								
Other Loans and Advances	X				X				
Mortgages	X				X				
Corporate Equities and Mutual Fund Shares	X				X				
Life Insurance Reserves	X				X				
Pension Entitlements	X			X	X				
Equity in Noncorporate Business	X				X				
Miscellaneous Assets	X				X				X
Home Mortgages	X		X					X	
Consumer Credit	X					X	X	X	
Depository Loans N.E.C.	X							X	
Other Loans and Advances	X							X	
Deferred and Unpaid Life Insurance Prem.	X							X	
Net Worth	X	X							

E Forbes Weights Correction

Though the SCF is precluded from sampling from the *Forbes* 400, the wealth of some SCF households is greater than the wealth of some *Forbes* families. As described here, we develop weights to incorporate the wealth of these omitted families into the SCF wealth totals. Our preferred treatment of coverage error involves adjusting the SCF sample weights at the top and including a weighted version of the *Forbes* 400 wealth. We do so in a “combining samples” weighting approach by leveraging the overlap between the *Forbes* wealth and the wealth of some SCF respondents (O’Muircheartaigh and Pedlow (2002)).⁵⁶ The *Forbes* list relies, in part, on public knowledge of wealth (through public filings for publicly traded companies, or through voluntary disclosure). Privately held forms of wealth, for example, can evade such public knowledge.

We begin by creating four wealth bins—(1) the minimum Forbes wealth (F_{min}) in a given year to $1.5 * F_{min}$, (2) $1.5 * F_{min}$ to $2.5 * F_{min}$, (3) $2.5 * F_{min}$ to $5 * F_{min}$, and (4) $5 * F_{min}$ or more—and counting the number of SCF and *Forbes* cases (weighted and unweighted) in the bins.⁵⁷ In each bin (b), we find the relative frequency (RF) of SCF and Forbes cases by the formula

$$RF_{b,d} = (n_{b,d}/N_{b,d}) / [(n_{b,SCF}/N_{b,SCF}) + (n_{b,Forbes}/N_{b,Forbes})] \quad (6)$$

for $d = \{SCF, Forbes\}$, b the four wealth bins as defined above, where n is an unweighted count in bin b , N is a weighted count in bin b , and $RF_{b,t}$ is defined in $[0,1]$.

The combined and adjusted weight is $adjusted_{wgt} = RF_{b,SCF} * SCF_{wgt} + RF_{b,Forbes} * Forbes_{wgt}$, where RF depends on b . With this weight we can use wealth information in the SCF and *Forbes*, weighted properly for the overlap in the two datasets.⁵⁸

⁵⁶We do so in a similar way to how the AP and list sample weights are woven together to create final weights for the SCF (Kennickell and Woodburn (1999)). See, for example, Vermeulen (2018) for a visual of the overlap in the 2010 SCF and the Forbes distribution, as well as Kennickell and Woodburn (1999). This overlap exists in every survey year used in this analysis.

⁵⁷We assume that Forbes families are self-representing with weight of one so the number of weighted cases is equal to the number of unweighted cases. We use the SCF survey weight when considering the SCF cases.

⁵⁸When SCF families with wealth greater than the minimum *Forbes* wealth have a sample weight greater than one, they represent not just themselves but other families with their wealth level. These are presumably families in the *Forbes* list. Thus, the SCF sample weights prior to this weight correction represent some of *Forbes* families.