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Introducing the Distributional Financial Accounts of the United States*

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Abstract

This paper describes the construction of the Distributional Financial Accounts (DFAs), a new dataset containing quarterly estimates of the distribution of U.S. household wealth since 1989, and provides the first look at the resulting data. The DFAs build 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 DFAs complement other existing sources of data on the wealth distribution by using a more comprehensive measure of household wealth and by providing quarterly data on a timely basis. We encourage policymakers, researchers, and other interested parties to use the DFAs to help understand issues related to the distribution of U.S. household wealth.
JEL Codes: E01, H31, H5, N3

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1 Introduction

Wealth concentration is an important characteristic of the United States economy, with evidence mounting that concentration has increased 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 increase in concentration has important implications for a number of 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)).

The explosion of interest in the wealth distribution has also highlighted several limitations of some of the existing data sources. For example, many of the existing measures of the household wealth distribution are not comprehensive in their concept of household wealth, are measured at a relatively low frequency, or are only available with a substantial lag. Separately, scholars who focus on national accounts have expressed interest in incorporating microeconomic heterogeneity into these frameworks.[1]

This paper describes the construction of the Distributional Financial Accounts (DFAs), a new initiative that provides quarterly, timely estimates of the wealth distribution based on a comprehensive measure of U.S. household wealth. The DFAs are constructed by integrating 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 provide quarterly measures of aggregate assets and liabilities for various economic sectors, including households, and the SCF collects detailed measures of a representative sample of household-level balance sheets (including of very wealthy households) every three years. The DFAs combine the SCF's distributional information with the Financial Accounts' quarterly national accounting framework in a manner that is consistent with both data sets. The DFA project is part of the Enhanced Financial Accounts (EFAs)

[1] 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 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 official measures currently in development at the Bureau of Economic Analysis (e.g., Furlong (2014), Fixler and Johnson (2014), Fixler et al. (2017)).

initiative, which seeks to expand the scope of the Financial Accounts by adding additional information from other data sources.[2]

We construct the DFAs in three steps: 1) we generate a balance sheet from the SCF that is conceptually consistent with the components of aggregate household net worth in the Financial Accounts, 2) we interpolate and forecast the reconciled SCF balance sheet for quarters where the SCF is not observed based on information in the Financial Accounts and other sources, and 3) we apply the distribution observed in the reconciled SCF to the Financial Accounts' aggregates. This approach produces rich and reliable measures of the distribution of the Financial Accounts' household-sector assets and liabilities for each quarter from 1989 to the present.

In this paper, in addition to detailing the construction of the data, we highlight three features of the DFAs that we believe will be particularly useful to analysts and researchers, with illustrative findings for each. First, the DFAs provide a comprehensive integration of disaggregated household-level wealth data with official aggregate wealth measures. As detailed below, the SCF directly measures nearly all household assets and liabilities accounted for in the Financial Accounts, and, for the few exceptions, we carefully impute the missing information. The incorporation of household-level asset and liability data reduces the need for strong assumptions to generate a distribution and results in a reliable and detailed measure of the wealth distribution. We find a marked increase in wealth concentration over the last 30 years that is consistent with prior studies, but with somewhat lower overall wealth concentration than measured in other data sets.

A second key feature of the DFAs is the relatively high-frequency of the measures of the wealth distribution, making it suitable for studying the business cycle dynamics of the wealth distribution. For example, with complete balance sheets since 1989, the DFAs show quarterly movements in relative financial positions for each wealth group before, during, and after the dot-com era and the Great Recession. We find that the wealth share of the top 1% was strongly pro-cyclical over this period. In contrast, the wealth share of households in the 90-99th percentiles of the wealth distribution varied counter-cyclically, while the share for households in the bottom 90% of the wealth distribution displayed little cyclical behavior over this period. These dynamics are typically difficult to observe in other data sets because

[2] More information about the EFA initiative, and additional EFA projects, can be found at `https://www.federalreserve.gov/releases/efa/enhanced-financial-accounts.htm`.

peaks and troughs often fall between times of survey measurement.

A third important feature of the DFAs is timeliness. As part of the Financial Accounts, the DFAs will be published about ten or eleven weeks after the end of each quarter, making the DFAs a "near-real-time" measure that can be used for studying recent changes in the wealth distribution. This feature could be especially valuable during turning points or times of economic turmoil. As an example, we note that the long-term trend of increased wealth concentration continued through the 3rd quarter of 2018 but that this trend reversed with the large stock market decline in the 4th quarter of 2018. In addition, we test how the DFA methodology would have performed during the Great Recession and find that the DFA estimates correspond well to the actual data that was published much later.

The paper proceeds as follows. In Section 2, we document the reconciliation between the measurement concepts used in the Financial Accounts and the SCF. In Section 3, we describe how we interpolate and forecast the reconciled SCF-balance sheets to unobserved quarters. In Section 4, we describe a few high-level results and their implications for understanding the distribution of household wealth. In Section 5, we test the sensitivity of these findings to alternative reconciliation approaches and to the sampling variability inherent in the SCF. Finally, Section 6 summarizes the DFA's key contributions and details future plans and extensions.

2 Reconciling the Financial Accounts and the SCF

The first step in constructing the DFAs is reconciling the measurement concepts used in the Financial Accounts and the SCF. To do so, we first organize the components of SCF net worth in a way that is as similar as possible to 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. Next, we generate SCF aggregates and compare the SCF and Financial Accounts aggregates over time. Naturally, this exercise has challenges, but overall reveals that the two datasets are broadly compatible. While we aim to construct close empirical and conceptual matches for each component, our primary goal is to understand the degree of potential bias from applying the SCF distribution to the Financial Accounts total when the match is less than perfect. For example, we are more interested in cases where the two measures differ because only one contains a component that likely skew towards one end of the wealth distribution, and we are less concerned with empirical level differences that are plausibly spread roughly proportionately across the wealth distribution. Based upon these criteria, we find that the two sources align quite well for most components of household net worth.

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, across the two data sets.[3] Our approach is similar in spirit to much of this prior work and extends it in several important ways. First, while prior work has reconciled the SCF (a household survey) with Financial Accounts Table B.101 (which includes nonprofit organizations), for the DFAs we are able to make use of the recently developed Financial Accounts Table B.101.h, which provides a less-detailed breakdown of wealth categories than B.101, but which 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., defined benefit pensions, insurance reserves, and annuities), for the DFAs we distribute the Financial Accounts totals to SCF respondents using other available information. We describe the methodology that we use to distribute these parts of the household balance sheet in this section and demonstrate how these assets and liabilities affect our distributional results in Section 5.

Finally, we build upon prior reconciliations by looking closely at areas of potential disconnect between the two datasets and developing solutions to bridge the gap when necessary. For example, as described in more detail below, we dig deeper into differences in values of non-corporate businesses, real estate, consumer durables, Individual Retirement Accounts (IRAs), and debt securities. In addition, while privacy concerns restrict the SCF from sampling households from the Forbes 400, we employ a weighting correction method to account for these households. This method adds the wealth and demographic characteristics of these households to the existing SCF data, providing a more complete distribution of wealth.[5]

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

[4] However, 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`

[5] The weighting correction is described in Appendix F and based on Bricker et al. (2018). For details on

Overall, the DFAs contain the most rigorous reconciliation to date of the SCF and Financial Accounts concepts of household net worth.

In the remainder of this section, we detail how we reconstruct all nineteen balance sheet lines from Table B.101.h using SCF data. Following the B.101.h classification scheme, we begin with nonfinancial assets, then move to financial assets, and finally to liabilities. We include the level of the 2016Q3 B.101.h balance sheet measure, as well as the share of total assets or liabilities, in the header for the reader's convenience.[6] While the overall reconciliation between the two data sources is good, in some cases, the totals do not align particularly well, even when the concepts are quite similar. These differences are unlikely to affect our overall wealth distribution measures for two reasons. First, significant differences between B.101.h and reconciled SCF measures are generally confined to smaller asset and liability categories that have limited effects on the overall distribution of wealth. Second, our analyses do not suggest that these differences are skewed towards either end of the wealth distribution. We therefore expect that the differences in our reconciled measure do not significantly affect our key results. We explore these issues further in Section 5, where we test the sensitivity of our results to alternative assumptions regarding the conceptual alignment of the two data sets. In particular, we show that excluding the categories where the match between the two data sets is not as strong has modest effects on the distributional results.

2.1 Reconciliation of Assets

2.1.1 Nonfinancial assets

Real estate ($22.6 trillion, or 22% of total assets in 2016Q3)

Real estate is one of the largest components of household wealth. Aggregate real estate measures in the Financial Accounts and SCF align reasonably well until the mid-2000s, although the SCF measure has consistently exceeded the B.101.h values.[7] The gap between

the Forbes list of wealthiest families, see `https://www.forbes.com/forbes-400/` .

[6]We choose this quarter because it coincides with the most recent SCF data. Note that because total B.101.h assets are approximately $100 trillion in this quarter, the shares are easily inferred from the dollar values.

[7]We also note that the reconciled SCF measure of residential real estate differs slightly from the typical "bulletin" SCF measure (Bricker et al. (2017)) in that it does not include income-producing residential real estate but does include real estate holdings of vacant land.

the two measures was around 10% before the mid-2000s, then increased considerably to 50% by 2010, and has since declined somewhat to about 29%. 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 generally moves with a repeat-sales house-price index.[8] Gallin et al. (2018) — and studies cited therein — show that owner self-reports and repeat-sales indexes can diverge notably during housing downturns due to known biases in both measures.[9]

The sizable, time-varying gap between the Financial Accounts and SCF measures of housing wealth is notable, but, as mentioned above, the key question for our purposes is whether it causes bias when we apply the SCF distribution to the Financial Accounts measures. In Section 5, we assess the sensitivity of our results to a different aggregate housing wealth series recently developed by Board staff. This alternative series is derived from a large-scale automated-valuation model and roughly splits the difference between the Financial Accounts and SCF measures.[10] Using this alternative measure, the resulting wealth shares are within 0.4% of the baseline, suggesting that the methodological differences in measuring aggregate housing wealth are not driving a large bias in our resulting distributional measures.

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

[8]In the Financial Accounts, housing wealth was benchmarked in 2005 to aggregated self-reported house values from the Census's American Housing Survey. CoreLogic's single family house price index and net fixed investment from the Bureau of Economic Analysis (BEA) are used to project the level of housing wealth since then.

[9]Owner self-reported house valuations tend to lag the market during market turns and tend to be overly optimistic, while repeat-sales indexes can overstate the effect of housing downturns on aggregate wealth if transacting homes are not fully representative of all homes. A smaller methodological difference is that the AHS survey that benchmarks the B.101.h measure may have less complete coverage of second homes than the SCF. Stripping second homes from the SCF results in in an aggregate series that is quite close to the B.101.h measure before 2005 but does little to address the divergence since then.

[10]The alternative measure is available as part of the Enhanced Financial Accounts at `https://www.federalreserve.gov/releases/efa/alternative-measure-of-owner-occupied-real-estate.htm`.

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.[11] 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.

2.1.2 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").[12] However, we must make additional assumptions to assign financial assets that are held indirectly through IRAs, trusts, and managed investment accounts.[13] For these types of investment vehicles, the SCF

[11] While 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?"

[12] One 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.

[13] Defined-contribution retirement accounts are included with pension plans, as described below.

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 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.[14]

Checkable deposits and currency ($970 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%).[15]

Time deposits and short-term investments ($8.7 trillion, or 9% 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

[14] Unless noted otherwise, each category below is calculated residually in the Financial Accounts.

[15] In 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.

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.

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 ($114 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 118% 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.[16] The corresponding SCF measure comprises directly held stocks and mutual funds, and the portion of other investment vehicles that are invested in equities (such as IRAs, trusts, managed investment accounts, 529 plans, and Health Savings Accounts). Historically, the SCF measure is quite close to the B.101.h measure, averaging about 106%, and is relatively consistent across years.

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.[17] 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.[18] We assume that the death benefit and cash surrender value are generally proportional to the reserve, and that these relationships do not systematically 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 for a set of sample insurance policies to estimate the mapping between death benefit and reserves (see Appendix A for a description of these calculations). 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.

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

[17] The Financial Accounts capture this information from insurers' statutory financial statements.

[18] Permanent 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).

Pension entitlements ($24.3 trillion, or 24% 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.[19] These three asset classes account for about 30%, 60%, and 10% of total pension entitlements in the Financial Accounts, respectively.[20]

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 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.[21] We use the respondents' current wage, years in the plan, and age to determine the allocation.[22]

[19]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.

[20]The 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.

[21]Benefits 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.

[22]All 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.

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).[23] 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 for details), 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.

Equity in noncorporate business ($11.5 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%).[24] 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 107%, and because, in certain ways,

[23] In 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.

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

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 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.[25]

[25] Specifically, 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

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.[26]

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 or postal service.

2.2 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.[27] 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 89%.[28]

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.[29] 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.

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.

[26] Participating 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.

[27] Mortgages on rental properties are included in the calculation of equity in noncorporate businesses.

[28] Note, the reconciled SCF measure used in the DFAs differs from the SCF bulletin measure because the former excludes rental properties.

[29] See `https://www.federalreserve.gov/releases/g19/current/default.htm` for G.19 details.

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 approximately 50% for credit card debt, 65% for auto and student loans, and 59% overall.[30] The remaining household liability categories are relatively small, together making up about 5% of B.101.h liabilities.

Depository institution loans not elsewhere classified ($228 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

[30]Some 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).

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).

2.3 Comparing the Reconciled Balance Sheets

Table 1 summarizes the results of the SCF-B.101.h reconciliation exercise described above 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. As stated above, an exact ratio of 100% (and double asterisks) implies that the B.101.h total is distributed to SCF respondents using an asset- or liability-specific imputation rule and the B.101.h and reconciled SCF lines 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 $110 trillion, compared with $103 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 102%) to B.101.h net worth.[31] Looking deeper, we find the two data sets also align reasonably well for most of the underlying asset and liability categories. Most importantly, for large asset categories that disproportionately affect the distribution of wealth, differences between the reconciled SCF

[31] While the match is reasonable in all years, the alignment further improves in recent years. For example, in 2016 the ratio of SCF to B.101.h assets, liabilities, and net worth are 100%, 84% and 102%.

and B.101.h balance sheets are quite small.

Still, there are several asset and liability categories where the match is worse than average. Consumer durable goods (61%), time deposits (55%), and debt securities (68%) in the SCF are consistently well below B.101.h; checkable deposits and currency is high in the SCF in most years (206% on average); and money market fund shares have an inconsistent relationship across time. On the liability side, consumer credit is lower in the SCF but the relationship is quite consistent across years, and the very small category of other depository institution loans is the only category with a very poor match. In Section 5, we construct a wealth measure that excludes these assets and liabilities, and show that the wealth distribution when focusing only on the categories in which we are confident in the match is very similar to the baseline results.

Despite the matching issues for some of the asset and liability categories documented above, the fact that most categories match reasonably well implies that the reconciled SCF is a useful tool for distributing aggregate B.101.h measures of household wealth. We are able to construct SCF measures that are conceptually very similar to the vast majority of B.101.h assets and liabilities, and the aggregate levels, while not perfectly in sync, are generally reasonable. As noted above, more important than agreement in the aggregate levels is whether we suspect a mismatch that varies systematically across the wealth distribution. For categories that are more difficult to reconcile, we have no reason to believe that the disconnect is driven by one end of 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 DFAs is that the SCF is fielded triennially, while the Financial Accounts Table B.101.h measures household wealth quarterly. Given that the DFAs aim to provide near real-time, quarterly measurement of assets and liabilities across various population groupings, 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

Table 1: 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	96	90	87	94	107	103	103	108	101	107	100	102,622	110,028
Nonfinancial assets	101	96	95	103	103	112	123	132	120	118	110	27,723	32,618
Real estate (1)	113	110	107	116	113	122	136	151	134	129	123	22,603	29,241
Consumer durable goods (2)	60	48	58	59	64	67	63	62	63	66	61	5,121	3,377
Financial assets	93	87	83	90	109	99	93	98	93	103	95	74,898	77,410
Checkable deposits and currency	70	49	54	93	151	210	842	268	162	160	206	970	1,548
Time deposits and short-term investments	59	62	58	63	64	57	49	53	40	47	55	8,741	4,146
Money market fund shares	100	90	82	73	92	125	95	103	150	147	106	1,442	2,122
U.S. government and municipal securities	69	53	55	52	102	90	79	66	72	87	72	3,373	2,935
Corporate and foreign bonds	87	51	27	28	60	55	47	41	59	95	55	1,036	987
Other loans and advances	333	123	187	63	62	43	35	53	72	54	102	835	450
Mortgages	110	94	91	84	97	98	102	96	179	225	118	114	255
Corporate equities and mutual fund shares	99	87	88	108	156	113	93	107	97	115	106	19,983	22,916
Life insurance reserves**	100	100	100	100	100	100	100	100	100	100	100	1,574	1,574
Pension entitlements (3)	101	100	96	100	100	100	100	100	100	100	100	24,252	24,304
Equity in noncorporate business (5)	111	103	85	91	105	99	105	134	111	124	107	11,457	14,243
Miscellaneous assets**	101	101	100	101	102	100	100	100	101	101	101	1,121	1,126
Total Liabilities	79	80	79	86	81	88	83	88	86	87	84	14013	12142
Home mortgages (5)	81	84	85	93	89	94	87	93	94	94	89	9,728	9,175
Consumer credit	59	57	55	60	52	59	66	69	59	68	60	3,577	2,413
Depository institution loans n.e.c.	1897	3133	278	210	470	-3153	216	89	95	36	327	228	82
Other loans and advances	100	100	100	97	100	100	100	100	100	100	100	448	448
Deferred and unpaid life insurance premiums	100	100	100	100	100	100	100	100	100	100	100	33	33
Net worth	98	91	89	95	112	106	107	113	103	111	102	88,609	97,887

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.

has been well-studied, beginning with the foundational paper Chow and Lin (1971). We apply the Chow-Lin approach (after applying several subsequent extensions) to interpolate and forecast quarterly data from the reconciled, triennial 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., 90^{th}-99^{th} percentile), the next 40% (50^{th}-90^{th} percentile), and the bottom 50%.[32] As a final step in constructing the DFA data, we calculate the share of the reconciled SCF total held by each wealth group and multiply these shares by the B.101.h total for each asset and liability to produce our quarterly distributional measures in the DFA. The details of this final step are presented in Appendix C.

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 from our imputations and forecasts that indicate our method captures fluctuations in assets and liabilities that one would intuitively expect.

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

[32]These 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.

quarterly.[33]

$$Y = B'X \tag{1}$$

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 relationship[34]

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

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

$$Y = B'Z'\beta + B'u. \tag{2}$$

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

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

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

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

[33] Formally, we suppose that $Y = [y_1, y_2, , y_m]'$ is observed m times, with $k-1$ unobserved periods between observations and e periods to extrapolate after the last observation of Y so that $X = [x_1, x_2, , x_n]'$ 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

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

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

[34] Z can be expressed as an $n \times q$ matrix $Z = [Z_1, Z_2, , Z_q]$, 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.

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. Appendix D compares several different possible 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.[35] We also include the S&P 500 stock index for almost all assets and liabilities, since this series is correlated with both financial assets and overall business cycle dynamics.[36] 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 indicator series for pensions 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 E.1 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. To do so, for each asset and liability category in the B.101.h table, we impute and forecast the quarterly balance sheet levels for each of the four wealth groups we study. These wealth group estimates are key inputs in constructing the DFA dataset but cannot be validated or invalidated against any existing data. However, for each wealth and liability category, summing across these wealth groups yields an aggregate series which — although not targeted

[35] Indeed, 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.

[36] We 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.

or used directly in our estimation — is directly comparable to its corresponding aggregate B.101.h series.

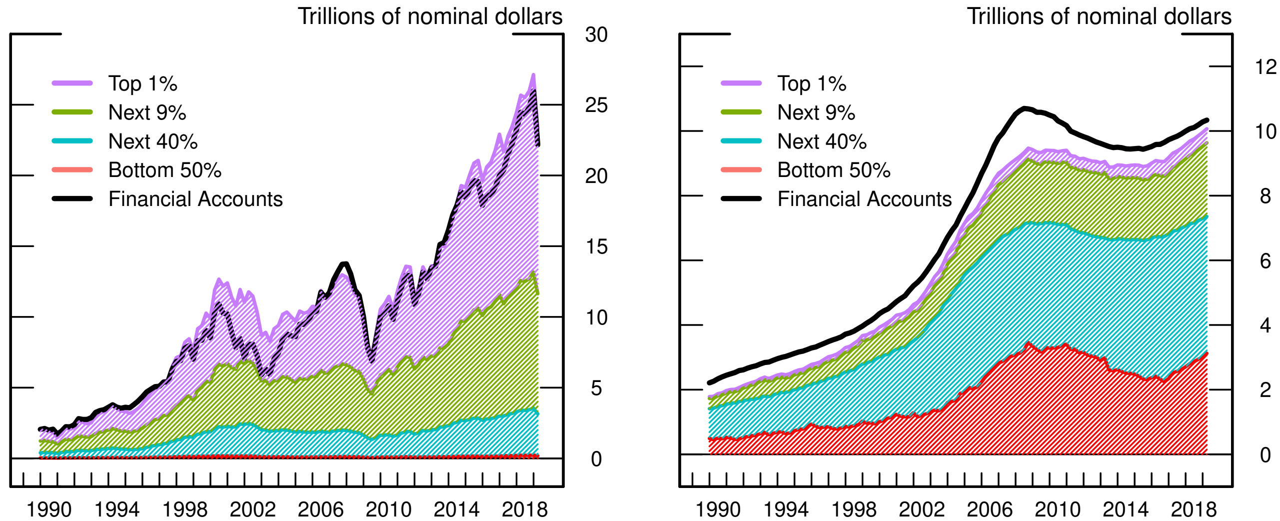
To determine whether our imputation and forecasting method is credible, we check whether fluctuations in estimates of both the specific wealth group levels and their implied aggregates appear plausible. Specifically, we first check whether contours in the constructed aggregate reconciled SCF series match the contours in its aggregate B.101.h counterpart. Second, we check whether the specific wealth group levels fluctuate in manners that are intuitively plausible. Although our second check is informal, it is still quite informative. For example, different wealth groups' asset and liability holdings will respond differentially to changes in indicator series, 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 second metric against which we can validate or reject our imputation and forecast procedure.

Figure 1 presents the imputed and forecasted quarterly time series for levels of (a) corporate equities and mutual funds and (b) mortgages for each of the four wealth groups we study.[37] Summing across these wealth groups yields the aggregate reconciled SCF level, which is directly comparable to the corresponding aggregate B.101.h series (presented as the black line for reference).

Panel (a) shows that both of our two validation criteria are satisfied for corporate equities and mutual funds. We find that the aggregate reconciled SCF measure of corporate equity and mutual funds closely tracks the aggregate B.101.h measure, including during the last two significant stock market boom and bust cycles.[38] For example, during the Great Recession, our imputation method estimates that total household equity holdings dropped sharply in 2008 before largely recovering by 2010 in a manner that closely mirrors the corresponding B.101.h series. Second, we observe amplified fluctuations for wealthier households, with capital gains and losses largest for the top 1% of households. Wealthier households hold

[37]Corporate equities and mutual funds were chosen for this illustration because they are a large asset class that varies at a high-frequency relative to other asset classes, while mortgages were chosen because they are a large liability that varies at a lower frequency.

[38]Although the B.101.h series is used as an indicator series in our imputation procedure for each asset and liability for each wealth group, the aggregate level is not targeted or matched by construction. Thus, our finding that our imputations and forecasts sum to produce aggregate reconciled SCF series that are consistent with patterns in corresponding B.101.h series, and that fluctuations across wealth groups differ in intuitively plausible ways, provides important evidence that our approach successfully imputes and forecasts the series outside and in-between the standard triennial SCF survey observations.



(a) Corporate Equities and Mutual Funds

(b) Mortgages

Figure 1: Predicted Measures of Corporate Equities/Mutual Funds and Mortgages

larger and riskier corporate equity and mutual fund portfolios, so our finding that their holdings are more responsive to aggregate fluctuations is credible.

Panel (b) similarly shows that our method predicts patterns in household mortgage liabilities that are consistent with the aggregate fluctuations and vary in credible ways across the wealth distribution. Our total measure of reconciled SCF mortgages slightly understates but otherwise closely tracks patterns in the B.101.h aggregate series. For example, both series capture a rapid build-up of mortgage debt prior to the Great Recession and subsequent reduction from 2007 to 2013, with mortgage debt levels beginning to increase again in 2014. We also observe that much of the mortgage debt build-up prior to the Great Recession was driven by increased borrowing by households in the next 40% and bottom 50% of the wealth distribution, and the post-Great-Recession decrease in mortgage debt was steepest for the bottom 50% of households. These patterns are consistent with a number of studies on debt dynamics during the Great Recession (e.g., Bhutta (2015), Adelino et al. (2016)), suggesting again that our data captures credible patterns in household balance sheets. Finally, B.101.h mortgage debt exhibits less high-frequency fluctuation than corporate equities and mutual funds, so it is reassuring that both our aggregate reconciled SCF and specific wealth percentile group levels are relatively smooth and exhibit fewer short-term fluctuations.

4 A First Look at the DFAs

The calculations described in Sections 2 and 3 give rise to a new dataset that breaks down B.101.h into four wealth percentile groups (top 1%, next 9%, the next 40%, and the bottom 50%) since 1989Q3. The DFA dataset also contains the share of each asset and liability class held by each wealth percentile group for each quarter.

Although we do not attempt to provide a comprehensive analysis of the dataset in this paper, we highlight some results that illustrate three new contributions made by the DFA. First, the DFAs provide a comprehensive measure of the distribution of household wealth built from both direct observations of household balance sheets and aggregate wealth measures in a national accounting framework. Second, the DFAs' quarterly observations allow for new insights into the cyclicality of the wealth distribution at higher frequencies. Finally, the DFAs provide near-real-time measures of the wealth distribution, as they are updated about ten or eleven weeks after the end of each quarter. In the rest of this section, we describe these contributions in more detail.

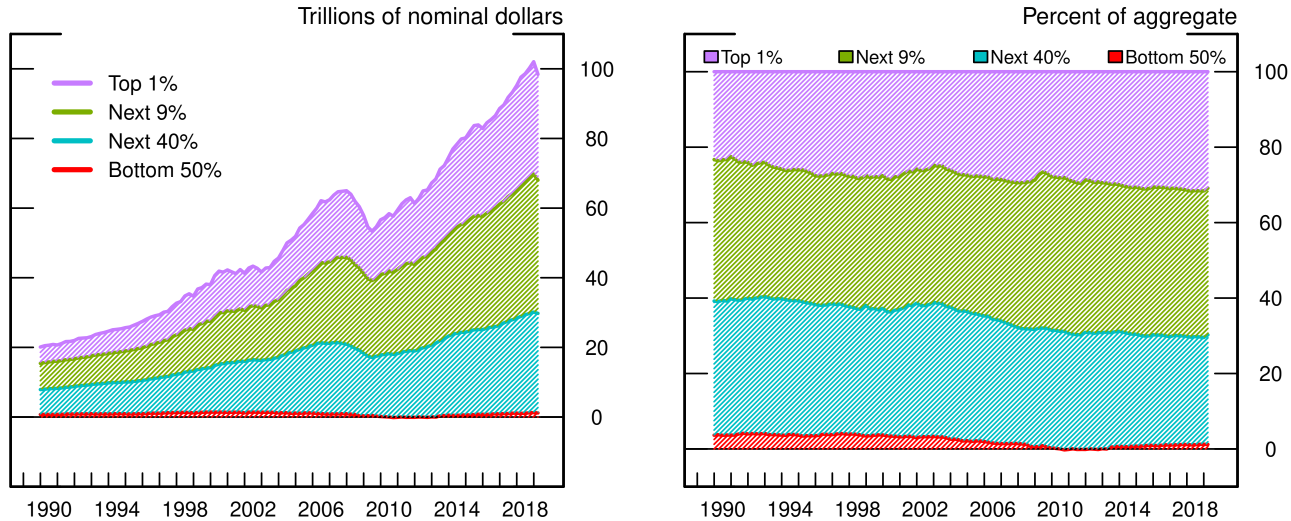
4.1 Insights from a Comprehensive Integration of Household-level and Aggregate Data

By merging survey data with national accounting data, the DFAs provide a comprehensive new measure of the distribution of aggregate household wealth. Thus, the DFAs help overcome some of the challenges that have impeded past efforts to integrate microeconomic data with macroeconomic analysis.[39] To illustrate this contribution, we briefly describe the trends in wealth concentration apparent in the DFAs and then highlight a few quantitative insights afforded by these data.

At the highest level, the DFAs show significant wealth concentration and a clear increase in wealth concentration since 1989.[40] These findings are seen in Figure 2, Panels (a) and (b), which show the level and share of total net worth for each of the four selected wealth percentile groups measured in the DFAs. The top 10% of the wealth distribution — the purple and green areas together — hold a large and growing share of U.S. aggregate wealth,

[39]See Carroll (2014) for a rich discussion of this issue.

[40]This is broadly consistent with a number of recent studies, e.g., Wolff et al. (2012), Piketty (2013), Bricker et al. (2016), Saez and Zucman (2016), and Rios-Rull and Kuhn (2016).



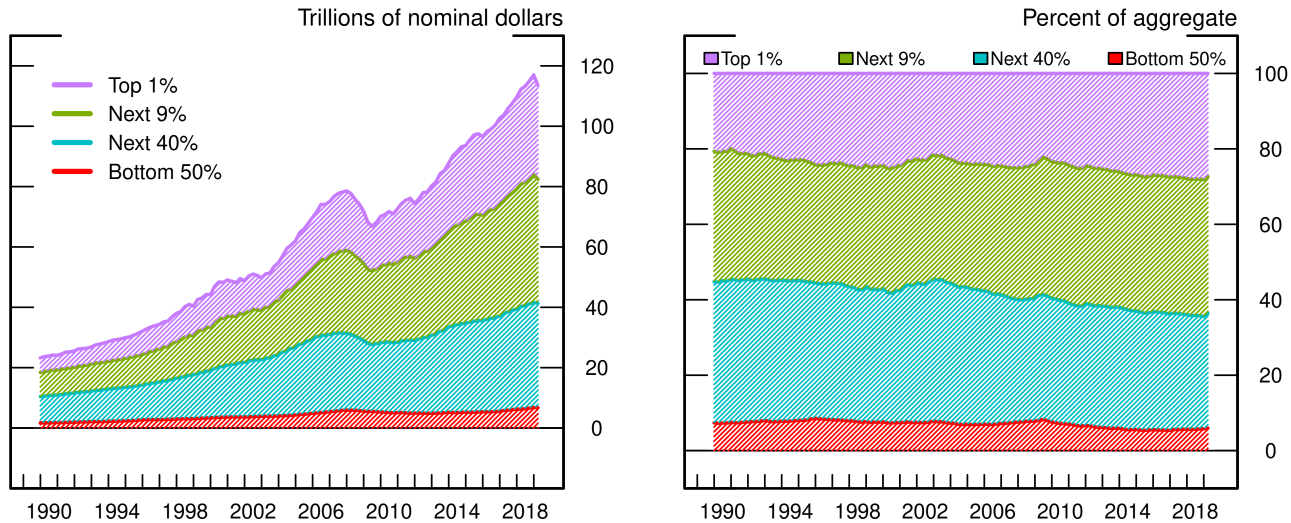
(a) Level

(b) Share

Figure 2: Net Worth by Wealth Percentile Group

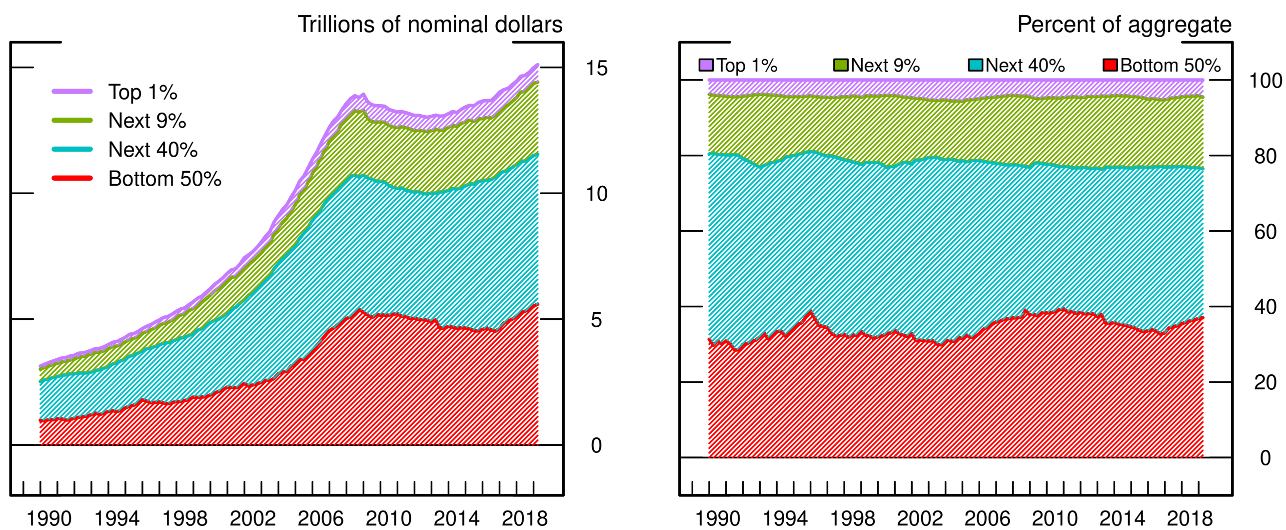
while the bottom half (the thin red area) hold a barely visible share. Looking at trends, while the total net worth of U.S. households has more than quadrupled in nominal terms since 1989 (Panel (a)), this increase has clearly accrued more to the top of the distribution than the bottom (Panel (b)). In 2018, the top 10% of U.S. households controlled 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 percent to nearly 32 percent from 1989 to 2018. The increase in the wealth share of the top 10% came at the expense of households in the 50^{th} to 90^{th} percentiles of the wealth distribution (blue region), whose share decreased from 36 percent to 29 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 percent in 2018.

The rise in wealth concentration stems primarily from increased concentration of assets (Figure 3) rather than a decreased concentration in liabilities (Figure 4), with trends for assets largely mimicking those for overall wealth. 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. These increases were mirrored by decreases for households in the 50-90^{th} percentiles of the wealth distribution. Figure 4(b) shows that, in contrast to assets, the distribution of liabilities is both much more equitable than the distribution of assets and little changed, on net, since 1989.



(a) Level **(b)** Share

Figure 3: Total Assets by Wealth Percentile Group



(a) Level **(b)** Share

Figure 4: Total Liabilities by Wealth Percentile Group

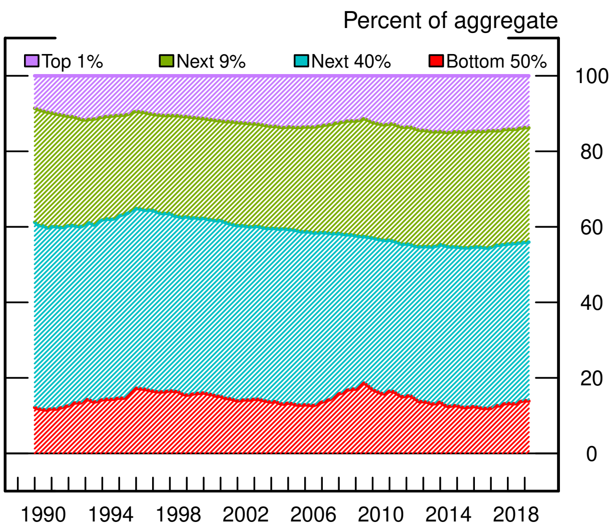
We next examine the four largest asset categories from the B.101.h table — real estate, pensions, corporate equity, and noncorporate business equity — in order from most to least equally distributed. Looking across the four panels of Figure 5, we see that real estate and pensions are somewhat more equally distributed than total assets (e.g., have larger red and blue areas), while noncorporate and corporate business equity are the most concentrated among the top 1%. Still, in Figure 5(a), we observe that the share of real estate held by the top 10% of the wealth distribution has increased by 5 percentage points from 39 percent to 44 percent, suggesting that increases in wealthy households' share of real estate holdings have contributed to the increase in concentration. In Figure 5(b), we observe that pension wealth is heavily concentrated among the two "middle" categories, representing the 50^{th} to 99^{th} percentiles of the wealth distribution. But again, we observe increasing concentration, evidenced by an increase in pension shares of households in the 90-99^{th} percentiles of the wealth distribution from 39 percent in 1989 to 46 percent today.

Finally, Figure 5, Panels (c) and (d) suggest corporate and noncorporate business equity have been large drivers of wealth concentration. The distribution of these assets has long been skewed: in 1989, the richest 10% of households held 80 percent of corporate equity and 78 percent of equity in noncorporate business. Since 1989, the top 10%'s share of corporate equity has increased, on net, from 80 percent to 87 percent, and their share of noncorporate business equity has increased, on net, from 78 percent to 86 percent. Furthermore, most of these increases in business equity holdings have been realized by the top 1%, whose corporate equity shares increased from 39 percent to 50 percent and noncorporate equity shares increased from 42 percent to 53 percent since 1989.

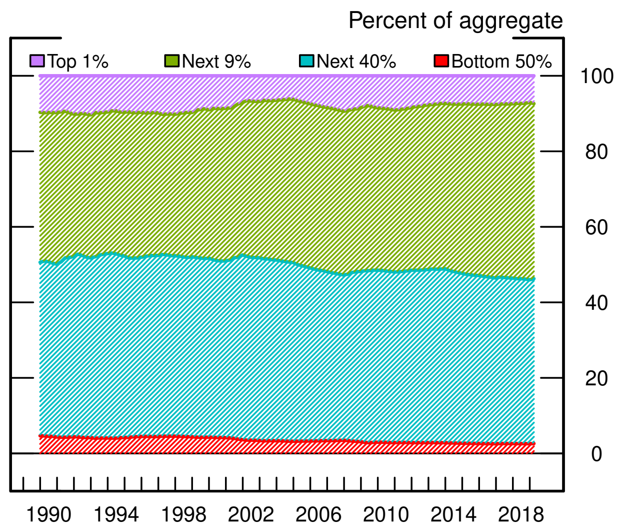
These patterns of high and increasing wealth concentration are broadly consistent with other studies; however, the DFAs contain some important differences from other studies in the level of and changes in the wealth distribution. To compare the quantitative findings of the DFAs to another study, Figure 6 shows measures of wealth concentration—the share of wealth held by different wealth percentiles and Gini coefficients—from the DFAs together with the corresponding measures from the World Inequality Database (WID), perhaps the most comparable data set.[41]

The DFAs show a somewhat more equitable distribution of wealth than the WID. Panel (a) presents the wealth shares of the top 1%, top 10%, 50-90%, and bottom 50% of households

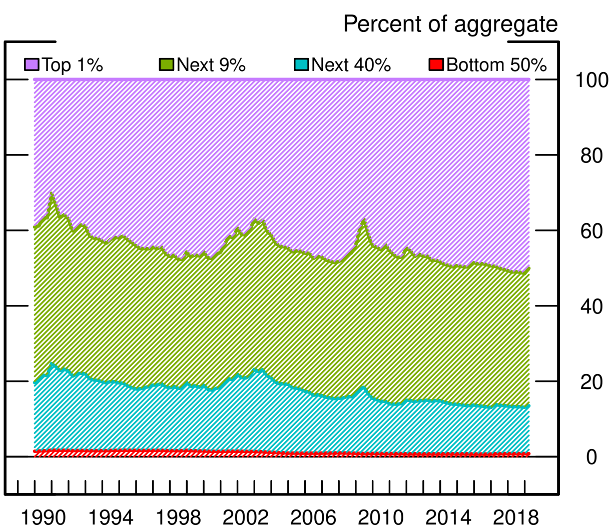
[41] The WID is a statistical database focused on measures of income and wealth concentration and funded by a consortium of public and nonprofit institutions. See `https://wid.world/` for more information and Alvaredo et al. (2016) for details on methodology. The wealth shares available for download through the WID website use individual adults as the unit of observation.



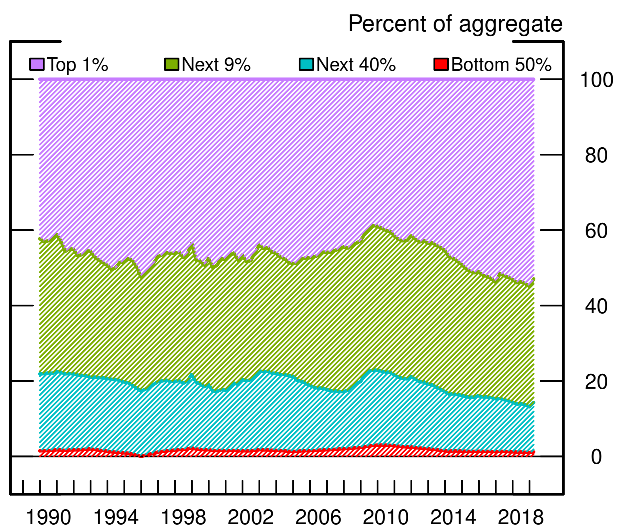
(a) Real Estate



(b) Pensions

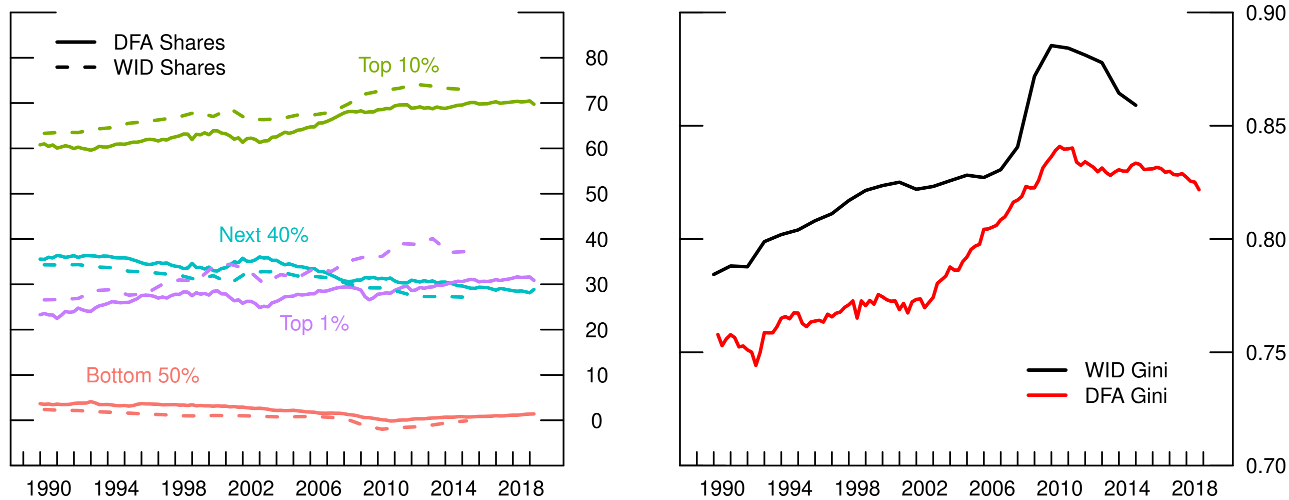


(c) Corporate Equity



(d) Noncorporate Business Equity

Figure 5: Pension, Real Estate, Corporate Equity, and Noncorporate Business Equity by Wealth Percentile Group



(a) Wealth Shares **(b)** Gini Coefficients

Figure 6: Wealth Concentration Measures from the DFAs and WID

in the wealth distribution for these two data sets.[42] We find that the wealth shares of the top 1% and top 10% are somewhat smaller in the DFAs than the WID (the solid lines are below the dashed lines) in particular, the share of the top 1% is around 31 percent in the DFAs, versus about 37 percent in the WID in 2014. At the same time, the wealth shares of the bottom 50% and 50-90th percentiles of households are higher in the DFAs than the WID. Looking at changes over time, the DFAs show a more gradual increase in the share of the top 1% after 2007. These differences can also be seen by comparing the Gini coefficient for the DFAs and WID (Panel (b)).[43]

There are several possible explanations for the differences between distributional measures in the DFAs and the WID. The first is methodological. Unlike the DFAs, the WID does not directly observe wealth, but imputes it by capitalizing income measures from tax records. This method imposes assumptions about realized asset returns across the wealth distribution, and requires additional assumptions to impute assets and liabilities that do not generate taxable income. As shown in Bricker et al. (2017) and Bricker et al. (2018), 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

[42]Note that, to illustrate the comparison more clearly, the second category here is the top 10%, rather than the next 9%.

[43]The Gini coefficient is a commonly used measure of the concentration of a distribution, with higher levels of the Gini coefficient representing greater concentration.

increase in the top 1% wealth share in the years following the Great Recession. Furthermore, certain asset classes like consumer durables and unfunded defined benefit pensions are omitted from the WID's wealth measure.

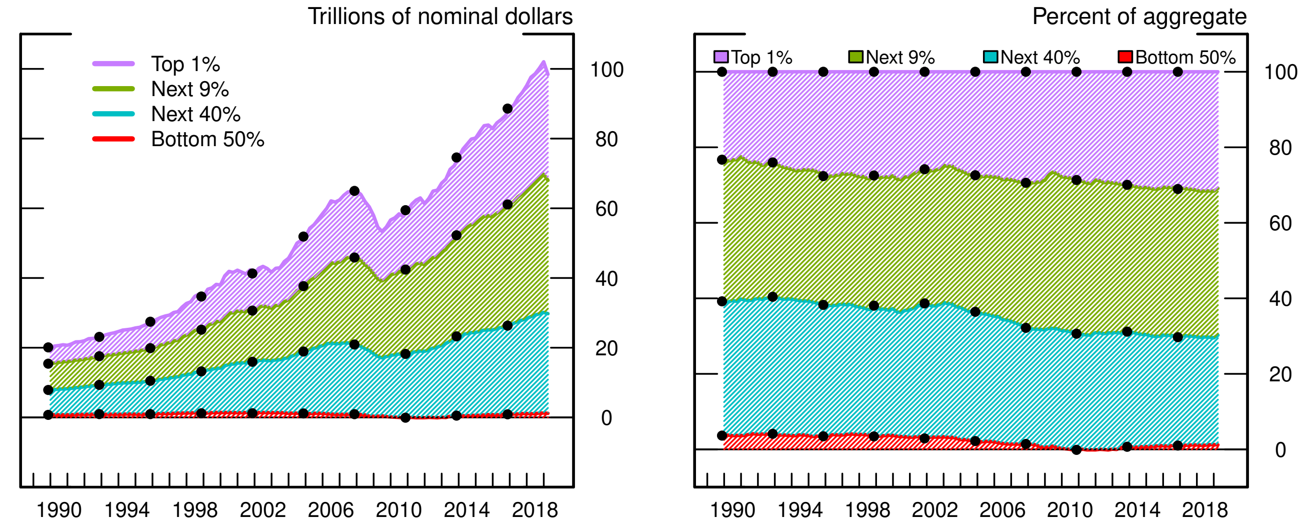
A second explanation for the differences between the DFAs and the WID is that historical data in the Financial Accounts are regularly updated to reflect new data availability and improved measurement. Recent historical revisions to Financial Accounts measures of pension reserves and interest-bearing assets could have an effect on wealth concentration estimates as both of these categories are key inputs into the WID calculation and have been substantially revised since the most recent WID release. Overall, the DFA results suggest that the level of wealth concentration among U.S. households is somewhat lower than that shown in the WID, though with a similar increasing trend.

4.2 Insights from Quarterly Measures of the Wealth Distribution

A second important contribution of the DFAs 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 DFAs are clearly visible in Figure 7. This figure overlays the DFA levels (Panel (a)) and shares (Panel (b)) (previously shown in Figure 2) with the triennial observations from the reconciled SCF (indicated with black dots). 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. These panels illustrate how the DFAs can be used to see higher-frequency detail than is available using the SCF waves.[44] A second illustration of higher-frequency dynamics visible in the DFAs is the business cycle between 1998 and 2001.

[44]The 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 DFAs.



(a) Levels **(b)** Shares

Figure 7: Wealth Levels and Shares in the DFAs and SCF

Notes: Dots indicate reconciled SCF observations. Series shown through 2018Q4, the most recent Financial Accounts release.

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.

The DFA data can also shed light on the cyclical variability of each wealth group's share of the wealth distribution. For example, wealthier households have had historically greater exposure to highly cyclical assets like corporate and noncorporate business equity.[45] These portfolio positions suggest that the net worth of the top 1% is likely to exhibit a larger fluctuation during economic cycles, with its share of total wealth rising during economic expansions and flattening or contracting during economic downturns. Indeed, Figure 8, which plots the four quarter moving averages of changes in wealth share for the top 1% (the purple line) and 90-99th percentiles (the green line), shows that the wealth shares of households in the top 1% have varied procyclically (e.g. fell during recessions) since 1989, while the share of the 90-99th percentiles have varied countercyclically (e.g. rising during recessions). Combined, these results suggest that wealth shares became temporarily less concentrated in the top 1% of the wealth distribution during these recessions, though not

[45]Indeed, our discussion in Section 4.1 indicated changes in the share of business equity have been the key driver of increases in long-term concentration.

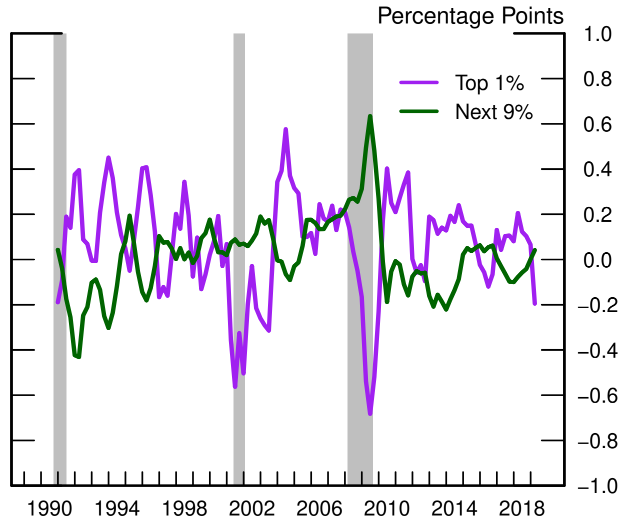


Figure 8: Annual Change in Net Worth Shares for the Top 1 and 90-99th Percentiles

Notes: Shaded areas represent NBER-defined recession quarters. Series shown are four-quarter moving averages through 2018Q4, the most recent Financial Accounts release.

necessarily less concentrated in the top 10%.[46]

4.3 Insights from Timely Measures of the Wealth Distribution

A third important new contribution of the DFAs is the timeliness of the data. Most survey-based data sets that measure the distribution of wealth require lags of at least a year to process the survey data, and measures using tax data (such as the WID) require even longer lags due to the time required to process and release tax data. These lags limit the ability of users to understand real-time changes in the wealth distribution and how they could relate to policy. By incorporating the most recent data from the Financial Accounts, the DFAs are updated and released relatively quickly, generally within about 10 or 11 weeks after the end of a quarter.

An example of "near-real-time" availability of DFA data is given in Figure 9, which shows cumulative changes in the wealth shares of each wealth group since 2014 (the last year the WID is available), with the dark shaded region indicating the time period after the fielding of the 2016 SCF. Through 2018Q3, the long-term trend of increased concentration continued,

[46]The bottom 90% of the wealth distribution is omitted from Figure 9 (b) as it exhibits little cyclical variation. Linking the trends on an increase in the equity share by the wealthy households with the business cycle results, it is reasonable to expect that the top 1% share could be increasingly more cyclical over time, as the wealthiest households hold a higher share of these cyclical assets.

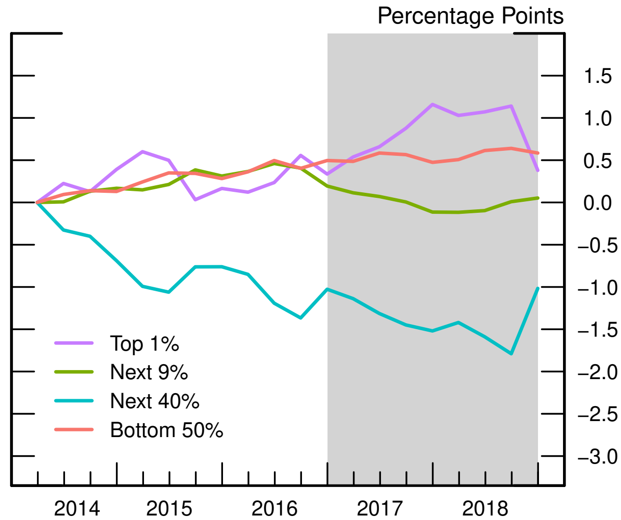


Figure 9: Cumulative Wealth Shares, 2014-Present

Notes: Shaded area represents quarters after 2016, the most recent SCF year. Series shown through 2018Q4, the most recent Financial Accounts release.

with the wealth shares of the top 1% (purple line) rising by over 1 percentage point and the wealth share of households in the 50-90th percentiles (blue line) declining by over 1.7 percentage points. This shift in wealth towards the top of the distribution largely reflects the increased value of business equity over this period.

These recent trends reversed with the large stock market decline in 2018Q4. Figure 9 shows that the top 1% – whose portfolio 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 (as shown in Figure 5, Panels (c) and (d)) are much less exposed to business equity risk. Provided that the rebound in equities seen thus far in 2019Q1 holds, we expect a substantial portion of the changes in 2018Q4 to reverse in the next DFA release. Thus, the DFA intuitively captures how near-real-time fluctuations in asset values affect the wealth distribution.

Timely DFA measures could be especially valuable in times of economic turmoil. For example, we know that elevated household leverage and illiquidity played an important role in the Great Recession, and having a near-real-time measure of the distribution of household wealth could be useful going forward.[47]

[47] As noted earlier, the 2009 panel re-interview of the 2007 SCF was commissioned to provide a glimpse of

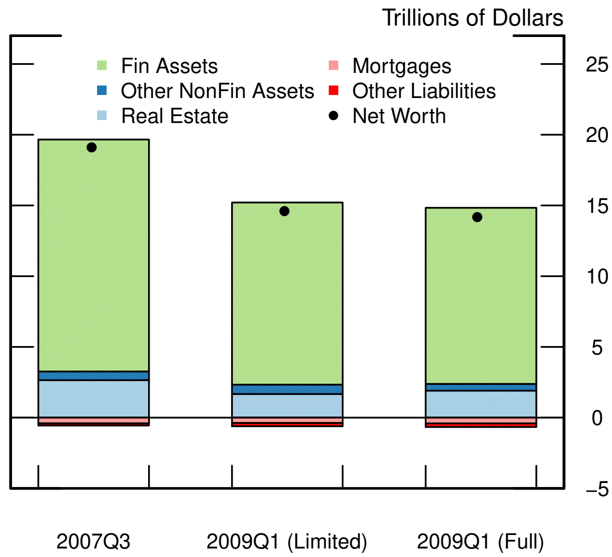
To test the predictive power of the DFAs during such times, we simulate how the DFAs would have evolved in real time during the Great Recession. To do so, we use data from the SCF only through 2007Q3 (i.e., the last available SCF prior to the Great Recession) and forecast household balance sheets through 2009Q1 using indicator series observations through this quarter (e.g., Financial Accounts 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.

Figure 10 presents results from this exercise for each of our four wealth percentile groups in Panels (a)-(d). In each panel, the first bar illustrates the household balance sheets during the quarter of the last pre-recession SCF (2007Q3), the second bar presents our pseudo "real-time" forecast in 2009Q1 based on limited data observations, 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 2018Q4). 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 bar indicate levels of liabilities (mortgages and other liabilities), and the black dots indicate net worth (assets minus liabilities).

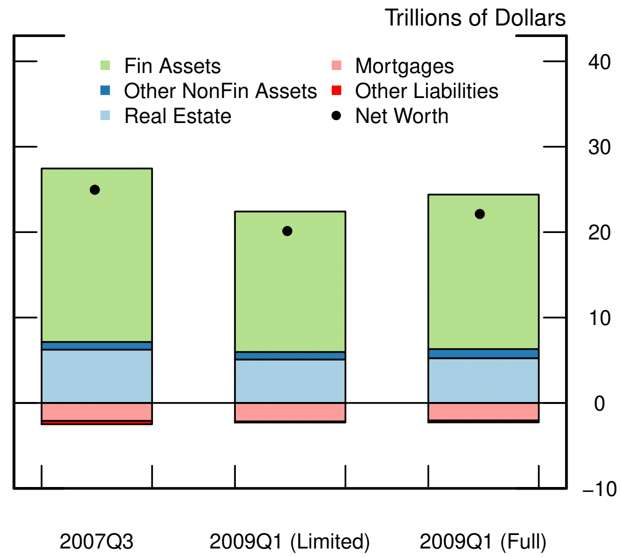
For the top 1% of households in the wealth distribution, comparing the first and second bar in Figure 10, Panel (a) shows that our pseudo real-time DFA forecast predicts a significant fall in net worth during the Great Recession. Comparing the asset categories indicated on these two bars, we observe 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), the key 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 bar shows that our pseudo real-time forecast predicts a drop in net worth (albeit smaller

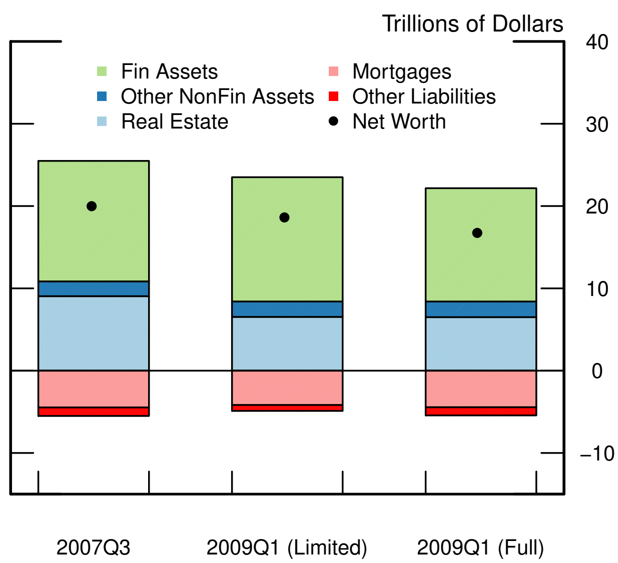
household balance sheets for this reason.



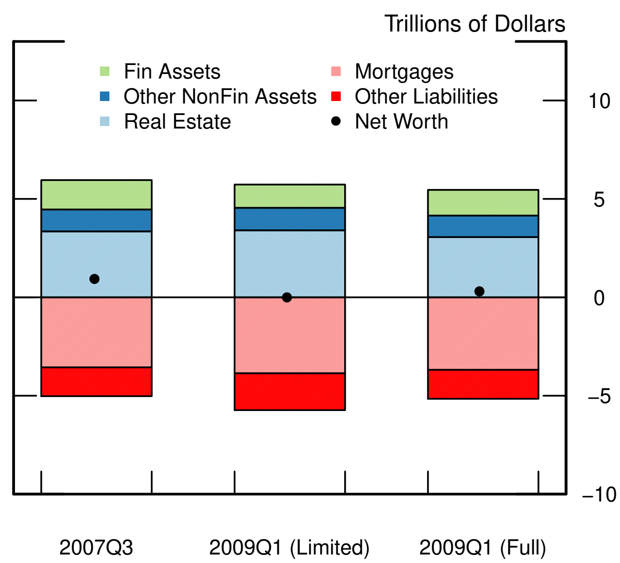
(a) Top 1



(b) Next 9



(c) Next 40



(d) Bottom 50

Figure 10: 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.

than for the top 1%) driven by a decrease in the value of real estate holdings. Comparing the second and third bar in each panel shows that our pseudo real-time forecast successfully predicts the qualitative patterns in the actual DFA data, although there are some notable 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)).[48]

Overall, these exercises suggests that the interpolation model is robust to the selection of the estimation sample, and that the DFAs can provide accurate, real-time insights into the composition of wealth across the wealth distribution at economic turning points.

5 Robustness and Sensitivity Analysis

In this section, we test the effect on our results of a number of our assumptions regarding data and empirical strategy.[49] In particular, we investigate two issues. First, as noted above, aggregates from the Financial Accounts and SCF do not always align, requiring us to make several assumptions to reconcile these two data sets. Second, we look at how sensitive the DFAs' wealth shares are to sampling variability in the SCF.[50]

As noted in Section 2, a few conceptual and quantitative differences between the Financial Accounts and SCF persist, even after our attempts to reconcile them. Table 2 explores the robustness of our results to alternative reconciliation approaches highlighted in Section 2. We calculate the average share for each of our wealth groups during three different periods (1989-99, 2000-09, and 2010-18 under alternative reconciliation assumptions, as well as the baseline wealth shares in Column (1).

First, we present results from a "naive" reconciliation strategy that excludes all data items not directly measured by the SCF.[51] As described in Section 2, these assets are included in

[48]In Appendix Figure E.1, we show more disaggregated asset and liability categories on the bars, illustrating that our pseudo-real time forecast also predicts changes in specific balance sheet lines with reasonable precision.

[49]See Appendix D for a comparison of alternative imputation and forecasting procedures.

[50]Sampling 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 distribution.

[51]Specifically, we exclude life insurance reserves, pension entitlements, miscellaneous assets, and deferred

Table 2: Sensitivity of Net Worth Shares to Alternative Balance Sheet Definitions

			Alternative Wealth Definitions	
		Baseline	Naive Reconciliation	Confident Wealth
Years	Wealth Group	(1)	(2)	(3)
1989-1999	Bottom 50	3.8	3.1	3.9
	Next 40	35.0	29.8	35.4
	Next 9	35.3	34.5	35.8
	Top 1	26.0	32.6	24.9
2000-2009	Bottom 50	2.1	1.1	2.5
	Next 40	33.2	27.8	33.3
	Next 9	37.3	35.8	37.8
	Top 1	27.4	35.3	26.5
2010-2018	Bottom 50	0.6	-0.9	1.3
	Next 40	29.8	23.0	30.0
	Next 9	39.2	37.8	39.6
	Top 1	29.9	40.1	29.1

		Real Estate	Non Corporate Business	
		AVM	Market Value	Cost Basis
Years	Wealth Group	(4)	(5)	(6)
1989-1999	Bottom 50	3.8	3.8	3.7
	Next 40	35.0	34.9	35.0
	Next 9	35.3	35.1	35.2
	Top 1	26.0	26.2	26.1
2000-2009	Bottom 50	2.4	2.1	2.1
	Next 40	34.0	33.3	33.1
	Next 9	38.0	36.7	37.2
	Top 1	25.5	27.8	27.6
2010-2018	Bottom 50	0.9	0.6	0.6
	Next 40	30.6	29.7	29.7
	Next 9	40.2	39.2	39.4
	Top 1	28.1	30.4	30.2

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.

our benchmark household net worth concept (Financial Accounts Table B.101.h), and, in our baseline strategy, we impute these asset values to the SCF when constructing our reconciled SCF balance sheet. Column (2) shows that doing so has significant effects on the distribution of wealth. Excluding these imputed assets and liabilities raises the wealth share of the top 1% by 6-10 percentage points, with an associated decrease in the wealth shares of the other wealth groups. Including these imputations decreases wealth concentration because most of the imputed components — especially DB pensions — are distributed more equitably across the population than other components. This analysis indicates that including these assets is important for understanding a fuller picture of the distribution of wealth.[52]

Next, we focus on several asset classes that are measured in the SCF but that do not align closely with B.101.h, including corporate and foreign bonds, time and saving deposits, and consumer durables. As noted in Section 2, an evenly distributed difference in levels is not as important for our purposes as would be differences that vary systematically across the wealth distribution. To get a sense of how much these level differences affect our results, we calculate an alternative measure, which we call "confident wealth," that includes only the components for which the reconciled SCF balance sheet line is within 25 percent of its B.101.h counterpart.[53] As shown in Column (3), the "confident wealth" measure results in wealth shares of the top 1% and next 9% wealth groups that are generally less than 1 percentage point lower, with the other two wealth shares generally slightly higher. These relatively small shifts in wealth shares indicate a modest effect on our distributional results arising from wealth components with poor quantitative match, suggesting that the level differences between the data sets for these components are roughly proportional across the wealth distribution.

Our next robustness check considers alternative treatments of real estate. As noted in Section 2, the B.101.h and SCF series for aggregate real estate holdings diverge somewhat after the mid-2000s. To test whether this divergence has significant implications for our distributional results, we reconstruct the DFAs using an alternative measure of aggregate

and unpaid life insurance premiums in this exercise.

[52]Including 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))

[53]Specifically, confident wealth excludes consumer durables, time deposits and short term investments, debt securities, and consumer credit.

real estate that is included in the Enhanced Financial Accounts.[54] As shown in Column (4), using the alternative measure of aggregate housing wealth has minimal effects on the distribution, indicating that the difference in the level of housing wealth between the SCF and B.101.h is relatively evenly distributed across wealth groups.

Our last set of robustness checks focus on the treatment of noncorporate business equity. As noted in Section 2, the Financial Accounts value household equity in noncorporate business with a blend of cost-basis, book value, and market value, while the SCF measures market and cost-basis, but not book, values of noncorporate businesses. Our baseline reconciled SCF balance sheet uses the average of the two SCF measures because this series has tracked the B.101.h measure reasonably closely historically. To test the effect of this assumption on the resulting distribution, Columns (5) and (6) report reconstructed DFAs using each SCF measure (market value and cost basis) separately. We find little divergence from our baseline when we use either the market or the cost-basis measures alone, suggesting the differences in the distribution between cost-basis and market value measures of business equity are not driving the distributional results.

Overall, with the exception of excluding imputed balance sheet items such as pensions, which reflect important components of household wealth, we find little evidence that our resulting distribution is sensitive to reasonable alternative definitions for our reconciled SCF balance sheet.

5.1 Sampling Variability

A second issue we investigate regarding our new data set is how sensitive the results might be to 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 capture the top of the distribution with more precision.[55] Nonetheless, as in any survey, sampling variability is present. To gauge the impact of sampling variability on the DFA estimates, we bootstrap the SCF balance sheet following the procedure described in Bricker et al. (2017).

[54]The alternative measure is based on an automated valuation model from Zillow, and roughly splits the difference between the Financial Accounts and the SCF. For more information about this measure, see https://www.federalreserve.gov/releases/efa/alternative-measure-of-owner-occupied-real-estate.htm.

[55]Pure 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.

The results are shown in Table 3. 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.[56]

Table 3: Average Net Worth Shares and Standard Errors from 999 Bootstrap Samples for Each Wealth Group in Selected SCF Years

		Wealth Groups			
Year		Top 1% (1)	Next 9% (2)	Next 40% (3)	Bottom 50% (4)
1989	**Share (%)**	23.2	37.4	35.6	3.7
	s.e.	1.7	2.1	2.5	0.4
1998	**Share (%)**	27.4	34.5	34.7	3.4
	s.e.	0.9	0.7	0.8	0.2
2007	**Share (%)**	29.3	38.4	30.8	1.4
	s.e.	0.9	0.7	0.6	0.2
2016	**Share (%)**	31.0	39.3	28.7	1.0
	s.e.	0.8	0.8	0.6	0.1

6 Conclusion

In this paper, we have introduced the Distributional Financial Accounts, a new data set that integrates microdata with a national accounting framework to provide quarterly, timely data 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, the DFAs comprehensively integrate 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 studies, though with a somewhat

[56]Standard 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.

lower measure of the share of wealth held by the top 1% than in some other studies. Another important contribution of the DFAs is their ability to measure distributional changes at a quarterly frequency, which allows for study of the relationship between the wealth distribution and business cycle fluctuations. Finally, the timeliness of the DFA updates 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.

As part of the Financial Accounts of the U.S., the DFAs are intended to contribute to a global conversation about national statistics and the distribution of household wealth, and we hope the DFAs 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/enhanced-financial-accounts.htm`, where it will be updated on a quarterly basis going forward.

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A Actuarial Calculations for Life Insurance and Payout Annuities

This appendix documents the actuarial calculations supporting the distribution methods for life insurance and individual annuity reserves described in Section 2.

For life insurance reserves, we use these calculations to estimate how the breakdown in total amount of permanent versus term insurance in force (as measured by death benefit and reported in the statutory financial statements) translates to the breakdown in reserve (for which the total is reported, but not the amount by product). 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.

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 DFAs to approximately 75% term more

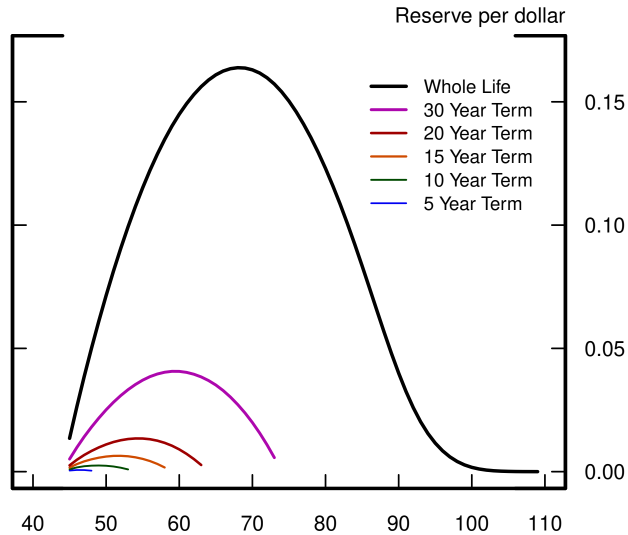


Figure A.1: Life Insurance Reserve per Dollar of Death Benefit for Sample Policies, Issue Age 45

recently. This results in reserve breakdown estimates that range from 90% permanent at the beginning of our sample to 75% permanent in 2018Q3. 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 marital status of the head of household.

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

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

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

$$\begin{aligned} V &= \begin{bmatrix} 1 & a & a^2 & ... & a^{n-1} \\ a & 1 & a & ... & a^{n-2} \\ a^2 & a & 1 & ... & a^{n-3} \\ \vdots & ... & ... & ... & \vdots \\ a^{3n-1} & ... & & ... & 1 \end{bmatrix} \\ &= A \times \frac{\sigma^2}{1-a^2}. \end{aligned}$$

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 $\left[Y - B'Z\hat{\beta}\right]$ is a^3. Iteratively using Equation 5 and Equation 3 and solving for a^3 by calculating the autocorrelation coefficient of $\left[[Y - B'Z\hat{\beta}\right]$ 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 $\left[[Y - B'Z\hat{\beta}\right]$.

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 DFAs 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's 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 Selecting a Temporal Disaggregation Model

Up to this point, we have introduced three distinct temporal disaggregation models based on three different assumptions on the error process: Chow Lin (1976), Fernandez (1981), and Litterman (1983). These three approaches yield qualitatively similar results, and the limited number of SCF waves complicates selecting the appropriate model from among this menu. Because there are only 10 observed SCF waves, coefficients for our indicator series as well as our target series estimates are unlikely to be statistically distinguishable across models. Nevertheless, below we employ objective criterion to select our baseline imputation and forecast model.

We construct several different measures of forecast accuracy, all of which are based on model predictions for the 2013 and 2016 SCF measures. First, we estimate the model using only the SCF observations from 1989-2010 and then calculate the sum of the squared differences (normalized by $1Trillion) between the 2013 model predictions and the 2013 reconciled SCF measures of net worth. 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. Second, we repeat this exercise by re-estimating the model on 1989-2013 SCF observations and examining predictions for the 2016 SCF. Third, we re-estimate the model on 1989-2010 and 2016 SCF observations, counterfactually assuming the 2013 SCF is not observed, and compare the model-predicted 2013 SCF balance sheet to that which was actually observed. Finally, we repeat this exercise assuming that the 2010 SCF is not observed. We conduct these three exercises for the net worth levels and shares of each wealth group: top 1%, 90-99%, 50-90%, and bottom 50%. Table D.1 presents the total sum of squared errors from these exercises.

The predictions of each model are generally quite similar — the total-wealth and wealth-by-percentiles total squared errors (TSEs) rarely differ substantially. The 2013 forecast errors are very low — about $3-7 trillion for total wealth and $3-8 trillion for wealth by percentiles. The 2016 forecast errors are somewhat larger at $37-46 trillion for total wealth and about $17-18 trillion for wealth by percentiles. Finally, the 2013 and 2010 imputation errors are quite modest both for total wealth ($ 11-16 trillion) and wealth by percentiles ($4-5 trillion). The Chow-Lin and Fernandez estimates are typically quite similar, and yield somewhat smaller errors than the Litterman method. Nonetheless, the TSEs differences

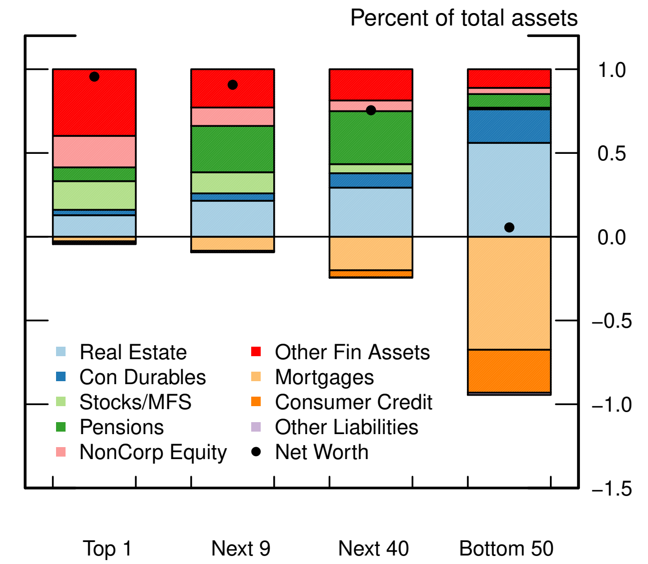
Table D.1: Comparison of Different Forecasting and Imputation Models

		Total Squared Errors of Quarterly Imputation		
		Chow-Lin	**Fernandez**	**Litterman**
		1	**2**	**3**
A. 2013 Forecast	**Total Wealth**	2.7	3.2	7.7
	Wealth by Percentiles	5.7	5.4	8.1
B. 2016 Forecast	**Total Wealth**	32.4	37.8	41.3
	Wealth by Percentiles	20.3	19.5	19.5
C. 2010 Imputation	**Total Wealth**	11.9	9.1	15.7
	Wealth by Percentiles	6.6	6.3	6.7
D. 2013 Imputation	**Total Wealth**	11.8	12.5	11.6
	Wealth by Percentiles	6.8	6.3	5.3

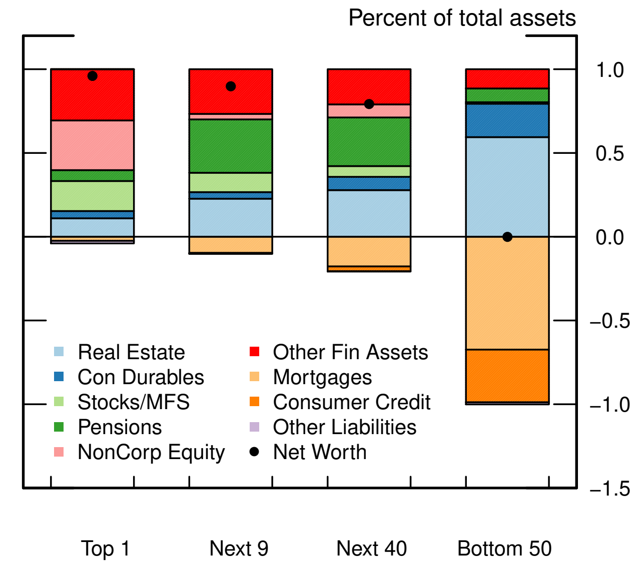
Notes: Each table entry shows the total sum of squared errors for reconciled balance sheet interpolations/extrapolations that selectively exclude an SCF year. The 2013 Forecast rows use SCF data through 2010 and Financial Accounts data through 2013Q3. The 2016 Forecast rows use SCF data through 2013 and Financial Accounts data through 2016Q3. The 2010 Imputation rows use all available SCF and Financial Accounts data except the 2010 SCF. The 2013 Imputation rows use all available SCF and Financial Accounts data except the 2013 SCF. All calculations use the 2018Q4 vintage of the Financial Accounts.

between these three approaches are not very large. Therefore, 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.

E Additional Tables and Figures



(a) Pseudo real-time estimate of 2009Q1 balance sheets



(b) DFAs measure of 2009Q1 balance sheets

Figure E.1: Household Balance Sheets Across the Wealth Distribution During the Financial Crisis (Detailed)

Notes: Panel (a) shows the extrapolated DFA balance sheets for 2009Q1 using SCF data only through 2007Q3 and Financial Accounts data through 2009Q1. Panel (b) shows the actual DFA balance sheet estimates for 2009Q1 using all available SCF and Financial Accounts data. All panels use the (current) 2018Q3 vintage of the Financial Accounts.

Table E.1: Summary of Indicator Series Used in Interpolating and Forecasting Household Balance Sheets

	FA 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		X						
Financial Assets	X	X								
Checkable Deposits and Currency	X	X				X				
Time Deposits	X					X				
Money Market Fund Shares	X					X				X
US Government and Municipal Securities	X	X				X				
Corporate and Foreign Bonds	X	X				X				
Loans	X	X								
Other Loans and Advances	X	X				X				
Mortgages	X	X				X				
Corporate Equities and Mutual Fund Shares	X					X				
Life Insurance Reserves	X	X				X				
Pension Entitlements	X	X			X	X				
Equity in Noncorporate Business	X	X				X				
Miscellaneous Assets	X	X				X				X
Home Mortgages	X			X					X	
Consumer Credit	X	X						X	X	
Depository Loans N.E.C.	X	X					X			
Other Loans and Advances	X	X							X	
Deferred and Unpaid Life Insurance Prem.	X	X							X	
Net Worth	X	X	X						X	

F 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 (OMuircheartaigh and Pedlow (2002)).[57] 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.[58] In each bin (b), we find the relative frequency (RF) of SCF and Forbes cases by the formula

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

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.[59]

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

[58]We 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.

[59]When 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.