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The Distributional Financial Accounts of the United States

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22.1 Introduction

There is a growing consensus that wealth inequality in the United States has increased substantially over the past 30 years (Bricker et al. 2016; Kuhn and Ríos-Rull 2016; Piketty 2014; Saez and Zucman 2016; Wolff, Zacha-

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rias, and Masterson 2012). This has undermined the ability of aggregate economic statistics to describe of the economic well-being of most Americans. Further, the increase in inequality has implications for other economic and social outcomes. For instance, studies have examined the relationship between wealth distribution and economic growth (Banerjee and Duflo 2003), monetary policy transmission (Auclert 2019; Gornemann, Kuester, and Nakajima 2016; Kaplan, Moll, and Violante 2018), aggregate saving rates (Fagereng et al. 2016), optimal tax policy (Albanesi 2006; Shourideh 2012), social mobility (Benhabib, Bisin, and Luo 2017), and even political engagement (Solt 2008).

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

This approach produces a rich and reliable measure of the wealth distribution that we believe is particularly useful for several reasons. First, the DFA exists in a national accounting framework, meaning it is consistent with the Financial Accounts aggregates that have become well-established tools for studying the macro economy.[2] Second, it is available quarterly in near real time (approximately 11 weeks after the quarter close). In contrast, alternative measures of the wealth distribution are available at an annual fre-

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

2. Scholars have often expressed interest in incorporating microeconomic heterogeneity into national accounting frameworks. For example, Carroll (2014) cites the need for distributional national statistics, while the Inter-Agency Group on Economic and Financial Statistics has called on G-20 nations to develop such statistics that are internationally comparable. Other efforts to construct distributional national measures in the United States include early work by King (1915, 1927, 1930), Kuznets, Epstein, and Jenks (1947), and Kuznets and Jenks (1953), more recent efforts by Piketty, Saez, and Zucman (2017), and prototype estimates recently released by the Bureau of Economic Analysis (Fixler, Gindelsky, and Johnson 2020; Fixler and Johnson 2014; Fixler et al. 2017; Furlong 2014; Gindelsky 2020).

quency at best, and typically have a lag of several years. Third, the Financial Accounts definition of wealth is quite comprehensive, including important components such as defined benefit pensions that are not easily measured in other sources. Finally, the SCF's detailed household-level information reduces the need to rely on strong assumptions to generate distributional statistics, and allows us to study how wealth is related to demographic characteristics.

The chapter proceeds as follows. In section 22.2, we describe the construction of SCF wealth concepts that are consistent with each component of household net worth in the Financial Accounts. In section 22.3, we document how we interpolate and forecast the SCF distributions between SCF observations. In section 22.4, we present high-level results, and illustrate how the DFA furthers our understanding the distribution of household wealth. In section 22.5, we show that our results are robust to key reconciliation assumptions, alternative approaches to interpolation and forecasting, and sampling variability inherent in the SCF. Finally, we summarize in section 22.6 the DFA's key contributions.

22.2 Reconciling the Financial Accounts and the SCF

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

Comparing and reconciling the SCF and Financial Accounts has a long history, including Antoniewicz (1996), Avery et al. (1987), Dettling et al. (2015), Henriques and Hsu (2014), and Maki and Palumbo (2001). Generally, these studies find that the aggregated SCF "bulletin" measures of assets and liabilities align reasonably well, but not perfectly, with the Financial Accounts.[3] Our approach, though similar in spirit to much of this prior

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. 2017a).

work, extends it in several important ways, thereby producing the most rigorous reconciliation of the SCF and Financial Accounts concepts of household net worth to date. First, prior work has reconciled the SCF (a household survey) with Financial Accounts table B.101 (which includes nonprofit organizations). We are able to make use of the recently developed Financial Accounts table B.101.h, which provides a slightly less detailed breakdown of wealth categories than B.101, but excludes nonprofits.[4] Second, while prior reconciliations have largely excluded assets and liabilities that are absent or difficult to measure in the SCF (e.g., the value of defined benefit pensions, insurance reserves, and annuities), for the DFA, we distribute these Financial Accounts totals to SCF respondents using other relevant information reported in the survey (e.g., pension benefits received and insurance ownership). In section 22.4, we demonstrate how incorporating these assets and liabilities produces a somewhat less skewed distribution of wealth. Finally, we also extend prior reconciliations by relying on a method that reweights the SCF to incorporate the wealth of the Forbes 400. These individuals are explicitly excluded from the SCF sample due to privacy concerns but contribute materially to the top of the wealth distribution.[5]

B.101.h assets and liabilities fall into three broad categories: (1) those for which there is an SCF analog with no or relatively little adjustment; (2) those for which substantial adjustment and/or investigation is necessary to construct a comparable SCF measure; and (3) those for which there is no analogous valuation in the SCF, but for which there is relevant information provided by SCF respondents that we use to distribute the B.101.h total. While the distinction between the first and second categories is somewhat subjective, table 22.1 shows how we categorize each line of B.101.h. In the remainder of this section, we focus on describing the reconciliation process for large assets and liabilities in categories two and three. The full description of how we reconstruct all nineteen balance sheet lines from table B.101.h using SCF data is available in online appendix A (http://www.nber.org/data-appendix/c14456/appendix.pdf).

22.2.1 Reconciliation Process for Large Assets and Liabilities

22.2.1.1 Pension Entitlements (Excluding Defined Contribution Pensions)

DB pensions and annuities make up 60 percent and 10 percent, respectively, of pension entitlements in the Financial Accounts. These include

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 Holmquist (2019).

5. See appendix E (http://www.nber.org/data-appendix/c14456/appendix.pdf) for a description of the reweighting method. The weighting correction is based on Bricker et al. (2016). For details on the Forbes list of wealthiest families, see https://www.forbes.com/forbes-400/.

Table 22.1 B.101.h assets and liabilities by reconciliation category

Minimal adjustment (1)	Substantial adjustment (2)	Indirectly measured in SCF (3)
Real estate	Corporate equities and mutual funds	Pension entitlements (excluding DC pensions)
Home mortgages (liability)	Equity in noncorporate business	Life insurance
DC pensions (a component of pension entitlements)	Time deposits and short-term investments	Miscellaneous assets
Checkable deposits and currency	Consumer durable goods	Deferred and unpaid life insurance premiums
Other loans and advances (asset)	US government and municipal securities	
Other loans and advances (liability)	Consumer credit	
Home mortgages (asset)	Money market mutual fund shares	
Depository institution loans not elsewhere classified	Corporate and foreign bonds	

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

accrued benefits to be paid in the future from defined benefit (DB) plans, and annuities sold by life insurers directly to individuals.[6]

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

6. 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. The annuities component also includes annuities held in individual retirement accounts (IRAs). IRA investments in other instruments, such as mutual fund shares, are included in the other asset categories described above.

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

The economic value of annuities is also not directly collected by the SCF in a manner that is comparable to B.101.h. However, the SCF reports the amount of income received from annuities that are in the payout phase, as well as the cash value of deferred annuities (which differs from the economic value due to surrender penalties and other policy benefits not immediately payable in cash). To reconcile the SCF and B.101.h annuity measures, we capitalize the payout annuity income reported by SCF households into a present value using a set of sample annuity policies (see online appendix A, http://www.nber.org/data-appendix/c14456/appendix.pdf) and then distribute the B.101.h annuity reserves according to the sum of the cash value of deferred annuities and capitalized value of payout annuities reported in the SCF. In online appendix A, we describe similar methods used to distribute life insurance reserves and property and casualty insurance reserves (the latter of which is a component of miscellaneous assets).

22.2.1.2 *Financial Assets Held through IRAs, Trusts, and Managed Investment Accounts*

It is relatively straightforward to assign financial assets directly held by SCF households to the appropriate B.101.h categories (e.g., directly held stocks and mutual funds are assigned to the B.101.h category "corporate equity and mutual fund holdings"). However, we must make additional assumptions to assign financial assets that are held by SCF households indirectly through IRAs, trusts, and managed investment accounts.[9] For these types of investment vehicles, the SCF asks what percentage of holdings are invested in equities versus interest-bearing assets. Using this percentage, we assign the share of these assets that are invested in equities to "corporate equity and mutual fund holdings." For the nonequity share, since we do not directly observe the composition of the interest-bearing

7. 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.

8. 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.

9. DC retirement accounts are included with pension plans, as described below.

assets, we use the *Investment Company Institute Fact Book* (Collins 2018) and IRA Database (Holden and Bass 2018) for the relevant year to estimate the breakdown, assuming each SCF respondent holds a representative portfolio. These adjustments are applied to time deposits and short-term investments, money market mutual fund shares, US government and municipal securities, corporate and foreign bonds, and corporate equities and mutual funds (and are the reason we place these assets in category 2).

22.2.1.3 Equity in Noncorporate Business

This category includes nonpublicly traded businesses and real estate owned by households for renting out to others. Notably, closely held S and C corporations are not included in this category. There are substantial differences in its measurement between the SCF and Financial Accounts. The B.101.h measure is a hybrid of different accounting bases. Real estate (e.g., rental properties), which accounts for approximately 60 percent 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 Bureau of Economic Analysis (BEA). Financial assets and liabilities are recorded at book value from tax data.

In the SCF, rental properties are reported at market value. For other noncorporate business assets, the SCF captures owners' self-reports of both the market value and the cost basis of their businesses. When we compare these two measures to B.101.h, we find (unsurprisingly) that the market-value SCF measure exceeds the B.101.h measure (with an average ratio of approximately 150 percent), while the cost-basis SCF measure falls below the B.101.h measure (with an average ratio of 70 percent).[10] To reconcile the SCF and B.101.h, we use the average of the two SCF valuations, which tracks the B.101.h measure quite well empirically. In section 22.5, we show our results are robust to this choice, which implies the SCF market and cost basis measures are roughly proportional to each other throughout the wealth distribution.

22.2.1.4 Corporate Equities and Mutual Funds

In addition to the indirectly held equities described above, two additional complications exist for the corporate equities and mutual fund category. First, similar to equity in noncorporate business, the value of closely held corporations (S and C corporations) is reported in the SCF both at market value and at cost basis. The market and cost-basis valuations in the SCF again straddle the Financial Accounts valuation, so we employ the average of the SCF measures in the DFA. Section 22.5 shows our results are also robust using either the SCF market or cost-basis valuations.

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

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

22.2.1.5 Consumer Durable Goods

This B.101.h category, taken from the BEA's stock of fixed assets and consumer durable goods, captures many durable assets: automobiles, trucks/motor vehicles, furniture, carpets/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 percent of B.101.h consumer durables. For the remaining assets, the SCF asks "Other than pension assets and other such retirement assets, do you (or anyone in your family living here) have any other substantial assets that I haven't already recorded . . . ?" If families indicate that they own any such assets, they are queried about the type of the asset and its value. We sum all nonfinancial assets included in responses to this question to obtain our reconciled SCF measure of consumer durable goods.

The SCF reports fewer consumer durables than the Financial Accounts, with the ratio typically around 60 percent. This occurs in large part because the BEA measure covers essentially any item that has resale value, whereas the SCF focuses on the most substantial assets.[12] To the extent that these significant assets are concentrated among the wealthy, and the regular household goods that the SCF may miss are more equally distributed, applying the SCF distribution to the Financial Accounts total may overstate inequality. To assess the significance of this potential bias, we group the SCF assets into the 28 BEA consumer durable categories with an eye toward understanding how evenly spread these assets might be. We find little systematic evidence that the SCF more severely underreports consumer durable goods that are likely more evenly distributed (such as "window covering" or "sport-

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

12. While the SCF question offers examples of items that fall into many of the BEA categories, its prompt begins with a list geared toward 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?"

ing 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.

22.2.2 Comparing the Reconciled Balance Sheets

After constructing measures that are conceptually aligned, we assess the degree to which the national aggregates implied by the SCF are numerically similar to those from the Financial Accounts. While close empirical matches are ideal, the measurement approaches employed by the two sources are different enough that we aim more for similarity in magnitude than a precise match.[13] Table 22.2 summarizes the results of the SCF-B.101.h reconciliation exercise by showing the ratio of the two measures for each line of table B.101.h, for each wave of the SCF since 1989. A ratio of 100 percent would indicate that the two series match exactly, while lower (or higher) percentages indicate that the reconciled SCF understates (or overstates) the B.101.h total. Note, the B.101.h and reconciled SCF lines for categories not directly measured in the SCF match by construction. For reference, the figure also shows the level of the B.101.h and SCF series in 2019 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 2019, reconciled SCF assets aggregate to \$123 trillion, compared with \$125 trillion on B.101.h, and reconciled SCF liabilities aggregate to \$14 trillion, versus \$14 trillion on B.101.h. Averaging across SCF waves, aggregate SCF net worth is very close (at 104 percent) to B.101.h net worth.[14] Looking deeper, we find the two data sets also align reasonably well for most, and importantly the largest, underlying asset and liability categories. Further, while there are numerical discrepancies, section 22.4 shows that if we distribute the reconciled SCF totals rather than the B.101.h totals, the overall wealth distribution and the trends over time are little changed. This gives us further confidence that combining the SCF and Financial Accounts provides reliable information about the wealth distribution.

13. 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.

14. While the match is reasonable in all years, the alignment further improves in recent years. For example, in 2019 the ratio of SCF to B.101.h assets, liabilities, and net worth are 99 percent, 108 percent and 102 percent.

Table 22.2 **The ratio of the reconciled SCF household balance sheet to B.101.h**

	Ratios in SCF years												Recent levels ($billion)	
	1989	1992	1995	1998	2001	2004	2007	2010	2013	2016	2019	Average	FA 2019Q3	SCF 2019
Total assets	98	91	91	97	108	104	102	106	102	108	101	101	123320	124905
Nonfinancial assets	97	92	91	99	97	105	113	117	115	110	106	104	35323	37416
Real estate[1]	107	105	101	110	105	113	123	131	127	119	114	114	29612	33718
Consumer durable goods[2]	60	48	58	58	64	67	63	62	63	66	65	61	5711	3699
Financial assets	98	91	91	97	114	103	96	100	98	107	99	99	87997	87489
Checkable deposits and currency	65	45	50	85	136	194	809	240	130	145	191	190	807	1545
Time deposits and short-term investments	60	63	59	65	58	63	51	54	42	47	45	55	9761	4436
Money market fund shares	83	80	76	59	72	101	71	93	133	128	102	91	1964	2006
US government and municipal securities	70	53	54	54	106	95	94	72	81	101	77	78	4380	3388
Corporate and foreign bonds	88	51	27	31	69	61	60	45	64	108	95	64	806	765
Other loans and advances	333	123	186	63	62	43	34	52	71	54	62	98	788	485
Mortgages	110	94	91	84	97	97	102	96	177	275	155	125	81	126
Corporate equities and mutual fund shares	144	120	121	132	187	142	112	128	111	128	110	130	27010	29812
Life insurance reserves**	100	100	100	100	100	100	100	100	100	100	100	100	1719	1719
Pension entitlements[3]	101	100	100	100	100	100	100	100	100	100	100	100	27166	27145
Equity in noncorporate business[4]	106	93	80	86	99	93	99	125	115	134	121	105	12259	14799
Miscellaneous assets**	101	101	100	100	101	100	100	100	101	100	100	100	1257	1263
Total liabilities	79	80	79	86	81	88	83	88	87	88	92	85	15305	14028
Home mortgages[5]	81	84	84	93	89	94	87	92	95	95	103	91	10415	10743
Consumer credit	59	57	55	60	52	59	65	69	59	68	66	61	4117	2727
Depository institution loans n.e.c.	1897	3134	278	210	470	–3153	216	89	95	36	33	300	256	85
Other loans and advances	99	99	99	97	99	99	98	90	98	99	91	97	480	437
Deferred and unpaid life insurance premiums	102	102	99	100	99	99	99	98	98	99	98	99	37	36
Net worth	100	93	93	99	112	107	106	109	105	111	103	103	108015	110877

Note: n.e.c. = not elsewhere classified.

[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.

22.3 Constructing Quarterly Distributional Measures from the Reconciled SCF Balance Sheets

Having shown that the SCF can reasonably approximate B.101.h after appropriate adjustments, the second main challenge in constructing the DFA quarterly is that the SCF is fielded triennially. Thus, we must impute and forecast the reconciled SCF balance sheets for quarters where SCF measures are not available. This "temporal disaggregation" problem of imputing higher-frequency data from lower-frequency observations has been well studied, beginning with the foundational paper, Chow and Lin (1971). We apply the Fernández (1981) extension of the Chow-Lin approach to interpolate and forecast quarterly data from the reconciled SCF to quarters where it is not observed. In particular, we use the empirical relationship between the SCF, the Financial Accounts, and other macroeconomic data when all three are observed to impute the SCF data in quarters when only the Financial Accounts and macroeconomic data are available. We apply this method to the reconciled SCF assets and liabilities described in the previous section for four wealth groups: the top 1 percent of the wealth distribution, the next 9 percent (i.e., 90th–99th percentile), the next 40 percent (50th–90th percentile), and the bottom 50 percent.[15] As a final step in constructing the DFA data, we calculate the share of the reconciled SCF total held by each wealth group each quarter, and multiply these shares by the B.101.h total for each asset and liability to produce the DFA.[16]

Section 22.3.1 and online appendix B (http://www.nber.org/data-appendix/c14456/appendix.pdf) present the mathematical details of this method. Section 22.3.2 shows how we implement the Fernández method, and section 22.3.3 presents selected results from our imputations and forecasts that indicate our method provides reliable estimates of the wealth distribution between SCF observations.

22.3.1 The Fernández Method of Temporal Disaggregation

The original 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 three years, while X is quarterly:[17]

15. 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.

16. The details of this final step are presented in online appendix C, http://www.nber.org/data-appendix/c14456/appendix.pdf.

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

$$(22.1) \qquad Y = B'X.$$

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:[18]

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

where the residual vector u is mean zero with covariance matrix $V = \mathbb{E}[uu']$. Linearity combined with equation (22.1) implies that

$$(22.2) \qquad Y = B'Z'\beta + B'u.$$

The Chow-Lin method solves the multiple regression model specified by equations (22.1) and (22.2) 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

$$(22.3) \qquad \hat{X} = Z\hat{\beta} + VB(B'VB)^{-1}[Y - B'Z\hat{\beta}]$$

$$(22.4) \qquad \hat{\beta} = [Z'B(B'VB)^{-1}B'Z]^{-1}Z'B(B'VB)^{-1}Y.$$

Here, $\hat{\beta}$ is a vector obtained from the generalized least squares regression specified in equation (22.2) with Y as the dependent variable, $B'Z$ as the dependent variable, and residual covariance matrix $(B'VB)$.

Equation (22.3) 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, that is, $\mathbb{E}[X|Z]$. The second component, $VB(B'VB)^{-1}[Y - B'Z\hat{\beta}]$, reflects the estimate of the vector of higher-frequency residuals obtained by distributing the vector of lower-frequency residuals $[Y - B'Z\hat{\beta}]$ across periods where the target series is unobserved. The distributing matrix $VB(B'VB)^{-1}$ is determined by the assumed covariance matrix V. Note that $\hat{X} = Y$ by construction for the periods that Y is observed.

A key input into this method is the assumed error structure of the higher-frequency residuals, represented by V. This covariance matrix is not observed and must be estimated—any consistent estimate for V can then be used to obtain FGLS estimates $\hat{\beta}$ and $\hat{X}$. We assess three different versions of

that $X = [x_1, x_2, \ldots, x_n]'$ 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

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

where ι 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.

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

this FGLS procedure corresponding to different assumption on the higher-frequency residuals. One version follows Chow and Lin (1971) and produces estimates under the assumption that these residuals are first-order autocorrelated. The other two adopt the methods in Fernández (1981) and Litterman (1983), which characterize solutions for error processes of the form

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

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

In particular, Fernández (1981) assumes a random walk ($\rho = 0$), while Litterman (1983) generalizes to a random walk, Markov model ($0 < \rho < 1$). Appendix B (http://www.nber.org/data-appendix/c14456/appendix.pdf) provides more detail on the estimation of V under these three methods. In practice, we reject the Chow-Lin method due to its tendency to estimate low autocorrelation of the residuals, which can produce implausible discontinuities in the data. The Fernández and Litterman models perform similarly, and we select the Fernandez method due to its relative ease of implementation. Section 22.5 compares the various models in greater detail.

22.3.2 Implementation of the Fernández Method

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

19. 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.

20. 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.

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 US Census Current Population Survey (CPS). We also include the ratio of B.101.h defined benefit assets to defined contribution assets as an indicator series for pension entitlements, and vehicle and student loans outstanding from the Federal Reserve's G.19 data release as indicator series for depository loans and consumer credit, respectively. Appendix table D.2 (http://www.nber.org/data-appendix/c14456/appendix.pdf) summarizes which indicator series are used for each asset and liability class on our reconciled household balance sheet.

Because the relative sizes of different demographic groups change over time, we estimate the models on a per-household basis so the wealth shares of different groups respond to population changes. That is, the target series in our models is the reconciled SCF wealth for each group divided by the number of households in that group,[21] and the FA aggregate indicator series is also divided by the count of total households. We then multiply the model output by the number of households in the applicable group to calculate the wealth levels and shares.

22.3.3 Predictions from the Fernández Method

In this section, we present selected imputation and forecast results to highlight the method's ability to generate plausible estimates of unobserved movements in household balance sheets. We begin by showing that the DFA makes predictions that are both consistent with broader economic conditions at the time and not apparent from the surrounding SCF observations. The corporate equities and mutual funds category, shown in figure 22.1a, is a salient example. Booms and busts in equity markets often occur in between SCF observations (marked with vertical black lines), and the DFA responds intuitively with the holdings of the top 1 percent and, to a lesser extent, the next 9 percent, rising and falling sharply. These movements are expected given that wealthier households hold larger and riskier corporate equity and mutual fund portfolios. Figure 22.1b shows that these movements in equity markets generate spikes and troughs in the top 1 percent overall wealth share at several points between SCF observations, such as the late 1990s equity

21. The count of households for each group is taken from the SCF. Between SCF periods, the number of households for each group is currently estimated using a cubic spline. In a future release, we will estimate changes in household counts between SCF periods using CPS data.

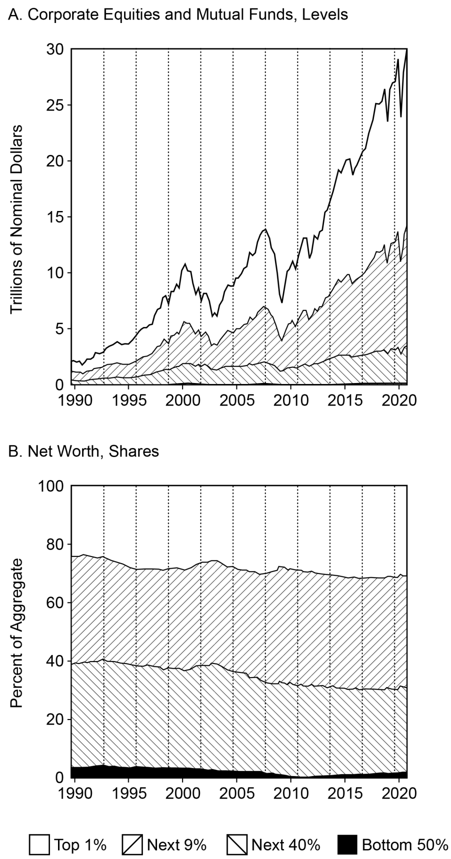

Fig. 22.1 Predicted corporate equities/mutual funds and net worth

boom, the bursting of the tech bubble in the early 2000s, and the Great Recession in the late 2000s.

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

While the Fernández predictions for periods between SCF observations cannot be validated against existing data, an alternative is to employ our interpolation/extrapolation method as if a given SCF observation did not exist, and then compare these predictions to the DFA for that period (which

Table 22.3 **Deviation from DFA wealth distribution**

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

Note: This table shows the DFA wealth shares for SCF periods and the wealth share predicted when that SCF is omitted.

are based upon the omitted SCF observation). For example, we compare the 2013Q3 DFA wealth shares to those produced when we omit the 2013 SCF and, instead, interpolate each period between the 2010 and 2016 SCF waves (which correspond to the 2010Q3 and 2016Q3 DFA periods). This exercise is considerably more ambitious than the baseline DFA because it interpolates over six years rather than three. Thus, we view it as a useful way to bound the amount of error that we could reasonably expect in the DFA between SCF observations.

Table 22.3 shows the baseline DFA wealth shares and those from the "leave one out" exercise for each SCF from 2001 through 2016. Overall, the "leave one out" method does an admirable job of replicating the omitted SCF observations. Although there are some modest numerical differences, the exercise does accurately capture important qualitative characteristics of the underlying data such as the top 1 percent wealth share's rapid increase before and then dip during the Great Recession and the prolonged decline in the bottom 50 percent wealth share after the Great Recession. In section 22.4, we perform similar tests that extrapolate over the Great Recession (assuming SCF releases beyond 2007 are not available) and suggest the DFA could be useful during times of economic turmoil.

22.4 The DFA in Action

The DFA breaks down aggregate B.101.h wealth and its components into four wealth percentile groups for the United States as a whole: top 1 percent, next 9 percent, the next 40 percent, and the bottom 50 percent. The DFA also gives wealth breakdowns along demographic characteristics: income, age, generation (birth cohort), and race. This section presents some high-level takeaways from the DFA and shows how these data compare to other sources of information on wealth inequality. We also show examples of how the frequency and timeliness of the DFA provide new insights, and we present results split by generation as an application of the available demographic information. The full dataset is available via an interactive visualization tool and for download here: https://www.federalreserve.gov/releases/z1/dataviz/dfa/.

22.4.1 Headline Results

The DFA shows wealth inequality is high and has grown considerably since 1989. Figure 22.2 shows the level and share of total net worth for the four wealth percentile groups. The top 10 percent of the wealth distribution—the areas in white and with diagonal lines going up to the right together—hold a large and growing share of US aggregate wealth, while the bottom half (the thin black area) holds a tiny share. While the total net worth of US households has more than quadrupled in nominal terms since 1989 (figure 22.2a), this increase has accrued more to the top of the distribution than the bottom (figure 22.2b). In 2020, the top 10 percent of US households controlled nearly 70 percent of total household wealth, up from 60 percent in 1989. The share of the top 1 percent of the wealth distribution increased from 23.6 percent to 31 percent over this period. The increase in the wealth share of the top 10 percent came primarily at the expense of households in the 50th to 90th percentiles of the wealth distribution (diagonal lines down to the right), whose share decreased from 35.5 percent to 28.7 percent over this period. In addition, figure 22.2a) shows that the wealth share of the bottom 50 percent fell from 3.7 percent in 1989 to just 2 percent in 2020.

The rise in wealth inequality stems primarily from asset accumulation of the top 1 percent percent, and to a lesser extent the next 9 percent, as opposed to an accumulation of debt throughout the middle and bottom of the distribution. Figure 22.3b shows the share of assets held by the top 10 percent of the wealth distribution rose from 55 percent to 64 percent since 1989, with asset shares increasing the most for the top 1 percent of households. In contrast, figure 22.3b shows that liabilities have remained much more evenly distributed, on net, with only modest increases at both the top and bottom of the distribution since 1989.

Figures 22.4a and 22.4b show that business equity is largely held by the top of the distribution. Business equity comprises nearly one-third of all household assets and is the largest driver of the increase in concentration over time. This category includes the value of both corporate and noncorporate business but not equities held through pension funds and annuities (which are included in pension entitlements). The distribution of these assets has long been skewed: in 1989, the richest 10 percent of households held 82 percent of corporate equity and 80 percent of equity in noncorporate business. Since 1989, the top 10 percent's shares of both corporate and non-

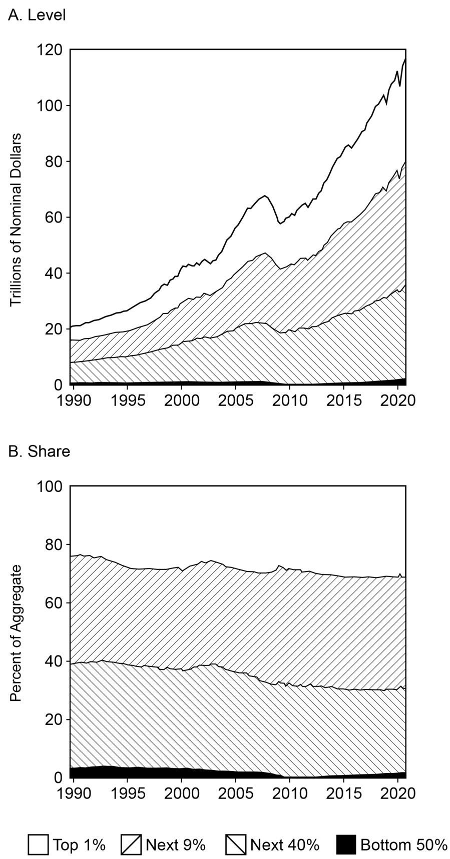

Fig. 22.2 Net worth by wealth percentile group

corporate equity have increased, on net, to 88 percent. Furthermore, only the top 1 percent has gained share in these assets. The top 1 percent shares of corporate equities and noncorporate business increased by approximately 10 percentage points, respectively, while the next 9 percent fell by 4 percentage points. As shown in figure 22.4c, pensions are spread more evenly, at least through the top half of the wealth distribution, and have not contributed to the growing share of the top 1 percent. Instead, they are the primary reason the next 9 percent has shown a small increase in its overall wealth share since 1989, with its share of pension entitlements increasing by 8 percentage points. Real estate (figure 22.4d) is also more evenly distributed and has contributed more modestly to growing inequality. The top 1 percent gained 6 percentage points, while the next 9 percent and the bottom 50 percent were mostly stable.

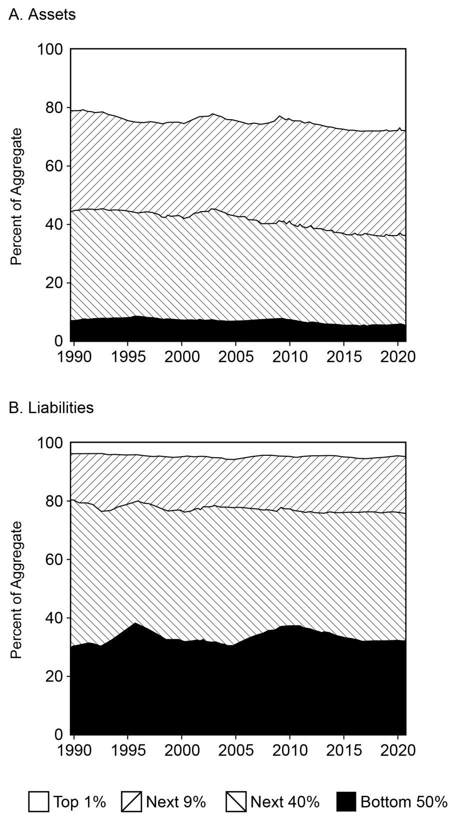

Fig. 22.3 Total asset and liability shares by wealth percentile group

22.4.2 Comparison with Other Distributional Statistics

The high and increasing wealth inequality documented in the DFA is broadly consistent with other studies, but there are also subtle differences that are interesting to explore.[22] Figure 22.5 plots our wealth shares along with those from the World Inequality Database (WID) and Smith, Zidar, and Zwick (2019), which are the most comparable datasets to the DFA.[23]

22. For example, see Bricker et al. (2016), Piketty (2014), Kuhn and Ríos-Rull (2016), Saez and Zucman (2016), Smith, Zidar, and Zwick (2019), and Wolff, Zacharias, and Masterson (2012).

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

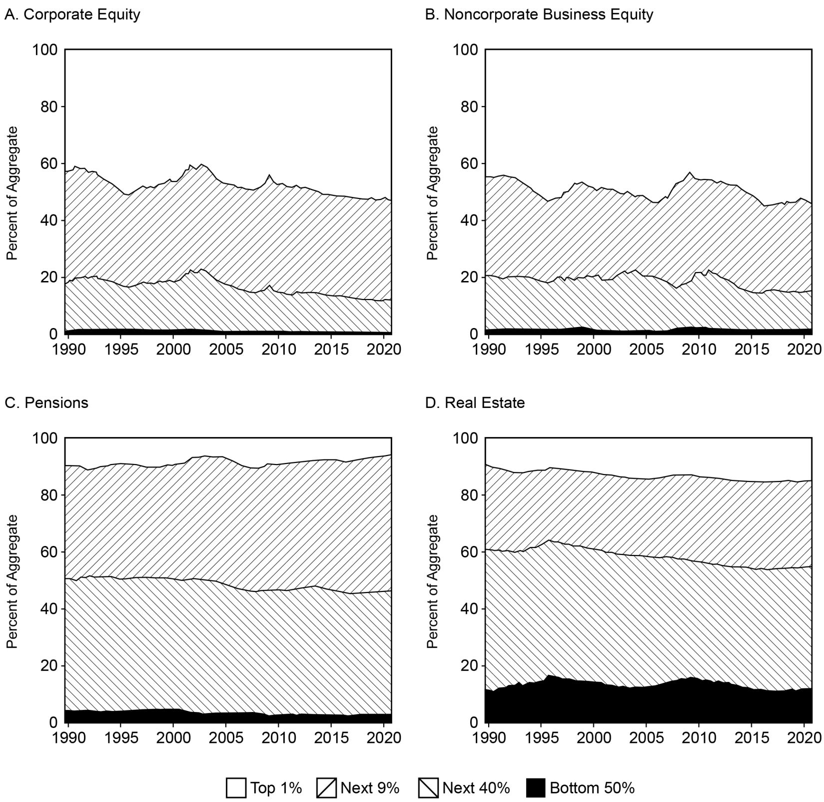

Fig. 22.4 Pension, real estate, corporate equity, and noncorporate business equity by wealth percentile group

Compared to the WID, the DFA shows somewhat less of the wealth within the top 10 percent belongs to the top 1, but the trends over time and through the rest of the distribution are generally similar (figure 22.5a). While both the DFA and WID data distribute aggregate wealth in the Financial Accounts, the primary source of distributional information differs. Unlike the DFA, the WID is based on the distribution of realized income and an assumed relationship between income and components of wealth.[24] Past iterations of both datasets differed somewhat more in the degree of inequality and its pace of increase,[25] but recent updates, such as those described in Zucman

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

25. For example, Bricker et al. (2016) show that differences in rates of return across the wealth distribution account for most of the discrepancy in the concentration measures observed in the WID versus the SCF, and play a particularly large role in the WID's sharper increase in the top 1 percent wealth share in the years following the Great Recession.

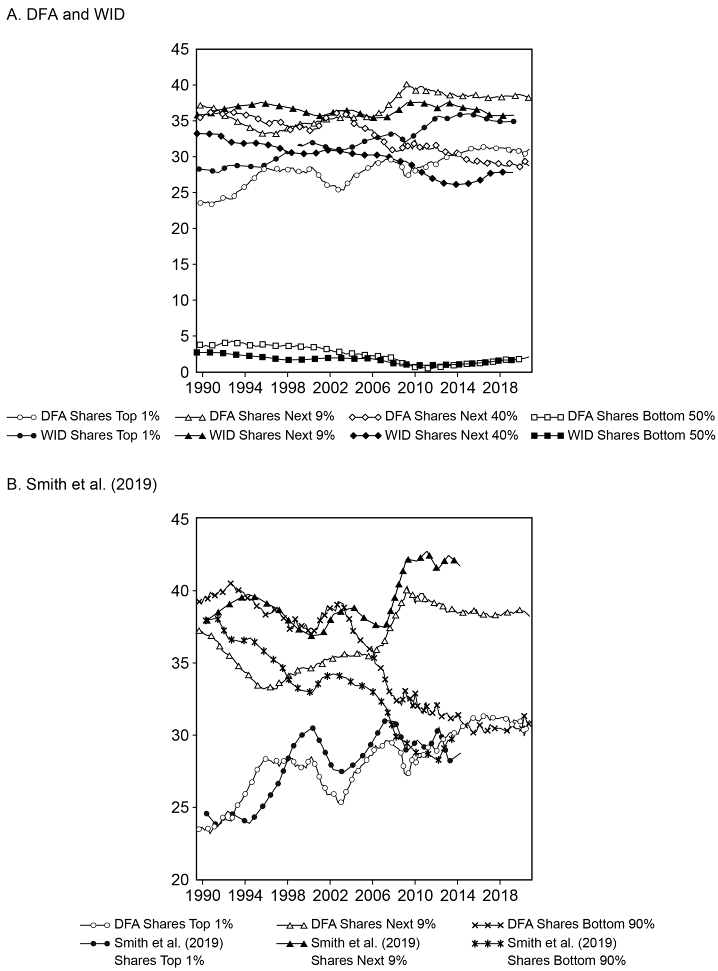

Fig. 22.5 Wealth shares from the DFA, WID, and Smith, Zidar, and Zwick (2019)

(2020) and Batty et al. (2020) have brought them in closer alignment. Methodological differences such as the DFA's inclusion of consumer durables (5 percent of household wealth) and unfunded defined benefit pensions (6 percent of household wealth) contribute to the remaining differences. These are among the more equally distributed asset classes in the DFA, and their inclusion modestly reduces inequality.

Several other models also allow rates of return on assets to vary by wealth. The model used in Bricker, Henriques, and Hansen (2018) allows wealthy families to have higher rates of return on interest-bearing assets. The model used in Smith, Zidar, and Zwick (2019) incorporates this insight, and also places more weight on dividend income, which is more equally distributed

Table 22.4 Directly and indirectly measured wealth

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

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

than taxable capital gains, to distribute corporate equity wealth.[26] In the model preferred by Smith, Zidar, and Zwick (2019), these assumptions produce a wealth distribution that is quite similar to the DFA (figure 22.5b).[27] In both the DFA and Smith, Zidar, and Zwick (2019), the top 1 percent share increases from the low to mid 20s in 1989 to approximately 30 percent in 2015. The next 9 percent is relatively flat in the mid to upper 30s over much of the 1990s and early 2000s before increasing around the time of the Great Recession. The bottom 90 percent share falls consistently over the window, from just below 40 percent to around 30 percent.

The SCF itself is also a tool to study wealth inequality. Measures of the wealth distribution derived exclusively from the SCF show somewhat more inequality than the DFA. The most important reason is the inclusion in the DFA of assets and liabilities not directly measured in the SCF (e.g., DB pensions, annuities, and insurance). Appendix D (http://www.nber.org/data-appendix/c14456/appendix.pdf) shows a detailed stepwise mapping from the SCF to the DFA. A summarized version is presented below in table 22.4.[28] Columns 3 and 4 show that these indirectly measured catego-

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

27. The data for figure 22.5b are borrowed with permission from an updated version of figure 1(b) from Smith, Zidar, and Zwick (2019).

28. See online appendix table D.1, http://www.nber.org/data-appendix/c14456/appendix.pdf.

ries are much more equally distributed than those that are directly measured.[29] Including these assets and liabilities has a material effect on the overall wealth distribution, lowering the top 1 percent share by nearly two percentage points in the 2010s, while leaving the next 9 percent roughly unchanged and increasing the share of the bottom 90. It has a particularly large effect for the bottom 50, nearly quintupling their share of total wealth, albeit from a very low starting point. Moreover, the effect of including these imputed categories has grown over time as their share of total net worth has increased from 9.4 percent in the 1990s, to 10.7 percent in the 2000s, to 12.4 percent in the 2010s.[30]

Another reason the wealth distribution of the DFA differs from that of the SCF is that, as shown in table 22.2, even after reconciling the Financial Accounts and SCF conceptually, some categories are larger numerically in the SCF, while others are larger in the Financial Accounts. Column 2 of table 22.4 shows what the DFA wealth distribution would be if, rather than using the B.101.h totals, we instead distribute the reconciled SCF balances. Overall, this has a relatively minor effect on the distribution of wealth in each of the time periods, and very little effect on the patterns over time. Thus, we believe that our methodology is robust to the level differences between the Financial Accounts and the SCF.

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

A primary advantage of the DFA is that it becomes available several weeks after the quarter close. In contrast, most survey-based data sets that measure the distribution of wealth require lags of at least a year to process the data, and measures using tax data (such as the WID and Smith, Zidar, and Zwick 2019) require even longer.

Timely DFA measures could be especially valuable in times of economic turmoil. For example, the DFA projects that the sharp fluctuations in aggregate wealth from COVID-19 in the first two quarters of 2020 was largely contained to the top 10 percent of the wealth distribution. This is because business equity valuations fell and then regained value, whereas real estate was stable. Looking farther back, we know that elevated household leverage played an important role in the Great Recession (Mian, Rao, and Sufi 2013), and having a current measure of the distribution of household wealth could support policymaking and analysis in similar situations in the future.[31] To

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

30. 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, Deaton, Gourinchas, and Christina Paxson 2002; Feldstein 1974; or Love, Palumbo, and Smith 2009).

31. As noted earlier, the 2009 panel reinterview of the 2007 SCF was commissioned to provide a glimpse of household balance sheets for this reason.

test the predictive power of the DFA during changing economic conditions, we simulate how the DFA would have evolved in real time during the Great Recession. To do so, we use data from the SCF only through 2007Q3 (i.e., the last available SCF prior to the Great Recession) and forecast household balance sheets for 2009Q1 using indicator series observations through this quarter (e.g., Financial Accounts and other macroeconomic data through 2009Q1). This provides a pseudo "real-time" forecast of household balance sheets at the trough of the S&P 500 during the Great Recession.

Figure 22.6 presents results from this exercise for each of our four wealth percentile groups. In each graph, the first bar illustrates the household balance sheet during the quarter of the last pre-recession SCF (2007Q3), the second bar presents our pseudo "real-time" forecast in 2009Q1 based on data available at that time, and the third bar presents the actual household balance sheets estimated from our full data set (i.e., all SCF and Financial Accounts data through 2020Q3). The regions of each bar above the x-axis indicate the level of assets (real estate, other nonfinancial assets, and financial assets), the regions below the x-axis indicate levels of liabilities (mortgages and other liabilities), and the black dots indicate net worth (assets minus liabilities).

For the top 1 percent of households, comparing the first and second bar in figure 22.6a 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 (region with diagonal lines going down to the right) and in the value of financial assets (region with diagonal lines up to the right) 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 figure 22.6a provides a check on the accuracy of our forecast for the top 1 percent. Although there are some small differences (for example, our forecast underestimates the fall in net worth by about $1 trillion, or 5 percent of the pre-recession level), the key qualitative changes in the household balance sheet of the top 1 percent are confirmed by comparing our pseudo real-time forecast with actual DFA data.

Figure 22.6b–d shows that similar patterns hold for households in the next 9 percent, next 40 percent, and bottom 50 percent of the wealth distribution. In each graph, comparing the first and second bars shows that our pseudo real-time forecast predicts a drop in net worth (albeit smaller than for the top 1 percent) driven by a decrease in the value of real estate holdings. Comparing the second and third bars in each graph shows that our pseudo real-time forecast successfully predicts the qualitative patterns in the actual DFA data, although there are some quantitative differences. For example, our pseudo real-time measures slightly overpredict the decrease in net worth

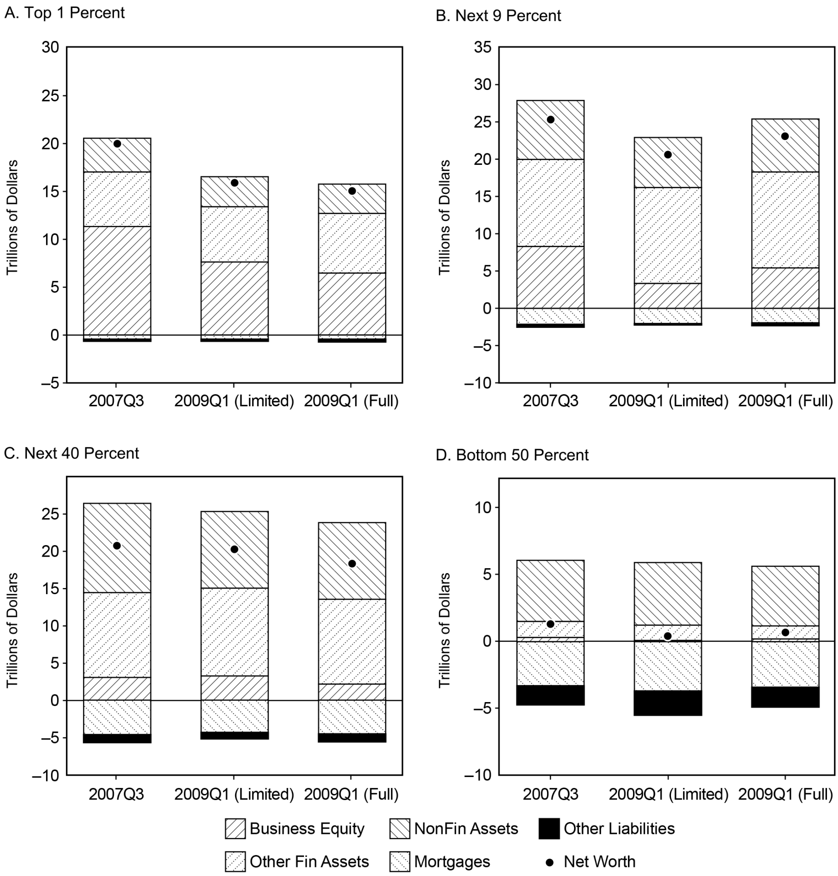

Fig. 22.6 Household balance sheets across the wealth distribution during the Financial Crisis

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 graphs use the (current) 2018Q4 vintage of the Financial Accounts.

for households in the next 9 percent and bottom 50 percent groups (figures 22.6b and 22.6d) and underpredicts the fall in net worth for households in the next 40 percent group (figure 22.6c). Overall, these exercises suggest that the DFA can provide meaningful, real-time insights into the level and composition of wealth across the wealth distribution at economic turning points.

Another important contribution of the DFA is to provide quarterly observations of the wealth distribution, thus making available detailed household balance sheets for different segments of the wealth distribution across busi-

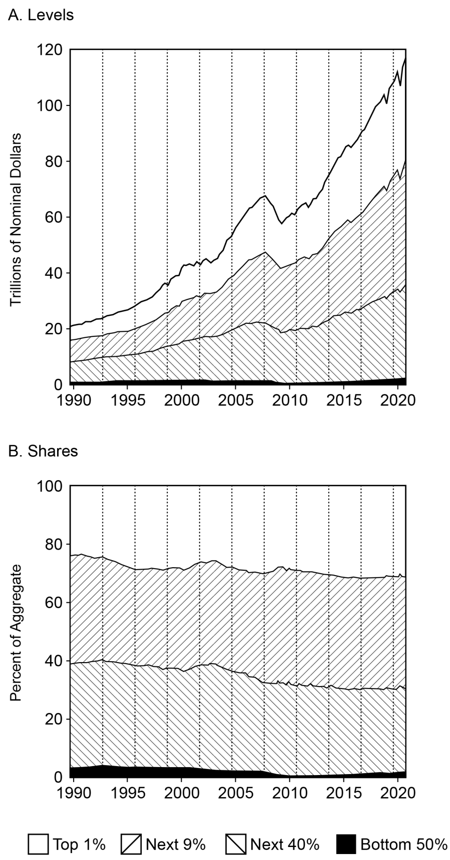

Fig. 22.7 Wealth level and share in the DFA and SCF

Notes: Vertical lines indicate reconciled SCF observations. Series shown through 2020Q3, the most recent Financial Accounts release.

ness and credit cycles. Such insights about the evolution of the distribution over business cycles have been limited in existing datasets, as peaks and troughs of asset price and credit cycles often fall between measurements.

The quarterly fluctuations in the wealth distribution captured by the DFA are clearly visible in figure 22.7. This figure overlays the DFA levels (figure 22.7a) and shares (figure 22.7b) with the triennial observations from the reconciled SCF (indicated by the vertical dotted lines). In figure 22.7a, 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 percent of US households (white 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, figure 22.7b shows a decrease in the wealth share of the top 1 percent from 2007Q3 to 2009Q1, followed by a steady increase in wealth share over the subsequent years. A second illustration of higher-frequency dynamics visible in the DFA is the business cycle between 1998 and 2001. In this case, the net worth of the top 1 percent of households increased rapidly from 1998 to 1999 but plateaued from 2000 to 2001 following the burst of the dot-com bubble, a pattern not seen among the other wealth groups. These figures illustrate how the DFA can be used to see higher-frequency detail than is available using the SCF waves.[32]

22.4.4 Demographics and the Wealth Distribution

Another contribution of the DFA is the ability to study how wealth is related to a set of demographic characteristics collected from SCF respondents. As an application, we explore trends in wealth accumulation education, race, age, and generation.[33] The figures below show real wealth, per household, indexed to 1989 for each group. Figure 22.8a shows that wealth of more educated groups has grown much more quickly over the past 30 years. Of course, the more educated groups were also wealthier at the start, so the patterns shown here both reinforce and reflect the overall growth in inequality. Those with less than a high school degree are poorer than they were in 1989, and saw a particularly large and sustained decrease in their wealth after the Great Recession. Interestingly, wealth growth for those with a high school degree has been very similar to that of those with some college, and their wealth levels are much more similar to each other than to the other groups. This is consistent with the narrative that the labor market offers relatively little reward for time in college that does not result in a degree.

Figure 22.8b shows that on net, there has been no progress closing the racial wealth gap since 1989.[34] In fact, Black households were keeping pace with whites until the Great Recession, but have fallen behind since. Hispanic households experienced particularly large swings in wealth with the housing boom and bust, and in aggregate have experienced similar wealth growth to that of Black households.

Figure 22.9a shows that wealth growth has been much stronger for older age groups. Older households have higher levels of wealth, so growing inequality has an important cross-age component. It is notable that younger people, particularly those under 40, experienced a huge loss in wealth during the Great Recession that took many years to recover. Further, while the real wealth of people in their 20s and 30s is now higher than at any point since 1989, relatively young people have spent much of this time with lower wealth than their predecessors had at comparable ages. Potentially most salient, they are now much farther behind older households, and thus likely

32. The SCF fielded a panel reinterview survey in 2009 of 2007 SCF respondents in order to capture some of the wealth dynamics of the Great Recession. We do not use these data in constructing the DFA.

33. The DFA also includes wealth by income groups.

34. Household race is determined by the self-identified race of the household member that responds to the SCF.

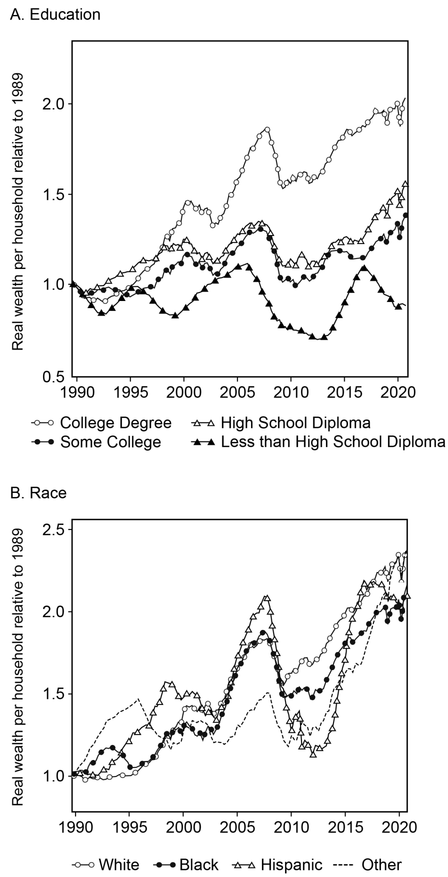

Fig. 22.8 Wealth by education and race

feel farther from the type of financial security they see in their elders. This is consistent with people entering the work force in the poor labor markets surrounding 9/11 and the Great Recession having struggled to find financial footholds, which is a narrative that has gained traction in academic work and the popular press (e.g., Gale et al. 2020; Rinz 2019; and Van Dam 2020).

As of 2020, the four age groups very closely correspond to the four generations in our data: silent = born before 1946, baby boomer = born 1946–1964, generation X = born 1965–1980, and millennial = born 1981–1996. Therefore, comparing the most recent data point on each line with a point around 2005 provides cross-generation comparisons. Millennials are roughly on pace with generation X, but each of the prior generations are well ahead of its predecessor. To make these comparisons concrete, figure 22.9b aligns the generations using the midpoint of its age range at a given point in time. This depiction suggests that over time, successive generations have outpaced

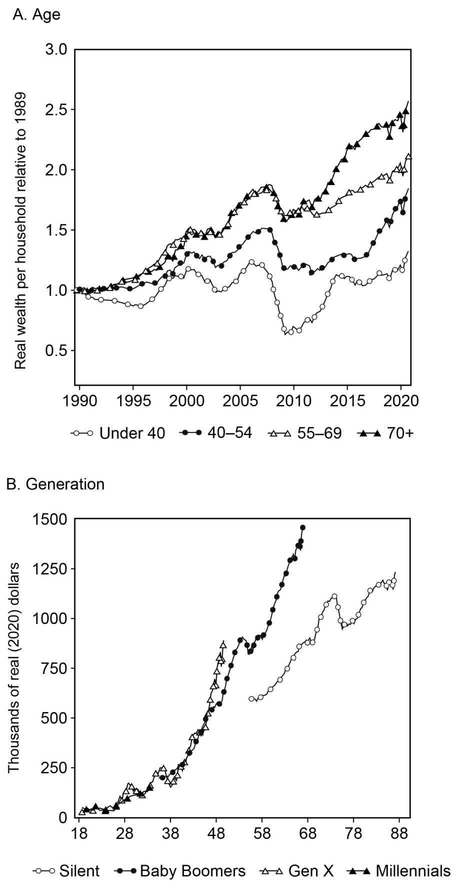

Fig. 22.9 Wealth by age and generation

their elders by decreasing amounts, to the point that thus far, progress has stopped for the millennials.

22.5 Robustness and Sensitivity Analysis

In this section, we test the sensitivity of our results to alternative assumptions in the data reconciliation step, to sampling variability in the SCF, and to different imputation and forecasting procedures.[35]

In previous sections, we showed that the asset and liability levels in the

35. 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 oversamples high-wealth households in order to reduce sampling variability at this end of the distribution.

Table 22.5 **Sensitivity of net worth shares to alternative balance sheet definitions**

			Closely held equity		Noncorporate business	
Years	Wealth group	Baseline (1)	Market value (2)	Cost basis (3)	Market value (4)	Cost basis (5)
1989–99	Bottom 50	4.0	3.9	3.9	4.1	3.9
	Next 40	34.9	34.7	35.0	34.9	35.1
	Next 9	34.8	34.7	34.9	34.8	34.9
	Top 1	26.3	26.7	26.2	26.4	26.2
2000–2009	Bottom 50	2.4	2.4	2.4	2.4	2.4
	Next 40	33.2	33.1	33.4	33.3	33.1
	Next 9	36.7	36.6	36.8	36.9	37.3
	Top 1	27.7	27.9	27.5	27.8	27.6
2010–19	Bottom 50	1.0	1.0	1.0	1.0	1.0
	Next 40	29.7	29.6	29.8	29.7	29.7
	Next 9	38.4	38.3	38.6	38.3	38.5
	Top 1	31.0	31.1	30.7	31.1	30.9

Notes: Table entries indicate the percent share of total wealth for the indicated groups averaged across all quarters in the indicated time periods. Column 2 excludes B101.h balance sheet lines not directly measured in SCF (i.e., life insurance reserves, pension entitlements, miscellaneous assets, and deferred and unpaid life insurance premiums). Column 3 excludes balance sheet lines for which the reconciled SCF and B101.h balance sheet lines differ by more than 25 percent 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.

Financial Accounts and the SCF are generally comparable, and that distribution of wealth would be quite similar if we instead distributed the reconciled SCF totals. However, at two points in the reconciliation process we make choices for constructing the SCF analogs that are guided as much by empirical match as they are by conceptual compatibility. These are the valuations of (1) noncorporate business equity and (2) closely held corporate equity (the latter includes S and C corporations and is part of the B.101.h category corporate equity and mutual funds). The SCF records both a subjective market value (i.e., what the respondent says the business could sell for) and the cost basis used for tax valuation for each. In both cases, the Financial Accounts valuation is below the SCF market value, above the SCF cost basis, but close to the average of the two. As a result, the DFA distributes the relevant B.101.h categories based upon an average of the two SCF valuations. Table 22.5 shows that the results are robust to using either the SCF market value or cost basis. Columns 3 and 4 deviate from the baseline by no more than two-tenths of a percentage point, and columns 4 and 5 deviate by no more than one-tenth of a percentage point. This implies that while the SCF market and tax valuations differ substantially in level, they are distributed similarly across the survey population, with market value slightly more concentrated than the cost basis value.

Table 22.6 **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	35.7	3.7
	s. e.	1.9	2.3	2.8	0.4
1998	Share (%)	27.4	34.4	34.6	3.6
	s. e.	0.8	0.9	0.8	0.2
2007	Share (%)	29.4	37.7	31.0	1.9
	s. e.	0.9	0.7	0.6	0.2
2016	Share (%)	31.3	38.5	29.0	1.2
	s. e.	0.7	0.7	0.6	0.1

We next investigate how precise the results are as a result of sampling variability in the SCF. Because the wealth distribution is known to be highly skewed, the SCF survey design goes to great lengths to oversample wealthy households in order to accurately capture the top of the distribution.[36] Nonetheless, as in any survey, sampling variability is present. To evaluate the impact of SCF sampling variability on the DFA estimates, we bootstrap the SCF balance sheet following the procedure described in Bricker et al. (2017a).

The results are shown in table 22.6. While sampling variability is evident, its effects (as measured by the standard errors) are generally modest. Even among the top 1 percent of households—where sampling concerns are most commonly raised—the standard errors are generally 1 percent or less in years after 1989.[37]

As mentioned in section 22.3, we consider three distinct temporal disaggregation models that vary based on their assumptions about the error process: Chow and Lin (1971), Fernández (1981), and Litterman (1983). Because as of this analysis, there were only 10 observed SCF waves, coefficients for our indicator series, and thus our target series estimates are unlikely to be statistically distinguishable across models. Nevertheless, below we employ objective criterion to select Fernández as our baseline imputation and forecast model. Reassuringly, these three approaches yield qualitatively similar results.

We construct four different measures of forecast accuracy, all of which

36. 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.

37. 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 percent the size of subsequent surveys.

Table 22.7 **Comparison of candidate forecasting and imputation models**

	Sum of squared errors ($ trillion)		
	Chow-Lin 1	Fernández 2	Litterman 3
2013 forecast	5.2	4.3	4.3
2016 forecast	24.2	23.0	23.0
2010 imputation	5.1	6.6	6.9
2013 imputation	7.0	6.7	6.7

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

compare model predictions made as if we did not have the data from one or more SCF waves to the actual DFA in the time period of the missing SCF. Specifically, we calculate the sum of squared differences between the model prediction and the DFA across the 19 B.101.h wealth categories for each of the four wealth groups. The 2013 forecast uses only the SCF observations from 1989–2010 to predict the 2013Q3 values. In other words, we pretend that our sample ends in 2010, use our method to forecast to 2013, and then compare our forecasts to the actual reconciled SCF totals. The 2016 forecast does the same using the 1989–2013 SCF observations. The 2010 imputation uses the 1989–2007 and 2013–2016 SCF observations to predict the values for 2010Q3, and the 2013 imputation predicts 2013Q3 using the 1989–2010 and 2016 SCF waves. Table 22.7 presents the results.

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

22.6 Conclusion

In this chapter, we introduced the Distributional Financial Accounts (DFA), a new dataset that integrates microdata with a national accounting framework to provide quarterly, timely information on the distribution of US household wealth. These data make several new contributions that we expect will support research on wealth distribution. For example, the DFA comprehensively integrates macroeconomic aggregates with direct observations of detailed household-level balance sheets. With this approach, we find that that wealth concentration has increased in a way that is broadly consistent with prior work, though with a slightly lower measure of the share of wealth held by the top 1 percent than in some other studies. Another important contribution is the timeliness of the DFA updates. It provides an ability to look at near-real-time trends in the wealth distribution, which could be useful during economic turning points or times of volatility. In addition, the ability to measure distributional changes at a quarterly frequency allows for study of the relationship between the wealth distribution and business cycle fluctuations. Finally, building from the SCF's detailed household-level information allows for studying how wealth relates to a range of demographic characteristics.

As part of the Financial Accounts of the US, the DFA is intended to contribute to a global conversation about national statistics and the distribution of household wealth. We hope the DFA will become a valuable tool that furthers understanding of the wealth distribution in the United States and around the world. We encourage policymakers, researchers, and other interested parties to explore and use the DFA data, which are now available at https://www.federalreserve.gov/releases/z1/dataviz/dfa/, which will be updated on a quarterly basis going forward.

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