The Business Cycle Dynamics of the Wealth Distribution*

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Abstract

We use new disaggregated household balance sheet measures to quantify the business cycle dynamics of the wealth distribution in the US since 1989. After introducing these data and establishing their credibility, we show that wealth inequality is highly procyclical, mostly reflecting heterogeneous exposures to aggregate price risk, although group-specific asset return and saving dynamics also contribute. We next show that a decrease in the output gap and increase in the unemployment rate cause wealth inequality to increase and contribute to its procyclicality, as do accommodative monetary policy shocks. Finally, we show that the distribution of household balance sheets evolved very differently during the last two recessions. Our results imply that accurate models of wealth dynamics require a sufficiently rich portfolio choice problem.

1 Introduction

Recent macroeconomic research suggests heterogeneity in household income and wealth is important in propagating aggregate shocks and determining macroeconomic outcomes (see, e.g., Krueger

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et al. (2016), Kaplan et al. (2018)). Despite recent advances in measuring long-term trends in the wealth distribution (Saez and Zucman (2016), Kuhn et al. (2018), Smith et al. (2019)), the income distribution (Piketty et al. (2018)), as well as business cycle dynamics of the income distribution (Guvenen et al. (2012), Guvenen et al. (2019)), data on the business cycle dynamics of household portfolios has until now been limited. This scarcity of such data has limited the understanding of the evolution of household balance sheets during recessions, as well as the ability to test and discipline theoretical advances in heterogeneous agent models featuring aggregate risk (Ahn et al. (2017)).

This paper bridges this empirical gap by providing the first analysis of the cyclical dynamics of the wealth distribution. Our analysis relies on the Distributional Financial Accounts (DFAs), a new quarterly time series of household balance sheets for different segments of the wealth distribution from 1989 to the present that are, by construction, consistent with the Financial Accounts of the United States. The data's quarterly measures permit higher frequency observation of household portfolios than are available in other data sets, and therefore allow a unique look at the wealth distribution's evolution through recent business cycles. The data also fulfill a long-standing demand for distributed household wealth data consistent with macro aggregates Deaton (2005), Piketty et al. (2018)). This paper extends the DFAs by including additional Financial Accounts data on wealth flows to decompose the sources of wealth accumulation across the business cycle, and by examining finer wealth groups at the top of the distribution to highlight their key role in wealth accumulation across the business cycle.

Our paper proceeds in several stages. Since the credibility of our analysis hinges critically on the accuracy of the DFA data, we first describe the methodology underlying our data. The DFAs infer quarterly changes across the wealth distribution by applying established "temporal disaggregation" methods (see, e.g., Chow and Lin (1971), Fernandez (1981), Litterman (1983), Mönch and Uhlig (2005)) to the Survey of Consumer Finances (a triennial measure of the household wealth distribution) and the Financial Accounts of the United States (a quarterly measure of aggregate household wealth). To demonstrate that our data are credible, we show that the DFA methodology recovers out-of-sample SCF balance sheets with reasonable accuracy. We also provide standard errors to show that our estimates are well identified, show that the methodology is robust to alternative error assumptions and estimation methods, and confirm that trends in inequality established in other studies are also well captured by our data.[1] Taken altogether, this analysis strongly suggests that our data provides credible insights into higher-frequency dynamics of the wealth distribution.

We then provide a first look at the cyclical dynamics of the wealth distribution captured by our data. We find that wealth inequality is highly procyclical, since wealth gains and losses incur disproportionately to the wealthiest of households during economic expansions and downturns. These cyclical dynamics can be explained in large part by systematic differences in portfolio composition and exposure to aggregate price changes across the wealth distribution. Intuitively, the wealthiest 1% of households hold riskier assets—mainly in the form of business equity—which have both higher expected but also more cyclical aggregate price returns, while households outside the top 1% hold a mixture of housing and equity wealth with less exposure to cyclical risk (consistent with Kuhn et al. (2018)). However, we also find that group-specific factors reflecting systematic differences in asset returns and savings dynamics that are unrelated to differences in portfolio composition are procyclical for wealthier households and therefore contribute to the overall procyclicality of wealth inequality. These patterns are consistent with evidence from other countries, with Bach et al. (2020) finding that systematic differences in portfolio composition are key in explaining inequality dynamics in Sweden, and Fagereng et al. (2020) finding that group-specific factors affect wealth accumulation in Norway.

Next, we exploit our quarterly time series to estimate the wealth distribution's response to shocks to key aggregate economic variables. An active structural literature considers the redistributional—and in some cases theoretically ambiguous—aspect of aggregate shocks.[2] Our analysis allows empirical tests of these predictions which thus far have been limited by lack of high-frequency distributional data. Applying standard local projection method (see e.g., Jordá (2005)), we show that a decrease in the output gap and increase in the unemployment rate increase wealth inequality and contribute to its procyclicality, as do accommodative monetary policy shocks.

Finally, we consider the evolution of household balance sheets in the Great Recession and

[1]See, e.g., Wolff et al. (2012), Piketty (2013), Bricker et al. (2016), Saez and Zucman (2016), Ríos-Rull and Kuhn (2016), Kuhn et al. (2018)), Smith et al. (2019)

[2]See, e.g., Doepke and Schneider (2006), Rubio (2011), Calza et al. (2013), Auclert (2019), Kaplan et al. (2018), Luetticke (2018), and Kekre and Lenel (2019), Garriga et al. (2015).

COVID-19 pandemic. We document very different trends during these two episodes, with an unprecedented deterioration in household balance sheets—especially for households in the middle of the wealth distribution—during the Great Recession due to a slow recovery in employment and house prices, and an unprecedented strengthening during the COVID-19 recession due to significant fiscal support. These patterns are consistent with the very different economic recoveries from these two episodes.

Taken altogether our findings support a key message: different segments of the wealth distribution hold different portfolios and are exposed to different shocks, and accurately modeling wealth distribution dynamics therefore requires a sufficiently rich portfolio choice problem to capture these differential exposures. The data and analysis in this paper highlight the need for a workhorse three-asset macro model with riskless bonds, illiquid real estate, and risky capital to capture both the long-run and short-run dynamics of the wealth distribution and its effects on macroeconomic aggregates (see, e.g., Kaplan and Violante (2014)) and risk premia (Kekre and Lenel (2019)) in future generations of macroeconomic modeling. We expect that numerical targets provided in this paper will aid in the development of and help discipline such models.

Our paper relates to several strands of economic research. First, several recent studies, including Saez and Zucman (2016) and Smith et al. (2019), have attempted to improve measurement of wealth inequality by capitalizing income tax returns, while Kopczuk and Saez (2004) do the same using estate tax filings. In Section 3.3 we benchmark our data against Saez and Zucman (2016) and Smith et al. (2019) and find that patterns are qualitatively consistent with both, but more similar quantitatively to Smith et al. (2019). Our paper complements these efforts by focusing on higher-frequency changes in wealth that are not well-measured by these prior studies that only provide annual measures and rely on taxable income that may be manipulated over the business cycle to minimize tax burdens (Dowd et al. (2019)).

A second set of empirical papers rely on the SCF to measure inequality (see, e.g., Wolff et al. (2012), Bricker et al. (2016), Ríos-Rull and Kuhn (2016)). In addition to providing higher frequency distributional measures, we build upon this work by fully reconciling the SCF with official aggregate household balance sheet measures.[3] More recent work by Kuhn et al. (2018) combines triennial SCF data post-1983 with annual survey data from 1952-1973 to provide insight into long-term dynamics of the distribution of wealth. Our findings that house price changes affect the middle class's wealth and that changes in equity prices affect the top of the wealth distribution are consistent with findings in Kuhn et al. (2018). However, the annual data used by these authors to study higher-frequency changes in wealth are only available pre-1973 and analysis afterwards relies on triennial SCF data. Our analysis therefore complements the work in Kuhn et al. (2018) by examining high-frequency quarterly changes in the wealth distribution during the past three decades.

Third, our work relates to a number of papers that model the dynamics of the wealth distribution, including Chatterjee (1994), Ferreira (1995), Piketty (1997), Álvarez-Peláez and Díaz (2005), Benhabib et al. (2011), Benhabib et al. (2016), and Benhabib et al. (2017). We complement these and similar studies by presenting model-free estimates of wealth distribution dynamics at higher frequencies. Additionally, in work developed contemporaneously with ours, Garbinti et al. (2021) and Blanchet and Martinez-Toledano (2022) estimate synthetic savings rates, where savings includes some of what we identify as capital gains. Consistent with this and other papers cited here, these two studies find that changes in asset prices have helped drive longer-run trends in wealth accumulation and wealth concentration.[4] Clearly, the considerable recent interest in wealth dynamics speaks to its importance.

Fourth, heterogeneous agent macro-models featuring aggregate risk are not new (see, e.g., Krusell and Smith (1998)) but have gained significant traction in macroeconomic research recently (see Kaplan and Violante (2018) for a review). In addition, recent work examines the interaction between inequality and aggregate economic measures like inflation (see, e.g., Doepke and Schneider (2006) and Meh et al. (2010), aggregate demand (see, e.g., Guerrieri and Lorenzoni (2017) and Auclert and Rognlie (2018)), fiscal policy (see, e.g., Kaplan and Violante (2014), McKay and Reis (2016), Hagedorn et al. (2019), Bhandari et al. (2018)), and monetary policy transmission

[3]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 (see Carroll (2014) for a rich discussion of this issue).

[4]In SCF cohorts, Feiveson and Sabelhaus (2019) also show that capital gains are the most important driver of lifecycle wealth accumulation.

(see, e.g., Werning (2015), Mckay et al. (2016), Kaplan et al. (2018), Gornemann et al. (2016), Luetticke (2018) and Auclert (2019), Kekre and Lenel (2019)). Our paper contributes to this increasingly important literature by providing the data needed to test business cycle dynamics of macroeconomic models that incorporate balance sheet heterogeneity.

Our paper proceeds as follows. Section 2 introduces the methodology used in producing the DFAs. Section 3 shows that the data credibly capture changes in household balance sheets across the wealth distribution and provides an overview of patterns in the DFAs. Section 4 provides a detailed look at the dynamics of the wealth distribution, Section 5 uses our data to estimate impulse responses to various economic shocks, and Section 6 applies our data to examine household portfolio dynamics during the Great Recession and Covid-19 pandemic. Finally, Section 7 concludes with a brief discussion of lessons for future modeling efforts.

2 Methodology

The data used in this paper build on and extend the Distributional Financial Accounts (DFAs)—the quarterly distributional data published by the Federal Reserve Board. The DFAs are a new data set which track the distribution of household wealth for four broad wealth groups—which we expand upon in this paper—as well as several other socio-economic groups.[5] The data complement and expand on other existing measures of household wealth inequality (Saez and Zucman (2016), Bricker et al. (2016), Smith et al. (2019)) by providing high frequency measures of changes in the wealth distribution that are consistent with the US national economic accounts—a feature that is lacking in most studies of wealth inequality.[6]

The DFA data are constructed by integrating two data sets 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 regular, timely, and comprehensive measures of the aggregate household balance sheet, with quarterly data releases within 10 weeks of the end of the quarter. These aggregate data do not provide any information on the distribution of the balance sheets, however. Complementing these aggregate series, the SCF collects detailed

[5]The data were first published in March 2019 and can be found at: https://www.federalreserve.gov/releases/efa/efa-distributional-financial-accounts.htm.

[6]See Deaton (2005), Carroll (2014), and Ahn et al. (2017) for discussion on the importance of distributional measures consistent with national statistics.

household balance sheet information for a representative cross-section of U.S. households (including of very wealthy households). However, the SCF is fielded triennially, which limits the ability of researchers to use these data to study changes in the distribution of household wealth during business cycles. The crux of the construction of the quarterly distributional data is to combine the SCF's rich distributional information with the Financial Accounts' quarterly aggregates in a manner that is consistent with both data sets.

The construction of the DFA data proceed in three key steps. First, we align the aggregate balance sheet implied by the SCF to the Financial Accounts' household net worth Table B.101.h, a recent data product that breaks out households from the long-standing table B.101 that also includes nonprofit organizations. Second, with the reconciled triennial SCF balance sheet in hand, we calculate the shares of the total SCF wealth held by each wealth group, and then estimate the SCF balances for each asset and liability category for quarters where the SCF is not observed using temporal disaggregation methods (see Section 2.2). The estimation allows us to populate the missing SCF quarters with estimates for each distributional stratum, as though the SCF were observed quarterly. Third, from the reconciled, quarterly SCF data, we construct the share of wealth held by each wealth group and apply this share to the aggregate Financial Accounts' balance to evaluate the amount of the national wealth held by this group.

2.1 Reconciling the Financial Accounts and the SCF

The first step in constructing the DFAs is reconciling the measurement concepts used in the SCF with those used in the Financial Accounts. Aggregate household wealth data in the Financial Accounts are found in Table B.101.h, which reports total U.S. household wealth and its 19 main components. The detailed nature of the SCF questionnaire allows us to create either direct or close analogues of most Financial Accounts balance sheet concepts. These categories include some of the largest balance sheets items (e.g., real estate, equities), but also a number of smaller asset and liability categories. We summarize these details in Appendix A.1.

The results of the SCF-B.101.h reconciliation are summarized in Table 1 by showing the ratio of the two measures for each line of Table B.101.h, for each wave of the SCF since 1989.[7] A ratio of

[7]The SCF baseline data are adjusted with weigths developed by the SCF staff to incorporate supplemental wealth data from Forbes 400 households to ensure full coverage of the wealth distribution (Bricker et al. (2019)).

100% would indicate that the two series match exactly, while lower (higher) percentages indicate that the reconciled SCF is understated (overstated) relative to the B.101.h total.[8] For reference, the figure also shows the level of the B.101.h and SCF series in 2019 in billions of dollars.

Overall, 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 $125 trillion, compared with $123 trillion on B.101.h. Moreover, reconciled 2019 SCF liabilities aggregate to $14 trillion, versus $15 trillion on B.101.h. Averaging across SCF waves, aggregate SCF net worth is very close (at 104%) to B.101.h net worth. While the match of top-line categories is reasonable in all years, the alignment further improves in recent years. In addition, the two data sets also align reasonably well for most of the underlying, granular asset and liability categories. For large asset categories that disproportionately affect the distribution of wealth, differences between the reconciled SCF and B.101.h balance sheets are quite small, despite the very different approaches in constructing the two data sets. Still, there are several smaller asset and liability categories (e.g., consumer durable goods, time deposits, or debt securities, consumer credit) where the match is imperfect, but we are naturally less concerned regarding differences in smaller balance sheet line that have a smaller impact on the distribution of household wealth.

Finally, to ensure that the SCF totals match the corresponding Financial Accounts aggregates, we scale the reconciled SCF balance sheet items up or down using a scaling factor that is independent of observables, consistent with prior evidence that mismeasurement in the SCF is not driven by any one group (Bricker et al., 2016). Both Batty et al. (2019) and Batty et al. (2022) provide several tests showing that the DFAs' reconciliation procedure is robust to alternative reconciliation assumptions.

2.2 Estimating SCF Balance Sheets in Unobserved Quarters in the DFAs

With the reconciled balance sheet in hand, the next challenge is estimating 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-

[8] 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. See Batty et al. (2019) and Batty et al. (2022) for details.

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**	**2019**	**Average**	**FA 2019Q3**	**SCF 2019**
Total Assets	97	91	91	97	107	104	102	106	102	108	101	101	123197	124951
Nonfinancial assets	97	93	92	99	97	106	114	117	115	110	106	104	35324	37405
Real estate (1)	108	105	102	110	105	114	123	131	127	119	114	114	29613	33715
Consumer durable goods (2)	60	48	58	58	64	67	63	62	63	66	65	61	5711	3690
Financial assets	97	91	90	96	113	103	96	101	97	107	100	99	87873	87546
Checkable deposits and currency	65	45	50	85	136	194	809	240	130	145	189	190	817	1545
Time deposits and short-term investments	60	63	59	65	58	63	51	54	42	47	45	55	9798	4437
Money market fund shares	83	80	76	59	73	102	71	93	133	128	102	91	1968	2006
U.S. government and municipal securities	70	53	54	54	106	95	94	71	81	100	77	78	4390	3359
Corporate and foreign bonds	88	51	27	31	67	60	59	45	62	105	90	62	888	799
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	143	119	119	131	186	141	111	128	111	129	112	130	26685	29789
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	103	91	79	85	97	94	103	136	115	134	121	105	12316	14872 (5)
Miscellaneous assets**	101	101	100	100	101	100	100	100	101	100	100	100	1257	1263
Total Liabilities	79	81	79	86	82	89	84	88	87	88	92	85	15300	14059
Home mortgages (5)	81	85	85	93	89	95	87	92	95	95	103	91	10414	10744
Consumer credit	59	57	55	60	52	59	65	69	59	68	66	61	4114	2727
Depository institution loans n.e.c.	1897	3133	278	210	470	-3152	216	89	95	36	39	301	256	99
Other loans and advances	99	99	99	97	99	99	98	90	98	99	94	97	480	452
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	110	105	111	103	104	107897	110892

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.

studied, beginning with Chow and Lin (1971) and extended to allow for richer error processes by Fernandez (1981), and Litterman (1983). We follow standard methods and use the empirical relationship between the SCF, the Financial Accounts, and other economic data to estimate latent reconciled SCF balance sheets in quarters when only the Financial Accounts and macroeconomic data are available.

The baseline approach adopted in the DFAs is based on methodology proposed in Chow and Lin (1971) and extended by Fernandez (1981). The Chow-Lin method assumes that the target series Y (in our case, the level of each reconciled SCF balance sheet line) to be estimated can be selected from a latent vector X. Let B be the matrix which selects the observed elements Y:

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

In our application, Y is observed every 3 years, while X is quarterly.[9]

The Chow-Lin method uses higher frequency indicator series, denoted here by Z, to estimate the underlying series X. If X and Z have a linear relationship[10]

$$X = \beta' Z + u, \tag{2}$$

where the residual vector u is mean zero with covariance matrix $V = \mathbb{E}[uu']$, then combining Equations 1 and 2 implies that

$$Y = B'Z'\beta + B'u. \tag{3}$$

The Chow-Lin method solves the multiple regression model specified by Equations 1 and 3 to

[9]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 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.

[10]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.

obtain an estimate of $\hat{X}$ given observations Y and Z and covariance matrix V. The DFA data use the Fernandez (1981) solution, which assumes a random walk in the error term, where $\rho = 0$ in the following set of equations:[11]

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

Mönch and Uhlig (2005) (among others) show that the Chow-Lin method can be recast in a state-space format that permits consistent estimates via maximum likelihood estimation of the resulting Kalman smoother problem. Given that this framework is more commonly employed in macroeconomic research, provide the state-space representation of the problem (assuming u is ar(1) with innovation η_t).

Let ζ_t be the state vector, which includes the most recent observations of y_t and error term u_t.[12] Then a generalized version of our state equation can be expressed as

$$\zeta_t = \begin{pmatrix} y_t \\ u_t \end{pmatrix} \begin{pmatrix} a & \rho \\ 0 & \rho \end{pmatrix} \begin{pmatrix} y_{t-1} \\ u_{t-1} \end{pmatrix} + \begin{pmatrix} x_t'\beta \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \end{pmatrix} \eta_t. \tag{4}$$

The observation equation is then expressed as

$$Y_t = B_t'\zeta_t \tag{5}$$
$$B_t = \begin{cases} [1, 0] & for\ t = 0, 12, 24... \\ [0, 0] & otherwise, \end{cases} \quad , \tag{6}$$

yielding a linear system equivalent to that defined by Equations 1 and 3. Further assuming normal errors yields a likelihood function that can be estimated using a Kalman smoother. Asymptotically, both the Chow Lin and the state-space formulation provide consistent estimates but might differ in small samples and due to the assumed normal errors when driving the likelihood function.

[11] Appendix A.2 describes the solutions proposed by Chow and Lin (1971), Fernandez (1981), and Litterman (1983).
[12] This is defined equivalently to Equation 19 in Appendix A.2.

Overall, the results from estimating the state-space model align closely with results from our baseline estimates; these comparisons (augmented with standard errors) are presented in Figure 4 in Section 3.1. The similarity in these two estimation methods indicates the robustness of our results to alternative, and likely more familiar, approaches to estimating latent household balance sheets for our wealth groups.

As a final step in producing the DFAs, we project the Financial Accounts data onto the reconciled quarterly SCF asset and liability share estimates. 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. Defining 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

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

and multiplying these balance sheet shares by the total B.101.h balance sheet line

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

yields estimates of assets and liability levels for each quantile that aggregate to the Financial Accounts household balance sheet table.[13]

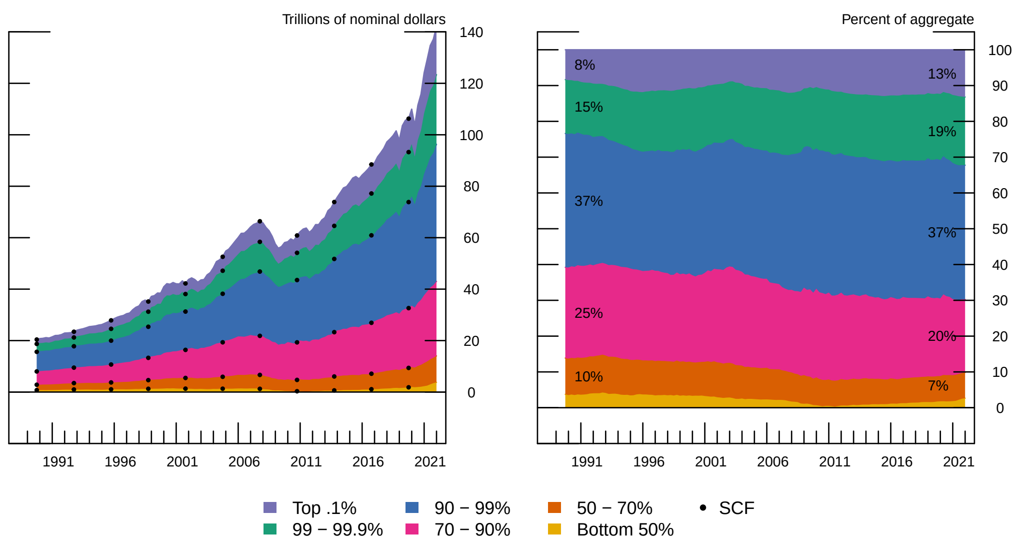
2.3 The Data Overview

Our core data set is presented in Figure 1, which shows the real wealth levels (Panel (a)) and shares (Panel (b)) of net wealth for households across the wealth distribution. The groups used in this paper are more granular than those used in the quarterly DFA data release. Rather than the standard bottom 50%, 50 - 90%, 90 - 99%, and top 1%, we use six groups: bottom 50%, 50 - 70%, 70 - 90%, 90 - 99%, 99 - 99.9%, and top .1%. Further dividing the middle class as well as the top 1% allows us to provide additional insight into the credibility of the data and business cycle dynamics.

[13]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.

Figure 1: Wealth Levels and Shares in the DFAs

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

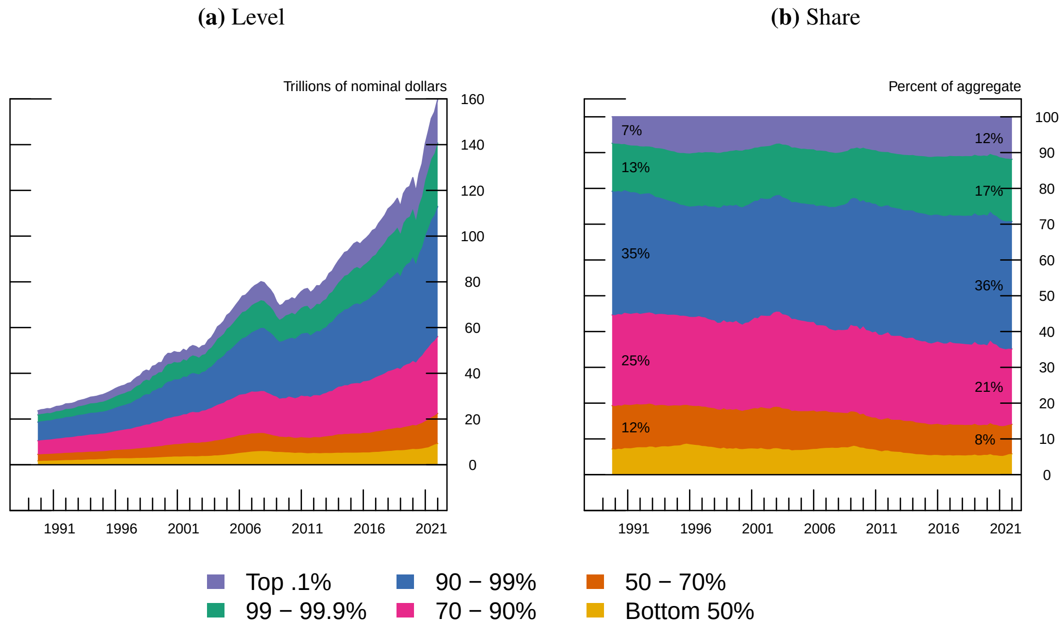


Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

The figures confirm the findings of a number of recent studies (see, e.g., Wolff et al. (2012), Piketty (2013), Bricker et al. (2016), Ríos-Rull and Kuhn (2016), Kuhn et al. (2018), and Smith et al. (2019)) that wealth inequality has increased substantially since 1989. During this time period wealth share of the top 10% of U.S. households (the teal, green, and purple portions of graph) increased from 61 to 70 percent, with this trend almost entirely driven by an increase in the top 1% wealth share (purple and green) from 23 percent to 31 percent. In contrast, the bottom 70% (yellow and orange) held very little wealth and experienced a notable decrease in wealth share over this period.

The rise in wealth concentration stems primarily from increased concentration of assets (Figure 2) rather than a decreased concentration in liabilities (Figure 3), 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 50-90th per-

Figure 2: Total Assets by Wealth Percentile Group



Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

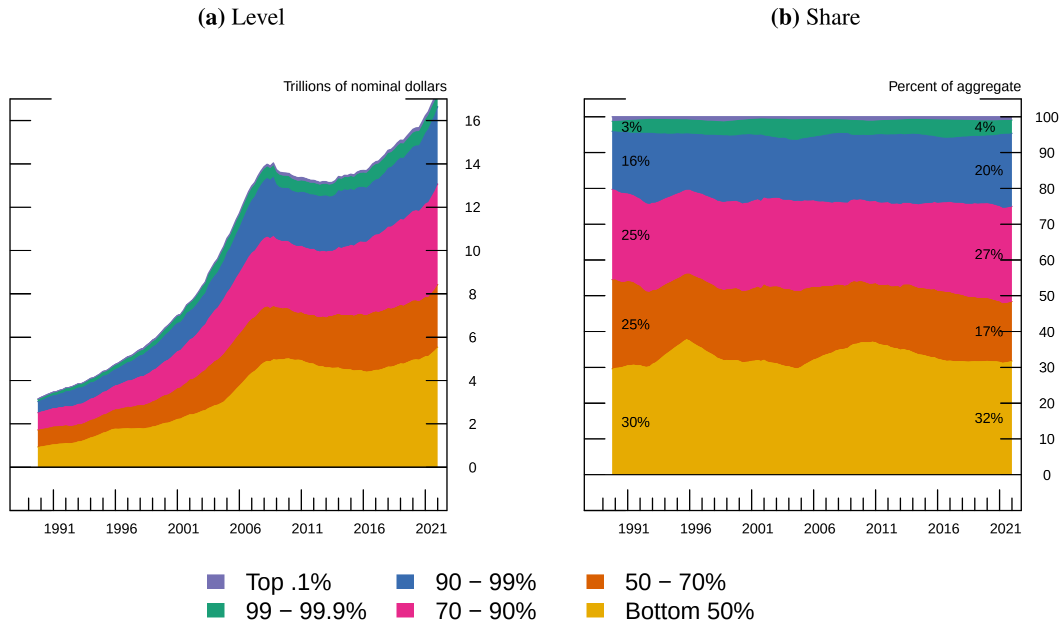
centiles of the wealth distribution.[14] Figure 3(b) shows that, in contrast to assets, the distribution of liabilities is both much more equitable than the distribution of assets and has changed relatively little since 1989.

Panel (a) in Figure 1 also shows that household wealth varies substantially between the SCF observations indicated by black dots. In particular, the figure shows the evolution of wealth for our six wealth groups during the dot-com boom and bust between 1998 and 2001, the early-2000s recession, the start of the housing boom between 2001 and 2004, the Great Recession between 2007-2010, a sharp equity market drop in 2018:Q4, and the Covid-19 pandemic.

The dynamics align intuitively with the economic events that drive them but are generally not captured by the lower frequency SCF. Panel (b) in Figure 1 shows that higher frequency changes in the wealth distribution generally occur during recessions and are relatively short-lived, and thus are often unobserved in lower-frequency data. For example, the top 1%'s share fell during both

[14] Appendix A.4 shows that the inequality of holdings within asset class generally increased as well.

Figure 3: Total Liabilities by Wealth Percentile Group



Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

the 2002 and Great recessions but had mostly recovered by the 2004 and 2010 waves of the SCF. Overall, Figure 1 suggests our data captures meaningful variation in wealth levels and shares between SCF waves, which we exploit starting in Section 4 to formally document the dynamics of the wealth distribution.

3 Credibility

Data credibility is paramount for our findings in the rest of the paper to be credible. In this section, we therefore establish that our estimates are well identified and robust to alternative modeling assumptions, that the estimation procedure works well out of sample, and that estimates align well with alternative, leading measures of wealth inequality at lower frequencies.

3.1 Estimate Uncertainty and Standard Errors

Our data is designed to be consistent with the Financial Accounts and SCF, so measurement bias in either data source—to the extent it exists—which is inherited by the DFAs would not diminish our data's value. n contrast, if our estimates of balance sheets in quarters when the SCF is unobserved were noisy, our higher frequency measures would be less valuable. We therefore next calculate standard errors for our balance sheet estimates for each wealth group to show that they are reasonably well identified.[15]

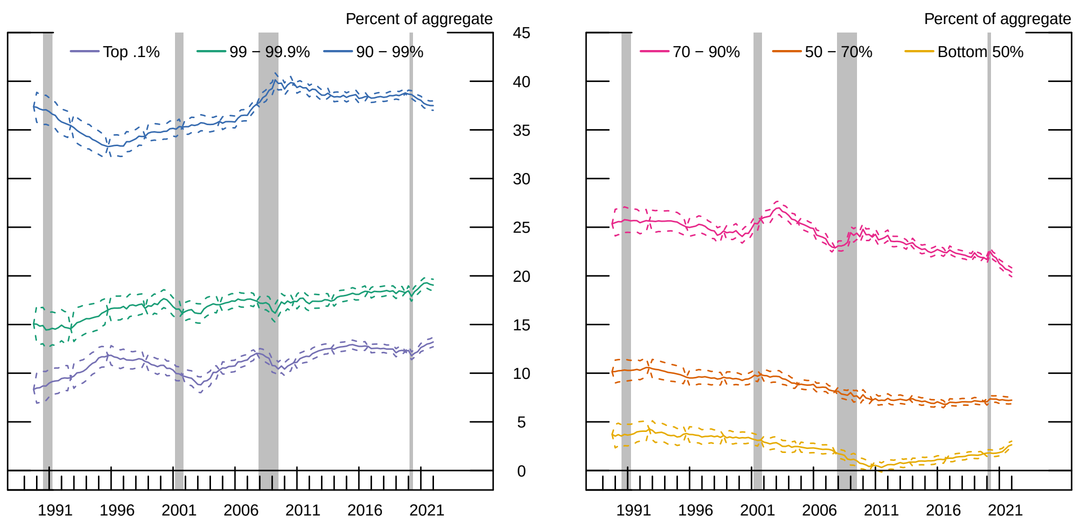
The error bands for the 95% confidence interval for each group's wealth share are presented in Figure 4. During SCF years there is no uncertainty and so the standard errors are therefore zero, but estimates increase in quarters that are further away from SCF observations. And although uncertainty around estimates is sufficiently large that we generally cannot exclude the possibility that wealth adjusts linearly between SCF waves, the standard errors are not overly large and wealth shares are generally identified within 1pp.

The relatively small standard errors from our estimation procedure are fairly intuitive: changes in net worth are primarily driven by capital gains and losses. The aggregate Financial Accounts series included as indicator series for each balance sheet line for each wealth group serve as a proxy for these capital gains and losses, thus limiting uncertainty in movements in households balance sheets. Furthermore, saving rates are generally fairly stable over time and well proxied by other indicator series. While there is some uncertainty in wealth changes due to other factors (e.g., group-specific returns), these changes are generally secondary and do not generate significant shifts in wealth shares. In short, the indicator series we have selected do a good job in capturing changes in household wealth, resulting in reasonably precise quarterly estimates of household balance sheets and net worth.

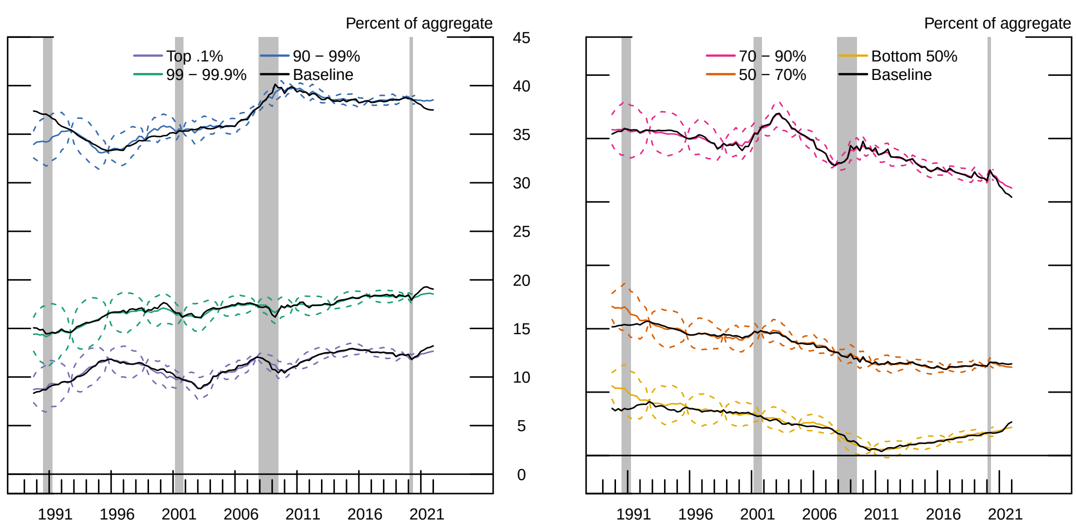
[15]See Proietti et al. (2017) for formulas for standard errors of asset and liability levels. We convert these standard errors for our level estimates to standard errors for share estimates via the delta method.

Figure 4: Standard Errors of Estimates

(a) Fernandez (baseline) shares and standard errors



(b) Kalman shares and standard errors



Note: Panel (a) shows baseline temporal disaggregation estimates and associated quarterly standard errors. In Panel (b), our temporal disaggregation is re-estimated with a Kalman filter smoother. Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

3.2 Consistency With Untargeted Moments

The DFAs success in matching actual measures of the wealth distribution not used in their construction is a better test of data quality. Opportunities for such external validity are limited, but a special SCF Panel was collected in 2009Q3 as a one-time follow-up to the regular 2007 SCF and was not used in constructing our data. This sample therefore offers an opportunity to compare the DFA estimates against a straight-read of household-level data, and poses a stringent validation test given the significant economic and asset price volatility during this time period. One caveat to this analysis is that the 2009 SCF is not designed to be nationally representative of the set of 2009 households; rather, it represents the 2009 experience of the set of households that were interviewed in 2007.[16]

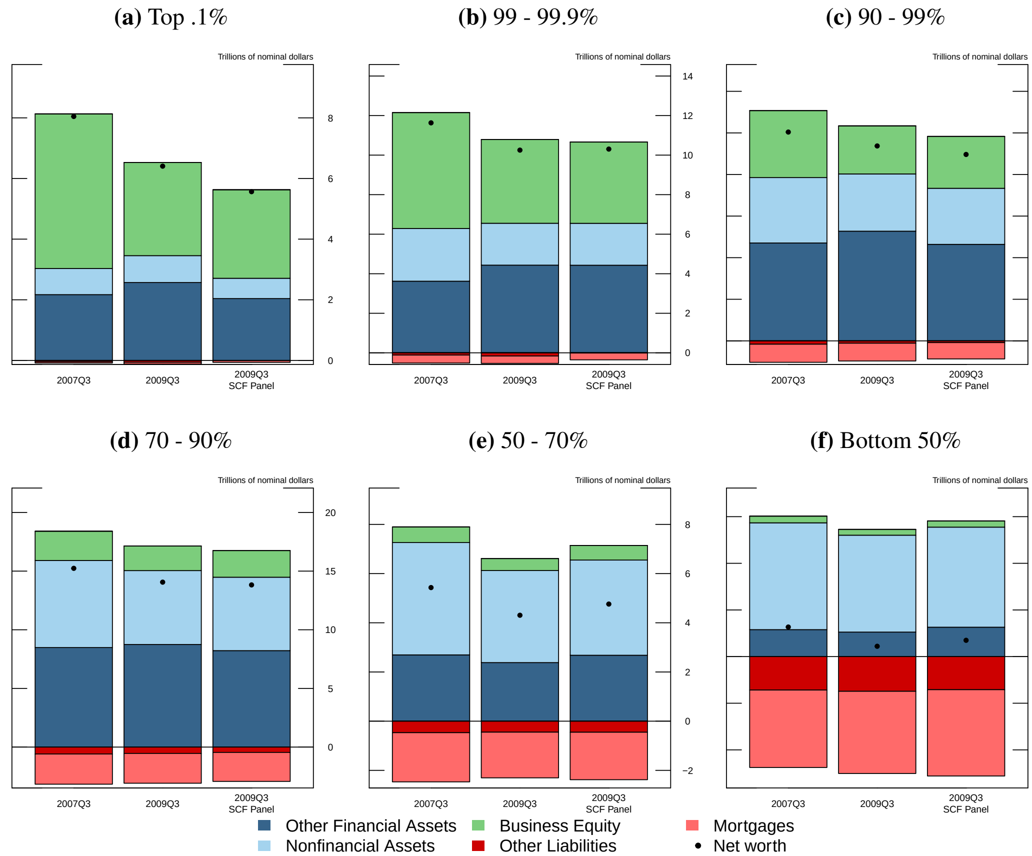
Figure 5 summarizes the DFA and 2009 SCF data for each of our six wealth percentile groups. In each panel, the first bar illustrates the DFA household balance sheets in the 2007:Q3 (aligned with the collection of the 2007 SCF data), the second bar presents the estimated DFA data for 2009:Q3, and the third bar presents the 2009 SCF Panel household balance sheet data (also collected in the third quarter). The regions of each bar above the x-axis indicate the level and composition of assets (real estate, other non-financial assets, and financial assets), and the regions below the x-axis indicate liabilities (mortgage and non-mortgage).

Panel (a) illustrates the two data sets for the wealthiest 0.1%. Entering the recession in the 3rd quarter of 2007, aggregate net worth for this top wealth group was about $8.2 trillion (first column), but by the third quarter of 2009 aggregate assets of this group had fallen to less than $7 trillion according to our DFA estimates (second column). The 2009 SCF Panel (third column) shows a similar decline in overall net worth, with a drop in business equity (green region) driving most of the decline in both the DFA and SCF data.

The DFAs are even more accurate for the remaining wealth groups, since they not only capture the decline in equity prices, but also the decline in house prices that weighed on middle-income balance sheets over this period. As a result, Panels (b)-(f) show that balance sheet measures in the 2009 DFA and SCF data across the wealth distribution are quite close. Overall, our exercise

[16] Furthermore, to reduce respondent burden, the 2009 Panel survey questionnaire did not repeat the detail found in the 2007 cross section. Hence, some of the finer detailed categories cannot be mapped, leading us to focus in this section on broader asset and debt categories than those shown in Table 1.

Figure 5: Comparison to 2007-2009 SCF Panel



Note: This figure shows aggregate wealth and its composition for six wealth groups in the DFA data (2007Q3 and 2009Q3 in the first two columns, respectively, of each panel) and in the 2009 SCF Panel (the third column in each panel). The interpolated DFA data in 2009Q3 (second column) is similar in aggregate and composition to independently-collected SCF Panel data from 2009 (third column). Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA) and Survey of Consumer Finances (SCF).

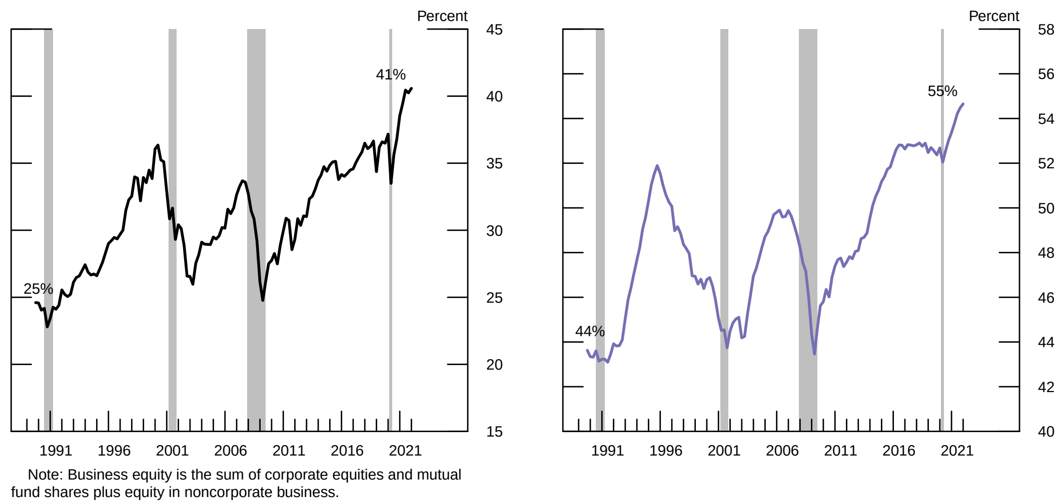
suggests that the DFAs provide credible measures of household balance sheets and net worth across the wealth distribution in quarters when the SCF is not collected.

3.3 Comparison to Alternative Lower-Frequency Wealth Distribution Measures

Although the high-frequency dynamics in our data are the focus of our study, our data also capture lower frequency dynamics that have been the focus of a substantial body of research, as shown in

Figure 6: Business Equity Holdings and the Top 1%

(a) Total Business Equity as a Share of Total Wealth **(b)** Top 1%'s Share of Total Business Equity



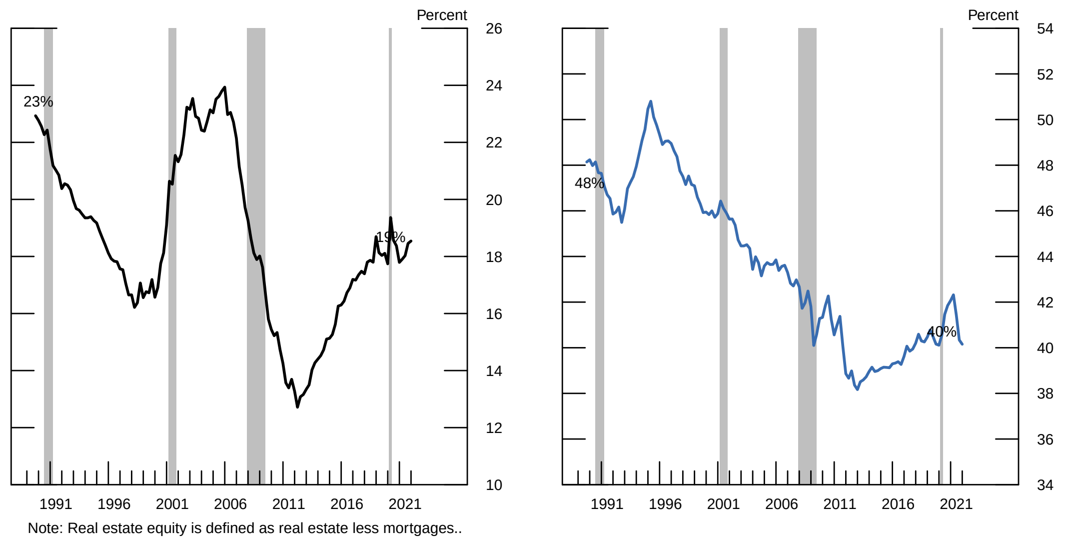
Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

this section.

The high-level drivers of the wealth distribution in the DFAs also align with patterns shown in recent work in Kuhn et al. (2018). These "historical SCF" data combine triennial SCF data post-1983 with annual survey data from 1952-1973 to show that differential changes in equity (which are predominantly held by wealthy households) and housing (which dominate portfolios of the middle class) returns have shaped postwar wealth trends. The DFAs show similar patterns. Figure 6 shows that despite clear cyclical booms and busts, business equity has increased as a share of total wealth (from 25% to 36%) while the top 1%'s share of business equity has risen (from 41% to 51%) since 1989. Thus, much of the increase in top wealth shares is explained by increased equity concentration. Figure 7 shows a similar set of charts for real estate equity and middle class families (as proxied by the 50-90th percentile). Despite a notable boom-bust cycle, housing as a share of total wealth (Panel (a)) has become a smaller since 1989 at the same time that the share of housing assets held by middle class families has also fallen (Panel (b)). These two patterns are major drivers of the overall decline in middle class wealth shown in Figure 1.

Figure 7: Real Estate Equity Holdings and the Middle Class

(a) Real Estate Equity as a Share of Total Wealth **(b)** 50-90th Percentiles Share of Total Real Estate Equity

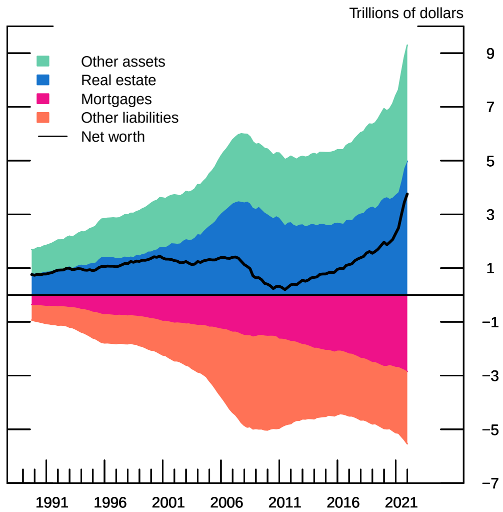


Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

Finally, several studies (e.g., Krusell and Smith (1998), Greenwald (2018), Jones et al. (2018), Kaplan et al. (2019), Garriga and Hedlund (2019)) have shown that household debt levels—which Kuhn et al. (2018) show have increased particularly for low wealth households—have become increasingly important drivers of macroeconomic dynamics. In Figure 8, the DFAs similarly show that debt growth drove overall wealth dynamics for the bottom half of the wealth distribution over the last 30 years. For example, a rapid increase in leverage during the housing boom pulled the bottom 50%'s net worth negative for several quarters after the housing bubble burst, and elevated debt holdings kept the bottom 50%'s nominal wealth below its level in the mid-1990s until very recently, despite substantial deleveraging after the Great Recession.

Taken altogether, the DFA data are generally consistent with the secular trends documented in other studies, and therefore appear credible. However, the DFAs also offer notable advantages relative to existing data products. First, our data cover the complete wealth distribution, while estimates from income tax returns (e.g., Smith et al. (2019) and Saez and Zucman (2016)) are less suited to measure balance sheets of lower-wealth households that largely hold assets without

Figure 8: Bottom 50% Balance Sheet



Note: This figure shows aggregate balance sheet of the bottom 50% in each quarter of the DFA data. Assets are divided into two categories: real estate (blue) and all other assets (green). Liabilities are divided into two categories: mortgages (red) and all other liabilities (orange). Aggregate net worth (the difference between assets and debts in each quarter) is shown as a black line. Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

income flows that are used to approximate asset holdings. Additionally, measures of the wealth distribution imputed from tax returns rely on *realized* capital gains and dividend payouts, which may differ from unrealized capital gains that likely affect household decisions. This is potentially problematic, as household's decisions to realize capital income and gains itself likely depends on on cyclical factors. For example, Dowd et al. (2019) estimate elasticities of realized gains to tax rates spiked during the Financial Crisis, and wealthier households that face larger tax bills have stronger incentives to shift capital income and gains across time. Such concerns are maybe not significant when studying the longer run evolution of wealth since capital income and gains must eventually be realized. However, without carefully modeling the tax incentives of households, it is unclear how these factors affect the cyclical properties of estimates imputed from tax data. Finally and most importantly, the DFAs are the only data available at a quarterly frequency, and therefore are uniquely positioned to analyze business cycle dynamics of the wealth distribution.

4 Business Cycle Dynamics of Wealth Distribution

Figure 1 showed that household wealth varies substantially between the SCF observations indicated by black dots. In this section, we will describe the dynamics of the wealth distribution at a quarterly frequency more fully.

Changes in the wealth distribution are driven by relative differences in wealth accumulation, since in a given period the wealth distribution will shift towards households that accumulate more wealth than the average household. There are two high-level reasons why wealth accumulation will vary across wealth groups: (i) differential returns to wealth due to differences in exposure to common aggregate asset returns and (ii) differential wealth accumulation due to group-specific factors, reflecting group-specific differences in returns and savings.[17] We will therefore use this framework—which is consistent with a growing body of influential research (see, e.g., Bach et al. (2020), Fagereng et al. (2020))—to frame our analysis. We first explore how exposure to different assets drive returns to wealth across wealth groups in Section 4.1 and then decompose returns to wealth and change in wealth shares into the two factors—aggregate price changes and group-specific changes—in sections 4.2 and 4.3, respectively.

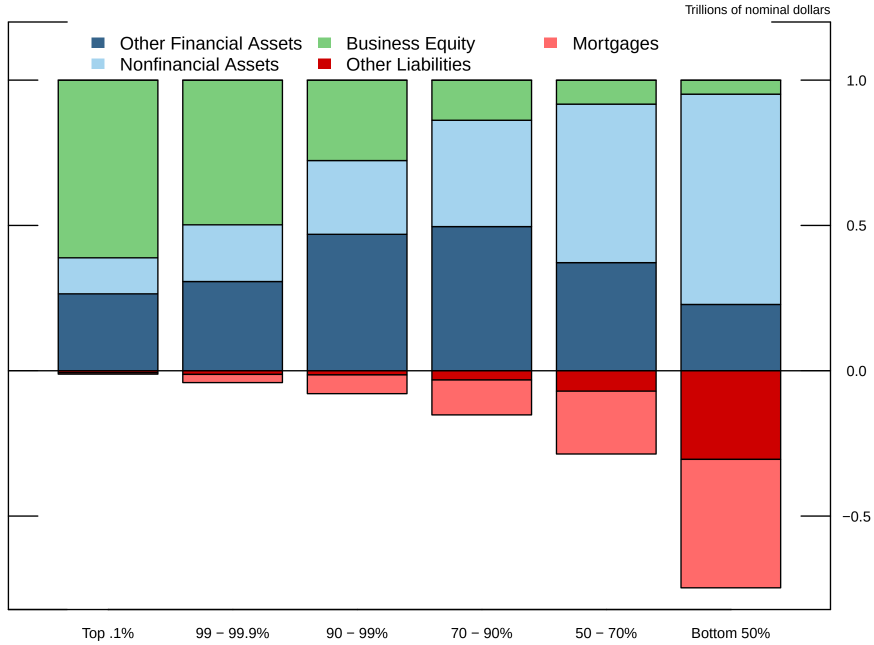
4.1 The Determinants of Household Portfolio Returns

Intuitively, one reason why wealth accumulation differs across wealth groups is differences in portfolios and exposure to aggregate asset price risks. To demonstrate the difference in exposures simply, Figure 9 shows the portfolio compositions for our six wealth groups—averaged across all quarters and rescaled so that total assets equal to one. The two wealthiest groups are heavily concentrated in business equity, and their wealth shares will change predominantly in response to changes in business values. Meanwhile, the middle wealth groups are better diversified across asset classes, while poorer households are more levered and invested in non-financial assets.

To provide an initial quantitative assessment of the drivers of household returns to wealth and compare drivers of wealth accumulation across the wealth distribution, we estimate a general factor

[17] Our data are not well-suited to distinguish between the latter two explanations (i.e., group-specific returns vs. differences in savings).

Figure 9: Portfolio Shares



Note: The figure shows the portfolio compositions for (rescaled so that total assets equal to one) for our six wealth groups averaged across all quarters. Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

model

$$\Delta Y_t^p = \beta_0^p + \sum_{k=1}^{K} \beta_{k,t}^p X_{k,t} + \epsilon_t^p \tag{7}$$

separately for each wealth group p. In our baseline analysis we focus on the pre-pandemic data through 2019Q4, but include results for our full sample in Appendix Table 4.

In specifying factors X_k, we choose variables that are likely to capture different sources of wealth variation. For example, we include excess equity returns (measured by the difference between realized S&P 500 returns and the one-year treasury rate) to capture exposure to cyclical assets, and excess housing returns (measured by the difference between realized Corelogic housing index returns and the one-year treasury rate) to capture exposure to housing returns. We also include the one-quarter change in the Fed Funds rate to capture exposure to short term changes in bond prices and cost of credit. Finally, we also include the unemployment rate to capture changes in household savings rates due to changes in income and a time-varying precautionary saving motive.

Table 2: Estimating Drivers of Wealth Gains, by Household. Sample 1989-2019.

	Dependent Variable: Percent Change in Net Worth of the					
	Top .1% (1)	99-99.9% (2)	90-99% (3)	70-90% (4)	50-70% (5)	0-50% (6)
S&P 500 (%)	0.281***	0.268***	0.213***	0.149***	0.103***	0.158***
	(0.020)	(0.018)	(0.014)	(0.010)	(0.009)	(0.045)
Core Logic House Price Index (%)	0.295***	0.300***	0.315***	0.404***	0.590***	2.175***
	(0.089)	(0.083)	(0.061)	(0.045)	(0.040)	(0.200)
FFR, 1 Quarter Change (pp)	−0.596	−0.586*	−0.502*	−0.398**	−0.368**	−0.913
	(0.377)	(0.351)	(0.259)	(0.210)	(0.170)	(0.845)
5 Year Forward Rates (%)	−0.489	−0.569	−0.2105	0.088	0.388	2.666*
	(0.711)	(0.661)	(0.489)	(0.359)	(0.320)	(1.594)
Unemployment Rate (%)	−0.896	−0.881	−0.551	−0.321	−0.384	−5.127***
	(0.588)	(0.547)	(0.404)	(0.2197)	(0.265)	(1.319)
Constant	0.095	0.028	−0.145	−0.168	−0.010	0.303
	(0.216)	(0.201)	(0.149)	(0.109)	(0.097)	(0.485)
Observations	103	103	103	103	103	103
R^2	0.734	0.749	0.783	0.812	0.844	0.722
Adjusted R^2	0.720	0.736	0.772	0.803	0.836	0.708
Residual Std. Error (df = 97)	1.410	1.312	0.970	0.712	0.635	3.162
F Statistic (df = 5; 97)	53.587***	57.742***	70.27***	83.945***	105.316***	50.469***

Note: *p<0.1; **p<0.05; ***p<0.01

The results of these regressions are presented in Table 2. The first key result is that the coefficient on the S&P 500 returns is positive and significant for all groups, although more so for high-wealth households. For example, a 1% excess return on the S&P 500 is associated with almost a .3% return for households in the top 1%, but the effect is less half as large for households in the bottom 70% of the wealth distribution. These patterns are consistent with the pattern shown in Figure 9 that exposure to equity returns increases significantly in wealth, as well as findings in recent academic work studying portfolio and return heterogeneity (e.g., Bach et al. (2020)).

The second key result is that the coefficient on house prices is also positive for all groups, but more so for lower-wealth households. This pattern reflects—again consistent with Figure 9 and recent research (e.g., Kuhn et al. (2018))—that real estate is the key asset in most lower-wealth households' portfolio and that exposure to house price risk decreases with wealth. For example, a 1% excess return on housing boosts returns for households in the 50-70th percentiles of the wealth distribution by .6%—over twice as much as for households in the top 1%— and is associated with a more than 2% increase in returns for households in the bottom half of the wealth distribution, with the large point estimate reflecting that real estate holdings of low-wealth households are highly levered.

The regressions also highlight more subtle differences in returns to wealth. Focusing on interest rates, we find that an increase in the effective federal funds rate (FFR) lowers changes in wealth for all households, with the effect decreasing from the top 1% (1 percentage point change in FFR is associated with a -.6% change in returns for the top 1%) to the 50-70th percentiles (-.4%), before rising sharply for the bottom 50% (-.9%, although the effect is not significant). For households in the top half of the wealth distribution, this pattern likely reflects that the value of bond holdings generally falls as the FFR increases. For low-wealth households that do not hold many fixed-income assets, the decline likely reflects a separate, consumer credit channel. Low wealth households are more likely to have floating rate and revolving debt, so an increase in interest rates will increase their debt servicing cost and lower wealth accumulation.

Finally, we also find that a higher unemployment rate is associated with lower returns on wealth for all households, but especially for low wealth households, for whom a 1 percentage point increase in the unemployment rent reduces excess wealth returns by 5.27%. This large, negative effect reflects that low wealth households are most exposed to cyclical layoffs, and so their income tends to be much more procyclical. As a result, low-wealth households savings drops as unemployment increases, thereby reducing wealth accumulation.

The share of wealth variation in wealth accumulation explained by our model is also of interest. We find that our factor model can explain over 70% of the percent changes in wealth accumulation for all wealth quintiles, with greater explanatory power for households in the middle of the wealth distribution. This hump-shaped pattern reflects two considerations. First—and consistent with Fagereng et al. (2020)—households at the top of the distribution hold riskier assets that are not as well priced by a broad equity index, including non-public assets that are less correlated with indices of public equities. Second, for households at the bottom, idiosyncratic fluctuations in saving and policy changes affect their wealth more, which are hard to capture with aggregate risk factors.[18]

4.2 Decomposing Returns to Wealth into Aggregate and Group-Specific Changes, by Wealth Group

As shown above, our factor model can explain a significant amount of wealth accumulation for all wealth groups. However, it cannot explain all changes and may overstate the importance of aggregate price changes that share a common component with group-specific factors.

For more complete examination of the drivers of wealth changes, we build on prior literature (Bach et al. (2020), Fagereng et al. (2020), Kuhn et al. (2018), Benhabib et al. (2017)) and define the intertemporal law of motion for each asset or liability j on group p's balance sheet is

$$Y_t^{j,p} = (1 + r_t^j + \epsilon_t^{j,p} + \theta^{j,p})Y_{t-1}^{j,p} + S_t^{j,p}, \tag{8}$$

where r_t^j is the aggregate return to asset j in period t common to all groups, $\epsilon_t^{j,p}$ is group's p scale-dependent idiosyncratic return for asset j in period t, $\theta^{j,p}$ is the sum of type-dependent returns for

[18]In Appendix Table 4 we repeat these regressions including observations for 2020. Given that variation in explanatory variables were unusually large during the pandemic we prefer to omit them from our baseline analyses. However, patterns from these regressions are broadly the same, with the exception that the unemployment rate is no longer significant for low wealth households. This reflects the well-documented pattern that wealth increased sharply, particularly for low wealth households, in the COVID-19 recession due to very high fiscal transfers. Additionally, in unshown analyses we find that other proxies—for example, wage growth—were associated with higher wealth accumulation for low-wealth households although the effects were not significant and so we omitted them from our baseline analyses (not shown).

members of the wealth group p for asset class j, and $S_t^{j,p}$ is group p's saving into asset class j.[19]

This expression can be decomposed into the contribution to next period's wealth due to capital gains from common aggregate price changes ($E_t^{j,p}$) and the contribution due to group specific returns and savings ($U_t^{j,p}$).

$$Y_t^{j,p} = Y_{t-1}^{j,p}\left(1 + \underbrace{r_t^j}_{E_t^{j,p}} + \underbrace{\epsilon_t^{j,p} + \theta^{j,p} + S_t^{j,p}/Y_{t-1}^{j,p}}_{U_t^{j,p}}\right). \tag{9}$$

Aggregating over all assets, group p's net worth can be expressed in aggregate price changes and group-specific factors

$$\begin{aligned} Y_t^{NW,p} &= \sum_j Y_{t-1}^{j,p} \times (1 + E_t^{j,p} + U_t^{j,p}) && (10)\\ &= Y_{t-1}^{NW,p} \times \sum_j \alpha_{t-1}^{j,p} \times (1 + E_t^{j,p} + U_t^{j,p}) && (11)\\ &= Y_{t-1}^{NW,p} \times (1 + E_t^p + U_t^p), && (12)\end{aligned}$$

where $\alpha_{t-1}^{j,p}$ is the portfolio share group p's wealth invested in asset j, and E_t^p and U_t^p denote the growth in wealth due to common aggregate capital gains and group-specific contributions, respectively.

Equation 12 can be transformed into a simple expression for the quarterly growth rate of group p's net worth

$$\Delta Y_t^{NW,p} = \frac{Y_t^{NW,p}}{Y_{t-1}^{NW,p}} - 1 = E_t^p + U_t^p, \tag{13}$$

which we will use below to decompose the contributions of E_t^p and U_t^p to each group p's quarterly wealth growth. In what follows, we use Equation 13 to separate the quarterly growth rate of group p's ($\Delta Y_t^{NW,p}$) into returns from common aggregate prices changes (E_t^p) and group-specific factors (U_t^p). Aggregate asset returns E_j^p are taken from the re-valuation adjustment from the Federal Reserve's Z.1 Financial Accounts, while changes from group-specific factors are calculated as the

[19]In terminology fashioned after Gabaix et al. (2016), scale-dependence is a positive correlations between household wealth and returns to wealth. Type-dependence is a fixed-effect, persistent heterogeneity in returns.

residual that cannot cannot be explained by aggregate price fluctuations.[20]

Figure 10 shows the resulting return decomposition. For each wealth group, aggregate asset price fluctuations (E_t^p, black lines) drive most of the changes in returns to net worth ($\Delta Y_t^{NW,p}$, blue lines). By construction, differences in the portfolio composition across wealth distribution documented in Section 4.1 drive the differences in the dynamics of E_t^p. Thus, our decomposition suggests that most variation in wealth over time is explained by aggregate price movements, consistent with our finding in Table 2 that aggregate variables can explain a large share of temporary variation in household returns.

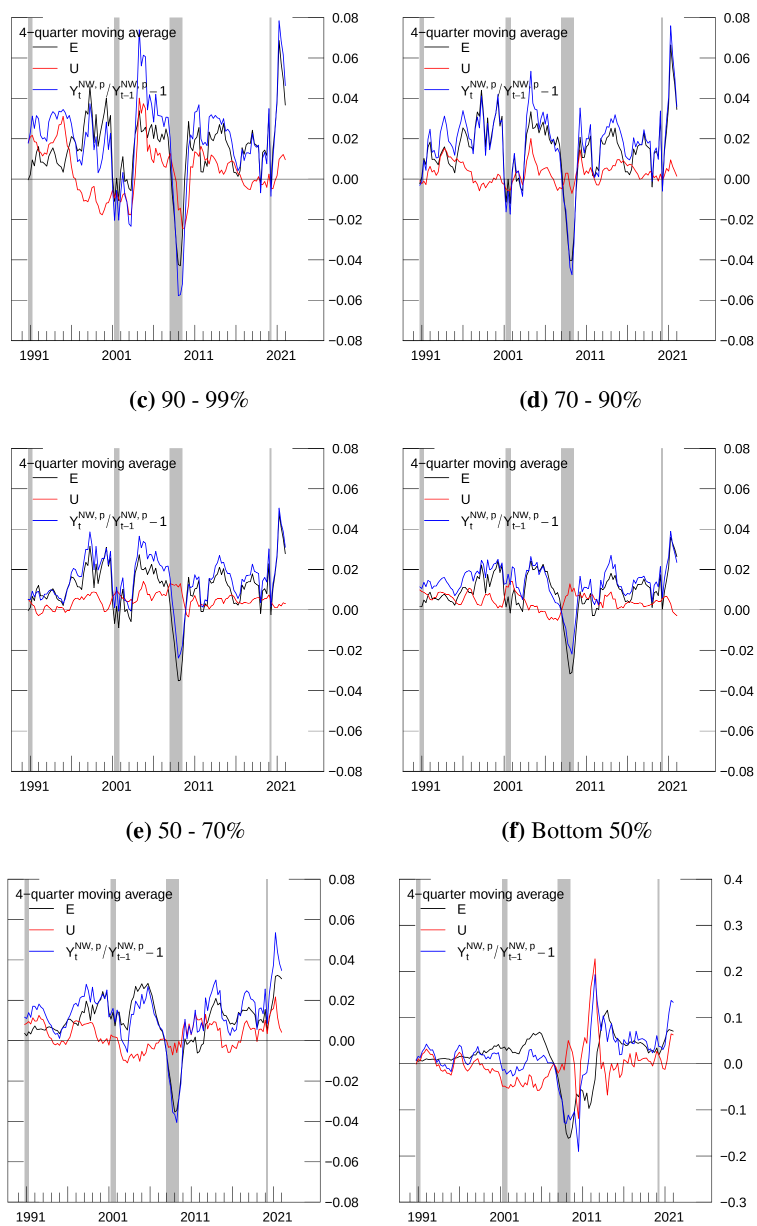
For most wealth groups, the group-specific return U_t^p (red line) is largely acyclical, suggesting that group-specific returns are mostly time-invariant. However, U_t^p is fairly procyclical for the wealthiest 0.1% and 99-99.9% groups, likely reflecting their tendency to hold assets that are more exposed to cyclical risk within a given asset class, as captured by by $\epsilon_t^{j,p}$ in Equation 8. For wealthier households, both type dependence and riskier holdings within a given asset class are consistent with the findings in Fagereng et al. (2020) and Bach et al. (2020).

Figure 10 also reveals a near-monotonic spread in returns to net worth ($\Delta Y_t^{NW,p}$) across the wealth groups, meaning that the level of returns is generally higher in expansions and lower in recessions for wealthier households. For example, in the build-up to the Financial Crisis, the quarterly returns for the wealthiest 1% of households (Panels (a) and (b)) reach a peak of 6 to 8 percent, roughly double of those realized by the households in the 90-99% and 70-90% of the wealth distribution (Panels (c) and (d)), thereby indicating an unequal pace of wealth accumulation. While opposite patterns are generally observed in downturns, the divergence in returns is generally more muted, and the returns of wealthy households tend to rebound quickly and early during economic recoveries.

Finally, the common return E_t^p exhibits different behavior for households in the top 50% and bottom 50% of the wealth distribution. During economic expansions, the E_t^p return increases monotonically with wealth for the top 50%, and is therefore a major driver of the increasing returns

[20] As in the past literature (Garbinti et al. (2021), Blanchet and Martinez-Toledano (2022), and Kuhn et al. (2018), for example) we do not attempt to disentangle mobility across wealth groups between quarters. That said, in a micro-simulation Roymans (2022) shows that such changes in composition contribute a negligible amount to changes in annual group wealth for wealth groups in the top 50% of the distribution. Our use of quarterly data should imply even less mobility across adjoining points in time.

Figure 10: Decomposition of $\Delta Y_t^{NW,p}$ into aggregate price changes, group-specific changes.



(a) Top .1%

(b) 99 - 99.9%

(c) 90 - 99%

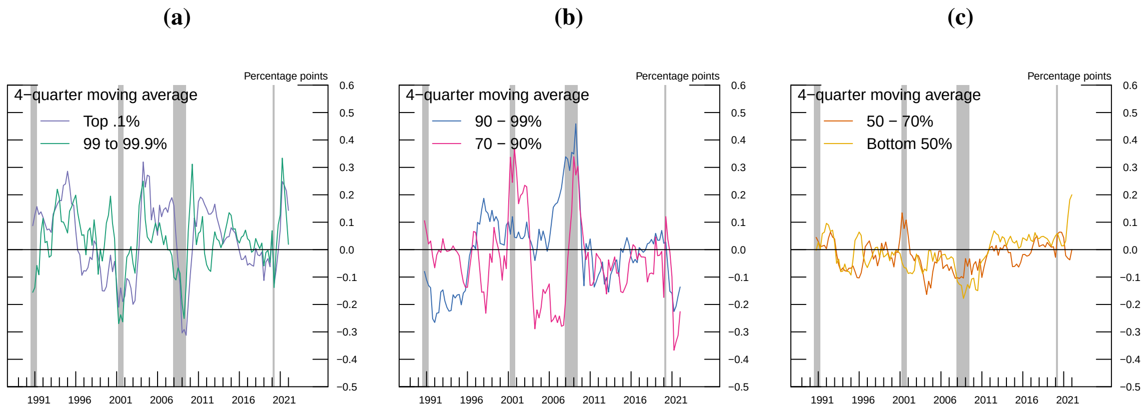
(d) 70 - 90%

(e) 50 - 70%

(f) Bottom 50%

Note: This figure shows a moving average of quarterly changes in net worth (blue line) in each DFA quarter for six wealth groups. These quarterly changes are decomposed into that attributable to aggregate price changes (black line) and other wealth group-specific changes (red line). Source: Authors' calculations using Distributional Financial Accounts and Z.1 revaluations.

Figure 11: Cyclical Variation in Wealth Shares.



Note: This figure shows a moving average of quarterly changes in the share of wealth held by six wealth groups in each quarter. Source: Authors' calculations using Distributional Financial Accounts.

to wealth mentioned above. For the bottom 50% of households, E_t^p is highly volatile and exhibits large positive and negative swings. Although wealth for lower-wealth households is primarily concentrated in assets with less cyclical risk (i.e., real estate) than households at the top of the wealth distribution (i.e., business equity), these households also hold high levels of mortgage debt and consumer credit. This leverage amplifies smaller price fluctuations, particularly following the run-up in household debt in the mid-2000's. Similarly, group-specific return U_t^p to wealth for the bottom 50% of households is highly volatile (again due to their substantial leverage) but exhibit little cyclical variation.

4.3 Decomposing Changes in Wealth Shares into Aggregate and Group-Specific Price Changes

In the previous subsection, we showed that wealthier households hold higher shares of more cyclical assets like corporate and noncorporate business equity, and therefore their *returns to wealth* are more sensitive to changes in the values of these assets. Additionally, group-specific return components also tend to be more procyclical for wealthy households, suggesting that their overall *wealth shares* should also vary procyclically. In this subsection we leverage the unique quarterly frequency of our data to confirm this pattern and provide novel quantitative measures of the cyclical variation in wealth shares.

In Figure 11, we start by plotting the quarterly changes in wealth shares for each of the six considered wealth groups, with gray bars indicating NBER recessions. The figure reveals systematic differences in the cyclical behavior of the wealth shares. Panel (a) in Figure 11 makes clear that the top 1% and the 0.1% shares vary procyclically, with notable drops during each of the three recessions captured in our data. In contrast, in Panel (b), the 90-99th and 70-90th percentiles of the distribution move countercyclically. Finally, Panel (c) shows that wealth shares of households in the Bottom 50% and in the 50-70th percentiles of the wealth distribution are roughly acyclical. Hence, cyclical variation in the wealth distribution is largely confined to the wealthiest 30% of households, with wealth shares shifting from the Top 1% to 70-90th and 90-99th percentile households during recessions and expansions.

Next, we decompose changes in wealth shares from Figure 11 into aggregate and group-specific price changes. Let ω_t^p represent the wealth share of group p at time t. Further transforming Equation 13, group p's quarterly *change* in wealth share can be conveniently obtained by dividing through by the total wealth across all groups. Rearranging terms yields

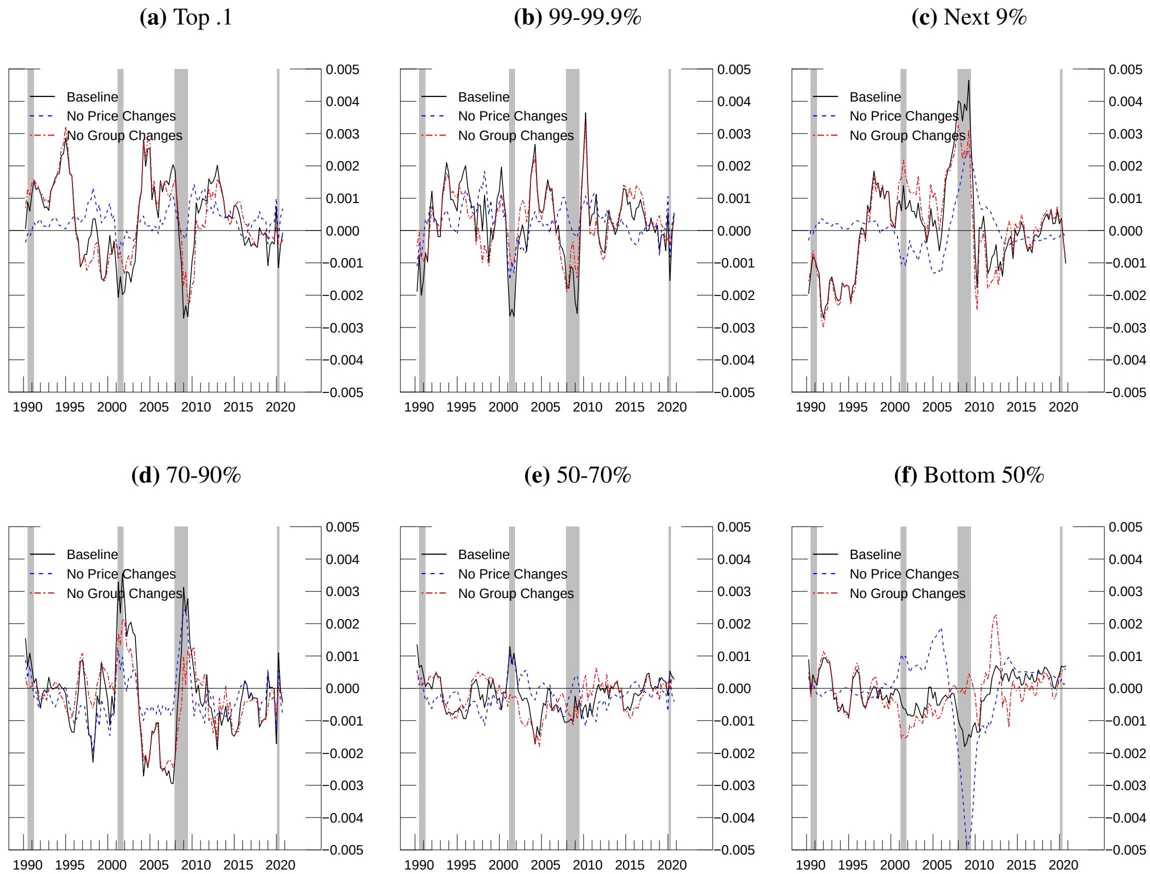
$$\omega_t^p - \omega_{t-1}^p = \frac{Y_{t-1}^{NW,p}}{\sum_{p'} Y_t^{NW,p'}} \left[(E_t^p + U_t^p) - \left(\frac{\sum_{p'} Y_t^{NW,p'}}{\sum_{p'} Y_{t-1}^{NW,p'}} - 1 \right) \right]. \tag{14}$$

The term inside the brackets in Equation 14 thus shows that—as long as $\frac{Y_{t-1}^{NW,p}}{\sum_{p'} Y_t^{NW,p'}} > 0$—each group p's wealth share (depicted in Figure 11) will increase between two quarters if the total net return on wealth for group p ($E_t^p + U_t^p$) is larger than the net return on aggregate wealth ($\sum_{p'} Y_t^{NW,p'} / \sum_{p'} Y_{t-1}^{NW,p'} - 1$).[21] This intuitively implies that wealth distribution dynamics are determined by differences in relative returns to wealth (inclusive of savings) across groups.

Through a series of counterfactual exercises, we quantify how much the group specific and aggregate returns shown previously in Figure 10 contribute to the overall cyclical changes in wealth

[21] The relationship $\frac{Y_{t-1}^{NW,p}}{\sum_{p'} Y_t^{NW,p'}} > 0$ generally applies, as both the aggregate and the group specific net worth are positive. However, as we shown in Section 3.3, the net worth for the bottom 50% of the wealth distribution turned temporarily negative in the wake of the Global Financial Crisis. During those quarter, the reverse would thus apply. Namely, the bottom 50%'s wealth share would increase if $(E_t^p + U_t^p) < (\sum_{p'} Y_t^{NW,p'} / \sum_{p'} Y_{t-1}^{NW,p'} - 1)$.

Figure 12: Counterfactual Wealth Shares, No Aggregate Price and Group Specific Changes.



Note: This figure shows quarterly changes in the share of wealth held by six wealth groups in each DFA quarter (as in figure 11 and the expected quarterly changes under two counterfactual scenarios. The first counterfactual (dashed blue line) captures cyclical changes in the wealth distribution only from aggregate price fluctuations (but preserving long-run changes in wealth shares), while the second (dashed red line) captures changes only from group-specific factors. Source: Authors' calculations using Distributional Financial Accounts and Z.1 revaluations data.

shares (ω_t^p) shown in Figure 11. In the first counterfactual, we assume that returns from aggregate price changes ($E_t^{j,p}$) align with each group's realized returns but that group specific returns are held fixed at their group specific average ($\bar{U}_{j,p}$) each period. In the second counterfactual, we assume that returns from aggregate price changes are constant at their group specific sample average ($\bar{E}_t^{j,p}$) each period and group specific returns align with each group's realized returns ($U_t^{j,p}$). The first

Table 3: Decomposition into aggregate price changes and group-specific changes

	Baseline Variance (1)	No Aggregate Price Changes % of Baseline (2)	No Group Factors % of Baseline (3)
Top .1%	0.00344	30.8%	93.8%
99-99.9%	0.00317	46.3%	83.8%
90-99%	0.00357	52.5%	85.2%
70-90%	0.00419	49.8%	71.1%
50-70%	0.00143	72.5%	105.5%
0-50%	0.00144	223.7%	113.3%

Note: This table summarizes the variance of the cyclical component of the actual (column 1) wealth shares, the shares absent aggregate price changes (column 2), and the shares absent other group factors (column 3). The variance of the cyclical component of wealth shares is much lower absent aggregate price changes (column 2) for families in the top 50%, confirming that most cyclical variation in wealth shares is attributable to fluctuations in aggregate prices. Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA) and Z.1 revaluations data.

counterfactual therefore captures cyclical changes in the wealth distribution only from aggregate price fluctuations (but preserving long-run changes in wealth shares), while the second captures changes only from group-specific factors.

The resulting quarterly changes in the counterfactual wealth shares are shown in Figure 12. For most households, changes in wealth shares would have been more muted and much less cyclical absent aggregate price changes. This is particularly true for households in the top 70% of the wealth distribution, as evidenced by the modest variability in the blue line but near overlap of the red and black lines.

To provide quantitative summaries of the contribution from each return component to the wealth share cyclicality shown in Figure 12, we apply a Hodrick-Prescott filter to the actual and two counterfactual wealth share profiles for each group and then calculate the variance of the cyclical component. Table 3 presents the baseline variance of each wealth group's cyclical wealth profile in Column 1, and the corresponding variance (as a percent of the baseline) for the two counterfactual profiles in Columns 2 and 3. As expected, the variance of the cyclical component of wealth shares is much lower absent aggregate price changes (Column 2). The average cyclical variance for households in the top half of the wealth distribution is only 50.4% as large as the baseline, with even larger reductions for households in the top 0.1 percent (30.8-100=-69.2%) and 90-99.9 percentiles (-53.7%). In contrast, average cyclical variance of wealth shares for the top half of the wealth distribution is 87.9% absent group specific factors, with variance reductions greatest for households in the 70-90th percentiles (-28.9%). These estimates confirm that most cyclical variation in wealth shares is attributable to aggregate price fluctuations.

4.4 Summary

Our analysis in this section provided several insights into the business cycle dynamics of the wealth distribution. First, wealthier households hold portfolios that are highly skewed towards assets with more cyclical returns. In addition, group-specific factors that affect returns for wealthy households also tend to be more cyclical. These two patterns generate notable cyclicality in the distribution of overall wealth, with wealth shares shifting from the very wealthy to moderately wealthy during downturns and from moderately wealthy to very wealthy in expansions. Finally, although both aggregate and group-specific factors contribute to changes in the wealth distribution, aggregate price changes account for a much larger share of cyclical variance in wealth shares and therefore are the main driver of cyclical fluctuations in the distribution of wealth.

5 The Effect of Specific Shocks on the Wealth Distributions

Section 4 documented the cyclical fluctuations in the distribution of wealth. These changes—regardless whether they reflect aggregate price or group specific changes—reflect the realized set of all economic shocks and the consumption, investment, and saving decisions households make in response to these shocks. However, economists and policy makers are often interested in the effects of specific shocks. In lower-frequency distributional data, estimating the effects of specific shocks is complicated because many shocks and decisions occur between observations, but our higher-frequency data offer more temporal variation that can help tease out the wealth distribution's response to economic shocks of interest. In this section, we therefore estimate impulse response functions of the wealth Gini coefficient (a summary measure of inequality) to innovations in key economic variables.

Our impulse response functions are estimated via local projection methods (Jordá (2005)). Specifically, we estimate the following regression

$$y_{t+h} = \mu_h + \beta_h x_t + \sum_{i=1}^{I} \delta'_{h,i} w_{t-i} + \xi_{h,t} \tag{15}$$

where y_{t+h} is the outcome of interest at horizon h, μ_h is the regression constant, x_t is the macroeconomic variable projected onto y, w_{t-i} are lagged vectors of x and y, and $\xi_{h,t}$ is the projection residual. The local projection impulse response function of y_{t+h} with respect to x_t is given by $(\beta_h)_{h\geq 0}$.

We first estimate the effects of four variables—the GDP gap, unemployment rate, CPI inflation, and the Fed Funds rate—on the wealth Gini coefficient by estimating Equation 15 separately for each variable (x_t). In this analysis, we control for six lags of the included variables, and the causal effect is identified based on the Cholesky decomposition with the Gini coefficient ordered first and indicated variable ordered last.[22] In a second analysis shown later in this section, we present instrumental-variable based estimates of the effect of monetary policy on the wealth Gini coefficient using monetary policy shocks identified based on the methodology in in Romer and Romer (2004).

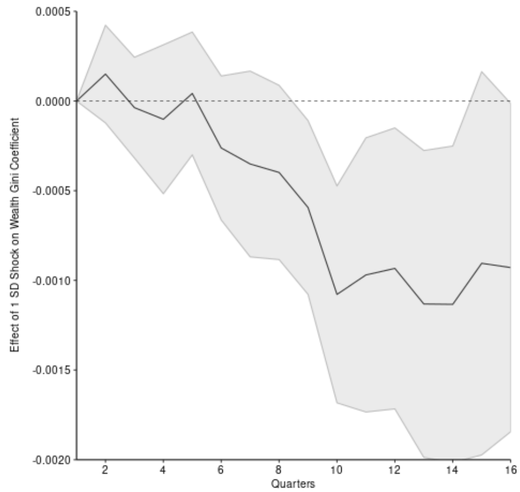
Our first set of results are presented in Figure 13. Figure 13 (a) shows that an increase in the output gap is associated with a statistically significant and persistent decline in wealth inequality, while Figure 13 (b) shows that an in increase in the unemployment rate causes a persistent, statistically significant increase in wealth inequality. These results are fairly intuitive, since changes in economic slack primarily affect wealth inequality through changes in income and saving, and 1) poorer households are disproportionately affected by changes in unemployment during economic downturns and 2) income for wealthier households is better buffered by a higher share of capital income (Gornemann et al. (2016)).

Figure 13 (c) shows the effect of an inflation shock on wealth inequality. The effects of inflation shocks on wealth inequality are theoretically ambiguous since they have two offsetting effects (Doepke and Schneider (2006)). First, inflation increases devalue cash-like assets relative to other

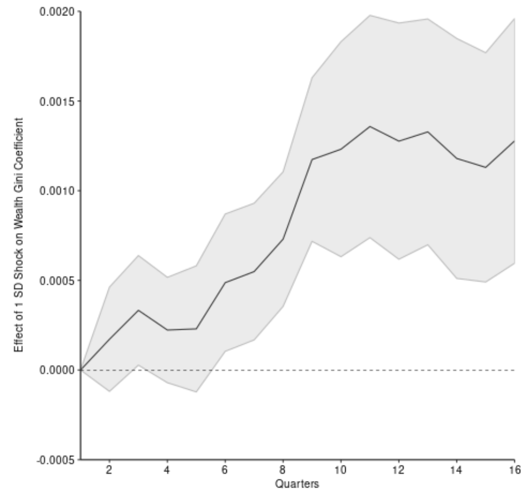
[22] Our analysis in this section only uses data through 2019Q3, but results are qualitatively similar for estimates using the full DFAs data through 2021.

Figure 13: Impulse response of Gini coefficient - Estimates based on Cholesky decomposition with Gini coefficient ordered first and indicated variable ordered last. Error bands indicate 90% confidence intervals. Estimation sample is 1989Q3-2019Q3.

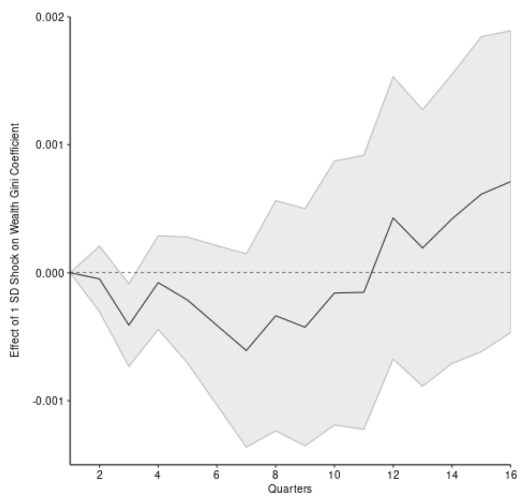
(a) Output Gap



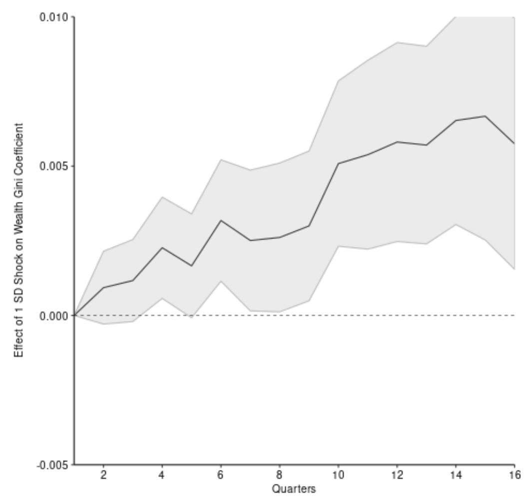
(b) Unemployment



(c) Inflation



(d) Fed Funds Rate Cut



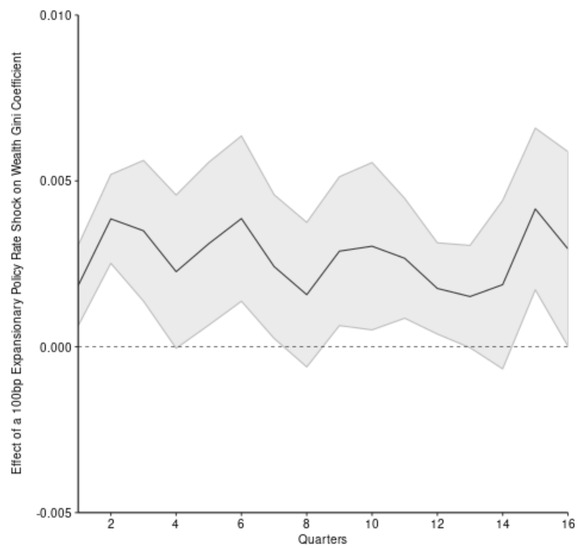
Note: Output gap estimates from Congressional Budget Office. Inflation defined as the quarterly annualized percent change in the GDP chain-weighed price index.

assets like business equity, which suggests increased inflation might increase inequality given the higher business equity exposure of higher-wealth households. However, increased inflation also devalues liabilities, which could lower inequality given that lower-wealth households are more levered (Figure 9). Our estimates imply a positive inflation shock causes a near-term decline and long-term increase in inequality, but our estimates are never statistically significant and therefore imply empirically ambiguous effects as well.

Finally, Figure 13 (d) shows the effect of a reduction in the Fed Funds rate on wealth inequality. The effect of monetary policy on inequality has received significant attention from policy makers in recent years due to concerns that accommodative monetary policy has contributed to the long-run increase in wealth inequality (see, e.g., Bernanke (2015), Bullard (2014), Mersch (2014), and Yellen (2014)). Like inflation, the effects of monetary policy on inequality are theoretically ambiguous. On one hand, reductions in the policy rate might increase wealth inequality by increasing prices of business equity and other assets (e.g., Bernanke and Kuttner (2005), Rigobon and Sack (2004), Paul (2018)) that are primarily held by wealthier households (Auclert (2019)). On the other hand, accomodative monetary policy is likely to boost earnings and wealth of households at the bottom of the distribution—as shown theoretically in Heathcote et al. (2010) and empirically in Coibion et al. (2012)—and therefore lower inequality. Our findings suggest that the former channel dominates, and that a reduction in the Fed Funds rate causes an increase in wealth inequality.

Although the results in Figure 13 are intuitive, our strategy for identifying shocks to the indicated variables is simple, and the usual concerns about confounding variables apply. This is especially true for our monetary policy effect estimates, since large changes in the Fed Funds rate often occur in volatile economic environments when other macroeconomic indicators are also changing rapidly. To address this challenge, we therefore re-estimate the effects of changes in the Fed Funds rate on wealth inequality by instrumenting for changes in the policy rate using monetary policy shocks identified by extending the methodology from Romer and Romer (2004) through 2015. We then apply the "local projections-IV" (LP-IV) estimator proposed in Stock and Watson (2018) and Jordà et al. (2020)—which is a simple extension of Equation 15—to estimate the impulse response

Figure 14: Impulse response of Gini coefficient - Estimates based on exogenous monetary policy shocks identified by extending the methodology in Romer and Romer (2004) through 2015. Error bands indicate 90% confidence intervals. Estimation sample is 1989Q3-2015Q4.



(β_h) to the identified shocks:

$$y_{t+h} = \mu_h + \beta_h SHOCK_t + \psi_t x_t + \sum_{i=1}^{I} \delta'_{h,i} w_{t-i} + \xi_{h,t}. \tag{16}$$

The resulting estimates, shown in Figure 14, again imply that accomodative monetary policy shocks cause a persistent, statistically significant increase in wealth inequality. Furthermore, the estimated effects are reasonably large, and our estimates imply that the wealth Gini coefficient increases by .003 on average in the 16 quarters following a 100bp accomodative monetary policy shock, an effect equivalent to about 6% of the 30 year increase. Our estimates therefore suggest that policy rate reductions designed to support the overall economy also have the unintended effect of increasing wealth inequality.

These results come with several caveats. First, our estimates reflect the effect of short-term changes in the Fed funds rate, and do not speak to the effects of unconventional monetary policy or persistently low rates. Second, our results do not speak to the effects of macroeconomic shocks on earnings, consumption and overall welfare, which may be of primary interest to policy makers. Third, our estimates are specific to the period since 1989 covered by our data. As a result, the policy implications of these reduced-form IRFs should be interpreted cautiously, and structural analysis is likely necessary to fully understand the effects of macroeconomic shocks on wealth inequality.

6 Household Balance Sheets: A Tale of Two Recessions

Our analysis thus far has focused on describing how wealth shares vary across business cycles generally. However, the last two recessions—the Great Recession and the Covid-19 Pandemic Recession—were atypical in depth and duration, and specific features of household balance sheets have garnered a significant amount of attention in academic research. For example, Mian et al. (2013), Mian and Sufi (2014), and Mian et al. (2017) showed that the build-up in household leverage and subsequent deleveraging amplified the downturn during and slowed the recovery from the Great Recession. In contrast, the aggregate household balance sheet swelled during the pandemic recession as saving rates spiked due to a surge in fiscal transfers and collapse in consumption (see, e.g., Romer and Romer (2021)), suggesting that a similar balance-sheet hangover was unlikely. In this section we compare and contrast quarterly evolution of disaggregated household balance sheets through the past two recessions—two economic episodes that will likely continue to be a focus of economic research in the coming years.

We first consider asset price dynamics during the two recessions in Figure 15. During the GFC, asset prices fell and recovered very slowly, with equity wealth (Panel (a)) remaining below its pre-recession level—particularly for high wealth households—until 2012, and housing wealth (Panel (b)) remaining depressed—particularly for middle-wealth households—until 2016. In the Covid-19 recession, an unprecedented set of fiscal and monetary policy actions to support businesses (Hanson et al. (2020)) led to quick improvements in investor sentiment (Cox et al. (2020)) and longer-term growth expectations (Gormsen and Koijen (2020)). This support, in combination with a economic recovery, led business equity to surge after a brief decline, significantly boosting wealthy households' balances sheets.

Housing prices show even more divergent trends across the two recessions (Panel (b)). Housing prices increased dramatically in the years ahead of the GFC, largely due to a shift in beliefs regarding future price growth (Kaplan et al. (2019)). After the housing bubble burst, house prices declined for several years due to weak demand, depressed income, and household deleveraging due to tighter credit standards (see, e.g., Garriga and Hedlund (2019)). This created a long-term drag on wealth, particularly for the bottom 90% of households. In contrast, prices surged during the pandemic as shifts in preferences spurred moves from cities to suburbs (Ramani and Bloom (2021)) and raised housing demand. This rapid increase in demand could not be matched by new construction in the short term, causing housing markets to tighten considerably and home prices to appreciate rapidly (Anenberg et al. (2021)). For example, the Case-Shiller home price index rose by 25% from Jan 2020 to July 2021, an even faster rate of increase than in run-up in housing prices prior to the GFC. The acceleration in home price growth has led to a significant expansion in wealth, particularly for middle-wealth households.

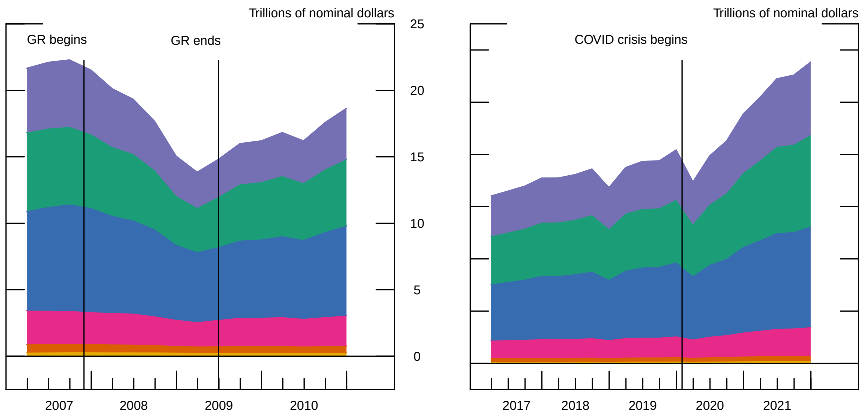
In Panel (c) we compare the accumulation of liquid assets—which include bank deposits, money market funds, and other cash-like holdings-during the two recessions. During the Great Recession, liquid assets for most groups moved sideways, as the large economic shock and slow recovery significantly slowed the accumulation in wealth. During the Covid-19 crisis, cash-like holdings increased sharply by almost $3 trillion with notable increases for all groups, with unprecedented cutbacks in spending leading to a large increase in liquid assets for wealthier households and large fiscal transfers supporting wealth accumulation among lower-wealth households. Overall, the aggregate increase in liquid assets were comparable in size to the total “excess savings" (Bilbiie et al. (2021)), suggesting that most extra savings during the pandemic had been held in cash-like assets.

We next compare liability dynamics during the two recessions in Figure 16. Mortgage debt (Panel (a)) fell during the Great Recession—particularly for middle- and low-wealth households—due to defaults and forced deleveraging following the collapse in house prices. In the COVID Recession, mortgage debt rose—again, particularly for middle- and lower-wealth households—due to an increase in home purchases.

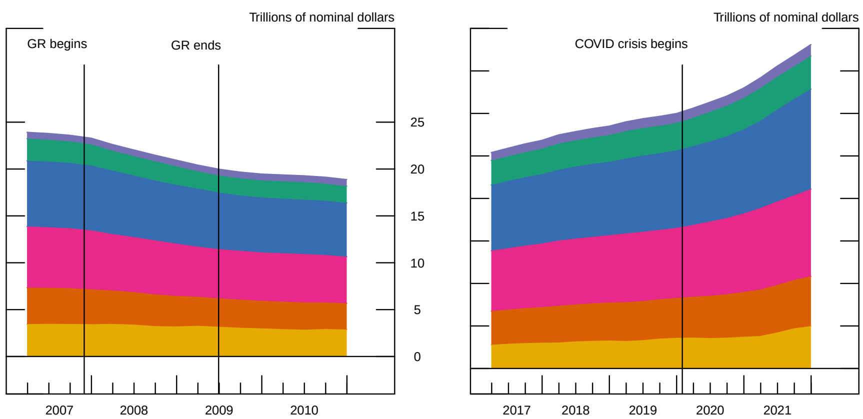
Panel (b) shows that non-mortgage debt (e.g., consumer credit) growth slowed after both downturns, but for very different reasons. The slowdown following the Great Recession reflected tighter credit standards and borrowing conditions that restricted credit to marginal borrowers and forced lower-wealth households to delever (Bhutta (2015), Cooper (2012)). During the pandemic re-

Figure 15: Assets During the Great Recession and COVID-19 Pandemic

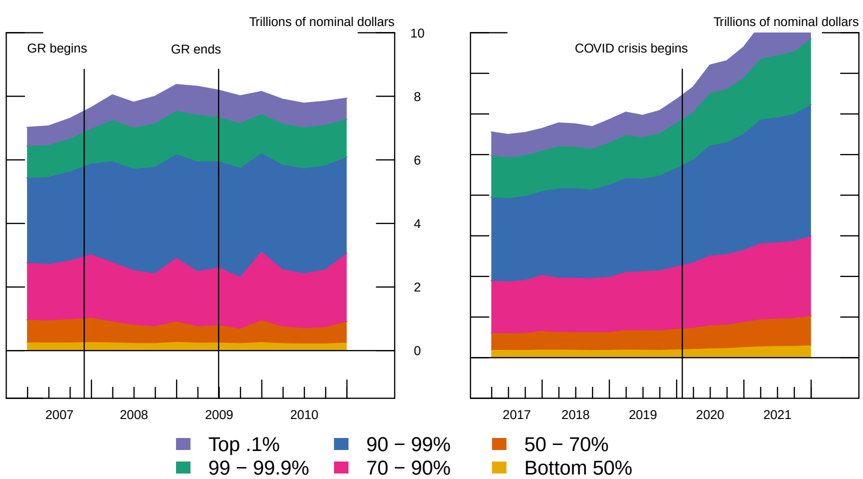
(a) Business equity



(b) Real estate



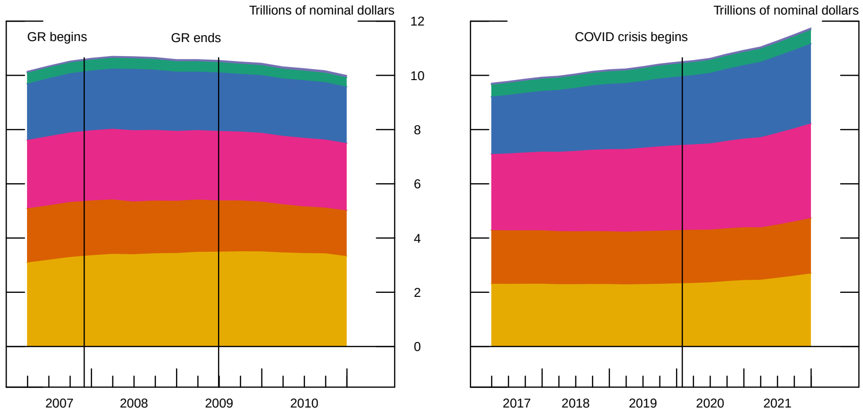
(c) Liquid assets



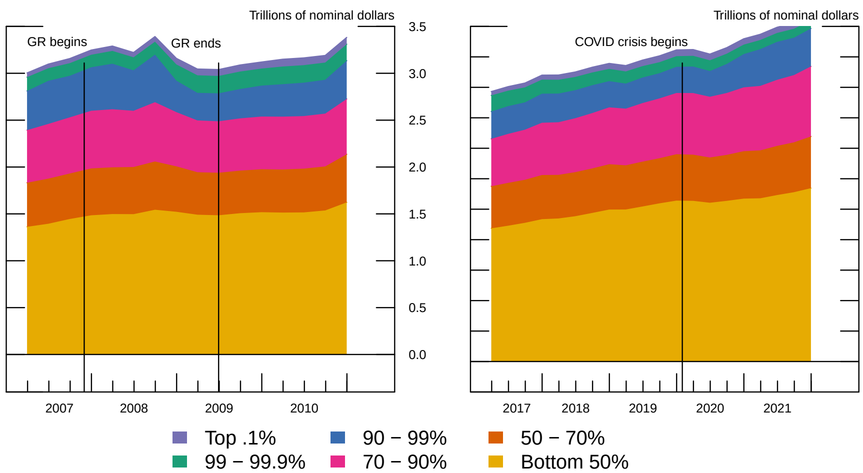
Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

Figure 16: Debt During the Great Recession and COVID-19 Pandemic

(a) Mortgages



(b) Other liabilities



Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

cession, many middle and lower-wealth households used their forced savings to pay down debts, resulting in a brief slowdown before growth resumed later in 2020 and 2021 (Horvath et al. (2021), Coibion et al. (2020), Armantier et al. (2020)).

In Figure 17 we show how these asset and liability trends have resulted in very different wealth dynamics for the different wealth groups. During the Great Recession, net worth for high wealth households fell through early-2009 before starting to grow again as asset prices recovered, while net worth for the bottom 50% of households continued to decline through 2010 due to continued declines in real estate and a sluggish labor market recovery. In contrast, during the Covid-19 crisis, net worth for all groups recovered after a decline in 2020Q1, with a rebound in business equity again driving gains among the top 10% wealthiest households, and housing wealth increases and increased savings due to forced spending cuts and increased fiscal transfers driving gains for the bottom 90% of households.

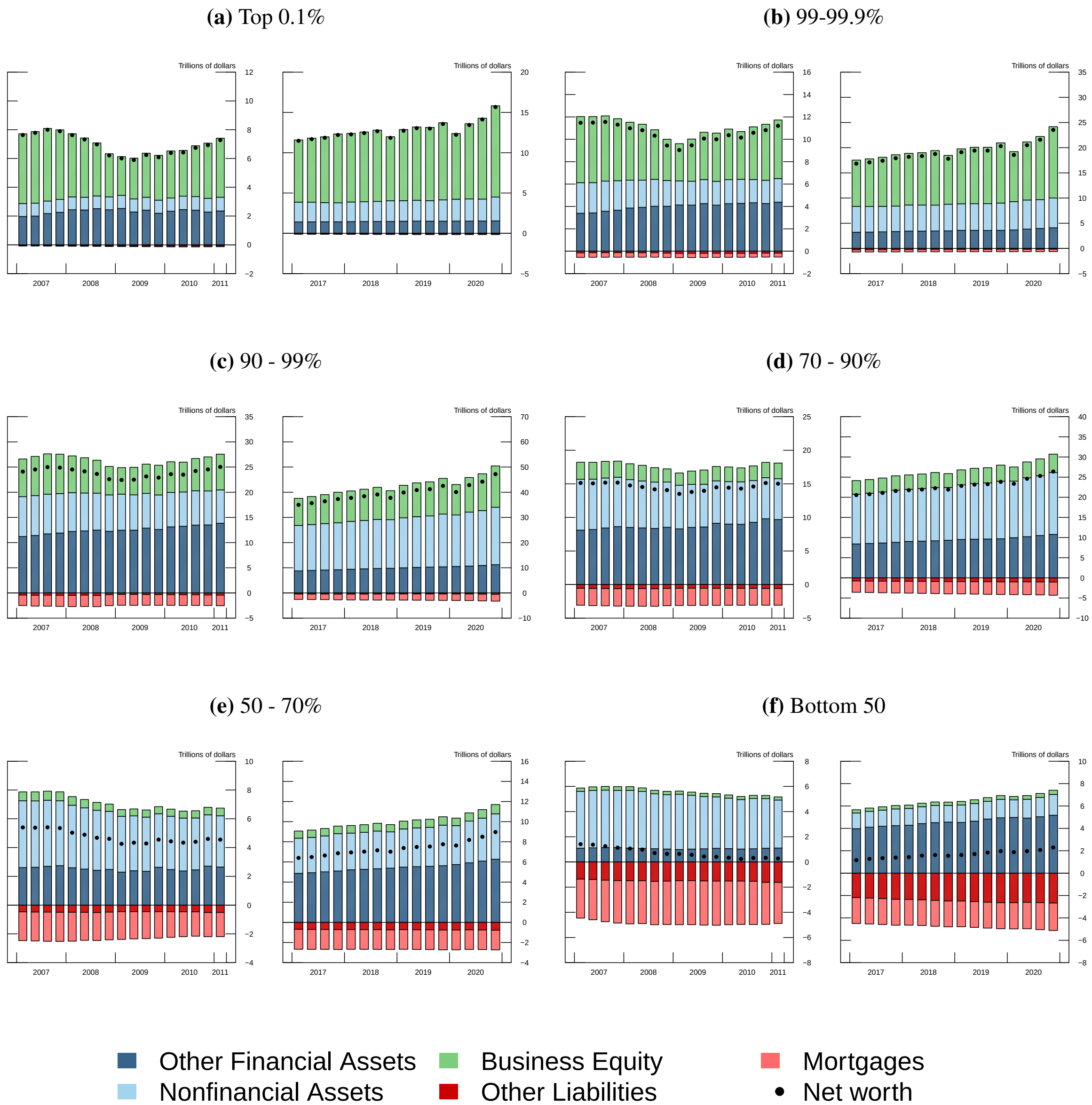
In addition to net worth, the distribution and dynamics of several other balance sheet measures that have attracted significant attention in recent applied macro research can be constructed from our data and their evolution tracked through the Great and Covid-19 pandemic recessions.

In Panel (a) of Figure 18 we show the evolution of household leverage—the ratio of total liabilities to total assets—to document the comovement of asset and debt levels. Most importantly, leverage is a valuable predictor of financial fragility, since highly levered households might be forced to cut back consumption following a negative economic shock (Mian et al. (2013) and Justiniano et al. (2015)). Prior to the Great Recession, mortgage liabilities increased rapidly for households in the bottom 50th and 50-70th percentiles of the wealth distribution, with the level of liabilities for these groups peaking in 2009Q3 and 2007Q3, respectively (see Panel (a) in Figure 18). Real estate is the main asset on the balance sheet of these households (Figure 9), so the fall in house prices sparked a notable increase in leverage even as debt levels began to fall (Figure 18). Very different patterns emerged in the COVID-19 pandemic. Leverage for all groups ticked up slightly in 2020Q1 as asset prices fell, but thereafter declined—particularly for lower wealth groups—due to the recovery in asset prices and widespread paydown of non-mortgage consumer debt.

Panel (b) shows household liquidity, defined as the ratio of cash-like assets to total assets.[23] Recent research has also shown that the distribution of balance sheet liquidity is important to understanding consumption dynamics during downturns, with Kaplan and Violante (2014) documenting that a large share of households have high MPCs due to binding liquidity constraints despite having a large amount of positive wealth. During the Great Recession, liquidity as a share of wealth actu-

[23] Specifically, we follow Kaplan and Violante (2014) and define liquidity as the sum of cash-line financial instruments (i.e, checking and savings accounts and money market funds), debt securities, mortgage and others loans on the asset side of the household balance sheet, and corporate equities, relative to household net worth.

Figure 17: Balance Sheets During the Great Recession and COVID-19 Pandemic

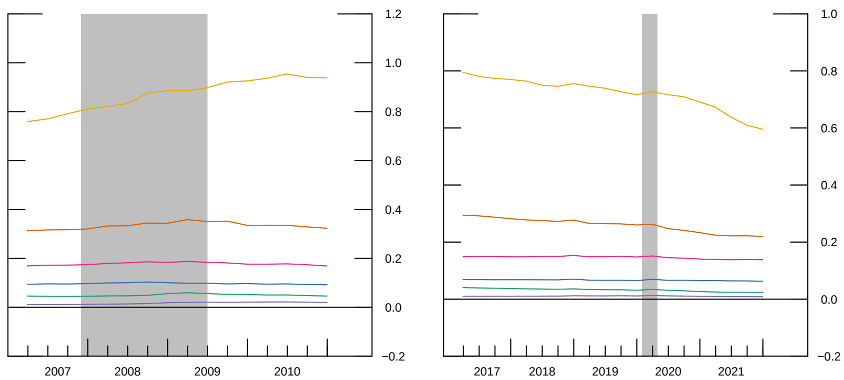


Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

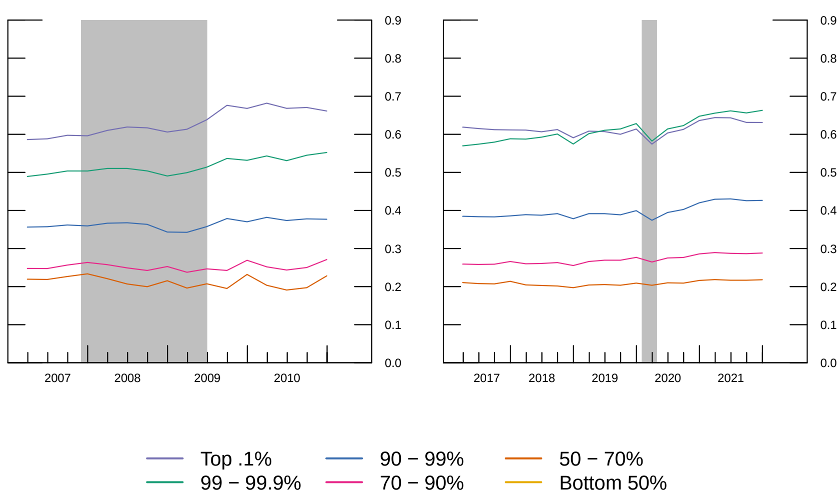
ally rose for wealthier households due to declines in other asset values, but declined or remained flat for the bottom 70% of households. During the Covid-19 crisis, liquidity rose for all wealth groups and particularly for those towards the bottom of the wealth distribution due to the increase in liquid asset holdings we documented previously in Figure 15.

Figure 18: Balance Sheets During the Great Recession and COVID periods

(a) Leverage



(b) Liquidity



Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

Taken altogether, our data document patterns during the Great Recession that are consistent with those proposed in a large applied macro literature (see, e.g., Corbae and Quintin (2015), Auclert (2019), Greenwald (2018), Jones et al. (2018), Kaplan et al. (2019), Garriga and Hedlund (2019)) that has studied how household balance sheet deterioration among specific parts of the wealth and earnings distribution prolonged the downturn and affected the transmission of macroeconomic shocks. However, opposite patterns have generally emerged in the COVID-19 crisis, as balance sheets for all groups and particularly lower- and middle-class households strengthened significantly.

The unique balance sheet dynamics—with unprecedented deterioration during the Great Recession and unprecedented strengthening in the COVID-19 recession—are one factor in the very different economic recoveries from these very different recessions. As a result, household balance sheet heterogeneity will likely remain an important research topic in the near- and medium-term, as applied and theoretical studies attempt to further our understanding of how heterogeneity interacts with aggregate and policy shocks. Our paper's empirical patterns and quantitative estimates provide a useful set of moments that we hope will help discipline models featuring balance sheet heterogeneity and advance this research.

7 Conclusion

Most of this paper's qualitative findings are fairly intuitive, especially since heterogeneity in household portfolios—which drives much of the variation in the wealth distribution—is observable in lower frequency data. Additionally, most of our findings—for example, how various aggregate shocks affect the wealth distribution—are consistent with the predictions of an active academic literature. However, this paper provides the first empirical documentation of these patterns, and therefore contributes to the strands of economic research discussed in Section 1.

Our findings have direct implications for macroeconomic models that aim to accurately capture wealth dynamics at business cycle frequencies. We show how the different portfolios held by different types of households lead to systematic shifts in the distribution of wealth following cyclical price changes and other aggregate shocks that cause inequality measures to vary procyclically. We also show how group-specific factors affect wealth accumulation and further reinforce the procyclicality of returns for wealthy households, while real estate holdings—which are less cyclical—dampen balance sheet fluctuations over the business cycle for the middle- and lower-wealth households that are highly exposed to this asset class.

These patterns suggest that accurately modeling wealth distribution dynamics at higher frequencies requires a sufficiently rich portfolio choice problem. Our findings suggest that a model featuring three assets—riskless bonds, illiquid real estate, and risky capital—will be necessary to capture both the long-run and short-run dynamics of the wealth distribution and its effects on macroeconomic aggregates. Research along these lines is rapidly developing, and our data and analysis provide a set of benchmarks and targets that will help advance this research, as well as our understanding of how household balance sheet heterogeneity interacts with aggregate shocks to determine aggregate outcomes.

References

Ahn, S., Kaplan, G., Moll, B., Winberry, T., and Wolf, C. (2017). When inequality matters for macro and macro matters for inequality. *NBER Macroeconomics Annual 2017*, 32.

Álvarez-Peláez, M. J. and Díaz, A. (2005). Minimum consumption and transitional dynamics in wealth distribution. *Journal of Monetary Economics*, 52(3):633–667.

Anenberg, E., Ringo, D. R., et al. (2021). Housing market tightness during covid-19: Increased demand or reduced supply? Technical report, Board of Governors of the Federal Reserve System (US).

Armantier, O., Goldman, L., Koşar, G., Lu, J., Pomerantz, R., and van der Klaauw, W. (2020). How have households used their stimulus payments and how would they spend the next? Liberty street economics, Federal Reserve Bank of New York.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6):2333–2367.

Auclert, A. and Rognlie, M. (2018). Inequality and aggregate demand. Working Paper 24280, National Bureau of Economic Research.

Bach, L., Calvet, L. E., and Sodini, P. (2020). Rich pickings? risk, return, and skill in household wealth. *American Economic Review*, 110(9):2703–47.

Batty, M. M., Bricker, J., Briggs, J. S., Friedman, S., Nemschoff, D., Nielsen, E., Sommer, K., and Volz, A. H. (2022). The Distributional Financial Accounts of the United States. In Chetty, R., Friedman, J. N., Gornick, J. C., Johnson, B., and Kennickell, A., editors, *Measuring Distribution and Mobility of Income and Wealth*. University of Chicago Press.

Batty, M. M., Bricker, J., Briggs, J. S., Holmquist, E. B., McIntosh, S. H., Moore, K. B., Nielsen, E., Reber, S., Shatto, M., Sommer, K., Sweeney, T., and Volz, A. H. (2019). Introducing the Distributional Financial Accounts of the United States. Finance and Economics Discussion Series 2019-017, Board of Governors of the Federal Reserve System (U.S.).

Benhabib, J., Bisin, A., and Luo, M. (2017). Earnings inequality and other determinants of wealth inequality. *American Economic Review*, 107(5):593–597.

Benhabib, J., Bisin, A., and Zhu, S. (2011). The distribution of wealth and fiscal policy in economies with finitely lived agents. *Econometrica*, 79(1):123–157.

Benhabib, J., Bisin, A., and Zhu, S. (2016). The distribution of wealth in the BlanchardâYaari model. *Macroeconomic Dynamics*, 20(2):466â481.

Bernanke, B. S. (2015). Monetary policy and inequality.

Bernanke, B. S. and Kuttner, K. N. (2005). What explains the stock market's reaction to federal reserve policy? *The Journal of Finance*, 60(3):1221–1257.

Bhandari, A., Evans, D., Golosov, M., and Sargent, T. J. (2018). Inequality, business cycles, and monetary-fiscal policy. Working Paper 24710, National Bureau of Economic Research.

Bhutta, N. (2015). The ins and outs of mortgage debt during the housing boom and bust. *Journal of Monetary Economics*, 76:284–298.

Bilbiie, F., Eggertsson, G. B., Primiceri, G. E., and Tambalotti, A. (2021). Excess savings are not excessive. Liberty street economics, Federal Reserve Bank of New York.

Blanchet, T. and Martinez-Toledano, C. (2022). Wealth inequality dynamics in Europe and the U.S.: Understanding the determinants.

Bricker, J., Hansen, P., and Volz, A. (2019). Wealth concentration in the U.S. after augmenting the upper tail of the Survey of Consumer Finances. *Economics Letters*, 2019.

Bricker, J., Henriques, A., Krimmel, J., and Sabelhaus, J. (2016). Measuring income and wealth at the top using administrative and survey data. *Brookings Papers on Economic Activity*, 2016(1):261–331.

Bullard, J. B. (2014). Income inequality and monetary policy: a framework with answers to three questions. Speech 235, Federal Reserve Bank of St. Louis.

Calza, A., Monacelli, T., and Stracca, L. (2013). Housing finance and monetary policy. *Journal of the European Economic Association*, 11:101–122.

Carroll, C. D. (2014). Representing consumption and saving without a representative consumer. In *Measuring Economic Sustainability and Progress*, NBER Chapters, chapter 5, pages 115–134. National Bureau of Economic Research, Inc.

Chatterjee, S. (1994). Transitional dynamics and the distribution of wealth in a neoclassical growth model. *Journal of Public Economics*, 54(1):97–119.

Chow, G. C. and Lin, A.-L. (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *The Review of Economics and Statistics*, 53(4):372.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2012). Innocent bystanders? Monetary policy and inequality in the U.S. Working Paper 18170, National Bureau of Economic Research.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). How did u.s. consumers use their stimulus payments? Working Paper 27693, National Bureau of Economic Research.

Cooper, D. (2012). Us household deleveraging: what do the aggregate and household-level data tell us? *Federal Reserve Bank of Boston Public Policy Brief*, (12-2).

Corbae, D. and Quintin, E. (2015). Leverage and the foreclosure crisis. *Journal of Political Economy*, 123(1):1–65.

Cox, J., Greenwald, D. L., and Ludvigson, S. C. (2020). What explains the covid-19 stock market? Technical report, National Bureau of Economic Research.

Deaton, A. (2005). Measuring poverty in a growing world (or measuring growth in a poor world). *Review of Economics and Statistics*, 87(2):395–395.

Doepke, M. and Schneider, M. (2006). Inflation and the redistribution of nominal wealth. *Journal of Political Economy*, 114(6):1069–1097.

Dowd, T., McClelland, R., and Mortenson, J. A. (2019). Tax policy center.

Fagereng, A., Guiso, L., Malacrino, D., and Pistaferri, L. (2020). Heterogeneity and persistence in returns to wealth. *Econometrica*, 88(1):110–170.

Feiveson, L. and Sabelhaus, J. (2019). Lifecycle patterns of saving and wealth accumulation. Working Paper 2019-010, Board of Governors of the Federal Reserve System.

Fernandez, R. B. (1981). A methodological note on the estimation of time series. *The Review of Economics and Statistics*, 63(3):471.

Ferreira, F. H. (1995). Roads to equality: Wealth distribution dynamics with public-private capital complementarity.

Gabaix, X., Lasry, J.-M., Lions, P.-L., and Moll, B. (2016). The Dynamics of Inequality. *Econometrica*, 84(6):2071–2111.

Gallin, J. H., Sommer, K., Nielsen, E., Molloy, R. S., and Smith, P. A. (2018). Measuring aggregate housing wealth: New insights from an automated valuation model. Finance and Economics Discussion Series 2018-064, Board of Governors of the Federal Reserve System (U.S.).

Garbinti, B., Goupille-Lebret, J., and Piketty, T. (2021). Accounting for wealth-inequality dynamics: methods, estimates, and simulations for france. *Journal of the European Economic Association*, 19(1):620–663.

Garriga, C. and Hedlund, A. (2019). Crises in the housing market: Causes, consequences, and policy lessons. *Oxford Research Encyclopedia of Economics and Finance*.

Garriga, C., Kydland, F. E., and Šustek, R. (2015). Mortgages and monetary policy.

Gormsen, N. J. and Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies*, 10(4):574–597.

Gornemann, N., Kuester, K., and Nakajima, M. (2016). Doves for the rich, hawks for the poor? Distributional consequences of monetary policy. *International Finance Discussion Paper*, 2016(1167):1–40.

Greenwald, D. L. (2018). The mortgage credit channel of macroeconomic transmission. *SSRN Electronic Journal*.

Guerrieri, V. and Lorenzoni, G. (2017). Credit crises, precautionary savings, and the liquidity trap. *The Quarterly Journal of Economics*, 132(3):1427–1467.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2019). What do data on millions of U.S. workers reveal about life-cycle earnings dynamics?

Guvenen, F., Ozkan, S., and Song, J. (2012). The nature of countercyclical income risk.

Hagedorn, M., Manovskii, I., and Mitman, K. (2019). The fiscal multiplier. Working Paper 25571, National Bureau of Economic Research.

Hanson, S. G., Stein, J. C., Sunderam, A., and Zwick, E. (2020). Business credit programs in the pandemic era. *Brookings Papers on Economic Activity*, 2020(3):3–60.

Heathcote, J., Perri, F., and Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States: 1967-2006. *Review of Economic Dynamics*, 13(1):15–51.

Horvath, A., Kay, B. S., and Wix, C. (2021). The covid-19 shock and consumer credit: Evidence from credit card data. *Available at SSRN 3613408*.

Jones, C., Midrigan, V., and Philippon, T. (2018). Household leverage and the recession. *IMF Working Papers*, 18(194):1.

Jordá, Ó. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2020). The effects of quasi-random monetary experiments. *Journal of Monetary Economics*, 112:22–40.

Justiniano, A., Primiceri, G., and Tambalotti, A. (2015). Household leveraging and deleveraging. *Review of Economic Dynamics*, 18(1):3–20.

Kaplan, G., Mitman, K., and Violante, G. L. (2019). The housing boom and bust: Model meets evidence. *SSRN Electronic Journal*.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary policy according to HANK. *American Economic Review*, 108(3):697–743.

Kaplan, G. and Violante, G. L. (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica*, 82(4):1199–1239.

Kaplan, G. and Violante, G. L. (2018). Microeconomic heterogeneity and macroeconomic shocks. *Journal of Economic Perspectives*, 32(3):167–94.

Kekre, R. and Lenel, M. (2019). Redistribution, risk premia, and the macroeconomy. *Working Paper*.

Kopczuk, W. and Saez, E. (2004). Top wealth shares in the United States, 1916-2000: Evidence from estate tax returns. *National Tax Journal*, 57(2):445–487.

Krueger, D., Mitman, K., and Perri, F. (2016). Macroeconomics and household heterogeneity. *Handbook of Macroeconomics*, pages 843–921.

Krusell, P. and Smith, A. A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, 106(5):867–896.

Kuhn, M., Schularick, M., and Steins, U. I. (2018). Income and wealth inequality in America, 1949-2016.

Litterman, R. B. (1983). A random walk, Markov model for the distribution of time series. *Journal of Business Economic Statistics*, 1(2):169–173.

Luetticke, R. (2018). Transmission of monetary policy with heterogeneity in household portfolios.

Mckay, A., Nakamura, E., and Steinsson, J. (2016). The power of forward guidance revisited. *American Economic Review*, 106(10):3133–3158.

McKay, A. and Reis, R. (2016). The role of automatic stabilizers in the U.S. business cycle. *Econometrica*, 84:141–194.

Meh, C. A., Ríos-Rull, J.-V., and Terajima, Y. (2010). Aggregate and welfare effects of redistribution of wealth under inflation and price-level targeting. *Journal of Monetary Economics*, 57(6):637–652.

Mersch, Y. (2014). Corporate credit conference.

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726.

Mian, A. and Sufi, A. (2014). What explains the 2007-2009 drop in employment? *Econometrica*, 82(6):2197–2223.

Mian, A., Sufi, A., and Verner, E. (2017). Household debt and business cycles worldwide*. *The Quarterly Journal of Economics*, 132(4):1755â1817.

Mönch, E. and Uhlig, H. (2005). Towards a monthly business cycle chronology for the Euro area. *Journal of Business Cycle Measurement and Analysis*, 2005(1):43–69.

Paul, P. (2018). Monetary Policy Cycles and Financial Stability. *FRBSF Economic Letter*.

Piketty, T. (1997). The dynamics of the wealth distribution and the interest rate with credit rationing. *The Review of Economic Studies*, 64(2):173.

Piketty, T. (2013). *Capital in the Twenty-First Century*. Harvard University Press.

Piketty, T., Saez, E., and Zucman, G. (2018). Distributional National Accounts: Methods and estimates for the United States. *The Quarterly Journal of Economics*, 133(2):553–609.

Proietti, T., Marczak, M., and Mazzi, G. (2017). Euromind-: A density estimate of monthly gross domestic product for the euro area. *Journal of Applied Econometrics*, 32(3):683–703.

Ramani, A. and Bloom, N. (2021). The donut effect: How covid-19 shapes real estate. *SIEPR Policy Brief, January*.

Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575.

Ríos-Rull, J.-V. and Kuhn, M. (2016). 2013 update on the u.s. earnings, income, and wealth distributional facts: A view from macroeconomics. *Quarterly Review*, 37(1).

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Romer, C. D. and Romer, D. H. (2021). The fiscal policy response to the pandemic. *Brookings Papers on Economic Activity*.

Roymans, I. (2022). Wealth dynamics of households: linking micro and macro.

Rubio, M. (2011). Fixed- and variable-rate mortgages, business cycles, and monetary policy. *Journal of Money, Credit and Banking*, 43(4):657–688.

Sabelhaus, J. and Volz, A. H. (2019). Are disappearing employer pensions contributing to rising wealth inequality? *FEDS Notes*, 2019(2308).

Saez, E. and Zucman, G. (2016). Wealth inequality in the United States since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics*, 131(2):519–578.

Smith, M., Zidar, O., and Zwick, E. (2019). Top wealth in the United States: New estimates and implications for taxing the rich.

Stock, J. H. and Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, 128(610):917–948.

Werning, I. (2015). Incomplete markets and aggregate demand. *NBER Working Paper*.

Wolff, E. N., Zacharias, A., and Masterson, T. (2012). Trends in American living standards and inequality, 1959-2007. *Review of Income and Wealth*, 58(2):197–232.

Yellen, J. L. (2014). Perspectives on inequality and opportunity from the survey of consumer finances.

A More on Data and Methodology

A.1 Reconciliation of Major Asset Classes and Other Challenges

Both the SCF and FA aim to provide comprehensive wealth measures of household balance sheets, but wealth concepts sometimes differ across the two data sets. Here we describe issues with, and solutions to, reconciling the four largest balance sheet items (which account for 78% of total assets) and briefly discuss key challenges in reconciling other asset categories. We refer readers interested in details on the mapping from SCF to the Financial Accounts for other balance sheet lines to Batty et al. (2019), a technical paper which details the data's construction.

Pension entitlements 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.[24] These three asset classes account for about 30%, 60%, and 10% of total pension entitlements in the Financial Accounts, respectively.[25] The SCF captures DC balances using a method that is compatible with the one used in the construction of 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. The DFAs consequently follow the method developed in Sabelhaus and Volz (2019) to distribute the DB component of the B.101.h aggregate across the SCF households. Specifically, we first split 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. We then use the benefit amount to assign DB pension wealth to those currently collecting, the expected timing and amount of future pension benefits to assign DB pension wealth to those with pensions from past jobs, and then allocate the residual DB pension reserves to those with pensions on their current job that are

[24] 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 corporate equity and mutual fund balance sheet line.

[25] 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.

not collecting according to wage, years in the plan, and age. See Sabelhaus and Volz (2019) for a more detailed description of this imputation methodology.

Similarly to accrued DB pensions, measures of annuity reserves are not directly collected by the SCF in a manner compatible with 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).[26] To reconcile the SCF and B.101.h annuity measures, the DFAs capitalize the payout annuity income reported by SCF households into a present value using a set of sample annuity policies (Batty et al. (2019) 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.

Real estate 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. Important methodological differences drive the divergence between the SCF and Financial Accounts measures of housing wealth during the mid-2000s housing cycle. Specifically, the SCF measure is based on owner-reported values, whereas the Financial Accounts measure applies an automated valuation model (AVM) from Zillow. Gallin et al. (2018)—and studies cited therein—show that owner self-reports values tend to lag the market during market turns and also tend to be overly optimistic, potentially explaining a portion of the discrepancy. The sizable, time-varying gap between the Financial Accounts and SCF measures of housing wealth is notable, but the key question for our purposes is whether it causes bias when we apply the SCF distribution to the Financial Accounts measures. Batty et al. (2019) assesses assess the sensitivity of the DFAs distributional measures to a different aggregate housing wealth series recently developed by Board staff and finds that using this series results in minimal effect on the distribution of housing wealth, therefore suggesting that the difference in the level of housing wealth between the SCF and B.101.h is relatively

[26] 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.

evenly distributed across wealth groups.

Equity in noncorporate business This B.101.h balance sheet item 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 using tax data. In the SCF, rental properties are reported at market value, as they are in the Financial Accounts, but 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%). However, the SCF's cost-basis and market-value measures are near identical. Because the shares implied by the reconciled SCF distribution are applied to the Financial Accounts levels in the final step of the DFAs, the similarity in distributions suggests that either measure is unlikely to bias our estimates, as they are distributed similarly. We therefore use the average of the two SCF noncorporate business valuations in the DFAs.

Corporate equities and mutual funds This category includes all public equity, private equity, and mutual fund holdings, except for equity and mutual funds held through DC pensions. The corresponding SCF measure is comprised of directly held stocks and mutual funds, in addition to 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 102%, and is relatively consistent across years.

Other Assets and Liabilities There are other existing differences between the reconciled SCF and Financial Accounts' balance sheets in smaller asset and liability categories. For instance, life insurance reserves are generally unknown by policy holders and thus are unmeasured in the SCF. We assign the B.101.h measures of term policy reserves according to the death benefit recorded in the SCF, and permanent policy reserves by the death benefit and the cash surrender value. Additionally, consumer durables, which are sometimes excluded from household balance sheets (see, e.g., Wolff et al. (2012); Saez and Zucman (2016)) are only 60% as large in the SCF as on B.101.h. This likely occurs because the BEA measure utilized in the construction of B.101.h covers any item that has resale value, whereas the SCF questions encourage respondents to focus only on the most substantial assets.[27] In unshown analyses, we divided the SCF assets into the twenty-eight BEA consumer durable categories and find no evidence that the SCF more severely underreports consumer durable goods that are likely more evenly distributed (such as "window covering" or "sporting equipment") than items that are more likely concentrated among the wealthy (such as "jewelry and watches" or "pleasure aircraft"). Finally, our reconciliation is not always perfect. For example, time deposits and short-term investments are understated in the SCF relative to B.101.h, while checkable deposits and currency holdings are overstated, despite these asset classes aligning conceptually between the two data sets. One partial explanation for this pattern could be misclassification by SCF respondents, while another could be mismeasurement of the B.101.h level, likely due to the residual nature of the construction of these series. Additionally, smaller asset and liability categories, e.g., corporate and foreign bonds (.7% of total assets) and depository institution loans (1.6% of liabilities), neither match well empirically nor is the difference easily explainable. However, given their relatively small contribution to household balance sheets, it is unlikely that these discrepancies will meaningfully affect our findings about the wealth distribution.

A.2 Estimating Covariance Matrices of the Error Process in the Chow-Lin Methodology

This appendix describes in greater detail the estimation process and how the higher-frequency covariance matrix V is identified in Chow and Lin (1971), Fernandez (1981), and Litterman (1983).

The Chow-Lin method solves the multiple regression model specified by Equations 1 and 3 to obtain an estimate of $\hat{X}$ given observations Y and Z and covariance matrix V. Chow and Lin

[27] While the SCF question about consumer durables 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?"

(1971) show that a linear unbiased estimate $\hat{X}$ is given by

$$\hat{X} = Z\hat{\beta} + VB(B'VB)^{-1}[Y - B'Z\hat{\beta}] \tag{17}$$

$$\hat{\beta} = [Z'B(B'VB)^{-1}B'Z]^{-1}Z'B(B'VB)^{-1}Y. \tag{18}$$

Here, $\hat{\beta}$ is a vector obtained from the generalized least squares regression specified in Equation 3 with Y as the dependent variable, $B'Z$ as the dependent variable, and residual covariance matrix $(B'VB)$.

Equation 17 shows that the estimate $\hat{X}$ can be expressed as the sum of two components. The first component, $Z\hat{\beta}$, represents the predicted values of the higher-frequency target series X given the higher-frequency observations of Z, i.e., $\mathbb{E}[X|Z]$. The second component, $VB(B'VB)^{-1}[Y - B'Z\hat{\beta}]$, reflects the estimate of the vector of higher-frequency residuals obtained by distributing the vector of lower-frequency residuals $[Y - B'Z\hat{\beta}]$ across periods where the target series is unobserved. The distributing matrix $VB(B'VB)^{-1}$ is determined by the assumed covariance matrix V. Note that $\hat{X} = Y$ by construction for the periods that Y is observed.

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

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

$$u_t = au_{t-1} + \epsilon_t, \tag{19}$$

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

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

Substituting Equation 19 into Equations 17 and 18 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 19 and Equation 17 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

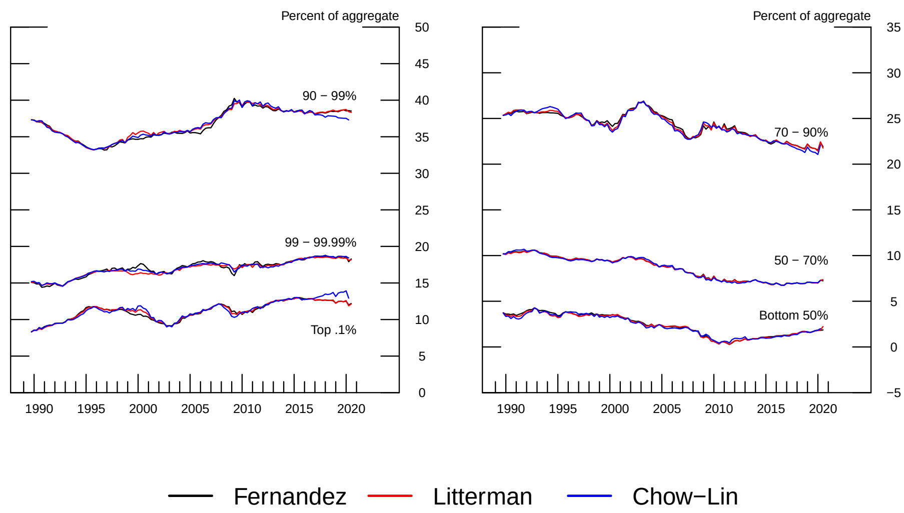
$$u_t = au_{t-1} + v_t$$
$$v_t = \rho v_{t-1} + \eta_t.$$

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 17 and 18 with covariance matrix V given by

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

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 autoregres-

Figure 19: Alternative Error Assumptions



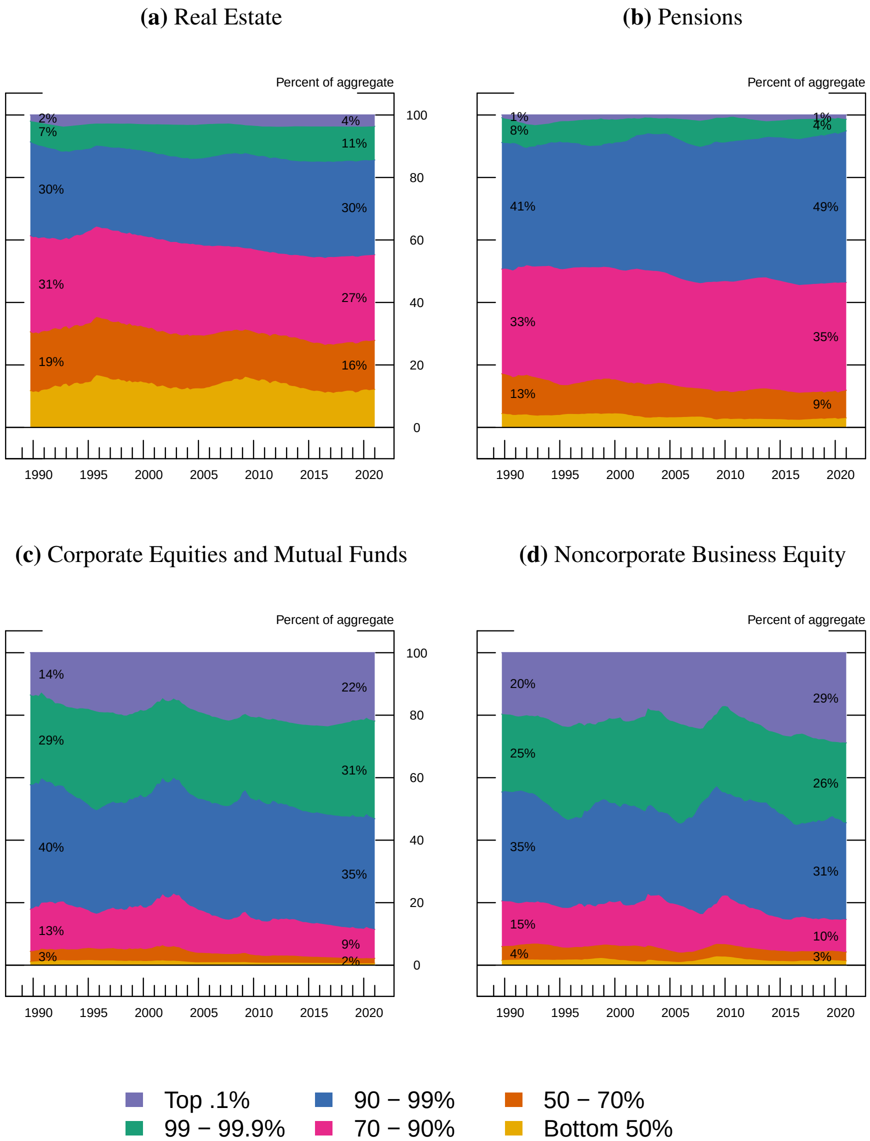
sive parameter ρ may be estimated by an iterative procedure similar to that proposed in Chow-Lin (1971) using Equations 17 and 18 and the first-order autocorrelation of the first difference of the residuals $\left[[Y - B'Z\hat{\beta}\right]$.

A.3 Alternative Error Processes

As noted in Section 2.2, our baseline estimation assumes an AR(1) error process. To explore whether this assumption affects our results, we reconstruct our data allowing for errors to follow a random walk as studied in Fernandez (1981) and Markov switching model as studied Litterman (1983). The resulting data series are presented in Figure 19. Overall, we find little difference between our baseline data series and those allowing richer residual dynamics, suggesting that our results are robust to alternative error assumptions.

A.4 The Data Overview: Zooming in on Major Asset Classes

Figure 20: Major Asset Class Shares



Source: Authors' calculations using Board of Governors of the Federal Reserve System, Distributional Financial Accounts (DFA).

To complete our initial exploration of the data in Section 2.3, Figure 20 zooms in on the evolution of wealth and its distribution for four major asset categories: real estate, pensions, corporate equity, and non-corporate equity.

B Factor Pricing Model with a Full Estimation Sample

In Table 4, we repeat estimation from Table 2 but extend our sample to include the Covid-19 period (i.e., 2020q1-present). The patterns from these regressions are broadly the same, with the exception that the unemployment rate is no longer significant for low wealth households. This reflects the well documented pattern that wealth increased sharply, particularly for low wealth households, in the COVID-19 recession due to very high fiscal transfers.

Table 4: Estimating Drivers of Wealth Gains, by Household. Full Sample (Including COVID-19 Pandemic).

	Dependent Variable: Percent Change in Net Worth of the					
	Top .1% (1)	99-99.9% (2)	90-99% (3)	70-90% (4)	50-70% (5)	0-50% (6)
S&P 500 (%)	0.306^{***}	0.295^{***}	0.230^{***}	0.160^{***}	0.109^{***}	0.177^{***}
	(0.020)	(0.019)	(0.014)	(0.010)	(0.009)	(0.045)
Core Logic House Price Index (%)	0.352^{***}	0.354^{***}	0.349^{***}	0.421^{***}	0.602^{***}	2.344^{***}
	(0.089)	(0.084)	(0.060)	(0.044)	(0.038)	(0.197)
FFR, 1 Quarter Change (pp)	−0.323	−0.297	−0.323	−0.279	−0.240	0.278
	(0.371)	(0.351)	(0.253)	(0.182)	(0.158)	(0.827)
5 Year Forward Rates (%)	−0.483	−0.579	−0.212	0.073	0.404	3.345^{**}
	(0.750)	(0.710)	(0.511)	(0.368)	(0.319)	(1.670)
Unemployment Rate (%)	0.182	0.192	0.110	0.070	0.031	−0.164
	(0.146)	(0.138)	(0.099)	(0.072)	(0.062)	(0.325)
Constant	0.099	0.024	−0.148	−0.176	−0.010	0.494
	(0.227)	(0.215)	(0.155)	(0.111)	(0.097)	(0.505)
Observations	107	107	107	107	107	107
R^2	0.754	0.764	0.798	0.825	0.851	0.682
Adjusted R^2	0.742	0.752	0.789	0.816	0.844	0.666
Residual Std. Error (df = 101)	1.504	1.424	1.026	0.739	0.641	3.351
F Statistic (df = 5; 101)	61.941^{***}	65.214^{***}	80.038^{***}	95.175^{***}	115.603^{***}	43.303^{***}

Note: *p<0.1; **p<0.05; ***p<0.01