Monetary Policy, Asset Prices, and the Distribution of Wealth in the US*

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This version: November, 2022

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Abstract

This paper uses novel quarterly data on the distribution of US household wealth to document several facts about the distributional consequences of conventional and unconventional monetary policy. After showing the large heterogeneity in the composition of household portfolios across the wealth distribution, we use an internal instrument approach in a Bayesian VAR to show that: (i) Interest rate cuts and asset purchases raise the wealth level of all households, in particular at the tails. (ii) Despite the generalized increase in wealth, the average dollar gain is largest at the Top 1%. (iii) The portfolio composition channel explains why monetary policy contributes to wealth accumulation at the top through its effect on capital gains from holding corporate equities and mutual fund shares.

Keywords: Monetary Policy, Wealth Distribution, Household Heterogeneity, Portfolio Composition Channel.

JEL codes: D31, E44, E52

*This paper has benefited from discussions with Franziska Disslbacher, Luca Gambetti, Paolo Santucci de Magistris, Salvatore Morelli, Sarah Zubairy, and seminar participants at the Wealth Inequality and Intergeneration Mobility Conference (WU Vienna), the 63rd Annual Conference of the Italian Economic Association (University of Turin), the 2nd Sailing the Macro Workshop (Ventotene), the XXXIV Italian Society of Public Economics Annual Conference 2022 and the Inequality in Rome Seminars (Roma Tre University). We would like to thank also Morten O. Ravn for helpful comments and suggestions on an early version of this paper. The views expressed are those of the authors and do not necessarily reflect those of the European Central Bank.

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1 Introduction

Since the Global Financial Crisis, unconventional monetary policy tools, such as asset purchases, have become increasingly important in the conduct of monetary policy. These instruments have eased financial conditions and lowered long-term rates (e.g., Swanson, 2021), but they have also drawn harsh criticism from the public regarding the Federal Reserve's role in widening wealth inequality. It is argued that expansionary monetary policy would benefit asset owners because low interest rates and asset purchases boost asset prices and, in turn, generate capital gains. Since assets are unequally distributed among households, expansionary monetary policies could potentially contribute to widening the nation's wealth gap.

In this paper, we explicitly address these criticisms and explore the effects of surprise changes in US conventional and unconventional monetary policy on wealth inequality. To do that, we use a novel quarterly dataset containing estimates of the distribution of US household wealth since 1989, the Distributional Financial Accounts (DFA) of the United States (Batty et al., 2020). Impulse responses are estimated using a Bayesian VAR with the *pure* federal funds rate shock of Jarociński and Karadi (2020), and the large-scale asset purchase shock of Swanson (2021) as internal instruments in the model.

Our results suggest that both federal funds rate and asset purchase shock leads to heterogeneous, U-shaped, effects on wealth levels across the distribution. The impulse responses, however, mask the rightly skewed US wealth distribution in the US. Once converting the responses in equivalent dollar per household changes we find large heterogeneous effects favoring the top tail of the distribution. To put things in perspective, a federal funds rate (asset purchase) shock raises wealth of the average household in the Bottom 50% by 1.27 (2.5) thousands dollars, and in the Top 1% by 168 (341) thousands dollars over a two-year horizon.

Monetary policy shocks lead to temporary changes in wealth shares. The top 1% benefits from the largest increase in the wealth share consistently with the fact that this group records above-average wealth growth after both conventional and unconventional monetary policy shocks. The wealth share of the bottom 50% mildly rises only after the asset purchase shock, while the share of wealth owned by the remaining groups falls regardless of the type of shock. However, neither federal funds rate nor asset purchase shocks have permanent effects.

We then look at the response of a few selected balance sheet components along the wealth distribution. We find that for households in the bottom 50% of the wealth distribution, where dwellings make half of total assets and mortgages are 2/3 of liabilities, the increase in real estates generated by the federal funds rate shock is offset by a similar increase in home mortgages. Our results suggests that the response of corporate equities and mutual funds to monetary policy shocks can be a crucial factor driving the distributional effects of monetary policy. While a monetary policy shock determines a similar percentage increase in this asset class for all groups, the associated dollar change experienced by the average household in the top 1% is significantly higher than that for the average household in the bottom 50%. This is due to the large concentration in the ownership of corporate equities and mutual funds in the top tail.

We frame these results within the portfolio composition channel of monetary policy on wealth inequality with particular reference to real estate and equity markets which are considered of primary importance for the transmission of monetary policy (see Bernanke and Kuttner, 2005; Mishkin, 2007). According to this channel, monetary impulses unevenly affect wealth accumulation across the distribution via heterogeneous capital gains. We document that both monetary policy shocks and particularly asset purchases explain an important share of capital gains from holding corporate equities and mutual fund shares for the top 1%. This finding is coherent with the large concentration of equities in the top tail and the higher sensitivity of these assets to changes in monetary policy.

In the last part of the paper, we document whether the distributional effects of monetary policy changes according to the size of the shock. This is important for at least two reasons. First, given the recent tightening cycle of the Federal Reserve. Second, because of recent contributions documenting the nonlinear macroeconomic effects of monetary policy (e.g., Angrist et al., 2018; Debortoli et al., 2020).

For both conventional and unconventional monetary policy, a tightening lowers wealth at the bottom 50% and at the top 1% by more than a loosening increases it. Interestingly, for these wealth groups, tightening shocks lead to more significant responses than expansionary ones. The findings indicate that both shocks are not largely asymmetric, except for the Next 40%, for which negative shocks are less harmful, and that a quantitative tightening has larger effects in absolute value.

Although our estimates capture the effect of short-term changes in interest rates and asset purchases (hence, they do not reflect the effect of persistent expansionary monetary policy), we are confident of the economic significance of our results. Our shocks are associated to temporary reductions in interest rates and spreads which return to their pre-shock level in about 1 year. This is generally coherent with the available evidence on the length of monetary policy cycles.[1]

Contribution to the literature. Our study contributes to the growing literature exploring the links between monetary policy and inequality. These topics have recently caught the attention of monetary policymakers (Bernanke, 2015; Draghi, 2016; Yellen, 2016; Honohan, 2019; Del Negro et al., 2022). As Schnabel (2021), member of the Executive Board of the European Central Bank, points out in a recent speech: *"Economic and social inequality is one of the biggest challenges facing societies worldwide. [. . .] Central banks are no longer considered bystanders in this discussion."*

On the one hand, the strand of literature analysing the role of monetary policy for income

[1]See for example the following blog posted by the Federal Reserve Bank of St. Louis: A Look at Fed Tightening Episodes since the 1980s: Part I.

and consumption inequality in the US and abroad is at a more advanced stage (e.g., Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017; Amberg et al., 2021; Holm et al., 2021). On the other hand, the comparatively underdeveloped literature on the effects of monetary policy on wealth inequality is primarily associated with data availability. Only recently, giant leaps have been made in characterizing the distribution of U.S. household wealth (e.g., Saez and Zucman, 2016; Kuhn et al., 2020), and in 2019 the Federal Reserve released quarterly estimates of the distribution of household wealth in the US, the DFA (Batty et al., 2020).[2] We chose these data for this paper because their higher relative frequency is well suited to studying the distributional consequences of monetary policy.[3] Within this literature, Albert and Gómez-Fernández (2021) conclude that accommodative monetary policy contributes advantages more households in the tails of the distribution, whereas Feilich (2021) finds that monetary policy tightenings are especially harmful for households in the bottom tail of the distribution. Of this literature, the last paper is the most similar to ours, as we both use the same novel dataset. However, our contribution differs in terms of methodology and scope. First, we consider both conventional and unconventional monetary policy in a VAR framework. Then, to provide evidence on the role of heterogeneous returns, we investigate key balance sheet components.

By showing the presence and relevance of the portfolio composition channel of monetary policy, our study is also related to the various contributions showing the importance of heterogeneous portfolio returns in explaining the dynamics of wealth accumulation (Bach et al., 2020; Benhabib et al., 2019; Hubmer et al., 2021; Xavier, 2021).

Lastly, our paper also speaks to the strand of the literature that places heterogeneous household balance sheets at the center of transmission mechanism of monetary policy (Kaplan et al., 2018; Auclert, 2019; Slacalek et al., 2020). In Heterogeneous Agents New-Keynesian (HANK) models, for example, the heterogeneity of households' portfolios and income sources imply that the real effects of monetary policy shocks are amplified or dampened relative to traditional channels. Therefore, in these models, there are several channels of monetary policy transmission linked with the distribution of income and wealth (see Violante, 2021, and references therein).

Road map. The structure of the paper is organized as follows. Section 2 introduces and describes the DFA. Section 3 outlines the econometric strategy and the monetary policy shocks. Section 4 presents evidence for the portfolio composition channel. Section 6 explores the asymmetric effects of monetary policy across the distribution and Section 7 concludes.

[2] See Kopczuk (2015); Bricker et al. (2016); Saez and Zucman (2020) for a survey of various approaches.

[3] Blanchet et al. (2022) recently published quarterly measures for the distribution of U.S. household wealth without information on wealth components.

2 The Distributional Financial Accounts of the United States

The analysis of the distributional effects of monetary policy is based on the Distributional Financial Accounts of the United States. The DFA combine household-level balance sheets from the Survey of Consumer Finances with the aggregate balance sheet of the household sector from the Financial Accounts to estimate the distribution of household wealth since 1989 (Batty et al., 2020). This section describes the distribution of wealth across the wealth groups considered by the DFA: bottom 50%, next 40% (or 50^{th}-90^{th} percentile), next 9% (or 90^{th}-99^{th} percentile), the top 0.9% (99^{th}-99.9^{th} percentile), and Top 0.1%. However, we narrow our analysis on the distributional effects of monetary policy on four wealth percentile: bottom 50%, next 40% (or 50^{th}-90^{th} percentile), next 9% (or 90^{th}-99^{th} percentile) and top 1%.[4]

2.1 Wealth inequality according to the Distributional Financial Accounts

Wealth is unevenly distributed across households in the US. On average, between 1989 and 2022, households in the bottom 50%, next 40%, next 9%, and top 1% held 2.33, 32.60, 36.75 and 28.22 percent of total wealth, respectively (see last row in Table 1). Figure 1 plots the wealth shares according to the DFA during the same period - wealth is computed as total assets net of liabilities. Overall, the rise in top wealth shares confirms the increasing trend in wealth concentration (Saez and Zucman, 2016; Smith et al., 2022).

Households in the bottom 50% of the distribution saw their share of total wealth halving between 1989 and 2019, and suddenly increasing during the pandemic. This group began to lose ground already in the mid-1990s and the Global Financial Crisis almost wiped out their wealth. After the crisis, it took more than a decade for the wealth share to reach the pre-2007 level. Similarly, the share of wealth owned by households in the next 40% has decreased over time, and the pandemic only exacerbated this trend. The next 9% of the distribution has seen its wealth share increasing between the mid-1990s and the Global Financial Crisis. Since then, the wealth share has been slowly decreasing. In contrast, the wealth share of the top 1% shows a clear upward trend and marked cyclicity; it systematically increases during periods of economic expansions while it falls in contractions. Such a cyclicity characterizes the top 0.9 and 0.1% wealth shares too, in particular for the former which wealth share is extremely more volatile than that of any other group.

Table 1 shows the distribution of assets and liabilities across wealth groups. It reports holdings of assets and liabilities for each group as a share of aggregate holdings from the balance sheet of the household sector. The bulk of non-financial assets (44%) is owned by the next 40%. Most of the financial assets are concentrated on the balance sheets of the top tail, in particular in the hands of households in the next 9%. The bottom 50% holds very few financial assets, mostly concentrated in the form of deposits and currency. The next 40% holds most of deposits, life

[4] The DFA consider also income percentiles, race, education levels, age groups and generations.

TABLE 1: DISTRIBUTION OF ASSETS, LIABILITIES AND WEALTH (1989-2022)

	Bottom 50%	50-90%	90-99%	Top 1%	99-99.9%	Top 0.1%
Assets	6.98	34.29	33.97	24.77	15.15	9.62
Nonfinancial assets	15.27	44.42	27.24	13.07	9.19	3.88
Real estate	13.50	45.04	28.70	12.76	9.52	3.24
Consumer durable goods	22.94	41.97	20.92	14.16	7.63	6.54
Financial assets	2.95	29.40	37.24	30.41	18.04	12.37
Checkable deposits and currency	11.45	37.52	32.34	18.69	12.36	6.34
Time deposits and short-term investments	3.99	37.65	36.46	21.91	14.07	7.84
Money market fund shares	1.37	23.65	41.45	33.52	22.24	11.29
Debt securities	1.09	15.47	31.70	51.72	26.55	25.17
Loans	0.64	10.21	32.77	56.37	31.62	24.75
Corporate equities and mutual fund holdings	1.15	15.28	35.83	47.74	27.94	19.80
Equity in noncorporate business	1.73	16.89	31.87	49.51	26.96	22.55
Pension entitlements	3.40	45.02	43.62	7.96	6.44	1.52
Liabilities	33.48	43.56	18.13	4.85	4.13	0.72
Home mortgages	27.73	47.17	20.58	4.52	4.04	0.47
Consumer credit	53.23	37.09	7.96	1.72	1.37	0.35
Wealth	2.33	32.70	36.75	28.22	17.07	11.16

Notes: The table shows average shares of wealth, assets, liabilities and their components owned or by each wealth group. The table report simple averages between 1989Q3 and 2022Q1. Table A.1 in Appendix provides a more detailed version of the distribution of assets, liabilities, and wealth.

insurance reserves, and pension entitlements. More than a third of money market fund shares, pension entitlements, deposits, and currency are held by households in the next 9%. The very top of the distribution owns the lion's share of debt and equity instruments. Liabilities are also very unequally distributed. While owning only less than seven percent of total assets, the bottom 50% owes a third of total liabilities. The next 40% owes almost half of total liabilities, in particular home mortgages.

2.2 Comparison with alternative estimates of wealth in the US

A widely established source of data on the distribution of household wealth in the US is Saez and Zucman (2016). Differently from the DFA, these series, now regularly published as part of the World Inequality Database (WID, hereafter), recover the wealth distribution using the income capitalization method applied to income tax data. In contrast, the DFA rely on estimates of wealth obtained from triennial waves of the Survey of Consumer Finances, supplemented with wealth estimates from Forbes 400. Trough interpolation between the survey waves, the DFA allocate quarterly aggregate wealth to different wealth groups.

Other differences between the DFA and WID concern *(i)* the treatment of consumer durables and pension entitlements, and *(ii)* the unit of observation. In the DFA, pension entitlements include the balances of defined contribution pension plans, accrued benefits to be paid in the future from defined benefit plans (which component includes total accrued benefits from private-sector, state-and-local government, and federal employment), and annuities sold by life insurers directly to individuals. The WID series, in contrast, excludes unfunded pensions as, it is argued, unfunded pensions entitlements are promises of future transfers that are not backed by actual wealth (Saez and Zucman, 2020). Similarly, durables are treated as non-financial assets in the DFA while they are not in the WID series. As a result, the top wealth shares according to the DFA are lower than those in the WID (Figure 1). Moreover, since the DFA rely on the Survey of Consumer Finances, the units of observation are households instead of individuals.

To highlight the implication of using different wealth concepts, we compare the original wealth shares from the DFA with the WID wealth shares which excludes consumer durables and pension entitlements (Figure 1). The WID wealth shares are retrieved from Blanchet et al.

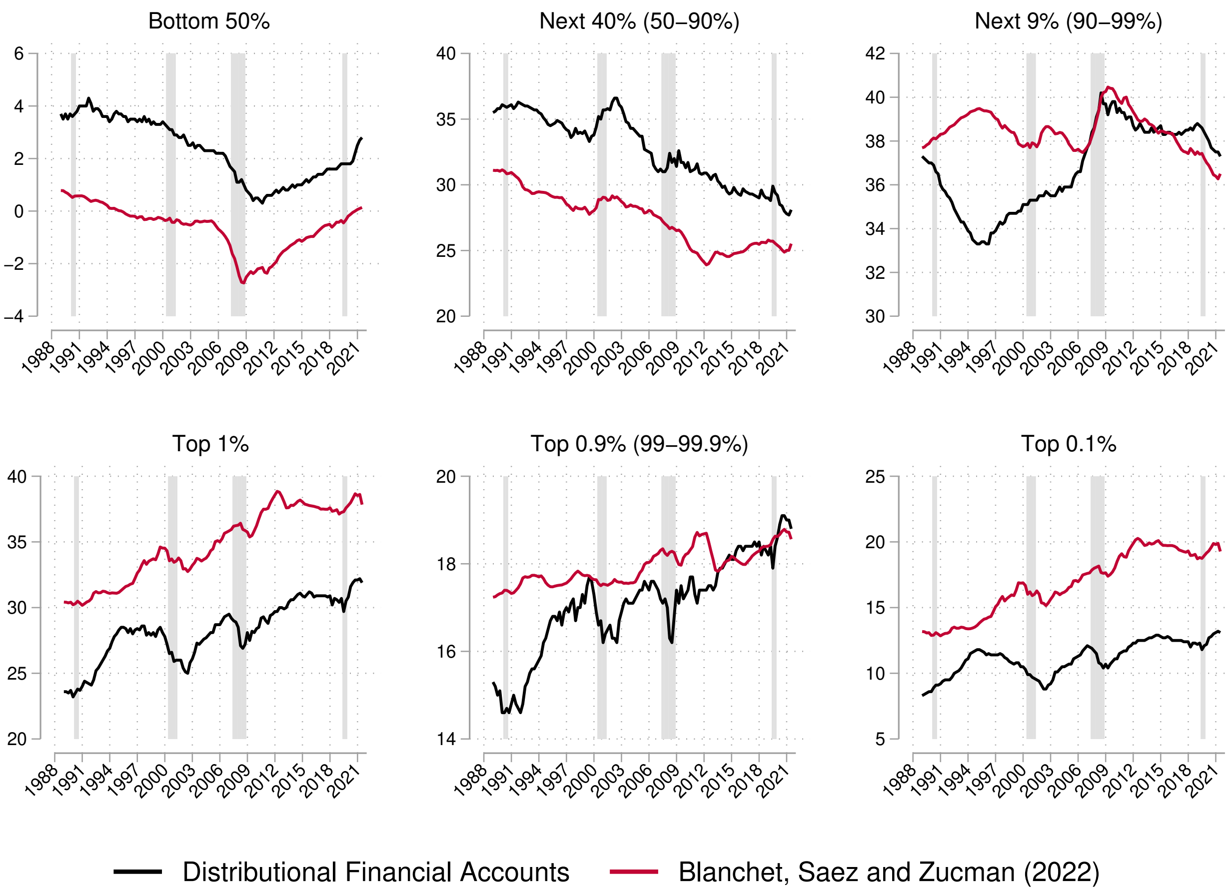


FIGURE 1: NET WORTH SHARES

Notes: This figure compares the evolution of wealth shares for the Bottom 50%, the Next 40%, the Next 9%, and the Top 1% of the wealth distribution. The green solid lines represent wealth shares from the Distributional Financial Accounts. The dashed blue lines represent wealth shares net of consumer durables and pensions from the Distributional Financial Accounts. Lastly, the red lines with markers are taken from Blanchet et al. (2022). The wealth share of the Next 9% of Blanchet et al. (2022) is derived using data for the Top 10% and the Top 1%.

(2022).[5] Excluding consumer durables and unfunded pension entitlements reduces the wealth share of the bottom 50% substantially. In particular, according to the WID series, the wealth of households in this group would have reached negative territory already in the mid-1990s as household debt rose. A further differences between the DFA and WID concepts of wealth arises during the pandemic period. According to the DFA, households in the bottom 50% of the wealth distribution saw their wealth share increasing much more than it is recorded by WID. Overall, excluding both consumer durables and pension entitlements increases the amount of wealth inequality in the US.

2.3 The unequal growth of wealth

In Figure 2, we compare real wealth growth across the wealth distribution. Between 1989 and 2022, real wealth growth has been unequally distributed with households in the top tail benefiting from, on average, higher growth than other groups. Excluding the top 1%, wealth growth converged for all groups until the early 2000s. Since then, wealth growth for the top 1% systematically outperformed that of all other groups. Wealth growth for households in the bottom 50%, in particular, was already stagnating in the early 2000s. Real wealth growth for the next 40% and 9% decoupled only in mid-2000s. For other groups, the effect of the crisis on wealth growth was much less dramatic than for the bottom 50% as households in the next 40% and 9% groups accumulated relatively less mortgage debt during the expansion and undertook a softer deleveraging. The top 1% of the wealth distribution, and the top 0.1% in particular, stands out as the winner of the wealth share race. Relative to 1990, households in the top 1% more than quadrupled their total wealth while those in the bottom 50% saw their wealth doubling. However, the doubling of wealth for the latter groups occurred almost exclusively during the pandemic period. Indeed, at the beginning of 2019, the wealth of the bottom 50% was at the same level of 1990.

2.4 Households' portfolios heterogeneity

The differences in wealth growth highlighted in Figure 2 result from (i) differences in income and saving growth, and from (ii) differences in capital gains and other returns. As pointed out by Kuhn et al. (2020), changes in asset prices influence the dynamics of wealth inequality through two channels. First, if households have heterogeneous portfolios across the wealth distribution, asset price movements induce heterogeneous capital gains. Second, when wealth-to-income ratios are high, the dynamics of the wealth distribution is affected more by asset prices than by saving flows. Asset price changes revalue the stock of existing wealth and induce

[5] These series have been downloaded from Realtime Inequality which provides monthly and quarterly estimates of the distribution of income and wealth in the US (see Blanchet et al. (2022) for a companion paper). The original series, however, are expressed in real terms and the wealth series for the next 9% of the distribution are not reported. To ensure comparability with the DFA series, we use households as the units of observations, obtain nominal wealth using the same deflator used in Blanchet et al. (2022), and calculate the wealth of the next 9%.

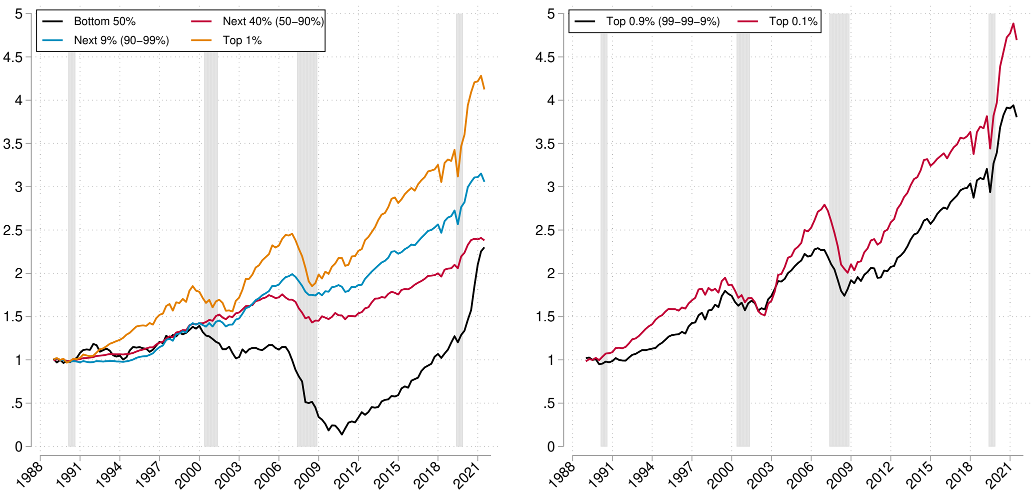


FIGURE 2: REAL WEALTH GROWTH ALONG THE WEALTH DISTRIBUTION SINCE 1990

Notes: This figure shows the evolution of wealth for the six wealth groups of the Distributional Financial Accounts. All time series are indexed to 1 in 1990Q1 and deflated using the CPI

shifts in the wealth distribution beyond changes in savings.

Households' portfolios need to exhibit persistent heterogeneity in their composition for asset prices to influence the distribution of wealth beyond savings. Table 2 suggests substantial portfolio heterogeneity across the wealth distribution. On average, moving upward along the distribution, households hold more financial assets than non-financial assets. Real estates and consumer durables make up half and a fifth of total assets for households in the bottom 50%, respectively. The importance of fixed-income assets (e.g., debt securities and money market fund shares) and equities increases moving upward in the wealth distribution. Corporate equities and mutual funds as well as equity in noncorporate business are among the most unequally distributed assets in the economy (see also Table 1). Pension entitlements, instead, are mostly concentrated on the balance sheets of households in the next 40% and next 9% of the distribution, and they represent almost a third of their assets.

For all wealth groups, home mortgages make up most of the liabilities, followed by consumer credit, except for the top 1%. However, substantial differences persist in the relative composition of liabilities. Home mortgages, for example, are mostly a liability of households in the next 40% of the distribution (Table 1) and represent almost 80% of total liability for this group (Table 2). For households in the bottom 50%, instead, home mortgages represent *only* 60% of total liabilities (the lowest share relative to other groups). Moreover, the bottom 50% is the most leveraged group with a wealth-to-asset ratio of about 28%. In contrast, the top 0.1% is the least leveraged group with a wealth-to-asset ratio of about 99%.

Do portfolios exhibit persistent differences across groups and over time? Figure 3 suggests that this is the case. As in Bauluz et al. (2022), we organized non-financial and financial assets

TABLE 2: PORTFOLIO HETEROGENEITY

	Bottom 50%	50-90%	90-99%	Top 1%	99-99.9%	Top 0.1%
Assets (% of total)						
Nonfinancial assets	71.64	42.31	26.23	17.32	19.83	13.34
Real estate	51.20	34.71	22.33	13.65	16.59	8.99
Consumer durable goods	20.44	7.60	3.89	3.67	3.24	4.35
Financial assets	28.36	57.69	73.77	82.68	80.17	86.66
Checkable deposits and currency	1.80	1.18	1.07	0.85	0.92	0.74
Time deposits and short-term investments	4.24	8.15	8.07	6.65	7.03	6.05
Money market fund shares	0.38	1.34	2.36	2.72	2.90	2.47
Debt securities	0.70	1.95	4.10	9.67	7.79	12.68
Loans	0.08	0.28	0.92	2.17	1.99	2.49
Corporate equities and mutual fund holdings	2.58	7.10	17.14	31.43	29.97	33.74
Equity in noncorporate business	2.49	4.96	9.52	20.36	18.18	23.77
Pension entitlements	10.81	29.32	28.53	7.22	9.54	3.53
Liabilities (% of total)						
Home mortgages	59.36	77.53	81.19	66.63	70.17	48.63
Consumer credit	36.67	19.49	10.12	8.21	7.60	11.11
Wealth-to-Asset ratio	27.91	81.21	92.11	97.08	95.95	98.88

Notes: For each wealth group, the table shows average shares of wealth and type of assets in total assets and type of liabilities in total liabilities. The table report simple averages between 1989Q3 and 2022Q1. Table A.2 in Appendix provides a more detailed version of the heterogeneity in portfolios across the wealth distribution.

in the following asset classes: real estates, consumer durables, fixed income assets, equities and mutual funds holdings, life insurance and pension funds, and miscellaneous assets.[6] The increase in the share of real estates in total assets in the years preceding the Global Financial Crisis is widespread across the distribution but more pronounced for the bottom 50%. For this group, since the crisis, consumer credit slowly gained importance relative to home mortgages on the liability side of the balance sheet (see Figure A.1 in Appendix for the composition of liabilities over time). Moreover, the share of fixed-income assets and equities and mutual funds in total assets at the top of the distribution is strongly cyclical, especially at the very top. This cyclicity in the share of these asset classes mirrors the cyclicity of the top wealth shares shown in Figure 1.

To sum up, households across the wealth distribution have very heterogeneous portfolios. Households in the bottom 50% have very little wealth, hold illiquid assets (up to 70% of assets consists of houses and consumer durable goods), and are the most leveraged. Fixed-income and other liquid assets make up only a small share of their portfolio. The portfolio of the next 40% is more diversified. Real estates and pension entitlements make up the largest share of

[6]In particular, the asset classes are real estates, consumer durables, fixed income assets (checkable deposits and currency, time deposits and short-term investment, money marker funds, US government and municipal securities, corporate and foreign bonds, loans), equities and mutual funds holdings (corporate equities, mutual fund holdings and equity in noncorporate business), life insurance and pension funds (life insurance reserves and pension entitlements) and miscellaneous assets.

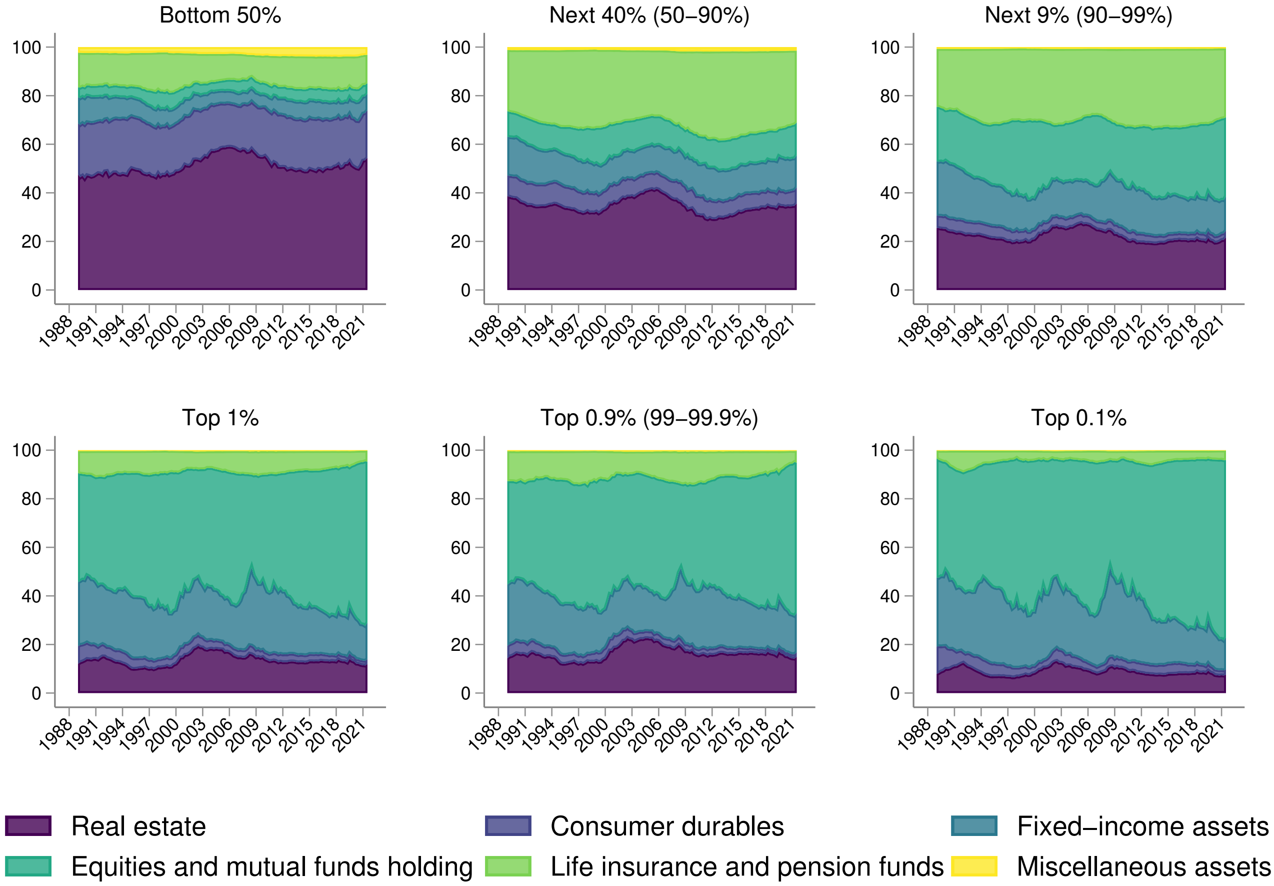


FIGURE 3: PORTFOLIO HETEROGENEITY

Notes: This figure shows the heterogeneity in the asset-side of household portfolios by showing the dynamic composition of major asset classes, as share of total assets, for each wealth group in the Distributional Financial Accounts.

their assets, and they hold significant shares of fixed-income assets. Moving towards the top tail, the share of financial assets increases significantly, with the top 1% holding most of its portfolio in fixed-income assets, equities, and mutual funds. The large heterogeneity among these groups of households - in terms of both leverage and portfolio composition - is a crucial factor that motivates the study of the distributional consequences of monetary policy.

3 Econometric methodology

In this section, we first present the identification strategy for conventional and unconventional monetary policy shocks. Then, we introduce the Bayesian VAR model for estimating the distributional effects of monetary policy.

3.1 Conventional monetary policy

A common approach to the identification of monetary policy shocks consists of measuring high-frequency interest rate changes, such as differences in the three-month fed funds futures, around Federal Open Market Committee (FOMC) announcements. The implicit assumption backing this strategy is that, around these announcements, asset prices respond only to monetary policy shocks. This is a convenient strategy, as focusing on interest rate changes in a narrow window around FOMC announcements plausibly rules out reverse causality and other endogeneity problems. However, a potential drawback of the high-frequency approach is that shocks identified in this fashion generate puzzling effects. Specifically, these shocks produce estimates that go in the opposite direction or that are too small relative to what standard macroeconomic models would predict. Some studies explain the puzzle relying on the *Fed information effect* (Romer and Romer, 2000; Nakamura and Steinsson, 2018). Following this explanation, FOMC announcements convey information about both monetary policy itself and about the central bank's assessment of the economy, causing the private sector to revise its forecasts. According to this explanation, the central bank has superior information than private forecasters. More recently, Bauer and Swanson (2021, 2022) propose an alternative explanation for these puzzling effects, the *Fed response to news* channel. According to this view, new publicly available economic news cause the Fed to change monetary policy and the private sector to revise its forecasts.

Therefore, we find convenient to use the *pure monetary policy shock* of Jarociński and Karadi (2020). These authors decompose monetary policy surprises into *pure monetary shocks* and *information shocks*. They identify *pure monetary policy shocks* when changes in the three-month fed funds rate and in the S&P 500 stock price index co-move negatively around FOMC announcements.[7] Instead, a positive co-movement identifies an *information shock*, potentially happening when the central bank responds more aggressively to publicly available news than markets expected.[8] In line with the new survey to forecasters conducted by Bauer and Swanson (2021), Jarociński and Karadi (2020) find few significant observations for the *information shock*.

Our identification strategy follows Gertler and Karadi (2015) and uses the series of *pure monetary policy shock* as an instrument for the structural monetary policy shock in a proxy-SVAR. We believe that this approach has several advantages over alternatives. First, using a proxy-SVAR, we can retrieve a sequence of monetary policy shocks for a longer period than the original instrument. This allows us to fully exploit the DFA which start in 1989. Second, we can identify the structural monetary policy shock from a monthly proxy-SVAR and then

[7] The three-month future is convenient as it reflects the shift in the expected federal funds rate following the next policy meeting. Hence, this horizon has the advantage of constituting a broad measure of the overall monetary policy stance.

[8] The original explanation given by Jarociński and Karadi (2020) is that the Fed releases a positive assessment about the economy by tightening its policy to prevent the economy to overheat. From an econometric point of view, this explanation is coherent with the *Fed response to news* channel of Bauer and Swanson (2021, 2022). In fact, the macroeconomic effects of monetary policy shocks shown in Figure 4 are consistent with Bauer and Swanson (2022).

aggregate the sequence of monetary policy shocks at quarterly frequency (as in Cloyne et al., 2018).[9] More formally, the monthly proxy-SVAR reads as follows:

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times 1}{\mathbf{c}} + \sum_{j=1}^{p} \underset{n\times n}{\mathbf{B}_j}\, \mathbf{y}_{t-j} + \underset{n\times 1}{\mathbf{u}_t} \tag{1}$$

where $\mathbf{y}_t$ is a $(n \times 1)$ vector of endogenous variables, $\mathbf{c}$ is a $(n \times 1)$ vector of intercepts, $\mathbf{B}_j$ are $(n \times n)$ matrices of parameters with $j = 1, \ldots, p$, $\mathbf{u}_t$ is a $(n \times 1)$ vector of innovations with zero mean and $(n \times n)$ variance-covariance matrix $\mathbf{\Omega}$. The vector $\mathbf{y}_t$ includes, in the following order, the 1-year government bond rate as policy variable, the log of industrial production, the log of the consumer price index and the excess bond premium of Gilchrist and Zakrajšek (2012).[10] The model is estimated from July 1988 to March 2020 with $p = 12$ lags. Under the assumption that the VAR is invertible, we can map the reduced-form innovations u_t to the structural shocks $\boldsymbol{\varepsilon}_t$ as follows:

$$\mathbf{u}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$ is a vector of structural shocks with unit variance and $\boldsymbol{S}$ is a non-singular matrix with the standard covariance restrictions $\mathbf{\Omega} = \boldsymbol{S}\mathbf{\Sigma}\boldsymbol{S}' = \boldsymbol{S}\boldsymbol{S}'$. Then, we denote $\boldsymbol{s}$ to be the column in matrix $\boldsymbol{S}$ that corresponds to the impact of the structural monetary policy shock ε_t^p on each element of the vector of reduced form residuals $\boldsymbol{u}_t$.

Formally, let z_t be a generic instrument, ε_t^p be the monetary policy shock and $\boldsymbol{\varepsilon}_t^q$ be a $(n-1) \times 1$ vector with structural shocks other than the policy shock. In our application, z_t is the *pure monetary policy shock* series of Jarociński and Karadi (2020). To be a valid instrument, z_t must be correlated with the shock of interest ε_t^p but orthogonal to all other shocks $\boldsymbol{\varepsilon}_t^q$, that is:

$$\mathbb{E}[z_t \varepsilon_t^{p'}] \neq 0 \qquad \text{(relevance condition)} \tag{3}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_t^{q'}] = \mathbf{0} \qquad \text{(exogeneity condition)} \tag{4}$$

Let u_t^p the reduced form residual from the equation for the policy indicator (1-year government bond) and let $\boldsymbol{u}_t^q$ be the vector collecting the reduced form residuals from the equations for variables $q \neq p$. Also, let $\boldsymbol{s}^q, s^p \in \boldsymbol{s}$ be, respectively, the response of $\boldsymbol{u}_t^q$ and u_t^p to a unit increase in ε_t^p. After estimating the residuals $\mathbf{u}_t$ of the reduced form VAR in equation 1 using OLS, and provided that conditions 3-4 hold, the estimation of the elements in the vector $\boldsymbol{s}$ proceeds in two steps. First, regress u_t^p on its structural counterpart ε_t^p, replaced by the external instrument z_t, to form the fitted value $\hat{u}_t^p$. Second, given that the variation in $\hat{u}_t^p$ is due only to ε_t^p, the second

[9] The relevance condition of the instrument fails to hold when estimating the proxy-SVAR with quarterly data while it holds using monthly data.

[10] The use of a safe interest rate with a longer maturity than the funds rate provides a better characterization of monetary policy during the ZLB period, i.e., when the Fed's forward guidance became strategically more important (Swanson and Williams, 2014; Hanson and Stein, 2015).

stage regression of $\boldsymbol{u}_t^q$ on the resulting fitted value of $\hat{\boldsymbol{u}}_t^p$ yields a consistent estimate of s^q/s^p:

$$\boldsymbol{u}_t^q = \frac{\boldsymbol{s}^q}{s^p}\hat{u}_t^p + \zeta \tag{5}$$

where $\hat{u}_t^p$ is orthogonal to the error term ζ, given assumption of equation 4. An estimate of s^p can be derived by using the estimated variance-covariance matrix of the reduced form model $\boldsymbol{\Omega} = \mathbb{E}[\boldsymbol{u}_t\boldsymbol{u}_t^{'}] = \mathbb{E}[\boldsymbol{S}\boldsymbol{S}^{'}]$ and equation 5. Finally, we can derive the implied series of structural monetary policy shocks by inverting the structural VAR impact matrix. We aggregate the resulting structural monetary policy shocks over quarters with a simple time sum to obtain a series of shocks at quarterly frequency. Hereafter, we refer to the quarterly conventional monetary policy shock extracted from the proxy-SVAR as the conventional monetary shock, federal funds rate shock, or $\hat{s}_t^{FFR}$.

3.2 Unconventional monetary policy: large asset purchases

To identify surprise changes in unconventional monetary policy, we rely upon the large-scale asset purchase (LSAP, hereafter) factor proposed by Swanson (2021). The author identifies the LSAP factor as one of the (three) principal components with the greatest explanatory power for asset price changes collected during the conventional 30-minute window around each FOMC announcement between July 1991 and June 2019.[11] The LSAP factor can be interpreted as *"the component of FOMC announcements that conveys information about asset purchases above and beyond changes in the federal funds rate itself"* (Swanson, 2021, p. 37). In line with the literature on the effects of quantitative easing in the US, changes in the LSAP factor have small effects on yields at short maturities while having large long-term rates, particularly on the 5 and 10-year Treasury Bond yields (Vissing-Jorgensen and Krishnamurthy, 2011). Notice that we do not find evidence for the relevance of the *"Fed response to news"* channel when focusing on LSAP shocks.[12] Specifically, we get virtually unchanged estimates when adjusting the LSAP factor using the Greenbook forecasts as done by Kim et al. (2020). Hereafter, we refer to the quarterly LSAP factor as the unconventional monetary shock, asset purchase shock, or $\hat{s}_t^{LSAP}$. Both shocks presented in this Section are plotted in Figure A.2.

3.3 Model

The baseline model to estimate the macroeconomic and distributional effects of conventional and unconventional monetary policy shocks is a standard VAR model:

$$\underset{n\times 1}{\mathbf{y}_t} = \underset{n\times 1}{\mathbf{c}} + \sum_{j=1}^{p} \underset{n\times n}{\mathbf{B}_j}\,\mathbf{y}_{t-j} + \underset{n\times 1}{\mathbf{u}_t} \quad \text{with} \quad \mathbf{u}_t \sim \mathcal{N}\left(\underset{n\times 1}{\mathbf{0}}, \underset{n\times n}{\boldsymbol{\Omega}}\right) \tag{6}$$

[11] Asset prices include federal funds futures, Eurodollar futures, several Treasury bond yields, S&P500, and exchange rates. By construction, the LSAP factor is orthogonal to the other two factors which capture changes in the federal funds rate and forward guidance.

[12] The results are not shown and are available upon request.

where $\mathbf{y}_t$ is a $(n \times 1)$ vector of endogenous variables, $\mathbf{c}$ is a $(n \times 1)$ vector of intercepts, $\mathbf{B}_j$ are $(n \times n)$ matrices of parameters with $j = 1, \ldots, p$, $\mathbf{u}_t$ is a $(n \times 1)$ vector of innovations with zero mean and variance-covariance matrix $\mathbf{\Omega}$. Time is indexed by $t = 1, \ldots, T$, each time period is a quarter, and the maximum lag length p is set to 4 as it is standard in VAR models using US macroeconomic time series.

This model may be subject to the "curse of dimensionality" due to the large number of parameters to be estimated relative to the sample length. Hence, we estimate the VAR with Bayesian techniques following the methodology outlined in Giannone et al. (2015). This setting treats the hyperparameters, which determine the prior distribution and describe their informativeness for the model coefficients, as random variables and conduct posterior inference also on them. The motivation for this strategy is twofold. First, the hierarchical approach greatly reduces the importance and numbers of subjective choices in the setting of the prior. Second, with respect to standard flat priors, the hierarchical approach increases the efficiency of impulse responses estimates at the cost of a relatively small bias.

An alternative method to estimate impulse responses is using Local Projections (LP) (Jordà, 2005). In this context, the main advantage of LP is when data are highly persistent (see Montiel Olea and Plagborg-Møller, 2021), which is the case for most wealth data. However, this approach is quite demanding given the short sample at hand, as it requires estimating a distinct regression at each horizon of the impulse response. Moreover, LP estimate responses that are often less precise and sometimes erratic. For these reasons, we also compare impulse responses derived using Smooth Local Projections (SLP), as it allows the same level of flexibility as in LP but brings higher estimation accuracy (see Barnichon and Brownlees, 2019). In Appendix C.2, we compare VAR impulse responses with the ones estimated using LP and SLP. Reassuringly, the responses turn out to be virtually unchanged.

3.3.1 Internal instrument approach

To estimate impulse response functions we use the two shocks as *internal instruments* following Plagborg-Møller and Wolf (2021). In addition to conditions 3 and 4, the *internal instrument* approach requires the instrument, say z_t, to be orthogonal to leads and lags of the structural shocks, say ε_t, that is:

$$\mathbb{E}[z_t \varepsilon_{t+k}] = \mathbf{0}, \quad \text{for } k \neq 0 \tag{7}$$

Under assumptions 3-4 and 7, we can estimate the dynamic causal effects of monetary policy by augmenting the VAR with the instruments presented in previous sections. If the instrument is contaminated with measurement errors or the VAR is non-invertible, the internal instrument (recursive) approach delivers valid estimation of relative impulse responses (see Li et al., 2021 and Plagborg-Møller and Wolf, 2021 for a formal treatment, and Känzig, 2021 for a recent application). Under the internal instrument approach, the vector of endogenous variables can be partitioned as:

$$\mathbf{y}_t = \left[\hat{s}_t^i, \tilde{\mathbf{y}}_t\right]' \tag{8}$$

where $\hat{s}_t^i$ is, alternatively, the conventional ($\hat{s}_t^{FFR}$) and unconventional ($\hat{s}_t^{LSAP}$) monetary policy shock, and $\tilde{\mathbf{y}}_t$ is a vector containing macroeconomic, financial and distributional variables. Intuitively, this allows the variables in the vector $\tilde{\mathbf{y}}_t$ to respond to the instrument $\hat{s}_t^i$ on impact.

4 Results

Before turning our attention to the distributional effects of monetary policy, we asses the effects of monetary policy shocks on the aggregate economy. We use a version of the VAR model in equation 6 in which the vector of endogenous variables $\mathbf{y}_t$ includes, in the following order: the monetary policy instrument, real GDP, the consumer price index, the excess bond premium (Gilchrist and Zakrajšek, 2012), and the policy variable. In the model for conventional (unconventional) monetary policy, the instrument is $\hat{s}_t^{FFR}$ ($\hat{s}_t^{LSAP}$) while the policy variable is the 1-year Treasury yield (term spread). The term spread is the difference between the 10-year Treasury and the 3-month Treasury yield. We refer to this specification as the baseline model and summarize variables, units, and sources in Table 3. The model with conventional monetary policy shocks is estimated using quarterly time series from 1989Q3 to 2019Q4 while the estimation sample for the models with unconventional monetary policy shocks runs from 1991Q3 to 2019Q2. All variables but the monetary policy shocks, interest rates and spreads enter in level of their natural logarithm. Interest rates and spreads enter in percent. Real variables are deflated using the consumer price index and the lag length is 4. Moreover, to compare the results

TABLE 3: MODELS AND VARIABLES DESCRIPTION

Series	Unit	Source
Panel A: *Baseline models*		
Conventional ($\hat{s}_t^R$)/unconventional ($\hat{s}_t^{LSAP}$) shock		Sections 3.1 and 3.2
Real GDP	BoC 2012$	Bureau of Economic Analysis
Consumer price index	2015 = 100	Bureau of Economic Analysis
Excess bond premium	Percent	Gilchrist and Zakrajšek (2012)
Interest rate or spread:		
1-year Treasury Constant Maturity Rate	Percent	McCracken and Ng (2021)
Term spread	Percent	McCracken and Ng (2021)
Panel B: *Models with Distributional Financial Accounts data for each wealth group i*		
Baseline model		
Real estate$_i$	Bil of 2015$	Distributional Financial Accounts
Pension entitlements$_i$	Bil of 2015$	Distributional Financial Accounts
Corporate equities and mutual fund holdings$_i$	Bil of 2015$	Distributional Financial Accounts
Equity in noncorporate business$_i$	Bil of 2015$	Distributional Financial Accounts
Home mortgages$_i$	Bil of 2015$	Distributional Financial Accounts
Net wealth$_i$	Bil of 2015$	Distributional Financial Accounts

across models, in the following sections we report impulse responses normalized to generate a 1% response of real GDP three quarters after the monetary policy shock.

4.1 Macroeconomic effects of monetary policy

In line with several studies on the macroeconomics effects of monetary policy (Ramey, 2016), both federal funds rate and asset purchase shocks raise real GDP and the price level, lower short-term interest rates and compress the term spread (Figure 4). The excess bond premium falls in response to both shocks, suggesting that monetary policy transmits to the economy by easing financial conditions (Gertler and Karadi, 2015). The responses of economic activity and prices to federal funds rate shocks are more persistent relative to the responses to asset purchase shocks. Notably, the hump-shaped response of GDP and the price level to the unconventional monetary policy shock are coherent with the findings in Inoue and Rossi (2021).[13]

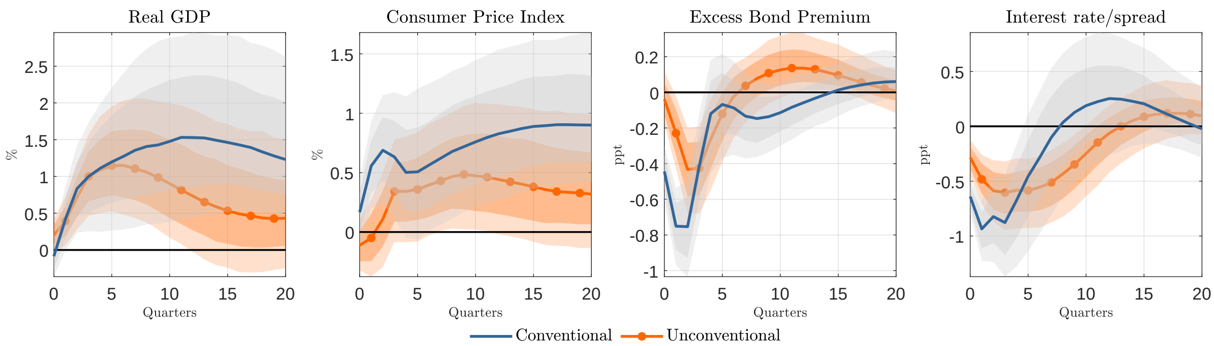


FIGURE 4: *Macroeconomic effects of monetary policy shocks*

Notes: Impulse responses to conventional (blue line) and unconventional (orange line) monetary policy shocks from a Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to induce a 1% response of real GDP. Shaded areas are 68% and 90% posterior coverage bands.

4.2 The distributional effects of monetary policy

We study the distributional effects of monetary policy by augmenting the baseline models with the components of the balance sheet for each wealth group in the DFA. Among the many components of the balance sheet, we choose to narrow our attention to real estate, pension entitlements, corporate equities and mutual funds, home mortgages, and net wealth. All components of the balance sheet are deflated using the consumer price index and enter in level of their natural logarithm.

We choose these components, in addition to net wealth, for a number of reasons. Dwellings are an important, if not the most important, asset class for most of the population, and their relationship with mortgages is an important aspect of the transmission of monetary policy to

[13] As shown in Figure A.2, we observe that the unconventional shock presents some fluctuations prior its implementation. Thus, we set the unconventional shock to zero prior to 2008 and re-estimate impulse responses for macroeconomic variables. Figure C.1 shows that the results are virtually unchanged to this robustness check.

the economy (Mishkin, 2007). Pension entitlements are, on average, the largest category of financial assets on the balance sheet, with the only exception of the top 1%. Corporate equities and mutual funds (which exclude those owned through defined contribution pensions) as well as equity in noncorporate business (which includes non-publicly traded businesses and real estate owned by households for renting out to others) are among the most unequally distributed financial assets (Table 1). Indeed, the top 1% owns almost half of this asset class.

The solid blue line in Figure 5 shows the impulse response functions to a federal funds rate shock. In the left panel, the level of real wealth for the bottom 50% increases by more than 5% at the peak (which occurs about five quarters after the shock), and then returns to its pre-shock level five years after the shock. For the next 40 and the next 9%, real wealth increases persistently over time, by about 2%. The top 1% experiences an increase in real wealth by almost 4% at the peak which occurs immediately after the shock. The effect then decreases over time although less quickly than for the bottom 50%. The orange line with marks, instead, shows the impulse response functions to an asset purchase shock. This shock has a more heterogeneous, U-shaped, effect on wealth across the distribution. The bottom 50% benefits from the largest percentage increase in wealth, followed by the top 1% and the next 9%. Households in the next 40%, in contrast, experience a fall - at the peak, real wealth diminishes by 2%.

The impulse response functions in Figure 5 suggest that the bottom 50% of the distribution gains the most from both types of shocks. The percentage changes, however, mask the strong concentration of wealth in the US. After all, the top 1% holds almost a third of total wealth, on average between 1989 and 2022. To shed light on the role of different wealth levels across the distribution, we convert the responses in equivalent dollar changes and report them in Table 4.

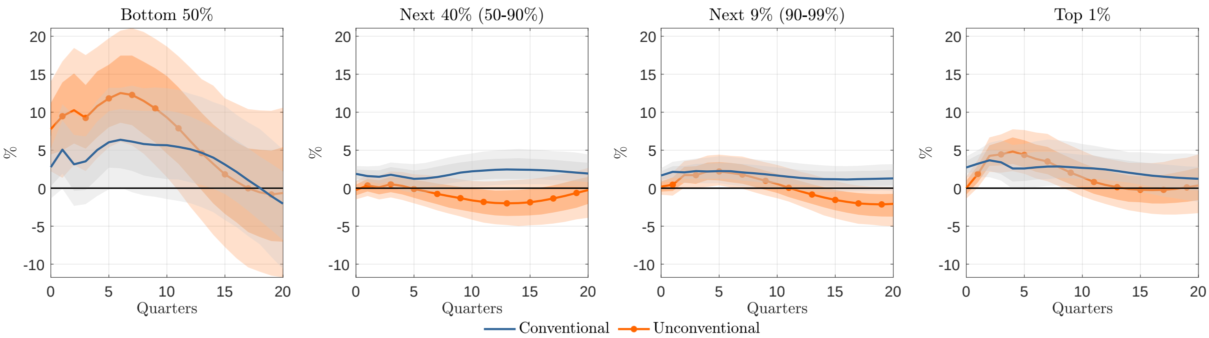


FIGURE 5: *Wealth*

Notes: Impulse responses of real wealth to conventional (blue line) and unconventional (orange line) monetary policy shocks from a Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to induce a 1% response in real GDP. Shaded areas are 68% and 90% posterior coverage bands.

The resulting calculation yields an approximate indication of the effective gain or loss in wealth experienced by households in each group as a result of monetary policy.[14] For the bot-

[14] The approximation derives from the fact that there is a distribution within each group. Whether reporting per household or aggregate values is a trade-off. We opt for reporting per household values, instead of aggregates, to

tom 50%, Table 4 shows that, while benefiting from the largest percentage change, per household wealth increases between 1.27 and 2.51 thousands of dollars in the short-run. The difference with the top 1% is striking; the short-run increase in wealth per household for the top 1$ is between 341 (433,92/1.27) and 168 (418.89/2.51) times larger than that of the bottom 50%. The differences between the bottom and top of the distribution in the dollar change in real wealth fives years after the shock are even larger as the rise in wealth at the bottom quickly dies out.

TABLE 4: *Dollar change in real wealth over short- and long-run (in thousands of 2015$)*

	Bottom 50%	Next 40%	Next 9%	Top 1%
Conventional monetary policy				
2 years after the shock	**1.27**	**7.44**	**43.02**	**433.92**
	[−0.21, 2.88]	[−0.60, 17.41]	[3.94, 83.29]	[56.61, 958.01]
5 years after the shock	**-0.45**	**8.29**	**28.17**	**187.98**
	[−2.32, 1.12]	[0.32, 19.09]	[−7.88, 69.11]	[−273.89, 677.22]
Unconventional monetary policy				
2 years after the shock	**2.51**	**-4.48**	**30.44**	**418.89**
	[0.99, 4.50]	[−14.36, 5.97]	[−11.56, 82.35]	[38.32, 950.34]
5 years after the shock	**-0.14**	**-1.07**	**-45.22**	**55.17**
	[−2.57, 2.32]	[−16.77, 11.47]	[−110.03, 2.93]	[−498.85, 674.69]

Notes: The table shows per capita gain or loss in wealth for each group. Values are expressed in thousands of USD and values in brackets are the corresponding gain or loss for the 90% posterior coverage bands.

Monetary policy shocks lead to differences in wealth growth across the distribution. Figure 5 shows that, in percentage, wealth growth for the bottom 50% and the top 1%, is higher than that of other group and of the response of aggregate wealth (see Figure A.3 in Appendix). When wealth growth for a group increases over the average growth, the share of wealth owned by that group will rise (Kuhn et al., 2020). If monetary policy leads to differential growth of wealth across the distribution, then we would expect it also changes the distribution of wealth within the economy. Figure 6 shows that this is indeed the case.[15] Consistently with enjoying above average percentage change in wealth (Figure A.3) and the largest dollar change (Table 4), the wealth share of the top 1% experiences the largest increase after both a monetary policy shock. The bottom 50% experiences also above average percentage change in wealth, in particular after the asset purchase shock (Figure A.3), but the dollar change is much more limited due to the low ex-ante level of wealth. Hence, the increase in the wealth share of this group observed after the asset purchase shock is small. The next 40 and 9%, instead, experience less-than-average or on-average growth in wealth after both monetary policy shock (Figure A.3) and, as a result, their wealth shares fall or barely move (Figure 6).

emphasize the difference in the size of wealth group. However, we are aware that the existence of a within-group distribution implies that the per household value we report is just an approximation of the gain/loss that household along the within-group distribution effectively experience.

[15]The impulse response functions for Figure 6 are obtained by estimating group-level models as in panel B of Table 3 but with distributional variables in shares rather than in levels.

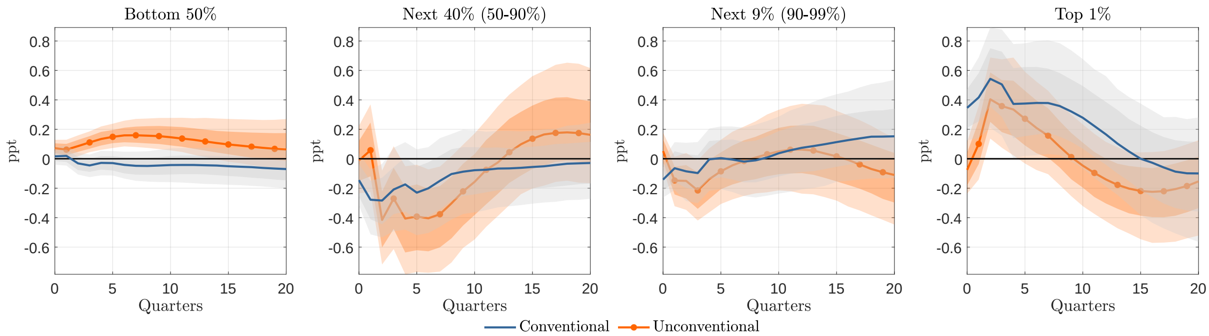


FIGURE 6: *Wealth shares*

Notes: Impulse responses of wealth shares to conventional (blue line) and unconventional (orange line) monetary policy shocks from Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to imply a 1% response of real GDP. Shaded areas are 68% and 90% posterior coverage bands.

As shown by Montiel Olea and Plagborg-Møller (2021), when the data are persistent and the forecast horizons are long, then local projections should perform better in the estimation of impulse responses compared to VARs. Given that wealth tends to change slowly over time, the data generating process implied by the VAR, which lacks of persistence, might not be suited to analysing wealth data. Hence, as a robustness check, in the Appendix we first present formally local projections and its smoothed version by Barnichon and Brownlees (2019), and then the use these alternative models to assess the robustness of our baseline results. Figures C.2 to C.7 present impulse responses that are in line with our baseline VAR estimates.

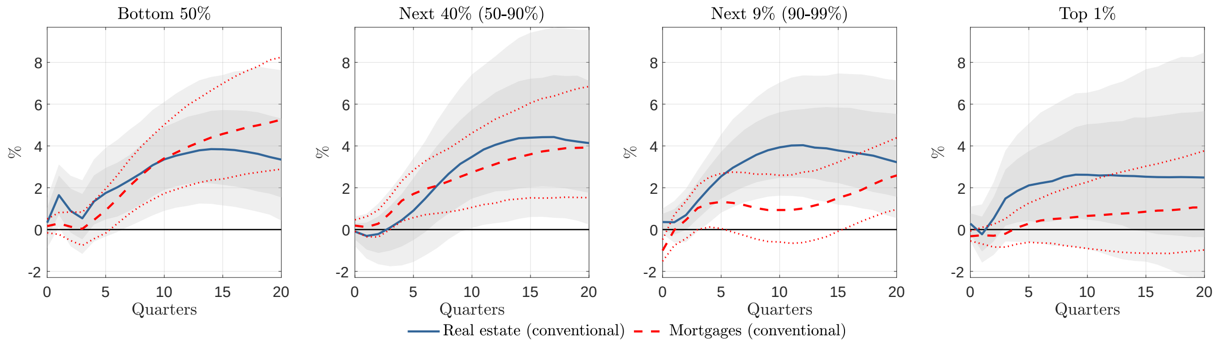
4.3 Beyond net wealth: the effects of monetary policy on balance sheets

We now look at the other elements of the household balance sheet included in each model: housing (real estate and home mortgage), and corporate equities and mutual fund holdings. We report the responses of pension entitlements in Figure B.1 in Appendix.

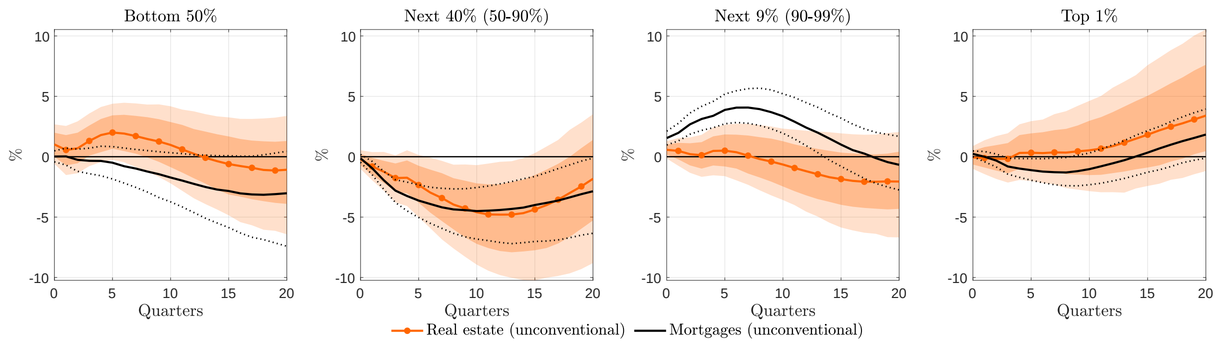
4.3.1 Housing

Housing and its financing through mortgages are critical elements through which monetary policy transmits to the economy (Mishkin, 2007; Cloyne et al., 2020; Amromin et al., 2020). Regardless of distributional considerations, home equity (the difference between the value of housing and the mortgage used to acquire it) has played a crucial role for household spending in the US, in particular during the Great Financial Crisis (Mian et al., 2013). Moreover, the dynamics of house prices, which is another important piece of the transmission of monetary policy, has large effects on home equity as it affects the valuation of real estates but not the value of mortgage. At the same time, real estates are the most important assets for 90% of households according to the DFA while home mortgages are the most important liability. Therefore, it is critical to explore the role of real estates and mortgages in driving the distributional effects of monetary policy.

Figure 7 shows the response of both real estate assets and home mortgages to federal funds rate and asset purchase shocks across the distribution. As with wealth levels, we obtain per household dollar changes but report them in Appendix (Table A.3). At the bottom 50%, where real estates make half of total assets and 2/3 of liabilities, these impulse responses are very informative about what drives the response of wealth in Figure 5. A federal funds rate shock increases both real estates and home mortgages by a very similar percentage. Immediately after the shock, the rise in real estate dominates that of mortgages, and this is mirrored by the positive though not significant increase in wealth. Roughly two years after the shock, the rise in real estates is almost completely offset by the rise in mortgages (see also Table A.3). In contrast, an asset purchase shock raises real estates and lowers mortgages, and this implies a positive net effect on wealth.



(A) *Conventional monetary policy*



(B) *Unconventional monetary policy*

FIGURE 7: *Real estate and home mortages*

Notes: Impulse responses of real estate (owner-occupied real estate including vacant land and mobile homes at market value) and (residential) home mortgages to conventional (Panel A) and unconventional (Panel B) monetary policy shocks from Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to imply a 1% response of real GDP.. Shaded areas are 68% and 90% posterior coverage bands and are not reported for the response of mortgages.

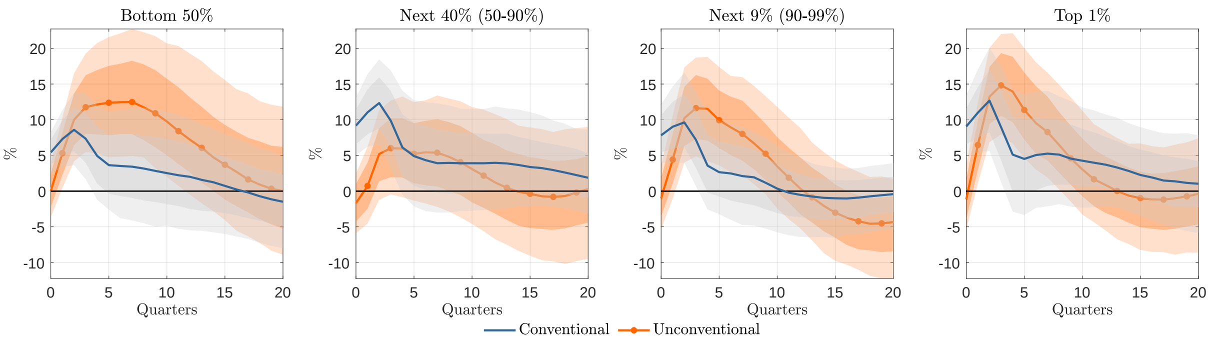
4.3.2 Corporate equities, mutual fund holdings, and equity in noncorporate business

Corporate equities, mutual fund holdings, and equity in noncorporate business are among the most unequally distributed financial assets in the DFA. The returns generated by these assets (being them capital gains or dividends) are among the factors contributing to wealth inequality

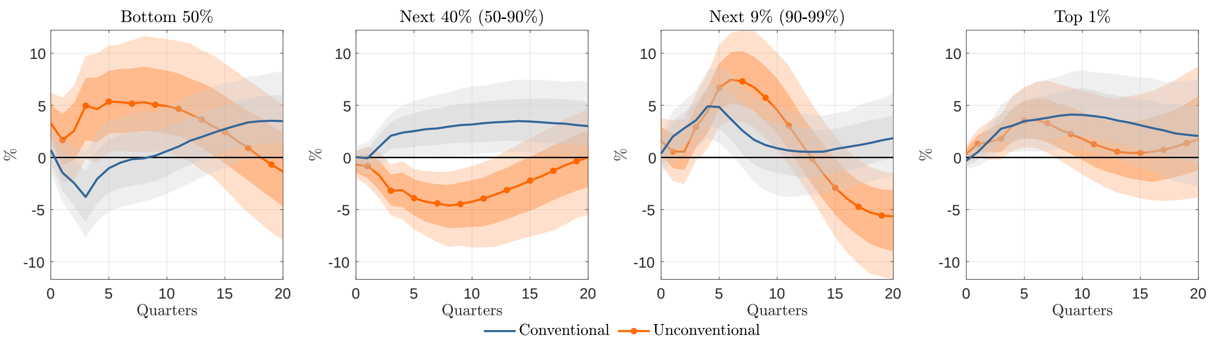
(Hubmer et al., 2021). Moreover, many of these assets are traded in financial markets which reaction to monetary policy is at the center of many theories of transmission mechanism.

Figure 8 shows the response of corporate equities and mutual funds to monetary policy shocks (panel A). A federal funds rate shock has a rather homogeneous percentage increase across the distribution. An asset purchase shock has similar effects with the next 40% experiencing the lowest percentage increase. However, as with wealth, impulse responses mask the strong concentration of these assets in the economy. Therefore, we translate the percentage change from Figure 8 into per household real dollar change (Table A.4 in Appendix). This calculation shows that the concentration of corporate equities and mutual funds is such high that, two years after a conventional monetary policy shock, the per household increase at the top 1% is about 3700 (259.58/0.07 thousands dollars) larger than it is at the bottom 50%.

Finally, it is important to pause on equities in noncorporate business (panel B in Figure 8). This asset class is very heterogeneous (it includes non-publicly traded business assets and real estates other than dwelling) and its valuation is not straightforward. For example, real



(A) *Corporate equities and mutual fund holdings*



(B) *Equities in noncorporate business*

FIGURE 8: *Equities*

Notes: The charts show the response of (Panel A) corporate equities and mutual fund shares (holdings of corporate equities and mutual fund shares excluding equities and mutual fund shares owned through DC pensions) and of (Panel B) proprietors' equity in noncorporate business (Includes non-publicly traded businesses and realestate owned by households for renting out to others) to conventional and unconventional monetary policy shocks from Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to imply a 1% response of real GDP.. Shaded areas are 68% and 90% posterior coverage bands and are not reported for the response of mortgages.

estates other than dwellings such as rental properties are recorded at market value. Instead, the valuation of business assets reported in the DFA is an average between market value and cost basis. Although the choice of the valuation basis has minimal distributional implications according to Batty et al. (2020), the implication for monetary policy of using different evaluation method of business assets (and of the asset class in general) can be dramatic. After all, monetary policy changes the discount rate at which assets are valued, and financial markets where many assets are market-to-market are very sensitive to monetary policy.

5 Portfolio composition and heterogeneous capital gains

In the previous section, it has been shown that monetary policy shocks trigger a generalized increase in wealth levels across the distribution and heterogeneous movements in wealth shares. Changes in wealth shares, in particular, would benefit the top 1%, although temporarily. What are the channels through which interest rate and asset purchase shocks lead to changes in wealth levels and shares? In this section, we explore the role of the portfolio composition channel as a framework to interpret these results.

5.1 The portfolio composition channel

In theory, changes in wealth levels occur as a result of changes in saving and because of realized capital gains (Kuhn et al., 2020; Saez and Zucman, 2016). Shifts in the saving rate affect wealth levels through quantity effects, that is, by changing the volume of wealth. Negative saving, for example, resulting from income falling short of consumption, would negatively affect wealth through a net increase in liabilities. Capital gains, instead, are associated to gains or losses produced by changes in the price of assets on the balance sheet, and influence the level of wealth through valuation effects. For the case of a single household, for example, an increase in house prices raises the value of wealth because housing assets are now worth more, all else equal. When portfolios are heterogeneous as in Figure 3, households are unevenly exposed to fluctuations in asset prices. A household which gross wealth consists predominantly of real estate will be extremely more vulnerable to falling house prices than another household which gross wealth is mostly allocated to corporate equities. The latter household, instead, will be more exposed to boom-and-busts in the stock market. This heterogeneity in the composition of portfolios across households generates heterogeneous capital gains.

To show how differences in the composition of portfolios generate heterogeneous capital gains, let $\left\{A^i_{j,t}\right\}_{j=1}^{J}$ be a portfolio of assets $j = 1, \ldots, J$ owned by households in wealth group i at time t. Formally, the total (dollar) capital gain/loss between t and $t+1$ resulting from holding the portfolio $\left\{A^i_{j,t}\right\}_{j=1}^{J}$ is the sum of capital gains/losses recorded by each asset j:

$$\Pi^i_t = \left(\frac{p_{1,t+1}}{p_{1,t}} - 1\right) A^i_{1,t} + \cdots + \left(\frac{p_{J,t+1}}{p_{J,t}} - 1\right) A^i_{J,t} = \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1\right) A^i_{j,t} \tag{9}$$

where $p_{j,t}$ is a price index for asset j in period t, under the assumption that different wealth groups face the same asset price index (Kuhn et al., 2020; Lenza and Slacalek, 2021). We can normalize capital gains by group i's level of total assets A_t^i and compute total capital gains as share of assets:[16]

$$\frac{\Pi_t^i}{A_t^i} = \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) \frac{A_{j,t}^i}{A_t^i} \tag{10}$$

where $A_{j,t}^i / A_t^i$ is the share of asset j for group i in period t in total assets. Equation 10 - which we denote as total capital gains as share of assets - shows that portfolio differences captured by the term $A_{j,t}^i / A_t^i$ lead to differential capital gains for a given asset price change. Therefore, differences in capital gains, determined by portfolio heterogeneity, will drive differences in wealth growth.

According to the portfolio composition channel, monetary impulses, by triggering changes in asset prices, would unevenly affect wealth accumulation across the distribution via heterogeneous capital gains. If a federal funds rate cut boosts the stock market, then households holding corporate equities would see their wealth increasing because of capital gains. As the ownership of corporate equities is concentrated at the top of the wealth distribution, we would expect the level of wealth at the top to increase by more than it increases for other groups (which hold fewer stocks), all else equal. For the portfolio composition channel to be operative and to explain (part of) the heterogeneous changes in wealth levels and shares in reaction to monetary policy shocks, it is necessary to test two predictions of this channel. First, for a given asset, the response of capital gains generated by holding that asset to monetary policy shocks needs to be heterogeneous across the wealth distribution. Second, monetary policy shocks need to be quantitatively important for explaining the variability observed in capital gains.

5.2 Measuring capital gains

To test the predictions of the portfolio composition channel we estimate the response of capital gains from asset prices across the wealth distribution. We restrict our analysis to two asset classes: (i) real estates and (ii) corporate equities and fund shares. The reason for narrowing our attention only to these assets is twofold. First, there is a clear pattern showing that real estates (corporate equities and fund shares) become the *least* (*most*) quantitatively important asset class as we climb the wealth distribution (see Table 2). Second, current debates on the distributional effects of low interest rates and asset purchase programs center on the inflationary effects these policies have on house and equity prices. Third, finding the correct index to price each asset in

[16] This equation is a slightly modified version of that appearing in Kuhn et al. (2020, equation 1). In there, the authors consider a law of motion of wealth of household i from Saez and Zucman (2016) such as: $W_t^i = W_t^i(1 + r_t^i + q_t^i + \sigma_t^i)$ in which r_t^i are returns on wealth other than capital gains (such as dividends) and σ_t^i is the contribution of savings to wealth growth. The term $q_t^i = \left[\Pi_t^i / W_{t-1}^i = \sum_{j=1}^{J} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) A_{j,t}^i / W_t^i \right]$ is defined as the growth rate of household wealth from capital gains. We substitute wealth at with assets to make sure that fluctuations in the ratios reflects the response of capital gains to monetary policy shocks. Moreover, we are concerned by the denominator effect of using wealth when the value of wealth approaches zero, as it is the case for the bottom 50%.

the DFA is not straightforward.[17]

The starting point for testing the predictions of the portfolio composition channel is measuring capital gains. According to equation 9, the missing ingredient to compute capital gains from holding asset j, $\Pi_{j,t}$, is a price index for asset j. For example, a national home price index could be used to price real estates in the DFA. However, different wealth groups hold dwellings of different quality, in different parts of the country, and with different characteristics. Similarly, it is not straightforward to find a price index for corporate equities and mutual funds without knowing the component of this asset class. Therefore, we take a different rout in computing capital gains from that in Kuhn et al. (2020). In the National Accounts, the change in the aggregate level (or stock) of asset j across periods can be decomposed as follows:

$$\underbrace{A_{j,t} - A_{j,t-1}}_{\text{Economic flow}} = \underbrace{F_{j,t}}_{\text{Transactions}} + \underbrace{R_{j,t}}_{\text{Revaluations}} + \underbrace{O_{j,t}}_{\substack{\text{Other changes} \\ \text{in volume}}} \tag{11}$$

where the economic flow is the change in the level across periods, transactions measure the exchange of assets, revaluations (readable in the Revaluation Account) measure holding gains and losses (capital gains), and other changes in volume measure every other variation such as changes in source data. Then, to compute capital gains from holding asset j for each wealth group, we distribute the aggregate revaluation $R_{j,t}$ using as weights the share of each group holding of asset j on the aggregate:

$$\begin{aligned} R_{j,t} &= \left(\frac{A_{j,t}^{\text{Bottom50}}}{A_{j,t}}\right) R_{j,t} + \left(\frac{A_{j,t}^{\text{Next40}}}{A_{j,t}}\right) R_{j,t} + \left(\frac{A_{j,t}^{\text{Next9}}}{A_{j,t}}\right) R_{j,t} + \left(\frac{A_{j,t}^{\text{Top1}}}{A_{j,t}}\right) R_{j,t} \\ &= \tilde{\Pi}_{j,t}^{\text{Bottom50}} + \tilde{\Pi}_{j,t}^{\text{Next40}} + \tilde{\Pi}_{j,t}^{\text{Next9}} + \tilde{\Pi}_{j,t}^{\text{Top1}} \end{aligned} \tag{12}$$

where $\tilde{\Pi}_{j,t}^{i}$ is nominal capital gains from holding asset j for group i based on the Revaluation Account. It is instructing, however, to compare these measures of capital gains against the alternative of using equation 9. To this end, for each asset j (real estate and corporate equities and mutual funds), we compute total price-based capital gains as share of total assets:

$$\frac{\Pi_{j,t}}{A_t} = \left(\frac{p_{j,t+1}}{p_{j,t}} - 1\right) \left(\frac{A_{j,t}^{\text{Bottom50}} + A_{j,t}^{\text{Next40}} + A_{j,t}^{\text{Next9}} + A_{j,t}^{\text{Top1}}}{A_t}\right) \tag{13}$$

and total capital gains based on the Revaluation Account as share of total assets:

$$\frac{\tilde{\Pi}_{j,t}}{A_t} = \tilde{\Pi}_{j,t}^{\text{Bottom50}} + \tilde{\Pi}_{j,t}^{\text{Next40}} + \tilde{\Pi}_{j,t}^{\text{Next9}} + \tilde{\Pi}_{j,t}^{\text{Top1}} \tag{14}$$

and report them in Figure 9. As we can see, the two measures track each other pretty well

[17] One attempt to overcome this issue is in Feilich (2021) who builds a composite price index that reflects the heterogeneity in portfolio compositions across wealth groups in the DFA. However, this rests on quite strong assumptions on price indexes. For instance, many asset prices are normalized to 1 or that both corporate and noncorporate equities can be priced with the same index.

apart from some periods when price-based capital gains exhibit smoother fluctuations. In the following, we use capital gains computed on the basis of the Revaluation Account.

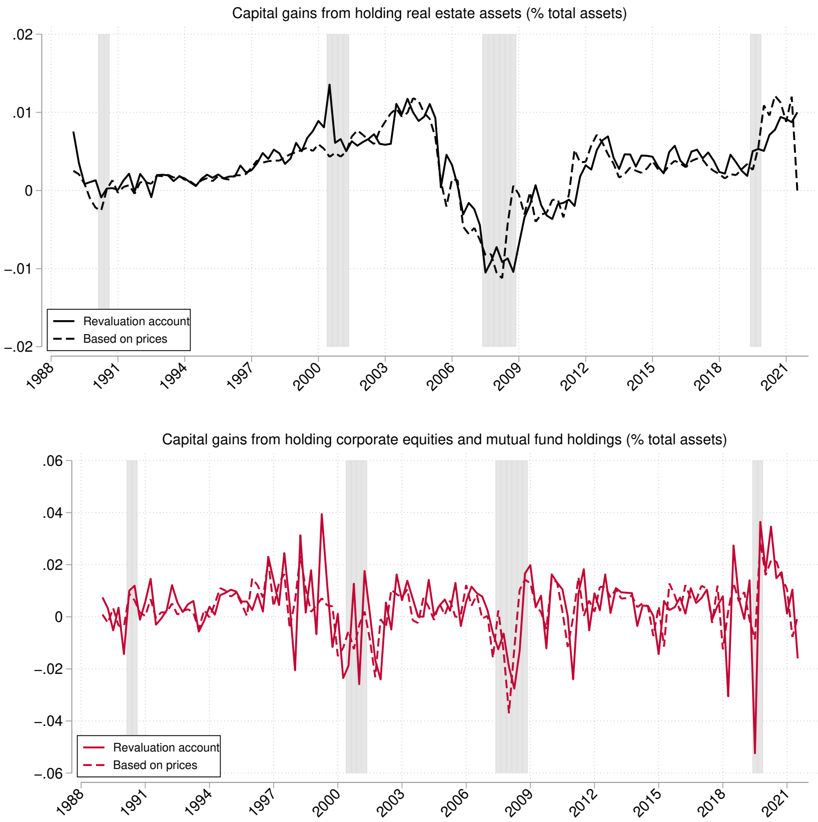


FIGURE 9: *Comparing different measure of total capital gains*

Notes: The figure compares two measures of capital gains from holding real estate assets (panel above) and capital gains from holding corporate equities and mutual fund holdings (panel below). For computing capital gains from holding real estate based on the Revaluation Account we use the Households and Nonprofit Organizations; Real Estate at Market Value, Revaluation (FR155035005) series from the R.101 Change in Net Worth of Households and Nonprofit Organizations Table of the Z.1 Financial Accounts of the United States. For computing capital gains from holding corporate equities and mutual fund holdings based on the Revaluation Account we combine the Households and Nonprofit Organizations; Corporate Equities; Asset, Revaluation (FR153064105) and the Households and Nonprofit Organizations; Mutual Fund Shares; Asset, Revaluation (FR153064205) series from the same table. For computing price-based capital gains we use the Case-Shiller House Price Index as the relevant index for real estates and the S&P500 as the relevant index for corporate equities and mutual funds.

5.3 What is the role of portfolio heterogeneity?

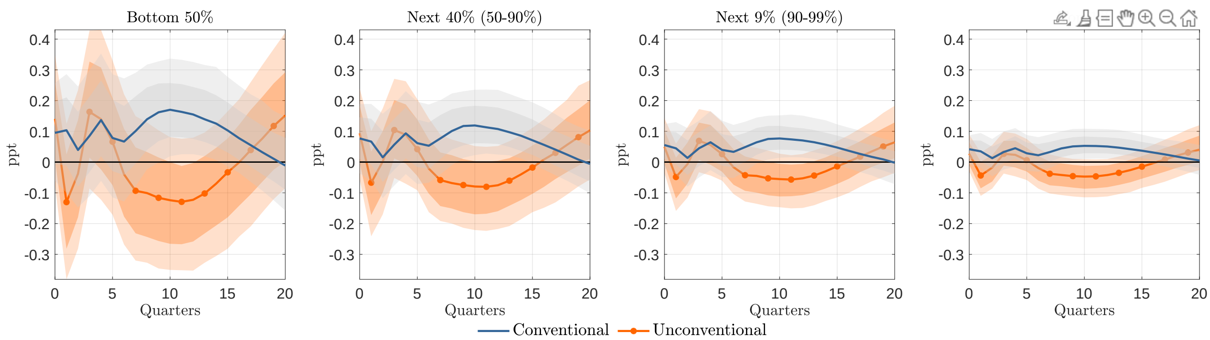
To test the first prediction of the portfolio composition channel, we estimate the effect of monetary policy shocks on capital gains from asset j for group i expressed as share of lagged total assets, that is: $\tilde{q}^i_{j,t} = \tilde{\Pi}^i_{j,t}/A^i_{t-1}$. The responses to conventional and unconventional monetary policy shocks are reported in Figure 10.[18]

[18] For each wealth group i, we recover the impulse response functions from a VAR consisting of the following variables: conventional/unconventional policy shock, real GDP, consumer price index, excess bond premium, interest rate/spread, the S&P500 index, the Case-Shiller House Price Index, $q_{CE,t}$, $q_{RE,t}$ (we suppress the wealth group indicator i for clarity). The term $q_{CE,t}$ measures capital gains from holding corporate equities and mutual fund shares as share of lagged assets while $q_{RE,t}$ is capital gains from holding real estates as share of lagged assets. The

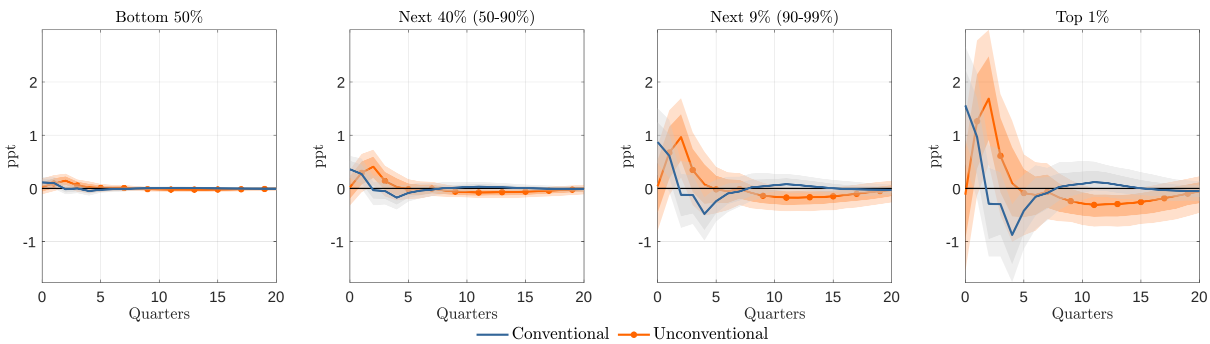
The response of capital gains from holding real estates is larger at the bottom of the distribution, in terms of total assets, than at the top, regardless of the nature of monetary policy (panel A). A federal funds rate shock leads to a hump-shaped increase in capital gains from holding real estates which becomes significant only around two years after the shock. The effect, however, is small. For the bottom 50%, which real estates make up half of total assets and gains from real estates averages at 1.61%, the 0.1pp impact increase yield a gain of 140 nominal dollar per household.

The responses of capital gains from holding corporate equities and mutual funds to federal funds rate and asset purchase shocks become larger as we move toward the top of the distribution (panel B). The top 1%, which holdings of corporate equities and mutual fund shares amount to almost 48% of total assets, benefits from the largest impact increase in capital gains in response both shocks. For this group, capital gains from holding corporate equities and mutual funds averages at 2.95% of total assets. The peak effect from an asset purchase shock would bring capital gains to 4.64% of total asset which translates in an increase in capital gains

specification and estimation of these models is unchanged from all other models estimated throughout the paper.



(A) *Response of capital gains from holding real estates*



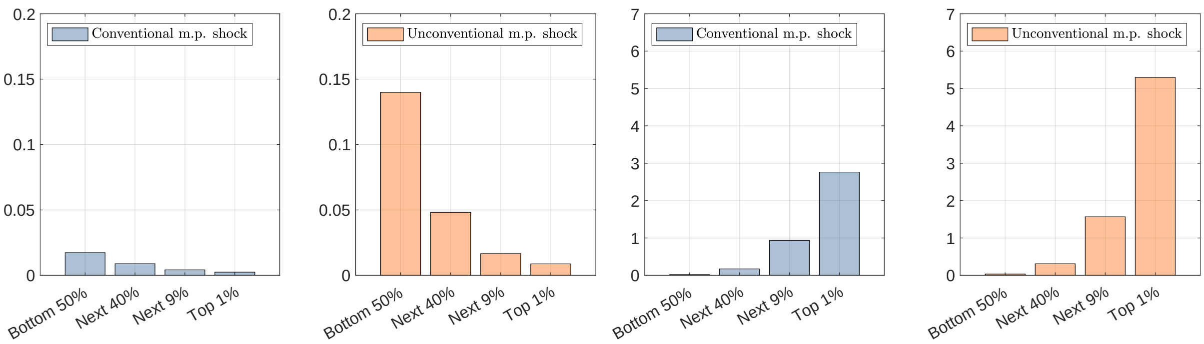
(B) *Response of capital gains from holding corporate equities and mutual fund holdings*

FIGURE 10: *Response of capital gains from asset prices to monetary policy shocks*

Notes: Impulse responses of capital gains from holding real estates (A) and corporate equities and mutual fund holdings (B). In each panel, the blue solid line is the response to a conventional monetary policy shock while the orange dotted line is the response to an unconventional monetary policy shock. The impulse responses for each wealth group are retrieved from a baseline VAR model augmented with capital gains, house and stock prices. Impulse responses are scaled to imply a 1% response of real GDP. Shaded areas are 68% and 90% posterior coverage bands.

by about 74,000 nominal dollars per household. On the contrary, the bottom 50% and the next 40%, which holdings of corporate equities and mutual fund shares amount to 2.5% and 7% of total assets, respectively, record an extremely small increase in capital gains from holding this asset class. These heterogeneous responses of capital gains are consistent with the first prediction of the portfolio composition channel.

Having tested the first prediction that monetary policy shocks have heterogeneous effects on capital gains depending on the exposure of each wealth groups to asset price changes, we now explore the quantitative importance of monetary policy shocks for the variability observed in capital gains. To this end, we compute the forecast error variance decomposition (FEVD) of capital gains from the same VAR models from which we estimated the impulse response functions above and report the results in Figure 11. We narrow our attention on the FEVD 1 quarter after the shock which we interpret at the short-term contribution of monetary policy to fluctuations in capital gains. A very little share of the variability in capital gains from holding real estates can be explained by monetary policy shocks. In contrast, monetary policy shocks explain a non-negligible share of variance of capital gains from holding corporate equities and mutual funds. For the top 1%, in particular, between about 3% and 5% of variance of capital gains can be explained by monetary policy. These findings suggest that households at the top of the distribution hold equities (and other risky assets) which are more exposed to monetary policy shocks.



(A) *Real estate* (B) *Corporate equities and mutual funds*

FIGURE 11: *FEVD of capital gains from holding different assets*

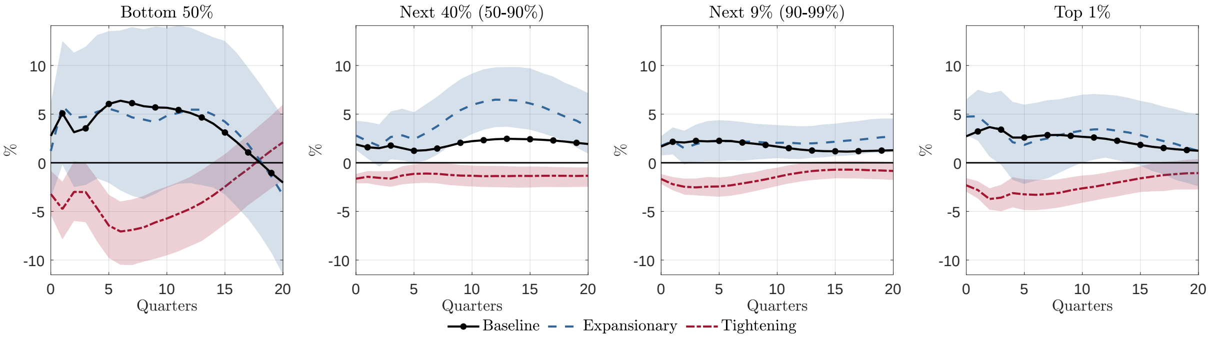
Notes: Forecast error variance decomposition (FEVD) of capital gains from holding real estates (A) and corporate equities and mutual fund holdings (B). In each panel, the blue bar is the share of variance explained by the conventional monetary policy shock while the bar is the share of variance explained by the unconventional monetary policy shock. The FEVD for each wealth group are retrieved from a baseline VAR model augmented with capital gains, house and stock prices.

Monetary policy shocks trigger a generalized increase in wealth levels across the distribution and heterogeneous movements in wealth shares. In this section we argued that the portfolio composition channel can be used to rationalize these results. Monetary policy shocks, through their effect on asset prices, lead to heterogeneous capital gains which, in turn, drive differences in wealth growth across the distribution, all else equal. These findings are coherent the patterns on heterogeneous returns across the wealth distribution found by other studies (Fagereng et al., 2020; Bach et al., 2020; Bricker et al., 2022).

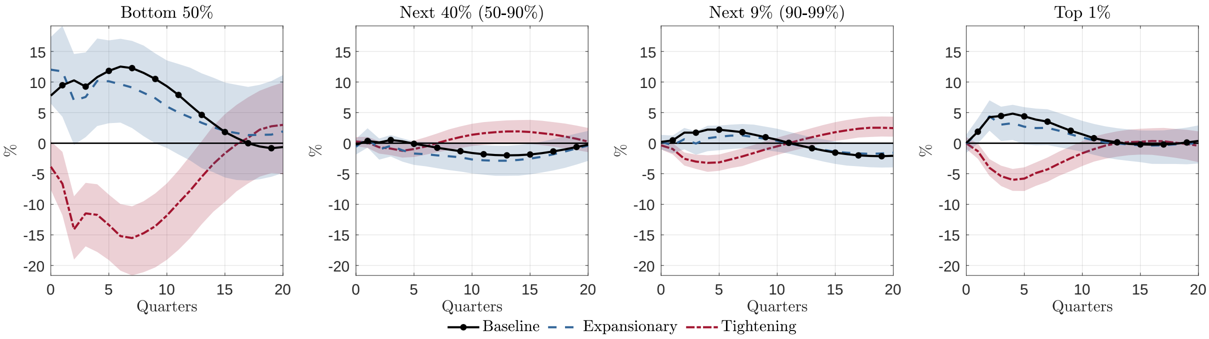
6 Asymmetric effect of monetary policy

Following a period of ultra-expansionary monetary policy, the Federal Reserve is now hiking interest rates and reducing the size of its balance sheet (quantitative tightening) to deal with the new inflationary environment. While expansionary policies contributed to the economic recovery and provided a lift for the stock market, a tightening on both conventional and unconventional monetary policies should have the opposite effect if shocks were symmetric. However, recent contributions suggest that these policy stances have unequal effects on the macroeconomy (Angrist et al., 2018; Debortoli et al., 2020). Motivated by this evidence, in this section we study the potential asymmetric effects of monetary policy shocks on household wealth levels across the distribution. To study whether there are asymmetries in the effects of contractionary and expansionary monetary policy shocks on the wealth distribution, we divide our monetary policy shock into positive (loosening) and negative (tightening) parts.

Figure 12 plots the effects of expansionary and contractionary monetary policy for a federal funds rate shock (Panel A) and an asset purchase shock (Panel B). Solid-dotted black lines represent the point estimates for impulse responses of the baseline (symmetric) model. Expansionary shocks are presented as blue dashed lines and contractionary shocks as red dash-dotted lines. Starting from a federal funds rate shock, we notice that the effects of monetary policy on wealth are largely symmetric, except for a few cases. First, while a positive shock increases by 6% in the third year the wealth of the next 40% a negative shock has a smaller and more stable effect around roughly 1%. Second, for the next 9% only a positive shock seems to have a persistent effect on the wealth in the group. Lastly, a negative shock has a much smaller impact effect on the wealth of the top 1% than a positive shock, although they become more symmetric over the response function. Moving on, we notice that an asset purchase shock has more asymmetric effects compared to its conventional counterpart, with a negative shock having larger effects in absolute value than a positive shock. This is true for all wealth groups, with the exception of the next 40%. Households in this group experience a decrease in wealth between the first and second year, albeit not statistically significant, following both a positive and negative shock, with an inversion of effect for the latter. Overall, the evidence brought forward by Figure 12 suggests that shocks are not largely asymmetric, except for the next 40%, and that a negative asset purchase shock has larger effects than a positive shock.



(A) *Conventional monetary policy*



(B) *Unconventional monetary policy*

FIGURE 12: *Asymmetric effects of monetary policy on wealth*

Notes: Asymmetric impulse responses of real wealth to monetary policy shocks from a Bayesian VAR. A federal funds rate shock is presented in (A) and an asset purchase shock in (B). Solid-dotted black lines report the response in the baseline model without asymmetries, blue dashed lines the response to an expansionary shock and red dash-dotted lines to a contractionary shock. Point estimates of impulse responses are the median from the posterior distribution, and are scaled to induce a 1% response of real GDP. Shaded areas are 68% posterior coverage bands.

7 Conclusions

In times of high income and wealth inequality, the expansionary stance of the Federal Reserve since the Global Financial Crisis has raised concerns about the distributional consequences of expansionary conventional and unconventional monetary policy.

Using the Distributional Financial Accounts of the United States, we have shown that monetary policy has heterogeneous effects on household balance sheets across the wealth distribution. Wealth levels increase across the distribution, with the largest percentage changes recorded at the tails. However, these effects mask the strong concentration of wealth at the top, which makes the wealthiest households benefit the most. Monetary policy shocks lead to temporary changes in wealth shares that benefit households in the top 1%. As expected, temporary changes in monetary policy do not have permanent effects on wealth shares. We have shown that these results are explained by the portfolio composition channel of monetary policy.

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A Appendix

A Additional charts and tables

TABLE A.1: DISTRIBUTION OF ASSETS, LIABILITIES AND WEALTH (1989-2022)

	Bottom 50%	50-90%	90-99%	Top 1%	99-99.9%	Top 0.1%
Assets	6.98	34.29	33.97	24.77	15.15	9.62
Nonfinancial assets	15.27	44.42	27.24	13.07	9.19	3.88
Real estate	13.50	45.04	28.70	12.76	9.52	3.24
Consumer durable goods	22.94	41.97	20.92	14.16	7.63	6.54
Financial assets	2.95	29.40	37.24	30.41	18.04	12.37
Checkable deposits and currency	11.45	37.52	32.34	18.69	12.36	6.34
Time deposits and short-term investments	3.99	37.65	36.46	21.91	14.07	7.84
Money market fund shares	1.37	23.65	41.45	33.52	22.24	11.29
US government and municipal securities	1.16	15.00	31.40	52.43	27.59	52.43
Corporate and foreign bonds	0.82	15.63	30.92	52.63	24.22	28.41
Loans	0.64	10.21	32.77	56.37	31.62	24.75
Corporate equities and mutual fund holdings	1.15	15.28	35.83	47.74	27.94	19.80
Equity in noncorporate business	1.73	16.89	31.87	49.51	26.96	22.55
Life insurance reserves	9.80	42.08	28.74	19.39	13.56	5.83
Pension entitlements	3.40	45.02	43.62	7.96	6.44	1.52
Miscellaneous assets	20.08	47.62	23.37	8.93	6.61	2.31
Liabilities	33.48	43.56	18.13	4.85	4.13	0.72
Home mortgages	27.73	47.17	20.58	4.52	4.04	0.47
Consumer credit	53.23	37.09	7.96	1.72	1.37	0.35
Deposit institution loans n.e.c.	29.90	29.52	16.01	24.57	15.81	8.76
Other loans and advances	22.69	21.63	31.30	24.38	18.76	5.62
Deferred and unpaid life insurance premiums	10.33	42.76	29.19	17.72	14.03	3.69
Wealth	2.33	32.70	36.75	28.22	17.07	11.16

Notes: The table shows average shares of wealth, assets, liabilities and their components owned or by each wealth group. The table report simple averages between 1989Q3 and 2022Q1.

TABLE A.2: PORTFOLIO HETEROGENEITY

	Bottom 50%	50-90%	90-99%	Top 1%	99-99.9%	Top 0.1%
Assets (% of total)						
Nonfinancial assets	71.64	42.31	26.23	17.32	19.83	13.34
Real estate	51.20	34.71	22.33	13.65	16.59	8.99
Consumer durable goods	20.44	7.60	3.89	3.67	3.24	4.35
Financial assets	28.36	57.69	73.77	82.68	80.17	86.66
Checkable deposits and currency	1.80	1.18	1.07	0.85	0.92	0.74
Time deposits and short-term investments	4.24	8.15	8.07	6.65	7.03	6.05
Money market fund shares	0.38	1.34	2.36	2.72	2.90	2.47
US government and municipal securities	0.58	1.49	3.20	7.53	6.26	9.56
Corporate and foreign bonds	0.12	0.46	0.89	2.14	1.52	3.13
Loans	0.08	0.28	0.92	2.17	1.99	2.49
Corporate equities and mutual fund holdings	2.58	7.10	17.14	31.43	29.97	33.74
Equity in noncorporate business	2.49	4.96	9.52	20.36	18.18	23.77
Life insurance reserves	2.25	1.97	1.36	1.22	1.40	0.94
Pension entitlements	10.81	29.32	28.53	7.22	9.54	3.53
Miscellaneous assets	3.02	1.44	0.70	0.37	0.45	0.25
Liabilities (% of total)						
Home mortgages	59.36	77.53	81.19	66.63	70.17	48.63
Consumer credit	36.67	19.49	10.12	8.21	7.60	11.11
Deposit institution loans n.e.c.	0.86	0.52	0.46	2.35	1.84	5.02
Other loans and advances	3.02	2.19	7.79	21.86	19.50	33.89
Deferred and unpaid life insurance premiums	0.09	0.27	0.45	0.95	0.89	1.35
Wealth-to-Asset ratio	27.91	81.21	92.11	97.08	95.95	98.88

Notes: For each wealth group, the table shows average shares of wealth and type of assets in total assets and type of liabilities in total liabilities. The table report simple averages between 1989Q3 and 2022Q1.

TABLE A.4: *Dollar change in equity instruments over short- and medium-run (in thousands of 2015$)*

	Bottom 50%	Next 40%	Next 9%	Top 1%
Conventional monetary policy				
2 years after the shock				
Corporate equities	**0.07**	**1.50**	**8.03**	**259.58**
	[−0.10, 0.26]	[−1.14, 1.64]	[−20.10, 34.49]	[−93.16, 675.07]
Noncorporate equities	**0.00**	**0.77**	**3.76**	**123.97**
	[−0.09, 0.10]	[0.01, 1.64]	[−5.12, 13.05]	[24.53, 239.29]
5 years after the shock				
Corporate equities	**-0.03**	**0.71**	**-1.78**	**52.34**
	[−0.18, 0.11]	[−1.18, 1.91]	[−22.22, 16.26]	[−296.23, 397.13]
Noncorporate equities	**0.08**	**0.79**	**4.10**	**63.96**
	[0.00, 0.18]	[−0.03, 1.91]	[−4.01, 13.61]	[−87.28, 234.38]
Unconventional monetary policy				
2 years after the shock				
Corporate equities	**0.26**	**1.83**	**27.80**	**328.03**
	[0.10, 0.49]	[−1.08, −0.37]	[3.97, 61.22]	[12.56, 756.44]
Noncorporate equities	**0.12**	**-1.21**	**14.95**	**83.33**
	[0.01, 0.25]	[−2.25, −0.37]	[6.42, 26.97]	[−7.83, 217.17]
5 years after the shock				
Corporate equities	**0.00**	**0.11**	**-18.05**	**-19.46**
	[−0.20, 0.26]	[−3.61, 1.24]	[−50.70, 7.05]	[−438.59, 375.65]
Noncorporate equities	**-0.03**	**0.00**	**-12.57**	**54.35**
	[−0.17, 0.11]	[−1.45, 1.24]	[−25.98, −3.29]	[−118.54, 270.29]

Notes: The table shows per capita gain or loss in corporate and noncorporate equities and mutual fund shares for each group. Values are expressed in thousands of USD and values in brackets are the corresponding gain or loss for the 90% posterior coverage bands.

TABLE A.3: *Dollar change in real housing assets and liabilities over short- and medium-run (in thousands of 2015$)*

	Bottom 50%	Next 40%	Next 9%	Top 1%
Conventional monetary policy				
2 years after the shock				
Real estate	**1.19**	**4.91**	**18.93**	**54.66**
	[0.18, 2.30]	[−0.85, 11.10]	[7.68, 33.45]	[−16.70, 134.78]
Home mortgages	**1.00**	**1.84**	**1.60**	**1.68**
	[0.06, 1.90]	[−0.18, 3.95]	[−2.49, 5.90]	[−5.21, 9.03]
5 years after the shock				
Real estate	**1.49**	**7.63**	**17.08**	**53.84**
	[0.19, 3.39]	[0.45, 17.63]	[2.88, 37.83]	[−48.67, 183.29]
Home mortgages	**2.04**	**3.14**	**4.03**	**3.30**
	[0.46, 4.26]	[−0.01, 7.45]	[−0.17, 9.31]	[−7.89, 16.56]
Unconventional monetary policy				
2 years after the shock				
Real estate	**0.65**	**-7.31**	**-1.03**	**7.37**
	[−0.54, 1.92]	[−14.02, −1.22]	[−14.73, 13.92]	[−56.16, 81.58]
Home mortgages	**-0.48**	**-3.49**	**6.14**	**-4.04**
	[−1.66, 0.64]	[−6.43, −1.17]	[2.82, 11.02]	[−9.98, 2.14]
5 years after the shock				
Real estate	**-0.48**	**-3.37**	**-10.89**	**73.56**
	[−2.86, 1.50]	[−16.25, 6.50]	[−35.41, 10.85]	[−25.77, 227.75]
Home mortgages	**-1.17**	**-2.28**	**-1.04**	**5.69**
	[−4.42, 0.99]	[−7.65, 1.72]	[−7.07, 6.09]	[−4.49, 18.87]

Notes: The table shows per capita gain or loss in real estate and home mortgages for each group. Positive and negative values for home mortgages are capital gains and losses, respectively. Values are expressed in thousands of USD and values in brackets are the corresponding gain or loss for the 90% posterior coverage bands.

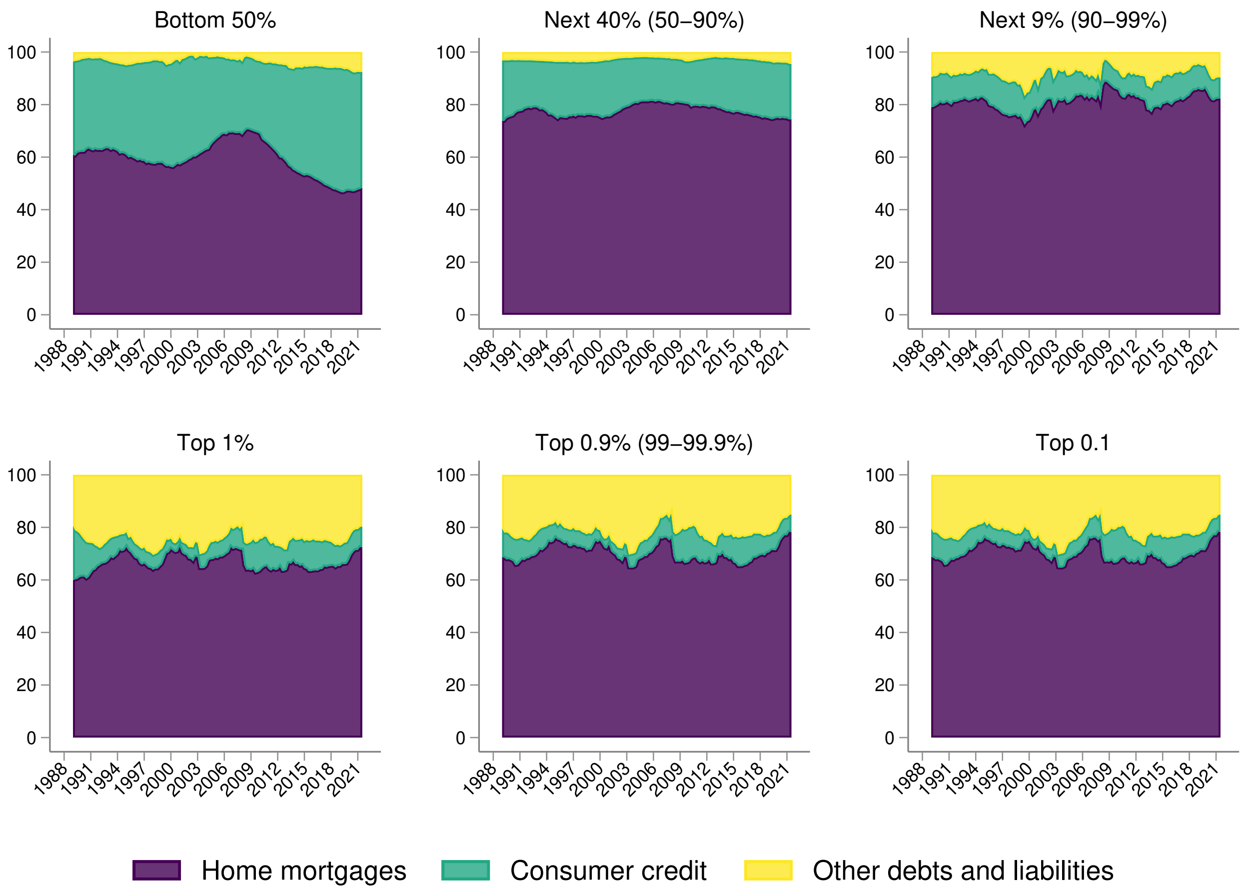


FIGURE A.1: COMPOSITION OF LIABILITIES ACROSS GROUPS

Notes: This figure shows the heterogeneity in the liability-side of household balance sheet by showing the dynamic composition of major liabilities, as share of total liabilities, for each wealth group in the Distributional Financial Accounts.

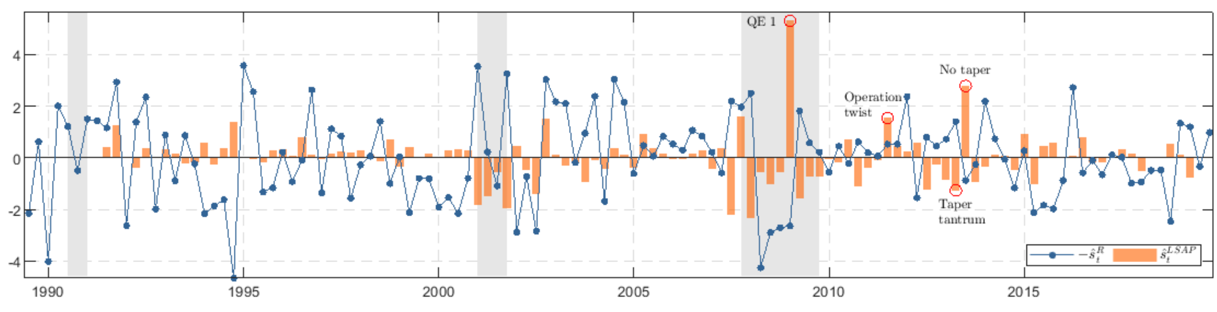
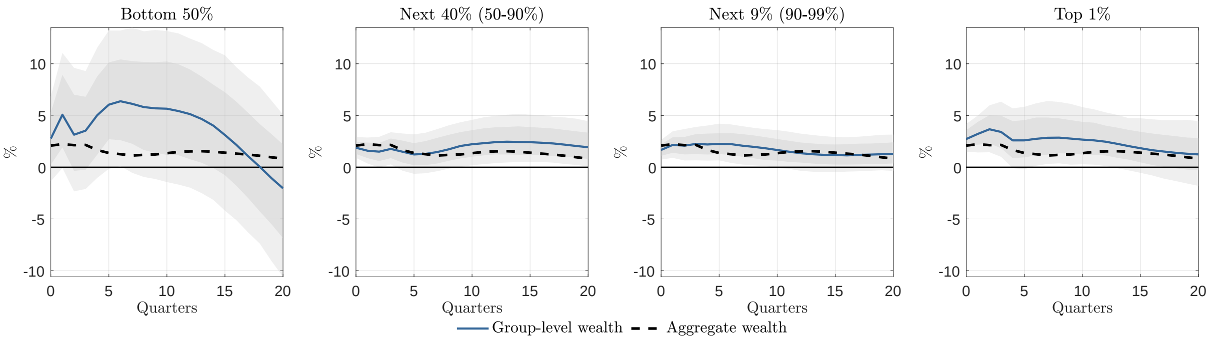
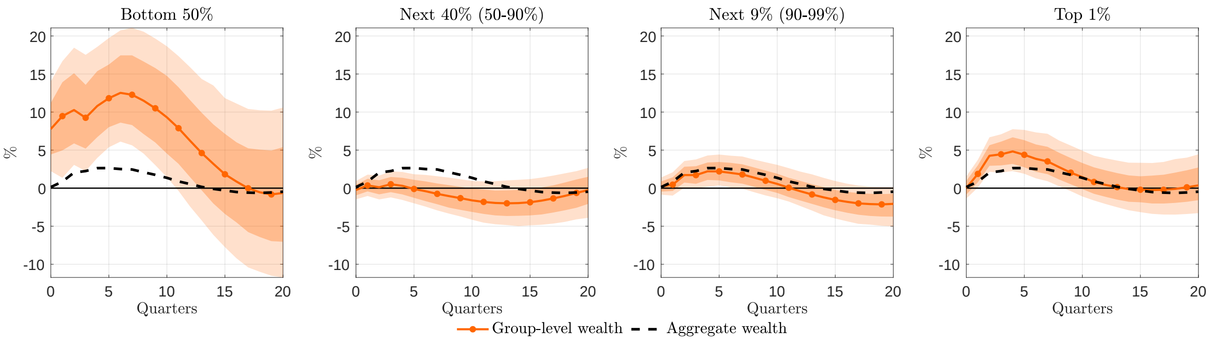


FIGURE A.2: *Monetary policy shocks*

Notes: This figure plots the monetary policy shocks presented used to estimate the macroeconomic and distributional effects of monetary policy.



(A) *Conventional monetary policy*



(B) *Unconventional monetary policy*

FIGURE A.3: *Group-level vs. aggregate wealth response to monetary policy*

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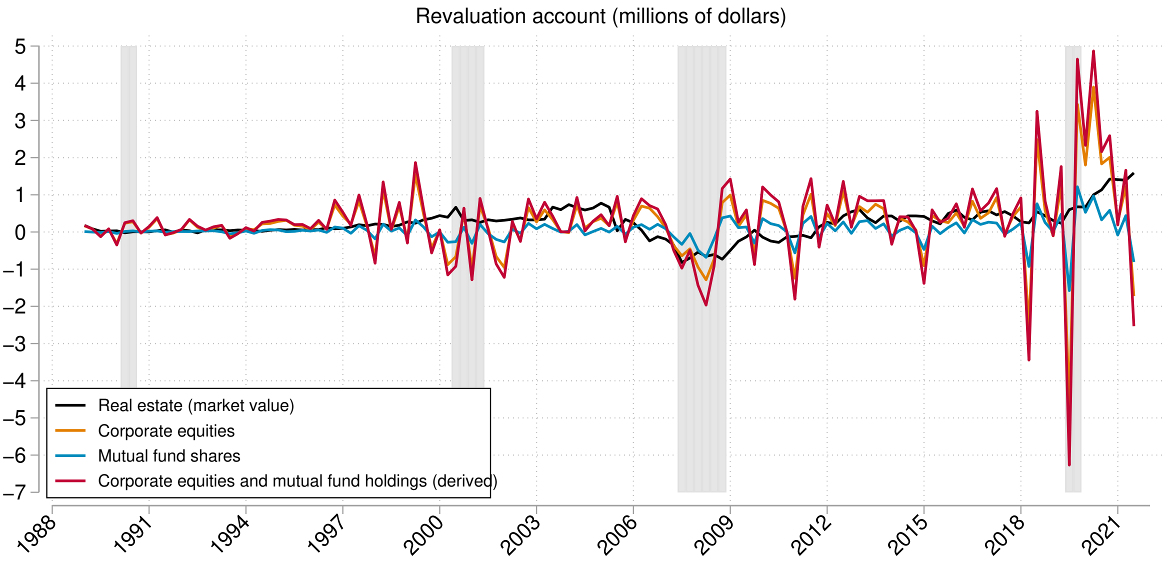

FIGURE A.4: -

Notes: Forecast error variance decomposition of capital gains from asset prices for conventional (A) and unconventional (B) monetary policy shock, 3 years after the shock. In each panel, the blue bar is the share of forecast error of capital gains from stock prices explained by conventional (A) and unconventional (B) monetary policy shock, 3 years after the shock. The red bar is the share of forecast error of capital gains from house prices explained by conventional (A) and unconventional (B) monetary policy shock, 3 years after the shock. Capital gains from house and stock prices are expressed as share of lagged wealth, that is: $\Pi^i_{j,t}/W^i_{t-1} = \left({}^{P_{j,t+1}}/{}_{P_{j,t}} - 1\right) A^i_{j,t}/W^i_{t-1}$ *for group i and asset j. The forecast error variance decomposition for each wealth group is retrieved from a baseline VAR model augmented with capital gains from house and stock prices for that wealth group. Impulse responses are scaled to imply a 1% response of real GDP. Shaded areas are 68% and 90% posterior coverage bands.*

B Beyond wealth: pension entitlements

Figure B.1 indicates that a federal funds rate shock has a small and sometimes not statistically significant effect on pension entitlements. On the other hand, an asset purchase shock has a U-shaped effect across the wealth distribution, with the Bottom 50% and the Top 1% experiencing a peak increase of roughly 7% in the first year. For the other groups (Next 40% and Next 9%), which are the largest holders of pension entitlements, we observe a small increase following a federal funds rate shock but this asset is not responsive to a federal funds rate shock. Overall, the difference in responses may be justified by the different holdings of pensions across wealth groups. In fact, pension entitlements constitute not more than 10% of total assets for the Bottom 50% and Top 1%, while it is roughly around 30% for households in the Next 40% and Next 9% (see Table 2 for more details).

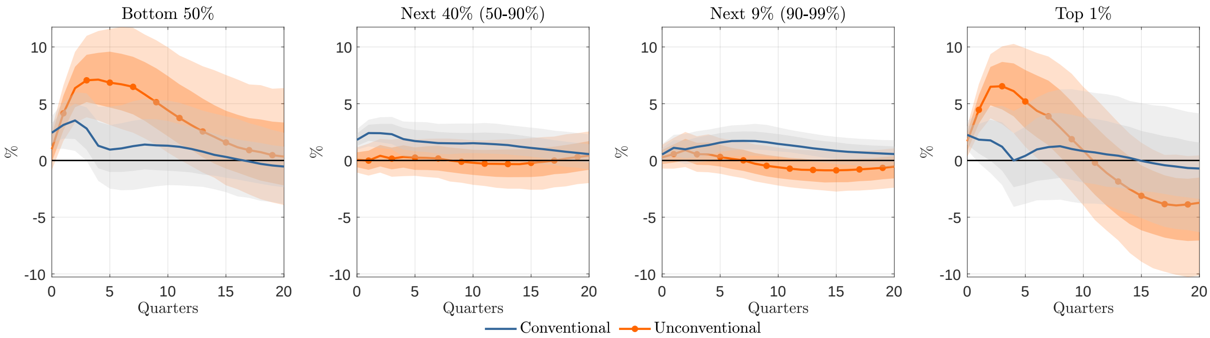

FIGURE B.1: *Pension entitlements*

Notes: Impulse responses of pension entitlements (accrued benefits to be paid in the future from defined benefit (DB) plans and defined contribution (DC) pension plans, and annuities sold by life insurers directly to individuals) to conventional (blue line) and unconventional (orange line) monetary policy shocks from a Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to induce a 1 percentage point increase in real GDP. Shaded areas are 68% and 90% posterior coverage bands.)

C Robustness

C.1 Robustness I: imposing pre-2008 restrictions on the unconventional monetary policy shock

As shown in Figure A.2, we observe that the unconventional shock (LSAP) presents some fluctuations prior its introduction in 2008. Hence, in this section, we want to directly assess the sensitivity of the main results when the unconventional shock is set to zero prior to 2008. In fact, this kind of policy was put in place in that year, when the zero lower bound on nominal interest rates became binding. Figure C.1 shows that when using the post-2008 shocks, the baseline results are virtually unchanged.

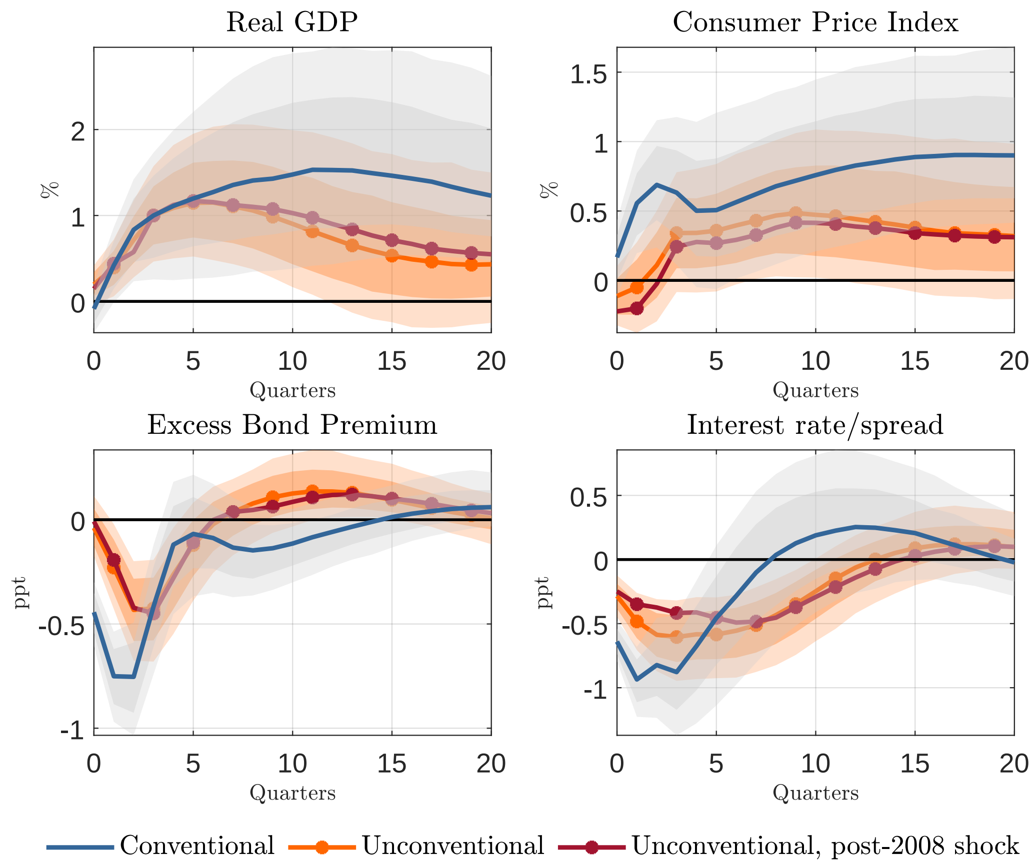

FIGURE C.1: *Macroeconomic effects of monetary policy shocks*

Notes: Impulse responses to conventional (blue line), unconventional (orange line), and post-2008 unconventional (red line) monetary policy shocks from a Bayesian VAR. Point estimates are median impulse responses from the posterior distribution. Impulse responses are scaled to induce a 1 percentage point increase in real GDP. Shaded areas are 68% and 90% posterior coverage bands.

C.2 Robustness II: local projections and smooth local projections

To shed light on the effects of monetary policy shocks on the wealth distribution, we rely on a VAR model estimated with bayesian techniques. As discussed in the main text, this choice is motivated by two reasons, both of which are associated with the short sample available. First, the bayesian estimation helps to tackle the "curse of dimensionality" due to the large number of parameters to be estimated relative to the sample length. Second, VARs, compared to LP, provide a more parsimonious characterization of the data. However, as shown by Montiel Olea and Plagborg-Møller (2021), when the data are persistent and the forecast horizons are long, then local projections should perform better in the estimation of impulse responses compared to VARs. Given that wealth tends to change slowly over time, the data generating process implied by the VAR, which lacks of persistence, might not be suited to analysing wealth data. Hence, as a robustness check, we compare impulse response functions derived in the baseline model with direct forecasts estimated within the LP framework proposed by Jordà (2005). The author suggests that the dynamic causal effects of a shock on the dependent variable can be recovered from the set of regression coefficients β_h associated with the set of h-step ahead predictive regressions. Formally:

$$y_{t+h} = \alpha_h + \beta_h \text{shock}_t + \Phi_h(L)x_{t-1} + u_{t+h} \quad \text{for} \quad h = 0, 1, 2, \ldots, \tag{C.1}$$

where y is the dependent variable of interest, x is a vector of control variables, $\Phi(L)$ is a polynomial in the lag operator, and *shock* is the monetary policy shock. For the sake of comparability, we keep the specification of the LP as close as possible to its VAR counterpart.

The nonparametric nature of LP allows more flexibility in the specification of the model compared to VARs but it comes at an efficient cost. Specifically, impulse responses estimated with LP are often less precise and sometimes erratic. Recently, Barnichon and Brownlees (2019) proposed a smoothed version of LP called SLP, which improves the estimation accuracy and keeps the same flexibility of LP.

We use both alternative models to assess the robustness of impulse responses estimated using VAR. Figures C.2 and C.3 show the responses of the baseline model with macroeconomic variables using VARs, LPs, and SLPs. We can see that the two alternative models produce consistent results to VARs with an efficient gain for SLPs in terms of smaller uncertainty around estimates.

Given the reassuring results with macroeconomic variables, we can now proceed to assess the reliability of VAR estimates for wealth data. Figures C.4 and C.5 plot the dynamic responses of real net worth in the four wealth groups of the DFA for conventional and unconventional monetary policy shock, respectively. The main benefit of SLP is the lower uncertainty around point estimates. This is particularly evident for the response of the Bottom 50% for both types of shock. Overall, Figures C.4 and C.5 show that LP and SLP produce consistent results when compared with the benchmark VAR model. Lastly, the next set of graphs show the response of wealth shares to conventional (Figure C.6) and unconventional (Figure C.7) monetary policy shocks. We can see that impulse responses derived using LP and SLP deliver virtually unchanged results.

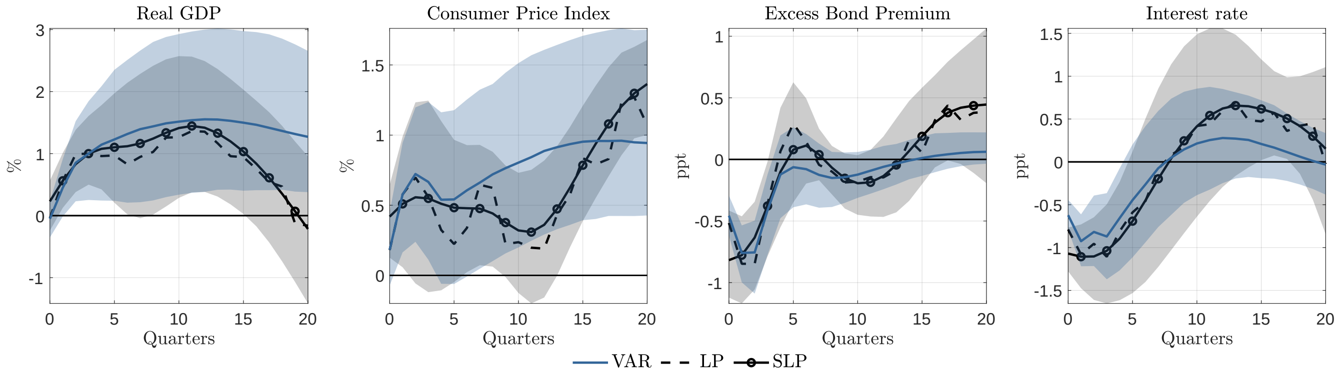

FIGURE C.2: MACROECONOMIC EFFECTS OF CONVENTIONAL MONETARY POLICY

Notes: Impulse responses to conventional monetary policy shocks from a Bayesian VAR (blue solid line), a LP (black dashed line), and the Smooth LP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (blue) and SLPs (grey).

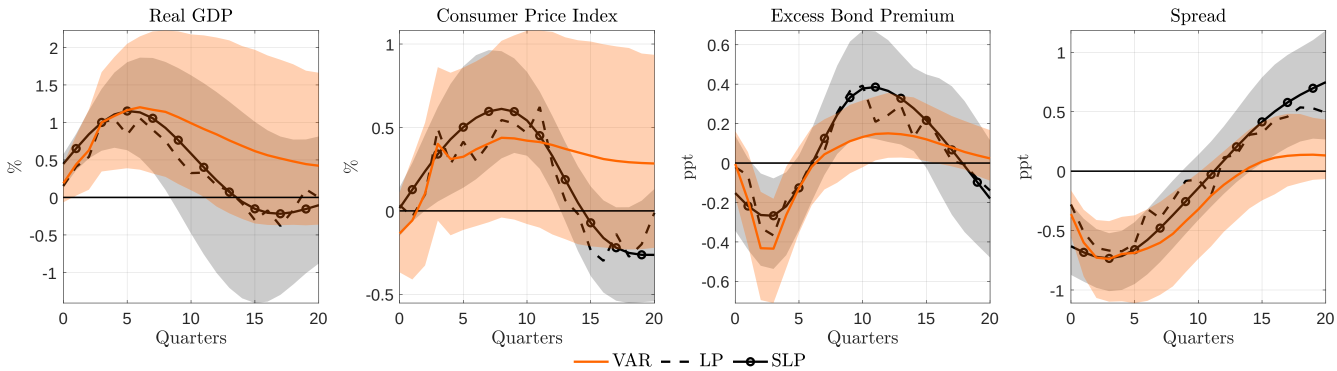

FIGURE C.3: MACROECONOMIC EFFECTS OF UNCONVENTIONAL MONETARY POLICY

Notes: Impulse responses to unconventional monetary policy shocks from a Bayesian VAR (orange solid line), the LP (black dashed line), and the Smooth LP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (orange) and SLPs (grey).

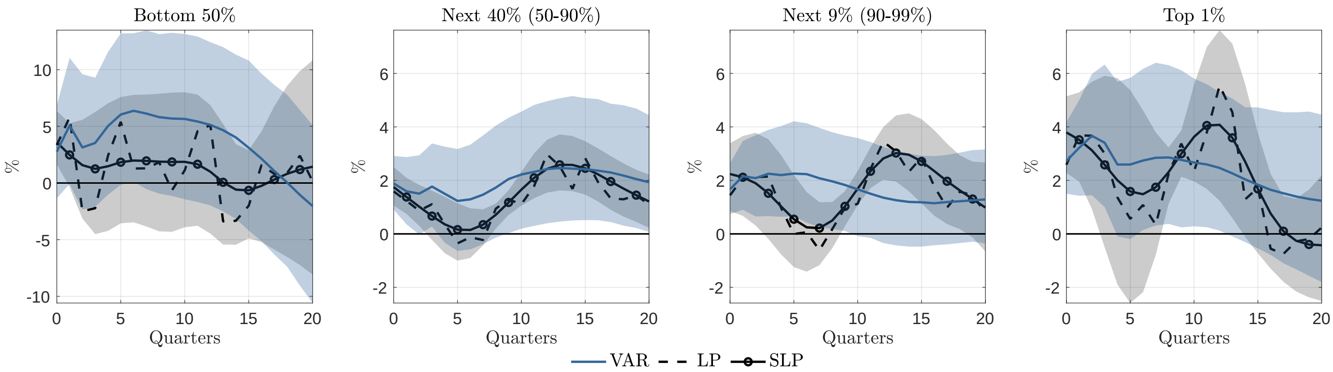

FIGURE C.4: *Wealth levels: conventional monetary policy shocks*

Notes: Impulse responses to conventional monetary policy shocks from a Bayesian VAR (blue solid line), a LP (black dashed line), and the Smooth LP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (blue) and SLPs (grey).

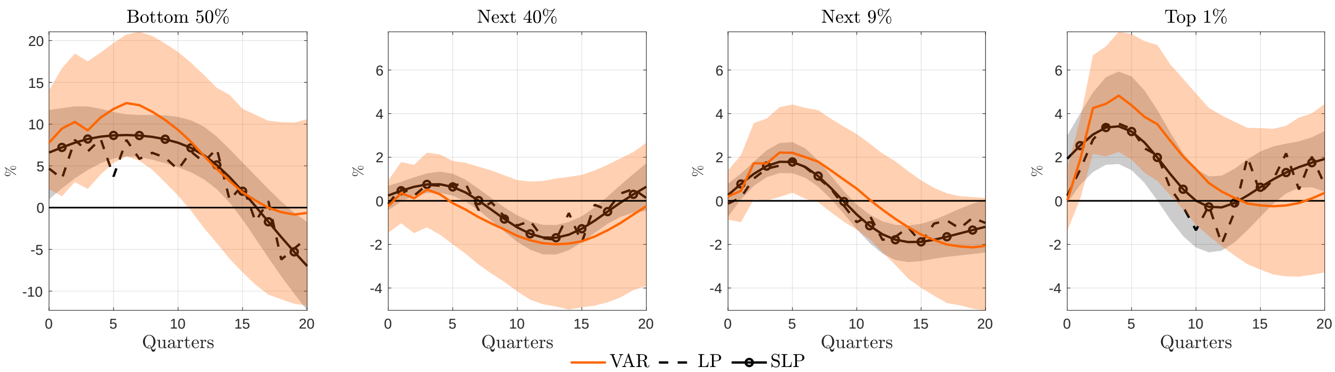

FIGURE C.5: *Wealth levels: unconventional monetary policy shocks*

Notes: Impulse responses to unconventional monetary policy shocks from a Bayesian VAR (orange solid line), the LP (black dashed line), and the Smooth LP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (orange) and SLPs (grey).

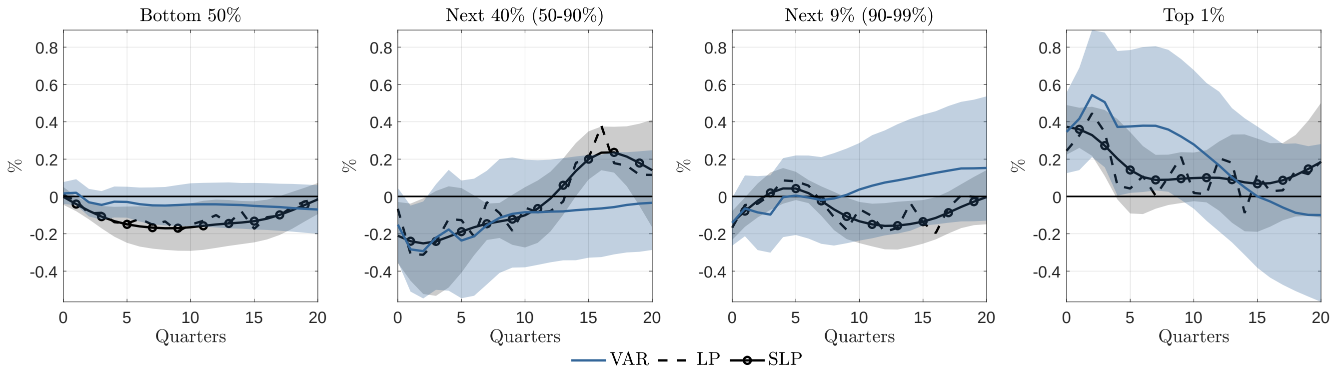

FIGURE C.6: *Wealth shares: conventional monetary policy shocks*

Notes: Impulse responses to conventional monetary policy shocks from a Bayesian VAR (blue solid line), a LP (black dashed line), and the Smooth LP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (blue) and SLPs (grey).

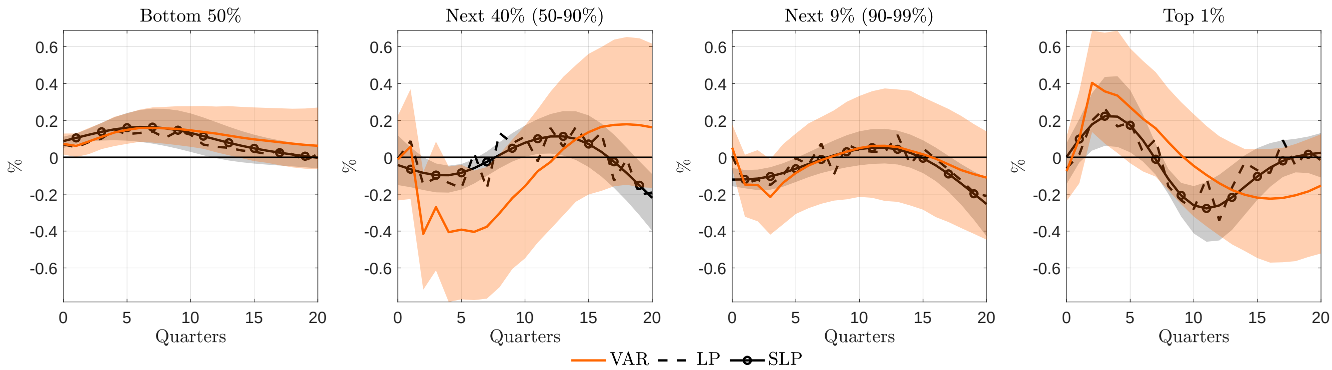

FIGURE C.7: *Wealth shares: unconventional monetary policy shocks*

Notes: Impulse responses to unconventional monetary policy shocks from a Bayesian VAR (orange solid line), the LP (black dashed line), and the SLP (black solid line with circles). Impulse responses are scaled to induce a 1 percentage point increase in real GDP after three quarters. Shaded areas are 90% confidence bands and are shown for VARs (orange) and SLPs (grey).