

Monetary policy and the wealth distribution

Alessandro Franconi

Banque de France

Giacomo Rella

UQAM, *Job Market Paper*

Using the Distributional Financial Accounts of the United States, we study the effects of monetary policy on the wealth distribution. The direction and persistence of these effects depend on the policy instrument. Interest rate cuts initially reduce wealth inequality but increase it in the medium run. Asset purchases, instead, increase wealth inequality but only temporarily. Housing is the main channel through which monetary policy affects wealth at the bottom while corporate equities explain wealth growth at the top. Using household-level data from the Panel Study of Income Dynamics, we document a wealth reversal at the bottom of the distribution: lower interest rates raise housing wealth in the short run but lead to higher mortgage debt and lower net wealth over time, contributing to the medium-term rise in inequality.

JEL codes: E52, D31, E44.

Keywords: Monetary Policy, Distributional Financial Accounts, Wealth Inequality.

Alessandro Franconi: Banque de France, alessandro.franconi@banque-france.fr.

Giacomo Rella: Université du Québec à Montréal, rella.giacomo@courrier.uqam.ca.

This paper has benefited from discussions with Andrea Ajello, Guido Ascari, Luis Bauluz, Yonatan Berman, Jacopo Cimadomo, Franziska Disslbacher, Bertrand Garbinti, Luca Gambetti, Marco Lombardi, Pascal Meichtry, Benoit Mojon, Salvatore Morelli, Jung Sakong, Gianluca Violante, Alice Volz, Ines Xavier, Sarah Zubairy, as well as participants of seminars and conferences at Federal Reserve Board, European Central Bank, Oesterreichische Nationalbank, CUNY (Stone Center), University of Pavia, Roma Tre University, UMass Boston, LSE, Bank of Italy Naples, WU Vienna, University of Torino, and University of L'Aquila. A previous version of this paper appeared as working paper in the Stone Center Working Paper Series (WP70). The views and opinions expressed in this paper are solely those of the authors and do not necessarily reflect those of Banque de France or the Eurosystem.

1. Introduction

In the aftermath of the Great Recession, unconventional monetary policy tools, such as asset purchases, have become increasingly central to the conduct of monetary policy. These tools have helped ease financial conditions and lower long-term interest rates, but they have also drawn harsh criticism from the public for their potential role in increasing wealth inequality. A common concern is that the benefits of expansionary monetary policy accrue disproportionately to asset owners in the form of capital gains, as lower interest rates and asset purchases boost asset prices. However, short-term interest rates and asset purchases may influence the distribution of wealth through several other channels, including changes in saving behaviour or portfolio rebalancing. Thus, the overall effects of different types of monetary policy on wealth inequality remain empirically unexplored.

In this article, we study the effects of monetary policy on the distribution of household wealth in the United States. We use vector autoregressive (VAR) models and local projections, distinguishing between interest rate and asset purchase shocks. Our primary data source is the Distributional Financial Accounts (DFA) of the United States, which combines household-level data from the Survey of Consumer Finances with the aggregate balance sheet of the household sector. Additionally, to provide a more granular view of how monetary policy affects wealth dynamics at longer horizons, we exploit the panel structure of the Panel Study of Income Dynamics.

Our first contribution is to demonstrate, using the DFA, that the impact of monetary policy on wealth levels depends largely on the type of policy instrument. An interest rate shock initially increases net wealth across the distribution, with the bottom 50% experiencing the largest percentage gain. Over time, however, the effect remains positive only for the top 10%, while it turns significantly negative for the bottom 50%. The analysis of unconventional monetary policy presents a different picture. An asset purchase shock initially raises net wealth for all groups, with the bottom 50% experiencing the largest percentage increase, followed by the top 0.1%. However, this increase in net wealth is short-lived, as the effects of monetary policy fade away.

The detailed nature of the balance sheet in the DFA allows us to explore the contribution of different asset classes to the observed changes in wealth. We focus on two asset classes: real estate, and corporate equities and mutual funds. These are particularly relevant because their ownership, relative to other assets owned by households, vary systematically with the position in the wealth distribution. We show that the effect of

monetary policy on net wealth for the bottom 50% of the distribution is entirely driven by the response of housing net wealth, especially following an interest rate shock. This is consistent with the fact that the bottom 50% is highly exposed to housing, with real estate assets accounting for more than half of total assets between 1989 and 2019. Consequently, as we move toward the top of the wealth distribution, the importance of housing wealth diminishes. Instead, the response of corporate equities and mutual funds becomes the main factor driving changes in net wealth after a monetary policy shock, particularly in the short run. Using data on aggregate revaluations, and in line with previous research, we also find that monetary policy shocks have heterogeneous effects on capital gains across the wealth distribution, especially in the short run. This is consistent with evidence suggesting that asset price revaluations contribute to unequal wealth growth following monetary policy shocks, beyond channels tied to income, inflation, and mortgage payments ([McKay and Wolf 2023](#)).¹

We then use the estimated responses of net wealth across wealth groups to monetary policy shocks to derive the implied effects on wealth inequality. Our results reveal a previously undocumented feature of the distributional effects of monetary policy. An expansionary interest rate shock initially reduces wealth inequality (as measured by the top 1% wealth share) but subsequently leads to a persistent increase. By contrast, an asset purchase shock initially increases wealth inequality, but this effect is temporary. We show that the responses of real estate and corporate equities and mutual funds across the wealth distribution play a key role in shaping these dynamics.

Our analysis shows that households in the bottom 50% of the wealth distribution experience a wealth reversal following an interest rate shock. The initial increase in total net wealth is driven by higher net housing wealth, reflecting an expansion in real estate holdings. Over time, however, a stronger increase in home mortgage balances dominates, compressing net housing wealth and, in turn, total net wealth. To rule out the role of mobility across the wealth distribution, we use household-level data from the Panel Study of Income Dynamics (PSID) and study how monetary policy affects wealth dynamics at the household level. We find that lower interest rates lead to an expansion of real estate along both the intensive and extensive margins: transitions from renting to owning increase, homeownership rises (especially among poorer households), and real estate holdings grow, likely reflecting both new purchases and valuation gains. Monetary shocks eventually trigger a lagged increase in home mortgage balances, potentially

¹For recent surveys on monetary policy and inequality, see [Colciago, Samarina, and de Haan \(2019\)](#) and [Kappes \(2021\)](#).

due to home equity extraction as well as the entry of new homeowners. The resulting rise in mortgage balances ultimately reduces net housing wealth and, given the strong exposure of these households to housing, lowers total net wealth, consistent with the evidence from the DFA.

1.1. Comparison with the literature

In comparison with the literature analyzing interest rate shocks on wealth inequality, we find two recent studies using the DFA. First, [Feilich \(2023\)](#) identifies a 100 basis points reduction in the one-year Treasury rate and finds a monotonic reduction in net worth for all household groups: households in the bottom 50% lose 2.8% on impact and up to 43% at the trough, while households in the top 1% experience a peak decline of almost 20%. By contrast, even after accounting for the different shock size, our estimates indicate a boom–bust dynamic for the Bottom 50% and smaller medium-run decline for the Bottom 50% and the Top 1%. For the other wealth groups, we find similarly monotonic medium-run dynamics but with more moderate effects in magnitude. Second, [Bricker et al. \(2025\)](#) find that a 100 basis points reduction in the interest rate raises the wealth Gini by about 0.01 over four years. Although our estimates are not directly comparable into changes in the Gini index, both sets of results indicate that an accommodative interest rate shock increases wealth inequality in the medium run. Studies using administrative data further highlight the distributional effects of monetary policy. [Andersen et al. \(2023\)](#) study an interest rate easing shock in Denmark and document a monotonic increase in asset values across the income distribution, with larger gains at the top driven primarily by equity revaluations. Their measure combines changes in housing and stock portfolios relative to ex-ante disposable income and is therefore not directly comparable to our wealth-based DFA estimates. Even when disaggregated by asset class, their results differ from ours: both housing and equity gains rise monotonically across the income distribution, whereas in our setting the response varies over time and differs markedly across wealth groups, with a short-run equalization and a medium-run re-concentration of wealth. These differences likely reflect both the use of income rather than wealth distributions and the substantially higher level of wealth inequality in the U.S. relative to Denmark.

Moving to the literature examining the distributional effects of an asset purchase shock, the closest study to ours is [Bügel, Hidalgo, and Luetticke \(2024\)](#). They estimate that an expansionary asset purchase shock increases the top 10% wealth share by about 1.5% at peak and reduces the Next 40% share by up to 2.5% within the first year. Our

estimates display a similar transitory increase in wealth concentration, with effects peaking within six to seven quarters and dissipating thereafter. When focusing on the top 10%, we obtain a 0.5 percentage point increase in average share at peak and a slightly larger decline for the Next 40%. Both studies agree that a key transmission channel of asset purchase shocks operates through asset-price revaluations, with equity-driven gains concentrated at the top and housing revaluations playing a comparatively larger role for the bottom of the distribution. Additional evidence on asset purchase shocks on wealth inequality using euro area data is provided by [De Luigi et al. \(2023\)](#). The authors show that relying exclusively on the Gini coefficient can mask movements in wealth inequality, as the Gini is highly sensitive to changes in the middle of the distribution. Using tail-sensitive measures, they find that an asset purchase shock increases wealth inequality via asset prices.² When assessing the effect of the shock on the Gini coefficient, they find equalizing effects, as in [Lenza and Slacalek \(2024\)](#), a result that reflects the fact that the Gini is primarily sensitive to changes in the middle of the distribution rather than in the tails.

Road map. The article is organized as follows. Section 2 introduces and describes the DFA. Section 3 outlines the econometric strategy and the identification of monetary policy shocks. Section 4 presents and discusses the main results. The robustness of these results is assessed in Section 5. Section 6 provides evidence of the wealth reversal using household-level data. Section 7 concludes.

2. The Distributional Financial Accounts of the United States

Our primary data source is the Distributional Financial Accounts (DFA), a new dataset that provides quarterly measures of household balance sheets across the wealth distribution ([Batty et al. 2021](#)). In this section, we present an overview of the dataset and highlight key findings on the distribution of household wealth, focusing on five wealth groups: the bottom 50%, the next 40% (50th-90th percentile), the next 9% (90th-99th percentile), the top 0.9% (99th-99.9th percentile), and the top 0.1% (99.9th-100th percentile). Throughout the article, we use the terms "wealth" and "net wealth" interchangeably to refer to total household assets, including consumer durables and unfunded defined benefit pensions, less all debts and other liabilities.

²A quantitative comparison is not feasible because these authors compare peak effects at significantly different horizons across countries and between asset classes. For instance, for Italy they compare the peak effect for equity at eight months with that for housing at twenty quarters, generating a timing mismatch that distorts distributional effects across assets and countries.

The DFA integrate the aggregate balance sheets of the household sector from Table B.101h of the Financial Accounts with micro-level balance sheets from the Survey of Consumer Finances (SCF). The SCF provides detailed cross-sectional data every three years, including information on high-wealth households, while the Financial Accounts provide quarterly aggregates. [Batty et al. \(2021\)](#) construct the DFA according to the following three main steps:

- *Reconciliation.* Assets and liabilities in the SCF are reorganized to match the Financial Accounts structure. For asset categories such as real estate and mortgages, the correspondence is direct and requires little adjustment. For others, such as corporate equities, adjustments are necessary. For instance, while the Financial Accounts report corporate equities at market value, the SCF provides both market- and cost-basis valuations; the DFA assigns an average between the two. Certain assets, like defined-benefit (DB) pension entitlements, are absent from the SCF but their aggregate from Table B.101h can be distributed to households based on reported plan participation and expected benefits. This step ensures that the aggregate levels from the reconciled SCF are close to those in Table B.101h.
- *Temporal disaggregation.* Once the SCF balance sheets are reconciled, quarterly estimates are constructed using the Chow–Lin approach. This method exploits the empirical relationship between the reconciled SCF data, aggregate Financial Accounts, and selected macro-financial indicators during periods when all are observed, and then uses this relationship to impute values for quarters between SCF waves. To be informative, the quarterly indicators must measure related quantities, capture the dynamics of the economy, and predict changes in the distribution of assets and liabilities. In all interpolations, the corresponding aggregate series from Table B.101h is included and, according to [Batty et al. \(2021\)](#), it is by far the most important predictor. Additional indicators, whose inclusion varies by asset and liability, include the S&P 500 index, house prices, the homeownership rate, the aggregate DB-to-DC (defined-contributions) pension ratio, the federal funds rate, the debt-to-income ratio, and measures of vehicle and student loan balances. Each wealth group is modeled separately by regressing reconciled SCF wealth per household in the group on these quarterly indicators. This group-specific modeling ensures that different wealth groups respond differently to changes in macroeconomic conditions. The imputed series are then multiplied by the number of households in each group to recover group-level wealth and shares.

- *Aggregation.* Finally, the estimated quarterly shares of assets and liabilities are applied to the aggregate levels in Table B.101h to construct the DFA.

A natural question is whether and how the interpolation affects the estimated effects of monetary policy. Conceptually, the DFA can be viewed as an estimate of a latent, unobserved quarterly process of household wealth, assets, and liabilities. The difference between the DFA series and the true process represents a disaggregation error, which is a form of measurement error ([Angelini, Henry, and Marcellino 2006](#)). Measurement error can affect the dynamic properties of interpolated data and, in turn, econometric estimates. The extent of the bias depends on the quality of the disaggregation method and on the specific econometric object under analysis. [Angelini, Henry, and Marcellino \(2006\)](#) show that the Chow–Lin approach minimizes this bias compared with alternative methods, provided that the high-frequency variables used are highly relevant for the target series. For example, interest rates affect the value of corporate equities and mutual funds by changing the rate at which future cash flows are discounted, and this empirical relationship can be exploited when imputing SCF values between survey waves. In constructing the interpolated variables, aggregate variables from the Financial Accounts are the dominant predictor, while macro-financial variables such as equity prices and interest rates play a minor role (see footnote 19 in [Batty et al. 2021](#)). Thus, although some of these variables are themselves affected by monetary policy, their inclusion primarily serves to reduce disaggregation errors.

Nonetheless, any remaining disaggregation error in the DFA may affect our impulse responses. For instance, measurement error could attenuate the estimated effects of monetary policy or inflate the uncertainty around these estimates ([Carriero et al. 2015](#)). In a Bayesian VAR framework, because the disaggregation error is not explicitly modeled, it may reduce the precision of the posterior distribution and thus widen the credible intervals. Overall, however, we believe that disaggregation error is unlikely to affect our results dramatically, as the estimates remain qualitatively unchanged when using household-level data from the PSID, where assets and liabilities are directly observed. This suggests that any bias induced by the methodology applied by [Batty et al. \(2021\)](#) is likely minimal and may result in wider credible intervals.

2.1. Wealth concentration and growth

According to the DFA, U.S. wealth inequality has increased since 1989, with trends in top wealth shares comparable to those reported in other studies ([Morelli et al. 2023](#);

Saez and Zucman 2016; Blanchet, Saez, and Zucman 2022).³ However, differences in the level of inequality persist due to disagreements in the definition of wealth. For example, according to the DFA, the top 0.1% wealth share stands lower than that estimated by [Blanchet, Saez, and Zucman \(2022\)](#) because wealth in the latter excludes consumer durables and unfunded pensions.⁴

Figure 1 compares real net wealth growth across wealth groups. Until the early 2000s, wealth growth followed a relatively uniform pattern across all groups, with the exception of the top 1%, which has always experienced higher growth. For the bottom 50%, wealth growth was already stagnant by the early 2000s. During the Great Recession, all groups experienced a slowdown, although the severity varied considerably. While the bottom experienced an almost complete erosion of net wealth, the impact of the crisis on the top 50% was much less severe. It is worth noting that the pandemic and its aftermath boosted wealth growth especially for the bottom 50% and the top 1% of the distribution.

2.2. Heterogeneous portfolios across the wealth distribution

Differences in wealth growth arise from changes in saving rates, capital gains, and other returns. Changes in asset prices can significantly affect the dynamics of wealth inequality through two channels ([Kuhn, Schularick, and Steins 2020](#)). First, if portfolios differ across the wealth distribution, changes in asset prices will affect wealth differently. Second, when the wealth-to-income ratio is high, changes in asset prices have a larger impact on the wealth distribution than savings alone. For asset prices to affect the distribution of wealth, it is crucial that households' portfolios across the distribution are heterogeneous. Table 1 shows a significant heterogeneity in the composition of portfolios across the wealth distribution. Moving toward the top, households hold a larger share of financial assets and a smaller share of non-financial assets. Throughout the paper, we will show how such heterogeneity in portfolios shapes the distributional effects of monetary policy. Real estate and consumer durables together account for

³Figure A.1 in Appendix A provides a comparison of the top 0.1% wealth share in the DFA with the high-frequency estimates of net wealth in [Blanchet, Saez, and Zucman \(2022\)](#). See [Batty et al. \(2021\)](#) for additional comparisons with other studies.

⁴Differently from the DFA, [Blanchet, Saez, and Zucman \(2022\)](#) estimate the wealth distribution using the income capitalization method applied to income tax data. 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, and annuities sold by life insurers directly to individuals ([Batty et al. 2021](#)). In contrast, [Blanchet, Saez, and Zucman \(2022\)](#) excludes unfunded pensions because these are promises of future transfers that are not backed by actual wealth. Similarly, durables are treated as non-financial assets in the DFA but not in [Blanchet, Saez, and Zucman \(2022\)](#).

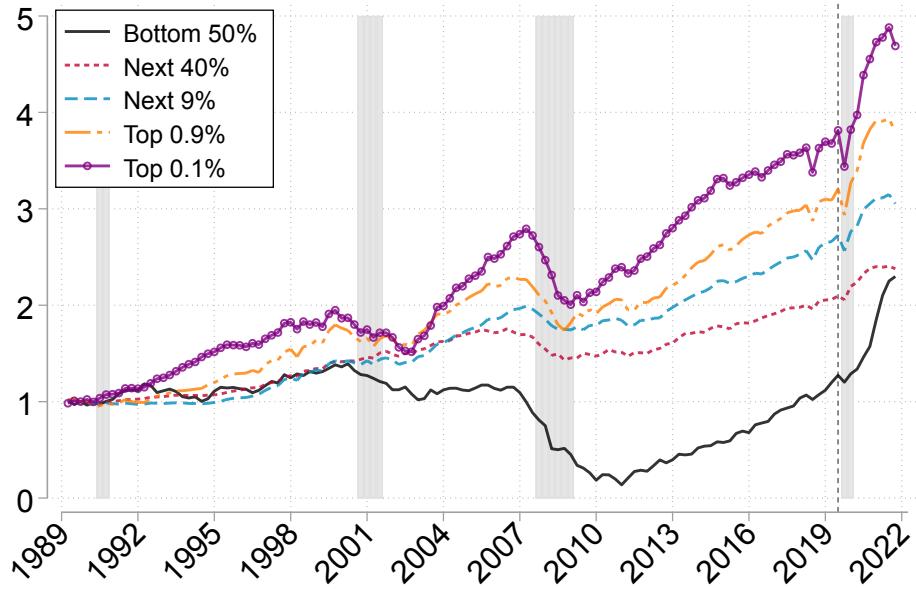


FIGURE 1. Real net wealth growth across the wealth distribution (1989Q3 - 2022Q1)

Notes: The figure shows real net wealth growth across wealth groups according to the Distributional Financial Accounts. All time series are indexed to 1 in 1990Q1 and deflated using the consumer price index. The dashed vertical line indicates the end of the estimation sample of our empirical analysis (2019Q4).

more than 70% of total assets for households in the bottom 50%, while the importance of corporate equities, mutual funds and private businesses increases for wealthier groups. Pensions account for nearly one-third of total assets for households in the next 40% and the next 9% of the distribution. Home mortgages make up the bulk of liabilities, and their relative importance grows with wealth levels except for the top 1%. Conversely, the share of consumer credit declines as we move up in the distribution.

3. Econometric methodology

In this section, we first present the econometric approach used to estimate the distributional effects of monetary policy. Then, we describe the identification of monetary policy shocks.

TABLE 1. Average composition of portfolios across the wealth distribution (1989Q3-2019Q4)

	Bottom 50%	Next 40%	Next 9%	Top 0.9%	Top 0.1%
Assets (% of total)					
Nonfinancial assets	71.65	42.41	26.46	20.04	13.57
Real estate	51.14	34.71	22.48	16.69	9.08
Consumer durables	20.51	7.70	3.98	3.35	4.49
Financial assets	28.35	57.59	73.54	79.96	86.43
Deposits	6.39	10.60	11.47	10.77	9.20
Corporate equities and mutual funds	2.57	6.98	16.65	28.90	32.77
Private businesses	2.52	5.02	9.63	18.45	23.70
Pension entitlements	10.78	29.30	28.52	9.91	3.60
Other assets	6.09	5.70	7.27	11.92	17.15
Liabilities (% of total)					
Home mortgages	60.24	77.74	81.03	69.79	49.08
Consumer credit	36.03	19.36	10.25	7.66	10.89
Other liabilities	3.72	2.90	8.72	22.55	40.02
Wealth-to-asset ratio	27.49	81.04	92.02	95.85	98.86

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 reports simple averages between 1989Q3 and 2019Q4. Other assets include U.S. government and municipal securities, corporate and foreign bonds, loans, life insurance reserves, and miscellaneous assets. Similarly, other liabilities are include depository institutions loans n.e.c., other loans and advances, deferred and unpaid life insurance premiums.

3.1. VAR Model

Model. The core framework for our analysis is the following VAR model:

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

where \mathbf{y}_t is a $(n \times 1)$ vector of endogenous variables, \mathbf{c} is a $(n \times 1)$ constant vector, \mathbf{B}_j are $(n \times n)$ matrices of parameters with $j = 1, \dots, p$, \mathbf{u}_t is a $(n \times 1)$ vector of reduced-form innovations with zero mean and variance-covariance matrix Σ . Time is indexed by $t = 1, \dots, T$, each time period is a quarter, and the lag length is $p = 4$. To address the challenge of dimensionality resulting from a relatively large number of parameters compared to the sample size, we estimate the model using a Minnesota prior whose hyperparameters are obtained through the hierarchical approach of [Giannone, Lenza, and Primiceri \(2015\)](#). Appendix B.1 provides additional implementation details.

Specification. We use different specifications of the VAR model in equation (1). We start with a standard model in which the vector of endogenous variables \mathbf{y}_t includes, in the following order, the monetary policy surprise series (described in Sections 3.2 and 3.3), 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 surprise series is \hat{s}_t^R (\hat{s}_t^{LSAP}), and the policy variable is the 1-year Treasury yield (term spread). The term spread is the difference between the 10-year and the 3-month Treasury yields. We refer to these specifications as the models with macroeconomic data, and all the details are summarized in Table 2, Panel A. We then augment these models with the balance sheet components from the DFA to study the distributional effects of monetary policy (Table 2, Panel B). More specifically, we estimate a separate VAR model for each wealth group and each type of monetary policy shock. Interest rates, spreads and ratios are expressed in percent. All remaining variables are expressed in levels of their natural logarithms. Nominal variables, including macroeconomic and distributional variables, are deflated using the consumer price index. Models for conventional monetary policy are estimated using quarterly time series from 1989Q3 to 2019Q4, and for unconventional monetary policy from 1992Q3 to 2016Q4.

Identification. To obtain impulse responses, we use a monetary policy surprise series as an internal instrument in a VAR. Specifically, the internal instrument approach involves ordering the instrument first in the VAR and then estimate the dynamic effects to the first orthogonalized residual ([Plagborg-Møller and Wolf 2021](#)). In our application, the instruments are the monetary policy surprise series \hat{s}_t^i (with $i = R, LSAP$) [and their construction is described in Sections 3.2 and 3.3](#).

Let z_t be a generic instrument (in our case, \hat{s}_t^R or \hat{s}_t^{LSAP}), ε_t^p be the monetary policy shock and ε_t^q be a $(n - 1) \times 1$ vector of other structural shocks. The internal instrument approach requires the instrument z_t to be correlated with the shock of interest ε_t^p , to be orthogonal to all other shocks ε_t^q as well as to all leads and lags of the structural shocks. Formally, we assume:

$$\mathbb{E}[z_t \varepsilon_t^{p'}] \neq 0 \quad (2)$$

$$\mathbb{E}[z_t \varepsilon_t^{q'}] = 0 \quad (3)$$

$$\mathbb{E}[z_t \varepsilon_{t+k}] = 0, \quad \text{for } k \neq 0 \quad (4)$$

where (2) is the relevance condition with the structural shock of interest, (3) is the

exogeneity condition with the remaining structural shocks, and (4) is the orthogonality condition to leads and lags of the structural shock. Under these assumptions, we can estimate the causal effect of monetary policy by augmenting the VAR with each monetary policy surprise series. The internal instrument strategy has the favorable property that it leads to consistent estimates of the impulse responses even if the instrument is not invertible (Plagborg-Møller and Wolf 2021; Li, Plagborg-Møller, and Wolf 2024; Forni, Gambetti, and Ricco 2022).

TABLE 2. Models and variables description

Series	Unit	Source
<i>Panel A: Models with macroeconomic data</i>		
1 Policy shock:		
Interest rate surprise (\hat{s}_t^R)		Sections 3.2
Asset purchase surprise (\hat{s}_t^{LSAP})		Sections 3.3
2 Real GDP	BoC 2012\$	Bureau of Economic Analysis
3 Consumer price index	2015 = 100	Bureau of Economic Analysis
4 Excess bond premium	Percent	Gilchrist and Zakrajšek (2012)
5 Interest rate or spread:		
1-year Treasury Rate	Percent	McCracken, Ng et al. (2021)
Term spread	Percent	McCracken, Ng et al. (2021)
<i>Panel B: Models augmented with Distributional Financial Accounts data for each wealth group i</i>		
Model with macroeconomic data +		
6 Consumer durables $_i$	Bil. of 2015\$	DFA
7 Real estate $_i$	Bil. of 2015\$	DFA
8 Deposits $_i$	Bil. of 2015\$	DFA
9 Pension entitlements $_i$	Bil. of 2015\$	DFA
10 Corporate equities and mutual funds $_i$	Bil. of 2015\$	DFA
11 Private businesses $_i$	Bil. of 2015\$	DFA
12 Home mortgages $_i$	Bil. of 2015\$	DFA
13 Consumer credit $_i$	Bil. of 2015\$	DFA
14 Net wealth $_i$	Bil. of 2015\$	DFA

Notes: DFA is the Distributional Financial Accounts. Bil. is billions. Real estate assets are owner-occupied real estate including vacant land and mobile homes at market value. Deposits include checkable deposits and currency, time deposits and short-term investments, and money market fund shares. Pension entitlements includes defined contribution (DC) pension plans, accrued benefits to be paid in the future from defined benefit (DB) plans, and annuities sold by life insurers directly to individuals. Corporate equities and mutual funds exclude equities and mutual fund shares owned through DC pensions. Private businesses (or equity in noncorporate business) is proprietors' equity in noncorporate business (including non-publicly traded businesses and real estate owned by households for renting out to others). Home mortgages are residential home mortgage loans as reported by lenders. Consumer credit includes credit card, student loan, and vehicle loan balances, and other loans extended to consumers.

3.2. Conventional monetary policy: interest rate shock

A common approach to the identification of monetary policy shocks is to measure high-frequency changes in interest rates around policy announcements. This strategy assumes that asset prices respond solely to monetary policy shocks within a short window around policy announcements. However, surprise series identified in this way may be subject to endogeneity problems if the central bank possesses private information about the state of the economy ([Miranda-Agrippino and Ricco 2021](#); [Jarociński and Karadi 2020](#)) or if both the central bank and economic agents react to publicly available economic news ([Bauer and Swanson 2023](#)). To address these problems, we use the series of [Jarociński and Karadi \(2020\)](#), which isolates *pure monetary policy* surprises based on the negative comovement between changes in the 3-month federal funds futures rate and the S&P500 stock price index around policy announcements. Changes in these futures reflect the overall stance of monetary policy by capturing both the actual rate setting and the near-term path of future rates.

In our application, using a monetary policy surprise series, such as that in [Jarociński and Karadi \(2020\)](#), as an internal instrument in a quarterly VAR is challenging for two reasons. First, the DFA starts in 1989, so identification relies on a relatively recent sample in which exogenous policy shocks are less frequent and smaller in magnitude ([Ramey 2016](#)). Second, the quarterly frequency of the DFA implies that monetary surprises are averaged over longer periods, reducing the information content that can be used for identification. Taken together, these features imply a lower signal-to-noise ratio of the surprise series in the post-1989 quarterly sample: the proxy contains less monetary-policy-related variation, while its idiosyncratic noise component does not necessarily shrink proportionally. As we show in a simple theoretical argument in Appendix B.2, when the variance of the structural monetary policy shock becomes smaller relative to the noise in the proxy, the correlation between the instrument and the structural shock declines, weakening the ability of the surprise series to identify the shock of interest.

To improve the informativeness of the surprise series in the internal-instrument VAR, we propose a two-step procedure, formally motivated in Appendix B.2. In the first step, we estimate a monthly Proxy VAR over the period July 1979–December 2019 and obtain a monetary policy surprise series.⁵ This allows us to exploit a longer sample

⁵The Proxy VAR includes six lags and the following variables: the log of industrial production, the log of the consumer price index, the unemployment rate, the excess bond premium of [Gilchrist and Zakrajšek \(2012\)](#), the log of a commodity price index, and the 1-year Treasury rate as the policy variable. The F-statistic in the first stage is 10.9, above the threshold of [Stock, Wright, and Yogo \(2002\)](#). We confirm the invertibility condition of the identified shock using the test in [Forni, Gambetti, and Ricco \(2022\)](#) (see

at a higher frequency with a richer information set, including episodes with greater exogenous variation in monetary policy (e.g., the Volcker disinflation). As a result, the estimated shock series is more tightly linked to monetary policy innovations and less affected by measurement noise. In the second step, we aggregate the monthly surprise series to a quarterly frequency and use it as an internal instrument in the VAR.⁶ In the text, we refer to the orthogonalized residual in the internal-instrument VAR for conventional monetary policy as the interest rate shock (\hat{s}_t^R).

3.3. Unconventional monetary policy: asset purchase shock

To identify surprise changes in unconventional monetary policy, we use the large-scale asset purchase factor of [Swanson \(2021\)](#). This factor represents one of the principal components that explain asset price changes around monetary policy announcements between July 1991 and June 2019. By construction, the large-scale asset purchase factor is uncorrelated with other factors capturing changes in the federal funds rate and forward guidance, making it an appropriate measure of "the component of FOMC announcements that conveys information about asset purchases above and beyond changes in the federal funds rate itself" (*ibid.*, p. 37).⁷

In contrast to the conventional monetary policy shock, the large-scale asset purchase factor of [Swanson \(2021\)](#) covers all major events associated with unconventional policies (QE1, QE2 and QE3) over the sample under analysis. This makes the identification strategy a straightforward task, as the signal-to-noise ratio of the surprise series is at its maximum. To enhance comparability between the two procedures, we purge the large-scale asset purchase factor from the information contained in Greenbook forecasts, as in [Miranda-Agrippino and Ricco \(2021\)](#), and obtain an informationally-robust asset purchase surprise series. In the text, we refer to its orthogonalized residual from the internal-instrument VAR as the asset purchase shock (\hat{s}_t^{LSAP}). Further details of this procedure can be found in Appendix B.4, along with a plot of both shocks (Figure B.1).

[Table B.1](#) in Appendix B.3).

⁶An alternative would be to use the surprises of [Jarociński and Karadi \(2020\)](#) as an external instrument in a quarterly Proxy VAR with distributional data. However, the low frequency and the short sample leads to the same weak instrument problem highlighted in Appendix B.2.

⁷[Swanson \(2021\)](#) shows that changes in the large-scale asset purchase factor have small effects on yields at short maturities but a larger impact on long-term rates, particularly on Treasury bonds.

4. Results

We now examine the effect of interest rate and asset purchase shocks on the wealth distribution.

4.1. Macroeconomic effects of monetary policy

We begin our analysis by examining the impact of monetary policy on macroeconomic aggregates using the models in Table 2, Panel A. Figure 2 plots the impulse responses normalized to produce a 1% response in real GDP three quarters after the shock. We adopt this normalization convention to facilitate comparison across models, and we maintain it throughout the article. In addition, following our sign convention, the impulse responses trace the effects of expansionary monetary policy shocks.

An interest rate shock leads to an immediate decline of about 60 basis points in the 1-year Treasury rate. Similarly, an asset purchase shock narrows the term spread by about 30 basis points. Both the decline in interest rates and the narrowing of the spread are statistically significant, with a faster reversion observed after an interest rate shock. Consistent with previous research on the macroeconomic effects of monetary policy, both shocks increase real GDP, raise the price level, and ease financial conditions as measured by the excess bond premium (Gertler and Karadi 2015; Ramey 2016).⁸

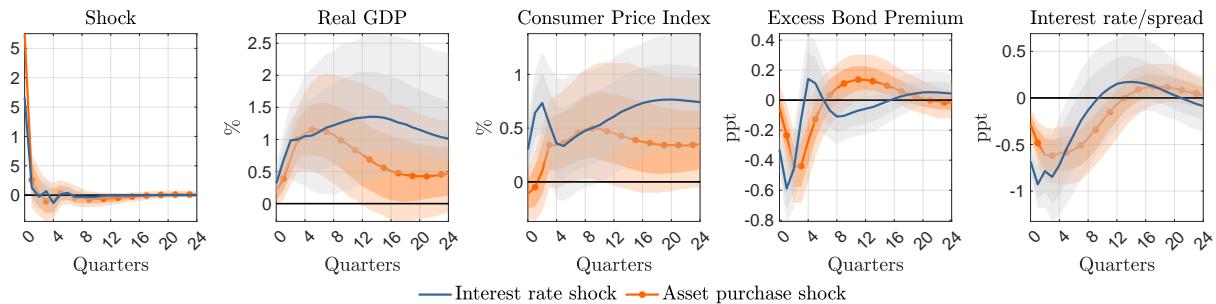


FIGURE 2. Macroeconomic effects of monetary policy

Notes: The figure shows the impulse response functions to an interest rate (solid line) and an asset purchase (solid line with markers) shock estimated using the Bayesian VAR described in Table 2, Panel A. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands.

⁸The persistent real effects of monetary policy are consistent with theoretical models that feature consumption habits, variable capital utilization, and staggered wage contracts (see, for example, Christiano, Eichenbaum, and Evans 2005). However, in a robustness check using local projections we find less persistence effects of monetary policy (see Figure D.5).

4.2. Monetary policy and wealth inequality

To evaluate the distributional effects of monetary policy shocks, we estimate the augmented models in Table 2, Panel B. We do so using a different model for each type of shock and wealth group. Each model includes consumer durables, real estate, deposits, pension entitlements, corporate equities and mutual funds, private businesses, home mortgages, consumer credit, and net wealth. Together, these categories account for most of assets (Figure A.2) and liabilities (Figure A.3) across wealth groups.⁹

To illustrate the impact of monetary policy shocks on net wealth across the wealth distribution, we focus on the percentage change in real net wealth resulting from monetary policy shocks at specific points in time (impact and one, three, and six years after the shock). We interpret the impact and one-year responses as short-term distributional effects of monetary policy. Similarly, the three- and six-year responses represent the medium-run effects. We report the short- and medium-run effects of monetary policy shocks on net wealth across the wealth distribution in Figure 3 and Figure 7, and discuss them separately for each type of shock in the following. In each figure, we report 68% and 90% credibility intervals from the posterior distribution. It is worth noting, however, that the posterior intervals are relatively wide, which may reflect the nature of the DFA. As discussed in Section 2, the disaggregation error introduced by the Chow–Lin interpolation method, although small, can potentially inflate the uncertainty surrounding the estimated effects of monetary policy.

We then examine the impact of monetary policy shocks on wealth inequality by using the estimated impulse responses to derive the implied changes in wealth shares induced by each shock. Specifically, for each group i , we denote w_{it} as real net wealth, $w_i = \frac{1}{T} \sum_{t=1}^T w_{it}$ as the average real net wealth in our sample, and $p_i = \frac{w_i}{\sum_{i=1}^I w_i}$ as the average wealth share. We then simulate the evolution of real net wealth for each group i using the following equation:

$$w_{ih} = w_i(1 + IRF_{ih}) \quad \text{with } h = 0, \dots, 24. \quad (5)$$

The term IRF_{ih} represents the response of net wealth of group i in period h to a monetary policy shock. Finally, we compute the implied deviation in net wealth share from its

⁹We focus our main analysis on net wealth and its distribution. The assets and liabilities included in the VAR models allow us to isolate the channels through which monetary policy shocks affect the distribution of household wealth. For completeness, we report the responses of all other balance sheet variables included in the model in Appendix E, Figure E.1 and Figure E.2.

average (Δp_{ih}) for each group i using the following formula:

$$\Delta p_{ih} = p_{ih} - p_i \quad \text{with} \quad p_{ih} = \frac{w_{ih}}{w_h} \quad \text{and} \quad w_h = \sum_{\forall i} w_{ih}. \quad (6)$$

We report the effect of monetary policy on wealth shares in Figure 4 and Figure 8 and consider the top 1% wealth share as measure of wealth inequality.¹⁰

Finally, we examine two channels that underlie the distributional effects of monetary policy. The first channel we study – the *housing wealth channel* – is particularly important for the lower part of the wealth distribution, owing to the prominence of housing in their asset holdings. The second channel we examine involves the response of corporate equities and mutual funds to monetary policy shocks. This channel is particularly important for the upper part of the wealth distribution, owing to the prominence of these assets in their portfolios.¹¹

Below, for each type of monetary policy, we present the estimated effects on the level of wealth, examine the implied effects on wealth inequality, and explore the channels through which these effects materialize.

4.3. Interest rate shock

Figure 3 shows that an interest rate shock generates a hump-shaped response in aggregate net wealth. This aggregate pattern, however, masks substantial heterogeneity across the wealth distribution, as the effects vary by group.¹²

Consider the bottom 50% and the top 0.1%. For the bottom half of the distribu-

¹⁰We focus on the top 1% because this is the share of wealth that, according to various sources, has increased significantly in the US since the 1980s (see Figure 2 in [Blanchet and Martínez-Toledano 2022](#)). However, when showing the impact of monetary policy on wealth inequality, we report changes in wealth shares for all groups, including the top 0.1% and the top 10%, for the sake of completeness.

¹¹We emphasize that in our analysis of the channels driving the effects of monetary policy, we focus on the influence of individual asset classes (e.g., real estate) and liabilities (e.g., mortgages) without separating the role of asset prices from non-price effects (e.g., saving). Hence, our impulse responses reflect both the effect of prices and investment, as it is for example for the case of real estate and corporate equities in Figure C.3. The asset price or capital gains channel has received considerable attention in the literature on the distributional effects of monetary policy also because the most direct effects of monetary policy are often observed in financial markets ([Paul 2020](#); [De Luigi et al. 2023](#)). We examine the role of this channel in detail in Appendix F where we show that the response of capital gains to monetary policy is larger at the top of the wealth distribution. Moreover, for individual assets, we show that the response of capital gains to a monetary policy shock depends on the relative importance of each asset in total wealth for each group. However, we find that the effects of monetary policy shocks are only temporary and cannot explain our findings of persistent effects on net wealth following an interest rate shock.

¹²Figures C.1 and C.2 in Appendix C plot the full impulse responses of the aggregate balance sheet and of net wealth across groups.

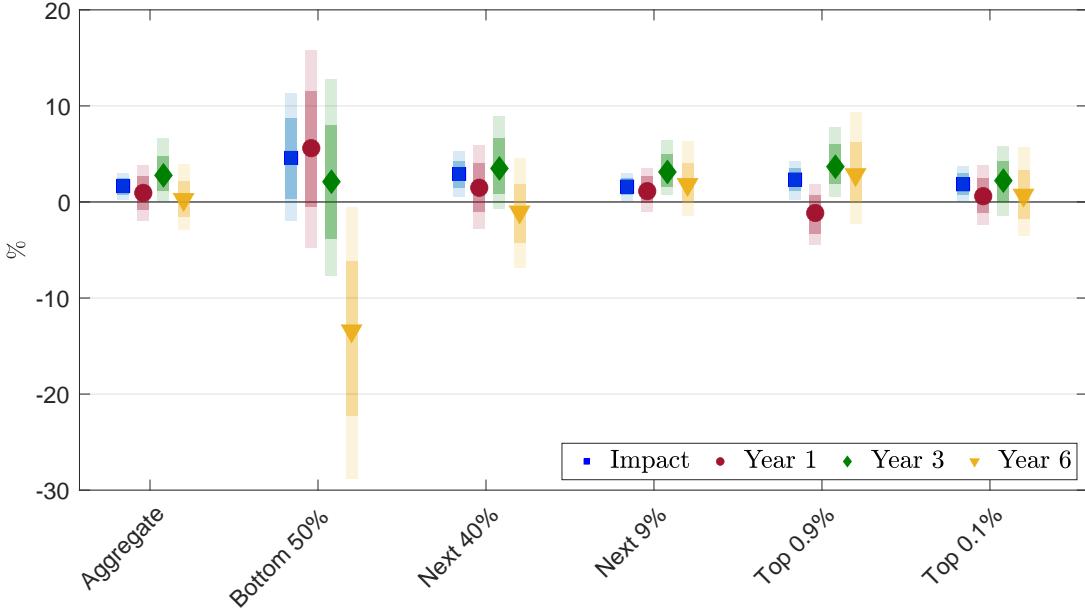


FIGURE 3. Change in net wealth after an interest rate shock

Notes: The figure shows the response of real net wealth to an interest rate shock estimated from the group-specific Bayesian VAR described in Table 2, Panel B. Net wealth is deflated using the consumer price index. Markers are median impulse responses from the posterior distribution. Intervals are 68% posterior coverage bands. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. See Figure C.2 in Appendix C for the full impulse response functions.

tion, net wealth initially rises, with a significant peak increase of 10.5% reached the quarter following the shock (see also Figure C.2 for the full dynamic response). In the medium-run, however, this initial gain fully reverses, with a striking and statistically significant decline of 13% six years after the shock. For the top 0.1%, the impact increase in net wealth is smaller in percentage terms but statistically significant. Thereafter, the response remains positive but is no longer significant. Across the remaining groups, the contemporaneous impact is always positive and statistically significant. The next 40% exhibits a similar pattern to the bottom 50%, though its medium-term decline is not statistically significant. Interestingly, for the next 9% and the top 0.9% of the distribution, net wealth continues to rise in the medium term, albeit these effects are not precisely estimated.

We next examine the effect of an interest rate shock on wealth inequality. Figure 4 plots the full dynamics of wealth shares, shown as deviations from their sample averages (solid lines with markers).¹³ An expansionary interest rate shock reduces inequality

¹³Table C.1 in Appendix C reports the percentage change in net wealth, the corresponding (real)

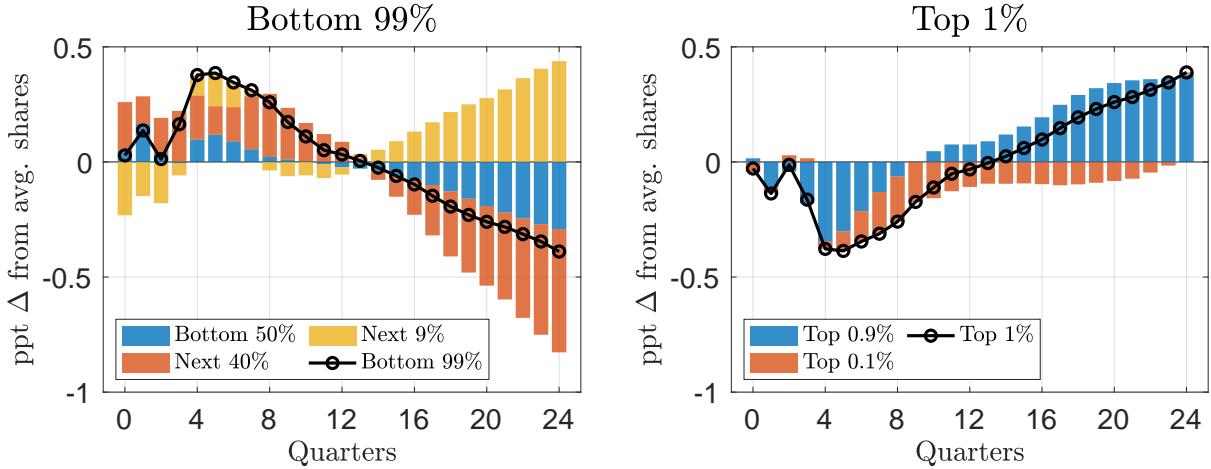


FIGURE 4. Change in wealth shares after an interest rate shock

Notes: The figure shows the implied response of wealth shares to an interest rate shock. Implied changes in wealth shares are expressed in deviation from their sample averages and using the median impulse response. See Section 4.2 for more details in the derivation of changes in wealth shares.

in the short-run but increases it in the medium-run, as indicated by the response of the top 1% wealth share. The initial decline in inequality is driven primarily by an increase in the wealth share of the next 40% and a decline in that of the top 0.9%. The bottom 50%, by contrast, experiences only a modest increase in its wealth share despite displaying the largest percentage increase in net wealth. This is a predictable outcome given that its average share of total wealth is just 2.34% over the sample period. In the medium-run, inequality rises: the top 1% wealth share increases, driven mainly by the top 0.9%. Within the bottom 99%, we observe a pronounced decline in the wealth share of the bottom 90%.

We next turn to the two channels driving these results: housing and corporate equities and mutual funds.

4.3.1. Housing wealth channel

An interest rate shock generates a pronounced boom–bust pattern in net wealth for the bottom 50%. For this group, the shock initially increases real estate values relative to home mortgage liabilities, producing a short-run expansion in net housing wealth (Figure 5, Panel A, first row). In the medium-run, however, mortgage balances rise

dollar change, and the implied change in wealth shares following an interest rate shock. Reporting dollar changes helps to highlight that seemingly uniform percentage responses can translate into highly heterogeneous effects on wealth accumulation and distribution, depending on initial wealth levels.

persistently relative to real estate holdings, causing net housing wealth to decline. Given the central role of housing in the balance sheet of households in the bottom 50%, it is plausible that the overall response of net wealth to monetary policy for this group is driven almost entirely by changes in net housing wealth.

To assess the importance of net housing wealth, we re-estimate the models in Table 2, Panel B, replacing net wealth with non-housing wealth (defined as net wealth minus net housing wealth). Figure 5, Panel A, second row, presents the outcomes of this exercise. For the bottom 50%, we now find no evidence of a boom–bust pattern but rather an essentially flat response, thus confirming the key role of housing for this group. For higher-wealth groups, particularly the top 1%, housing constitutes a smaller share of total assets and plays a more limited role in shaping their response to an interest rate shock. Accordingly, the difference between net wealth and non-housing wealth largely disappears as we move toward the top of the distribution.

We now turn to the implications of housing for the distributional effects of an interest rate shock. Figure 6, Panel A, plots the implied changes in wealth shares derived from the response of non-housing wealth (bars). We compare the dynamics of the bottom 99% and top 1% wealth shares based on non-housing wealth (solid line with circles) with the baseline results from total net wealth (solid line with crosses). When housing is excluded, the initial reduction in inequality is more short-lived: by the second year (quarter 8) after the shock, the non-housing wealth share of the top 1% begins to rise while that of the bottom 99% falls, and both trends persist thereafter. This pattern arises because the expansion in net housing wealth experienced by the bottom 50%, and, to a lesser extent, by the next 40%, is removed. The importance of housing for the bottom 50% is further highlighted from their negligible contribution to movements in the bottom 99% share of non-housing wealth.



FIGURE 5. Interest rate shock: channels

Notes: The figure shows the impulse response functions to an interest rate. Baseline refers to the response of net wealth. W/o housing refers to the response of non-housing wealth (net wealth net of real estate and home mortgages) in Panel A. W/o corp. eq. refers to the response of net wealth net of corporate equities and mutual funds in Panel B. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid and dashed lines are median impulse responses from the posterior distribution. Shaded areas are 68% posterior coverage bands.

4.3.2. Corporate equities and mutual funds channel

We now turn to the role of corporate equities and mutual funds, applying the same strategy used for housing. Figure 5, Panel B (first row), shows that these assets increase briefly in the short-run following an interest rate shock. This response closely tracks the dynamic of stock prices (see Figure C.3 in Appendix).

Panel B (second row) then reports the response of net wealth excluding corporate equities and mutual funds, alongside the baseline results. For the bottom 50%, these assets play virtually no role in shaping the response of net wealth to an interest rate shock. Their importance, however, increases steadily across the distribution. For the top 1% in particular, the short-run increase in net wealth observed in the baseline disappears once these assets are excluded, indicating that corporate equities and mutual funds constitute the primary channel through which monetary policy affects wealth at the top. Moreover, the strong similarity between the responses of corporate equities and mutual funds and those of stock prices (see Figure C.3 in Appendix) suggests that the wealth gains at the top largely reflect revaluation effects.

Figure 6, Panel B, illustrates how corporate equities and mutual funds contribute to the distributional effects of an interest rate shock. In the baseline model, an interest rate shock initially reduces inequality but raises it in the medium-run (solid line with crosses). When these assets are excluded, the short-run reduction in inequality becomes slightly stronger, while the medium-term increase is much smaller (solid line with circles). This difference is partly driven by the behavior of corporate equities and mutual funds held by the top 0.9%, whose gains rise beyond the increase in stock prices. Because corporate equities constitute almost one third of the top 0.9%'s portfolio, shutting down this source of wealth growth nearly eliminates the medium-run rise in the wealth share of the top 1%.

Finally, the wealth share of the bottom 50% is almost unchanged when corporate equities and mutual funds are excluded, as these assets represent less than 3 percent of their balance sheets. For this group, we still observe a sizable medium-term decline in its wealth share, reinforcing the central role of net housing wealth documented earlier.

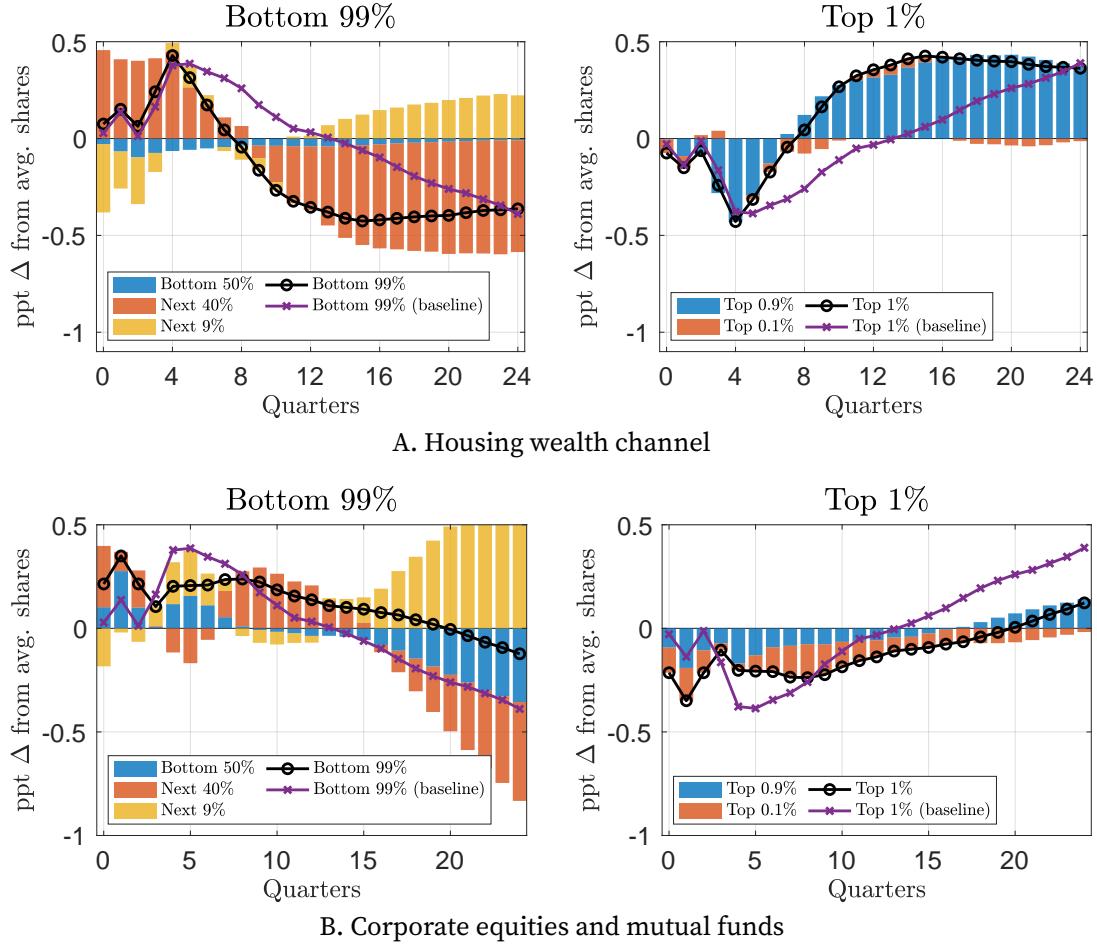


FIGURE 6. Interest rate shock and wealth inequality: channels

Notes: The figure shows the implied response of wealth shares to an interest rate shock. In Panel A, vertical bars and solid lines with circles are changes in wealth shares with wealth defined as non-housing wealth (net wealth net of real estate and home mortgages). In Panel B, vertical bars and solid lines with circles are changes in wealth shares with net wealth defined as total assets minus all debts and liabilities, net of corporate equities and mutual funds (Panel B). In both panels, Solid lines with crosses are changes in wealth shares with net wealth defined as total assets minus all debts and liabilities (baseline). Implied changes in wealth shares are expressed in deviation from their sample averages and using the median impulse response. See Section 4.2 for more details in the derivation of changes in wealth shares.

4.4. Asset purchase shock

We now turn to the distributional effects of unconventional monetary policy. An asset purchase shock initially increases net wealth both in the aggregate and across wealth groups with the effects dissipating in the medium-run. The only exception is the next 40%, the shock has almost no effect on net wealth at all horizons. However, although

the shape of the responses is similar across groups, the size varies. As before, it is useful to contrast the bottom 50% with the top of the distribution, as these groups present very different portfolio compositions. For the bottom 50%, an asset purchase shock significantly raises net wealth in the short-run with larger responses relative to all other groups (7.4% at impact and 7.9% after one year). Thereafter, the effect reverts toward zero. For the top 0.1%, instead, we observe a stronger cyclical: net wealth initial increases, then decreases, and finally fully reverts toward zero. These effects, however, are significant only at the 68% credibility intervals.

Figure 8 indicates that an asset purchase shock initially increases wealth inequality, but this effect is transitory (solid lines with markers).¹⁴ An expansionary asset purchase shock increases inequality (as measured by the top 1% wealth share) in the short-run, with no lasting effect in the medium-run. Despite recording the largest growth in net wealth, the bottom 50% experiences a comparatively small increase in its wealth share, reflecting its very low initial level of wealth. The initial rise in inequality is mainly driven by a decline in the wealth share of the next 40%, reflecting that their net wealth remains unchanged in the short-run while it increases for all other groups. The top 0.9% also contributes substantially to the increase in inequality. Over time, consistent with the transitory effects on wealth of most groups, the top 1% share gradually returns to its pre-shock level. Following the same approach we used for conventional monetary policy, we now proceed to examine the role of housing and corporate equities and mutual funds.

4.4.1. Housing wealth channel

An asset purchase shock has mixed effects on real estate and home mortgages across the wealth distribution (Figure 9, Panel A, first row). For the bottom 50%, real estate values initially increase but subsequently decline, though not persistently. For households between the 50th and 99th percentiles, real estate falls on impact but gradually reverts toward its pre-shock level. At the top of the distribution, the response is small and not statistically significant. Interestingly, house prices appear to play little or no role in driving these movements in real estate values (see Figure C.3). The response of home mortgages also varies across groups: mortgages fall for the bottom 50% and the next 40%; they rise temporarily for the next 9% before declining; they increase together with real estate for the top 0.9%; and they rise, though somewhat erratically, for the top 0.1%.

¹⁴As with the interest rate shock, Table C.2 in Appendix C reports the changes in wealth sharers along with the corresponding dollar changes in real net wealth.

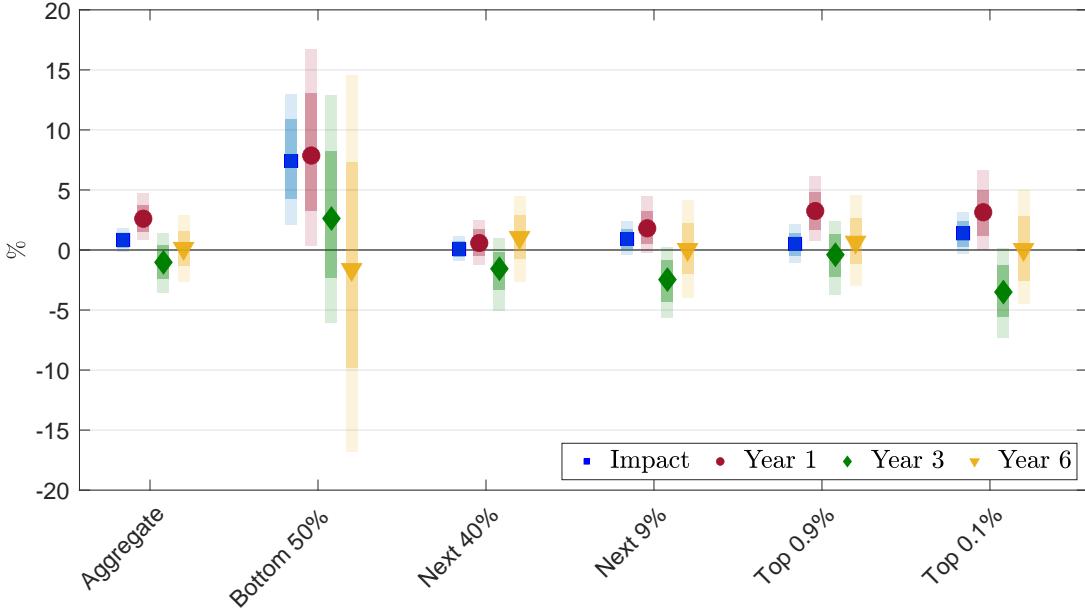


FIGURE 7. Change in net wealth after an asset purchase shock

Notes: The figure shows the response of real net wealth to an asset purchase shock estimated from the group-specific Bayesian VAR described in Table 2, Panel B. Net wealth is deflated using the consumer price index. Markers are median impulse responses from the posterior distribution. Intervals are 68% posterior coverage bands. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. See Figure C.2 in Appendix C for the full impulse response functions.

To better understand how the housing wealth channel operates for very different types of households, we focus again on the bottom 50% and the top 0.1%. For the bottom 50%, the combination of a temporary increase in real estate and an immediate, persistent decline in mortgages leads to a rise in net housing wealth. The implication of this pattern is visible in the second row of Figure 9, Panel A: when the influence of real estate and mortgages is removed, the short-run increase in net wealth becomes noticeably smaller. Non-housing wealth (dashed line) does increase for this group, but much less than total net wealth (solid line with markers). The rise in non-housing wealth appears to be driven primarily by other components, most notably pension entitlements. At the opposite end of the distribution, we find no meaningful contribution from the housing wealth channel, consistent with the greater portfolio diversification of wealthy households. Likewise, this channel plays only a limited role for all groups in between.

Figure 10, Panel A, illustrates the implications for wealth inequality. An asset purchase shock initially raises inequality, both in non-housing wealth (solid line with circles) and in net wealth (solid line with crosses). Inequality in non-housing wealth

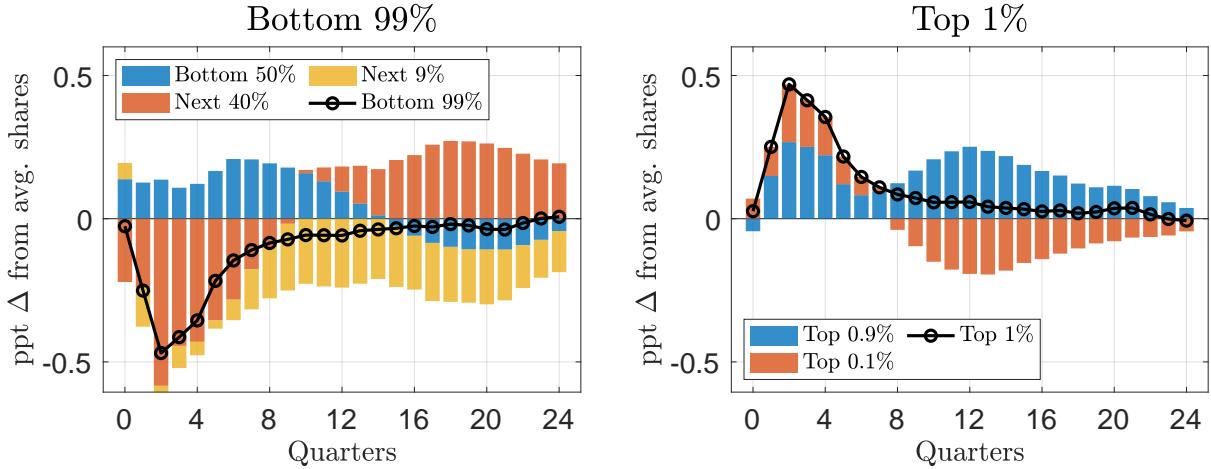


FIGURE 8. Change in wealth shares after an asset purchase shock

Notes: The figure shows the implied response of wealth shares to an interest rate shock. Implied changes in wealth shares are expressed in deviation from their sample averages and using the median impulse response. See Section 4.2 for more details in the derivation of changes in wealth shares.

increases in the medium-run before gradually returning to baseline. The wealth share of the bottom 50% in non-housing wealth remains essentially flat, reflecting the fact that housing is by far the dominant component of their balance sheets. Overall, excluding housing only marginally alters the movements in wealth shares, and the transitory nature of the distributional effects remains.

4.4.2. Corporate equities and mutual funds

An asset purchase shock raises corporate equities and mutual funds across the distribution for roughly two to three years before these assets revert (Figure 9, Panel B, first row). For the bottom 90%, this response closely mirrors movements in stock prices (Figure C.3). For the top 10%, however, two interesting dynamics emerge. First, although the initial rise in corporate equities and mutual funds matches the response of stock prices, the response of these assets begin to revert earlier. Second, before returning to baseline, their response briefly turns negative. These patterns suggest that households in the top 10% may rebalance their portfolios after the appreciation, either by realizing capital gains or by shifting appreciated assets into retirement accounts not subject to capital gains taxation (Campbell, Robbins, and Wylde 2025).

Figure 9, Panel B, second row, examines how these movements contribute to the response of net wealth. For the top 10%, corporate equities and mutual funds explain

the short-run increase and subsequent medium-run decline in net wealth, especially for the next 9%. For all other groups, particularly the bottom 50%, corporate equities and mutual funds play only a marginal role.

Finally, we assess the role of these assets in shaping the distributional effects of an asset purchase shock (see Figure 10, Panel B). When these assets are excluded, the short-run increase in the wealth share of the top 1% is noticeably smaller than in the baseline (solid lines with circles against solid lines with crosses). In the medium-run, however, excluding these assets causes the asset purchase shock to raise inequality even at longer horizons. This pattern reflects the fact that corporate equities and mutual funds rise sharply in the short-run but smoothly decline in the medium-run.

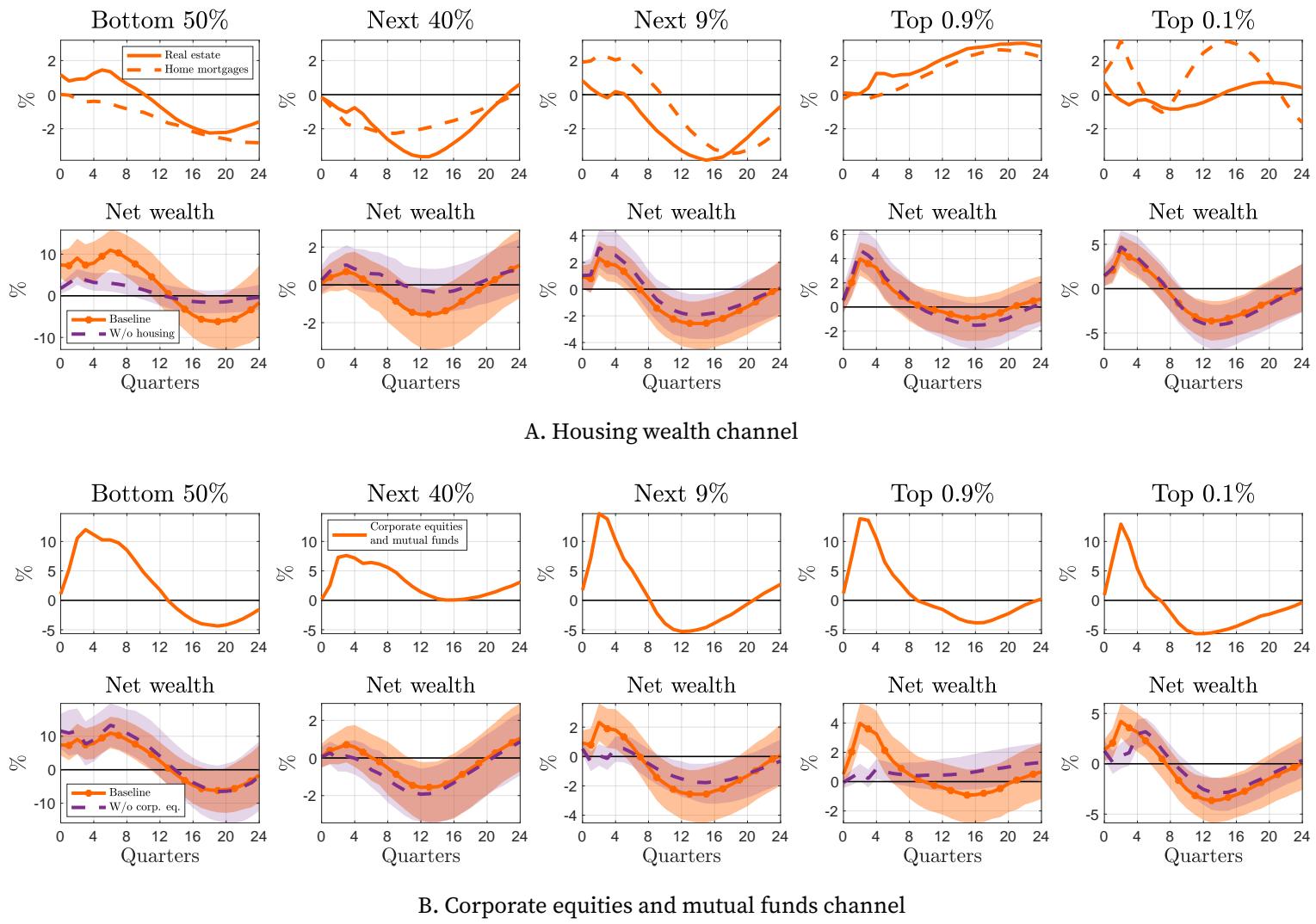


FIGURE 9. Asset purchase shock: channels

Notes: The figure shows the impulse response functions to an asset purchase. Baseline refers to the response of net wealth. W/o housing refers to the response of non-housing wealth (net wealth net of real estate and home mortgages) in Panel A. W/o corp. eq. refers to the response of net wealth net of corporate equities and mutual funds in Panel B. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid and dashed lines are median impulse responses from the posterior distribution. Shaded areas are 68% posterior coverage bands.

4.5. Discussion

The results in this section provide new evidence on how different types of monetary policy affect wealth inequality. A central stylized fact emerges: interest rate and asset purchase shocks generate very different distributional dynamics. An interest rate shock leads to long-lasting changes in the wealth share of the top 1%, whereas an asset purchase shock induces cyclical fluctuations that largely dissipate at longer horizons. Moreover, monetary policy shocks matter for the dynamics of wealth shares well beyond the simple top 1% versus bottom 99% split, indicating persistent effects across the entire wealth distribution. These patterns are consistent with recent heterogeneous-agent models, which also find persistent movements in wealth shares in response to business-cycle shocks ([Bayer, Born, and Luetticke 2024](#)). Another important result is the reversal in net wealth for the bottom 50% following an interest rate shock, which contributes both to the evolution of their wealth share and to the overall distributional impact of monetary policy. Before studying this reversal in more detail in Section 6, it is useful to review the distinct mechanisms through which asset purchases and interest rate policies generate different distributional consequences.

First, asset prices respond differently to interest rate and asset purchase shocks (see Figure C.3). An interest rate shock produces a persistent, hump-shaped increase in house prices, but only short-lived, albeit large, effects on stock prices. By contrast, an asset purchase shock has small effects on house prices but large and persistent effects on stock prices.¹⁵ Understanding the distributional consequences of these price movements requires considering the structure of portfolio compositions. For example, we find that groups with portfolios heavily concentrated in housing, such as the bottom 50%, experience relatively larger gains in net wealth after an interest rate shock that raises house prices. Other groups also benefit from higher house prices, but the impact on their net wealth is smaller because their portfolios are more diversified and, at the top of the distribution, skewed toward equities. Similarly, the rise in stock prices following monetary policy shocks primarily boosts the net wealth of households that hold a large share of equities in their portfolios. For the United States, previous work has shown that asset price changes following interest rate shocks have distributional effects precisely because the ultimate effect on net wealth depends on portfolio composition ([Bartscher et al. 2022](#)). Our findings confirm this mechanism for interest rate policy

¹⁵The small response of house prices to an asset purchase shock is consistent with [Gorea, Kryvtsov, and Kudlyak \(2025\)](#), who find that list prices for properties that eventually sell do not respond to monetary policy shocks. Most house price indices, including the Case–Shiller index used here, are based on sale prices rather than list prices.

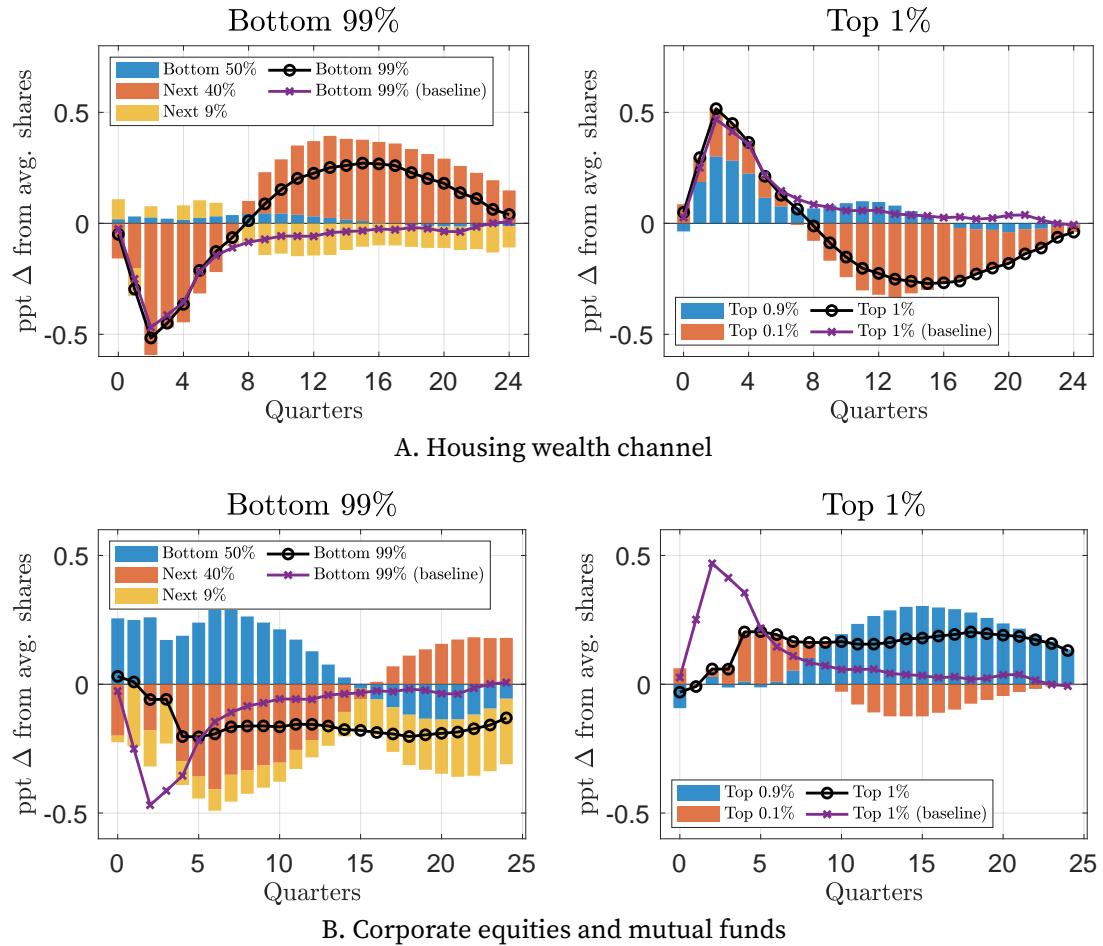


FIGURE 10. Asset purchase shock and wealth inequality: channels

Notes: The figure shows the implied response of wealth shares to an asset purchase shock. In Panel A, vertical bars and solid lines with circles are changes in wealth shares with wealth defined as non-housing wealth (net wealth net of real estate and home mortgages). In Panel B, vertical bars and solid lines with circles are changes in wealth shares with net wealth defined as total assets minus all debts and liabilities, net of corporate equities and mutual funds (Panel B). In both panels, Solid lines with crosses are changes in wealth shares with net wealth defined as total assets minus all debts and liabilities (baseline). Implied changes in wealth shares are expressed in deviation from their sample averages and using the median impulse response. See Section 4.2 for more details in the derivation of changes in wealth shares.

and extend it to unconventional policy.

Second, borrowing helps explain further why asset purchases and interest rate policies produce different distributional outcomes. After an interest rate shock, we document that the value of real estate assets increase consistently across the distribution, but home mortgages rise more at the bottom than elsewhere. A relatively larger increase in mortgages at the bottom is consistent with the idea that lower interest rates induce previously constrained households to enter homeownership ([Bhutta and Ringo 2021](#)) and stimulate refinancing activity ([Berger et al. 2021](#)). These forces, combined with the different relevance of housing in household portfolios, are central to understanding the heterogeneous effects of an interest rate shock.

The response of mortgages is also crucial for the distributional effects of an asset purchase shock. In this case, we find that an asset purchase shock leads to a permanent decline in home mortgages for the bottom 90% and an increase for the top 10%. This divergence is consistent with the segmentation of the U.S. mortgage market, which causes the effects of monetary policy to vary along several dimensions. One important dimension is eligibility for purchase by the Federal Reserve under QE programs. [Di Maggio, Kermani, and Palmer \(2020\)](#) show that QE1, which largely focused on purchasing conforming MBS, raised refinancing activity and reduced interest payments more for QE-eligible mortgages than for non-eligible ones. [Fuster and Willen \(2010\)](#) find that the QE1 announcement affected mortgage rates unevenly across borrowers, had little effect on home purchases, and stimulated refinancing disproportionately among borrowers with high credit scores. Other studies show that refinancing activity also varies along other dimensions of inequality, including income ([Agarwal et al. 2024](#)) and race ([Gerardi, Willen, and Zhang 2023](#)). Although our data do not allow us to observe credit scores, loan-to-value ratios, or other borrower characteristics across the wealth distribution, it is plausible that low-credit-score, low-income, and minority borrowers are concentrated outside the top 10% of the wealth distribution. Our finding of heterogeneous responses of mortgages to asset purchase shocks across wealth groups thus likely reflects underlying segmentations in the mortgage market. This suggests that the interaction between the composition of large-scale asset purchases and mortgage market segmentation is a key determinant of the distributional effects of asset purchases, an important avenue for future research.

5. Sensitivity analysis

In this section, we discuss some potential pitfalls of the econometric methodology we use and show that the results are robust to deviations from our baseline specification.

Interest rate shock. The method adopted by [Jarociński and Karadi \(2020\)](#) to isolate pure monetary policy surprises assumes a non-negative response of stock prices. Because stocks are an important component of household wealth, the assumption might imply a specific response of wealth to the shock. We test the robustness of our findings to this assumption by using alternative measures of interest rate surprises. Specifically, we use the surprise series of [Gertler and Karadi \(2015\)](#), [Miranda-Agrippino and Ricco \(2021\)](#), and [Aruoba and Drechsel \(2022\)](#). Based on these alternative measures of interest rate shocks, the results remain largely unchanged as shown in Figure D.3 in Appendix D.

Asset purchase shock. The large-scale asset purchase factor of [Swanson \(2021\)](#) takes nonzero values in the years before the Great Recession, when the Federal Reserve did not rely on unconventional policy. To rule out the possibility that our results are driven by fluctuations in the large asset purchase factor before 2008, we set the factor to zero for the quarters before 2008. Figure D.1 and Figure D.2 in the Appendix D.1 show that neither the macroeconomic nor the distributional effects of an asset purchase shock are driven by pre-2008 fluctuations in the factor.

Model specification. To rule out that our medium-run estimates of the distributional effects of monetary policy are sensitive to using a VAR model, we increase the lags of the model and use local projections as robustness checks. Figure D.4 shows that our baseline results are robust to increasing the VAR lag length to 6 and 8. As a further check, we estimate the dynamic effects of monetary policy shocks using local projections.¹⁶ Figure D.6 shows that our findings are robust to using local projections.

6. Conventional monetary policy and the wealth reversal

An important finding from the previous section is the wealth reversal experienced by households at the bottom of the distribution following an interest rate shock. In this

¹⁶Local projections are an alternative and popular method of estimating the dynamic impulse response to a shock of interest. We use traditional ([Jordà 2005](#)) and smooth ([Barnichon and Brownlees 2019](#)) local projections (see Appendix D.4 for more details).

section, we provide additional evidence on this reversal. We proceed in two steps. First, we separate changes in net housing wealth that are driven by price revaluation from those driven by changes in quantities. Second, we use household-level data from the Panel Study of Income Dynamics (PSID) to study the reversal in a panel setting, thereby addressing a key limitation of the SCF (and therefore of the DFA), namely the lack of a true panel structure.

For an asset purchase shock, the joint responses of real estate and home mortgages also matter, but they play a smaller role. Even when we turn off housing, net wealth still increases slightly, likely due to the response of pension assets. Several features of the PSID, however, make it ill-suited for analyzing the distributional effects of an asset purchase shock. First, asset purchases are likely to interact with mortgage market segmentation and the PSID contains no detailed information on mortgage characteristics. Second, the distributional effects of an asset purchase shock occur also through corporate equities which are poorly covered by the PSID as it underrepresents the very top of the wealth distribution. Third, the PSID offers no information on pension wealth (apart from IRAs). For these reasons, in this section we focus on conventional monetary policy and do not attempt to study the distributional effects of asset purchase shocks using the PSID.

6.1. Price vs. Quantity

Figure 11 zooms in the dynamics of the wealth reversal for the bottom 50%. After a shock, real estate holdings rise before gradually returning toward their pre-shock level (panel A, solid line). The response of home mortgages is more sluggish (panel B, solid line), but its response surpasses that of real estate and remains significantly positive throughout the impulse response horizon. The combined responses of real estate and home mortgages can potentially explain short-run wealth growth and the medium-run reversal. This can be seen more clearly in panel C, where we overlay the response of housing net wealth (real estate net of home mortgages) with that of total net wealth. This mechanism underlies what we term the wealth reversal at the bottom of the wealth distribution.¹⁷

Part of the increase of real estate holdings can be explained by rising prices, as

¹⁷To obtain the impulse response of net housing wealth, we first compute the difference in dollar changes in real estate and home mortgages implied by their respective impulse responses. Then, we express the impulse response of housing net wealth as $IRF_h = w_h/w - 1$, where w_h denotes real housing net wealth h periods ahead and w is the average real housing net wealth over the estimation sample (see also equation 5).

shown in panel A.¹⁸ Revaluations and house prices, however, rise with a lag of about four quarters before gradually reverting, suggesting that the initial jump in real estate is driven by new investment activity stimulated by lower rates and stronger housing market conditions, consistent with a reduction in the external finance premium (Bernanke, Gertler, and Gilchrist 1999) and increase participation (Bhutta and Ringo 2021). Lower borrowing costs and higher net housing wealth may encourage households to increase borrowing via home equity loans. Indeed, Panel B shows that home equity loans increase in response to an interest rate shock.¹⁹

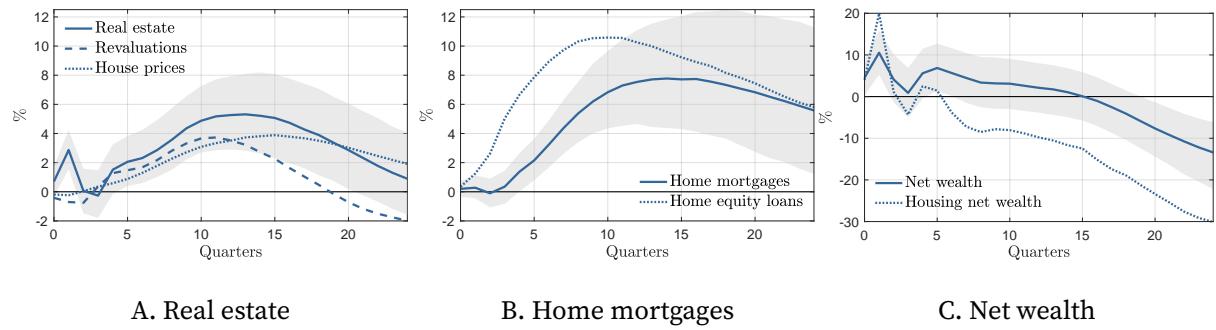


FIGURE 11. The wealth reversal at the bottom 50%

Notes: The figure shows impulse response functions to an interest rate shock. Panel A reports median posterior impulse responses of real estate (solid line, with 68% posterior coverage bands), revaluations (dashed line), and house prices (dotted line). Panel B reports median posterior impulse responses of home mortgages (solid line, with 68% posterior coverage bands) and home equity loans (dotted line). Panel C reports median posterior impulse responses of net wealth (solid line, with 68% posterior coverage bands) and the implied response of housing net wealth (dotted line).

6.2. The Panel Study of Income Dynamics

While the DFA provide a valuable starting point for estimating the effects of monetary policy across the wealth distribution, their group-level structure introduces an important limitation. Changes in wealth by percentile groups can conflate two mechanisms:

¹⁸Revaluations, or capital gains, are taken from Table R.101 of the Financial Accounts. We allocate the aggregate revaluations of real estate holdings to the bottom 50% of the wealth distribution using their share of total real estate assets as weights. These revaluations are then cumulated over time to construct a measure of the stock of real estate reflecting only price changes. The resulting series is used to estimate impulse responses within a group-level VAR, in which real estate assets are replaced by revaluations.

¹⁹To estimate home equity loans for the bottom 50% of the wealth distribution, we allocate aggregate home equity loans reported for the total household sector in the table B.101h Balance Sheet of Households table of the Financial Accounts. The allocation uses the bottom 50%'s share of total mortgages as weights. The resulting series is then used to estimate impulse responses within a group-level VAR, in which home mortgages are replaced by home equity loans.

within-group changes in wealth for the same households, and between-group (composition) effects, where households become poorer or richer and move across the wealth distribution. As a result, relying solely on the DFA does not allow us to disentangle whether our estimates reflect the effect of monetary policy on the same households over time or the effects of mobility across wealth groups.

To better understand how monetary policy affects wealth dynamics at the household level, we require a panel structure. The SCF, the gold standard for measuring household wealth and the survey underlying the DFA, has only a repeated cross-sectional structure. A natural alternative is the PSID, which has collected wealth information every two years since 1999.

Before introducing the PSID in more detail, it is useful to recall some key differences relative to the SCF and, by extension, the DFA ([Insolera, Simmert, and Johnson 2021](#); [Cooper, Dynan, and Rhodenbiser 2019](#); [Pfeffer et al. 2016](#)). Compared with the PSID, the SCF oversamples wealthy households, which is essential for studying of wealth concentration. The SCF also provides a more detailed breakdown of assets and liabilities, capturing highly concentrated forms of wealth such as private business ownership. Another important difference concerns pension assets: the PSID excludes pensions other than IRAs, whereas the SCF includes defined-contribution (DC) retirement accounts such as 401(k)s. The DFA further augment SCF-based wealth by incorporating defined-benefit (DB) pensions and annuities recorded in the national accounts but not directly measured in the SCF. These differences prevent us from establishing a clear mapping between wealth groups in the DFA and the PSID when using the latter to estimate the effects of monetary policy. Despite these limitations for analyzing assets concentrated at the very top, the PSID is well suited for studying housing wealth, which dominates the balance sheets of middle- and lower-wealth households.

To study the wealth reversal, we use the PSID–SHELF Longitudinal File ([Pfeffer, Daumler, and Friedman 2025](#)), which provides a harmonized version of core PSID variables, including wealth and its components. We exploit all available waves between 1999 and 2019. Sample restrictions follow [Blundell, Pistaferri, and Saporta-Eksten \(2016\)](#). We exclude households from the Survey of Economic Opportunities and focus on households whose head was born after 1920, is aged between 20 and 70, and for whom net wealth can be observed. In addition, we drop household-wave observations (138 in total) with extreme changes in net wealth. When estimating the effects of monetary policy, we further restrict the sample to households observed for at least four consecutive waves. This setup allows us to trace wealth responses at the household level over a horizon

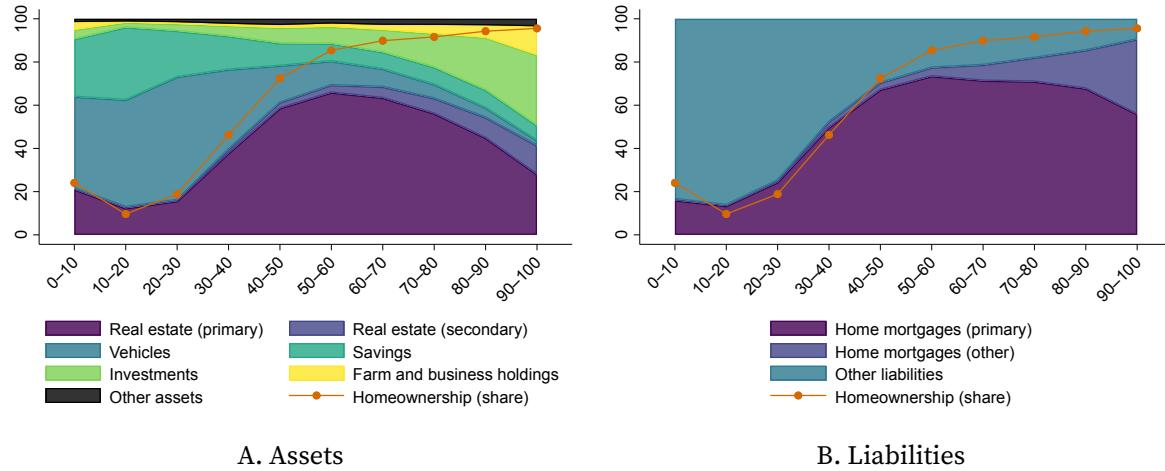
comparable to the impulse response functions obtained from the DFA-based VAR.

In the PSID, net wealth is defined as the sum of the following components: the gross value of the primary residence (or primary real estate); the value of real estate other than the primary home (reported only net of debts before 2013); the net value of vehicles; savings (cash and checking accounts, bonds, and CDs); investments (stocks, IRAs, and annuities); farm and business holdings (net equity); and other assets, net of mortgages and other liabilities (credit cards, student loans, medical bills, etc.). In Figure 12, we sort households into deciles of the wealth distribution and plot average asset holdings (Panel A) and liabilities (Panel B) for each decile, averaging across all waves from 1999 to 2019.

In terms of portfolio composition, the PSID paints a picture that is qualitatively similar to the DFA, with housing wealth losing importance for richer households (see Table 1). However, the PSID also reveals substantial heterogeneity within the bottom 50%, which the DFA aggregates into a single group. Primary housing is the most important asset for households between the 30th and 90th percentiles. Likewise, mortgages on the primary residence are the largest component of liabilities for households above the 30th percentile. We therefore expect households in this range to be most exposed to the wealth reversal. Below the 30th percentile, vehicles are the largest component of wealth, followed by savings such as bank accounts. Households in the poorest percentile reports holdings of farm and personal businesses in shares comparable to households in the 70th–80th percentiles. However, for many of these households equity in these businesses enter with negative sign. The share of investments (which include corporate equities) rises quickly starting around the 70th percentile and becomes the largest asset class for households in the top 10%. In each panel, we also plot the share of homeowners by decile. Virtually most households in the richest half of the distribution are homeowners. In contrast, less than a fifth of households in the first three deciles own a home, implying that most households at the bottom are renters. This pattern is also reflected in the large importance of non-mortgage liabilities among households at the bottom of the wealth distribution.

6.3. Household-level evidence on the wealth reversal

Our empirical model follows [Holm, Paul, and Tischbirek \(2021\)](#). We divide households into groups and estimate separate impulse responses for each wealth group. A household i is allocated to group g in period t if its net wealth in $t - 1$ lies between the $g - 1$ -th and g -th percentiles of the distribution. Ordering households according to lagged net wealth



A. Assets

B. Liabilities

FIGURE 12. PSID portfolio composition, 1999-2019

Notes: The figure plots the average composition of assets (Panel A) and liabilities (Panel B) across wealth groups using the Panel Study of Income Dynamics (1999-2019).

ensures that group allocation is unaffected by the contemporaneous monetary policy shock, thus avoiding the problem of mobility across wealth groups. It is important to stress that, due to differences in wealth definitions and population coverage, there is no direct correspondence between PSID and DFA wealth groups. Specifically, we consider the following wealth groups: 0–20, 20–40, 40–60, 80–90, and 90–100. For each wealth group g , we estimate the following local projections:

$$y_{i,t+h} = \delta_i^h + \beta_g^h \hat{s}_t^R + \sum_{k=1}^K \gamma_{g,k}^h X_{i,t-k} + u_i^h \quad \forall i \in g, \quad (7)$$

where $y_{i,t}$ is a household-level i outcome variable, δ_i is a constant, \hat{s}_t^R is the interest rate shock, and $X_{i,t-k}$ includes controls such as one lag of the shock, three lags of the dependent variable, and 10-year age group dummies to capture life-cycle effects. Because the PSID is conducted every two years, the horizons of the local projections are set to $h = 0, 2, 4, 6$ years. We cluster standard errors at the household level and report 90% confidence intervals.

We begin by estimating a version of equation (7) in which the outcome variable is, alternatively, real estate assets, outstanding home mortgages, net housing wealth, or total net wealth, all expressed in natural logarithms. For this specification, we consider all households in the sample but focus our interpretation on those above the 20th percentile. As discussed earlier, the bottom 20% is a highly heterogeneous group in

which about 85% of households have zero or negative wealth, which drastically reduces the effective sample size. Moreover, in all specifications, we focus on primary real estate and mortgages on the primary home, as ownership of additional real estate is highly concentrated at the top (Figure 12).

Figure 13, Panel A, shows that real estate holdings rise following an interest rate shock across all wealth groups, including those at the extremes of the distribution, which are less exposed to housing in terms of portfolio composition. The response of home mortgages (which includes all mortgage balances on primary homes, including home equity loans) is initially not statistically significant but exceeds that of real estate between the second and fourth years after the shock and remains positive throughout the projection horizon. Panel B displays the wealth reversal. An interest rate shock boosts net housing wealth in the short run, with the peak increase occurring between impact and the second year after the shock, depending on the wealth group. Thereafter, the effect diminishes, and the response turns negative around four years after the shock. Although the timing of the reversal in net housing wealth does not perfectly match the DFA results, the qualitative pattern is similar. For wealth groups more exposed

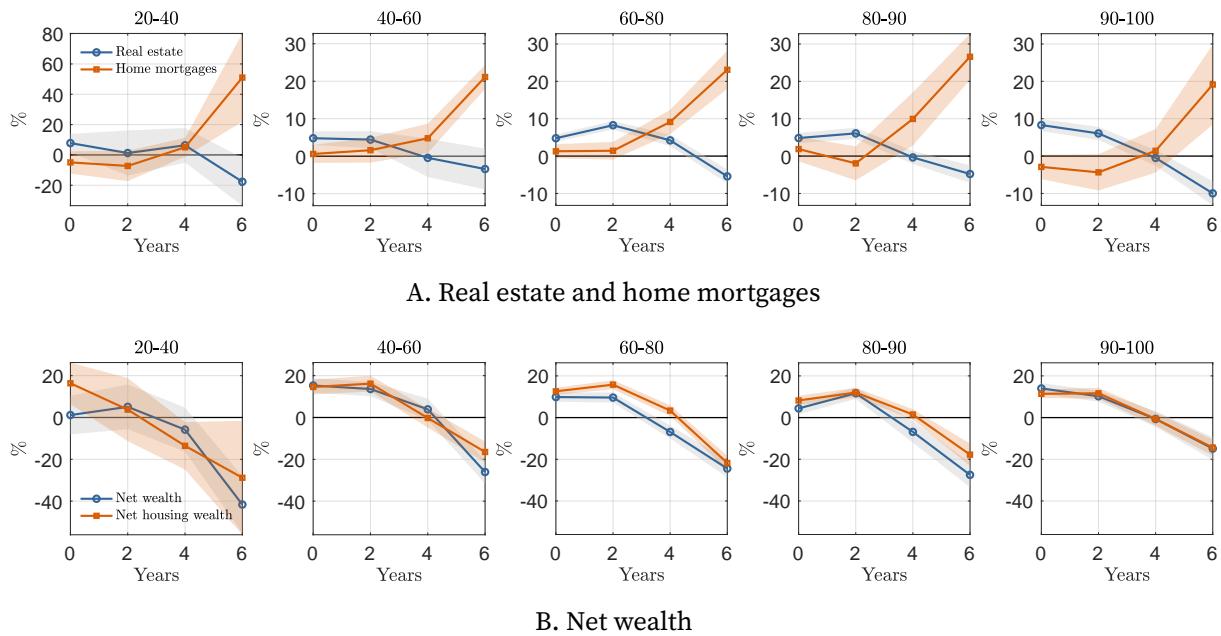


FIGURE 13. The wealth reversal: all households

Notes: The figure shows impulse response functions to an interest rate shock. Panel A reports impulse responses of the probability of being in real estate and home mortgages while Panel B reports impulse responses of net wealth and net housing wealth. Shaded bands are 90% confidence intervals.

to housing, we observe a strong correlation between the responses of net housing wealth and total net wealth. The relative movements of net wealth across groups are particularly informative, as they confirm, despite the use of a different dataset, that the medium-term contraction in net wealth is especially pronounced at the bottom of the distribution. In Figure C.4, we show that these effects are driven by indebted homeowners. These households experience a revaluation of their homes following a monetary policy shock and have stronger incentives to borrow against home equity, either to finance consumption or to invest further in housing (Cloyne, Ferreira, and Surico 2020).

For households at the bottom of the distribution that are financially constrained, a reduction in interest rates may also increase participation in homeownership, implying that part of the rise in real estate and net housing wealth reflects new home purchases. In Figure 14, we explore this mechanism by estimating a specification in which the outcome variable is a dummy indicating whether the household owns its primary residence. In Panel A, we estimate these specifications on a sample containing only households that were renters just before the shock. We also include the 0-20 percentile group which response overlays that of the 20-40 group. The impulse response then estimates the probability of being a homeowner by horizon h , conditional on being a renter before the shock. In Panel B, we do not restrict the sample and thus estimate the effect on the homeownership rate. The results suggest that at least part of the rise in net housing wealth stems from increased participation: the probability of being a homeowner increases for all groups, albeit larger estimates are observed at the top. The average within-group ownership rate increases too, with larger responses observed at the bottom of the wealth distribution. Overall, these results suggest that an interest rate shock increases the likelihood of becoming a homeowner, thus contributing to the initial rise in net wealth, providing additional evidence on the relationship between monetary policy and homeownership (Dias and Duarte 2022).

Finally, we examine whether part of the increase in home mortgages reflects borrowing against rising home values. In the PSID, households report the number of mortgages taken on their primary home. Using this information, we construct a dummy variable equal to one if the household has taken at least one additional mortgage beyond the first on its primary residence. We do not distinguish among multiple additional mortgages, as most households with more than one mortgage report only a single extra loan. We then use this indicator as the outcome variable in equation (7) and report the impulse responses in Figure 14, Panel C. For this specification, we restrict the sample

to homeowners with positive home equity, as they are the most likely to borrow against rising house prices, and that hold exactly one mortgage on their primary residence prior the shock. This allows us to estimate the effect of an interest rate shock on the probability that a single-mortgage homeowner takes out an additional mortgage by horizon h . We interpret this as evidence of increased borrowing against home equity. Our findings indicate that the probability of reporting an additional mortgage on the primary residence increases after an interest rate shock. To the extent that this indicator captures the use of home equity lines of credit, these results support the view that part

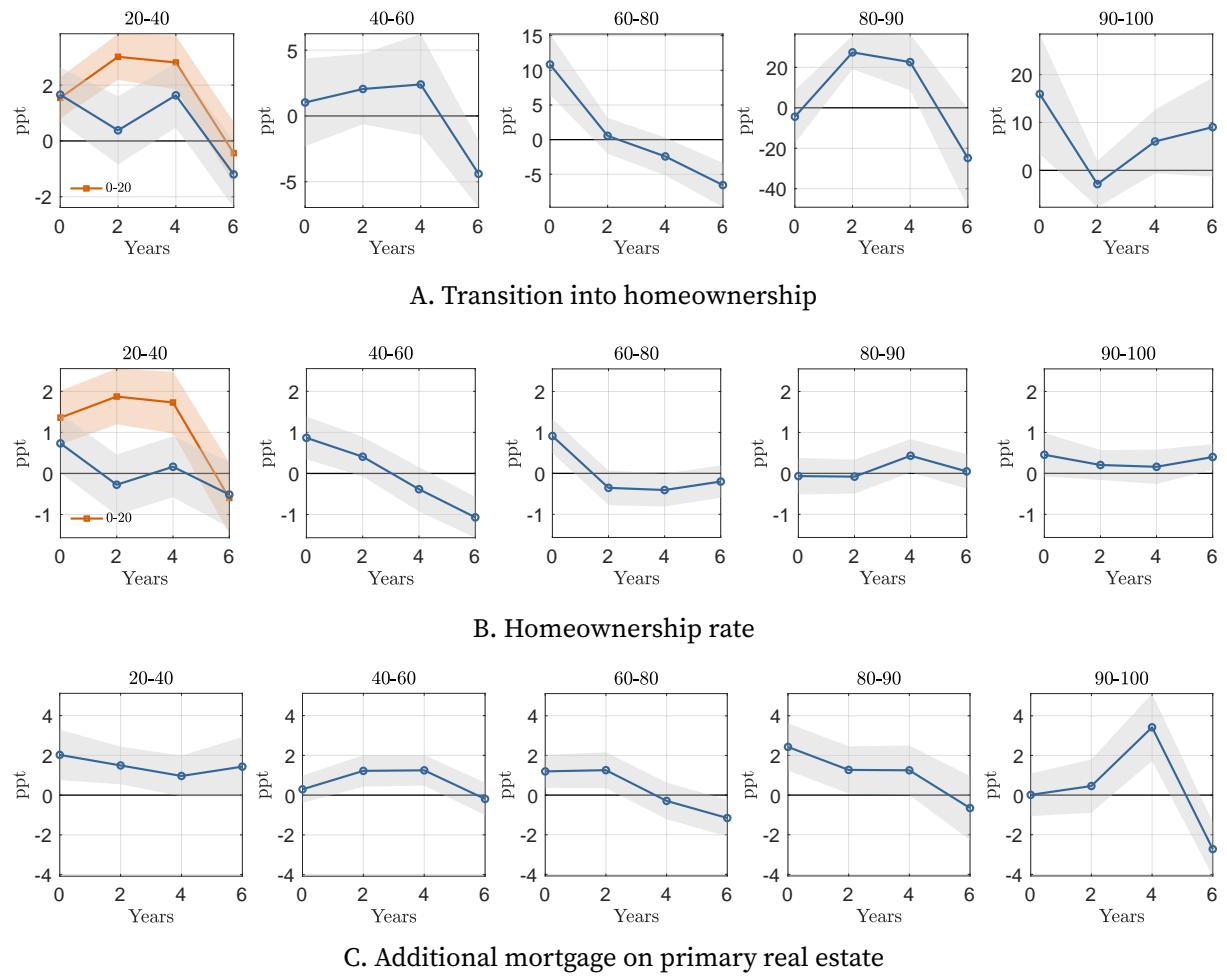


FIGURE 14. Ownership and borrowing

Notes: The figure shows impulse response functions to an interest rate shock. Panel A reports impulse responses of the probability of being a homeowner, conditional on being a renter before the shock. Panel B reports impulse responses of homeownership rate. Panel C reports the impulse responses of the probability that a single-mortgage homeowner takes out an additional mortgage. Shaded bands are 90% confidence intervals.

of the rise in home mortgage balances reflects borrowing against home equity.

To sum up, household-level PSID data also point to the existence of a wealth reversal following an expansionary interest rate shock. Lower interest rates lead to an expansion of real estate assets along both the intensive and extensive margins. This expansion eventually triggers an increase in borrowing, potentially driven by home equity loans and by more households entering homeownership. The resulting increase in home mortgage balances ultimately reduces net housing wealth and also lowers total net wealth. This mechanism contributes to the medium-term increase in wealth inequality after an expansionary interest rate shock.

7. Concluding remarks

In this paper, we provide new evidence on the effects of expansionary monetary policy on the wealth distribution in the United States. Our primary data source is the Distributional Financial Accounts, which provides quarterly estimates of the distribution of household wealth. We then use VAR models and distinguish between interest rate and asset purchase policies to estimate the distributional effects of monetary policy.

The distributional impact of monetary policy depends to a large extent on the type of policy instrument and the composition of net wealth. Expansionary interest rate shocks initially reduce wealth inequality but increase it in the medium term, while asset purchase shocks increase wealth inequality, albeit temporarily. Monetary policy affects household balance sheets mainly through housing wealth and corporate equities. However, the intensity of these channels vary across the wealth distribution.

Our findings inform the debate on the distributional effects of monetary policy and macroeconomic models that place household heterogeneity at the core of the monetary policy transmission mechanism. However, whether monetary policy should take distributional considerations into account in its formulation remains an open question.

References

- Agarwal, Sumit, Souphala Chomsisengphet, Hua Kiefer, Leonard C Kiefer, and Paolina C Medina. 2024. “Refinancing inequality during the COVID-19 pandemic.” *Journal of Financial and Quantitative Analysis* 59 (5): 2133–2163.
- Amromin, Gene, Neil Bhutta, and Benjamin J Keys. 2020. “Refinancing, monetary policy, and the credit cycle.” *Annual Review of Financial Economics* 12: 67–93.
- Andersen, Asger Lau, Niels Johannessen, Mia Jørgensen, and José-Luis Peydro. 2023. “Monetary policy and inequality.” *Journal of Finance* 78 (5): 2945–2989.
- Angelini, Elena, Jérôme Henry, and Massimiliano Marcellino. 2006. “Interpolation and backdating with a large information set.” *Journal of Economic Dynamics and Control* 30 (12): 2693–2724.
- Aruoba, S Boragan, and Thomas Drechsel. 2022. “Identifying monetary policy shocks: A natural language approach.” *American Economic Journal: Macroeconomics (forthcoming)*.
- Bach, Laurent, Laurent E Calvet, and Paolo Sodini. 2020. “Rich pickings? risk, return, and skill in household wealth.” *American Economic Review* 110 (9): 2703–47.
- Barnichon, Regis, and Christian Brownlees. 2019. “Impulse response estimation by smooth local projections.” *Review of Economics and Statistics* 101 (3): 522–530.
- Bartscher, Alina K, Moritz Schularick, Moritz Kuhn, and Paul Wachtel. 2022. “Monetary policy and racial inequality.” *Brookings Papers on Economic Activity* 2022 (1): 1–63.
- Batty, Michael, Jesse Bricker, Joseph Briggs, Sarah Friedman, Danielle Nemschoff, Eric Nielsen, Kamila Sommer, and Alice Henriques Volz. 2021. “The Distributional Financial Accounts of the United States.” In *Measuring Distribution and Mobility of Income and Wealth*, 641–677: National Bureau of Economic Research, Inc.
- Bauer, Michael D, and Eric T Swanson. 2023. “An alternative explanation for the Fed information effect.” *American Economic Review* 113 (3): 664–700.
- Bauluz, Luiz, Filip Novokmet, and Moritz Schularick. 2022. “The Anatomy of the Global Saving Glut.” *CESifo Working Paper (No. 9732)*.
- Bayer, Christian, Benjamin Born, and Ralph Luetticke. 2024. “Shocks, Frictions, and Inequality in US Business Cycles.” *American Economic Review* 114 (5): 1211–1247.
- Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra. 2021. “Mortgage pre-payment and path-dependent effects of monetary policy.” *American Economic Review* 111 (9): 2829–2878.
- Bernanke, Ben S, and Mark Gertler. 1995. “Inside the black box: the credit channel of monetary policy transmission.” *Journal of Economic Perspectives* 9 (4): 27–48.

- Bernanke, Ben S, Mark Gertler, and Simon Gilchrist. 1999. "The financial accelerator in a quantitative business cycle framework." *Handbook of Macroeconomics* 1: 1341–1393.
- Bernanke, Ben S, and Kenneth N Kuttner. 2005. "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of Finance* 60 (3): 1221–1257.
- Bhutta, Neil, and Daniel Ringo. 2021. "The effect of interest rates on home buying: Evidence from a shock to mortgage insurance premiums." *Journal of Monetary Economics* 118: 195–211.
- Blanchet, Thomas, and Clara Martínez-Toledano. 2022. "Wealth inequality dynamics in europe and the united states: Understanding the determinants." *Journal of Monetary Economics*.
- Blanchet, Thomas, Emmanuel Saez, and Gabriell Zucman. 2022. "Real-Time Inequality." *NBER Working Paper* 30229.
- Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten. 2016. "Consumption inequality and family labor supply." *American Economic Review* 106 (2): 387–435.
- Bricker, Jesse, Joseph Briggs, Sarah Friedman, and Kamila Sommer. 2025. "The Business Cycle Dynamics of the Wealth Distribution." *Journal of Political Economy Macroeconomics* 3 (3): 343–381.
- Bügel, David, Albert Hidalgo, and Ralph Luettkieke. 2024. "Unconventional Monetary Policy Shocks and their Distributional Implications." *CEPR Discussion Paper No. 19163*.
- Campbell, Cole, Jacob A Robbins, and Sam Wylde. 2025. "The distribution of capital gains in the United States." Technical report, Working Paper (Washington Center for Equitable Growth, 2025), available at
- Carrier, Andrea, Haroon Mumtaz, Konstantinos Theodoridis, and Angeliki Theophilopoulou. 2015. "The impact of uncertainty shocks under measurement error: A proxy SVAR approach." *Journal of Money, Credit and Banking* 47 (6): 1223–1238.
- Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans. 2005. "Nominal rigidities and the dynamic effects of a shock to monetary policy." *Journal of Political Economy* 113 (1): 1–45.
- Cloyne, James, Clodomiro Ferreira, and Paolo Surico. 2020. "Monetary policy when households have debt: new evidence on the transmission mechanism." *The Review of Economic Studies* 87 (1): 102–129.
- Colciago, Andrea, Anna Samarina, and Jakob de Haan. 2019. "Central bank policies and income and wealth inequality: A survey." *Journal of Economic Surveys* 33 (4): 1199–1231.
- Cooper, Daniel H, Karen E Dynan, and Hannah Rhodenizer. 2019. "Measuring household wealth in the Panel Study of Income Dynamics: the role of retirement assets." Technical report, Federal Reserve Bank of Boston.

- De Luigi, Clara, Martin Feldkircher, Philipp Poyntner, and Helene Schuberth. 2023. “Quantitative Easing and Wealth Inequality: The Asset Price Channel.” *Oxford Bulletin of Economics and Statistics*.
- Degasperi, Riccardo, and Giovanni Ricco. 2021. “Information and Policy Shocks in Monetary Surprises.”
- Di Maggio, Marco, Amir Kermani, and Christopher J Palmer. 2020. “How quantitative easing works: Evidence on the refinancing channel.” *The Review of Economic Studies* 87 (3): 1498–1528.
- Dias, Daniel A, and Joao B Duarte. 2022. “Monetary policy and homeownership: Empirical evidence, theory, and policy implications.” *International Finance Discussion Paper* (1344).
- Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2020. “Heterogeneity and persistence in returns to wealth.” *Econometrica* 88 (1): 115–170.
- Feilich, Ethan. 2023. “Monetary policy and the dynamics of wealth inequality.”
- Forni, Mario, Luca Gambetti, and Giovanni Ricco. 2022. “External instrument SVAR analysis for noninvertible shocks.” *CEPR Discussion Paper No. 17886*.
- Fuster, Andreas, and Paul Willen. 2010. “1.25 trillion is still real money: Some facts about the effects of the Federal Reserve’s mortgage market investments.” *FRB of Boston Public Policy Discussion Paper* (10-4).
- Gerardi, Kristopher, Paul S Willen, and David Hao Zhang. 2023. “Mortgage prepayment, race, and monetary policy.” *Journal of Financial Economics* 147 (3): 498–524.
- Gertler, M., and P. Karadi. 2015. “Monetary policy surprises, credit costs, and economic activity.” *American Economic Journal: Macroeconomics* 7(1): 44–76.
- Giannone, Domenico, Michele Lenza, and Giorgio E Primiceri. 2015. “Prior selection for vector autoregressions.” *Review of Economics and Statistics* 97 (2): 436–451.
- Gilchrist, Simon, and Egon Zakrajšek. 2012. “Credit spreads and business cycle fluctuations.” *American Economic Review* 102 (4): 1692–1720.
- Gorea, Denis, Oleksiy Kryvtsov, and Marianna Kudlyak. 2025. “House price responses to monetary policy surprises: Evidence from the US listings data.” Available at SSRN 5398541.
- Greenwald, Daniel L, Matteo Leombroni, Hanno Lustig, and Stijn Van Nieuwerburgh. 2021. “Financial and total wealth inequality with declining interest rates.” *National Bureau of Economic Research* (No. w28613).
- Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek. 2021. “The transmission of monetary policy under the microscope.” *Journal of Political Economy* 129 (10): 2861–2904.

- Hubmer, Joachim, Per Krusell, and Anthony A Smith Jr. 2021. “Sources of US wealth inequality: Past, present, and future.” *NBER Macroeconomics Annual* 35 (1): 391–455.
- Insolera, Nora E, Beth A Simmert, and David S Johnson. 2021. “An overview of data comparisons between psid and other us household surveys.” *Technical Series Paper*: 21–02.
- Jarociński, Marek, and Peter Karadi. 2020. “Deconstructing monetary policy surprises—the role of information shocks.” *American Economic Journal: Macroeconomics* 12 (2): 1–43.
- Jordà, Òscar. 2005. “Estimation and inference of impulse responses by local projections.” *American Economic Review* 95 (1): 161–182.
- Kaplan, Greg, Benjamin Moll, and Giovanni L Violante. 2018. “Monetary policy according to HANK.” *American Economic Review* 108 (3): 697–743.
- Kappes, Sylvio Antonio. 2021. “Monetary Policy and Personal Income Distribution: A Survey of the Empirical Literature.” *Review of Political Economy*: 1–20.
- Kuhn, Moritz, Moritz Schularick, and Ulrike I Steins. 2020. “Income and wealth inequality in america, 1949–2016.” *Journal of Political Economy* 128 (9): 3469–3519.
- Lenza, Michele, and Jiri Slacalek. 2024. “How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area.” *Journal of Applied Econometrics* 39 (5): 746–765.
- Li, Dake, Mikkel Plagborg-Møller, and Christian K Wolf. 2024. “Local projections vs. vars: Lessons from thousands of dgps.” *Journal of Econometrics* 244 (2): 105722.
- McCracken, Michael W, Serena Ng et al. 2021. “FRED-QD: A Quarterly Database for Macroeconomic Research.” *Federal Reserve Bank of St. Louis Review* 103 (1): 1–44.
- McKay, Alisdair, and Christian K Wolf. 2023. “Monetary Policy and Inequality.” *Journal of Economic Perspectives* 37 (1): 121–44.
- Miranda-Agrrippino, Silvia, and Giovanni Ricco. 2021. “The transmission of monetary policy shocks.” *American Economic Journal: Macroeconomics* 13 (3): 74–107.
- Mishkin, Frederic S et al. 2007. “Housing and the monetary transmission mechanism.” In *Proceedings-Economic Policy Symposium-Jackson Hole*,: 359–413, Federal Reserve Bank of Kansas City.
- Morelli, Salvatore, Twisha Asher, Frincasco Di Biase, Franziska Disslbacher, Ignacio Flores, Adam Rego Johnson, Giacomo Rella, Manuel Schechtl, Francesca Subioli, and Matteo Targa. 2023. “The GC Wealth Project Data Warehouse v. 1-Documentation.”
- Paul, Pascal. 2020. “The time-varying effect of monetary policy on asset prices.” *Review of Economics and Statistics* 102 (4): 690–704.

- Pfeffer, Fabian T, Davis Daumler, and Esther Friedman. 2025. “PSID-SHELF, 1968–2021: The PSID’s Social, Health, and Economic Longitudinal File (PSID-SHELF), Beta Release.” *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]* 2.
- Pfeffer, Fabian T, Robert F Schoeni, Arthur Kennickell, and Patricia Andreski. 2016. “Measuring wealth and wealth inequality: Comparing two US surveys.” *Journal of economic and social measurement* 41 (2): 103–120.
- Piketty, Thomas. 2014. *Capital in the twenty-first century*.: Harvard University Press.
- Plagborg-Møller, Mikkel, and Christian K. Wolf. 2021. “Local projections and VARs estimate the same impulse responses.” *Econometrica* 89 (2): 955–980. Publisher: Wiley Online Library.
- Ramey, Valerie A. 2016. “Macroeconomic shocks and their propagation.” *Handbook of macroeconomics* 2: 71–162.
- Saez, Emmanuel, and Gabriel Zucman. 2016. “Wealth inequality in the United States since 1913: Evidence from capitalized income tax data.” *The Quarterly Journal of Economics* 131 (2): 519–578.
- Stock, James H, and Mark W Watson. 2018. “Identification and estimation of dynamic causal effects in macroeconomics using external instruments.” *The Economic Journal* 128 (610): 917–948.
- Stock, James H, Jonathan H Wright, and Motohiro Yogo. 2002. “A survey of weak instruments and weak identification in generalized method of moments.” *Journal of Business & Economic Statistics* 20 (4): 518–529.
- Swanson, Eric T. 2021. “Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets.” *Journal of Monetary Economics* 118: 32–53.
- Xavier, Inês. 2021. “Wealth inequality in the US: the role of heterogeneous returns.” Available at SSRN 3915439.

A. Distributional Financial Accounts of the United States: additional tables and charts

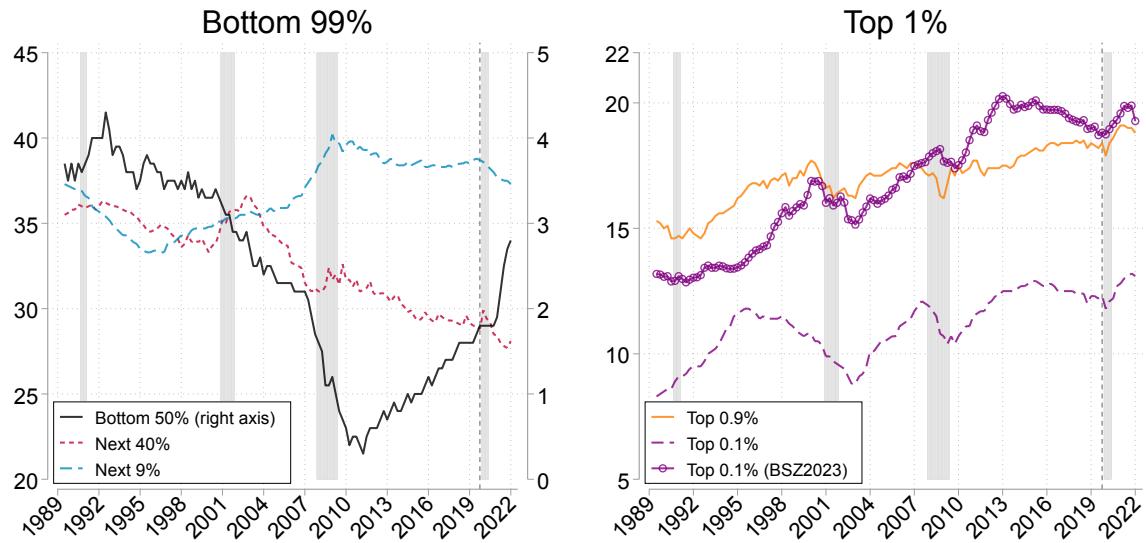


FIGURE A.1. Wealth shares (1989Q3 - 2022Q1)

Notes: The figure shows the evolution of wealth shares for the bottom 50%, next 40%, next 9%, the top 0.9%, and top 0.1% of the wealth distribution between 1989Q3 and 2022Q1. The dashed vertical lines indicate the end of the estimation sample of the empirical analysis (2019Q4). BSZ2023 refers to the series by [Blanchet, Saez, and Zucman \(2022\)](#). Table A.1 in Appendix C reports average wealth shares together with the distribution of balance sheet components between 1989Q3 and 2019Q4.

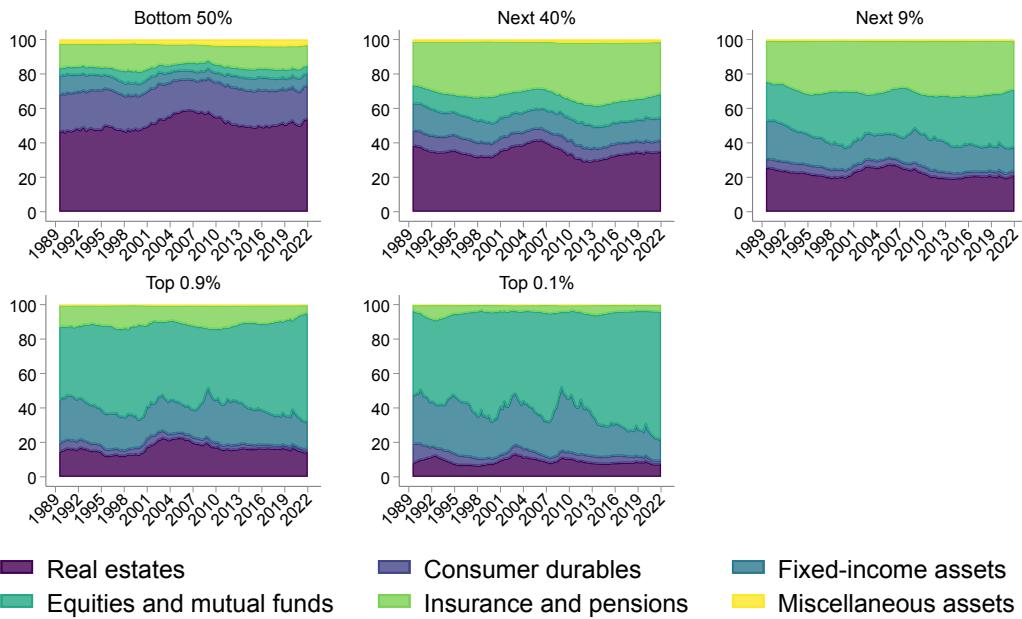


FIGURE A.2. Composition of portfolios across the wealth distribution (1989Q3 - 2022Q1)

Notes: The figure shows the composition of assets across wealth groups in the Distributional Financial Accounts. Following [Bauluz, Novokmet, and Schularick \(2022\)](#), we organise non-financial and financial assets in the following asset classes: real estates, consumer durable goods, fixed income assets, equities and mutual funds holdings, life insurance and pension funds, and miscellaneous assets. Fixed income assets include: checkable deposits and currency, time deposits and short-term investment, money market funds, US government and municipal securities, corporate and foreign bonds, loans. Equities and mutual funds holdings include: corporate equities, mutual fund holdings and private businesses. Insurance and pension funds include: life insurance reserves and pension entitlements.

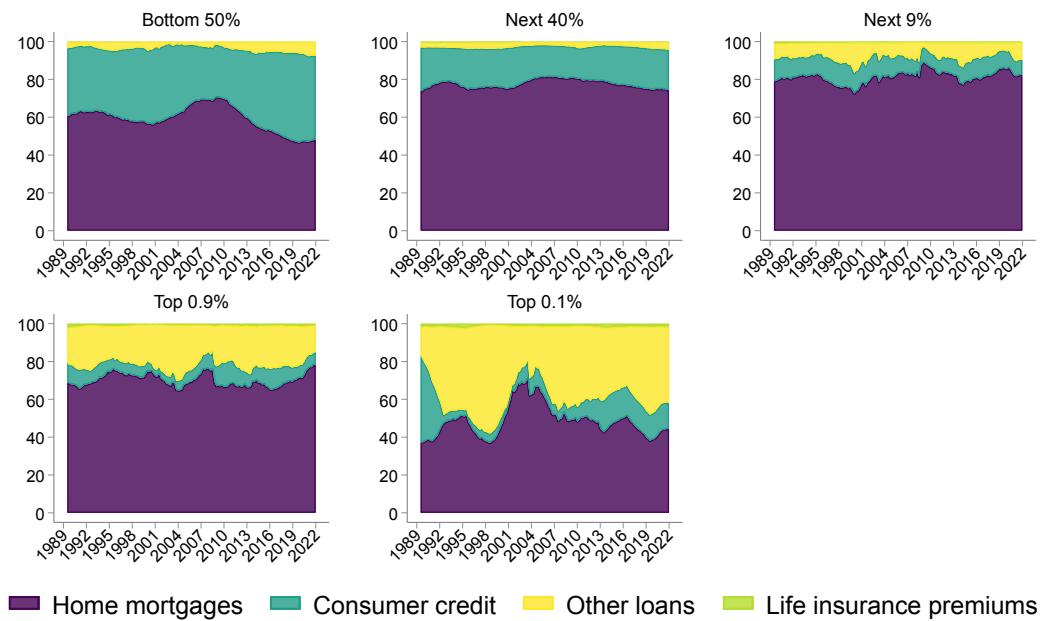


FIGURE A.3. Composition of liabilities across groups

Notes: The figure shows the composition of liabilities across the wealth distribution. Each liability type is expressed as share of total liabilities. Other loans include depository institutions loans n.e.c. and other loans and advances. Life insurance premiums include deferred and unpaid life insurance premiums.

TABLE A.1. Distribution of assets, liabilities, and wealth (1989Q3-2019Q4)

	Bottom 50%	Next 40%	Next 9%	Top 0.9%	Top 0.1%
Assets	7.07	34.59	33.83	15.01	9.49
Nonfinancial assets	15.37	44.51	27.13	9.13	3.87
Real estate	13.60	45.16	28.59	9.43	3.21
Consumer durables	22.85	41.98	20.88	7.70	6.58
Financial assets	3.00	29.72	37.14	17.90	12.24
Deposits	4.30	35.07	36.88	15.40	8.35
Corporate equities and mutual funds	1.19	15.61	35.87	27.69	19.65
Private businesses	1.76	17.14	31.99	27.05	22.06
Pension entitlements	3.43	45.18	43.22	6.65	1.53
Other assets	5.23	24.07	29.95	21.62	19.13
Liabilities	33.58	43.61	17.97	4.13	0.71
Home mortgages	28.11	47.15	20.26	4.01	0.47
Consumer credit	52.98	37.21	8.07	1.40	0.35
Other liabilities	23.00	23.96	29.29	18.26	5.48
Net wealth	2.34	33.01	36.66	16.94	11.05

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 2019Q4. Other assets include US government and municipal securities, corporate and foreign bonds, loans, life insurance reserves, and miscellaneous assets. Similarly, the other liabilities are include depository institutions loans n.e.c., other loans and advances, deferred and unpaid life insurance premiums.

B. Econometric methodology: additional results and details

B.1. Bayesian VAR

We estimate the following VAR model using Bayesian techniques and standard macroeconomic priors:

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

where \mathbf{y}_t is a $(n \times 1)$ vector of endogenous variables, \mathbf{c} is a $(n \times 1)$ constant vector, \mathbf{B}_j are $(n \times n)$ matrices of parameters with $j = 1, \dots, p$, \mathbf{u}_t is a $(n \times 1)$ vector of innovations with zero mean and variance-covariance matrix Σ . Time is indexed by $t = 1, \dots, T$, each time period is a quarter, and the lag length is $p = 4$.

Following standard practice, we place a Normal–Inverse Wishart prior on (β, Σ) ,

$$\Sigma \sim W^{-1}(\Psi, \nu), \quad \beta \mid \Sigma \sim N(b, \Sigma \otimes \Omega),$$

where $\beta = \text{vec}([c, B_1, \dots, B_p]')$, Ψ is diagonal with elements proportional to the residual variances from univariate autoregressions, and $\nu = n + 2$ ensures the existence of the prior mean. The matrix Ω encodes the Minnesota prior on the autoregressive coefficients. Specifically, following the Minnesota specification

$$E[(B_i)_{jk}] = \begin{cases} \delta_j, & i = 1, j = k, \\ 0, & \text{otherwise,} \end{cases} \quad \text{Var}[(B_i)_{jk}] = \begin{cases} \frac{\lambda^2}{i^2}, & j = k, \\ \frac{\lambda^2 \sigma_k^2}{i^2 \sigma_j^2}, & j \neq k, \end{cases} \quad (\text{B.2})$$

where $(B_i)_{jk}$ is the coefficient on variable k in equation j at lag order i , σ_j^2 is the residual variance of equation j , and λ controls the overall tightness of the prior.²⁰ Crucially, we follow [Giannone, Lenza, and Primiceri \(2015\)](#) and treat these hyperparameters as additional elements of the hierarchical model to estimate, allowing the data to determine the appropriate amount of shrinkage.

B.2. Two-step identification procedure: theoretical argument

Let ε_t^p denote the structural monetary policy shock and z_t the proxy (the surprise series of [Jarociński and Karadi, 2020](#)). A standard measurement equation for the proxy is

$$z_t = \theta \varepsilon_t^p + \nu_t, \quad (\text{B.3})$$

where the *relevance condition* in (2) states that $\theta \neq 0$, and ν_t is an idiosyncratic noise term uncorrelated with ε_t^p and with other structural shocks. Equation (B.3) states that the proxy is an imperfect measure of the true monetary policy shock. Now, consider the (reduced-form) policy equation in the VAR

$$i_t = x_t' \gamma + u_t^i, \quad (\text{B.4})$$

²⁰The initial values used to initialize the hierarchical optimization are chosen as in [Miranda-Agrippino and Ricco \(2021\)](#) and are: $\lambda = 0.4$ (overall tightness), $\alpha = 2$ (lag decay), $\mu = 1$ (sum-of-coefficients prior), $\theta = 2$ (cointegration prior), and $\lambda_C = 10^5$ (variance of the intercept).

where i_t is the policy rate, x_t are lagged controls, and u_t^i is the corresponding reduced-form residual. Under the usual structural representation, we can write

$$u_t^i = a\varepsilon_t^p + \eta_t, \quad (\text{B.5})$$

where $a \neq 0$ and η_t collects the contribution of all other structural shocks, with η_t being orthogonal to ε_t^p and ν_t . In an internal-instrument VAR, relevance of the proxy for identifying ε_t^p hinges on the correlation between z_t and u_t^i , which is defined as

$$\text{Corr}(z_t, u_t^i) = \frac{\text{Cov}(z_t, u_t^i)}{\sqrt{\text{Var}(z_t) \text{Var}(u_t^i)}}$$

with the covariance being defined as

$$\text{Cov}(z_t, u_t^i) = \text{Cov}(\theta\varepsilon_t^p + \nu_t, a\varepsilon_t^p + \eta_t) = \theta a \text{Var}(\varepsilon_t^p),$$

since $\varepsilon_t^p, \eta_t \perp \nu_t$ as well as $\varepsilon_t^p \perp \eta_t$ by assumption, and the variance terms are

$$\begin{aligned} \text{Var}(z_t) &= \theta^2 \text{Var}(\varepsilon_t^p) + \text{Var}(\nu_t) \\ \text{Var}(u_t^i) &= a^2 \text{Var}(\varepsilon_t^p) + \text{Var}(\eta_t) \end{aligned}$$

therefore, the correlation between z_t and u_t^i is

$$\text{Corr}(z_t, u_t^i) = \frac{\theta a \text{Var}(\varepsilon_t^p)}{\sqrt{(\theta^2 \text{Var}(\varepsilon_t^p) + \text{Var}(\nu_t))(a^2 \text{Var}(\varepsilon_t^p) + \text{Var}(\eta_t))}}. \quad (\text{B.6})$$

In our monetary policy application, the idiosyncratic noise component $\text{Var}(\nu_t)$ in equation (B.6) reflects measurement errors around FOMC announcements and is generally not expected to fall proportionally when the variance of true monetary policy shocks declines.²¹ Therefore, in a post-1989 sample, the smaller $\text{Var}(\varepsilon_t^p)$ worsens the signal-to-noise ratio of the proxy $\left(\frac{\text{Var}(\varepsilon_t^p)}{\text{Var}(\nu_t)}\right)$. Equation (B.6) makes this clear: a lower $\text{Var}(\varepsilon_t^p)$ weakens the correlation between z_t and u_t^i , making the proxy a weaker instrument for isolating the true (monetary policy) shock.

One way to overcome this issue is to adopt our proposed two-step identification procedure. First, we obtain the monetary shock from a higher frequency model spanning a longer period with larger exogenous variations in monetary policy.²² In that longer

²¹The same is true for $\text{Var}(\eta_t)$, as this term reflects the variance of shocks orthogonal to ε_t^p .

²²The shock is estimated according to equation (B.9) using a monthly Proxy VAR.

sample, with a larger $Var(\varepsilon_t^p)$ and $Var(\nu_t)$ not increasing systematically, the proxy z_t can use stronger signals to better recover the mapping between z_t and ε_t^p . In the second step, we aggregate the estimated monthly shock series from the Proxy VAR to a quarterly frequency, yielding a series whose variation in the post-1989 sample is more tightly linked to true monetary policy innovations and less affected by measurement noise. This improves the identification in the internal-instrument quarterly VAR with DFA data.

B.3. Unit-variance shock estimation and invertibility test

A shock is invertible if it is a linear combination of contemporaneous VAR residuals. To test the validity of this assumption, we use the theoretical result of [Forni, Gambetti, and Ricco \(2022\)](#), which shows that if the shock is not invertible, then it is a function of current and future VAR residuals. Formally, the test is performed by projecting the instrument (z_t) on the current value and the first r leads of the Wold residuals u_t :

$$z_t = \sum_{k=0}^r \lambda'_k u_{t+k} + \nu_t \quad (\text{B.7})$$

The invertibility test is an F-test for the significance of the r leads, where the null hypothesis is $H_0 : \lambda_1 = \dots = \lambda_r = 0$ against the alternative that at least one of the coefficients is nonzero. We estimate the regression in equation (B.7) using different numbers of leads ($1 \leq r \leq 6$)

If the invertibility assumption holds, which is the case in our Proxy VAR, the Wold residuals, say u_t , can be written as a linear combination of the structural shocks, say ε_t . The external instrument identification allows us to obtain covariance restrictions from proxies for the latent structural shock of interest, in line with the relevance and exogeneity conditions (see [Stock and Watson 2018](#)). We proceed with the first-stage regression by projecting the instrument z_t onto the Wold residuals. Formally:

$$z_t = \lambda' u_t + \nu_t \quad (\text{B.8})$$

[Forni, Gambetti, and Ricco \(2022\)](#) show that if the shock is fundamental we can obtain an estimate of the standardized unit-variance structural shock i as:

$$\hat{\varepsilon}_{it} = \frac{\hat{\lambda}' \hat{u}_t}{std(\hat{\lambda}' \hat{u}_t)} \quad (\text{B.9})$$

Table B.1 presents the results of the test by showing the p -values over different specifications of the test. The p -values are very large and therefore we cannot reject the null of invertibility for all values of r .

TABLE B.1. Invertibility test.

	Number of leads r					
	$r = 1$	$r = 2$	$r = 3$	$r = 4$	$r = 5$	$r = 6$
p -value	0.775	0.922	0.946	0.915	0.769	0.799

Notes: The table shows the p -values for each regression including the current value and up to r leads of the Wold residuals. The null hypothesis is invertibility, i.e., $H_0 : \lambda_1 = \lambda_2 = \dots = \lambda_r = 0$.

B.4. Building an informationally-robust asset purchase shock

To build an informationally-robust asset purchase shock, we follow [Miranda-Agrippino and Ricco \(2021\)](#) and *purge* the large-scale asset purchase factor of [Swanson \(2021\)](#) according to a two step procedure.

- (a) To control for the private information of the Federal Reserve, we project the large-scale asset purchase factor on Greenbook forecasts and on forecast revisions for real output growth, inflation (GDP deflator), and the unemployment rate at FOMC meeting frequency. We rely on the GDP deflator to measure inflation and use only nowcasts for the unemployment rate. These controls are collected in the vector x in the following regression:

$$MPF_m = \alpha_0 + \sum_{i=-1}^3 \beta_i \underbrace{F_m^{cb} x_{q+i}}_{\text{Forecast}} + \sum_{i=-1}^2 \phi_i \underbrace{[F_m^{cb} x_{q+i} - F_{m-1}^{cb} x_{q+i}]}_{\text{Forecast revisions}} + \widehat{MPF}_m \quad (\text{B.10})$$

where $F_m^{cb} x_{q+i}$ denotes Greenbook forecasts for the vector of variables x at horizon $q + i$ that are produced prior to each meeting, and $F_m^{cb} x_{q+i} - F_{m-1}^{cb} x_{q+i}$ denotes revisions to forecasts between consecutive FOMC meetings.

- (b) To account for the slow absorption of information by economic agents, we aggregate the residual series from the equation above \widehat{MPF}_m to a quarterly frequency and

estimate the following regression:

$$\widehat{MPF}_t = \alpha + \sum_{j=1}^4 \psi_j \widehat{MPF}_{t-j} + \hat{s}_t^{LSAP} \quad (\text{B.11})$$

The series of residuals \hat{s}_t^{LSAP} is then used as internal instrument in the VAR.

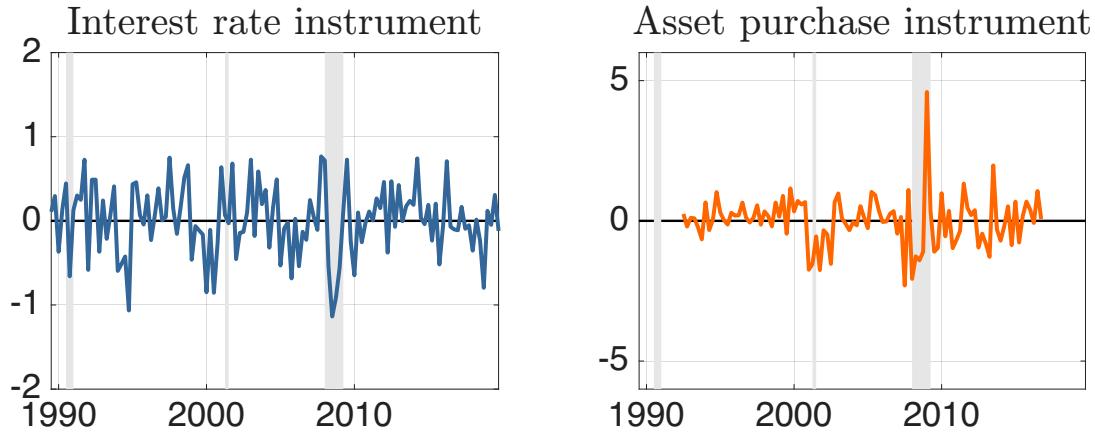


FIGURE B.1. Shocks

Notes: This figure plots the monetary policy shocks used as internal instruments in the VAR models (see Section 3 for more information).

C. Macroeconomic and distributional effects of monetary policy: additional results

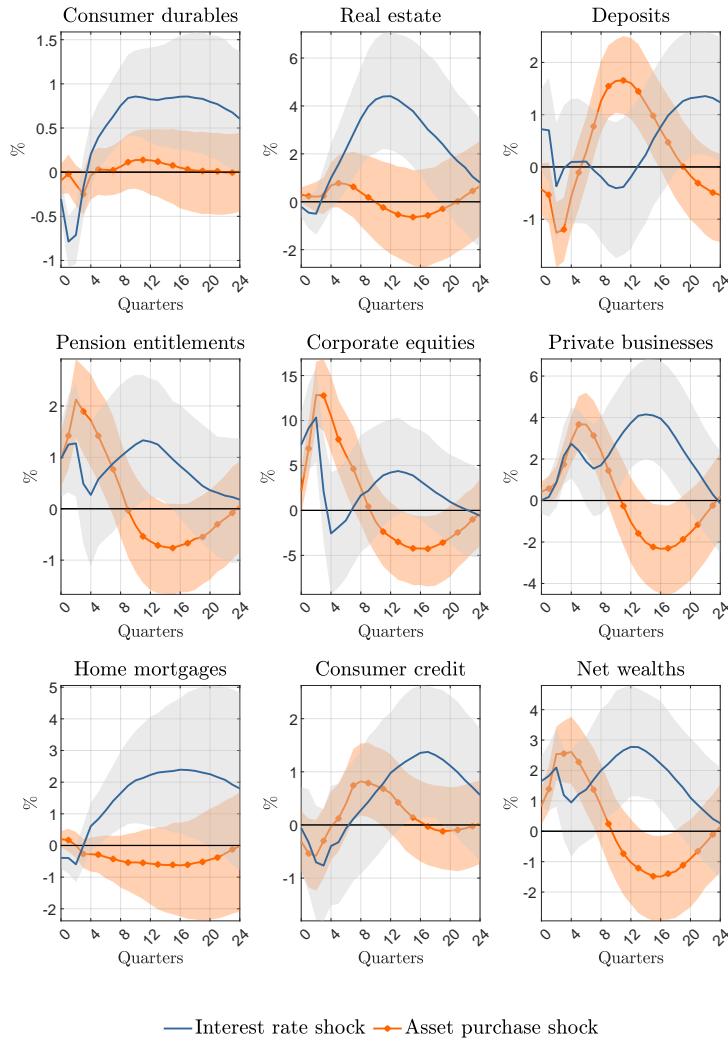
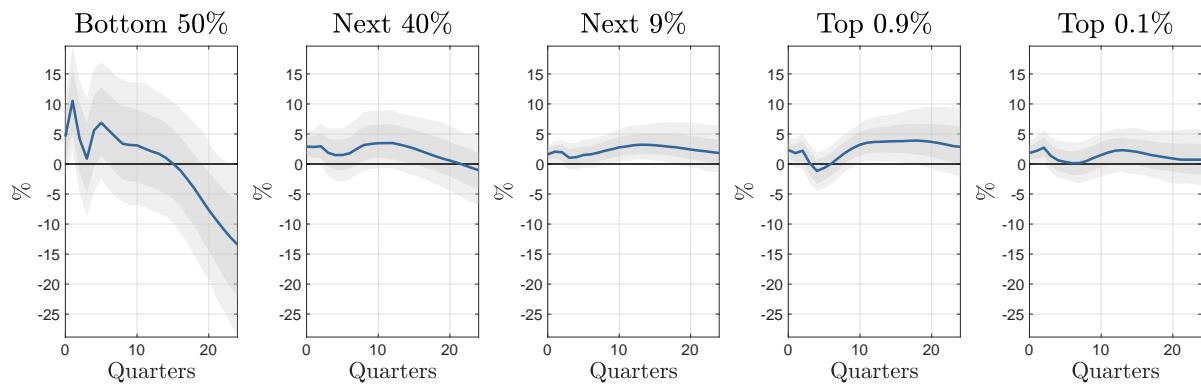
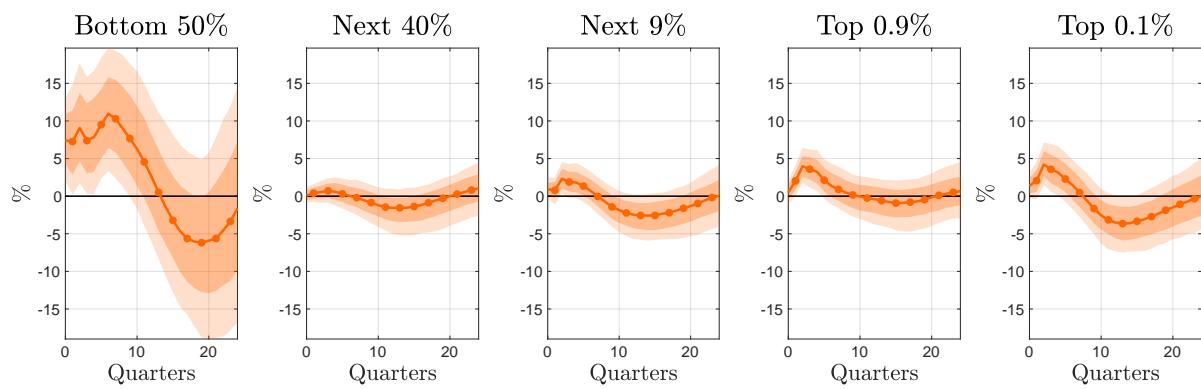


FIGURE C.1. Aggregate balance sheet effects of monetary policy

Notes: The figure shows the impulse response functions to an interest rate (solid line) and an asset purchase (solid line with markers) shock estimated using the Bayesian VAR described in Table 2, Panel B. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. Shaded areas are 68% posterior coverage bands.



A. Interest rate shock



B. Asset purchase shock

FIGURE C.2. Effects of monetary policy on net wealth

Notes: The figure shows the impulse response functions to an interest rate (solid line) and an asset purchase (solid line with markers) shock estimated using the Bayesian VAR described in Table 2, Panel B. Net wealth is deflated using the consumer price index. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands.

TABLE C.1. Implied changes in wealth levels and shares: interest rate shock

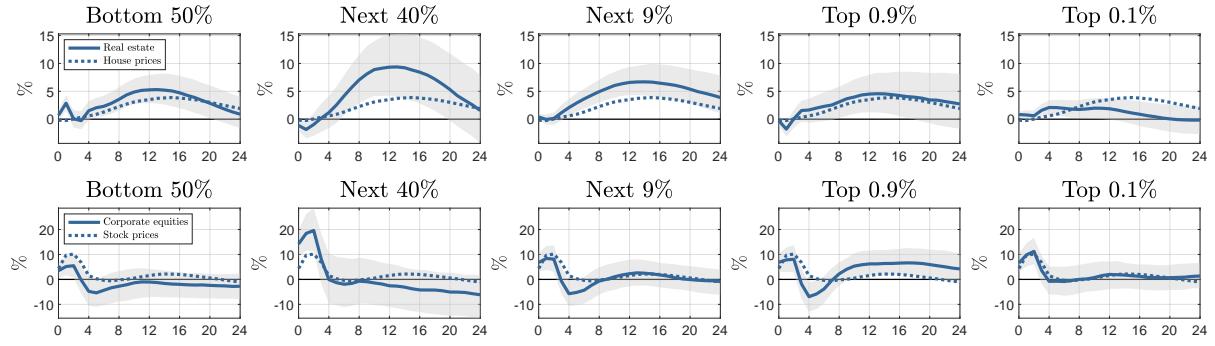
	<i>Bottom 50%</i>	<i>Next 40%</i>	<i>Next 9%</i>	<i>Top 0.9%</i>	<i>Top 0.1%</i>
IMPACT					
Percent change (IRF_{ih} , %)	4.58	2.91	1.60	2.34	1.84
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	59.80	589.10	370.51	250.78	129.66
Implied share (ω_{ih} , %)	2.14	32.62	36.80	17.21	11.24
Change in share ($\Delta\omega_{ih}$, p.p.)	0.05	0.21	-0.23	0.02	-0.04
1 YEAR					
Percent change (IRF_{ih} , %)	5.60	1.48	1.13	-1.14	0.60
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	73.06	299.78	260.45	-122.68	42.34
Implied share (ω_{ih} , %)	2.19	32.60	37.12	16.85	11.25
Change in share ($\Delta\omega_{ih}$, p.p.)	0.10	0.19	0.09	-0.35	-0.03
3 YEAR					
Percent change (IRF_{ih} , %)	2.11	3.49	3.12	3.67	2.22
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	27.50	706.49	721.75	393.92	156.45
Implied share (ω_{ih} , %)	2.07	32.49	36.99	17.27	11.17
Change in share ($\Delta\omega_{ih}$, p.p.)	-0.02	0.09	-0.03	0.08	-0.11
6 YEAR					
Percent change (IRF_{ih} , %)	-13.41	-1.03	1.82	2.85	0.72
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	-174.95	-208.76	420.87	305.73	50.73
Implied share (ω_{ih} , %)	1.80	31.87	37.47	17.57	11.29
Change in share ($\Delta\omega_{ih}$, p.p.)	-0.29	-0.54	0.44	0.38	0.01

Notes: For each type of monetary policy shock, wealth group and horizon, the table reports percent change in real net wealth (IRF_{ih} , %), dollar change in real net wealth ($\bar{w}_i IRF_{ih}$, billions), implied wealth share (ω_{ih} , %), and percentage point (p.p.) change in wealth share ($\Delta\omega_{ih}$, p.p.). See the main text for more information on the computation.

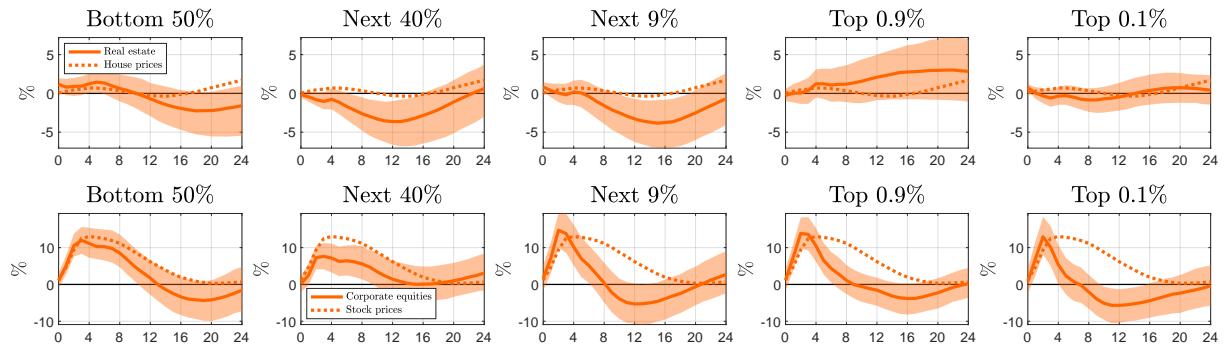
TABLE C.2. Implied changes in wealth levels and shares: asset purchase shock

	<i>Bottom 50%</i>	<i>Next 40%</i>	<i>Next 9%</i>	<i>Top 0.9%</i>	<i>Top 0.1%</i>
IMPACT					
Percent change (IRF_{ih} , %)	7.41	0.07	0.92	0.51	1.39
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	96.67	15.12	211.96	54.23	97.78
Implied share (ω_{ih} , %)	2.23	32.19	37.08	17.15	11.35
Change in share ($\Delta\omega_{ih}$, p.p.)	0.14	-0.22	0.06	-0.04	0.07
1 YEAR					
Percent change (IRF_{ih} , %)	7.87	0.58	1.81	3.25	3.14
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	102.62	117.84	417.31	348.62	221.23
Implied share (ω_{ih} , %)	2.21	31.98	36.98	17.42	11.42
Change in share ($\Delta\omega_{ih}$, p.p.)	0.12	-0.43	-0.05	0.22	0.13
3 YEAR					
Percent change (IRF_{ih} , %)	2.62	-1.56	-2.47	-0.39	-3.50
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	34.20	-316.15	-569.82	-42.26	-246.79
Implied share (ω_{ih} , %)	2.18	32.49	36.79	17.44	11.09
Change in share ($\Delta\omega_{ih}$, p.p.)	0.09	0.09	-0.24	0.25	-0.19
6 YEAR					
Percent change (IRF_{ih} , %)	-1.62	1.04	0.06	0.66	0.05
Dollar change ($\bar{w}_i IRF_{ih}$, bil.)	-21.13	211.25	12.82	71.30	3.61
Implied share (ω_{ih} , %)	2.05	32.60	36.88	17.23	11.24
Change in share ($\Delta\omega_{ih}$, p.p.)	-0.04	0.19	-0.14	0.04	-0.04

Notes: For each type of monetary policy shock, wealth group and horizon, the table reports percent change in real net wealth (IRF_{ih} , %), dollar change in real net wealth ($\bar{w}_i IRF_{ih}$, billions), implied wealth share (ω_{ih} , %), and percentage point (p.p.) change in wealth share ($\Delta\omega_{ih}$, p.p.). See the main text for more information on the computation.



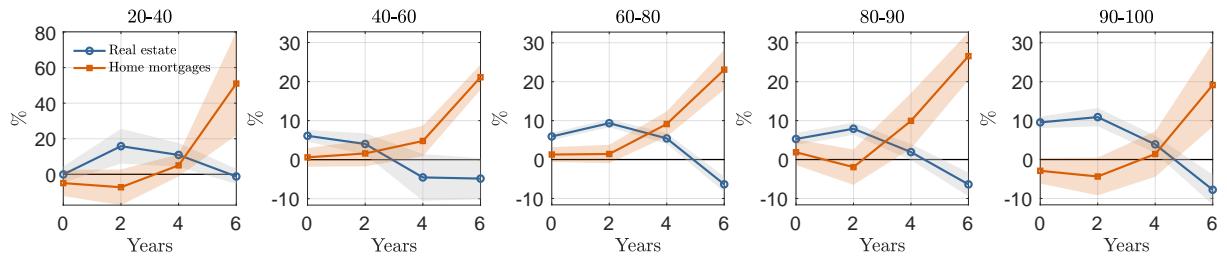
A. Interest rate shock



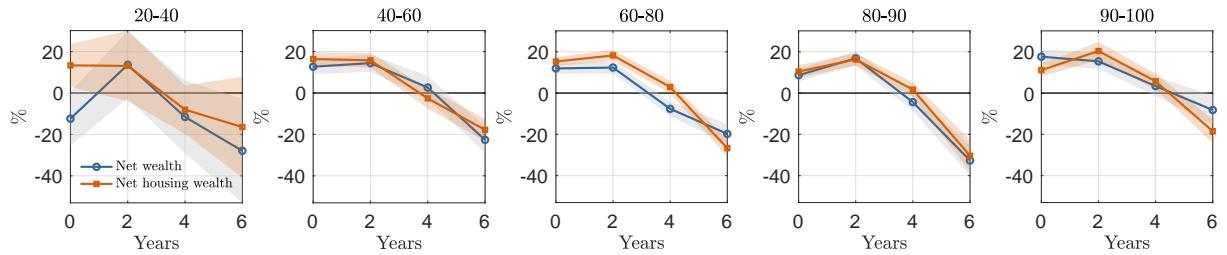
B. Asset purchase shock

FIGURE C.3. Effects of monetary policy shocks on assets and price indexes

Notes: The figure shows the impulse response functions to an interest rate (Panel A) and asset purchase (Panel B) shocks estimated using the Bayesian VAR described in Table 2, Panel B (solid lines). The impulse response functions of price indexes are estimated using the Bayesian VAR described in Table 2 augmented with house and stock prices. The real house price index is the Case-Shiller house price index deflated using the CPI. The real stock price index is the S&P stock price index deflated using the CPI. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Shaded areas are 68% posterior coverage bands.



A. Real estate and home mortgages



B. Net wealth

FIGURE C.4. The wealth reversal: indebted homeowners

Notes: The figure shows impulse response functions to an interest rate shock. Panel A reports impulse responses of the probability of being a homeowner while Panel B reports impulse responses of net wealth and net housing wealth. Shaded bands are 90% confidence intervals. For this specification, we restrict the sample to households that own a primary home and have at least one mortgage on it.

D. Macroeconomic and distributional effects of monetary policy: sensitivity analysis

D.1. Restricted asset purchase shock

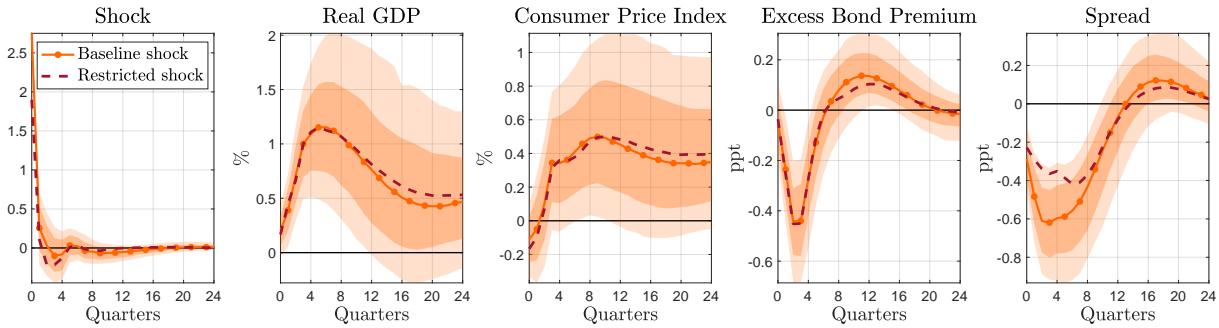


FIGURE D.1. Macroeconomic effects of an asset purchase shock: robustness

Notes: The figure shows the impulse responses to a baseline asset purchase shock (solid line with markers) and the restricted asset purchase shocks (dashed line) from a Bayesian VAR described in Table 2, Panel A. The restricted shocks restrict pre-2008 observation to zero. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid and dashed lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands. (omitted for the restricted).

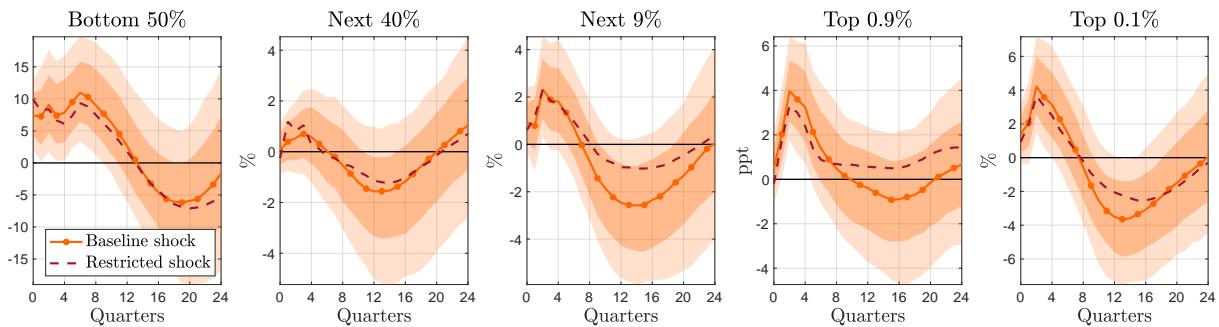


FIGURE D.2. Effects of asset purchase shock on net wealth: robustness

Notes: The figure shows the impulse responses to a baseline asset purchase shock (solid line with markers) and the restricted asset purchase shocks (dashed line) from a Bayesian VAR described in Table 2, Panel B. The restricted shocks restrict pre-2008 observation to zero. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid and dashed lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands. (omitted for the restricted).

D.2. Interest rate shocks: robustness to alternative identification assumptions

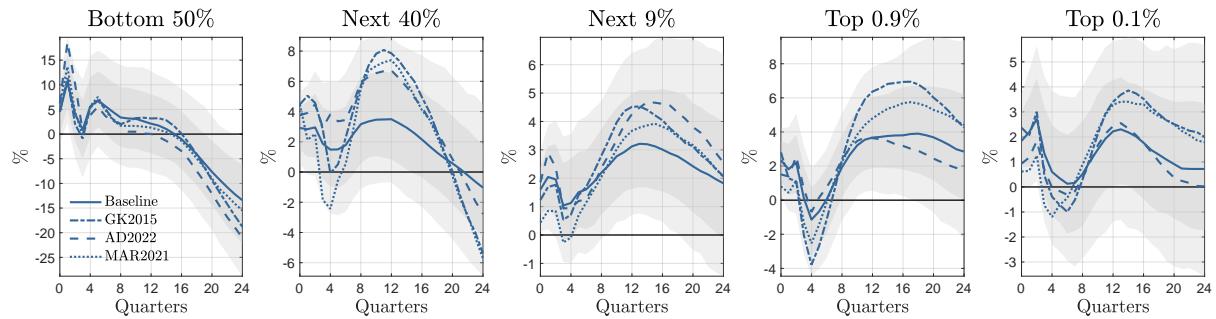


FIGURE D.3. Alternative interest rate shocks

Notes: The figure shows the impulse response functions to the baseline interest rate shock (solid line) and to alternative shocks estimated using the Bayesian VAR described in Table 2, Panel B. Baseline is [Jarociński and Karadi \(2020\)](#), GK2015 is [Gertler and Karadi \(2015\)](#), AD2022 is [Aruoba and Drechsel \(2022\)](#), MAR2021 is [Miranda-Agrippino and Ricco \(2021\)](#). For MAR2021 we use the extended series by [Degasperi and Ricco \(2021\)](#). Net wealth is deflated using the consumer price index. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands.

D.3. Model specification: robustness to lag length choice

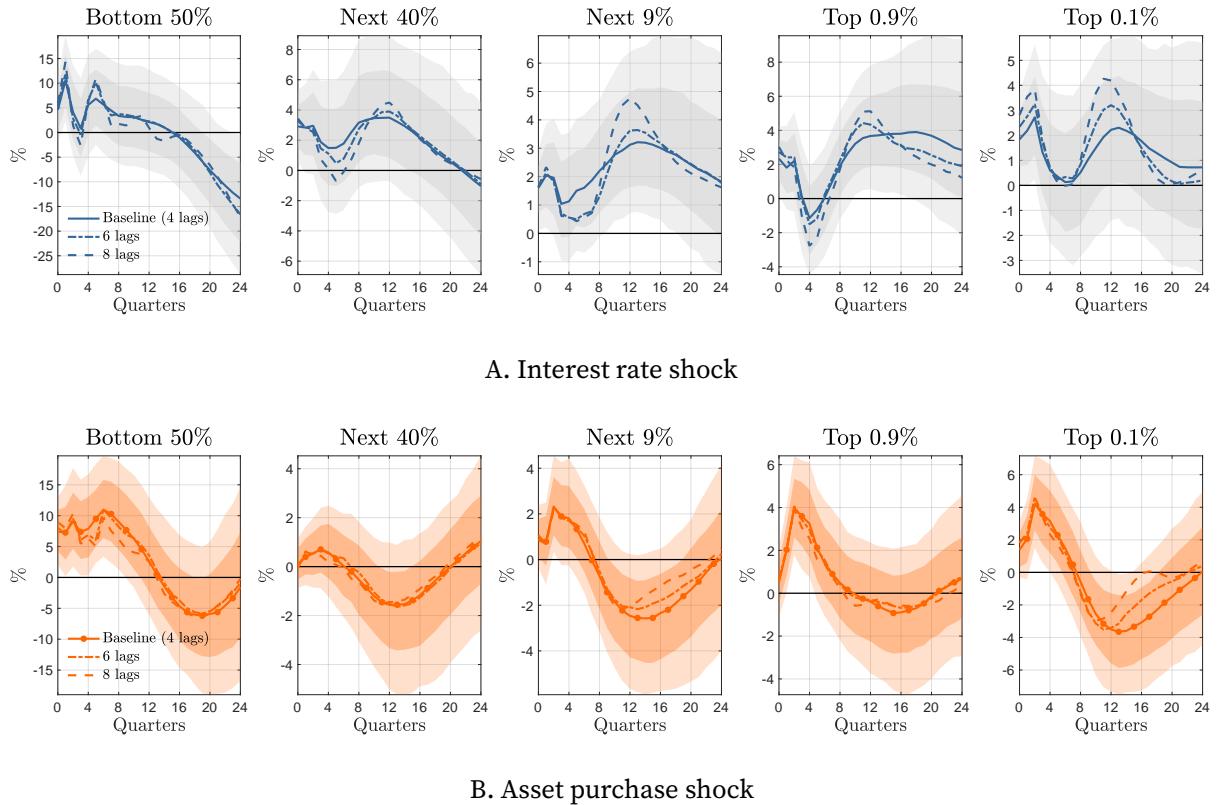


FIGURE D.4. Effects of monetary policy on net wealth: robustness

Notes: The figure shows the impulse response functions to an interest rate (solid line) and an asset purchase (solid line with markers) shock estimated using the Bayesian VAR described in Table 2, Panel B. Baseline refers to the model with 4 lags. Net wealth is deflated using the consumer price index. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. Shaded areas are 68% and 90% posterior coverage bands.

D.4. Model specification: robustness to model choice

In a local projection framework, the impulse response function is the series of regression coefficients β_h associated with the set of h -step ahead predictive regressions. Formally:

$$y_{t+h} = \alpha_h + \beta_h \hat{s}_t^j + \Phi_h(L)x_{t-1} + u_{t+h} \quad \text{with } h = 0, 1, 2, \dots, 24 \quad (\text{D.1})$$

where y is a dependent variable of interest (e.g., real net wealth), x is a vector of control variables, $\Phi(L)$ is a polynomial in the lag operator, and \hat{s}^j is a monetary policy surprise

with $j = \{R, LSAP\}$. Because impulse responses estimated with local projections are often less precise and erratic, we estimate also a smooth local projection version of equation (D.1) following the approach of [Barnichon and Brownlees \(2019\)](#). In both cases, we keep the specification of the local projection as close as possible to the baseline VAR models.

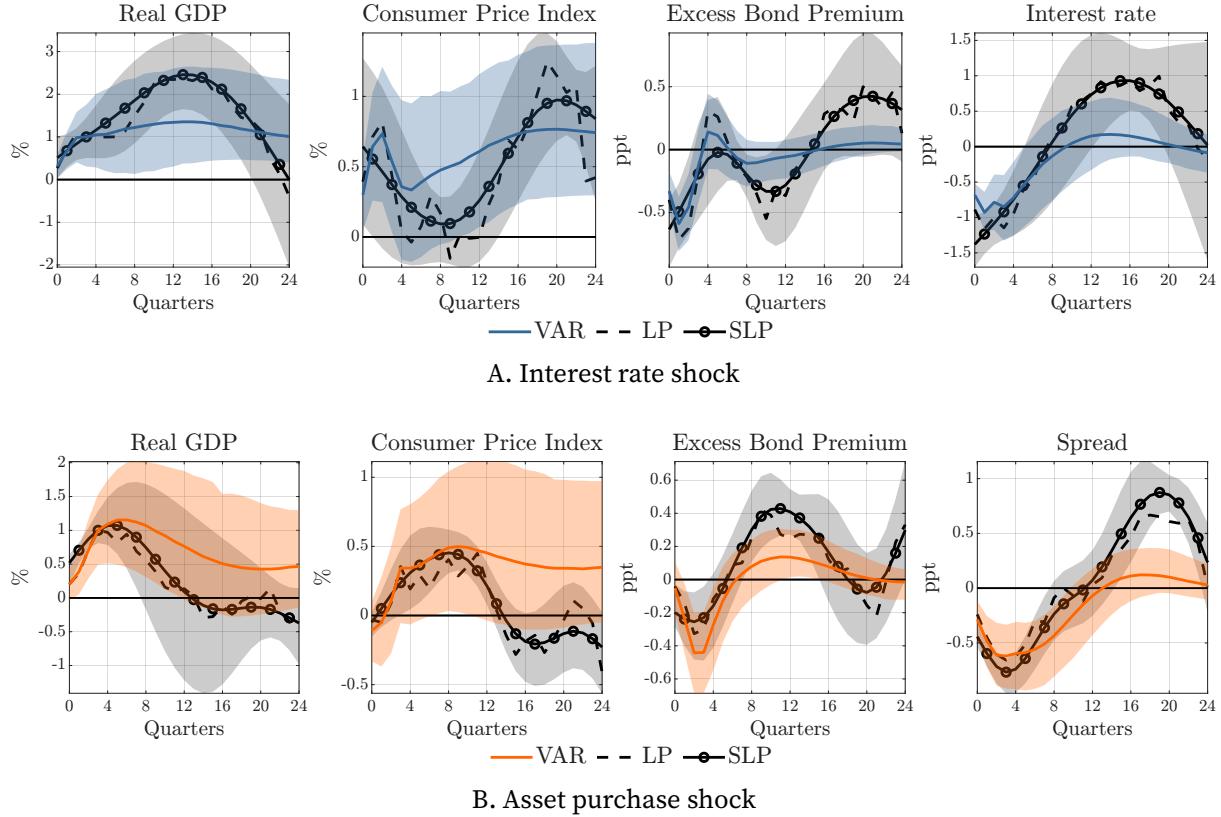
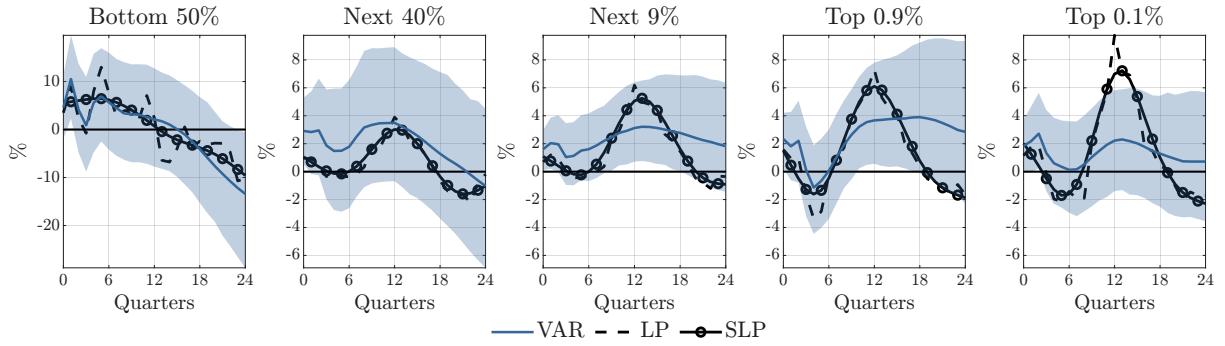
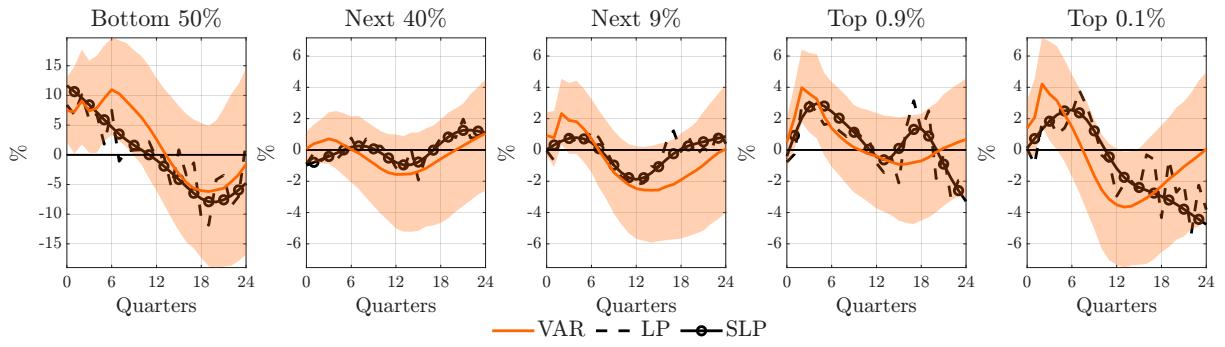


FIGURE D.5. Macroeconomic effects of monetary policy: robustness

Notes: The figure shows the impulse response functions to an interest rate (Panel A) and an asset purchase (Panel B) shock estimated using the Bayesian VAR described in Table 2, Panel B, and local projections. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. LP is Local Projections (dashed black line) and SLP is Smooth Local Projections (solid black line with markers). Impulse responses are normalized to generate a 1% response of real GDP. Shaded areas are 90% posterior coverage/confidence bands and are shown for the baseline VAR and the LP.



A. Interest rate shock



B. Asset purchase shock

FIGURE D.6. Effects of monetary policy on net wealth: robustness

Notes: The figure shows the impulse response functions to an interest rate (Panel A) and an asset purchase (Panel B) shock estimated using the Bayesian VAR described in Table 2, Panel B, and local projections. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Solid lines are median impulse responses from the posterior distribution. LP is Local Projections (dashed black line) and SLP is Smooth Local Projections (solid black line with markers). Impulse responses are normalized to generate a 1% response of real GDP. Shaded areas are 90% posterior coverage bands and are shown for the baseline VAR.

E. Beyond net wealth: the effect of monetary policy on balance sheets

The documented changes in net wealth across the wealth distribution due to monetary policy shocks are potentially influenced by several factors, including asset accumulation, disinvestment, borrowing, debt repayment, and asset price fluctuations. To varying degrees, these factors contribute to the channels through which monetary policy affects aggregate consumption, output, and prices, as predicted by both new and traditional theories analysing the transmission mechanism of monetary policy (e.g., [Bernanke and Gertler 1995](#); [Kaplan, Moll, and Violante 2018](#)). In this section, we use the rich information on balance sheets available in the DFA to show that monetary policy also has heterogeneous effects on assets and liabilities across the wealth distribution.

Figures E.1 and E.2 plot the responses of assets and liabilities to an interest rate shock and an asset purchase shock, respectively. This analysis focuses on four time horizons: the initial impact, one year, three years, and six years after the shock. The height of each bar in both figures (first row) roughly corresponds to the growth in total assets induced by monetary policy.²³

Housing. The housing sector plays a crucial role in the transmission of monetary policy to the broader economy ([Mishkin et al. 2007](#); [Cloyne, Ferreira, and Surico 2020](#); [Amromin, Bhutta, and Keys 2020](#)) and for wealth inequality ([Kuhn, Schularick, and Steins 2020](#)). Following an interest rate shock, all wealth groups experience a sluggish increase in real estate that peaks about three years after the shock (Figure E.1). On the liabilities side, the response of home mortgages to an interest rate shock is more heterogeneous across the distribution. While there is a lagged increase in mortgage debt for all groups, the bottom 90% of the distribution experiences a disproportionately larger growth in debt, especially the bottom 50%. Consequently, while the transmission of interest rate policy to the housing market contributes to the expansion of gross wealth through both the appreciation and accumulation of real estate, the simultaneous growth of debt acts as a countervailing force, leading to a contraction of net wealth for the bottom 90%. Instead, an asset purchase shock has mixed effects on real estate and home mortgages across the wealth distribution (Figure E.2). Real estate assets show a modest increase in the short run, followed by a decline for all wealth groups three years after

²³Note that a direct comparison with Figure 3 and Figure 7 is not feasible due to the exclusion of certain asset components, such as government, municipal and corporate bonds, insurances, miscellaneous assets, and other liabilities that are not classified as home mortgages or consumer credit.

the shock. On the liabilities side, an asset purchase shock reduces home mortgages for the bottom 90%. Six years after the shock, however, the reduction extends to all groups, except the next 40%.

Corporate equities and mutual funds. This asset class exhibit significant inequality in their distribution, and the returns generated by these assets play a crucial role in shaping wealth inequality (Hubmer, Krusell, and Smith Jr 2021). Despite persistent differences in magnitude, we find limited heterogeneity in the patterns of responses to both interest rate and asset purchase shocks across wealth groups. Following an interest rate shock, most of the immediate increase in total assets for all wealth groups can be attributed to the response of corporate equities and mutual funds, likely driven by the impact of monetary policy on the stock market (Figure E.1). In the medium run, corporate equities and mutual funds continue to account for a significant portion of the variation in total assets over time for most groups, particularly for the top 0.9%. Similarly, corporate equities and mutual funds play a crucial role in driving asset growth after an asset purchase shock (Figure E.2). In this case, however, the impulse response exhibits a cyclical pattern, peaking about a year after the shock (panel B) and then declining over the medium term, temporarily for the next 49% (panels C and D).

Private businesses. This asset class encompass a wide range of assets, including non-publicly traded business assets and real estate owned by households for rental purposes.²⁴ For the top 90% of the wealth distribution, an interest rate shock has a positive impact on private businesses, especially in the medium term (see Figure E.1, panels B to D). Conversely, for the bottom 50% and the top 10% of the distribution, the response of private businesses to an asset purchase shock shows a cyclical pattern, with a short-term increase followed by a decline in the medium term (see Figure E.2). For the next 40% of the distribution, private businesses experience a temporary decline for most of the horizon considered.

²⁴It is important to note that the valuation of private businesses can be complex. For instance, while real estate assets such as rental properties are valued at market value, the valuation of business assets reported in the DFA is the average of market value and cost basis (Batty et al. 2021).

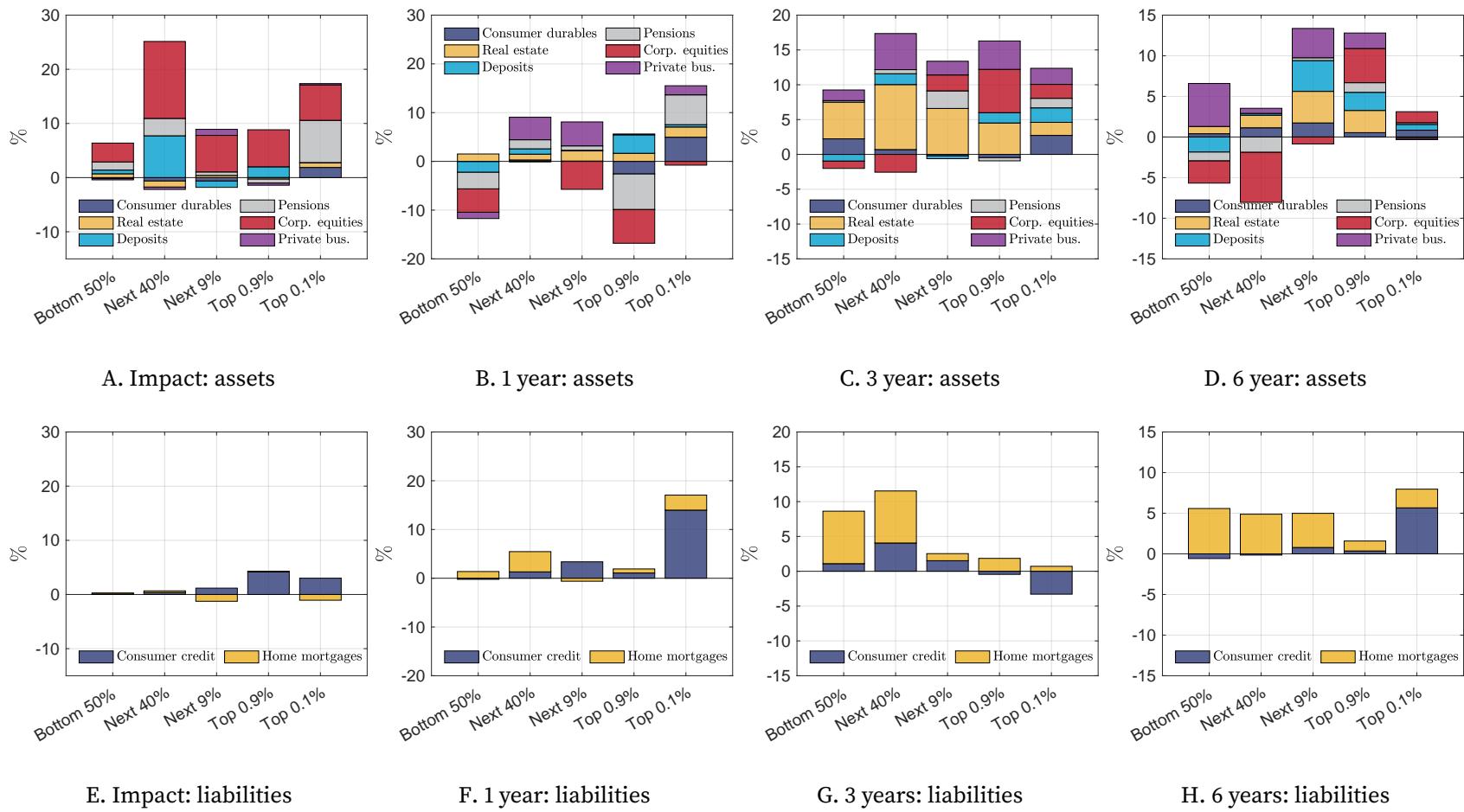


FIGURE E.1. The effects of an interest rate shock across the balance sheet: selected horizons

Notes: Impulse response functions to an interest rate shock estimated using Bayesian VAR described in Table 2, panel B. Stacked bars correspond to the median impulse responses from the posterior distribution. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Balance sheet components are deflated using the consumer price index.

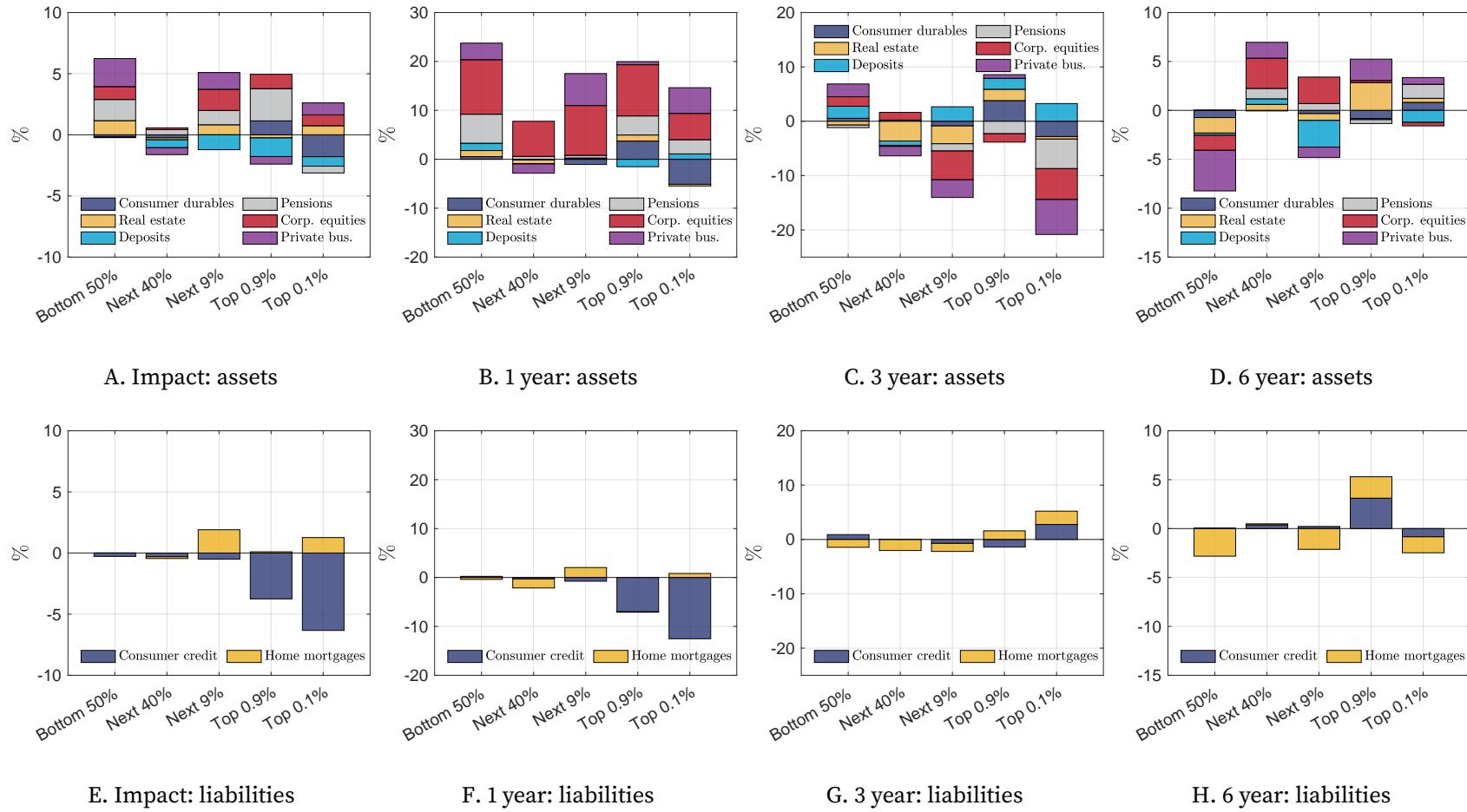


FIGURE E.2. The effects of an asset purchase rate shock across the balance sheet: selected horizons

Notes: Impulse response functions to an asset purchase shock estimated using Bayesian VAR described in Table 2, panel B. Stacked bars correspond to the median impulse responses from the posterior distribution. Impulse responses are normalized to generate a 1% response of real GDP after 3 quarters. Balance sheet components are deflated using the consumer price index.

F. Monetary policy and heterogeneous capital gains

The role of asset prices in shaping the dynamics of wealth and its distribution has been widely recognized in the literature (Blanchet and Martínez-Toledano 2022). At the same time, the most direct effects of monetary policy are often observed in financial markets (Bernanke and Kuttner 2005). In this Appendix, we examine the relationship between monetary policy, asset prices, and unequal wealth growth across the distribution. In particular, we show that the effects of monetary policy on capital gains are highly heterogeneous across wealth groups, with wealthier groups experiencing larger increases in capital gains following both shocks.

F.1. Measuring capital gains

To emphasise the role of capital gains in the dynamics of wealth accumulation, we consider a simple law of motion for net wealth where W_t^i is net wealth of group i at time t :

$$W_{t+1}^i = W_t^i + \Pi_t^i + O_t^i. \quad (\text{F.1})$$

where Π_t^i are total capital gains of group i between time t and $t + 1$, and O_t^i captures any other factor that affects wealth at time t , such as savings, other returns, dividends, and any other unobserved factor. In addition, we assume that capital gains and other factors affecting wealth accumulation occur simultaneously. This law of motion can be extended to any gross asset A_{jt}^i on the balance sheet of group i :

$$A_{jt+1}^i = A_{jt}^i + \Pi_{jt}^i + O_{jt}^i. \quad (\text{F.2})$$

In this equation, A_{jt}^i is the level of asset j for group i at time t , Π_{jt}^i are capital gains or losses generated by that asset between time t and $t + 1$, and O_{jt}^i captures any other factor contributing to the accumulation of that specific asset. Equations F.1 and F.2 show that capital gains resulting from changes in asset prices contribute to the accumulation of both net wealth and asset accumulation. However, the magnitude of capital gains or losses depends on the exposure to a particular asset, which can be measured by the share of that asset in total assets. As a result, capital gains from changes in the price of a particular asset should be heterogeneous due to differences in portfolio composition across groups.

To better illustrate the role of portfolio composition, let's consider the standard formula used to calculate capital gains. Assuming that wealth group i holds a portfolio

of J assets denoted by $\{A_{jt}^i\}_{j=1}^J$ at time t , the total (dollar) capital gains between time t and $t + 1$ can be computed as $\Pi_t^i = \sum_{j=1}^J \Pi_{jt}^i = \sum_{j=1}^J (p_{jt+1}/p_{jt} - 1) A_{jt}^i$, where p_{jt} is the price index for asset j . This formula is commonly used in the literature to calculate asset-specific capital gains and to assess their role in wealth accumulation ([Kuhn, Schularick, and Steins 2020](#)). However, extending this formula to total capital gains requires the choice of a price index for each asset on the balance sheet, including assets that are not traded in financial markets or for which there is no market price readily available.

In this study we use a different approach to overcome the limitation of choosing a price index for each asset on the balance sheet. To calculate capital gains, we begin by noticing that at the aggregate level, changes in any asset j between the beginning of time t and the beginning of time $t + 1$ can be decomposed as follows:

$$A_{jt+1} - A_{jt} = F_{jt} + R_{jt} + V_{jt}, \quad (\text{F.3})$$

where F_{jt} represents transactions, which capture the exchange of assets, R_{jt} represents revaluations, which measure holding gains and losses (capital gains), V_{jt} represents other volume changes, which capture other events (e.g., natural disasters). This decomposition separates the economic flow that reflects the change in asset levels over time, into its constituent components. In the context of national accounts, expression F.3 also applies to aggregate wealth, where R_t represents changes in wealth due to nominal holding gains and losses.

To estimate total capital gains, we allocate the aggregate revaluation R_t to different wealth groups using their respective wealth shares as weights:

$$\Pi_t^i = \left(\frac{W_t^i}{W_t} \right) R_t, \quad (\text{F.4})$$

where Π_t^i is the capital gains for group i at time t , W_t^i is the wealth of group i at time t , and W_t is aggregate wealth. We obtain the aggregate revaluation R_t from Table R.101 of the Financial Accounts of the US, which provides information on changes in aggregate net wealth resulting from holding gains and losses recorded on all financial and nonfinancial asset on the aggregate household balance sheet. This approach allows us to estimate total capital gains without assuming a specific price index for each asset class on the balance sheet, as is typically done in other studies ([Kuhn, Schularick, and Steins 2020](#)). Figure F.3 compares the capital gains on real estate and on corporate equities and mutual funds obtained using the traditional formula with our approach of

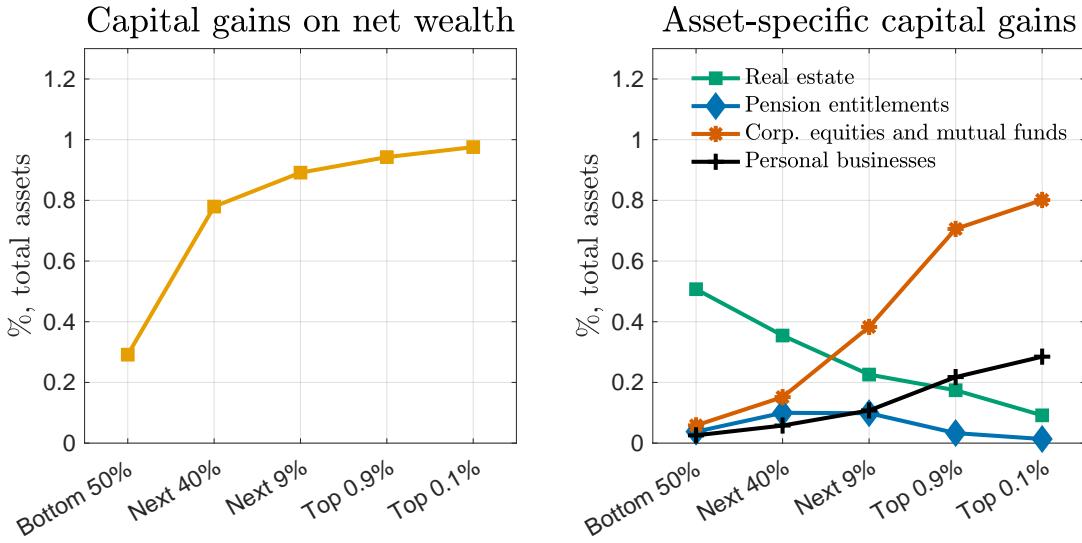


FIGURE F.1. Scale dependence (average capital gains to total assets, 1989-2022)

Notes: The figure plots average capital gains on (lagged) total assets for each wealth group. The average is computed over the full sample (1989-2022). For the computation of capital gains see the main text.

distributing the aggregate revaluation. We find that the two measures of capital gains are qualitatively similar.

In Figure F.1, the left panel shows the feature of scale dependence in capital gains, indicating that wealthier groups tend to experience higher capital gains relative to poorer ones. The graph shows the average capital gains to total assets across the wealth distribution from 1989 to 2022. To avoid distorting the ratio for groups with minimal wealth, capital gains are normalized to total assets (or gross wealth). The formula for capital gains to total assets, $\pi_t^i = \frac{\Pi_t^i}{A_{t-1}^i}$, quantifies the "income" generated per dollar of assets. However, it should not be interpreted as a return on assets because dividends, realised capital gains, and debt service costs are not observed. The right panel of Figure F.1 plots the average capital gains from a selected set of asset classes. Not surprisingly, the magnitude of capital gains (relative to total assets) is larger for wealth groups whose portfolios are predominantly composed of the asset class in question. For example, as we move toward the top of the distribution, where the importance of real estate declines, the magnitude of capital gains generated by real estate holdings also declines. Scale dependence in returns to wealth can contribute to wealth inequality (Piketty 2014) and has also been confirmed by studies using data from Norway (Fagereng et al. 2020), Sweden (Bach, Calvet, and Sodini 2020) and the US (Xavier 2021).

F.2. The effects of monetary policy shocks

When interest rates are lowered, the discount rate falls, leading to an increase in the present value of future cash flows generated by assets. Similarly, central bank asset purchase programs can reduce long-term yields and increase the valuation of long-lived assets. Depending on the composition of households' portfolios and the sensitivity of their assets to monetary policy, these changes in asset prices can have heterogeneous effects across the wealth distribution. As a result, if asset prices are the only channel through which monetary policy affects wealth, when interest rates are cut or asset purchase programs are implemented, wealth tends to increase more for households at the top of the wealth distribution than for those at the bottom.²⁵

We quantify the role of monetary policy in generating heterogeneous capital gains across the distribution by estimating a VAR model augmented with capital gains on total assets ($\pi_t^i = \frac{\Pi_t^i}{A_{t-1}^i}$) for wealth group i (Table F.1). We estimate a separate model for each monetary policy type, with identification and estimation following the approach outlined in Section 3.

Figure F.2 plots the effect of monetary policy on capital gains, expressed as a share of total assets, across the wealth distribution and at three different time horizons: the immediate impact, six months after the shock, and one year after the shock. The results show that the effects of monetary policy become more pronounced as we move up the wealth distribution. Note that for an interest rate shock, the peak response is immediate, while for an asset purchase shock it is delayed by a few quarters. Interestingly, most of the heterogeneity in the response of capital gains to monetary policy shocks is observed between the bottom 50% and the top 50% of the wealth distribution. These disparities in the response of capital gains to monetary policy shocks diminishes over the medium run.

If there were no differences in the composition of households' portfolios, the impact of monetary policy shocks on capital gains would be homogeneous across the wealth distribution, with no distributional consequences through asset prices. In reality, however, this is not the case. Capital gains are scale dependent, meaning that wealthier groups tend to experience higher capital gains. The effects of monetary policy shocks on capital gains also exhibit scale dependence, with wealthier groups experiencing

²⁵It is important to note that the measures of capital gains used in this paper, which are based on revaluation data from national accounts, do not directly account for the heterogeneous composition of portfolios. However, the ratio of capital gains to total assets does reflect the underlying portfolio heterogeneity. In particular, $\pi_t^i = \Pi_t^i/A_{t-1}^i = \sum_1^J (A_{jt}^i/A_{t-1}^i) (R_{jt}/A_{jt-1})$, where (A_{jt}^i/A_{t-1}^i) reflects the exposure of group i to asset j and this exposure differs across groups (portfolio heterogeneity).

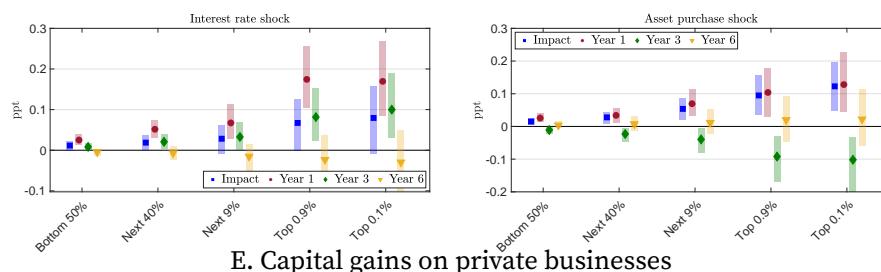
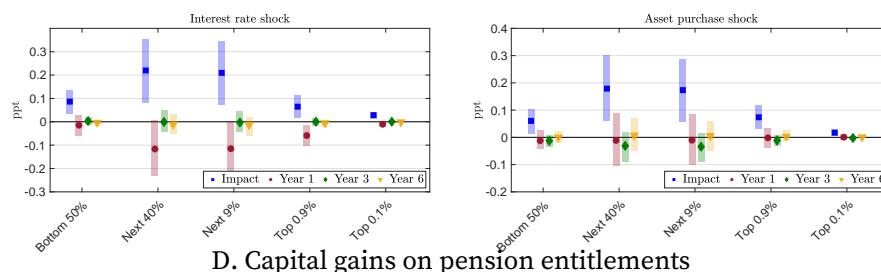
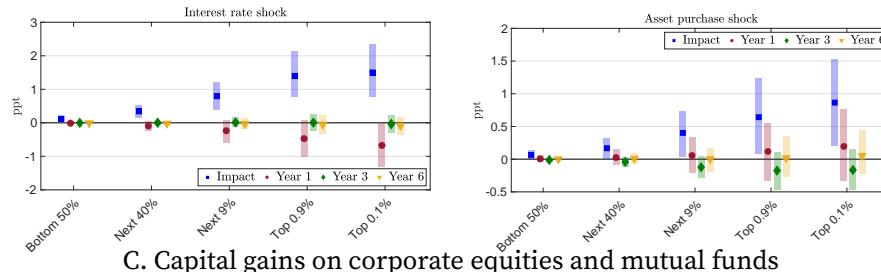
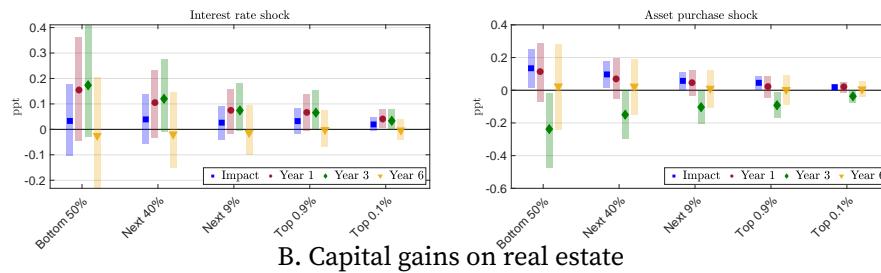
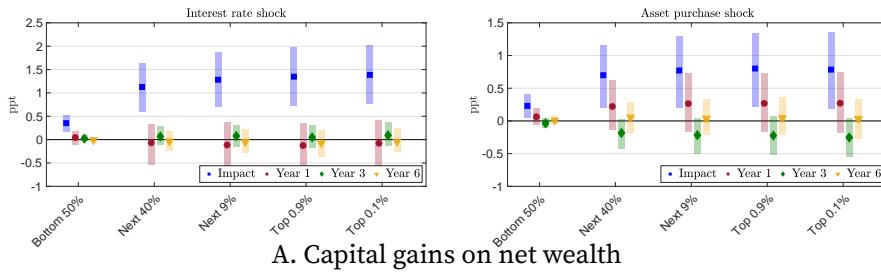


FIGURE F.2. Monetary policy and capital gains

Notes: This figure plots the response of capital gains (as share of total assets). Impulse responses for each wealth group are retrieved from a baseline VAR model augmented with capital gains to total assets for each wealth group. Impulse responses are scaled to imply a 1% response of real GDP. Intervals are 68% posterior coverage bands.

TABLE F.1. Models and variables description

Series	Unit	Source
Panel A: Baseline models with capital gains		
1 Policy shock:		
Conventional shock (\hat{s}_t^R)		Sections 3.2
Unconventional shock (\hat{s}_t^{LSAP})		Sections 3.3
2 Real GDP	BoC 2012\$	Bureau of Economic Analysis
3 Consumer price index	2015 = 100	Bureau of Economic Analysis
4 Excess bond premium	Percent	Gilchrist and Zakrajšek (2012)
5 Interest rate or spread:		
1-year Treasury Rate	Percent	McCracken, Ng et al. (2021)
Term spread	Percent	McCracken, Ng et al. (2021)
6 Capital gains, bottom 50%	%, total assets	Own estimates (Section F)
7 Capital gains, next 40%	%, total assets	Own estimates (Section F)
8 Capital gains, next 9%	%, total assets	Own estimates (Section F)
9 Capital gains, top 0.9%	%, total assets	Own estimates (Section F)
9 Capital gains, top 0.1%	%, total assets	Own estimates (Section F)

Notes: DFA is Distributional Financial Accounts. Bil. is billions. Capital gains are computed using wealth shares from the Distributional Financial Accounts and nominal holding gains and losses on aggregate wealth from Table R.101 of the Financial Accounts of the United States. See Section F for a detailed treatment of the estimation of capital gains.

larger increases in capital gains following these shocks, with these differences reflecting heterogeneity in portfolio composition across the wealth distribution. In particular, exposure long-term and price-sensitive assets is associated to larger capital gains following a monetary policy shock (Greenwald et al. 2021).

F.3. Estimating capital gains: further details

In this section, we provide further details on the original series used to obtain capital gains. To compute group-specific total capital gains (that is, capital gains on net wealth), we use the following formula:

$$\Pi_t^i = \left(\frac{W_t^i}{W_t} \right) R_t. \quad (\text{F.5})$$

where W_t^i/W_t is the share of wealth owned by wealth group i and R_t is aggregate capital gains. For capital gains on net wealth, R_t is computed as:

- **Total capital gains (capital gains on net wealth)** = Households and Nonprofit Organizations: Assets Less Liabilities with Revaluations, Revaluation (FR158000005Q) - Non-profit Organizations; Equipment, Current Cost Basis, Revaluation (FR165015205Q)

- Nonprofit Organizations; Nonresidential Intellectual Property Products, Current Cost Basis, Revaluation (FR165013765Q).

To compute group- and asset-specific capital gains (that is, capital gains on specific asset classes), we use the following formula:

$$\Pi_{j,t}^i = \left(\frac{A_{j,t}^i}{A_{j,t}} \right) R_{j,t}. \quad (\text{F.6})$$

where $A_{j,t}^i/A_{j,t}$ is the share asset j owned by wealth group i and $R_{j,t}$ is aggregate capital gains generated by asset j . More specifically, $R_{j,t}$ is computed as:

- **Capital gains from holding real estate** = Households and Nonprofit Organizations; Real Estate at Market Value, Revaluation (FR155035005Q).
- **Capital gains from holding corporate equities and mutual funds** = Households and Nonprofit Organizations; Corporate Equities; Asset, Revaluation (FR153064105Q) + Households and Nonprofit Organizations; Mutual Fund Shares; Asset, Revaluation (FR153064205Q).
- **Capital gains from private businesses** = Households and Nonprofit Organizations; Proprietors' Equity in Noncorporate Business, Revaluation (FR152090205Q).
- **Capital gains from holding pension entitlements** = Households and Nonprofit Organizations; Pension Entitlements; Asset, Revaluation (FR153050005Q).

F.4. Comparing estimates of capital gains

In this section, we compare our method of estimating capital gains with the traditional formula used in the literature for obtaining asset specific capital gains ([Kuhn, Schularick, and Steins 2020](#)). We focus on real estate and on corporate equities and mutual funds. Let RE identify real estate while CE identify corporate equities and mutual funds such that j is alternatively RE or CE , we compute capital gains as follows:

$$\Pi_{j,t}^i = \left(\frac{A_{j,t}^i}{A_{j,t}} \right) R_{j,t} : \text{revaluation-based capital gains generated by asset } j \quad (\text{F.7})$$

$$\tilde{\Pi}_{j,t}^i = \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right) A_{j,t}^i : \text{price-based capital gains generated by asset } j \quad (\text{F.8})$$

where $A_{j,t}^i$ is the stock of asset j held by group i , $A_{j,t}$ is the aggregate stock of asset j held by the household sector, $R_{j,t}$ is the aggregate revaluation (or capital gain) on asset

j according to the Revaluation Accounts (see above), $p_{j,t}$ is the (real) price index of asset j which is assumed to be common across groups. The price index is the Case-Shiller house price index for real estate and S&P 500 index for corporate equities and mutual funds. To ease interpretation and comparison, we work with capital gains expressed as share of total group-specific group, that is:

$$\pi_{j,t}^i = \frac{\Pi_{j,t}^i}{A_t^i} : \text{revaluation-based capital gains generated by asset } j \quad (\text{F.9})$$

$$\tilde{\pi}_{j,t}^i = \frac{\tilde{\Pi}_{j,t}^i}{A_t^i} : \text{price-based capital gains generated by asset } j \quad (\text{F.10})$$

In Figure F.3, we compare the two approaches in estimating average capital gains on real estate (left panel) and corporate equities and mutual funds (right panel). Both the revaluation-based and price-based approaches yield quantitatively similar results for average capital gains on real estate. In contrast, the two approaches diverge in measuring capital gains on corporate equities and mutual funds with the divergence increasing across the wealth distribution. This happens because the price-based measure is not able to capture the influence of mutual funds and of equity prices not tracked by the S&P 500 index. This finding suggests that previous studies may have had underestimated the magnitude of capital gains across the wealth distribution if a price index like the S&P 500 index is used.

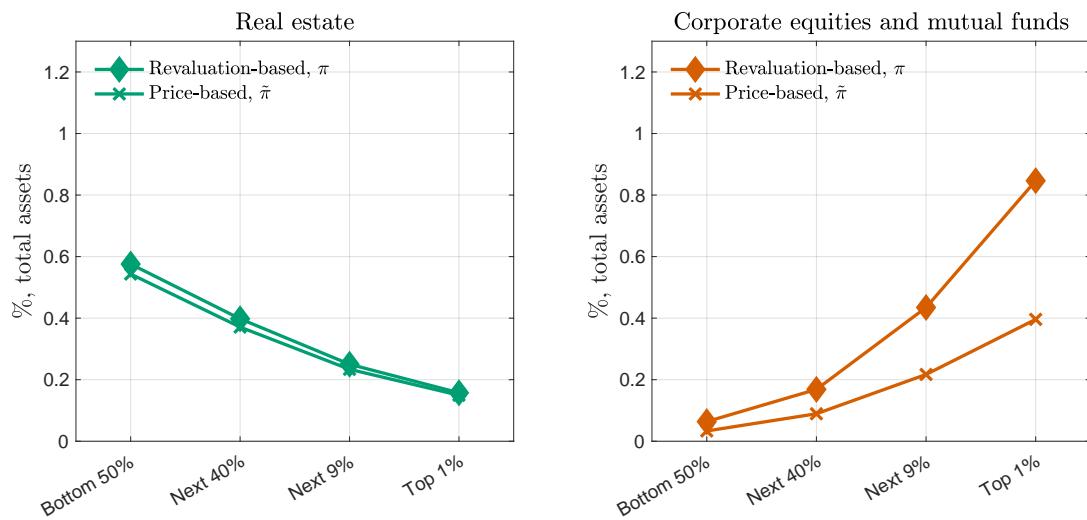


FIGURE F.3. Comparing estimates of capital gains: revaluation-based vs. price-based approach

Notes: The figure compares two measures of average capital gains (as share of lagged total assets) from holding real estate assets (left panel) and corporate equities and mutual funds (right panel) for the household sector as a whole. Averages are obtained for the 1989-2022 period.