Distributional spillover effects of US monetary policy[*†]

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Abstract

US monetary policy is likely to affect income inequality not only domestically, but also abroad. We study the distributional spillovers of US monetary policy to European economies. Combining annual distributional data from the World Inequality Database with quarterly macroeconomic data for the period from 1990 to 2019, we estimate Mixed-Frequency Bayesian Proxy Structural Vector Autoregressions and find that US monetary policy spillovers to European income distributions are substantial. For Germany, the effects are most pronounced and indicate that income inequality deteriorates after monetary policy tightenings in the US. For the remaining countries, distributional spillovers are less clear-cut and heterogeneous.

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1 Introduction

Monetary policy operations of the United States (US) Federal Reserve (Fed) impact economies around the world. The spillovers to real economic activity and financial conditions in most advanced economies are substantial on aggregate (Dedola et al., 2017; Miranda-Agrippino & Rey, 2020; Brusa et al., 2020). On a disaggregated level, the exposure of non-US individuals to internationally affected real and financial markets might vary, since individuals have heterogeneous income sources and wealth structures. Thus, Federal Open Market Committee (FOMC) decisions are likely to have distributional consequences not only domestically, but also abroad. Understanding whose income is more affected by US monetary policy spillovers is essential to assessing the economic conditions underlying domestic policy decisions. This might be particularly relevant in times of diverging business cycles and policy stances, like the Fed's and the ECB's policy stances before the pandemic crisis. Whether some households are more affected by spillovers than others and if so who bears the skin load of spillovers is still unclear.

In this paper, we empirically investigate the potential spillovers from US monetary policy to foreign income distributions. In our estimation, we draw on the longest and most detailed homogeneous dataset on income and wealth distributions across countries that is currently available: the World Inequality Database (WID). It combines information on income and wealth from national administrative data, national surveys and matches the micro-data on income with macroeconomic aggregates according to the national income concept. We perform a quantitative analysis on the US and the four biggest European economies with high-quality granular data (Burq & Chancel, 2020) for the period from 1990 to 2019: France, Germany, Italy and the United Kingdom (UK). We consider that monetary policy decisions are taken on a monthly basis, but distributional data is only available annually. To estimate monetary policy spillovers, we use a Mixed-Frequency Bayesian Proxy Structural Vector Autoregressive (MF-BPSVAR) model, identifying monetary policy shocks via an external instrument.

We build country-specific models including aggregate real and financial variables on the US economy, an instrumental variable, country-specific macroeconomic aggregates as well as country-specific income distribution variables for the respective country. In particular, we include selected pre-tax income decile and percentile shares.[1] Micro-level literature[2] suggests that it is essential to carve out the differential effects in the tails of the distribution that might offset each other at the aggregate level. This is why we follow Piketty et al. (2018) and look at income shares of particular parts of the income distribution.

Our results suggest that US contractionary monetary policy shocks indeed have substantial distributional effects, both in the US and abroad. For Germany, the effects are most pronounced and indicate that the income share of the bottom 50% of the income distribution declines following monetary policy tightenings in the US. In contrast, German high-income individuals, the top 10% and top 1%, gain income shares. For the remaining countries, namely France, Italy and the UK, distributional spillovers are less clear-cut and heterogeneous.

This study brings together two strands of literature, namely research on the distributional effects of monetary policy and on the international spillovers of US monetary policy. To the best of our knowledge, we are the first to empirically estimate the effects of US monetary policy on the income distributions abroad, in particular, on distributions of four European economies. We look at selected percentile and decile shares of the income distributions that are built with highly informative tails to represent the top 1% individuals. Thereby, our approach complements empirical studies focusing on the effects of monetary policy for the domestic income distribution (Coibion et al., 2017; Mumtaz &

[1] We focus on pre-tax rather than post-tax income to ensure that the estimated effects are not distorted by a redistribution of income via the national fiscal authorities after taxation.

[2] See for example Atkinson et al. (2011) as well as Alvaredo et al. (2013) and references therein.

Theophilopoulou, 2017; Furceri et al., 2018). Most of these studies investigate the monetary policy impact on summary measures of income inequality, like the Gini coefficient and changes of average incomes at specific deciles or percentiles based on distributional data that lack information at the right tail or even exclude the top 1% of the income distribution. Finally, we estimate the effects using a MF-BPSVAR model and put forward a Bayesian estimation algorithm. Both are - to our knowledge - novel to the literature.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the empirical methodology and describes the data that is used throughout the analysis. The empirical results are discussed in section 4 and section 5 concludes.

2 Background and literature review

This paper contributes to two lines of literature, namely research on the distributional effects of monetary policy and on the international spillovers of US monetary policy.

2.1 Distributional effects of monetary policy

From a theoretical point of view, the distributional effects of monetary policy cannot be determined *a priori*, because monetary policy affects income and wealth through a number of channels, with some exacerbating and others mitigating inequalities. The overall distributional effects on household income and wealth depend on the relative importance of each channel, which, in turn, is determined by the composition of the different income sources and wealth structure of households as well as other country-specific characteristics.

The literature has established five channels through which monetary policy may redistribute income and wealth at the domestic level.[3] First, the *Earnings Heterogeneity Channel* postulates that monetary policy affects labor incomes heterogeneously across the income distribution. Labor earnings are the primary source of income for most households (Coibion et al., 2017). Yet, monetary policy shocks do not affect these earnings uniformly across the income distribution. Labor incomes of individuals at the bottom of the income distribution tend to be more sensitive to monetary policy shocks than those at the middle or top of the distribution (Amberg et al., 2022). For example, Carpenter & Rodgers (2004) find that contractionary monetary policy disproportionately raises unemployment for low-income individuals as compared to other income groups and in turn increases income inequality.

According to the *Income Composition Channel* and the *Portfolio Composition Channel*, the distributional effects will also depend on the composition of households' income and wealth sources. With labor income being the primary (and often only) source of income at the bottom of the distribution, increases in unemployment will further reinforce income inequality. In contrast, individuals at the top of the income distribution receive larger shares of income from business and capital income. As asset prices tend to decline following monetary contractions, households with financial assets may be more adversely affected than those without financial assets, which may cushion income inequality. In the same vein, the *Portfolio Composition Channel* argues that the composition of individuals' balance sheets determines how strongly they are affected by monetary surprises. With stock and equity prices falling following contractionary monetary policy shocks (see, for instance, Breitenlechner et al. (2022)) and given that high-income households tend to hold more of these assets than low-income households, monetary contractions may contribute to mitigating wealth inequality.

On the other hand, households that are more connected to and frequently trade in fi-

[3]See also Coibion et al. (2017) for an extensive discussion.

nancial markets can better exploit their knowledge advantage and react more quickly to changes in asset prices than those without access to financial markets. This *Financial Segmentation Channel* benefits high-income and more financially acquainted individuals, as they can rebalance their portfolios more quickly than others.

Another factor that might exacerbate inequalities is the *Savings Redistribution Channel*. Given that monetary contractions raise interest rates, savers - that are wealthier to begin with - tend to benefit relative to borrowers (Doepke & Schneider, 2006). This will increase income inequality. On the other hand, inflation rates tend to fall following contractionary monetary policy shocks. This may benefit low-income households, as they rely more heavily on labor earnings and thus hold more liquid assets and spend a larger share of their income.

Given the myriad of counterveiling forces that affect the income and wealth distribution, the overall distributional effects are difficult to predict *ex ante* and depend on the relative importance of each of the discussed channels. In addition, the effects are likely to vary across countries, as they depend on the respective labor-market institutions, the share of labor income in overall income and whether fiscal redistribution policies are in place to buffer the adverse effects of monetary policy shocks.

So far, the literature remains undecided as to which of these channels prevails and whether monetary policy ultimately raises or lowers domestic income and wealth inequality. The seminal paper of Coibion et al. (2017) documents that US contractionary monetary policy leads to increases in consumption, income and wage inequality. Relying on quarterly microdata from the Consumer Expenditures Survey since 1980, they estimate reactions of different inequality measures using the narrative instrument of Romer & Romer (2004). They highlight the importance of the *Income Composition Channel* and the *Savings Redistribution Channel* as drivers of the results.

Mumtaz & Theophilopoulou (2017) find similar outcomes in a structural VAR approach including inequality measures using several UK household surveys. Their findings suggest that earnings, income and consumption inequality increases following monetary contractions. This is mainly the result of a decrease in wages and labor income for households at the bottom of the income distribution, while labor incomes of high-income households are less affected and make up a smaller share of overall income. They also find that quantitative easing may have contributed to an increase in inequality measures. This is due to the fact that households with financial assets experienced price appreciations and thereby benefited more than households without assets or access to financial markets, thus highlighting the role of the *Portfolio Composition Channel* as well as the *Financial Segmentation Channel*.

Simulating effects of unconventional monetary policy on income and wealth distributions of euro area countries that are taken from the ECB's Household Finance and Consumption Survey and the EU Labor Force Survey, Lenza & Slacalek (2018) document, in contrast, that quantitative easing by the ECB compresses the income distribution and increases wealth inequality, but only to a very limited extent. Their results are mainly driven by an increase in employment at the bottom of the income distribution following monetary expansions, which reduces income inequality, and emphasizes the role of the *Earnings Heterogeneity Channel*. In addition, they document that middle- and high-wealth households benefit from higher housing and stock prices, thereby slightly increasing wealth inequality.

Amberg et al. (2022) investigate the effects of expansionary monetary policy shocks on the income distribution for Sweden. They document a U-shaped response of incomes, with increases in labor income for the bottom and capital income increases at the top of the income distribution. Andersen et al. (2022) investigate the distributional effects of monetary policy in Denmark, while Casiraghi et al. (2018) focus on Italian households. Furceri et al. (2018) examine a panel of 32 advanced and emerging market economies.

2.2 Spillover effects of US monetary policy

Up to now, the literature on the international spillovers of the Fed's monetary policy operations focuses on the effects on core macroeconomic variables, like real economic activity, and on which economic characteristics explain differences in spillover effects (Canova & De Nicolo, 2002; Maćkowiak, 2007; Di Giovanni & Shambaugh, 2008; Georgiadis, 2016). Iacoviello & Navarro (2019) distinguish between three channels (based on Ammer et al. (2016)), through which US interest rate changes may affect foreign economies.

According to the *Exchange Rate Channel* and the *Trade Channel*, US monetary tightenings affect real economic activity abroad. Yet while the *Exchange Rate Channel* postulates that the appreciation of the US dollar following domestic monetary contractions shifts world demand away from US goods towards goods produced in other countries and thereby stimulates foreign GDP, the *Trade Channel* relies on the idea that higher US interest rates reduce domestic incomes and expenditures. This lowers US demand both for domestic as well as imported goods, leading to a decline in economic activity abroad, especially for those countries with a high trade exposure to the US. Irrespective of which of these two channels prevails, the effects likely have repercussions for the distribution of incomes abroad as well, as changes in foreign economic activity will affect employment and labor incomes heterogeneously across the income distribution.

Financial Channels subsume the effects of a US monetary tightening on the prices of the financial assets and liabilities abroad, as prices of (risky) assets tend to fall as global financial conditions tighten following changes in US monetary policy (Rey, 2015; Bernanke, 2017). This may feed through to wealth inequality abroad, as changes in asset prices affect individuals differently across the distribution.

The literature consistently provides empirical evidence in favor of the *Trade Channel*. For the *Financial Channels*, the evidence is less clear-cut. For example, the study of Dedola et al. (2017) finds that a US contractionary monetary policy shock decreases economic activity and increases unemployment across advanced and emerging economies. Yet they postulate that only in emerging countries US monetary policy shocks lead to capital outflows, a decline in domestic credit, and a fall in housing prices. In contrast, Miranda-Agrippino & Rey (2020) show that US monetary policy is an important driver of the global financial cycle that, in turn, affects local capital outflows, domestic credit, and housing markets homogeneously for the majority of advanced and emerging countries.

3 Empirical methodology and data

3.1 Mixed-Frequency VAR

The MF-VAR used in this paper is based on the companion form of a VAR(p) in quarterly frequency $t = 1, \dots, T$:

$$z_t = C + \Phi z_{t-1} + G\Sigma^{\frac{1}{2}} u_t \qquad u_t \sim N(0, I_n), \tag{1}$$

where the state vector z_t collects the current and lagged values of observed quarterly variable $y_{q,t}$ as well as the variables $y_{a,t}$, which are only partially observed at an annual frequency. As such, the initial state vector is of dimension $(n_q+n_a)p\times 1$, where $n_q+n_a = n$ is the number of endogenous variables in the VAR process. The first n rows of the $np\times np$ matrix Φ collect the autoregressive coefficients $(\Pi_1, ..., \Pi_p)$ of the underlying VAR, while the remaining $n(p-1)$ rows are defined to yield identities of lagged values of $y_{q,t}$ and $y_{a,t}$. The first n entries in C collect the constant terms of the VAR process, while the remaining entries are set to 0. G is a selection matrix, with $G = [I_n, 0_{(n(p-1))}]$ and $\Sigma^{\frac{1}{2}}$ as the Cholesky factor of the $n \times n$ variance-covariance matrix of the VAR innovations (Σ).

We augment the companion form of the VAR(p) in equation (1) by the $n_{a,x}$ aggregator variables $x_{a,t}$ to create the augmented state vector $\tilde{z}_t = [z_t, x_{a,t}]$, which is of dimension $(n_q + n_a)p + n_{a,x}$. The aggregator variable links the unobserved series $y_{a,t}$ for our inequality measures to the observed four quarter average of the underlying series $y_{a,t}$

$$x_{a,t} = 1/4(y_{a,t} + y_{a,t-1} + y_{a,t-2} + y_{a,t-3}). \tag{2}$$

To incorporate the aggregator equation into the state transition equation, we also change C, Φ and G accordingly. To be more precise, we define

$$\tilde{C} = [C; 0_{n_{a,x}}], \quad \tilde{\Phi} = [\Phi, 0_{[(n+n_{a,x})\times 1]}; D], \quad \tilde{G} = [G, 0_{[n\times 1]}],$$

where the matrix D forms the last $n_{a,x}$ rows of $\tilde{\Phi}$ and is designed to replicate the dependence of $x_{a,t}$ on the lags of $y_{a,t}$ as described in equation (2). At last, to take care of the contemporaneous relation between the state variables defined in equation (2), we create the matrix A, which is defined as

$$\tilde{A} = I_{np+n_{a,x}} + F,$$

where the $(np+n_{a,x}) \times (np+n_{a,x})$ matrix F is a matrix of zeros with entries of $-\frac{1}{4}$ at the position that links $x_{a,t}$ to the contemporaneous values of $y_{a,t}$. The augmented state space system, that includes the aggregator equation, can then be written as

$$\tilde{A}\tilde{z}_t = \tilde{C} + \tilde{\Phi}\tilde{z}_{t-1} + \tilde{G}\Sigma^{\frac{1}{2}}u_t \qquad u_t \sim N(0, I_n).$$

As $\tilde{A}$ is always invertable, this can be rewritten as

$$\tilde{z}_t = \bar{C} + \bar{\Phi}\tilde{z}_{t-1} + \bar{G}\Sigma^{\frac{1}{2}}u_t \qquad u_t \sim N(0, I_n) \tag{3}$$

with

$$\bar{C} = \tilde{A}^{-1}\tilde{C}, \quad \bar{\Phi} = \tilde{A}^{-1}\tilde{\Phi}, \quad \bar{G} = \tilde{A}^{-1}\tilde{G}.$$

Equation (3) is the state transition equation of our state space model.

As in Schorfheide & Song (2015), the dimension of the observed variables (y_t^{obs}) and, as such, of the measurement equation varies over time. In particular, the measurement equation reads as

$$y_t^{obs} = S_t \tilde{z}_t, \tag{4}$$

where the selection matrix S_t at each point in time selects the observable quarterly series $y_{q,t}$ and, if at time t the four quarter average of the $y_{a,t}$ is part of y_t^{obs}, it selects the row for the corresponding aggregator $x_{a,t}$. Equations (3) and (4) form a linear Gaussian state space model and we employ the simulation smoother of Durbin & Koopman (2002) to draw from the conditional posterior of the missing observations $y_{a,t}$ conditional on the data and the parameters.

3.2 Inference by Bayesian proxy SVAR

To identify distributional spillover effects of a US monetary policy shock, we apply a Bayesian proxy SVAR to the mixed-frequency VAR outlined in the previous section. Defining the structural *impact* matrix B, the structural elasticity matrix as D with $D = B^{-1}$ and the structural lagged coefficients B_1, we can express the coefficients in (1) as $\Pi = BB_1$, $\Sigma = (B'B)$ and $u_t = B\epsilon_t$.[4] Thus, we can write the reduced form in (1) as a system of structural equations

$$Dy_t = B_1 y_{t-1} + \epsilon_t, \qquad \epsilon \sim N(0, I_n) \tag{5}$$

[4]Notice that, for the sake of exposition, we assume that $p = 1$.

which can also be expressed as

$$y_t = \Pi y_{t-1} + B\epsilon_t, \qquad \epsilon \sim N(0, I_n), \tag{6}$$

whereby D and B_1 are the parameters of the structural model and B is the structural impact matrix, which is assumed to be invertible. ϵ is Gaussian with mean zero and covariance matrix I_n. Following the proxy SVAR approach of Stock & Watson (2012), Caldara & Herbst (2019), Mertens & Ravn (2013) and Arias et al. (2021), we identify a US monetary policy shock by using high-frequency financial data as a proxy variable, m_t, for monetary policy shocks, $\epsilon_{mp,t}$. Then the identification builds on the assumptions that the proxy variable is (i) correlated with the monetary policy shocks $\epsilon_{mp,t}$, and is (ii) orthogonal to the remaining structural shocks $\epsilon_{\backslash mp,t}$. Formally, the identifying assumptions are

$$E[\epsilon_{mp,t} m_t] = \sigma_{mp}, \tag{7}$$

$$E[\epsilon_{\backslash mp,t} m_t] = \underset{(n-1\times 1)}{0}, \tag{8}$$

and represent the relevance and the exogeneity condition, respectively.

To include the proxy variable in the structual MF-VAR of equation (6), we augment the model such that $\tilde{y}_t \equiv (y_t, m_t)$, $\tilde{B}$ and $\tilde{\Pi}$ are the corresponding impact coefficient matrices of dimension $\tilde{n} \times \tilde{n}$ with $\tilde{n} = n + k$ and $\tilde{\epsilon} \equiv (\epsilon_t, v_t')' \sim N(0, I_{n+k})$, where v_t are the measurement errors that affect the proxy variables. The augmented model is then given by

$$\tilde{y}_t = \tilde{\Pi}\tilde{y}_{t-1} + \tilde{B}\tilde{\epsilon}_t \tag{9}$$

with

$$\tilde{\Pi} = \begin{bmatrix} \Pi & \Pi_{m,y} \\ 0_{1\times n} & \Pi_{m,m} \end{bmatrix} \text{ and } \tilde{B}\tilde{\epsilon}_t = \begin{bmatrix} B_{\backslash mp,t} & B_{mp} & 0 \\ 0 & \sigma_{mp} & \sigma_v \end{bmatrix} \begin{bmatrix} \epsilon_{\backslash mp,t} \\ \epsilon_{mp,t} \\ v_t \end{bmatrix}, \tag{10}$$

where the model in (10) is a model that links the proxy variable to the instrumented structural shock. The zero restrictions in $\tilde{B}$ are implied by the exogeneity condition in (8), whereas the zero restrictions $\tilde{\Pi}$ make sure that the proxy does not enter the equation of the endogenous variables. Then the joint likelihood function of the data, conditional on the parameters and the missing observations for the annual variables, is

$$\begin{aligned} \mathcal{L}(\widetilde{Y}|\widetilde{Y_a},\widetilde{B},\widetilde{\Pi}) \propto &|B|^{-T} exp\Big(-\frac{1}{2}\Big[vec(\widetilde{Y}) - (I_{\tilde{n}} \otimes Y_{t-1})vec(\widetilde{\Pi})\Big]' \\ &[(\widetilde{B}\widetilde{B}')^{-1} \otimes T]\Big[vec(\widetilde{Y}) - (I_{\tilde{n}} \otimes Y_{t-1})vec(\widetilde{\Pi})\Big]\Big). \end{aligned} \tag{11}$$

We follow the Georgiadis & Schumann (2022) and sample from the joint posterior of parameters $\widetilde{\Pi}$, $\widetilde{B}$ and adapt their Metropolis-Within-Gibbs algorithm to incorporate the sampling of the missing data $\widetilde{Y}_a$. In order to initialize the algorithm, we numerically search for the joint posterior mode of the parameters and the missing data. We do so by first running a restricted EM algorithm (which only takes into account the likelihood) and use the result as a starting point for a series of Newton- and simulated annealing steps, which numerically maximize the joint posterior distribution.

Given the initial (modal) values for the autoregressive parameters $\widetilde{\Pi}$, the free parameters (b) of the structural impact matrix $\widetilde{B}$ and the missing values $\widetilde{Y}_a$, we cycle through the respective conditional posteriors using a Metropolis-Hastings step for b, a Gibbs step for $\widetilde{\Pi}$, and the Durbin & Koopman (2002) simulation smoother for $\widetilde{Y}_a$.

3.2.1 Drawing the free parameters ($\widetilde{b}$) of the impact matrix $\widetilde{B}$

We are interested in drawing from the conditional posterior distribution of

$$P(\widetilde{b}|Y_q, Y_a, \widetilde{\Pi}) \propto P(\widetilde{b})P(\widetilde{B}_1|\widetilde{b})\mathcal{L}(\widetilde{Y}|\widetilde{Y_a},\widetilde{B},\widetilde{\Pi}), \tag{12}$$

where $P(\widetilde{b})$ represents the independent Student-$\mathcal{T}$ priors, discussed in section 3.3, and $P(\widetilde{B}_1|b)$ is the normal prior for B_1, which we specify conditional on $\widetilde{b}$ along the lines of Sims & Zha (1998) and as described in section 3.2.2.

Since the posterior is of unknown form, we use an adaptive Metropolis-Hastings algorithm to simulate it. In particular, our proposal density for $\widetilde{b^j}$ at iteration j is a truncated normal ($\mathcal{N}_{tr}$) centered at the previous value $\widetilde{b^{j-1}}$, with variance-covariance matrix $\widehat{V}_{b,j}$, scale parameter ξ_j and upper and lower bounds defined by the normalization of the main diagonal of $\widetilde{B}$ and possible sign restrictions. In order to improve the efficiency of the algorithm, we initialize the $\widehat{V}_{b,j}$ at the inverse Hessian at the posterior mode and iteratively adapt it along the lines of Haario et al. (2001). We do so because the posterior covariance of the parameters at some points in the parameter space may be poorly approximated by the inverse Hessian at the mode, which by definition is only a local approximation. We also adaptively scale ξ_j using the Robbins–Monro process to ensure an acceptance rate of 24% in the spirit of Garthwaite et al. (2016).

Thus, at iteration j, we draw of proposal from $\widetilde{b^j_j} = \mathcal{N}_{tr}(\widetilde{b^{j-1}}, \xi_j \widehat{V}_{b,j}, lb, ub)$ and accept it with probability

$$\alpha_b = min\Big\{1, \frac{P(\widetilde{b^j}|\widetilde{Y}_q, \widetilde{Y}_a, \widetilde{\Pi})}{P(\widetilde{b^{j-1}}|\widetilde{Y}_q, \widetilde{Y}_a, \widetilde{\Pi})} \frac{\Phi_{tr}(\widetilde{b^{j-1}}, \xi\widehat{V}_b, lb, ub)}{\Phi_{tr}(\widetilde{b^j}, \xi\widehat{V}_b, lb, ub)}\Big\} \tag{13}$$

with $\Phi_{tr}(\cdot) =$ being a CDF of truncated multivariate normal calculated using the method put forward in Botev (2017).

3.2.2 Drawing the autoregressive parameters $\widetilde{\Pi}$

Given the zero restrictions in $\widetilde{\Pi}$ outlined in equation (10), we cannot use standard conjugate priors and the corresponding sampling algorithms to draw from the conditional posterior of $\widetilde{\Pi}$. Instead, we observe that, (i) conditional on $\widetilde{B}$, knowing the structural lagged coefficients $\widetilde{B}_1$, which carry the same zero restrictions, is sufficient to recover $\widetilde{\Pi}$ as $\widetilde{\Pi} = \widetilde{B}B_1$, (ii) due to the structure of B, the zero restrictions in $\widetilde{B}_1$ translate into zero restrictions on $\widetilde{\Pi}$, (iii) the transformation is one to one, (iv) conditional on B, the structural equations are independent and therefore we can sample B_1 equation by equation, which speeds up computation time. As such, instead of sampling $\widetilde{\Pi}$ directly, we sample $\widetilde{B}_1$ along the lines of Waggoner & Zha (2003) and transform it into $\widetilde{\Pi}$ by multiplying the draw with $\widetilde{B}$.[5] To be more precise: Let $\widetilde{b}_{1,i}$ be a column vector containing the ith column of $\widetilde{B}_1$ and let $\widetilde{d}_i$ be the ith column of $\widetilde{D} = \widetilde{B}^{-1}$, let A_i and R_i be a $n \times n$ and $np+1 \times np+1$ selection matrix, such that

$$R_i\widetilde{b}_{1,i} = 0, \qquad A_i\widetilde{d}_i = 0.$$

Furthermore, let the columns of the matrices U_i and V_i form a basis for the null space of R_i and A_i. As shown in Waggoner & Zha (2003), if the columns of $\widetilde{b}_{1,i}$ are supposed to satisfy the zero restrictions, it needs to be the case that

$$\widetilde{b}_{1,i} = U_i\widetilde{b}_{1,i}^{free}, \qquad \widetilde{d}_i = V_i\widetilde{d}_{0,i}^{free},$$

where $\widetilde{b}_{1,i}^{free}$ and $\widetilde{d}_i^{free}$ are the free parameters of the equation captured in $\widetilde{b}_{1,i}$ and $\widetilde{d}_i$. The original Sims & Zha (1998) prior on the parameters in $\widetilde{B}_1$ is specified such that, after multiplying them with $\widetilde{B}$, the prior over $\widetilde{\Pi}$ resembles the original Minnesota prior. This

[5] Note that, while we use the framework of Waggoner & Zha (2003), we do not specify their normal prior for the parameters of the structural elasticity matrix $\widetilde{D}$, but rather specify the prior over the structural impact matrix $\widetilde{B}$.

is achieved by specifying the prior for each column i of $\widetilde{B}_1$ as

$$P(\widetilde{b}_{1,i}|\widetilde{d}_{0,i}) \sim N(\bar{P}_i\widetilde{d}_i, \bar{H}_i),$$

where $\bar{P}_i = [I_n; 0_{n(p-1)+1\times n}]$ and $\bar{H}_i$ is a symmetric positive definite matrix that specifies the tightness of the priors beliefs. Waggoner & Zha (2003) show how to incorporate the linear restrictions specified by R_i and A_i into this prior. The resulting prior takes the following form:

$$P(\widetilde{b}_{1,i}^{free}|\widetilde{d}_0^{free}) \sim N(\widetilde{P}_i\widetilde{d}_i^{free}, \widetilde{H}_i)$$

with

$$\widetilde{H}_i = (V_i'\bar{H}_iV_i')^{-1}, \qquad \widetilde{P}_i = \widetilde{H}_iV_i'\bar{H}_i^{-1}\bar{P}_iU_i.$$

The joint prior for the free elements of $\widetilde{B}_1$, which we evaluate in the computation of the posterior density of $\widetilde{B}$ is then given by

$$P(\widetilde{B}_1|b) = \mathcal{I}_{\widetilde{\Pi}}^{st}\prod_{i=1}^{n} P(\widetilde{b}_{1,i}^{free}|\widetilde{d}_i^{free}),$$

where $\mathcal{I}_{\widetilde{\Pi}}^{s}$ is an indicator function that takes the value of 1, if the implied draw for $\widetilde{\Pi}$ is stationary and 0 otherwise.

Lastly, it can be shown that, conditional on the draw being stationary, the posterior distribution of the free elements in the individual columns of $\widetilde{B}_1$ is also normal and reads as

$$P(\widetilde{b}_{1,i}^{free}|\widetilde{Y}_q, \widetilde{Y}_a, \widetilde{d}_0^{free}) \sim N(\widehat{P}_i\widetilde{d}_i^{free}, \widehat{H}_i), \tag{14}$$

where

$$\widehat{H}_i = (V_i' X' X V_i + \widetilde{H}_i^{-1})^{-1}, \qquad \widehat{P}_i = \widehat{H}_i (V_i' X' Y U_i + \widetilde{H}_i^{-1} \widetilde{P}_i)$$

and Y and X as the usual stacked matrices of endogenous variables and regressors.

3.2.3 Sampling the missing values $\widetilde{Y}_a$

As discussed in section 3.1, equations (3) and (4) form a linear Gaussian state space model. To sample from the posterior distribution of the missing values, we use the Durbin & Koopman (2002) simulation smoother. In particular, we implement algorithm 2a outlined in Jarociński (2015) and initialize the filter and smoother as in Bańbura et al. (2015).

3.3 Data, priors and estimation

To estimate the distributional effects of US monetary policy shocks on income inequality in the US and abroad, we employ data on the national income distributions from the world inequality database (WID) for the period from 1990 to 2019. This database was pioneered by Thomas Piketty and Emmanuel Saez and combines information on income and wealth from national administrative data with available national survey data. Thereby, it forms a representative and comparable micro dataset on income and wealth distribution for each country.[6] Specifically, we use annual data on the shares of pre-tax national income that accrue to the bottom 50, the top 10 as well as the top 1% of the income distribution of the adult population, i.e. individuals over age 20, in France, Germany, Italy, the UK and the US.[7] The unit of observation is the individual, yet resources are distributed equally within couples following the equal-split method. We focus on pre-tax rather than post-tax

[6] The combination of income and wealth from national administrative data and available national surveys is important to ensure that the dataset is informative on both the left and right tails of the distributions. On the one hand, this circumvents the shortage of high-income individuals in surveys as well as top coding issues. On the other hand, the dataset includes low income non-tax-filers that are usually absent in administrative data.

[7] Pre-tax national income comprises all pre-tax personal income flows accruing to the owners of the production factors, labor and capital, before taking into account the operation of the tax and the transfer system, but after taking into account the operation of pension system.

income to ensure that the distributional effects of US monetary policy are not distorted by a redistribution of incomes via the national tax and transfer systems that differ across countries. Micro-level literature suggests that it is essential to include informative tails of the income distribution (Atkinson et al., 2011; Alvaredo et al., 2013). Moreover, differential effects in the tails of the distribution might offset each other at the aggregate level. To account for this, we follow Piketty et al. (2018) and look at income shares of particular parts of the income distribution.

We set up our country-specific MF-BPSVAR models with US and foreign aggregate real and financial variables that are commonly included in SVAR models, examining domestic and spillover effects of US monetary policy on aggregate variables. This encompasses quarterly data on US real gross domestic product (GDP) and consumer prices (CPI), the Gilchrist & Zakrajšek (2012) excess bond premium, as well as the one-year US Treasury Bill, US dollar nominal effective exchange rate (NEER), the VXO as a measure of global risk aversion, country-specific and rest-of-the-world gross domestic product. We take the logarithm of all GDP, CPI and exchange rate series. We augment the system of aggregate variables by different income shares, respectively. A detailed overview of variables and the data sources can be found in Table 1.

To identify our US monetary policy shock series, we follow Gertler & Karadi (2015) and use intra-daily interest rate surprises in a narrow time window on FOMC meeting days of Gürkaynak et al. (2005) as a proxy variable.[8] We purge these surprises from central bank information effects using the 'poor-man's' approach of Jarociński & Karadi (2020).

One major advantage of our estimation approach relative to the existing ones in the

[8]The rationale behind is that, shortly prior to the monetary policy announcement, interest rate futures already incorporate the expected endogenous response of monetary policy to economic conditions. Therefore, any interest rate change from prior to after the announcement can be considered as reflecting the surprise component of monetary policy revealed by the underlying announcement.

literature is that we can follow the suggestion of Baumeister & Hamilton (2015) and make our prior on the object of interest (in our case impulse responses) explicit. We incorporate our prior knowledge on the impact effects of a standard deviation monetary policy shock on the endogenous variables by specifying $P(\widetilde{b})$ using results from Jarociński & Karadi (2020) and Breitenlechner et al. (2022). In particular, we specify independent Student-$\mathcal{T}$ priors with 10 degrees of freedom for the impact response of US GDP, RoW-GDP, the excess bond premium, the one-year US Treasury Bill rate and the country-specific GDP. For the US variables, we center the prior on the quarterly average of the respective posterior medians estimated in Jarociński & Karadi (2020) and calibrate our prior standard deviation to roughly match their the corresponding credible sets. Regarding spillovers to the rest of the world, we apply the same procedure using the results of Breitenlechner et al. (2022). However, we give a higher prior variance to the country-specific GDP spillovers than to the aggregate RoW-GDP spillovers in order to express the fact that the authors do not directly estimate those. For the remaining shocks and endogenous variables, we postulate virtually flat priors.

For the elements of $\widetilde{B}_1$, we specify a flat Minnesota-type prior subject to our prior believe that the system is stationary, i.e. that impulse response functions are non-explosive. We also specify flat priors for the missing data, with the initial conditions of the Kalman filter being specified similar to the approach of Bańbura et al. (2015). In particular, we center the initial conditions for the series with missing values at their linearly interpolated values and specify a variance of twice the estimated empirical sample variance of the series for these conditions.

We estimate the models using 4-lags of the endogenous variables and a constant as regressors. We take at minimum 300 000 draws from the posterior distribution of each country- and variable-specific model using our Metropolis-Within-Gibbs algorithm and ensure that (i) the number of effective draws as calculated in Herbst & Schorfheide (2015) is always above 5000, and (ii) the Markov chain converged to its stationary distribution as indicated by the test procedures put forward in Geweke (1992).

4 Results

In this section, we present the results of our MF-BPSVAR estimations. Before we turn to the distributional spillovers of US monetary policy, we first assess domestic effects and aggregate spillovers in order to cross-validate our estimation with results from the literature.

4.1 Domestic effects of US monetary policy

Figure 1, Figure 2 and 3 display the baseline impulse responses to a 1 standard deviation contractionary US monetary policy shock of the domestic MF-BPSVARs including the income shares of the bottom 50, top 10 and top 1%, respectively. The solid lines show the responses of the pointwise posterior means, while the dark and light shaded areas represent the corresponding 68% and 90% credible sets, respectively. Across the three US models, for the macroeconomic aggregate variables, the credible sets of the responses mostly do not contain the 0 response for many horizons. This is in line with literature on monetary policy effects.[9] In particular, the monetary policy shock raises the one-year Treasury Bill rate, leads to a persistent decline in consumer prices and temporarily lowers real GDP in the US. These findings are in line with the empirical literature on the effects of monetary policy shocks on macroeconomic variables (see, for instance, Coibion et al. (2017) and Christiano et al. (1999) for an overview). Moreover, the monetary policy shock tightens financial conditions via a temporary increase in Gilchrist & Zakrajšek (2012)'s excess bond premium. It is accompanied by an exchange rate appreciation of the US dollar vis-à-vis other currencies, as displayed by a positive response of the nom-

[9]Minor quantitative differences in the reaction of the macroeconomic and financial variables to a monetary policy shock can be discerned across the three models. These arise naturally in the inclusion of different variables. However, the overall qualitative effects remain valid.

inal effective exchange rate, and an increase in the VXO. This suggests that global risk aversion increases following US monetary contractions.[10] These results conform to the empirical findings in the recent literature on Bayesian Proxy SVARs (Caldara & Herbst, 2019; Breitenlechner et al., 2022).

With respect to the domestic effects of US monetary policy on the pre-tax national income shares, we document a positive response for the bottom 50% of the income distribution of about 0.2 percentage points on impact gradually vanishing over the first five quarters (Figure 1). Thus, the low- to middle-income individuals lose less income relative to the upper-middle to high-income individuals following a monetary policy tightening. Coherently, the effect on the income shares of the top 10 (Figure 2) and the top 1% (Figure 3) decline on impact by nearly 0.4 and 0.3 percentage points, respectively, and gradually decay after six to seven quarters.

Overall, our results point towards a decrease in inequality after a monetary policy tightening that is driven by a sharp decline in income shares for the top-income households. This points to the importance of the *Income Composition Channel*. In particular, high-income individuals tend to hold relatively more financial assets than those at the middle and the bottom of the income distribution. As asset prices tend to decline in response to contractionary monetary policy shocks (see Dedola et al. (2017), Degasperi et al. (2020) and Miranda-Agrippino & Rey (2020)), high-income individuals are more adversely affected than low-income individuals who hold little or no financial assets to begin with. These results comply with findings from the empirical literature on the domestic distributional effects of monetary policy from Amberg et al. (2022) for Sweden and Andersen et al. (2022) for Denmark.[11]

[10]For a discussion of the response of rest-of-the-world real GDP to monetary contractions, we pass the interested reader on to the next subsection on the macroeconomic spillover effects of US monetary policy.

[11]Admittedly, both papers investigate the domestic effects of expansionary monetary policy shocks. They document increases in total income for high-income individuals that are largely driven by capital income gains. These emerge from rising property and stock prices following monetary policy expansions. While we gauge the effects of contractionary monetary policy shocks in our analysis, the use of a linear model

Our results complement findings of previous studies on domestic distributional effects of monetary policy. Although seminal papers by Coibion et al. (2017) for the US and Mumtaz & Theophilopoulou (2017) for the UK suggest that income inequality increases in response to a monetary policy shock, our results are not contradicting this evidence, but rather contribute to paint the full picture. This is so because we focus on broader distributional indicators, the income shares, and we use inequality data that is informative on the very upper tail, the top 1%, of the income distribution. A stance of empirical research[12] on the compilation of comprehensive and representative wealth and income distributions suggests that purely survey based distributions are uninformative at the right tail of the income distribution. This is because very top-income households are underrepresented and information on certain capital income is missing in commonly used surveys like the Consumer Expenditure Survey. Analysing specific inequality measures, like the Gini coefficient, from this data, might suggest that income inequality increases after a monetary policy tightening. However, the effect of rising income inequality might pick up differential effects of the upper-middle to lower-middle income households, as it is compiled from distributional data that is less informative on the tails.

Moreover, empirical approaches and data coverage across studies differ substantially. Coibion et al. (2017) gauge the effects of US monetary contractions for the Gini coefficient, the difference between the 90th and the 10th percentiles and cross-sectional standard deviations using data from the Consumer Expenditure Survey (CEX) for the period from 1980 to 2008. They use local projections for the estimation of the impulse response functions. Mumtaz & Theophilopoulou (2017) use micro-level data from the British Family Expenditure Survey (FES) on disposable income and consumption to assess the distributional effects of UK monetary policy for the period from 1969 to 2012.

implies that our results would be the exact mirror image following monetary expansions. This allows tentative comparisons with studies that examine the effects of expansionary monetary policy shocks rather than of contractionary ones, as used in our analysis.

[12]See Atkinson et al. (2011) as well as Alvaredo et al. (2013) and references therein.

They use sign restrictions to identify a monetary policy shock. The usefulness of such an approach has recently been put into question, for instance in Wolf (2022) and Baumeister & Hamilton (2015).

4.2 Macroeconomic spillover effects of US monetary policy

Our results also speak to the empirical literature on the macroeconomic spillover effects of US monetary policy. Our baseline specification (see Figure 1) shows that rest-of-the-world real GDP declines in a hump-shaped manner and contracts in tandem with US real GDP. The size of the reduction in the rest of the world mirrors the one in the US. This hints at the importance of *Financial Channels* and of the *Trade Channel*, as proposed by Iacoviello & Navarro (2019): The increase in US interest rates reduces US demand for domestic and imported goods, inducing a decline in real economic activity, both in the US and the rest of the world (see the extensive discussion in section 2). These findings are consistent with the spillovers documented in the empirical literature (see Dedola et al. (2017), Iacoviello & Navarro (2019), Degasperi et al. (2020), Breitenlechner et al. (2022)).

Figure 4 displays the impulse responses of real GDP for France, Germany, Italy and the UK.[13] The results are noteworthy in several regards. First, we find that there are indeed sizeable spillover effects from US monetary contractions to real GDP in our sample countries, as proclaimed by the empirical literature (Georgiadis, 2016; Dedola et al., 2017; Iacoviello & Navarro, 2019; Degasperi et al., 2020). Second, the response of real GDP in our sample countries essentially mirror the hump-shaped decline for US, as well as for

[13]Specifically, we extract the responses of real GDP for France, Germany, Italy and the UK from the four country-specific estimations, where we include the same macroeconomic and financial variables as in our baseline specification from Figure 1. Yet, we replace the response of the pre-tax income share for the bottom 50 in the US with the respective country-specific responses for the bottom 50. Furthermore, we augment each country-specific model by the respective reaction of real GDP of that country (the detailed impulse responses of all variables included in each of the country-specific estimations for France, Germany, Italy and the UK are available upon request).

rest-of-the world GDP. Real GDP decreases in France, Italy, the UK and, most notably and persistently, in Germany in the first quarters following the US monetary contraction.

4.3 Distributional spillover effects of US monetary policy

We now turn to the discussion of the spillover effects of a US contractionary monetary policy shock on the income distributions in France, Germany, Italy and the UK that constitutes the main contribution of our paper.

Figures 5, 6 and 7 show the impulse responses of the pre-tax income shares for the bottom 50%, the top 10% as well as the top 1% of the income distributions in France, Germany, Italy and the UK.[14] Spillovers to these income shares in France and Italy follow a similar pattern as the US response; the bottom 50% income shares increase after a tightening of US monetary policy. But the increases are slightly smaller, and decay rather quickly (see Figure 1). Similar to the domestic effect in the US, the spillovers to France and Italy result in a decrease of top 10% income shares. However, the decline is of larger magnitude on impact, but vanishes faster than the domestic effect in US. Here, credible sets for Italy include nil over all horizons. For the bottom 50% and top 10% income shares in the UK, there is no clear evidence for spillover effects, as credible sets of the responses are rather wide and always include nil. For income shares of the top 1%, France and Italy reveal a declining tendency, but are rather volatile, contrasting the top 1% income share for the UK that shows a clear increase on impact.

The German economy seems to absorb international spillovers quite differently from its European counterparts. Firstly, the spillovers to Germany are of larger magnitude and mostly exclude the nil for over a year. Secondly, the bottom 50% of the German income

[14] More precisely, the results emerge from the 4 estimation models, in which we include the macroeconomic variables for the US from our baseline model (see Figure 1) and add, country by country, a measure of real GDP, as well as of the income share of the bottom 50%, the top 10% or the top 1% of the income distribution in the respective country.

distribution declines, while the top 10% and top 1% increase after a US monetary policy shock. In consequence, while a tightening of US monetary policy tends to decrease income inequality in France and Italy, it increases income inequality in Germany.

The differences in the spillover effects across countries possibly reflect the underlying divergences in household income sources and structures in the respective countries. These differences in the sources of household income and wealth structures underlying the respective income distribution imply that monetary policy effects are transmitted through different channels depending on the country. A potential explanation for our findings is thus the allocation of income types at the very top of the income distribution, particularly the share of income gained from capital and asset holdings. Differences in our results may be indicative of the importance of the 'global financial cycle', as proclaimed in Rey (2015) and Miranda-Agrippino & Rey (2020). Miranda-Agrippino & Rey (2020) show that US contractionary monetary policy tightens financial conditions across the globe, causing local stock market indices to plummet in the UK and the euro area. This is confirmed by Dedola et al. (2017), Degasperi et al. (2020) and Breitenlechner et al. (2022), who report a reduction in global equity, stock and housing prices for most advanced countries. Given that high-income individuals draw a large share of their income from capital ownership (see Coibion et al. (2017)), declines in asset prices around the globe may serve as explanation to the declines in income shares for high-income individuals in France and Italy and underpin the importance of the *Income Composition Channels*, as well as of the *Portfolio Composition Channel*. Due to the fact that stock holdings are lower in Germany than in most other advanced countries, pre-tax income shares of the top 10% may also be less sensitive to changes in stock prices. Instead, capital income in the form of retained earnings or other business related income might less sensitive to US financial tightenings than other assets, as business losses might be passed over to the labor force.

In summary, we find that US contractionary monetary policy shocks indeed have substantial distributional effects, both in the US and abroad. For Germany, the effects are most pronounced and indicate that the income share of the bottom 50% declines after a monetary policy tightening in the US. In contrast, German high-income individuals, top 10% and top 1%, gain income shares. For the remaining countries, namely France, Italy and the UK, distributional spillovers are more volatile and heterogeneous.

5 Conclusion and next steps

US monetary policy is likely to affect not only domestic income inequality, but also income distributions abroad. This is owed to the fact that the exposure of non-US households to US policy spillovers may differ due to variations in income and wealth sources across these households. In this paper, we empirically investigate the distributional spillovers of US monetary policy to the biggest European economies, namely France, Germany, Italy and the UK.

We use the longest and most detailed homogeneous dataset on income and wealth distributions across countries that is currently available: the World Inequality Database (WID). The contained data are based on the distributional national accounts of Piketty et al. (2018) and is particularly informative about the tails of the income distributions. In our estimation approach, we consider the frequency mismatch between the high-frequently changes on US monetary policy and the availability of income distribution indicators at the annual level. To this end, we estimate country-specific MF-BPSVARs that contain a block of aggregate macroeconomic variables for the US and the respective European country, comparable to studies on aggregate monetary policy spillovers. We further augment these models with selected income shares as to capture the potential distributional spillovers.

Our results suggest that US contractionary monetary policy shocks indeed have substantial distributional effects, both in the US and abroad. For Germany, the effects are most pronounced and indicate that the income share of the bottom 50% declines after a monetary policy tightening in the US. In contrast, German high-income individuals, the top 10% and top 1%, gain income shares. For the remaining countries, namely France, Italy and the UK, distributional spillovers are less clear-cut and heterogeneous, indicating differences of income and wealth structures across countries.

Specifically, we document an increase in the income shares of pre-tax income for the bottom 50% of the income distributions in France, Italy and the UK, while the corresponding income share decreases in Germany. For the top 10% of the income distributions, we find slight declines for France, Italy and the UK, yet an increase for the top 10% of the German income distribution. The results for the top 1% of the income distribution confirm the widening of the income distribution following US monetary contractions for Germany and corroborate the decline in the income shares for the highest income groups in France. Conversely, we find a reversal of the results for the top 1% of the income distributions for Italy and the UK, which show slight increases in their income shares.

To conclude, this study complements two fields of macroeconomic research on monetary policy: international spillovers and distributional consequences. Since our results may give rise to questions, particularly when comparing with seminal papers about the monetary policy effects on domestic income inequality, we intend to extend our analysis in various respects. First, we aim at carving out in more detail the importance of distinct data sources and data length in connecting our domestic income distribution response to that of papers that solely use survey-based indicators. To this end, we will vary the proxy variable, the estimation length and the inequality indicator for our US models. This serves the purpose of better capturing the reasons why our results depart from those obtained in Coibion et al. (2017) and Mumtaz & Theophilopoulou (2017). Second, we aim to investigate the distributional spillovers in more detail. Therefore, we conduct the analysis for more percentile shares and additional inequality indicators for the European countries, as to understand the distributional response in more detail. We aim at receiving additional information on the composition of the different income sources for each income group, especially on the respective shares of labor and capital income. At the current state, we can only speculate about the relative importance of the different channels that may drive the results. Incorporating further data on the income composition of each income group in our estimation would allow us to pin down more precisely the underlying mechanisms that drive the overall results. Third, we want to extend our analysis and investigate the effects of US monetary policy for the wealth distributions of our sample countries. Finally, we intend to increase our sample countries to work out in more detail the differences in the income distributions across countries and to gauge which country characteristics drive these differences.

References

Alvaredo, F., Atkinson, A. B., Piketty, T., & Saez, E. (2013). The top 1 percent in international and historical perspective. *Journal of Economic perspectives*, *27*(3), 3–20.

Amberg, N., Jansson, T., Klein, M., & Picco, A. R. (2022). Five Facts about the Distributional Income Effects of Monetary Policy Shocks. *American Economic Review: Insights*, *4*(3), 289–304.

Ammer, J., De Pooter, M., Erceg, C. J., Kamin, S. B., et al. (2016). *International Spillovers of Monetary Policy* (Tech. Rep.). Board of Governors of the Federal Reserve System (US).

Andersen, A. L., Johannesen, N., Jørgensen, M., & Peydró, J.-L. (2022). Monetary Policy and Inequality. *Journal of Finance, Forthcoming*.

Arias, J. E., Rubio-Ramírez, J. F., & Waggoner, D. F. (2021). Inference in bayesian proxy-svars. *Journal of Econometrics*, *225*(1), 88-106. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0304407620303985` (Themed Issue: Vector Autoregressions) doi: https://doi.org/10.1016/j.jeconom.2020.12.004

Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top incomes in the long run of history. *Journal of economic literature*, *49*(1), 3–71.

Bańbura, M., Giannone, D., & Lenza, M. (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of forecasting*, *31*(3), 739–756.

Baumeister, C., & Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica*, *83*(5), 1963–1999.

Bernanke, B. S. (2017). Federal Reserve Policy in an International Context. *IMF Economic Review*, *65*(1), 1–32.

Botev, Z. I. (2017). The normal law under linear restrictions: simulation and estimation via minimax tilting. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *79*(1), 125–148.

Breitenlechner, M., Georgiadis, G., & Schumann, B. (2022). What goes around comes around: How large are spillbacks from US monetary policy? *Journal of Monetary Economics*, *131*, 45–60.

Brusa, F., Savor, P., & Wilson, M. (2020). One central bank to rule them all. *Review of Finance*, *24*(2), 263–304.

Burq, F., & Chancel, L. (2020). *Inequality transparency index* (No. 2020/12). World Inequality Lab Technical Note.

Caldara, D., & Herbst, E. (2019). Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars. *American Economic Journal: Macroeconomics*, *11*(1), 157–92.

Canova, F., & De Nicolo, G. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, *49*(6), 1131–1159.

Carpenter, S. B., & Rodgers, I. W. M. (2004). The Disparate Labor Market Impacts of Monetary Policy. *Journal of Policy Analysis and Management*, *23*(4), 813–830.

Casiraghi, M., Gaiotti, E., Rodano, L., & Secchi, A. (2018). A “reverse Robin Hood”? the distributional implications of non-standard monetary policy for Italian households. *Journal of International Money and Finance*, *85*, 215–235.

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics*, *1*, 65–148.

Coibion, O., Gorodnichenko, Y., Kueng, L., & Silvia, J. (2017). Innocent Bystanders? Monetary policy and inequality. *Journal of Monetary Economics*, *88*, 70–89.

Dedola, L., Rivolta, G., & Stracca, L. (2017). If the Fed sneezes, who catches a cold? *Journal of International Economics*, *108*, 23–41.

Degasperi, R., Hong, S., & Ricco, G. (2020). The Global Transmission of U.S. Monetary Policy.

Di Giovanni, J., & Shambaugh, J. C. (2008). The impact of foreign interest rates on the economy: The role of the exchange rate regime. *Journal of International economics*, *74*(2), 341–361.

Doepke, M., & Schneider, M. (2006). Inflation and the Redistribution of Nominal Wealth. *Journal of Political Economy*, *114*(6), 1069–1097.

Durbin, J., & Koopman, S. J. (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika*, *89*(3), 603–616.

Favara, G., Gilchrist, S., Lewis, K. F., & Zakrajšek, E. (2016). Updating the Recession Risk and the Excess Bond Premium.

Furceri, D., Loungani, P., & Zdzienicka, A. (2018). The effects of monetary policy shocks on inequality. *Journal of International Money and Finance*, *85*, 168–186.

Garthwaite, P. H., Fan, Y., & Sisson, S. A. (2016). Adaptive optimal scaling of metropolis–hastings algorithms using the robbins–monro process. *Communications in Statistics-Theory and Methods*, *45*(17), 5098–5111.

Georgiadis, G. (2016). Determinants of global spillovers from US monetary policy. *Journal of international Money and Finance*, *67*, 41–61.

Georgiadis, G., & Schumann, B. (2022). *Modelling US and Euro Area Monetary Policy - an overidentified Bayesian proxy VAR approach* (Tech. Rep.). DIW Discussion Paper (forthcoming).

Gertler, M., & Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, *7*(1), 44–76.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculations of posterior moments. *Bayesian statistics*, *4*, 641–649.

Gilchrist, S., & Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American economic review*, *102*(4), 1692–1720.

Gürkaynak, R. S., Sack, B., & Swanson, E. (2005). The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models. *American economic review*, *95*(1), 425–436.

Haario, H., Saksman, E., & Tamminen, J. (2001). An adaptive metropolis algorithm. *Bernoulli*, 223–242.

Herbst, E. P., & Schorfheide, F. (2015). Bayesian estimation of dsge models. In *Bayesian estimation of dsge models.* Princeton University Press.

Iacoviello, M., & Navarro, G. (2019). Foreign effects of higher U.S. interest rates. *Journal of International Money and Finance*, *95*, 232–250.

Jarociński, M. (2015). A note on implementing the durbin and koopman simulation smoother. *Computational Statistics & Data Analysis*, *91*, 1–3.

Jarociński, M., & Karadi, P. (2020). Deconstructing Monetary Policy Surprises—The Role of Information Shocks. *American Economic Journal: Macroeconomics*, *12*(2), 1–43.

Lenza, M., & Slacalek, J. (2018). *How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area* (No. 2190 / October 2018). ECB Working Paper Series.

Maćkowiak, B. (2007). External shocks, US monetary policy and macroeconomic fluctuations in emerging markets. *Journal of monetary economics*, *54*(8), 2512–2520.

Mertens, K., & Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American economic review*, *103*(4), 1212–47.

Miranda-Agrippino, S., & Rey, H. (2020). US monetary policy and the global financial cycle. *The Review of Economic Studies*, *87*(6), 2754–2776.

Mumtaz, H., & Theophilopoulou, A. (2017). The impact of monetary policy on inequality in the UK. An empirical analysis. *European Economic Review*, *98*, 410–423.

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

Rey, H. (2015). *Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence* (Tech. Rep.). National Bureau of Economic Research.

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

Schorfheide, F., & Song, D. (2015). Real-time forecasting with a mixed-frequency var. *Journal of Business & Economic Statistics*, *33*(3), 366–380.

Sims, C. A., & Zha, T. (1998). Bayesian methods for dynamic multivariate models. *International Economic Review*, 949–968.

Stock, J. H., & Watson, M. W. (2012). Disentangling the channels of the 2007-09 recession. *Brookings Papers on Economic Activity*.

Waggoner, D. F., & Zha, T. (2003). A gibbs sampler for structural vector autoregressions. *Journal of Economic Dynamics and Control*, *28*(2), 349–366.

Wolf, C. K. (2022). What can we learn from sign-restricted vars? In *Aea papers and proceedings* (Vol. 112, pp. 471–475).

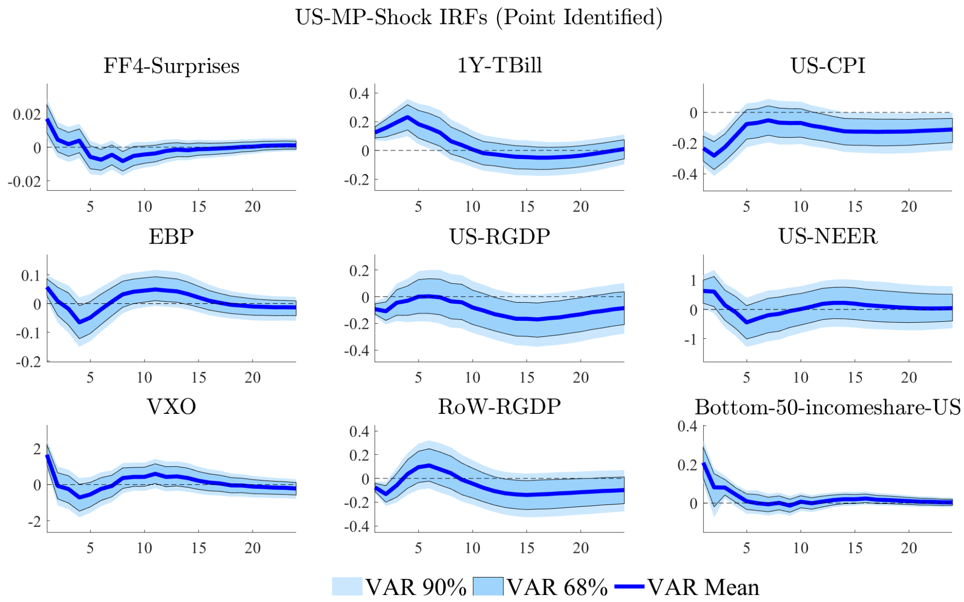
Tables and Figures

Table 1: Data description

Variable	Description	Source	Frequency	Coverage
DE, FR, GB, IT, US bottom10, bottom50, top10, top1 income share	Pre-tax national income share	WID	Annual	1990 - 2019
US 1Y-TBill	1-year Treasury Bill yield at constant maturity	US Treasury/Haver	Quarterly	1990q1 - 2019q2
US CPI	Consumer price index	BLS/Haver	Quarterly	1990q1 - 2019q2
US EBP	Excess bond premium	See Favara et al. (2016)	Quarterly	1990q1 - 2019q2
DE, FR, GB, IT, US RGDP	Real gross domestic product	OECD	Quarterly	1990q1 - 2019q2
RoW RGDP	Real gross domestic product	OECD	Quarterly	1990q1 - 2019q2
VXO	CBOE market volatility index VXO	Wall Street Journal/Haver	Quarterly	1990q1 - 2019q2
US dollar NEER	Nominal broad trade-weighted dollar index	FRB/Haver	Quarterly	1990q1-2019q2

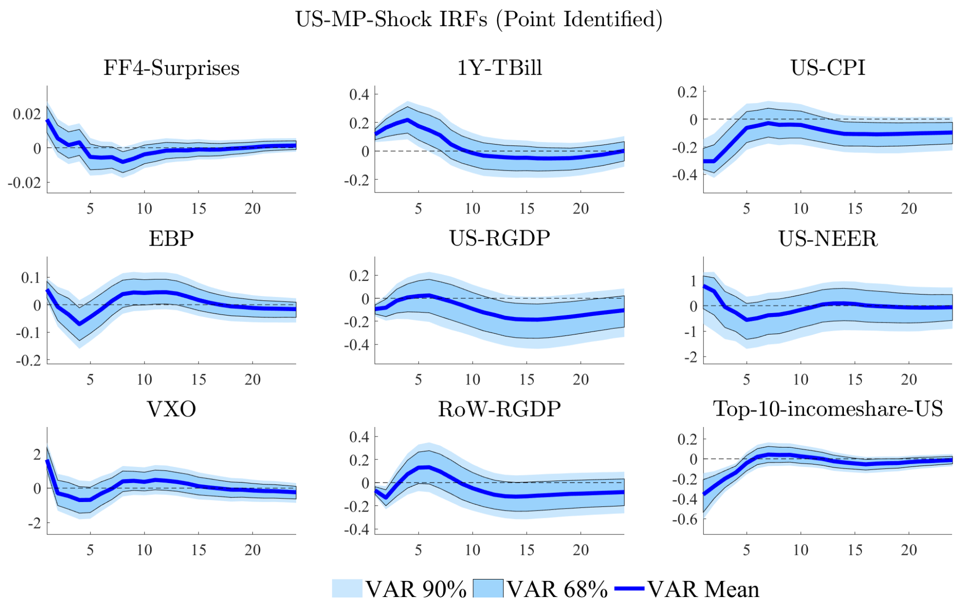
Notes: WID stands for World Inequality Database, BLS for Bureau of Labor Statistics, OECD for Organisation for Economic Co-operation and Development, and FRB for Federal Reserve Board.

Figure 1: US Bottom 50 Income Share



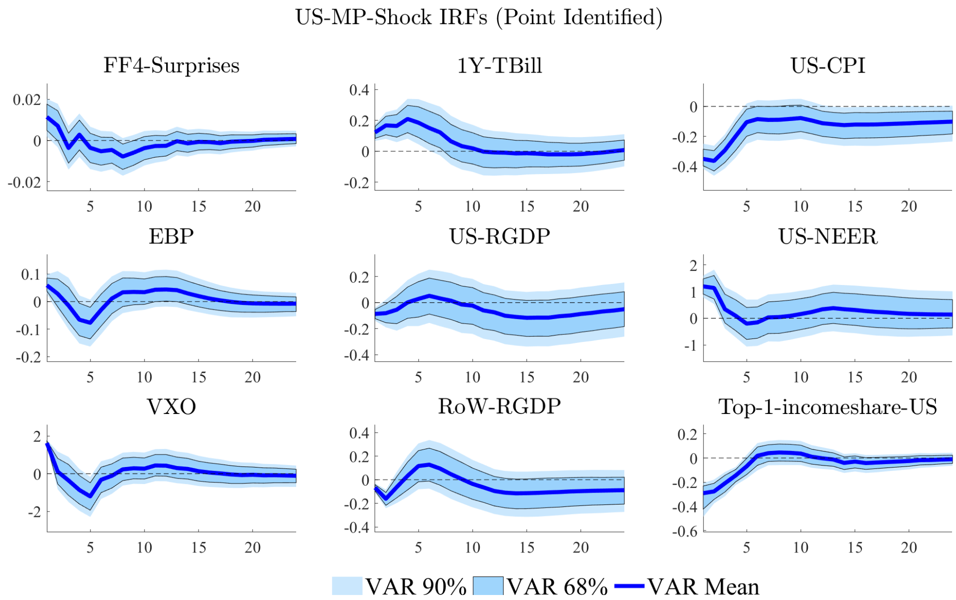
Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock.

Figure 2: US Top 10 Income Share



Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock.

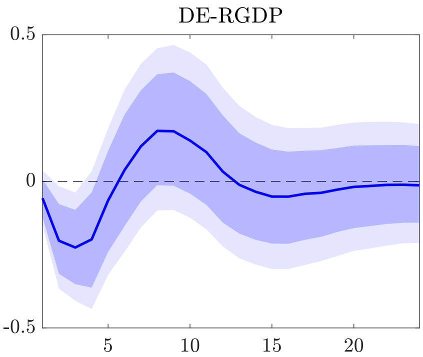
Figure 3: US Top 1 Income Share



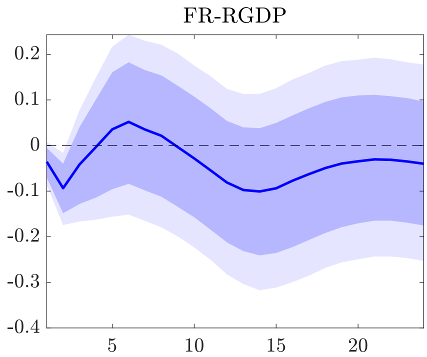
Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock.

Figure 4: Spillover effects to real GDP

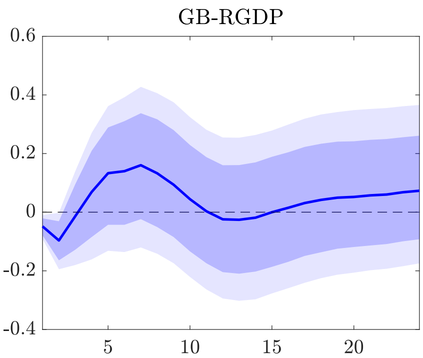
(a) DE



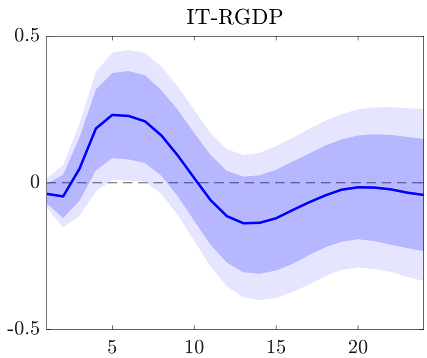
(b) FR



(c) GB



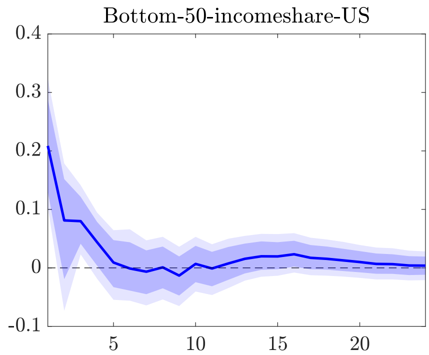
(d) IT



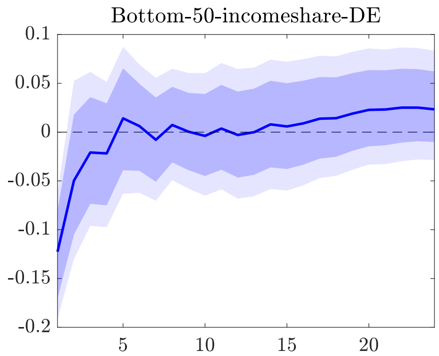
Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock for real GDP in Germany (DE), France (FR), the UK (GB) and Italy (IT). The results are obtained from the country-specific estimations.

Figure 5: Response to a MP Shock of Bottom 50 Income Share

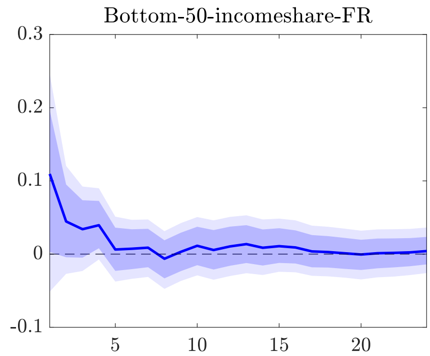
(a) US



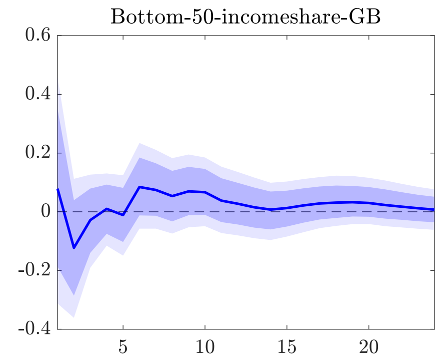
(b) DE



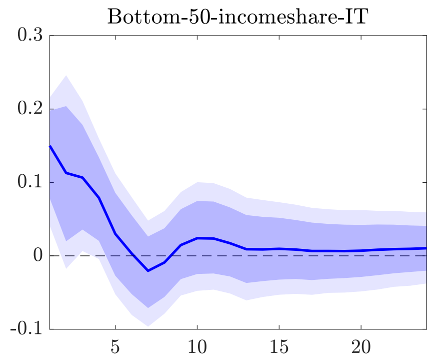
(c) FR



(d) GB



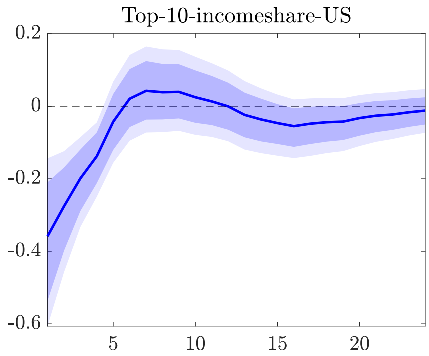
(e) IT



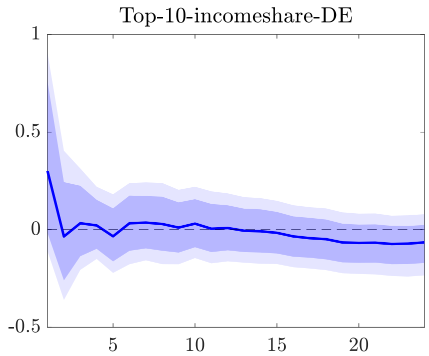
Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock for the pre-tax national income share for the bottom 50% of the income distributions in the US, Germany (DE), France (FR), the UK (GB) and Italy (IT). The results are obtained from the country-specific estimations.

Figure 6: Response to a MP Shock of Top 10 Income Share

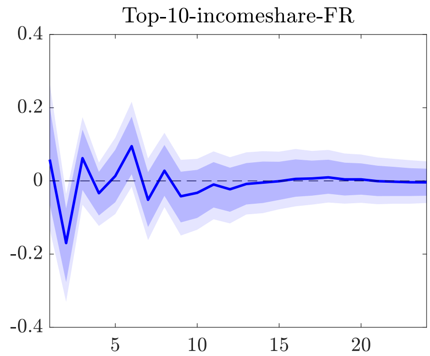
(a) US



(b) DE

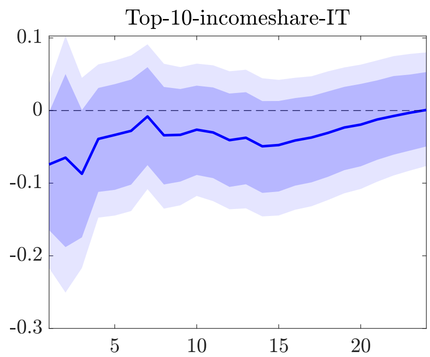


(c) FR



(d) GB

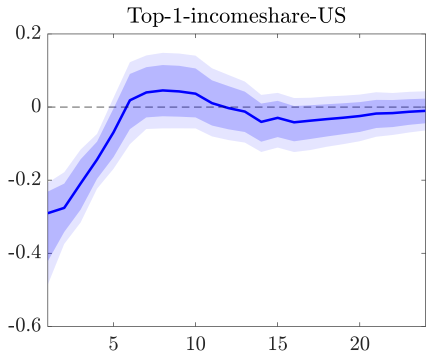
(e) IT



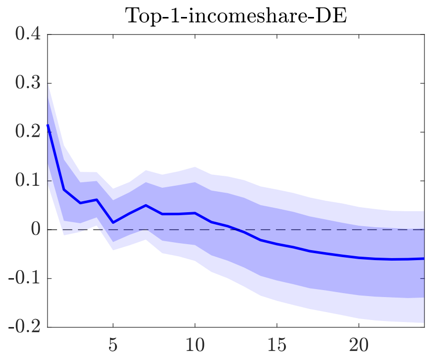
Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock for the pre-tax national income share for the top 10% of the income distributions in the US, Germany (DE), France (FR), the UK (GB) and Italy (IT). The results are obtained from the country-specific estimations.

Figure 7: Response to a MP Shock of Top 1 Income Share

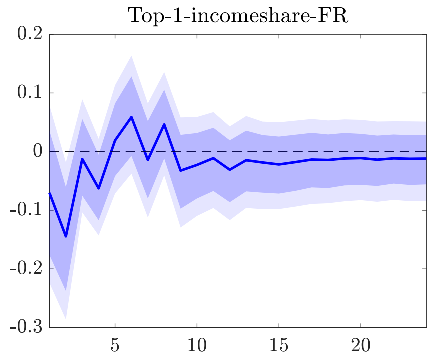
(a) US



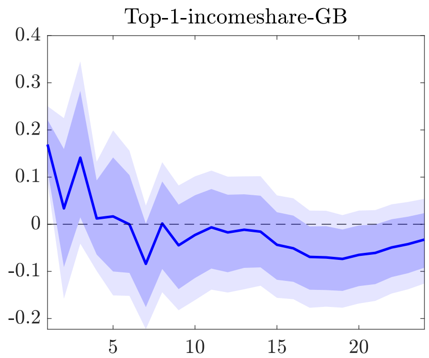
(b) DE



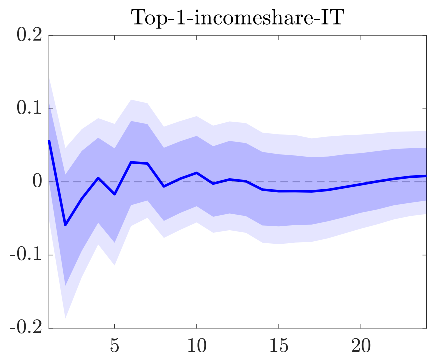
(c) FR



(d) GB



(e) IT



Notes: The figure shows the point-wise posterior means of the impulse responses (blue solid lines) together with the 68% and the 90% centered point-wise probability bands (blue and light blue areas, respectively) obtained from the MF-BPSVAR model in response to a 1 standard deviation contractionary monetary policy shock for the pre-tax national income share for the top 1% of the income distributions in the US, Germany (DE), France (FR), the UK (GB) and Italy (IT). The results are obtained from the country-specific estimations.