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The Time-Varying Effect of Monetary Policy on Income Inequality in the US

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Abstract

There is evidence highlighting the time-varying effects of monetary policy shocks, however, no attempts so far, investigate the impact of such variations on inequality. We examine the impact of monetary policy shocks on income inequality in the US from January 1991 to September 2017 using a TVP-VARX model. Identification is achieved via a high-frequency instrument. We derive percentile ratios as inequality measures at a monthly frequency. Our results suggest that a contractionary monetary policy shock increases inequality, as measured by the P80/P20 percentile ratio. This effect increases over time stating that the responsiveness of inequality to monetary policy shocks is higher for the more recent observation periods. Insights from an income decomposition document the time-varying effects of monetary policy shocks via the earnings heterogeneity- and income composition channel revealing that monetary policy shocks are more prominent in moving income inequality.

1 Introduction

The time-varying effects of monetary policy shocks have been extensively studied in the macroeconomic literature, particularly in the context of the US economy. In doing so, numerous studies focused on the significant reduction of output volatility and inflation after the 1980s defined as the Great Moderation and established the overall consensus of non-linearities in the transmission mechanism[1]. This recognition has led to the well-known "bad policy vs. bad luck" debate, confirming that the transmission of monetary policy depends on the specific circumstances at the time the policy action is taken[2]. The literature frequently mentions two examples of factors that cause shifts in the economy: persistent

[1] Giannone *et al.* (2008) provide a review of studies that address this aspect.

[2] Note that the existence of this debate is about whether the time-varying effects are due to different shock sizes (volatility) or a different transmission mechanism (parameter shifts). Hence, the sole existence of this debate confirms the existence of time-varying monetary policy effects.

events such as financial market liberalization and changes in the Federal Reserve's priorities, and short-term unexpected shocks like policy decisions or announcements[3].

However, studies on the effects of monetary policy on inequality still do not take into account the insights provided by time-varying estimations. For instance, consider a study that investigates the impact of monetary policy on inequality covering a period from 2000 to 2020. Based on the current stance of this research area, an investigation most likely will use regression analyses (Romer and Romer (1999)), local projections (Coibion *et al.* (2017), Inui *et al.* (2017), Furceri *et al.* (2018)), or VAR models (Guerello (2018)) to calculate impulse response functions of monetary policy shocks on the economy and in turn try to answer the above-stated research question[4]. Particularly, such a study may find significant effects whether positive or negative. Undoubtedly, such an investigation may be misleading because one could argue that the way monetary policy affects the economy changed substantially for the more recent periods in the sample due to the zero lower bound period. This change probably should be seen in different coefficients of the estimated VAR, which in turn would lead to different responses to a monetary policy shock[5]. As stated above, current approaches that look at the distributional channels of monetary policy suffer from this limitation.

This study addresses this shortcoming when looking at the US. An economy characterised by both confirmed time-varying monetary policy effects (Giannone *et al.* (2008), Korobilis (2013), Aastveit *et al.* (2017)) and relatively high inequality (Michael (2014)). Appendix (A) displays the long-term trend of the real factor income share by percentile. Over time, the income share gap between the bottom 50 and the top 10 has consistently widened, creating a significant disparity in the distribution of income, which makes the US an appropriate testing ground for a study like ours, which focuses on the time-varying distributional effects of monetary policy.

We construct monthly measures of inequality from granular income data coming from Blanchet *et al.* (2022) and derive percentile values of income for our investigation. One of the advantages of this database is that it enables us to decompose total income into its main components in order to detect the time-varying distributional channels of monetary policy shocks. Following Paul (2020) we then use a high-frequency instrument of monetary policy shocks as an exogenous variable in the VAR equation for identification.

[3] While Korobilis (2013) differentiates between persistent and transitory events to the US economy, Steelman (2011) explains the evolution of the Fed's dual mandate.

[4] Colciago *et al.* (2019) provide an extensive overview of this research field. However, no time-varying estimation is mentioned.

[5] Other intuitive examples of non-linearities that justify time-varying estimations are mentioned in Koop and Korobilis (2010) or Lubik and Matthes (2015).

Our results suggest that an unexpected monetary policy shock that increases the Federal Funds Rate (FFR), leads to higher inequality responses in the recent periods of our sample. The responsiveness of inequality to a monetary policy shock gradually increased over time peaking in the last decade of our sample which covers the zero lower bound. These findings are robust to several sensitivity checks regarding prior and model specification as well as lag lengths. The monetary shock stretches the income distribution. Both tails display a continuous rise in their responsiveness for the whole period examined. Insights from an income decomposition place our work next to the findings of Coibion *et al.* (2017) and Furceri *et al.* (2018) but in a time-varying setting, stating that inequality in the US became more responsive to monetary policy shocks which is based on more prominent effects of the earnings heterogeneity and the income composition channel. Our findings indicate that the strengthening of these distributional channels lead to a more responsive economy.

The remainder of the paper is structured as follows: section 2 gives a summary of the related literature, section 3 describes the Data and the instrument we used, section 4 presents the methodological approach, section 5 presents our baseline results, section 6 looks at the time-varying distributional channels, section 7 provides sensitivity checks and section 8 concludes.

2 Related Literature

This research paper combines a time-varying parameter VAR estimation with insights from the high-frequency literature to examine the impact of monetary policy on income inequality. Therefore, to fully understand the scope of this study, it is necessary to consider three different research areas that are related to it.

Considering the first research field, the time-varying effects of monetary policy have long been confirmed. Early benchmark studies, gave rise to the "bad policy vs. bad luck" debate; hence, it is not questioned if there are time-varying monetary policy effects but rather what makes the most important part of it: time-varying parameters (change in the transmission mechanism) or time-varying volatility (change in the size of the shocks).
Early attempts to study the time-varying effects of monetary policy can be placed around this debate: while Cogley and Sargent (2002, 2005), find bad policy to be the reason for the change of monetary policy effects, there are others like Bernanke and Mihov (1998b), Bernanke and Mihov (1998a) and Sims and Zha (2006), who present evidence for a specification with fixed coefficients but time-varying volatility and argue that bad luck is the key driver for the different effects of monetary policy between these two decades. Studies that emerged later advanced the modelling procedure, but should still pick up this

debate. A benchmark study is provided by Primiceri (2005), who provided not only the time-varying counterparts to the fixed-parameter structural VARs but also added to the bad luck side of the story as did Benati and Mumtaz (2007) in the upcoming years based on sign restrictions.

Regarding more recent investigations on the time-varying effects of monetary policy, Aastveit *et al.* (2017) examines whether the FED responded to the house and stock price changes. The findings state that stock price growth (represented by the S&P500) entered the reaction function with a positive and significant coefficient. Similar conclusions are provided for house prices. A study that looks at the response of asset prices to a monetary policy shock, i.e. deviations from the monetary policy rule and hence, the other side of the picture compared to Aastveit *et al.* (2017) is provided by Paul (2020). The author states that a monetary policy shock always leads to decreased industrial production, inflation and house prices. Thereby, stock and house prices show a substantial time variation in their responses.

The second research field this study relates to is the high-frequency literature. Reconsidering the conditions stated in Stock and Watson (2012), a suitable proxy needs to be 1. relevant and 2. exogenous, to serve as an instrument. However, recent studies questioned the appropriateness of high-frequency surprises derived in a fashion as proposed by Gertler and Karadi (2015). Related to condition 1, Ramey (2016) finds that estimations of macroeconomic effects after 1984 are only poorly captured and directly questions the relevance of the instrument. Additionally, Miranda-Agrippino and Ricco (2015), find that high-frequency surprises are predictable when taking into account macroeconomic and financial variables and provide evidence for the lack of exogeneity. To address these shortcomings, Bauer and Swanson (2022) provide a new shock instrument by including speeches in the underlying set of events when deriving the surprises (relevance), and orthogonalizing these surprises to financial and macroeconomic variables (exogeneity). Further contributions are provided by Lewis (2019), who proposes an announcement-specific decomposition of shocks, where identification is achieved via time-varying volatility. His approach enables him to decompose every single surprise into 4 different shocks - Fed Funds, forward guidance, asset purchase, and Fed information - at event frequency.

Turning to the third research field, researchers explain the effects of monetary policy on inequality by deriving distributional channels either based on theoretical models or empirical estimations. The overall picture of this research area confirms that monetary policy can affect inequality (Colciago *et al.* (2019)). Although recent theoretical studies have attempted to advance the structure of the micro foundation of the representative agent model (see Kaplan *et al.* (2018) and Gornemann *et al.* (2021)), they do not change the understanding of the broad patterns of transmission of monetary policy, as explained in McKay and Wolf (2023). The crucial insights are that new heterogeneous agent approaches are placing more weight on the indirect effects (i.e., general equilibrium forces) to explain the transmission channels of monetary policy shocks (Ampudia *et al.* (2018).

The empirical front of this area presents mixed findings of monetary policy on inequality concerning the signs of the effects. A concise yet inclusive list of benchmark studies reveals evidence that suggests expansionary monetary policies can increase inequality (Inui *et al.* (2017), Cloyne *et al.* (2018)) while others confirm that a monetary tightening leads to an increase in inequality especially in the US (Coibion *et al.* (2017)), the UK (Mumtaz and Theophilopoulou (2017)), the EU (Guerello (2018), Samarina and Nguyen (2019)) as well as a sample of countries (Furceri *et al.* (2018)).

3 Data and Instrument

We use household data from the real-time inequality database[6]. Following Blanchet *et al.* (2022) this database produces monthly income distributions that become available within a few hours after the official high-frequency national account aggregates are published. It uses publicly available data sources and combines monthly and quarterly survey data with corresponding monthly and quarterly national account statistics. One positive feature of this approach is that it is free of the common drawback of pure survey-based data that tend to underestimate the level of inequality[7].

The final database comprises income aggregates, such as factor, pre-tax, disposable, and post-tax income, at a monthly frequency. To do this, the authors use national accounts provided by the Bureau of Economic Analysis and combine them with annual data provided by Piketty *et al.* (2018). Converting annual to monthly data is summarised as follows: Blanchet *et al.* (2022) need to ensure an accurate representation of a monthly income distribution. Therefore, the existing annual income data is normalized for each component of the population. Since income components may change differently on a month-to-month basis, it is important to update the data files monthly to capture these different changes in the income components. The updated files are then used to adjust the monthly evolution of income components in the dataset to accurately reflect these changes.

We analysed the microfiles provided online to derive deciles of the income distribution. Each microfile comprises the US income distribution for a specific month, starting from January 1976 to the present month. We focus on factor income, as defined by Blanchet *et al.* (2022), which is the total income earned from labour and capital. It is a suitable

[6]The inequality database is available at Realtime Inequality Database.

[7]Research by Korinek *et al.* (2007) finds that the participation in US surveys declines, the higher the income of the participant.

measure to decompose growth since it adds up to national income. We calculate the sum of income by ID and define income at the household level. Based on the provided weights, we derive the deciles of factor income and its main components. Our final dataset comprises the deciles of total income, capital income, labour income, as well as the subcomponents of capital income (i.e., interest income, corporate profits and proprietors' income). Thereby, the first decile comprises the average income of households from the 0 to the 10th percentile, the second decile comprises households between the 10th and the 20th percentile, and so on. Using the deflator provided in the database, we then calculate real income values[8].

We use the instrument provided by Bauer and Swanson (2022). This monetary policy shock series comes with several improvements regarding the appropriateness of high-frequency instruments. The authors increase the dataset and include speeches and testimonies to satisfy the relevance condition as stated in Stock and Watson (2012). Regarding the exogeneity condition, the authors orthogonalise the resulting series to macroeconomic and financial predictors. The final shock series is defined as the residual of an OLS regression:

$$z_t^{\perp} = z_t - \hat{\alpha} - \hat{\beta} X_{t-} \tag{1}$$

where t denotes the event, $z_t^{\perp}$ is the orthogonalized shock series, z_t is the surprise coming from the principal component, α and β are regression parameters and X_{t-} is the set of predictors that are known before the monetary event t. Following Bauer and Swanson (2022), the vector X_{t-} includes six different predictors: 1. nonfarm payrolls shocks, 2. employment growth, 3. the S&P 500, 4. the yield curve slope, 5. commodity prices and 6. the treasury skewness.

4 Methodology

We follow Paul (2020) closely and include the instrument as an exogenous variable in the VAR equation. Consider the following TVP-VAR:

$$Y_t = B_{0,t} + \sum_{i=1}^{p} B_{i,t} Y_{t-i} + A_t z_t + u_t \tag{2}$$

Where $B_{0,t}$ is a vector of time-varying intercepts, $B_{i,t}$ is the matrix of the time-varying coefficients of the endogenous variables, A_t is the time-varying vector of coefficients of the exogenous variable z_t and u_t is a vector of innovations. The author shows that deriving a ratio of the coefficients in the A_t matrix delivers consistent estimates of impulse response

[8]For all of our presented estimations, we kept only positive values in the income variable.

functions. The relative IRF can be derived by:

$$r_{k,j} = \frac{a_k}{a_j} \tag{3}$$

where a_k and a_j are the posterior means of the elements k and j in the coefficient matrix of the exogenous variable.

The relation between the unobserved shock and the exogenous variable is captured by:

$$z_t = \varphi \varepsilon_{1,t} + \eta_t \tag{4}$$

where we assume that without loss of generality, the shock of interest is the first shock in the system $\varepsilon_{1,t}$. The error term η_t is orthogonal to all the shocks in the system and follows $\eta_t \sim N(0, \sigma_\eta^2)$.

Stacking all coefficients in equation (2) in a vector, including the coefficients of the exogenous variable, the model defines a driftless random walk for the time-varying parameters according to:

$$B_t = B_{t-1} + v_t \tag{5}$$

The specification assumes a block diagonal variance-covariance matrix and jointly normally distributed error terms:

$$V = VAR \begin{pmatrix} u_t \\ v_t \end{pmatrix} = \begin{pmatrix} \Omega & 0 \\ 0 & Q \end{pmatrix} \tag{6}$$

Here Ω and Q are the hyperparameters of the model. These are defined after estimating a constant parameter VAR for a training sample of length $\tau = 135$. Expressly, the training sample ranges from November 1978 until December 1990 where all missing observations in the proxy are set to 0. Having derived the parameters from the constant VAR estimation the priors take the following form:

$$\begin{pmatrix} B_0 \sim N(\hat{B}_{OLS}, 4 * V(\hat{B}_{OLS}) \\ \Omega \sim IW(I_n, n+1) \\ Q \sim IW(\kappa_Q^2 * \tau * V(\hat{B}_{OLS}), \tau) \end{pmatrix} \tag{7}$$

We define $\kappa_Q = 0.015$, which controls the time-variation of the parameters. The model uses a Gibbs sampler to generate draws from the posterior. We simulate 5000 iterations and keep the last 1000 draws to calculate the impulse response functions. The lag length is set to $p = 3$[9].

[9] The optimal lag length is based on the AIC criterion for a constant VAR over the same estimation period. However, in the robustness section we present checks for both different values of time-variation and lag-length specifications.

5 Baseline Results

Our baseline results are presented in figure (1), which shows the time-varying effects of a monetary policy shock on the US economy from January 1991 to September 2017. While it is common to normalize the shock to make the impact response of the policy rate equal for every year, this method would result in rescaled shock sizes every year. Therefore, in our estimation, we normalize the shock to produce a 20 basis point impact increase in the Federal Funds Rate (FFR) in January 1991. This ensures that the same shock size is used every year, enabling us to highlight the patterns of time variation. Considering the posterior mean of the Federal Funds Rate coefficient $\bar{a}_{1991M1,1}$, we define $\bar{z}_t * \bar{a}_{1991M1,1} = 0.2$. The same particular value of $\bar{z}$ is then used to derive any other impulse response analogously along the coefficient matrix A_t. The final time-varying impulse responses are derived by calculating the ratio between these elements of the posterior mean coefficients following equation (3).

All macro variables are downloaded from the FRED database. We use the FFR as the monetary policy indicator, the consumer price index to measure inflation, the S&P 500 index to measure share prices, industrial production to measure economic activity, and the P80/P20 percentile ratio of factor income to measure inequality. All variables, except the FFR, enter the model in first differences.

Our study finds fluctuations in the policy rate based on the same shock over time. A shock that led to a 0.2 per cent increase in the FFR in January 1991, moves the FFR by less in more recent years. The effect of the shock in the FFR matches the narrative and is close to zero after 2008 consistently capturing the zero lower bound period. Inflation always decreased after a contractionary monetary policy shock, with more pronounced reactions after 2007. Share prices and industrial production also decreased during the estimation period. Overall, a contractionary monetary policy shock always led to a downturn in the economy.

Turning to the effect on inequality, the findings show the increasing responsiveness to a contractionary monetary policy shock. Such a shock consistently leads to an increase in income inequality, as measured by the P80/P20 percentile ratio of total factor income and has a persistent effect over the IRF horizon, remaining high even 5 years after the impulse. When interpreting the results from a time-varying perspective, we find substantial time variation in the impact of the shock, with recent years displaying an equally persistent but higher impact of monetary policy on inequality.

Figure (2) highlights our findings on time variation. The plot shows the impulse response functions from figure (1), 1 year after the shock (blue line) together with the level of the

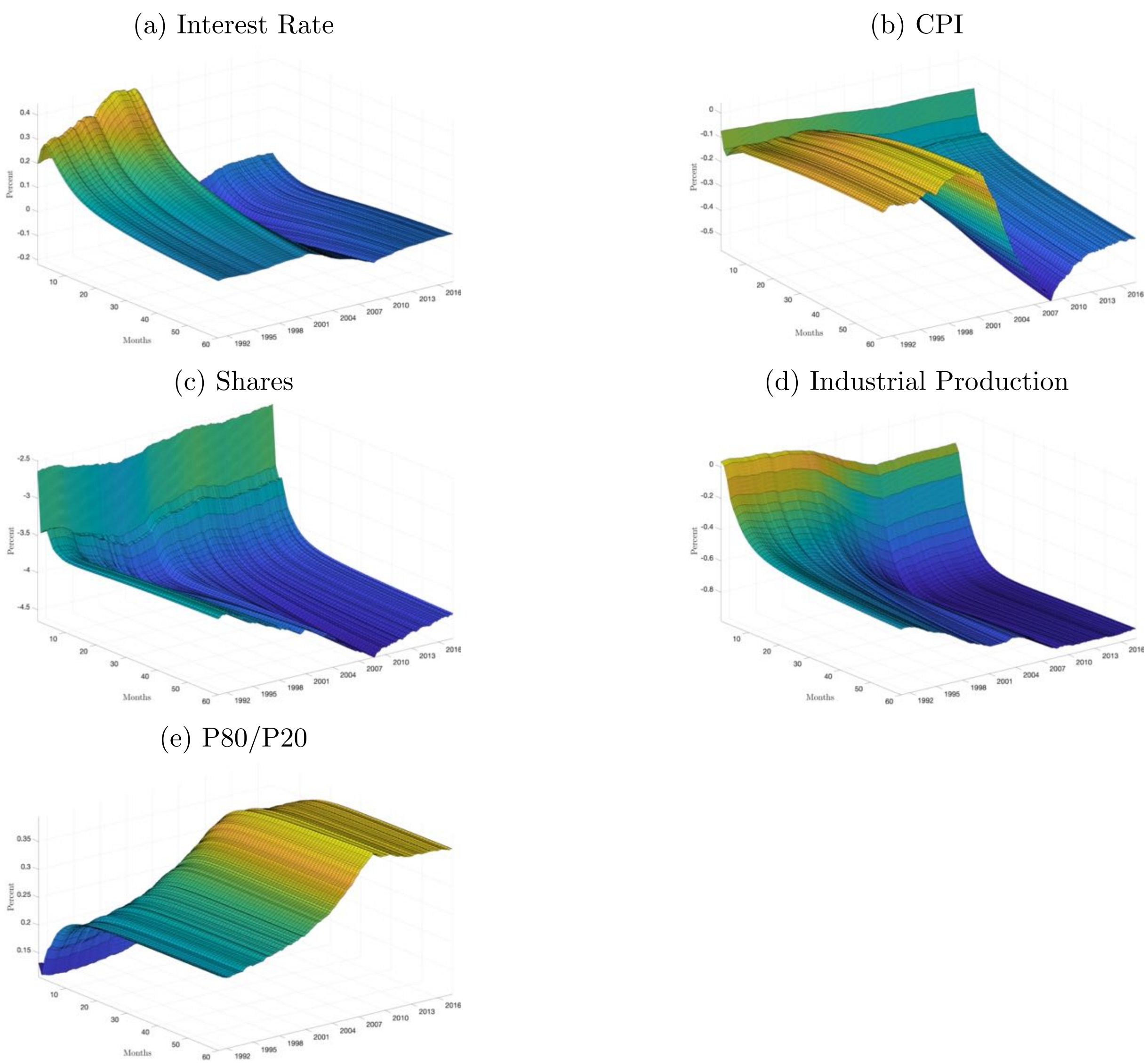


Figure 1: Baseline Results - cumulative IRFs to a contractionary monetary policy shock that lead to an increase of 20 Bps in the FFR in 1991M1. All variables entered the model in log differences except the FFR.

P80/P20 ratio (red line) in a 2D format along the time axis. Looking at the levels of inequality, the figure displays high fluctuations over the observation period. The P80/P20 ratio decreased substantially during the first decade of the sample reaching the lowest level closely after the dotcom crisis. The period between the dotcom crisis and the great financial crisis in 2008 was characterized by rather stagnating levels of income inequality. The great financial crisis left the US unequal with a P80/P20 ratio peaking right after 2008 and remaining high for the upcoming years, however, with a mild downward trend. Turning to the effects of the monetary policy shock, we observe great changes in the impulse response function of the P80/P20 ratio over time, suggesting that the impact of a monetary policy shock has increased in recent years. Throughout the observation period, the responsiveness of inequality rose and peaked in the 2008 financial crisis. In the latest observation periods, we observe a stagnating behavior of high responsiveness, indicating

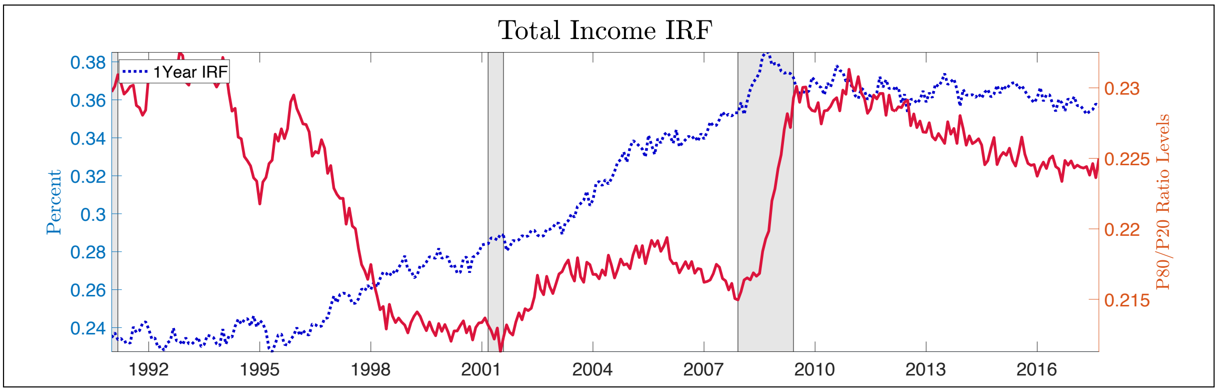


Figure 2: The time-varying effect of monetary policy shocks. The Graph displays the median IRF of the posterior distribution, 1-year after the shock along the time axis together with the levels of the P80/P20 ratio of total factor income. The shaded areas display crises.

that during the zero lower bound period inequality was highly reactive to monetary policy measures[10].

Following previous studies in the literature (Coibion *et al.* (2017) or Colciago *et al.* (2019)), we use percentile ratios for the tails and re-estimate the baseline specification to better understand how the shock affects various sections of the income distribution. Figure (3) illustrates the outcomes of this exercise displaying the P50/P20 (left tail) percentile ratio and the P80/P50 (right tail) percentile ratio. Both tails of the distribution display a rise in inequality. Beginning with the left tail of the income distribution, our results show that an increase in income inequality, caused by a monetary contraction, has long-lasting effects throughout the entire IRF horizon. This impact is persistent and leads to a wider gap over time. At the same time, the right tail of the income distribution experiences a similar reaction i.e., a short-term increase that gradually rises with the more recent periods developing more pronounced "humped-shaped" IRFs. Overall, the monetary policy shock stretches both ends of the income distribution, affecting it entirely. Additionally, the results indicate that the reaction of inequality was more profound during the 2008 Great Financial Crisis.

In figure (4), we use the 2-dimensional format to display the time-varying behaviour of the percentile ratios. The upper part of figure (4) displays the time variation of the left tail which shows great fluctuations in its levels (red line). During the 1990s income inequality at the lower end of the distribution was at its highest and sharply declined. After the crisis in 2001, income inequality in the left tail stagnated and reached its lowest level in 2007. The financial crisis in 2008 lead to an abrupt increase of inequality which gradually decreases in the last years of our observation period. Regarding the responsiveness of the

[10] Appendix (B) provides credibility bands in a similar 2D-format for various horizons of the median responses plotted in figures (1),(2), (3) and (4).

(a) P50/P20 (b) P80/P50

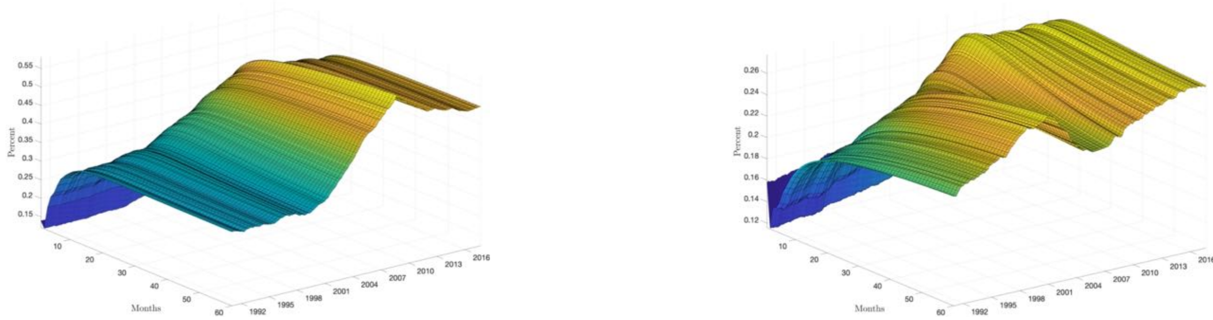


Figure 3: Tails of the Income Distribution - cumulative IRFs to a contractionary monetary policy shock. All specifications equal the Baseline estimation.

left tail (blue line), the 1990s had the lowest responsiveness of income inequality in the left tail compared to the upcoming decades. The effect of the shock continuously increased and reached its peak exactly when the crisis hit in 2008. During the aftermath of the great financial crisis in 2008 the responsiveness of the left tail remained on high levels.

The lower graph in Figure (4) shows the behavior of the right tail. Unlike the left tail, inequality in the right tail was at its lowest levels in the 1990s. While the left tail experienced an abrupt increase after the Great Financial Crisis, the right tail saw a constant increase throughout the entire observation period, peaking in the most recent years of our sample. After the crisis, inequality in the right tail remained at its highest levels compared to previous decades.
The impulse response functions indicate that the right tail has become more responsive over time. There has been a consistent increase in responsiveness from 1990 to 2001, with a brief interruption in the trend between the two crises. However, after 2004, the responsiveness of the right tail aligns with the movement of the percentile ratio, indicating that the same monetary policy shock now has a greater impact on inequality compared to earlier years, especially when inequality is at its highest level.

As shown above, the responsiveness of the left and the right tail increased continuously over the period examined. This indicates that for more recent periods monetary policy affects inequality in the US by more. Nevertheless, the left tail does not show the same response as the right tail regarding the magnitudes. This links our results to another important finding in the literature, which explains the asymmetric effects of monetary policy along the distribution based on the composition of income. It is the time-varying behaviour of these asymmetric effects that we are interested in, to understand the change in the distributional channels over time. Following Colciago *et al.* (2019) households receive their income from several sources. As these income sources differ throughout the distribution, households go through different income reactions.

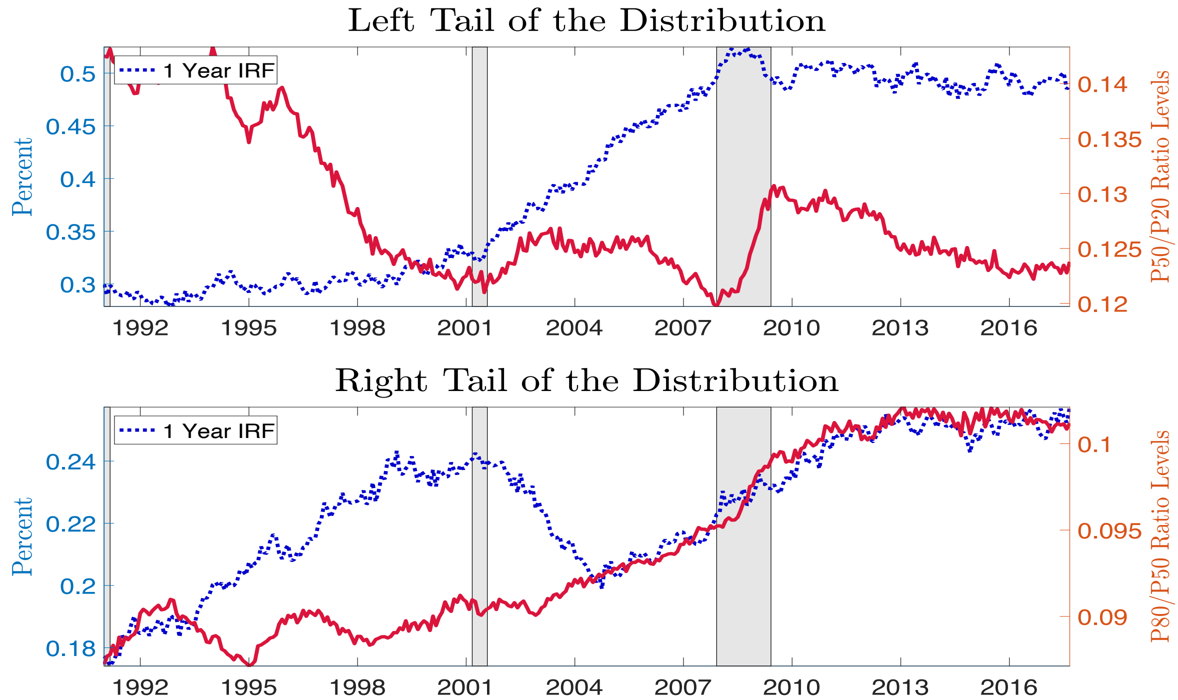


Figure 4: The time-varying effect of monetary policy shocks. The Graph displays the median IRF of the posterior distribution, 1-year after the shock along the time axis together with the levels of the percentile ratios. The shaded areas display crises. The upper part of the Graph displays the P50/P20 percentile ratio (left tail) while the lower part of the graph displays the P80/P50 percentile ratio (right tail) of the distribution.

6 The Time-Varying Distributional Channels of Monetary Policy

In figure (5), we decompose factor income into its main components for each decile group over time from January 1976 to December 2020. Particularly, we define factor income as the sum of labour and capital income. To calculate labour income, we follow Blanchet *et al.* (2022) and add the compensation of employees (code: flemp) and 70% of proprietors' income (code: proprietors). For capital income, we add 30% of proprietors' income with corporate profits (code: profits) and interest income (code: fkfix). The latter captures the income from currency, deposits, and bonds. Hence, the sum of the upper components adds up to total income[11]. Our analysis shows that the proportion of labour income decreases

[11]Since some components (e.g. rental income) take negative values for certain periods we were forced to leave them out of our decomposition.

as we move up the income distribution. Households at the top end of the distribution tend to receive a significant proportion of their income from other sources than labour i.e., businesses and interests. Consequently, capital income, whose main components are corporate profits and interest income, plays a significant role for high-income households, indicating a higher exposure to financial markets of this group[12]. While the literature states that business income (i.e., corporate profits and proprietors' income) is negatively affected by contractionary monetary policy, it is income from interests that should increase[13].

We aim to detect the time-varying effects of both, the earnings heterogeneity channel and the income composition channel. Specifically, the earnings heterogeneity channel suggests that the slowdown in economic activity resulting from a monetary contraction leads to job losses. Since low-income households typically rely on labour income as their primary source of income, they are hit harder by this channel[14]. The income composition channel explains monetary transmission based on all different income components and their reactions to a monetary shock.

Figure (6) presents the estimations based on the main income components. Inequality of capital income increases persistently at the lower end of the distribution. This effect was mitigated during the great financial crisis but increased again in recent periods. Since low-income households have only a small proportion of capital income, this inequality movement indicates that their capital income is more vulnerable to the business cycle, causing these households to lose relative to the median. In terms of income coming from labour, inequality also increases and the gap in labour income widens after a monetary contraction. Particularly, the IRFs show a persistent increase lasting over the whole horizon with the latter periods displaying a highly responsive behavior. Turning to the right tail, inequality in capital income increases on impact however, this increase gradually fades away and in contrast to the left tail, is not persistent. Inequality even decreases, indicating that the rich and the median households move closer together by facing similar income reactions. This picture is in stark contrast to the one of labour income inequality. Here, the results state that inequality increases and persists similarly to the left tail.

Based on the income decomposition in figure (5), we decomposed capital income into its main components to shed light on the different forces that come from each income component separately after a monetary policy shock. Beginning with corporate profits, the IRFs of the left tail show both high time variation and high responsiveness. The first

[12] The breakdown of capital income is in line with explanations in Blanchet *et al.* (2022), who created the datasets.

[13] Ampudia *et al.* (2018) offer a detailed description of these indirect effects of monetary policy that result from general equilibrium forces.

[14] Theophilopoulou (2022) shows that low-income households are more vulnerable to job losses when analysing the effects of an uncertainty shock on inequality.

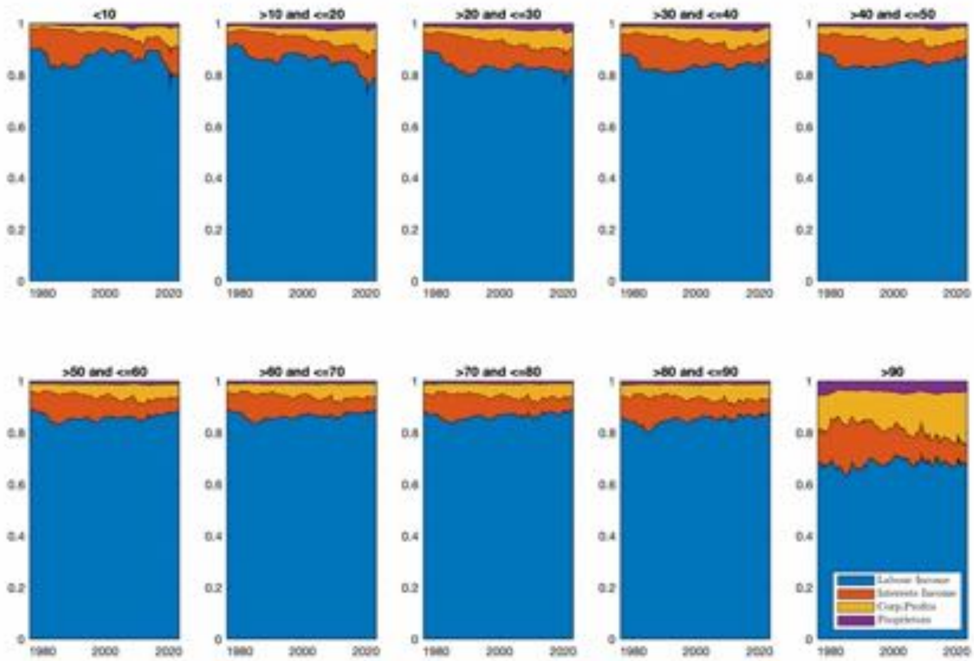


Figure 5: Income Decomposition for every decile group of the income distribution. The figure displays real income values. Labour income is defined as the sum between 0.7*proprietors' income and the compensation of employees. Interest income is the total income generated from currency, deposits, and bonds. Corporate profits are defined as income from businesses, while proprietors' income is the share of income earned by proprietors, classified as capital income (i.e., 30%). Hence, the total of the upper components (interest-, corporate- and proprietors' income) represents capital income.

decade of the estimation period displays a strong increase in inequality with the IRFs remaining above zero over all horizons. The crisis in 2008 dampened this effect and caused a reduction in the persistence of the shock. However, the more recent periods show a sharp increase in inequality which is persistent for the whole IRF horizon indicating that corporate profits are highly affected by an interest rate increase.

Turning to the reaction of the right tail, we find that inequality increases on impact. Compared to the reaction of the left tail we see a short-term effect which is characterized by lower time variation. This suggests that both household groups face a similar reaction of their income to the monetary policy shock, indicating that corporate profits are a crucial income component for households above the median income level.

Particularly, our findings indicate that an unexpected interest rate increase slows down the busyness cycle and corporate profits decrease. However, this decrease is unevenly distributed along the distribution and inequality rises. The increase of inequality indicates that corporate profits at the lower end of the distribution are more vulnerable to such unexpected monetary shocks.

(a) Capital Income Left Tail

(b) Labour Income Left Tail

(c) Capital Income Right Tail

(d) Labour Income Right Tail

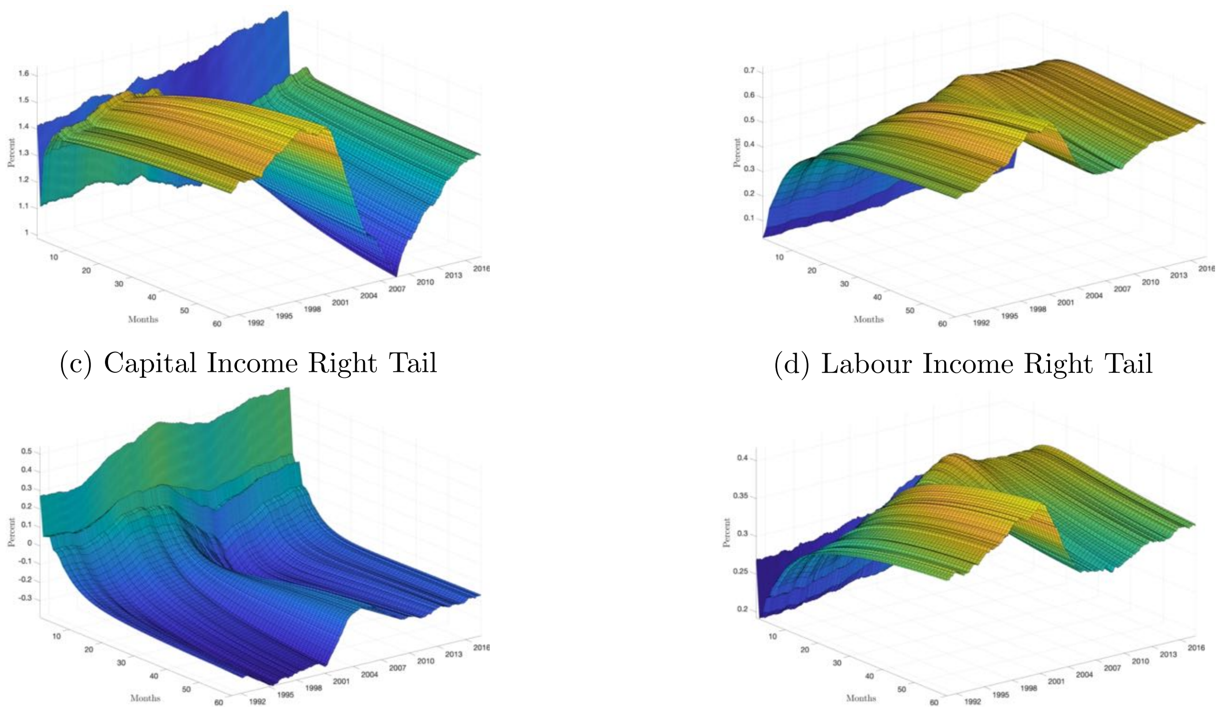
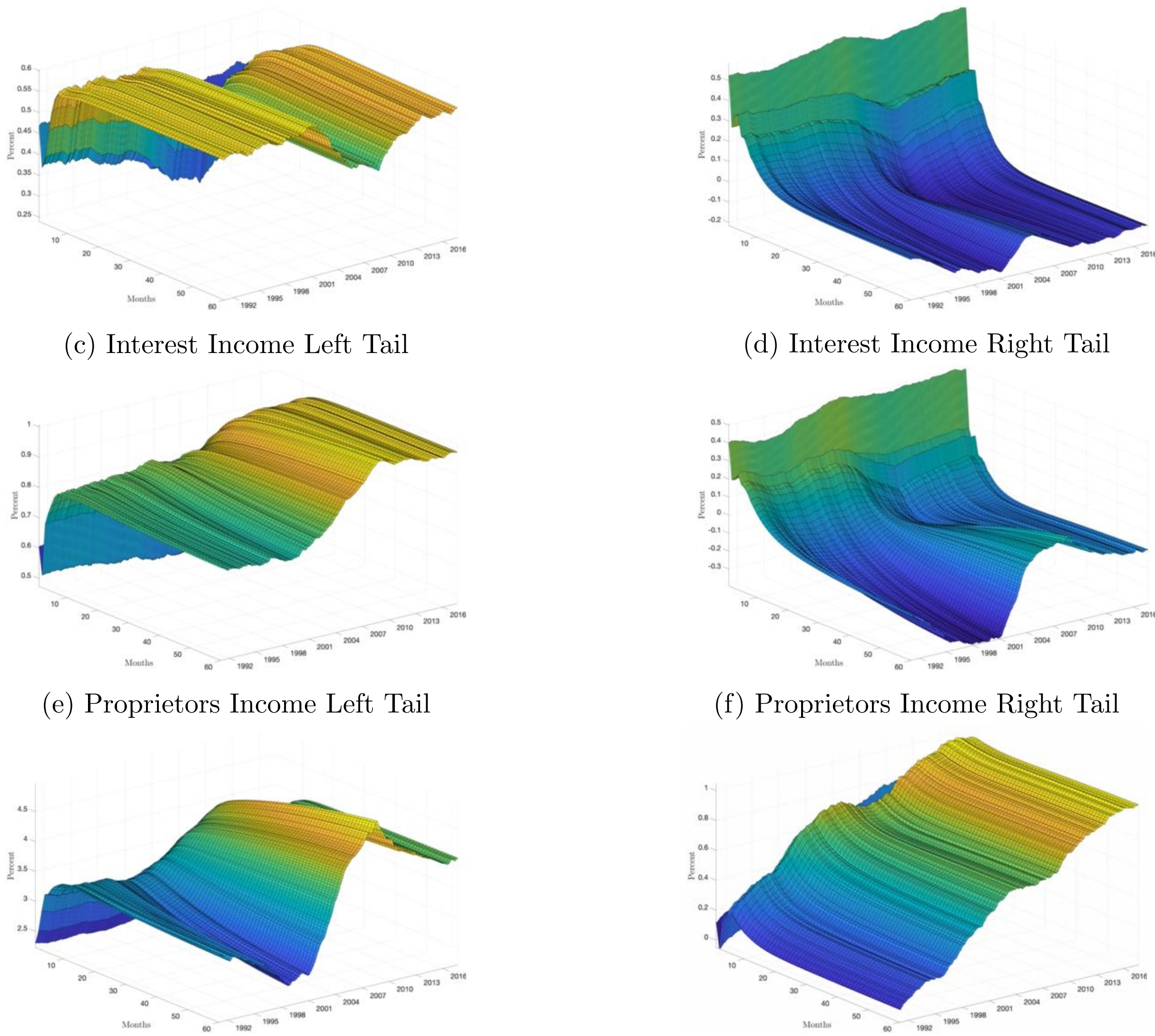


Figure 6: Impulse Response Functions of the main Income components. The Figure presents the two tails of the income distribution. All settings of the estimation equal the benchmark specification.

Looking at the response of interest income inequality, we observe that the impact of the shock varies considerably over time. In more recent years, the IRFs indicate both more persistent and more pronounced reactions. The highest point of this increase was reached during the crisis of 2008. After the crisis the responsiveness remains at high levels. At the same time, the right tail displays a short-term increase in inequality in the right tail which remains homogeneous over time.

Turning to inequality in proprietors' income, the left tail displays a similar shape as seen for the previous component. The responsiveness of inequality in the first decade of the sample remains low and slightly increases above zero. However, this behaviour changed after the dotcom crisis in 2001. Inequality becomes more responsive and even displays persistent increases after a monetary shock. The peak of this behaviour is reached in the crisis of 2008. In the right tail, inequality shows a continuous increase in the responsiveness to a monetary shock. This shock even becomes more persistent. The most recent years display the strongest effects of monetary policy on the inequality of proprietors' income indicating that proprietors' income for households at or below the median is more vulnerable to business cycle fluctuations. This vulnerability even increased during the more recent periods of our sample (e.g. the zero lower bound period) causing the same monetary policy shock to have more pronounced effects on proprietors' income inequality.



(a) Corp. Profits Left Tail

(b) Corp. Profits Right Tail

(c) Interest Income Left Tail

(d) Interest Income Right Tail

(e) Proprietors Income Left Tail

(f) Proprietors Income Right Tail

Figure 7: Impulse Response Functions of the main components of Capital Income. The Figure presents the two tails of the income distribution. All settings of the estimation equal the benchmark specification.

7 Sensitivity Analysis

Figure (8) displays the various exercises we conducted in order to provide robustness checks of our baseline results. Each plot presents the outcome of the P80/P20 income inequality ratio similarly to the baseline specification.

1. Stochastic volatility: in plot (a) of figure (8) we modified the baseline specification with respect to stochastic volatility. Since the baseline model in section (5) assumed constant volatility, the results might be affected by this assumption. Specifically, we allow the variance-covariance matrix of the errors' main diagonal to follow a geometric random walk[15].

[15] The exact setup of the model is presented in Appendix (C).

2. Hyperparameter selection: as noted by Primiceri (2005), time-varying parameter VARs are very sensitive to the prior hyperparameter κ_Q. Therefore, plots (b) and (c) in figure (8) provide estimations with a different value of κ_Q. Specifically, we set $\kappa_Q = 0.01$ and $\kappa_Q = 0.02$, which lowers/increases the time variation in the coefficients. As shown in the plots, the resulting estimations are in line with the baseline findings.

3. Pre-sample: the estimation is further refined by varying the pre-sample. We expand the pre-sample used in the baseline estimation backwards and establish the prior values based on the pre-sample from Jan 1976 to Dec 1990, which includes the whole dataset available. As presented in figure (d), this exercise confirms the baseline findings[16].

4. Inequality Measure: we re-estimated the baseline specification based on the Palma ratio (plot (e)), which is a frequently used measure of inequality. The findings on the time-varying effects of monetary policy broadly match our baseline.

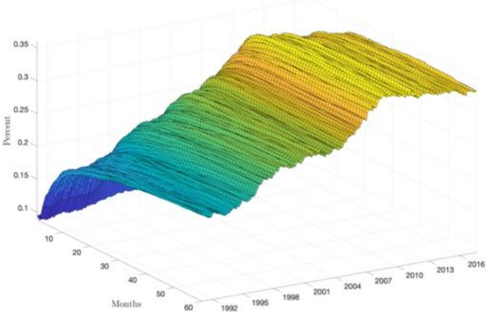
5. Lag length: we vary the lag length of the model and find that setting the lag length to either $p = 2$ or $p = 4$ does not alter the results[17].

6. The zero lower bound period: As explained in Paul (2020), the effective lower bound during the aftermath of the great financial crisis was characterised by very low volatility in the interest rate. Since our study uses an instrument for shock identification, a period with low information in the data (as the ZLB), may affect our findings. Therefore, plot (h) shows an estimation that starts in Jan. 1991 and ends in Dec. 2007. The results broadly match the baseline findings and confirm that the instrument identifies the shock consistently.

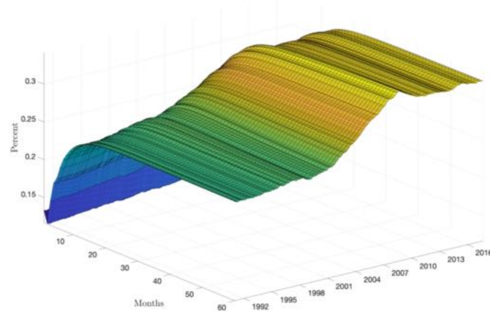
[16] The selection of the pre-sample setting is based on suggestions in Paul (2020). However, the data availability allows only to capture a slightly smaller time span.

[17] In this section we set the lag length according to the HQ information criterion for a fixed parameter VAR over the same estimation period.

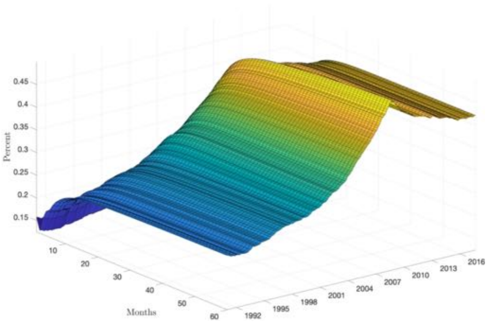
(a) Time-Varying Volatility



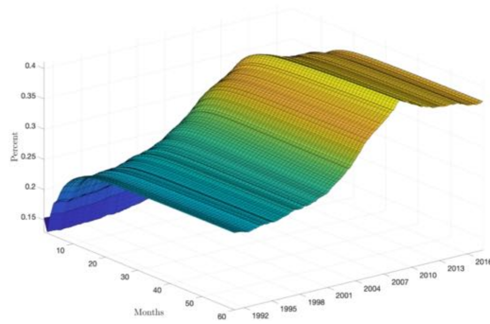
(b) Lower Time-Variation in the Coefficients



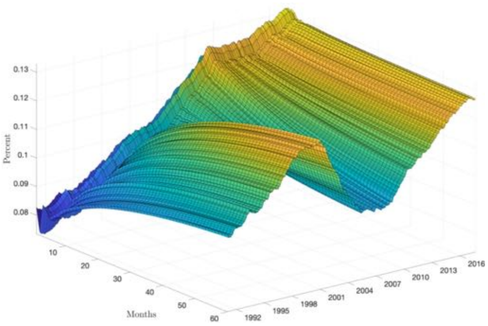
(c) Higher Time-Variation in the Coefficients



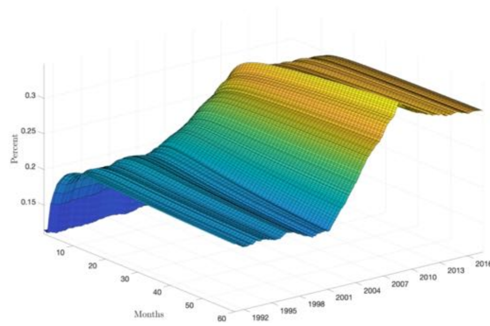
(d) Pre-Sample: Jan. 1976 to Dec. 1990



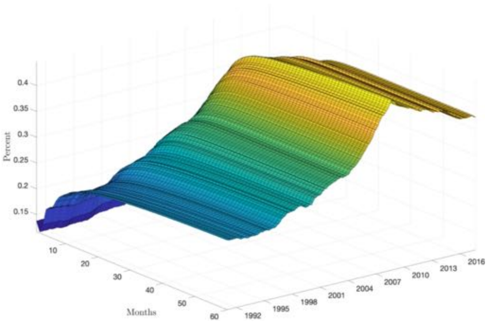
(e) Palma Ratio



(f) 2 Lags in the Baseline Specification



(g) 4 Lags in the Baseline Specification



(h) ZLB Episode Excluded

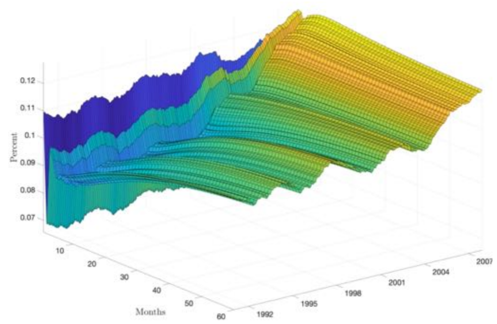


Figure 8: We present the robustness exercises described in the caption of every Subfigure. The displayed IRF always shows the P80/P20 ratio of real factor income.

8 Conclusion

While non-linear models are commonly used to examine monetary transmission, this approach has not been used in research that detects distributional channels. This research question legitimately arises when looking at the confirmed time variation of the effects of monetary policy shocks on the real sphere of the economy (Cogley and Sargent (2002, 2005), Primiceri (2005), Benati and Mumtaz (2007), Korobilis (2013)). We aimed to fill this gap with this study by making use of the time-varying parameter VARX of Paul (2020).

Taking into account recent developments in the high-frequency literature, we incorporate the instrument from Bauer and Swanson (2022) to identify a monetary policy shock. Our study investigates the US from January 1991 to September 2017 using inequality data that is derived from the real-time inequality database recently introduced by Blanchet *et al.* (2022). Using percentile ratios we analysed the time-varying effects of monetary policy shocks on income inequality.

First, our results find that the effect of monetary policy on income inequality increased. The same monetary policy shock, produced higher inequality responses in more recent observation periods, indicating that inequality in the US became more responsive to monetary policy during the zero lower bound period. Looking at the tails of the distribution we find that the income distribution is stretched by a shock. Moreover, both tails display a continuous rise in their responsiveness for the whole period examined.

When decomposing total income into its main components (labour and capital income), we find that capital income plays a more important role for high-income households. Keeping this in mind, our estimations provide a persistent increase in both inequality of capital income and inequality of labour income in the left tail of the distribution. While labour income inequality always increases and persistently remains high over the IRF horizon for all observation periods, capital income inequality shows a higher time variation. We observe that the response to monetary policy shocks was disrupted during the financial crisis, but this period of low responsiveness was short-lived and the response to shocks increased again in recent periods. Additionally, our study indicates that labour income at the lower end is more vulnerable to business cycle fluctuations since low-income households lose relatively to the median.

Turning to the right tail of the distribution our study displays a decrease in inequality of capital income which states that high-income households move closer to the median. Labour income inequality, however, persistently increases in this group as well, which leads to an overall "stretching" of the distribution. To further understand the dynamics of capital income inequality, we decomposed capital income into its main components. We find substantial time variation in the responsiveness to a monetary policy shock for each component of the left tail with all components indicating a persistent increase in the left tail that lasts over the whole IRF horizon. Compared to these findings the results regarding the right tail display a short-term increase in inequality which gradually fades away over the IRF horizon. This effect is less time-varying with the only exception being inequality in proprietors' income. Here, our findings reveal that the responsiveness of this component continuously increased, peaking in the most recent observation periods.

We explain these findings based on the earnings heterogeneity channel (persistence of the shock in the left tail especially coming from labour income) and the income composition channel (short-term movements in both tails induced by the different proportions of the various income components). In contrast to other studies in the literature, our analysis goes a step beyond and states that these channels became more pronounced during the more recent periods of our investigation.

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A Appendix: The Evolution of the Real Factor Income Share Gap in the US

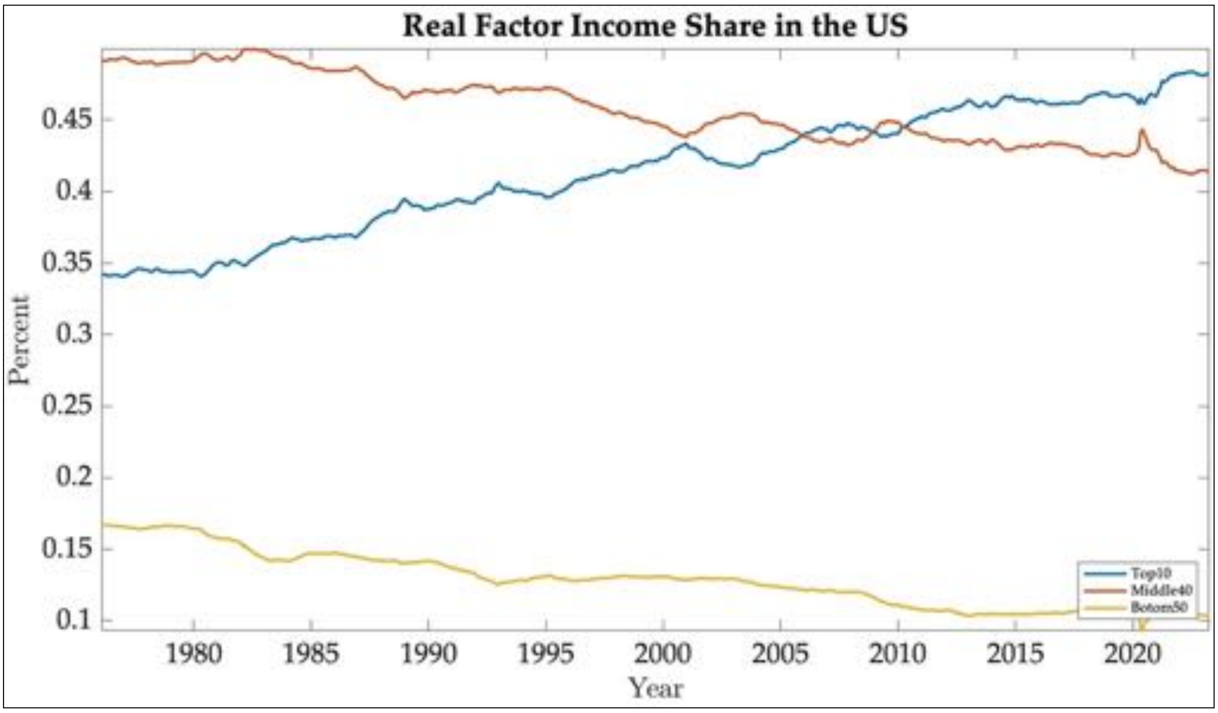

Figure 9: The evolution of real factor income share in the US by the corresponding percentile. Factor income is defined as the sum between labour and capital income and deflated by the GDP deflator. The data is available at the Realtime Inequality Database which can be accessed here.

B Appendix: Credibility Bands for the Baseline Specification and the Tails of the Distribution

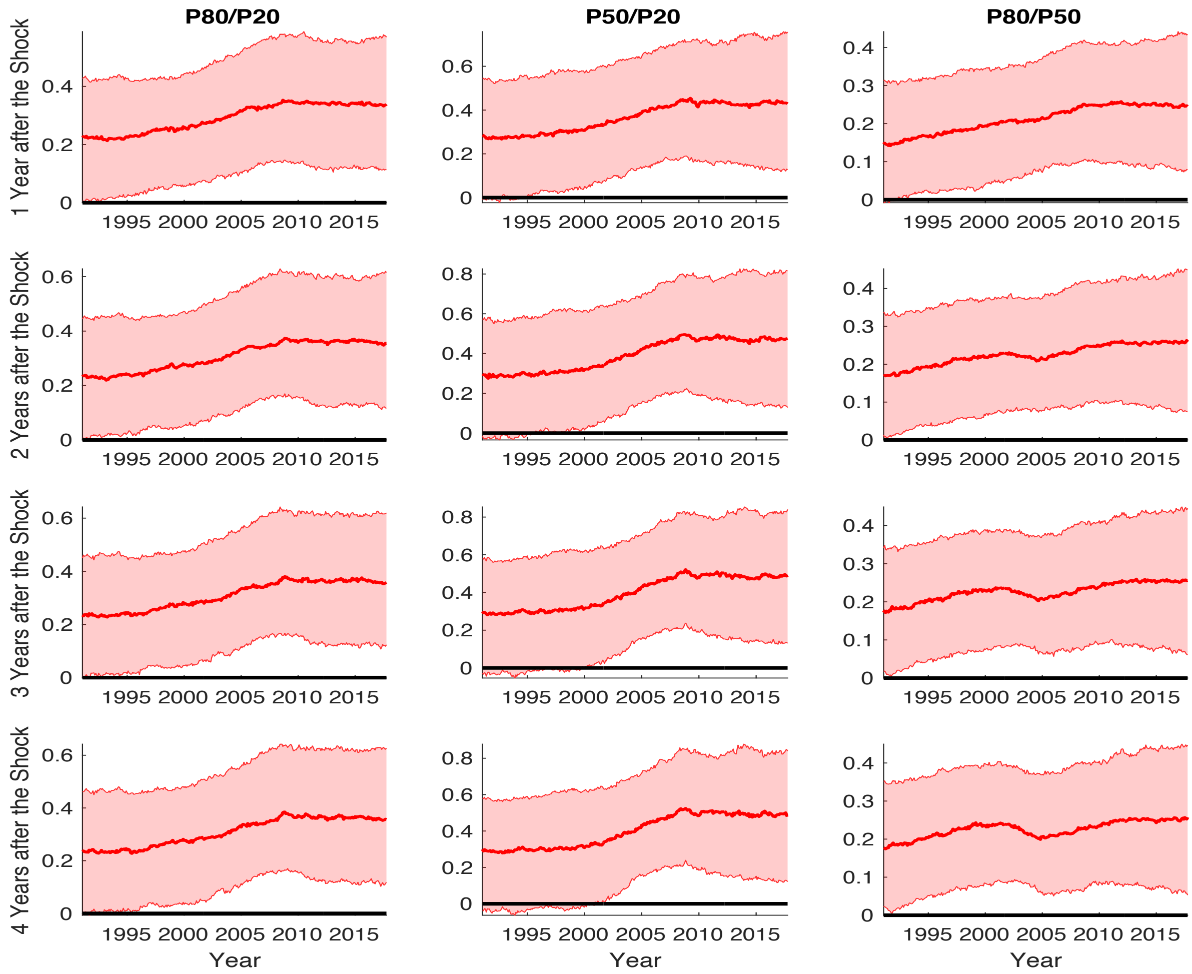

Figure 10: The Figure displays the 68% credibility Bands of the Tails together with the P80/P20 ratio over different horizons and corresponds to figures (1) to (4) in the main text.

C Appendix: Stochastic Volatility Extension: Overall setup and priors

In our robustness check of plot (a) in figure (7), we extend the volatility setup following Cogley and Sargent (2005). Consider the following decomposition of the variance-covariance matrix of the VAR errors from equation (6) in the main text:

$$\Omega = C^{-1} H_t C^{-1'} \tag{8}$$

with C being a lower triangular matrix of covariance parameters and H_t a diagonal matrix of variances. We define a geometric random walk for the elements in H_t based on explanations in Jacquier *et al.* (2002) after stacking them into a vector h_t according to:

$$log(h_t) = log(h_{t-1}) + \sigma_i \psi_t \tag{9}$$

With ψ_t being standard normal and independent of all other shocks in the system. As stated in equation (8), the lower triangular matrix C, which orthogonalizes the residuals is not time-varying. The role of these parameters can be described as:

$$C^{-1} u_t = \epsilon_t \tag{10}$$

note that ϵ_t is a vector of uncorrelated errors. The variance of these errors is known and equals h_t. This leads to a set of seemingly unrelated regressions with the first equation being the identity $u_{1t} = \epsilon_{1t}$. We follow Cogley and Sargent (2005), who define normal loose priors for every equation of this system.
The priors of the above take the following form:

$$p(ln(h_{i0})) \sim N(ln(\bar{h_{it}}), 10)) \tag{11}$$

where $\bar{h_{it}}$ is an initial estimate of the variance of variable i in the system. The prior of the variance σ_i is inverse gamma:

$$p(\sigma_i) = IG(\frac{100}{2}, \frac{1}{2}) \tag{12}$$

For the parameters of the matrix C we define:

$$p(c) \sim N(0, 10^3 * I_n) \tag{13}$$