Macroeconomic Shocks and Income Inequality:

An empirical investigation on the distributional channels of monetary policy and oil price news shocks

A thesis submitted for the degree of Doctor of Philosophy by Theodossios Drossidis

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Dedication

Completing a PhD is an investment in one's future, education, and personal development. However, if there is someone to whom I would dedicate this thesis, it would be my family, who supported me every step of the way. During my learning journey (which I hope is not ending here), my parents never stopped motivating and encouraging me. They convinced me that it's not just about finishing, but also about enjoying the journey. This includes all the ups and downs that come with such a project. Their support helped me stay focused on the bigger picture and make the most of an inspiring (albeit sometimes challenging) working environment, such as London. Although this chapter is ending, I recognize that none of it would have been possible without my parents' help.

Declaration

I hereby declare that the thesis is based on my original work, except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Brunel University or other institutions.

Concerning the status of potential publications, it should be noted that: The first chapter is unpublished, the second chapter is also unpublished, and the third chapter has been published and is accessible via the following link:
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Abstract

This thesis provides a deeper insight into the connection between macroeconomic shocks and income inequality across various economies. Through empirical analysis of the distributional channels of propagation, the study reveals that macroeconomic shocks, such as monetary policy and oil price news, impact the income distribution asymmetrically. This observation is consistent across both economies studied, the US and the UK. Particularly, a contractionary monetary policy shock in the UK is found to produce an increase in inequality through the earnings heterogeneity and income composition channel. While low-income households are mainly left unaffected due to their high exposure to social benefits, high-income households race away because of the higher proportion of capital income components.

These asymmetric effects also exist in the US, an economy investigated by looking at the time-varying effects of a contractionary monetary policy shock. In line with previous findings in the UK, the study finds that the same channels are in place. However, by adding another layer of complexity to the model, the study shows that the US income distribution became more responsive to monetary contractions in the more recent periods of the sample. This is mainly rooted in the dominant effects of the capital income components leading to a stronger effect of the income composition channel.

Finally, the thesis examines a different macroeconomic shock: oil price news shocks. When including all deciles of the income distribution in the modelling approach the asymmetric effects of these shocks again are detected. The overall picture i.e. capital income components make up a significant part of rich households and hence, are the main drivers for the different reactions of this group, is confirmed.

Keywords: Monetary Policy, Oil Supply News Shocks , Macroeconomic Shocks,

Distributional Effects, High-Frequency Identification, Local Projections, TVP-VARS, FAVARS

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Abbreviations

TVP-VARX	Time-Varying Parameter Vector Autoregression
FAVAR	Factor Augmented Vector Autoregression
HFI	High Frequency Identification
DSGE	Dynamic Stochastic General Equilibrium
RANK	Representative Agent New Keynesian
HANK	Heterogeneous Agent New Keynesian
URE	Unhedged Rate Exposure
FOMC	Federal Open Market Committee
SVAR	Structural Vector Autoregression
IRF	Impulse Response Function
HF	High Frequency
FES	Family Espenditure Survey
NFS	National Food Survey
EFS	Expenditure and Food Survey
LCF	Living Costs and Food Survey
GFD	Global Financial Database
MPC	Monetary Policy Committe
IV	Instrument Variable
LP-IV	Local Projection Instrumental Vriable
FEVD	Forecast Error Variance Decomposition
VAR	Vector Autoregression
ARCH	Autoregressive Conditional Heteroscedasticity
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
OLS	Ordinary Least Squares
BoE	Bank of England

1 Introduction

This work explores the complex relationship between macroeconomic shocks and income inequality by focusing on the distributional effects of monetary policy and oil supply news shocks across different economies. By analysing how these economic disturbances affect income distribution, the thesis contributes to a deeper understanding of the channels through which exogenous macroeconomic shocks influence inequality.

The theoretical studies of this research profited from contributions of Kaplan *et al.* (2018) and Gornemann *et al.* (2021), who introduced a DSGE model incorporating heterogeneous agents in the household sector. This represents a departure from traditional representative agent models, which assume a homogeneous household. Following the line of this literature, the current study takes an empirical approach to investigate the indirect or general equilibrium effects that replace the dominant substitution effect in the Euler equation of classic representative agent models, particularly focusing on the earnings heterogeneity and income composition channels. The study's testable implications arise from these distributional channels, particularly the income composition channel. For instance, the direction of these channels may not be consistent across economies, as the primary sources of household income can vary significantly from one country to another. This variation suggests that the income composition channel might change direction depending on the specific economic context, with the relative importance of labour income, capital income, and other sources influencing household behaviour in different ways across countries.

The first chapter investigates the distributional effects of monetary policy shocks in the United Kingdom from January 1992 to March 2020. By employing a high-frequency identification approach with local projections, the study reveals that contractionary monetary policy significantly increases income inequality. A 25 basis point increase in interest rates is found to raise the Gini-Coefficient of total disposable income by 0.22 per cent, highlighting the regressive impact of an unexpected monetary tightening. Further analysis of the tails of the income distribution reveals that while the lower end (50/10 percentile ratio) is adversely affected, the upper end (90/50 percentile ratio) experiences gains, suggesting that monetary policy disproportionately benefits higher-income groups. These effects are explained through the income composition and earnings heterogeneity channels, underlining the importance of the various income components of each household for the overall transmission mechanism of the shock. The findings are placed next to previous work that confirms these effects, especially for the U.S. (see Coibion *et al.* (2017) and/or Furceri *et al.* (2018)). A crucial aspect to reach this conclusion and hence, to detect the above distributional channels, is to look at the main income sources along the distribution. An insight into such an income decomposition shows the higher proportion of social benefits for poor households and an indication of a countercyclical behaviour of the working hours similar to the results presented in Cantore *et al.* (2022). At the same time, capital income components are found to drive the responses of more affluent households, ultimately linking them closer to financial markets.

The second chapter extends the analysis to the United States, examining the time-varying effects of monetary policy shocks on income inequality from January 1991 to September 2017. Using a Time-Varying Parameter Vector Autoregression with a high-frequency instrument as an exogenous variable (TVP-VARX), the study introduces nonlinear estimations of this type into the research field of monetary policy and inequality and finds that the responsiveness of the economy to contractionary monetary policy shocks has increased over time. The P80/P20 percentile ratio - the measure of inequality in the baseline specification - rises in response to a monetary tightening, with more pronounced effects observed in recent years. The chapter emphasizes the dynamic nature of monetary policy's distributional effects, revealing that the sensitivity of income inequality to policy shocks has increased, particularly through the earnings heterogeneity and income composition channels. The findings indicate that the earnings heterogeneity channel always remained crucial for understanding the distributional effects of monetary policy. However, the income composition channel reveals that especially capital income components are the main reason for the stronger impact of monetary policy on inequality over time. In order to reach the conclusions stated above, this analysis provides insight into income decomposition and its responsiveness over time.

The third chapter shifts focus to the effects of oil supply news shocks on the distribution of income in the United States. Using a Factor-Augmented Vector Autoregression (FAVAR) model with an external instrument, the study provides comparable insights regarding the distributional effects by looking at a different macroeconomic shock and uncovers that oil supply news shocks have pronounced negative impacts on both the lower and upper tails of the income distribution. Compared to the previous chapters, this analysis comprises the deciles of the income distribution, enabling the authors to include an approximation of the whole income distribution into the empirical model and finally highlight the asymmetric effects of the shock. For low-income individuals, the decline in wages and proprietor's income drives the adverse effects, while for affluent individuals, the reduction in corporate profits and interest income is the primary factor. This chapter provides novel insights into how exogenous oil supply news shocks can exacerbate income inequality through similar channels revealed by the previous examinations.

Summing up, this thesis demonstrates how macroeconomic shocks propagate to the real sphere of the economy and potentially lead to inequality movements. A main overall finding when looking at the effects along the distribution is that when trying to understand the transmission of macroeconomic shocks, researchers and/or policymakers need to take into account that such shocks hit the income distribution asymmetrically. This finding is rooted in the different compositions of income along the distribution. Low-income households primarily rely on wages and/or social benefits (country-specific), with decreasing importance of these income sources as income levels rise. This leads to different effects a household experiences when facing an exogenous macroeconomic shock. By employing state-of-the-art econometric techniques and high-frequency data, this research underlines the importance of these distributional effects when evaluating macroeconomic policies. The findings have profound implications for policymakers, suggesting that both the design and implementation of monetary policy, as well as the response to other exogenous shocks (here: oil supply news), must account for their potential to widen income inequality.

2 Monetary Policy and Income Inequality in the UK - An HFI Approach with Local Projections

Abstract

Recently central banks in Western economies raised interest rates and ignited considerations regarding the distributional effects of monetary policy shocks. This chapter answers this question by looking at the U.K. from Jan. 1992 to Mar. 2020. The monetary policy shock is identified using a high-frequency instrument. The findings state that a contractionary monetary policy shock of 25 bps leads to a 0.22 per cent increase in the Gini-Coefficient of total disposable income suggesting that an unexpected monetary tightening deteriorates overall income inequality in the U.K. Additionally, the 50/10 percentile ratio falls significantly while the 90/50 percentile ratio increases. These results are grounded in the income composition and the earnings heterogeneity channel. A finding which is revealed after decomposing total income into its main components for every quintile of the distribution.

2.1 Introduction

The aftermath of the last major financial crisis caused an overall reduction in the interest rate environment. At the same time, the Western world faced an increase in inequality, which not only concerned institutions like the OECD (OECD (2011), Brian (2015)) but also caught the attention of policymakers who compared monetary policy with other potential drivers of inequality such as globalization, technological progress, and demographic trends (as discussed by Bernanke (2015)).

Compared to the above, the current economic environment is stigmatised by high inflation which provoked central banks to increase interest rates. Legitimately, the question about the distributional effects of monetary policy again appears to be crucial. The research in this field produces mixed results. While some studies find that expansionary monetary policy has negative effects on inequality (Romer and Romer (1999), Inui *et al.* (2017), Cloyne *et al.* (2018)), others contradict this finding and state that contractionary monetary policy increases inequality (Mumtaz and Theophilopoulou (2017), Guerello (2018), Furceri *et al.* (2018) or Samarina and Nguyen (2019).

Focusing on the U.K., several studies find a recovery in inequality movements during the aftermath of the crisis but tend to coincide with the fact that this development will be offset in the future and hence, is only transitory (Belfield *et al.* (2014), Hood and Waters (2017)). Figure (1) shows the great inequality changes in the U.K. over time. It becomes obvious that income inequality reached its peak in the period from 1990 to 2000 and experienced a decrease since the last financial crisis. However, even though the Gini-Coefficient decreased over the last decade, the U.K. still portrays great inequality in international comparison[1].

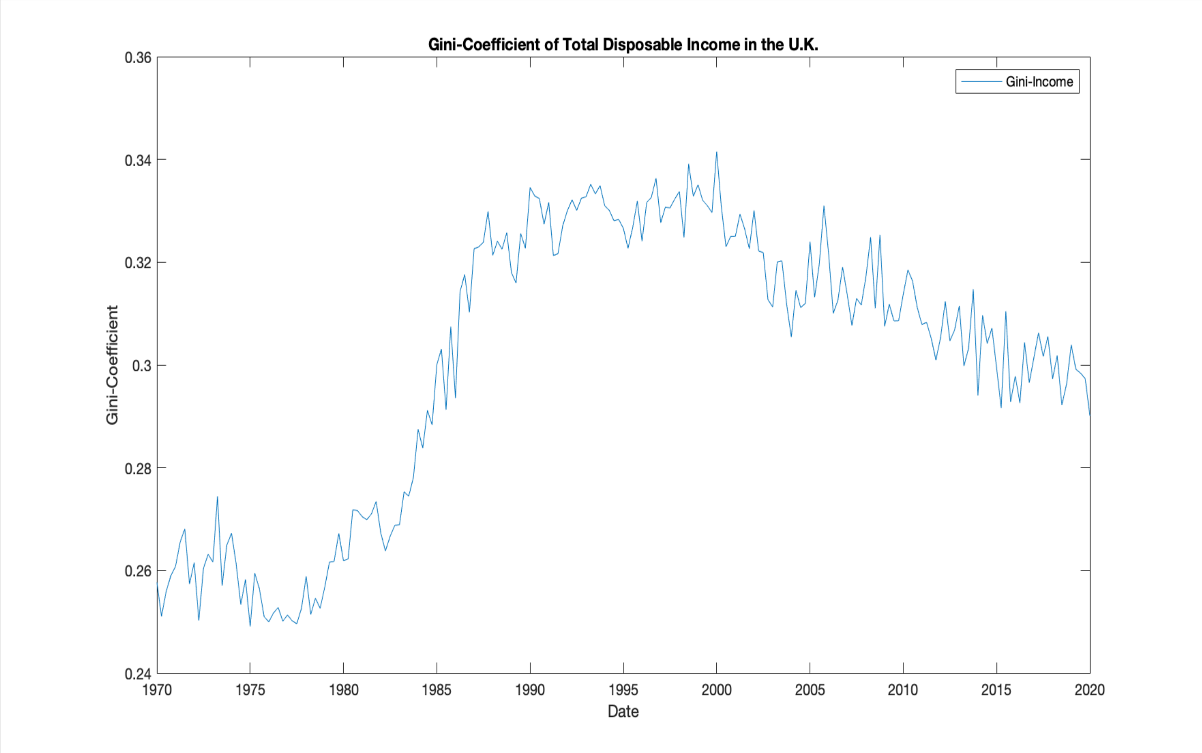


Figure 1: Gini-Coefficient of total disposable Income in the U.K. The graph is computed based on the data from the Family Expenditure Survey. It comprises quarterly seasonally adjusted Gini-Coefficients from Jan. 1970 to Jan 2020

This chapter aims to analyse the effect of monetary policy shocks on income inequality in the U.K. In our approach, we borrow insights from the high-frequency literature (Kuttner (2001), Gürkaynak *et al.* (2004), and Gertler and Karadi (2015)) and identify the monetary shock via Proxy-Local Projections as presented in Stock and Watson (2012) and Stock and Watson (2018). To derive inequality measures we use granular data from the Family Expenditure Survey ranging from 1970 to 2020. In addition to the Gini-Coefficient, we calculate quantile ratios and standard deviations of logs as measures of inequality.

Our study contributes to two different literature strands. It merges the HFI literature with monetary policy and inequality research. Even though, making use of external instruments to identify monetary policy shocks is not new (Coibion *et al.* (2017), Cloyne *et al.* (2018), these instruments are defined based on the narrative approach as shown in Romer and Romer (2004), which is a substantially distinct procedure to ours. A paper that is taking advantage of the HFI methodology and analyzing the same aspect similarly,

[1]Based on the OECD database the U.K. remains in the top 5 of the most unequal OECD members (18th of September 2024).

is provided by Samarina and Nguyen (2019). However, compared to this study our work comes with several distinct features: 1. To our knowledge, this is the first work in this research field, which analyses the impact of monetary policy on income inequality in the U.K. based on the high-frequency identification approach, 2. In contrast to Samarina and Nguyen (2019), we can disaggregate our data to a monthly frequency and provide insights from a Proxy-SVAR and Proxy-Local Projections estimation using Bayesian methods.
Turning to the HFI literature we can confirm the findings provided by Cesa-Bianchi *et al.* (2020) for a greater observation period. Specifically, Cesa-Bianchi *et al.* (2020) look at the period from January 1992 to January 2015, whereas ours ranges from January 1992 to March 2020. In doing so, we extend the series of monetary policy surprises with the one provided by Kaminska and Mumtaz (2022). That leaves us with an instrument that covers a total period of 23 years (i.e. from January 1997 to March 2020).

Our results state that a contractionary monetary policy shock of 25 bps leads to a 0.22 per cent increase in the Gini-Coefficient of total disposable income. Thereby, the response is not equal across the distribution. Particularly, the 90/50 quantile ratio rises, which indicates that the difference between the median household and the upper 10 per cent of the distribution increases. In contrast to this, the 50/10 quantile ratio falls, which shows that the median and the lower 10 per cent of the income distribution move closer together.
To detect distributional channels of monetary policy, we include the set of macroeconomic variables as stated in Cesa-Bianchi *et al.* (2020). In particular, we identify the credit channel and prove that monetary policy shocks can have redistributive effects. We explain our findings regarding inequality by the simultaneous interaction of the income composition and earnings heterogeneity channel when looking at the percentile reactions. Regarding the income composition channel, we find that low-income households (10th percentile) face a very short-term income increase. After that, this group mainly responds insignificantly to the shock. The median households (50th percentile) lose whereas the high-income households even see an increase in their income. Considering the earnings heterogeneity channel, we illustrate that the increase in income for low-income households is associated with an increase in working hours and a countercyclical behaviour of social benefits. The loss of the median households is because earnings are more vulnerable to business cycle changes. The same holds for high-income households. However, since the latter has a higher proportion of income coming from investments, total income recovers fast for this group, leading to an overall increase in inequality.

The remainder of this chapter is structured as follows: Section 2.2 gives an overview of the current literature stance and examines the two different research fields to which this work is related. Section 2.3 explains the data, the derivation of the inequality measures, and the macroeconomic variables we use for our estimation. Section 2.4 introduces the methodology. Section 2.5 presents our baseline results and section 2.7 offers a robustness analysis. Finally, Section 2.8 concludes.

2.2 Literature

This study relates to the literature examining the distributional channels of monetary policy on inequality by borrowing insights from the high-frequency identification approach. Although the first research field is still in its infancy, results are provided continuously, leading to a rapidly growing body of literature. Researchers aim to understand if and how monetary policy has distributional effects. In this case, theoretical and empirical studies are in a continuous interplay.

Looking at the theoretical side of this research field dynamic stochastic general equilibrium models (DSGE) are the classic workhorse to analyse the distributional effects of monetary policy shocks. However, early specifications did not incorporate household heterogeneity, which gave rise to theoretical modifications in the household sector. The reason is that in the Representative Agent New Keynesian Model (RANK), the substitution effect in the Euler equation entirely describes the crucial transmission channel induced by a monetary policy shock. However, as stated in Kirman (1992) it is not assured that this individual agent is acting as the aggregate of individuals in the economy, that it aims to represent. It rather has to be seen as a mathematical construct, that matches a model's properties. Related to this criticism is the work provided by Carroll (2000), who shows that a key feature, that is unrealistic in this setup is that households can insure their income and wealth perfectly against idiosyncratic shocks. The author highlights that the failure to match microeconomic characteristics is an essential weakness of this model. Two features that Carroll (2000) includes in his analysis are 1. The high skewness of the wealth distribution, 2. The high average marginal propensity to consume. When modifying the model concerning that, the author finds that the equilibrium implications differ substantially from the representative agent approach.

The benchmark study that introduced heterogeneity was provided by Kaplan *et al.* (2018), who introduced the heterogeneous agent (HANK) model. Heterogeneity in the household sector and uninsurable idiosyncratic shocks for individuals lead to crucial findings concerning the impact of monetary policy shocks. In order to understand the distributional effects of monetary shocks, the authors highlight the importance of differentiating between direct and indirect effects.

Direct effects display the immediate response to a change in interest rates, whereby labour income remains unchanged. The key mechanism of the direct effect is the intertemporal substitution effect defined in the Euler equation. Another example of a direct effect is the change in a household's net income. This may arise because maturing assets and liabilities respond differently to a monetary shock. On the contrary, indirect effects are harder to distinguish since they are the result of general equilibrium responses in the economy. Following Ampudia *et al.* (2018), who focus on these effects in the Euro Area, the indirect effects can be described as the following chain of events induced by a monetary policy shock: consider an unexpected decrease in the monetary policy rate. Initially, the direct effect occurs, causing a shift in households' intertemporal preferences due to the intertemporal substitution effect. This leads to increased consumption. Simultaneously, firms experience lower capital costs, prompting increased investments. The outcome is a rise in aggregate demand, resulting in increased prices, production, wages, and employment. However, especially the increase in wages and employment causes demand to rise further, which again increases output, etc. Following Ampudia *et al.* (2018), the above-described multiplier effect is the main characteristic of the indirect channel.

The work of Kaplan *et al.* (2018) established the importance of this indirect channel. Consequently, the implications resulting from this work differ from the ones provided in the classic RANK model: Consider a monetary policy that aims to boost consumption. Since direct effects play a dominant role in the RANK model, the monetary authority has to change interest rates so that real rates move. After that, intertemporal substitution will move consumption. On the contrary, in a HANK model, indirect effects dominate. The monetary authority has to rely on general equilibrium feedback to influence consumption. This complicates the way a shock transmits to the household sector, which in turn affects the monetary authority's ability to fine-tune its policy actions. The current stance of the literature affirms that a monetary policy shock triggers wealth-, income- and substitution effects. Thereby, the findings in theoretical works emphasize the income and wealth effect resulting in indirect effects taking over from their counterparts.

A more recent paper that builds upon these developments and provides crucial contributions to the distributional effects of monetary policy shocks was introduced by Auclert (2019). In his paper, the author establishes the importance of marginal propensities to consume and unhedged interest rate exposure. Auclert (2019) develops a DSGE model with household heterogeneity and analyses the distributional effect of monetary policy shocks. In doing so, he explains that a monetary expansion increases real income, boosts inflation, and lowers real interest rates. Since households are affected differently by these changes, the author aims to trace back the overall effect to these three different sources of redistribution, which yields three distributional channels. The first one is the earnings heterogeneity channel. The starting point for this channel is the increase in labour earnings and profits due to a monetary expansion. Since agents in the household sector participate unequally in these gains, some will lose while others will win from the monetary expansion. The second source is the Fisher Channel. In this case, the crucial effect is the unexpected increase in prices, which causes creditors to lose relative to debtors. Third, a monetary expansion will reduce real interest rates, which in turn increases financial assets. Here, Auclert (2019) emphasizes the net position of households when looking at this channel. The decisive aspect is if asset holdings have longer durations than liabilities. Based on this consideration the author suggests that the unhedged interest rate exposure (URE) at a specific point in time is the correct measure to detect the interest rate exposure channel. Following the author's derivations, a household that holds assets with a longer duration than its liabilities has a positive URE and vice versa. An expansionary monetary policy shock will cause a fall in interest rates and hence, redistribute from the households with negative UREs to the ones with positive UREs.

Williamson (2008) presents further theoretical contributions to distributional channels, which set the groundwork for the financial market segmentation channel. The author presents insights into the distributional effects of monetary policy shocks concerning goods market segmentation. In his DSGE model, the author explores the non-neutrality of money based on other reasons than price stickiness, which is usually assumed in the classic model setup (RANK). The study introduces two types of agents, connected and unconnected ones. While unconnected agents do never trade, their connected counterparts are always active. As an example of connected agents, Williamson (2008) mentions banks and other financial intermediaries. Additionally, the author assumes that each party prefers to trade goods with its own kind. This leads to goods market segmentation. The interdependence of the two markets (connected and unconnected) is explicitly captured in a parameter in the agents' preferences, which enables the author to influence the connectedness. Williamson allows for inter-market trade with a stronger preference towards the own kind. This model setup shows that expansionary monetary policy does not distribute the money evenly across the agents. The connected agents are the ones who are affected immediately by monetary expansions. These expansions in turn increase prices in the connected markets. After time elapses, the money reaches the unconnected market since trade is taking place. Consequently, the money stock decreases in the connected market. As a result the prices in the connected market drop, while the ones in the unconnected market increase. The model shows an overshooting reaction of the connected markets, whereas the unconnected markets gradually adapt their prices according to the monetary shock. However, the faster reaction of the connected agents leads to a redistribution of wealth, which moves from the unconnected to the connected sector. These considerations gave rise to the financial market segmentation channel of monetary policy and state that since financial market participants tend to be wealthier than those who are not connected to the markets, a monetary expansion should raise consumption inequality.

Taking into account the findings from theoretical studies, researchers on the empirical forefront aim to confirm these distributional channels. In this case, some distributional channels seem well detected and understood, whereas others remain hard to find and confirm empirically. Thereby, the majority of recent empirical works explain the theoretical indirect effects via the income composition and earnings heterogeneity channel. The empirical counterpart to the direct effects is the interest rate exposure channel.
Older empirical studies focused on the inflation channel. In this case, the literature still does not show an overall consensus. Empirical results provide insights into both: the negative and positive effects of inflation on inequality leading to an "inflation-inequality puzzle" as stated in Galli and van Der Hoeven (2001). Following the authors' statements, it is crucial to differentiate between the short and long-run effects of inflation.
Romer and Romer (1998) also highlight this aspect and state that these effects contradict each other. To analyze the short-term effects of a monetary policy action the authors look at the post-war period in the U.S. ranging from 1969-1994. Thereby, they find that expansionary monetary policy leads to a short-term cyclical boom. This in turn improves conditions for the households. However, the long-run effects differ. In this case, the authors conducted a cross-country regression analysis for a panel of 76 countries in 1988. The findings report that after the short boom, the output returns to its natural level. The only difference to the previous state of the economy is the now existing higher inflation level. The latter is according to the authors, the long-run effect of a monetary expansion. Furthermore, it is not possible to return to the previous state of the economy via contractionary monetary policy. The reason is that the latter will increase unemployment and poverty and even offset the positive short-term boom in the first place. Based on their results the authors suggest conducting a monetary policy that points to low inflation and stable output growth.

Turning to more recent empirical approaches the income composition channel seems to be confirmed at the empirical forefront. The essence of this distributional channel is heterogeneity in the primary income source of households. While the majority of households derive their income from labour, there are others whose primary source is business or financial income. Since monetary policy shocks affect these sources differently one can expect different reactions from households. For instance, richer households receive financial income, which tends to rise more than wages after an expansionary monetary policy shock. This may cause inequality to increase.
Hereby, the benchmark study is provided by Coibion *et al.* (2017), who analysed the U.S. economy during the period from 1980 to 2008. The authors use the methodology first introduced by Romer and Romer (2004) to derive a monetary policy shock variable. They

focus on the Federal Reserve's Greenbook forecasts at every FOMC meeting to derive monetary policy shocks, that are not part of the committee's information set.
To quantify the impact of monetary policy shocks on inequality Coibion *et al.* (2017) conducted an impulse response analysis using local projections. Thereby they derive 3 different inequality measures i.e. the Gini-Coefficient, the cross-sectional standard deviation, and the differences between percentiles of the distribution. The study finds that contractionary monetary policy increases total income, labour earnings, and consumption inequality at the 5 per cent significance level. The relevance of this work can be seen in its implications: 1. It established the fact that monetary policy has an impact on inequality, 2. It highlighted the importance of household heterogeneity when looking at the distributional effects, which in turn indirectly questioned the appropriateness of the (standard) representative agent model and hence, relates to the suggestions in Kaplan *et al.* (2018). Regarding the distributional channels, the authors also refer to the work of Williamson (2008), who established the financial segmentation channel. However, due to a lack of data availability, the detection of this channel remains puzzling even though the authors suggest that its overall effect is relatively small.

Further insights on the income composition channel are provided by Cloyne *et al.* (2018), who focus on the U.S. and the U.K. The authors analyze survey data from the Living Costs and Food Survey for the U.K. from 1975-2007 and the Consumer Expenditure Survey for the U.S. from 1981 to 2007. Having divided the households into mortgagors, outright owners, and renters to be able to differentiate the effect across the income distribution, the authors identify the monetary policy shock using external instruments. In short, they incorporate an updated version of the shock series provided by Romer and Romer (2004) for the U.S., whereas the U.K. shock series is derived from Cloyne and Hürtgen (2016). Their analysis concludes that household indebtedness matters for the transmission mechanism of a monetary policy shock. When looking at the baseline results, the study finds that a 25 bps cut in the policy rate increases the expenditure of mortgagors and renters, while outright owners do not change their expenditure significantly from zero. This effect is similar between both the U.K. and the U.S. The author's suggestion when looking at this result is that mortgagors and renters determine the overall effect of the movement in expenditure. Turning to the income variable, the study finds that net income (i.e. excluding taxes) responds significantly and increases in all of the 3 different groups in a similar fashion. This delivers the crucial insight that even though expenditure reacts heterogeneously, this phenomenon seems not to hold for earnings. In short, expenditure heterogeneity is not always accompanied by earnings heterogeneity, which leads to the fact that earnings increase for every group, while expenditure only increases for mortgagors and renters. This finding shows another crucial aspect: Cloyne *et al.* (2018) categorize mortgagors as "wealthy hand-to-mouth" households. That is, they may be wealthy but react as hand-to-mouth households because most of their liquidity is invested in a single asset such as housing. All in all, this study highlights the heterogeneous response of households to a monetary policy shock and states that this response is not driven by demographics.

Additionally, it is worth noting that the authors contradict the findings from Coibion *et al.* (2017) although they focused on the same distributional channel. The study finds that expansionary monetary policy shocks have negative impacts on inequality. However, Coibion *et al.* (2017) were also aware of this bidirectional characteristic of the income composition channel and mentioned that the income composition channel may change its direction if the most important income source in a household sector changes.
An additional distributional channel, which is also mentioned in Coibion *et al.* (2017) and confirmed in other studies is the earnings heterogeneity channel. Hereby, the crucial starting point is the heterogeneity of earnings. As presented before, earnings at the top of the distribution depend on other factors than earnings at the bottom of the distribution. This leads to heterogeneous feedback effects after a monetary policy shock. A study closely related to Coibion *et al.* (2017) is provided by Mumtaz and Theophilopoulou (2017), who confirm similar findings when looking at the U.K. economy. The authors use a Bayesian SVAR approach to investigate the impact of a contractionary monetary policy shock on similar inequality measures. Compared to Coibion *et al.* (2017), they focus on a larger observation period ranging from 1969 to 2012 and derive quarterly Gini-Coefficients for income, consumption, and wage. The results state that contractionary monetary policy leads to an increase in wage and income inequality at the lower end of the distribution. The upper end remains less affected underlining an asymmetric effect of the monetary shock. All in all, a contractionary monetary shock of one standard deviation causes a 1 percentage point increase in the Gini-Coefficient.

Additional evidence on this distributional channel is provided by Furceri *et al.* (2018), who analyze the impact of a monetary policy shock on a sample of 32 countries during 1960-2013. Thereby, the identification of the monetary policy shocks follows two steps. First, Furceri *et al.* (2018) compute forecast errors of policy rates (i.e. the actual short-term rate at the end of the year minus the rate expected by analysts for the end of the same year). In a second step, they regress those errors on similar computed errors for inflation and output growth. The residuals of the second regression display the monetary policy shocks. This procedure is done for every country. Finally, the shocks are used to compute IRFs via local projections. The authors find that an unexpected increase of 100 bps in the policy rate increases inequality by 1.24 per cent in the short-term (i.e. 1 year after shock) and 2.25 per cent in the medium-term (i.e. 5 years after the shock). These findings underline the importance of persistent effects due to monetary policy shocks.

Further results portray that the strength of the impact depends on the policy measure. According to Furceri *et al.* (2018), the effects of a contractionary shock are stronger, which highlights asymmetry. Apart from the fact that this study comprises a panel of countries rather than a single economy, its implications appear to be closely related to the previous ones. To emphasize this aspect the authors report slightly larger effects for the U.S. when comparing their results to the ones provided by Coibion *et al.* (2017). However, the difference in their results is not significant.

Further insights from a panel study are provided by Guerello (2018), who conducts a VAR analysis for the Euro Area. The study provides a comparison of a Panel VAR approach with a single, aggregate VAR estimation. Identification of the monetary shocks is achieved using the Cholesky decomposition. In addition, the analysis includes a qualitative inequality measure, defined as income dispersion. It displays a percentage deviation to a qualitative question, that can be answered based on a 5-point ordinal scale. Following the author's explanations, this inequality measure yields sufficient estimates of Gini-Coefficients. The analysis finds that a contractionary monetary shock raises income and earnings inequality and detects the earnings heterogeneity channel. When looking at the Euro Area as a whole, the study confirms the findings shown in Coibion *et al.* (2017) and reports that expansionary monetary policy decreases income dispersion in the medium term.

Inui *et al.* (2017) provide further evidence of the earnings heterogeneity channel when looking at Japan. The authors use survey data to derive inequality measures (i.e. the variance of logs, the Gini-Coefficient, and the P90/10 ratios) and conduct an impulse response analysis via local projections. The baseline estimation comprises quarterly data from 1981 to 1998 and includes only households whose head is working. Thereby, their findings state that a monetary expansion is followed by a pro-cyclical behaviour of inequality. The variance of disposable income, -earnings, and -pre-tax income increases significantly at the 5 per cent level. Furthermore, the authors show that this movement is mainly driven by the reaction of earnings underlining the importance of the earnings heterogeneity channel. When extending the sample the authors find that the effects of monetary policy shocks on inequality are weakening. However, when changing the observation period of the data set Inui *et al.* (2017) detect a procyclical reaction of earnings. The suggestion is that this is due to economic conditions rather than monetary policy shocks. Keeping the relevance of the earnings heterogeneity channel in mind, the authors include in the second step of their analysis households, whose heads are not working. This modification enables them to provide evidence for the job creation channel. The latter is an alternative (even "sub-channel") of earnings heterogeneity and states that monetary policy actions are eager to increase or decrease job opportunities in an economy. This in turn changes the number of households with zero earnings leading to changes in inequality. However, even though the authors find an indication of this mechanism in the data, the overall effect is insignificant.

Referring to the indirect effects in theoretical findings, Samarina and Nguyen (2019) partition these effects into two distinct channels, when trying to detect them for the E.U. The first is the macroeconomic channel, which captures the dynamics explained in Ampudia *et al.* (2018). The second is the financial channel, which mainly emerges because of the reaction of asset prices and capital returns. The study finds that a one standard deviation expansionary monetary policy shock leads to a peak increase of 0.26 per cent in output. Prices rise by 0.13 per cent. Additionally, GDP increases with an effect lasting for 10 months. The price level (HICP) increases persistently and lasts over the medium term. All in all, the findings state that monetary policy has a significant impact on income inequality in the EU: a one standard deviation negative monetary policy shock causes the log Gini-Coefficient of income to decline by about 0.045 per cent. Thereby, the two channels seem to operate in different directions. The authors find that the macroeconomic channel enhances the redistribution due to a monetary policy expansion (i.e. it shows positive effects on inequality) whereas the financial channel seems to have negative impacts on inequality. The authors derive this conclusion based on the increase in share prices and returns.

Taking into account the above empirical findings, the overall picture confirms the statements of Colciago *et al.* (2019), who mention four influencing factors of empirical results. First, the characteristics of household income. As previously shown the primary income source has a great influence on how a monetary policy hits the household sector and hence, the channel of its distribution. The second is the economic structure of the underlying country. As suggested by Inui *et al.* (2017) a change in economic surroundings may affect the way, earnings react to monetary policy shocks. Third, the distributional channel plays an essential role and may change its direction depending on the previous circumstances (see the contradiction between Cloyne *et al.* (2018) and Coibion *et al.* (2017). Fourth, the Policy measure and its identification. The latter arises due to the challenge of coping with endogeneity and hence, displays a methodological issue. Concerning this issue, researchers have to provide a reasonable explanation of why a detected statistical correlation can be interpreted as a causal relationship between the underlying variables (see Ramey (2016)). However, an alternative to make up for the endogeneity problem in empirical works was recently provided by the high frequency (HF) literature.

The high-frequency literature is the second research field this work contributes to and borrows insights from. It analyses the transmission of monetary policy on the economy using high-frequency price changes from the futures market. The approach was pioneered by Kuttner (2001), who studied the effect of monetary policy shocks on Bond, Bill, and Note yields when incorporating data from the FED Futures Market. His central finding states that although Bond rates are nearly unresponsive to an expected (i.e. anticipated) monetary shock, they respond highly significantly to unexpected shocks. Kuttner's work establishes the appropriateness of fed funds futures to act as a proxy for the expected FED policy. At the same time, he underlines the necessity of filtering unexpected components from the data to analyze the effects of a monetary policy shock. Improvements in this approach were delivered by Gürkaynak *et al.* (2004), who calculated the surprise component in the same fashion but suggested a tighter window instead, i.e. intraday (30 minutes around a policy announcement) to derive unbiased surprises. Following the author's statements, this small time window minimizes the likelihood that a monetary policy shock appeared due to other reasons than the monetary policy announcement. Based on the analytical frame that was established by those two articles several new works emerged, that build upon this approach to derive instruments for monetary policy shocks.

Recent influential contributions are provided by Gertler and Karadi (2015), who focus on credit costs in the U.S. The authors find that the reaction of the credit costs after a monetary policy shock is enhanced. An implication is that the large response of credit costs may be the reason why an observed short-term rate movement causes significant impacts on economic activity. Furthermore, a comparison between the external instruments approach and the classic Cholesky decomposition shows that the Proxy-SVAR delivers findings that are consistent with the literature, whereas the Cholesky approach is characterized by puzzling results in both CPI and Industrial Production. Following the same identification approach, Nakamura and Steinsson (2018) analyze the effect of monetary policy on real interest rates and break-even inflation, which is the essence of monetary non-neutrality. To derive the high-frequency instrument, the authors conduct the approach of Gürkaynak *et al.* (2004) and calculate price changes in the Eurodollar futures contract and the Federal Funds futures in a 30-minute time window. The findings suggest that monetary policy can affect real interest rates for a substantial amount of time. Nevertheless, in the long-run monetary policy remains neutral as the theory suggests.

Further applications are provided by Gerko and Rey (2017), who analyze the effectiveness of monetary policy in the U.K. and the U.S. In doing so, the authors look at the monetary transmission mechanism and try to detect spillover effects between these two countries. The study conducts a proxy-SVAR analysis for both monetary systems. Similar to Gertler and Karadi (2015), it uses the Fed Funds' future contract to derive the shock instrument for the U.S. When looking at the U.K., it incorporates the short Sterling future. The results can be subsumed in the following: Beginning with the reaction of the U.S. economy to U.S. monetary shocks Gerko and Rey (2017) confirm the results of Gertler and Karadi (2015). The results show that a 20 bps tightening in the 1-year rate is accompanied by an increase of the mortgage spread, an appreciation of the U.S. Dollar (direct quotation against the Pound Sterling), an increase of the 5-year gilt yield as well as a delayed decrease in production and the CPI. Looking at the U.K., the study shows that a shock in the 5-year gilt yield leads to an appreciation of the Pound against the U.S. Dollar, a rise in the corporate and the mortgage spread as well as a delayed decrease in industrial production. However, there is no significant movement in the price level measured by the retail price index. Turning to international spillover effects, the study highlights the asymmetric effects of monetary policy shocks. A 20 bps tightening in the 1-year U.S. rate causes an increase in the mortgage spread, and an appreciation of the Sterling against the Dollar but no significant movement in industrial production or the 5-year rate. Additionally, another specification that includes the corporate spread, finds that it goes down after a U.S. monetary tightening. On the contrary, the study does not find any significant effects of a U.K. tightening on the U.S. economy, which leads to the author's conclusion that the U.S. is the current predominant in the international monetary system.

The paper closest to our work is provided by Cesa-Bianchi *et al.* (2020), who analyze the transmission channel of monetary policy to the U.K. financial and real sectors. In doing so, the authors derive an external instrument series for the U.K. based on the approach of Kuttner (2001) and Gürkaynak *et al.* (2004) and in turn, include this instrument in a proxy-SVAR analysis similar to Gertler and Karadi (2015). The baseline results state that a 25 bps monetary tightening causes a decline in economic activity, an appreciation of the Pound, a significant decrease in prices, an increase in mortgage and corporate bond spreads and an increase in the U.S. corporate bond spreads. These findings provide evidence for the credit channel of monetary policy as presented by Bernanke and Gertler (1995). However, the latter focuses only on domestic credit conditions to explain the transmission of monetary policy. In this study, the authors underline the finding that U.S. corporate bond spreads rise after a U.K. monetary tightening, which portrays the importance of international spillover effects and links their study to both Gertler and Karadi (2015) as well as Gerko and Rey (2017).

All in all, notwithstanding that some works provide evidence that expansionary monetary policy increases inequality (Inui *et al.* (2017), Cloyne *et al.* (2018)), the overall consensus seems to be established that a monetary tightening leads to an increase in inequality. These results are confirmed for the U.K. (Mumtaz and Theophilopoulou (2017), the EU (Guerello (2018), Samarina and Nguyen (2019)) as well as a sample of developed and emerging countries (Furceri *et al.* (2018)), forming the main stream in this research field. Taking into account recent developments in the HFI literature it can be said, that this identification approach represents a suitable tool to analyse the transmission mechanism of monetary policy. However, the literature does not show any empirical work that adapts the HFI approach in an analysis of the U.K. to derive the effects of monetary policy shocks on inequality. Therefore, an examination that incorporates the HFI approach and points it to inequality would fill the niche between these two literature strands presented above.

2.3 Data

2.3.1 The Family Expenditure Survey

We use household data from the Family Expenditure Survey (FES). The FES is a continuous survey that provides detailed information about household characteristics in the U.K. The main purpose of this survey is to collect economic and social data that is used for national account estimates of household expenditures and the retail price index. Throughout its long history, the survey was subject to numerous changes. The beginning dates back to the 1950s. Initially, in 1950, the National Food Survey (NFS) existed as a demographic study. Seven years later (1957) the Family Expenditure Survey (FES) was initiated and the two coexisted until their merger in 2001 which formed the Expenditure and Food Survey (EFS). Yet, 7 years after this merger, in 2008, the EFS became the Living Costs and Food Survey (LCF) as it is still known today.

The survey collects information on its participants via 3 schedules: 1. A household questionnaire, 2. An individual questionnaire, 3. A diary. The household questionnaire covers expenses of a habitual nature i.e. housing costs, fuel, light, or power. It is based on the household level and derives information from a reference person. In contrast to that, the individual questionnaire obtains information about income, national insurance contributions, income tax, and employment status for every individual.
Finally, the diary schedule asks every participant to keep track of his spending behaviour on a daily basis. The diary covers 14 days and each household member aged 16 or older participates in it. The final data set from the FES combines all the above questionnaires throughout the year and enables the researcher to index every single observation to its corresponding calendar week.

The sample of this study includes on average 7000 households per year from 1970Q1 to 2020Q1. This results in a data set covering in total about 350000 observations of household data over the entire period. Based on these observations we construct our income variable. According to our definition, the income variable comprises disposable income. It embodies gross disposable income excluding tax and national insurance contributions. We use the square root of the number of household members to normalize this variable as suggested by the OECD. Following the statement of the OECD the needs of a household increase with every member. However, it would be misleading to assume that this increase is proportional, due to economies of scale in consumption. The square root scale takes this into account. It implies that a household consisting of 4 members needs twice as much as a household of a single person.

Having defined the income variable we exclude the top and bottom 1 per cent as well as all negative values. After trimming the data we have 6000 observations per year, which leaves us with 300000 observations in total for the whole period. However, the FES does not provide weighting factors for the period ranging from 1970 to 1996/1997. Therefore, we make use of the weighting factors provided by Banks *et al.* (1997) to ensure a comparable data set for the upcoming years and hence, construct a uniform distribution for the entire period.

2.3.2 Measures of Inequality

Based on the above, we calculate Gini-Coefficients, percentile ratios, and the standard deviation of logs for income. The Gini-Coefficient is a frequently used descriptive statistic to portray inequality. It takes values between 0 (all individuals hold the same proportion) and 1 (one individual holds all). Thereby, we take advantage of the granular household data, which enable us to provide Gini-Coefficients on a higher frequency level i.e. quarterly in a similar fashion as in Mumtaz and Theophilopoulou (2017).

Turning to the percentile ratios, we calculate three different ratios of percentiles. First, the 50/10 ratio indicates how the lower part of the distribution is affected compared to the median household. The second is the 90/50 ratio, which compares the previous effect when focusing on the upper part of the distribution. Third, the 90/10 percentile ratio, is a suitable measure to display overall inequality based on a distribution's quantiles. Compared to the Gini-Coefficient, we expect this measure to be more elastic and hence, to suitably capture the short-term changes in our income distribution.

The last inequality measure is the standard deviation of logs, which offers insights into a variable's dispersion around its mean at a specific point in time. Since our approach combines the inequality measures with the monetary shock series provided in Cesa-Bianchi *et al.* (2020), we decided to calculate the analysis on a monthly frequency. This way we ensure data availability of all financial variables for the entire observation period. In order to display our inequality measures on a monthly frequency, we disaggregate the data using cubic splines. The result is a monthly time series for every inequality measure ranging from Jan. 1970 to Mar. 2020.

2.3.3 Macroeconomic Variables

Turning to the macroeconomic variables some aspects are worth mentioning: Even though there is a great availability of macroeconomic series on different frequency levels, we were forced to combine different sources to derive a consistent data set for the entire observation period. Table (1) provides an overview of all the sources used to construct these variables.

Macroeconomic Variables	
Variable	Source
The 1-year Gilt Yield	Bank of England (BoE)
Consumer Price Index (CPI)	ONS, Millennium data set (BoE)
Unemployment Rate	FRED database
Moody's BAA corporate bond yields	FRED database
FXBIS narrow index	Bank of International Settlements
Mortgage Spreads	Millennium data set, GFD
Corporate Spreads	Millennium data set, GFD

Table 1: Data Sources for the UK.

A breakdown is as follows: (1) The 1-year gilt yield, which we use as the monetary policy indicator. This series is provided by the Bank of England (BoE). (2) The consumer price index (CPI), is our measure of inflation. We downloaded the series from the FRED database. (3) The unemployment rate. We used the series provided by the ONS from 1971 to 2020. Before 1971, we used the data from the Millennium data set provided by the BoE. (4) Moody's BAA corporate bond yields relative to the 10-year U.S. government bond yield to display international spillovers. This series is available in the FRED database. (5) The FXBIS narrow index is the nominal effective exchange index of the British Pound Sterling. This series is provided by the Bank of International Settlements. Additionally, we use a mortgage spread series to display credit costs in the economy. From Jan. 1970 to Mar. 2017 we use the M12-series in the Millennium data set of the BoE. After that, we merged this series with the updated data provided by the BoE (code: IUMBV24). Since the latter has a large number of missing values, we filled these gaps with data from the Global Financial Database (GFD). All in all the series is defined as the spread between the mortgage lending rate and the 5-year gilt yield.
As presented by Cesa-Bianchi *et al.* (2020), Corporate Spreads are also included to model the credit costs in the economy. However, due to the lack of data availability of option-adjusted spreads, we were forced to keep this series out of our baseline estimation. Nev-

ertheless, we tried to construct a corporate spreads series to prolong the provided series by Cesa-Bianchi *et al.* (2020) and use this variable for robustness checks to show that the inclusion of this variable does not affect our findings. Our corporate spread series ranges from Jan. 1970 to Mar. 2020. The subsets of the series are defined as follows: from Jan. 1970 to Jan. 2015 this series is a spliced interpolated series from the Millennium data set of the BoE. Thereby, the values from Jan. 1970 to Dec. 1996 are defined as the difference between the Debentures and the 20-year yield. From Jan. 1997 to Jan. 2015 the millennium data set uses the option-adjusted Spread of Sterling Corporate Bond yields on industrials rated AAA-BBB. However, since we are covering a greater observation period we were forced to prolong the series from Feb. 2015 with the data provided by the GFD. We used the Corporate Bond Yields data set (code: INGGRW) minus the 10-year Government Bond yields (code: IGGBR10D). The difference in the term structure (20-year yield from 1970 to 1996 versus 10-year yield from 1996 onward) is based on the work provided by Gerko and Rey (2017).

2.3.4 The Monetary Shock Instrument

For our estimation, we combine the proxy provided by Cesa-Bianchi *et al.* (2020) with the one by Kaminska and Mumtaz (2022).
Beginning with Cesa-Bianchi *et al.* (2020), the authors focus on risk-neutral financial contracts (i.e. 3-month Sterling future contracts) that are linked to the London interbank offered rate and define the shock to be the price movement that occurred in a 30-minute time window around a monetary policy committee (MPC) meeting following Kuttner (2001) and Gürkaynak *et al.* (2004). Hence, the monetary policy instrument is defined as:

$$Z_t^{HF} = -(P_{t,\tau+20}^{h} - P_{t,\tau-10}^{h+90})$$

where t,τ denotes the exact time τ (in minutes) in day t when a monetary event occurred. This series covers the observation period ranging from Jun. 1997 to Jan. 2015. To incorporate a longer time series in our analysis we prolong this shock series with the shocks provided by Kaminska and Mumtaz (2022) (henceforth KM), who focus on the same contracts and conduct the same derivation of price changes. However, one distinct feature has to be highlighted between these two approaches. Unlike Cesa-Bianchi *et al.* (2020) (henceforth CB), who define the shock as the price difference between two specific points in time, KM look at the difference between the median values in a 10-minute pre- and post-window, 20 minutes around an MPC meeting. For instance, consider the MPC meeting to be at 12 pm. The CB shock series is defined as the price difference between 11:50 am and 12:20 pm. On the contrary, KM define the shock as the difference in the median values between 11:40 am to 11:50 am and 12:20 pm to 12:30 pm. In this case, the latter displays a more robust method concerning outlier values. To compare both series we plotted the overlapping period from Jun. 1997 to Jan. 2015 in Appendix (2.9). Additionally, we included a scatter plot to get a better understanding of the correlation in Appendix (2.10). Both variables are highly correlated with a correlation of 0.81. The variance of the CB series yields 0.053 compared to a variance of 0.057 for KM.

2.4 Methodology

We derive impulse response functions using direct methods as proposed by Jordà (2005). In doing so, we include the external instrument in our estimation. That is, we conduct the LP-IV approach as described by Stock and Watson (2018). As a starting point, we write the impulse response function (IRF) as the difference between the two forecasts:

$$IR(t, s, d_i) = E(Y_{t+s}|\varepsilon = 1) - E(Y_{t+s}|\varepsilon = 0) \tag{1}$$

Where $\varepsilon = 1$ comprises the shock of interest (i.e. in our case the monetary policy shock). In order to compute direct IRFs, the instrument has to fulfil the conditions as presented in Stock and Watson (2018):

1. relevance: $E(\varepsilon_1 Z_t') = \alpha$
2. contemporaneous exogeneity: $E(\varepsilon_{2:n} Z_t') = 0$
3. lead/lag exogeneity: $E(\varepsilon_{1+j} Z_t') = 0$

The first two conditions refer to the classic IV conditions in the econometric literature (see Stock and Watson (2012)). According to 1, the instrument variable must be relevant and correlated with the true unobserved shock. Condition 2 displays the exogeneity condition and assures that the instrument variable is not related to other shocks in the structural form equation. Condition 3 defines the fact, that the entire history of all shocks is relevant to model the dependent variable at hand. Hence, the high-frequency instrument Z_t, which only follows the purpose of modelling one specific shock, has to be uncorrelated with all other shocks as well as their past and future observations. Based on the implementations of Cesa-Bianchi *et al.* (2020), the "second front contract", which captures the 3-to-6-month ahead expectation on the 3-month Libor, is a suitable instrument for the 1-year gilt rate. To satisfy condition 3, we follow Stock and Watson (2018) and include control variables (i.e. lagged values of Y) in our estimation. The set of h linear regression equations is defined as:

$$y_{i,t+s} = \alpha^s + \beta^s Z_t + \gamma^s X_{i,t} + u^s_{t+s} \tag{2}$$

where s=0,1,2...h. y_t is the forecast of every variable included in the system, α^s is a constant, Z_t is the monetary policy shock instrument, and $X_{i,t}$ is a vector of control variables, which is set to equal the lagged macroeconomic variables in the system.

2.5 Baseline Results

The baseline results comprise a sub-sample of our data ranging from Jan. 1992 to Mar. 2020. We define the starting point of our baseline estimation to coincide with the beginning of the inflation-targeting regime in the U.K. Since the Bank of England exited the European Exchange Rate Mechanism in 1992, the estimation over the whole sample will be affected by a structural break. Figure (2) displays the impulse response functions. The graph shows the response to a 25bps increase in the 1-year gilt yield instrumented by the high-frequency time series. The included inequality measure is the Gini-Coefficient of total disposable income. We set the number of lags equal to 2 and the IRF horizon to 41 periods.

Beginning with the policy rate, the shock lasts significantly for more than 2 years.

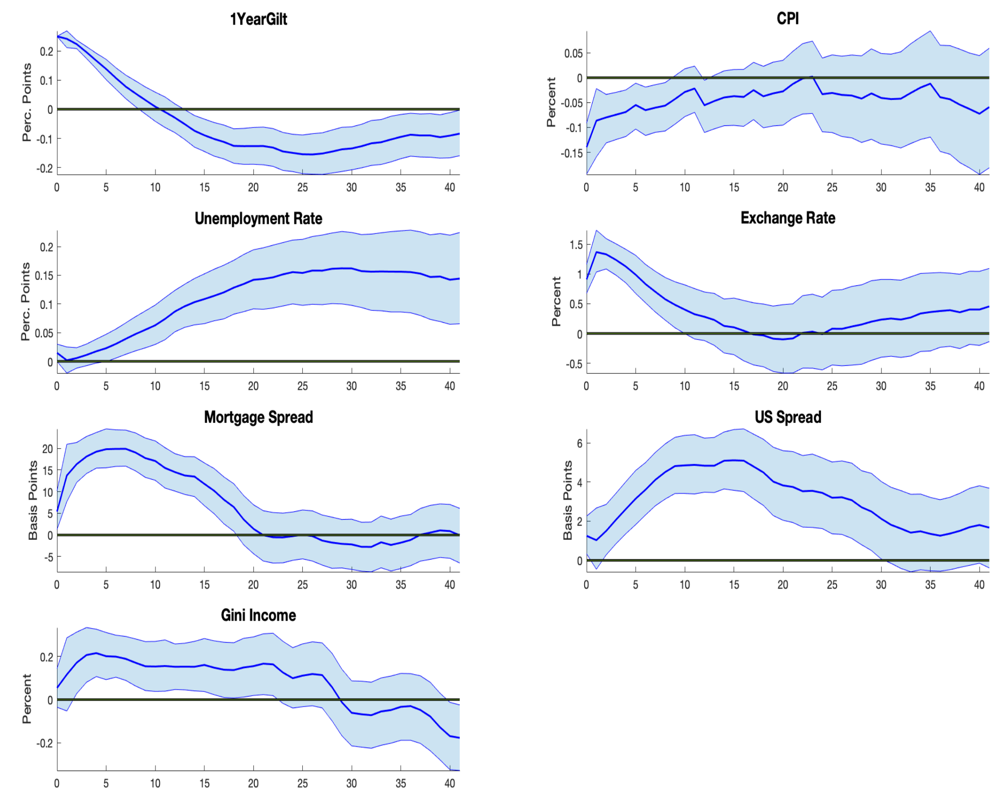


Figure 2: IRFs to a 25 bps contractionary monetary policy shock using Bayesian local projections with 10,000 draws from the posterior. The specification is set to 2 lags, a 41-period horizon, and all variables entered seasonally adjusted and in log levels. The observation period ranges from Jan. 1992 to Mar. 2020. We display the 95 per cent credibility bands.

The unexpected increase in the 1-year gilt yield leads to a significant drop in consumer prices (i.e. inflation). The latter shows a significant decrease on impact and slowly recovers during the first 10 months after the shock. These effects are accompanied by a delayed reaction of unemployment. Unemployment increases significantly reaching its peak median response of 0.16 percentage points, 30 months after the monetary shock. Looking at the results provided by Cesa-Bianchi *et al.* (2020), we can confirm the finding that the unemployment rate is increasing after a monetary tightening. However, we find a slightly enhanced reaction in the peak median response. The exchange rate reacts with an immediate median response of 0.91 per cent and reaches its peak at 1.37 per cent, 2 months after the shock.

Turning to the credit costs of the economy, the results present an immediate and significant increase in the mortgage spread. The peak median response is reached after 8 months equalling 19.87 basis points. In line with theoretical considerations provided by Bernanke and Gertler (1995), credit costs increase after a monetary tightening. The monetary tightening also shows international spillover effects. This can be seen by the immediate increase in the U.S. Bond spreads with a peak response of 5.11 basis points 16 months after the shock.

Turning to the response of the Gini-Coefficient of income, we find a significant rise in income inequality. This persistent effect reaches a peak median response of 0.22 per cent only 5 months after the shock. The effect remains significant for 22 months.
However, the reaction of the Gini-Coefficient only allows us to report the aggregate inequality movement. In order to understand how monetary policy affects the distribution of income, we focus on the reaction of percentile ratios to look at the tails of the distribution as presented by Coibion *et al.* (2017). Figure (3) displays the IRFs of both tails of the income distribution (i.e. $(P_{50} - P_{10})$ and $(P_{90} - P_{50})$) to a shock of the same magnitude as in the baseline scenario. The $(P_{50} - P_{10})$ difference drops significantly by 0.67 units (peak median response) only 3 months after the shock hits. This indicates that the monetary policy shock drives the poor and the median households closer together.

In comparison, the response of the $(P_{90} - P_{50})$ percentile difference shows a significant rise in inequality. The peak response equals 0.36 per cent, 22 months after the shock indicating that the gap between the rich and the median household increases. The delayed reaction can be attributed to the changing composition of income, as illustrated in Figure (4). The income composition between the 50th and 10th percentiles differs more significantly than between the 50th and 90th percentiles. The delayed movement in the significance of the right tail occurs because, initially, both percentiles respond more similarly than those in the left tail. Consistent with this, Figure (5) presents the reac-

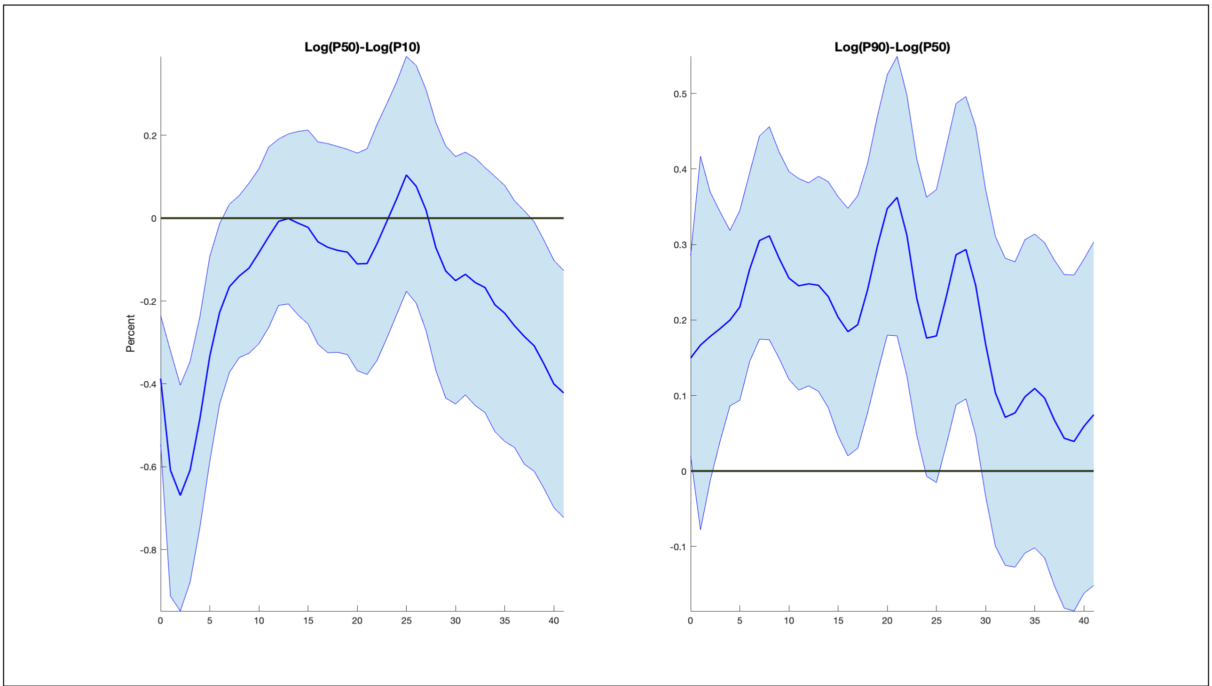


Figure 3: IRFs of both tails of the Income distribution after a 25 basis point monetary policy shock. All other settings equal the baseline estimation.

tions of the income components, revealing that financial income and social security react immediately, while wages and ambiguous income exhibit a more delayed response.
Taking into account the above, these results confirm distinct effects of monetary policy shocks along the income distribution. In particular, we place our work next to previous findings in the literature, that confirm a negative effect of contractionary monetary policy on income inequality (see Coibion *et al.* (2017), Mumtaz and Theophilopoulou (2017) or Furceri *et al.* (2018)). These studies find a possible explanation for these results in the difference of the primary income source of the rich compared to the one of the poor (i.e. the income composition channel). Closely related to this is the earnings heterogeneity channel, which focuses on the different reactions of earnings across the distribution instead of total income.

Reconsidering the income composition channel, Coibion *et al.* (2017) explain that richer households receive more business and financial income which tend to adapt faster to monetary policy changes than wages. To verify if these explanations apply to our study, we analyzed household income by breaking it down into its four primary components for each quarter from 1970 to 2020. Figure (4) illustrates the income decomposition of our dataset and displays similar findings to the literature regarding the trend in income components across the distribution and over time. We show that the proportion of income received from investments increases the further up we go in the distribution. Additionally, the proportion of income coming from social benefits is one of the main income sources for low-income households, while the middle class (households at the median of the distribution) mainly receives income from wages.

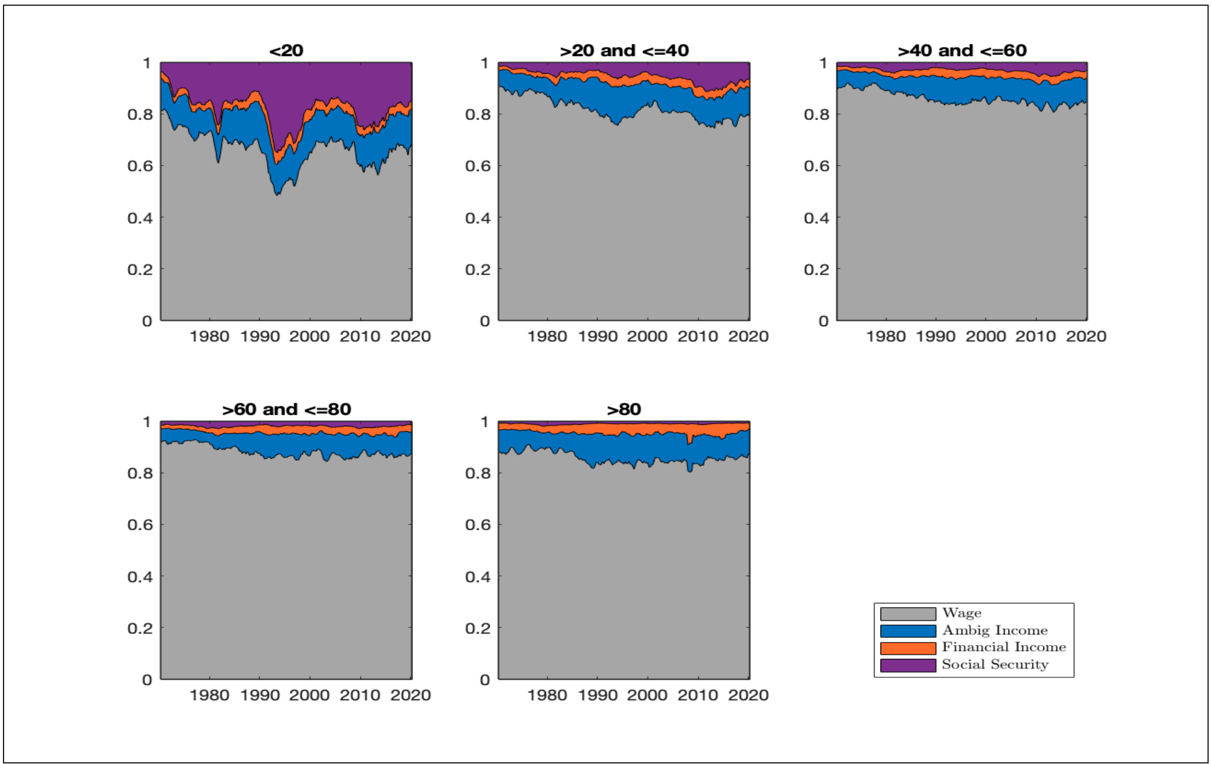


Figure 4: The evolution of the proportions of the four main income components. We used quarterly data from 1970Q1 to 2020Q1 and smoothed the data with a moving average.

Keeping this in mind and with the help of Appendix (2.11) which displays the IRFs of each percentile value, we can derive an explanation for the reaction of the ratios in Figure (3). Since low-income households receive a large share of their income from social benefits, a monetary contraction mainly leaves those households unaffected. Notably, the IRF of the 10th percentile increases on impact and remains insignificantly different from zero after 6 months (Appendix (2.11)). This finding relates to the explanation provided by Theophilopoulou (2022), who underlines the importance of changes in working hours for low-income households when discussing the earnings heterogeneity channel. Respectively, our finding suggests that the countercyclical behaviour of working hours over the business cycle in the left part of the income distribution combined with the great loss of the median household leads to inequality movements in the U.K. Recent findings by Cantore *et al.* (2022) provide evidence for this income effect on labour supply after a monetary tightening in the U.K. based on a FAVAR estimation. Additionally, Kolasa *et al.* (2021) detect this phenomenon when looking at the European Area (EA). A monetary tightening forces low-income households to work more. This is displayed in a short-term increase in income in the left part of the distribution.

Turning to Figure (3), the $(P_{50} - P_{10})$ ratio drops significantly. This movement is dominated by a sharp loss of the median household. The median household experiences a strong and persistent loss after a monetary tightening (Appendix (2.11)).
At the same time, the $(P_{90} - P_{50})$ ratio rises and remains significantly different from zero for 25 months after the shock. This result indicates that the gap between the median and the rich increases. Since our analysis simulates an increase in the policy rate, rich households experience a short-term shock in their income coming from wages. Reconsidering that the income, received from investments makes a relatively greater proportion for the rich this short-term loss is only transitory (and insignificant), and income again rises as shown in Appendix (2.11)[2].

To support our proposed mechanisms, we have expanded our baseline specification by including the $(P_{80} - P_{20})$ difference of each income component from our income decomposition. Figure (5) illustrates the results of this analysis.
Starting with wages, our findings indicate an increase in wage inequality between the rich and the poor, particularly for longer periods, which confirms previous explanations regarding the earnings heterogeneity channel. Ambiguous income, which refers to income from self-employment, does not significantly differ from zero. Therefore, inequality movements are not driven by this income component.
Moving on to financial income, we observe an immediate increase in inequality, indicating that the rich race away based on this income component. Finally, income inequality based on social security decreases initially and then remains largely unaffected, indicating a countercyclical behaviour of social benefits, especially for the lower end of the distribution.

To summarize, social benefits may provide a short-term increase in income for the poor, but they are also required to work longer hours (Cantore *et al.* (2022)). On the other hand, the median household experiences a significant and persistent loss of income (11 months) due to the loss of earnings, which mainly affects their wages. The rich also experience a short-term and insignificant negative impact on their income for the first two months, but their income starts to increase after three months due to the financial sector recovering faster, leading to higher interest income. As a result, income inequality increases overall, as indicated by the Gini-Coefficient. The monetary policy shock pushes the middle class closer to the lower income bracket, and our research identifies two channels responsible for this. Firstly, the income composition channel states that the gap between the rich and the poor increases because of the movements of financial income. Second, the middle class faces a persistent decrease in income due to negative

[2] Theophilopoulou (2022) also finds that income (especially wages) for the median and P90 percentiles are more vulnerable during recessions and also provides evidence for the earnings heterogeneity channel.

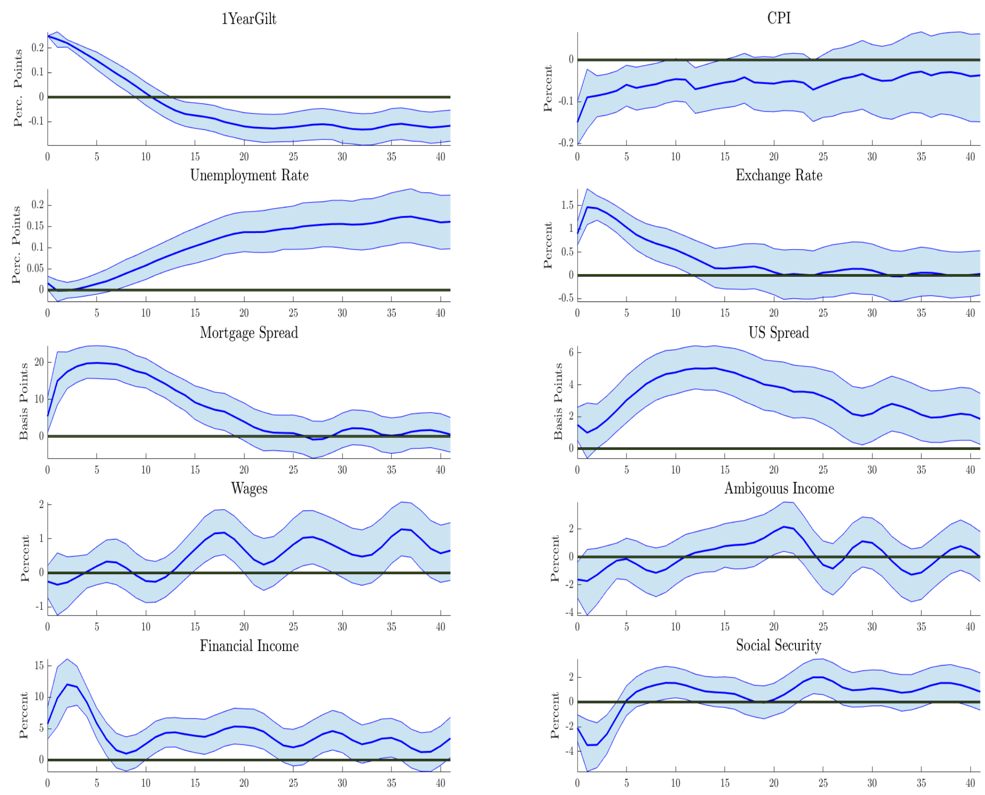


Figure 5: The extended baseline specification by the difference of log levels between the 80th and the 20th percentile of every income component. All other settings are unchanged. The data is disaggregated by interpolation as before.

wage movements, known as the earnings heterogeneity channel.

2.6 The Contribution of Monetary Shocks to Income Inequality

Figure (6) presents the contribution of a monetary policy shock to the forecast error variance (FEV) of the Gini-Coefficient. We detect a continuous rise in the contribution while time elapses. Comparable to Coibion *et al.* (2017), the contribution of monetary shocks to the forecast error variance of inequality increases significantly as time elapses. The FEVD reaches a peak median response of 13.12 per cent after 41 months[3].

2.7 Robustness

In this section, we provide robustness checks from different estimations. Specifically, we look at the modelling approach, conduct estimations regarding different specifications and finally, provide IRFs when changing the inequality measures. For convenience, we

[3]The Appendix 2.12 presents insights from a historical decomposition (HD) of monetary policy shocks on inequality.

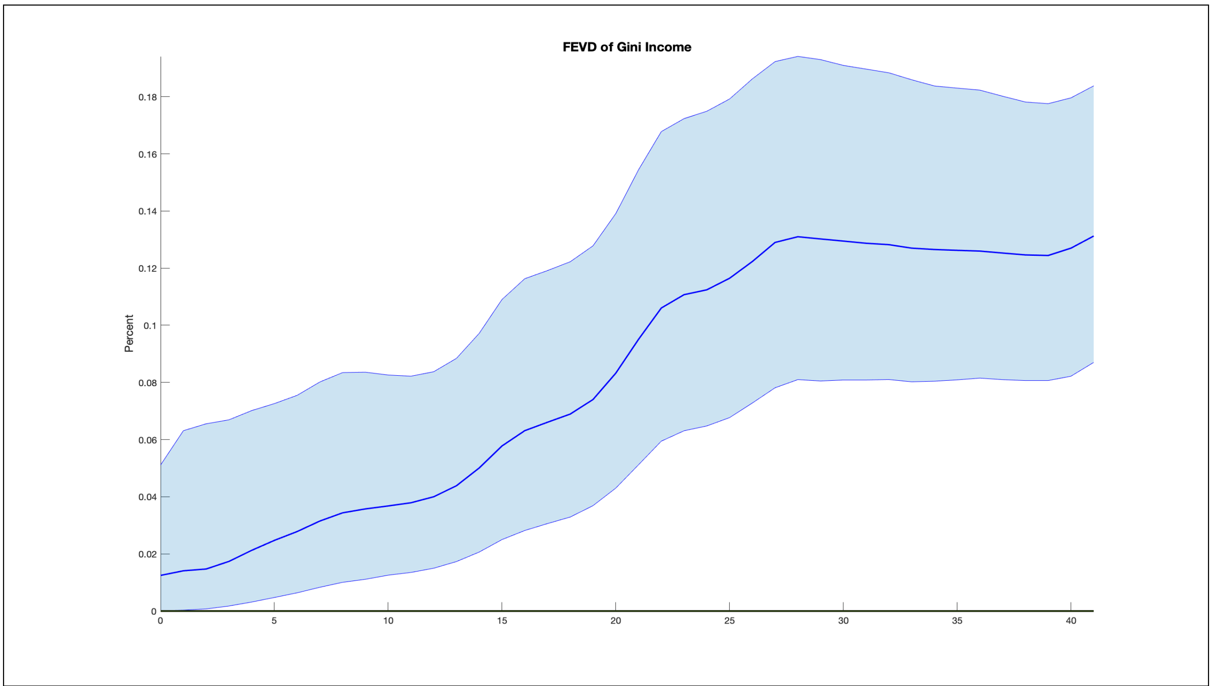


Figure 6: The contribution of monetary policy shocks to the forecast error variance: we display the 95 per cent confidence bands around the median response of a one standard deviation monetary shock. The set of variables equals the one from the baseline estimation.

first present every single modification compared to the baseline model. At the end of each section, we then discuss the results.

2.7.1 Model and Specification

An alternative model specification to the Proxy-Local Projections is the Proxy-SVAR approach introduced by Stock and Watson (2012) and Mertens and Ravn (2013). The SVAR model is defined as:

$$B_0 Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + \varepsilon_t \tag{3}$$

Where B_0 captures the contemporaneous effects, B_i displays the matrix of coefficients, Y_t is a vector of observed variables and ε_t are the structural shocks. We assume that $E[\varepsilon_t] = 0$, $E[\varepsilon_t \varepsilon_t^{'}] = I$ and $E[\varepsilon_t \varepsilon_s] = 0$ for $s \neq t$. That is, the structural shocks are uncorrelated with their past values and all other structural shocks. Y_t comprises the 1-year gilt rate, the CPI, the unemployment rate, the exchange rate (direct quotation of the British Pound), two measures of credit costs (i.e. corporate bond spreads and mortgage spreads) as well as the spread between the Moody's BAA Corporate Bond Index and the U.S. 10-year government bonds. This SVAR is adjusted for every inequality measure. If we multiply both sides with B_0, we derive the reduced form model equation:

$$Y_t = \sum_{i=1}^{p} B_0^{-1} B_i Y_{t-i} + B_0^{-1} \varepsilon_t \tag{4}$$

This equation is estimated based on Bayesian Methods. We use a flat prior and calculate the draws from the posterior distribution via a Gibbs sampling algorithm.
With respect to equation (4) we express the reduced errors as weighted sums of structural shocks:

$$u_t = B_0^{-1} \varepsilon_t \tag{5}$$

where $E[u_t u_t^{'}] = B_0^{-1} B_0^{-1'} = \Sigma$. We now can partition the matrix B_0^{-1} concerning its columns, such as:

$$u_t = b_1 \varepsilon_1 + ... + b_n \varepsilon_n \tag{6}$$

where b_1 is the first column of the impact matrix and ε_1 is the structural shock of interest. Combining equation (6) with the instrument conditions (1)-(3) in section (2.4), we can define:

$$E[Z_t, u_t] = E[Z_t, (b_1 \varepsilon_1 + ... + b_n \varepsilon_t)] = b_1 \alpha \tag{7}$$

Equation (7) states that using a suitable external instrument we can estimate sufficient values of the first column of the impact matrix B_0^{-1} that are scaled by the unknown correlation α, which is defined in condition (1). When conducting the 2SLS approach and deriving ratios of coefficients, the constant α can be cancelled out, which leaves us with the estimate of the first column of the impact matrix. The instrument helps to estimate the following set of equations:

$$\begin{aligned} u_{1,t} &= \gamma_1 Z_t + v_{1,t} \\ u_{2,t} &= \gamma_2 Z_t + v_{2,t} \\ &... \\ u_{n,t} &= \gamma_n Z_t + v_{n,t} \end{aligned} \tag{8}$$

Where the first equation comprises the shock of interest. Straightforwardly, the ratio can be derived from the following relationship:

$$\frac{E[Z_t, u_{j,t}]}{E[Z_t, u_{1,t}]} = \frac{\gamma_j}{\gamma_1} \tag{9}$$

For $j = 1 : n$. Finally, the first column of the impact matrix that we are aiming to identify takes the form:

$$b_1 = \begin{pmatrix} 1 \\ \frac{\gamma_2}{\gamma_1} \\ \dots \\ \frac{\gamma_n}{\gamma_1} \end{pmatrix} \tag{10}$$

and captures the impacts of the structural shock of interest (i.e. the monetary policy shocks).

Additionally, we include the FTSEall index as a measure of share prices. Especially, financial markets should react significantly to a monetary policy shock and display the reaction of financial wealth and income sources. Further modifications to the baseline estimation refer to the lag structure of our local projections estimation. That is, we increase the lag length of our estimation equation to 4. On top of that, we increase the observation period and estimate the model for the whole observation period ranging from Jan. 1970 to Mar. 2020. Turning to the identification of the shock, we conducted the same analysis based on sign restrictions. Particularly, we included 3 restrictions in our estimation. First, we define the policy indicator to increase (25 bps increase in the 1-year gilt). Second, we force inflation to decrease after the shock. Third, we define unemployment as reacting with an increase to this monetary shock. The results are shown in Figure (7).

Beginning with the results derived from an estimation with 4 lags, we find that the Gini-Coefficient rises significantly and reaches its peak median response of 0.24 per cent, 11 months after the shock. The reaction differs slightly from the baseline finding showing a longer delay of inequality until it is significantly larger than zero. Nevertheless, it confirms the finding that contractionary monetary shocks induce a significant and persistent increase in income inequality. The more erratic shape of the IRF is due to the higher lag order.
The estimation over the whole sample draws a similar picture to our baseline estimation when looking at the significant impact response and the persistent increase in inequality. Here the peak median response is slightly higher and equals 0.41 percent, 23 months after the shock. Overall, this specification can be interpreted as an average response over the whole period. Disregarding the structural break mentioned in the baseline specification, the change in the shape of the IRF is based on the significantly larger estimation period. Turning to the results of the Proxy-BVAR, we see a significant rise in the Gini-Coefficient during the first 3 months after the shock. The response passes the 0.2 percentage point increase in its peak median response. The results show a similar behaviour compared to the baseline specification. In line with the local projections estimation in section 5.1, we

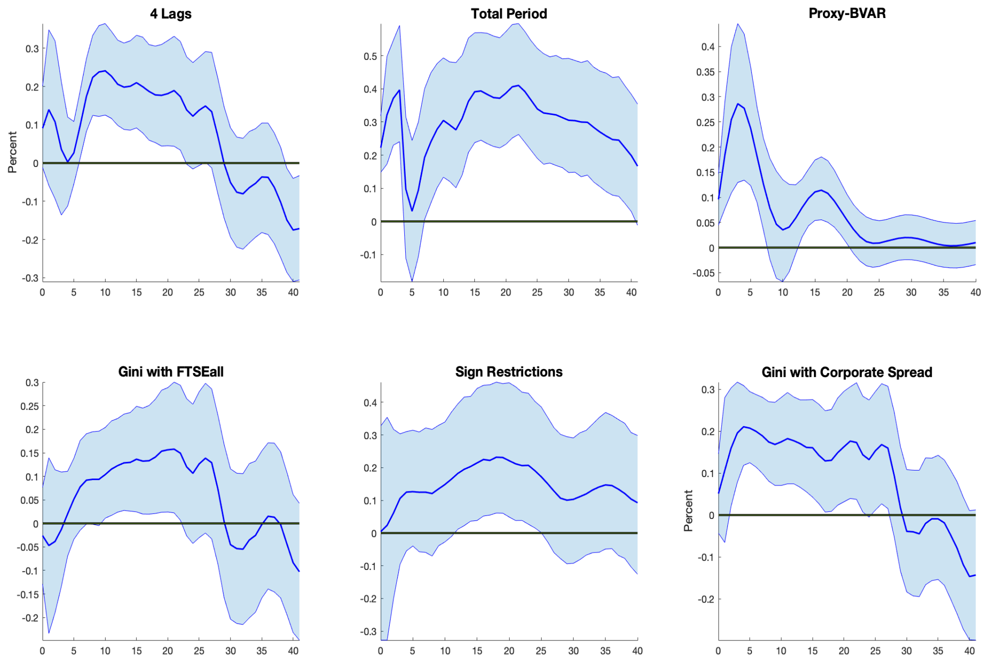


Figure 7: We display the IRFs of the Gini-Coefficient based on different estimations. The title of each graph refers to the modification compared to the baseline specification. Every shock is set to a 25 bps increase in the policy rate and we display the 95 per cent credibility bands.

see that the effect dies out 20 months after the shock. The Proxy-BVAR results confirm monetary policy shocks' significant and persistent effects on income inequality. Note, the displayed IRF of the BVAR model seems "smoother" compared to the one in the baseline specification. This feature is a common characteristic of IRFs that come from a VAR specification and is due to the lower variance of the estimator.

Including share prices in the model leads to a delay until the significant effects in the Gini coefficient kick in. A possible reason for this is the now overwhelmingly large signal of financial income, which is mainly found in the right tail.

Changing the identification method changes the shape of the IRF. Even though the increase in inequality is confirmed, it takes longer for the Gini coefficient to distance significantly from zero. This highlights the importance of identification methods in structural analysis. However, the main finding –"contractionary monetary policy shocks increase income inequality" remains regardless of the identification method.

The last exercise sows that including corporate spreads into the model does not alter the results substantially and confirms the baseline findings. This specification equals the baseline estimation in Cesa-Bianchi *et al.* (2020) and points the credit channel to inequality. The overall finding confirms the baseline specification when looking at inequality.

2.7.2 Data

In our last exercise, we focused on two alternative inequality measures. First, is the standard deviation of logs. This measure is a robust alternative to outlier values. Second, the $(P_{90} - P_{10})$ difference. This measure is a suitable alternative to the Gini-Coefficient due to its straightforward interpretation. Figure (8) presents the IRFs of the two alternative inequality measures. We can see that both react similarly. After the shock hits, a short-term (insignificant) drop in inequality appears. The $(P_{90} - P_{10})$ difference drops in the first 2 months and rises above zero 5 months after the shock. Likewise, the standard deviation of logs shows the same pattern with a slightly weaker response. Here, the reaction reverses even faster rising above zero 4 months after the shock. Both measures display a significant increase in inequality for some periods. When looking at the $(P_{90} - P_{10})$ difference we see a slightly stronger reaction than in the baseline scenario, with a peak median response of 0.36 per cent. Turning to the standard deviation of logs we can confirm this movement but with a weaker reaction (peak median response of 0.14 per cent). It is worth noting, that both variables react similarly. The main difference is that the IRF of the standard deviation of logs is moving in a smaller interval, which is based on the characteristics of this statistic.

Compared to the baseline estimation, these inequality measures provide an even more detailed insight into the short-term effect of the shock. Since by construction, the ratios react more elastically, it allows us to display the short-term movements of inequality. Thereby, the immediate drop in inequality displayed in Figure (8), is in line with the percentile reactions in Appendix (2.11) and confirms previous explanations regarding the income composition channel. It is worth noting that after the financial sphere recovers from the shock and the income of the rich increases because of higher interest income, both inequality measures display a rise in inequality that is similar to the one in the baseline estimation.

2.8 Conclusion

Recent economic studies focus on the impact of monetary policy and inequality. Beginning with the theoretical side of this research field, heterogenous agent models seem to displace the representative agent framework as suggested by studies like Kaplan *et al.* (2018) and Gornemann *et al.* (2021). This development gave rise to the importance of indirect effects and states that household inequality matters in the sense that it influences the way a monetary policy shock transmits to the economy. Based on this several distinct channels arose as a result of an interaction of general equilibrium forces[4].

The empirical side of this research field only detects a few of the theoretical channels

[4]Colciago *et al.* (2019) provide an extensive survey regarding the distributional channels of monetary policy.

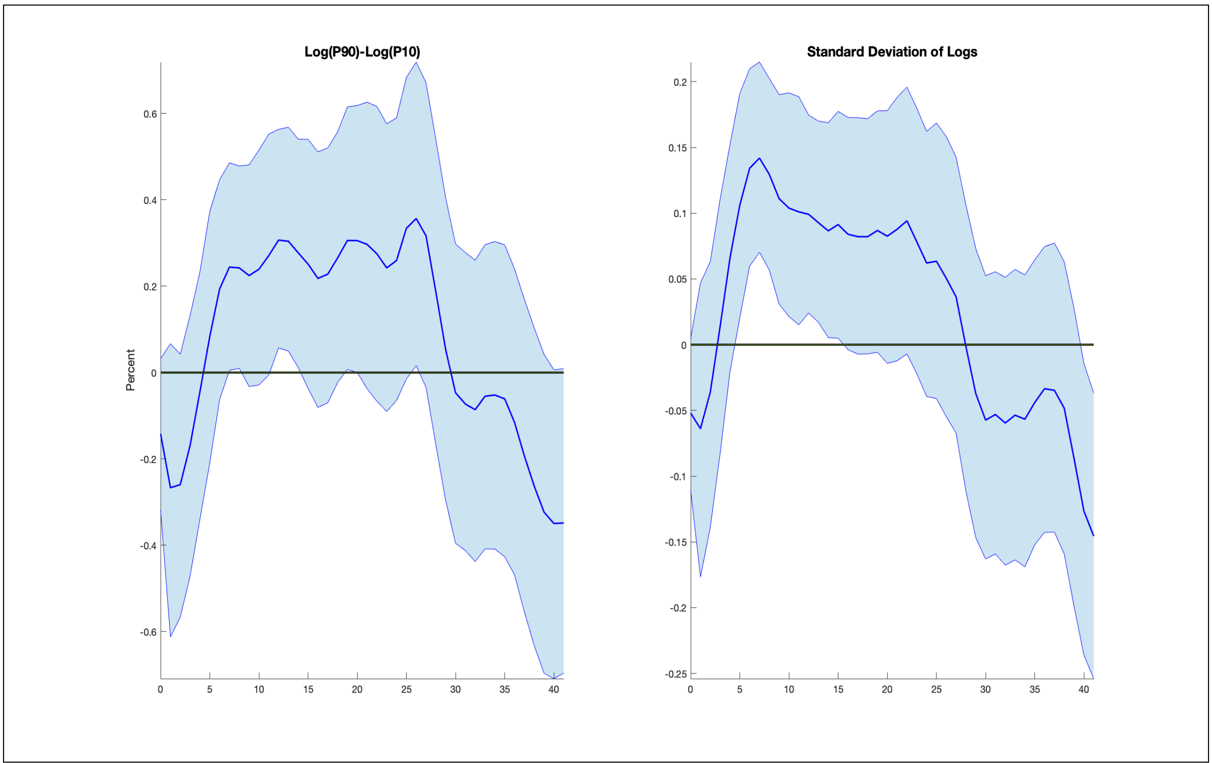


Figure 8: IRFs of the baseline model including the alternative inequality measures. We computed a 25 basis point monetary policy shock. The estimation is based on local projections with 10,000 draws from the posterior (equal to the baseline scenario).

appropriately. Concerning the indirect effects, empirical studies provide evidence for the income composition channel (Coibion *et al.* (2017), Guerello (2018), Cloyne *et al.* (2018)), the earnings heterogeneity channel (Inui *et al.* (2017), Furceri *et al.* (2018), Theophilopoulou (2022)) or the inflation channel (Romer and Romer (1999), Easterly and Fischer (2001)). Thereby, researchers have to keep in mind that these channels explain the effects of a monetary policy shock based on different characteristics in the economy and especially in the household sector. This leads to the fact that one channel can point to positive effects coming from a monetary policy shock, while another contradicts these statements when looking at the same shock.

A central challenge in this research field is to address endogeneity. In this case, new approaches tend to incorporate external instruments from high-frequency price changes to identify monetary policy shocks. However, to the best of our knowledge, only one attempt has been made to combine the high-frequency approach with the research question of monetary policy and income inequality, i.e. Samarina and Nguyen (2019), who look at the EU. We aimed to fill this gap and looked at the U.K. A country that experienced great changes in income inequality from 1970 to 2020. In doing so, we combined the high-frequency shock series of Cesa-Bianchi *et al.* (2020) with the one from Kaminska and Mumtaz (2022) to analyse the distributional effects of monetary policy shocks. We used household data from the Family Expenditure Survey to derive inequality measures at monthly frequency and computed the Gini-Coefficient, percentile ratios and the standard deviation of logs for the period ranging from 1970 to 2020.

Our baseline findings are in line with the previous work of Cesa-Bianchi *et al.* (2020) concerning the macroeconomic variables. We confirm a significant drop in prices, a rise in the unemployment rate, a worsening of credit conditions and detect the credit channel of monetary policy as introduced by Bernanke and Gertler (1995). The significant rise in U.S. Spreads indicates international spillovers and links our study to the results in Gerko and Rey (2017).

Most importantly we find that a contractionary monetary policy shock of 25 basis points produces a significant rise in income inequality in the short term (0.22 per cent increase). Thereby, the effects differ across the distribution. The median household and the poor (P_{10}) move closer together, as indicated by a significant drop in the percentile ratio of 0.67 per cent, whereas the gap between the rich (P_{90}) and the median household rises (significant rise of 0.36 per cent in the percentile ratio). Insights from an income decomposition show that the rich are closer connected to financial markets and hence, race away after a monetary tightening due to the increase in interest income. The median household appears to be very vulnerable to the loss in wages and faces a persistent loss that pushes it closer to the lower end of the distribution. At the same time, the poor mainly are left unaffected because of the relatively high proportion of social benefits in their income. However, the slight short-term increase indicates a countercyclical behaviour of the working hours of the poor and links our study to Kolasa *et al.* (2021), Cantore *et al.* (2022) and Theophilopoulou (2022)). Apart from that, our findings confirm previous studies in the literature, that looked at the U.S. (Coibion *et al.* (2017), the U.K. (Mumtaz and Theophilopoulou (2017)) or a sample of countries (Furceri *et al.* (2018)). When looking at the forecast error variance decomposition our findings show that monetary shocks determine up to 13.12 per cent of the variance, 41 months after the shock (peak median response). This finding confirms the results provided by Coibion *et al.* (2017), who find a relatively large contribution of monetary shocks to income inequality, especially at longer horizons.

To show the robustness of our results, we included estimations based on a Proxy-BVAR approach, different model specifications (including share prices, corporate spreads, the lag length and the observation period), different inequality measures as well as identification techniques (Sign-Restrictions). We conclude that contractionary monetary policy shocks can cause an increase in inequality by deteriorating financial conditions in the economy suggesting that policymakers should focus especially on the income composition and the earnings heterogeneity channel.

2.9 Appendix: The Overlapping Period of the two Instruments

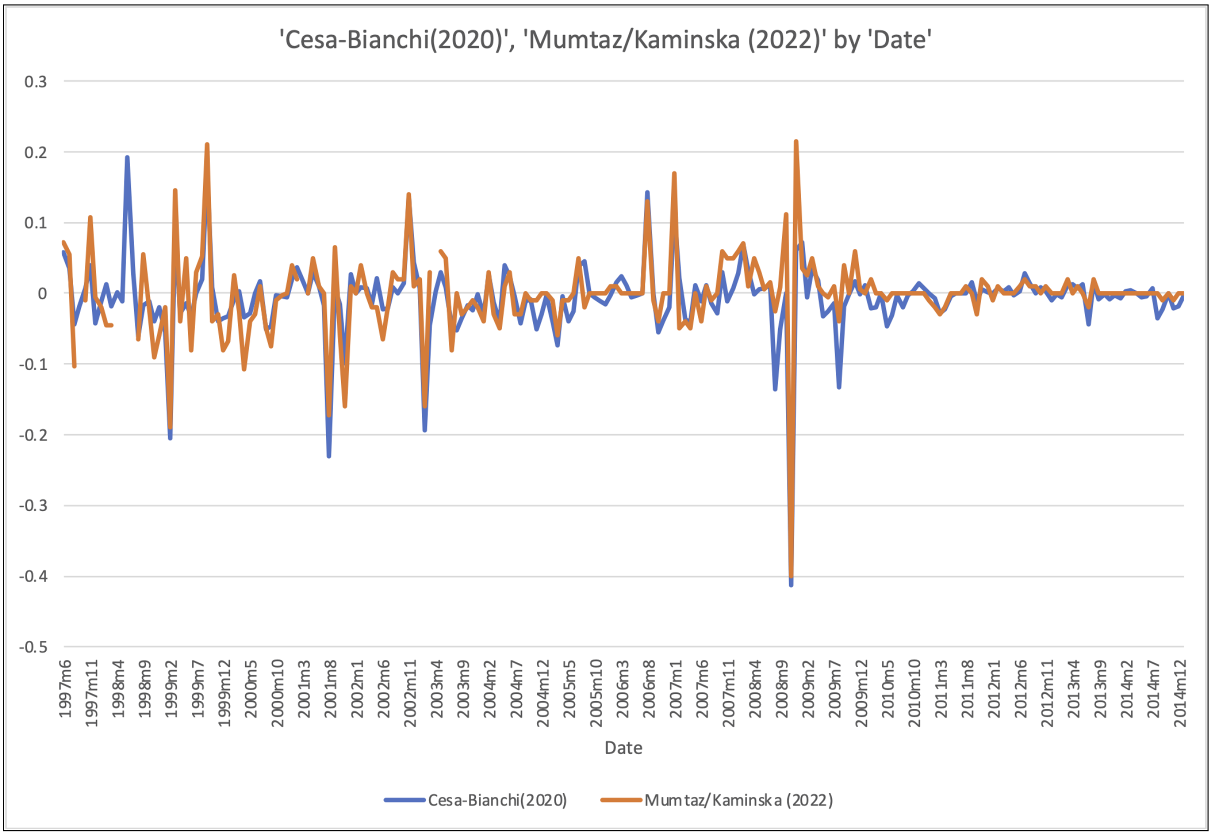


Figure 9: A comparison between the two monetary policy shocks for the overlapping period ranging from June 1997 to December 2014.

2.10 Appendix: The Correlation between the two Instruments

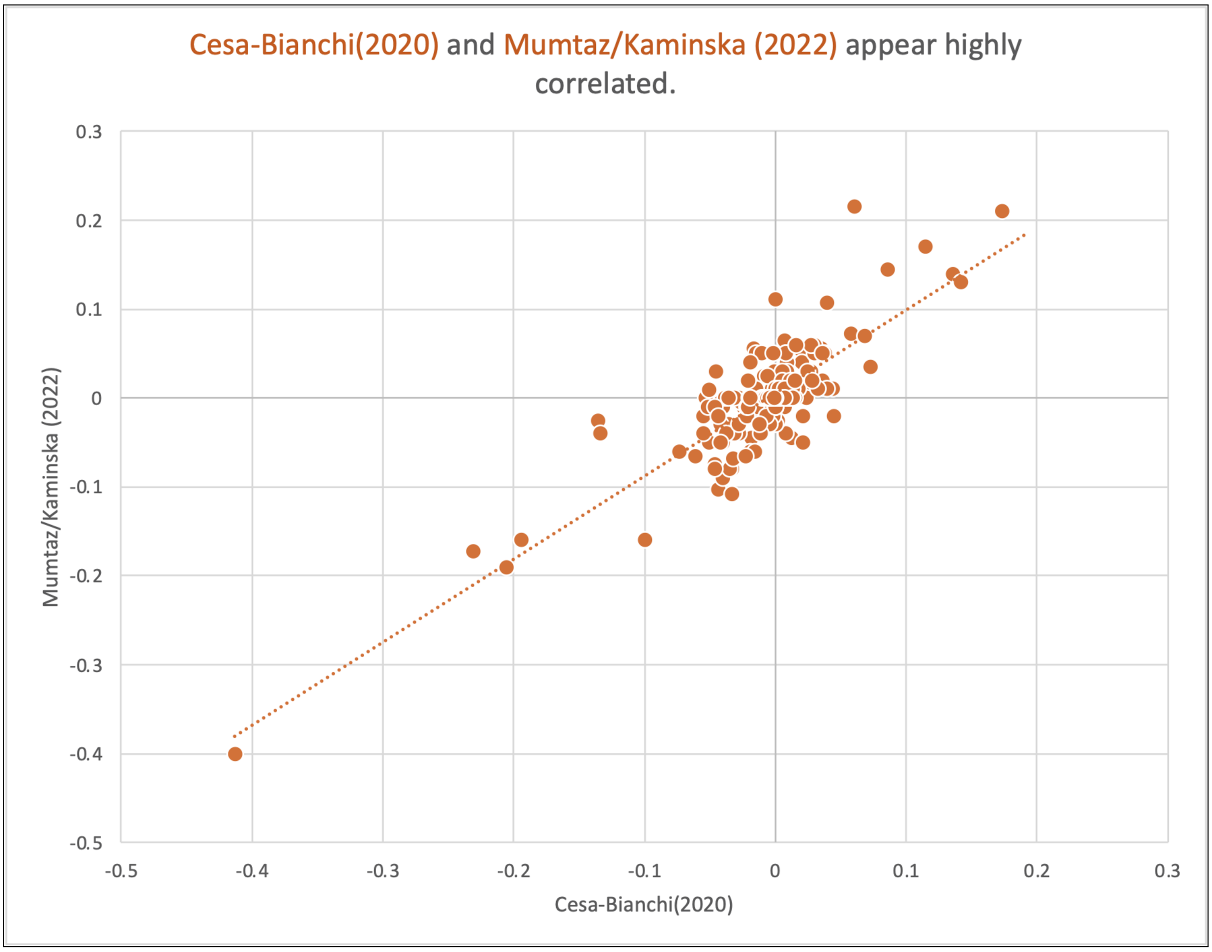


Figure 10: A plot of the two instruments.

2.11 Appendix: The IRFs of the Percentiles

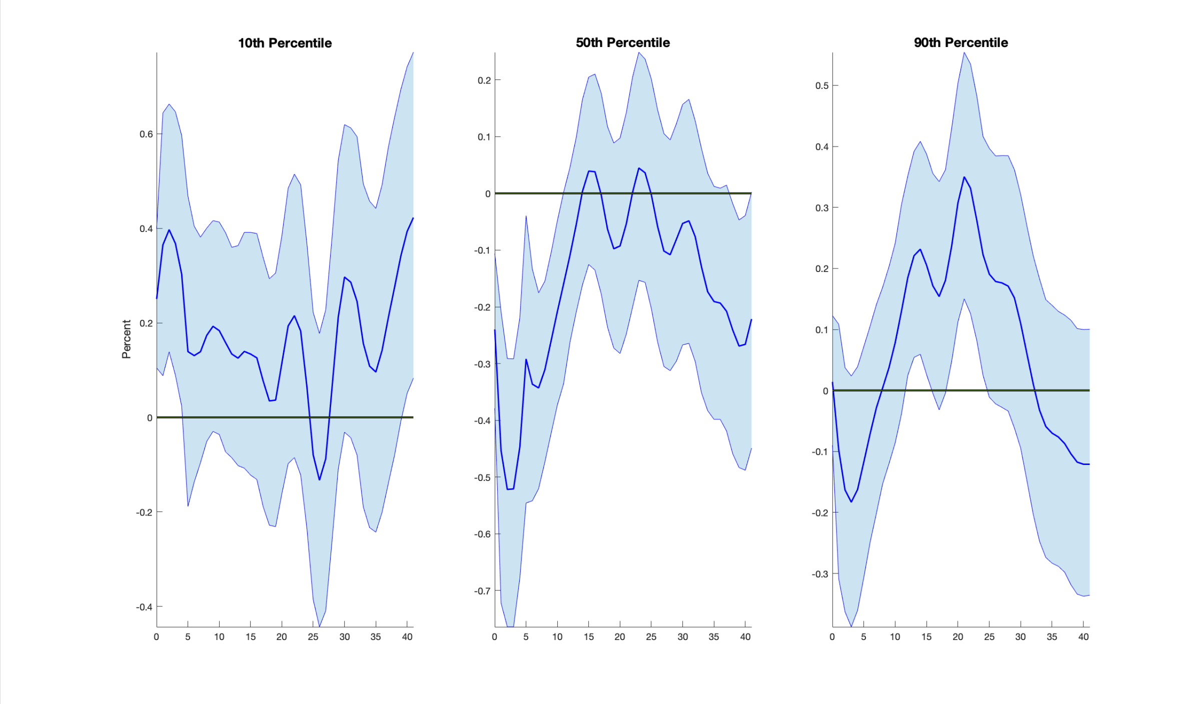


Figure 11: The IRFs of the percentile values. The specification equals the baseline estimation.

2.12 Appendix: Historical Decomposition of Monetary policy Shocks

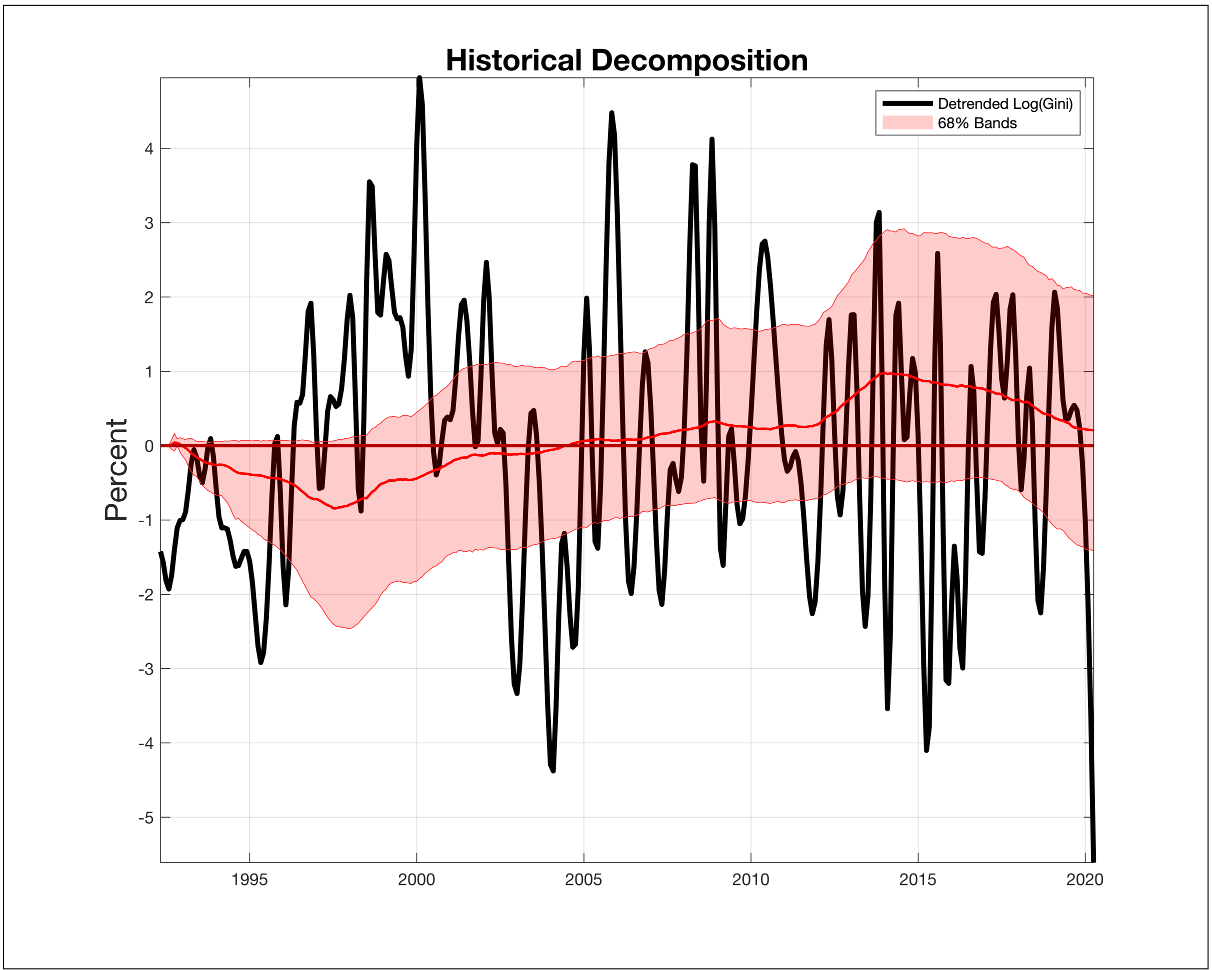


Figure 12: Historical contribution of a monetary policy shock to the detrended Gini coefficient together with the 68% credible bands.

Figure 12 illustrates the historical contribution of a monetary policy shock to deviations in the Gini coefficient from its long-run trend. This analysis isolates the effect of a single identified shock by setting all other shocks to zero, effectively constructing a counterfactual scenario in which only the monetary policy shock is active (represented by the red line and shaded area). The results align with previous literature—particularly Mumtaz and Theophilopoulou (2017)—which also finds no significant impact of monetary policy shocks on inequality based on various income components for the period considered above.

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

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.

3.1 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[5]. 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[6]. The literature frequently mentions two examples of factors that cause shifts in the economy: persistent events such as financial market liberalization and changes in the Federal Reserve's priorities, and short-term unexpected shocks like policy decisions or announcements[7].

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

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

[6] 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.

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

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[8]. 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[9]. 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 (3.9) 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.

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 specifications 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)

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

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

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 chapter is structured as follows: section 3.2 gives a summary of the related literature, section 3.3 describes the Data and the instrument we used, section 3.4 presents the methodological approach, section 3.5 presents our baseline results, section 3.6 looks at the time-varying distributional channels, section 3.7 provides sensitivity checks and section 3.8 concludes.

3.2 Literature

This study contributes to the literature examining monetary policy's distributional effects by expanding the analysis in a time-varying setting. In this research field, the focus is on identifying how monetary policy shocks impact different parts of income and its distribution. Some distributional channels are more difficult to confirm through empirical evidence than others. Recent studies have mainly found evidence of the impact on earnings heterogeneity and income composition. This has been achieved for the US (Coibion *et al.* (2017)), the UK (Mumtaz and Theophilopoulou (2017)), the EU (Guerello (2018)), or a panel of countries (Furceri *et al.* (2018)). Regarding Japan, Inui *et al.* (2017) provide evidence for the savings redistribution channel while older attempts by Romer and Romer (1999) or Easterly and Fischer (2001) are looking at the inflation channel.

Highlighting the methodology in this research field, the majority of the studies conduct regression analysis (Romer and Romer (1999)), use local projections (Coibion *et al.* (2017), Inui *et al.* (2017), Furceri *et al.* (2018)), or derive impulse responses from a multivariate time series analysis i.e., VAR models (Mumtaz and Theophilopoulou (2017)). However, the common limitation of these approaches is that they cannot take into account the time-varying effects of monetary policy shocks on the real sphere of the economy. Regarding the latter, it becomes evident that having fixed coefficients may be a limiting assumption in the modelling approach (hereon a VAR). Examples from the literature are the existing non-linearities in macroeconomic time series or a change in the economy which may result in structural breaks.

Aspects like the ones mentioned above increased the popularity of time-varying parameter VARs. Thereby, the literature gradually advanced the modelling procedure over the last years, leading to more complex estimation approaches. An early work incorporating a time-varying setting was provided by Canova (1993), who uses a Bayesian TVP-VAR to model and forecast out-of-sample exchange rates and interest rate markets. The author finds that a time-varying parameter model produces complex nonlinear dependencies in the moments of the generated time series. This replicates features of the conditional and unconditional distributions of actual exchange rates, delivering better point forecasts than a random walk model. A crucial aspect that needs to be highlighted is that the model only allowed for time variation in the coefficients and the volatility was still assumed to be fixed over time. Considering time variation in the volatility, Uhlig (1997) provided a modelling approach to incorporate variation in the variance of the model in order to model the size of the fluctuation in the data. He separates this modelling procedure from the well-known ARCH family and uses a (G)-ARCH(1,1) model to illustrate his distinction. In this case, the author may provide time variation in the variance but assumes the coefficients to be fixed over time.

A first benchmark study using a TVP-VAR in the research field of macroeconomics was provided by Cogley and Sargent (2002) whose aim was to analyse the inflation - unemployment - interest rate dynamics in the U.S. in a time-varying setting and look for a drift in the parameters. The sample of the study ranges from January 1948 to April 2000. The authors find that the mean and persistence of inflation are highly correlated. Also, they provide empirical evidence to back up Taylor's warning regarding that period, stating the so-called recidivism to the natural rate hypothesis. According to that, it is likely that policymakers could find themselves again in the situation of inflation-unemployment trade-off. The methodology of the paper uses Bayesian methods to estimate a time-varying parameter VAR, where the coefficients evolve as driftless random walks. Thereby, the authors involve reflecting barriers to keep the VAR stable. The argument is that an explosive setup implies infinite variance for inflation. The latter is not suitable for an economy such as the U.S. since the central bank minimises its loss function by reacting to the variance of inflation. The model is defined to be Gaussian where all hyperparameters come from an inverse Wishart distribution. As standard in the TVP literature, the convenient aspect, in this case, is that this prior is a natural conjugate for a Gaussian distribution. In order to derive draws from the posterior distribution the authors follow Kim and Nelson (2017) and adapt a Gibbs sampler. A limitation of this work which the authors also were aware of, is the constant volatility in the model. No time-varying volatility implies that the size of the shocks did not evolve or change over the observation period. Only the way agents reacted to the shock has changed. An assumption that contradicts the claims of Bernanke and Mihov (1998a), Bernanke and Mihov (1998b) and Sims (1999) who show evidence for a specification with fixed coefficients but time-varying volatility.

Related to this study is the criticism of Sims (2001), who claims that the paper may have a doubtful conclusion but a path-breaking methodology of data description that is worth looking at. Following these developments and as an answer to Sims's comment, the same authors provide a modified estimation approach in Cogley and Sargent (2005). The authors re-estimate the previous findings in this study based on a different modelling procedure and state that the shock variance evolved systematically over time, but so did the AR coefficients, confirming most of the findings in the previous study. Providing a first modelling technique that incorporates both, time-varying parameters and time-varying volatility made this study path-breaking in the research field of TVP-VARs. One crucial implication that resulted and should be picked up by several upcoming studies, is the debate about whether the era of the 1960s to 1970s was characterised by bad policy or bad luck by the central bank. That is, did the central bank understand the correct model and the natural rate hypothesis but was just tempted to exploit a trade-off that has never existed, or was the key driver of the structural break the change of the size of the shocks to the economic system?

At this stage, it is worth summing up the crucial features adopted so far to highlight the literature's stance at the current point in time: According to the developments described above most studies can be separated by either incorporating time-varying parameters or time-varying volatility. Thereby, Bayesian methods dominate the estimation procedure in this research field. As Koop and Korobilis (2010) point out, allowing for time variation in the model increases the worries of over-parametrisation. In this case, Bayesian methods display a possible way of conducting shrinkage via the prior. Turning to the two lines of modelling approaches, Cogley and Sargent (2005) were the first who combined time variation in parameters with time variation in volatility in a holistic approach. In particular, the decomposition of the variance-covariance matrix of the model is defined as:

$$\Omega_t = A^{-1}\Sigma_t A^{-1'} \tag{11}$$

with Σ_t being a diagonal matrix of variances and A^{-1} being a lower triangular matrix with ones in the diagonal. It becomes obvious, that this specification may orthogonalise the shocks but it is no identification scheme. In fact, the modelling technique so far does not allow for an identification procedure. Hence, it is a reduced-form model. The seminal work with regards to the time-varying models becoming structural and hence displaying the time-varying counterparts to the structural VARs was provided by Primiceri (2005). The author addresses the weakness of the time-invariant relation in the lower triangular matrix of the variance-covariance decomposition and allows the whole structure (the A matrix) to vary over time. This setting equals a Cholesky decomposition for each period in time and makes the model structural. Using this model the author investigates the high unemployment and inflation period of the 70s and early 80s in the US to derive conclusions about to what extent monetary policy played an important role in this development. The results of the empirical study contribute to the bad policy - bad luck debate in the literature. The author stresses the importance of heteroskedastic non-policy innovations in order to understand the poor economic performance of the 60s and 70s. Hence, he places his work closer to the bad luck story of the debate. Implications coming from the modelling approach are that the researcher leaves it up to the data to determine where the crucial change in the economy comes from. That is, because of the size of the shock (impulse) or the propagation mechanism (response). However, the increased variability in the model comes with some disadvantages. Apart from the classic ordering limitation that comes hand in hand with the Cholesky identification scheme, one other disadvantage that is mentioned in this case is the complicated nature of the identification procedure. In fact, a shock that hits the economy has different sources: First, it can be a shock in the time-varying parameters (response of the economy to the shock). Second, it can be a shock in the orthogonal structural errors of the VAR as in the classic time-invariant case. Third, it can be a shock in the moving elements of the lower triangular part of the variance-covariance matrix A_t implying a change in how one variable affects the other. Fourth, it can be a shock in the time-varying volatility of the innovation. However, the author claims that this issue is a natural consequence of models becoming more realistic regarding their flexibility. This study marks a critical point of departure for most subsequent empirical research on time-varying effects.

Related to these contributions is the work provided by Benati and Mumtaz (2007). The authors fit a time-varying VAR model with stochastic volatility to the US economy and look specifically at the reason why the U.S. macroeconomic environment has stabilised during the last 10-15 years. In doing so, they add to the bad luck vs. bad policy debate. The study is structured in two parts - a reduced form analysis and a structural analysis -. Beginning with the reduced form analysis, the authors interpret the covariance matrix as the total amount of noise hitting the system at each point in time. The evolution of this matrix over time shows a dramatic decrease under Paul Volcker and the first half of Alan Greenspan. Additionally, the authors claim that the reduced form shocks of all variables in the system reached a peak around the time of Volcker disinflation. Also, the sign of the correlation between the reduced form shocks changed from positive for the time before the Volcker disinflation to negative after that. Following the authors' explanations, these reduced-form insights hint that during the first half of the sample, the US was hit by large structural inflationary disturbances and that it is most likely that monetary policy was catching up with the circumstances. This explains the positive correlation between the reduced-form shocks to inflation and the Federal Funds rate. Turning to the structural analysis of this study, the authors provide insights using sign restrictions in a TVP-VAR

setting, identifying 4 structural shocks - monetary policy, demand non-policy, supply, and money demand. The findings show that during the Volcker period, monetary policy was not reacting to output growth with no or only a mild, negative reaction to money growth and a comparatively low reaction to inflation. All in all, the main findings show that 1. the evolution of long-run coefficients of the VAR is in line with narrative accounts of macroeconomic history, 2. systematic monetary policy may have improved in recent years, however, this has not been the dominant aspect of the story. The study sees good luck being the key driver for the transition from great inflation to great moderation.
In a similar methodological approach, Canova and Gambetti (2003) find that the transmission of shocks has been relatively stable over time which makes monetary policy more powerful in affecting the real economy only in the later part of the sample. The authors confirm a significant decrease in the volatility of shocks as documented by Sims and Zha (2006). Additionally, the study provides evidence for monetary policy shocks making up only a small fraction of the average variability and persistence in inflation and output growth and finds evidence for the "bad policy" proposition.

Turning to more recent studies, the research field concerning the time-varying effects of monetary policy is improving constantly. Kapetanios *et al.* (2019) provide a non-parametrical approach to estimating large time-varying VARs. In doing so, the study tries to overcome the computational issues of these models. The starting point is the driftless random walk assumption of coefficients in the standard estimation procedure. Casting this into the state-space form the coefficient becomes an unobserved state and the usual approach makes use of the Kalman filter and the metropolis hastings algorithm in order to solve the model. The authors explain that the Kalman filter limits the scale of the model, being the main reason why TVP-VARs are not able to incorporate big datasets. As a solution, the paper presents a non-parametric approach to overcome these computational issues. The provided methodology shows that it matches the results of its parametric counterpart if the data-generating process is assumed to be the same in both cases. However, the authors claim to find that the non-parametric approach shows higher robustness in the results if the underlying data-generating process changes. Additionally, a forecasting exercise shows that this approach outperforms constant parameter models and large Bayesian TVP-VARs. In the structural analysis, the study looks at the reaction of different production indices to oil price shocks. The findings state that the largest changes in the reaction to oil price shocks occurred for durable consumption- and material goods.

Further contributions are provided by Aastveit *et al.* (2017), who investigate if the FED responded to the house and stock price changes. The study uses the same methodology as Primiceri (2005). That is a time-varying Cholesky identification approach where the interest rate equation in the VAR is interpreted as the extended monetary policy rule. This enables the authors to recover the systemic component of monetary policy. With regard to that, the study analyses whether stock and house prices entered the central bank's reaction function with a positive and significant coefficient and whether there was a time variation in the strength of the reaction. 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. The response to house prices declined in the pre-recession period and increased again afterwards confirming the time-varying effects.

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 coin compared to Aastveit *et al.* (2017) is provided by Paul (2020). The author states that a monetary policy shock (normalised to produce a 20 Bps increase at the beginning of the IRF horizon) always leads to a decrease in industrial production, inflation and house prices. Thereby, stock and house prices show a substantial time variation. A further interesting aspect of this study is the methodological approach the author provides in order to investigate this research question. In fact, Paul (2020) provides insights from a time-varying VARX estimation with constant volatility. The advantage of this setup is that it enables the author to incorporate exogenous variables in the VAR in a time-varying setting. In this case, the author goes a step further and proves that the identified relative impulse responses are consistent. Additionally, when incorporating the same controls the author provides proof of equivalent impulse responses compared to the Proxy LP-IV approach of Stock and Watson (2018). This is why, he derives a high-frequency instrument of monetary policy shocks from future price changes and incorporates it as an exogenous variable in the VAR. The author highlights the convenient aspect that, compared to the case where the proxy is used as an instrument, a time-varying parameter VARX largely simplifies the analysis since it does not require any external steps that would have to account for a time-varying contemporaneous relation between the proxy and the reduced-form errors. Even though this study provided a further identification method for time-varying parameter estimations, it suffers from some shortcomings. First, this methodological approach only provides consistent relative IRFs. When the data is subject to measurement error one cannot derive the variance of the structural shock. Second, if a researcher aims to shed light on the contribution of the shock as in a FEVD or historical decomposition this methodology cannot be used.

Taking these shortcomings into account, the answer to a further identification approach for time-varying VARs was provided by Mumtaz and Petrova (2023). The authors analyse the effect of US and UK tax shocks on GDP and investigate if these effects have changed over time. The findings state that the tax multiplier declined and tax shocks have become less important in terms of the forecast error variance decomposition. As mentioned above the main contribution of the study is the methodological approach. That is, the authors provide insights from a Proxy TVP-VAR estimation. The methodology extends the approach of Caldara and Herbst (2019) for the time-varying case. Caldara and Herbst (2019) augment the Proxy-SVAR in the constant parameter case with a measurement equation. The latter relates the proxy to the unobserved structural shock and enables the researcher to set priors for this definition. Hence, the model jointly estimates the interaction between the VAR and the proxy (not in two stages as in the classic approach), which (as Mumtaz and Petrova (2023) show) makes it suitable for a time-varying extension.

The second research field this study relates to is the high-frequency literature. Considering recent developments in this research field, new insights are provided by Lewis (2019), who proposes an announcement-specific decomposition of shocks. 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. This approach contributes crucial new insights to the high-frequency identification (HFI) approach by comparing the effect of each decomposed shock from one announcement to the other. Underlining the instrument 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. This leads to the question of whether the high-frequency surprises are informative enough to serve as an instrument, which directly questions the relevance condition. Additionally, Miranda-Agrippino and Ricco (2015), find that high-frequency surprises are predictable when taking into account macroeconomic and financial variables, which in turn provides evidence for the lack of exogeneity and questions that these surprises are true shocks to the economy. To address these recent developments in the literature, Bauer and Swanson (2022) include speeches in the underlying set of events when deriving the surprises (relevance), and orthogonalize these surprises by taking the residuals after regressing them on financial and macroeconomic variables.

3.3 Data and Instrument

We use household data from the real-time inequality database[10]. 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[11].

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 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[12].

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

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

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

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:

$$z_t^{\perp} = z_t - \hat{\alpha} - \hat{\beta} X_{t-} \tag{12}$$

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.

3.4 Methodology

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

$$Y_t = B_{0,t} + \sum_{i=1}^{p} B_{i,t} Y_{t-i} + A_t z_t + u_t \tag{13}$$

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 functions. The relative IRF can be derived by:

$$r_{k,j} = \frac{a_k}{a_j} \tag{14}$$

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:

$$z_t = \varphi \varepsilon_{1,t} + \eta_t \tag{15}$$

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

$$B_t = B_{t-1} + v_t \tag{16}$$

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

$$V = VAR\begin{pmatrix} u_t \\ v_t \end{pmatrix} = \begin{pmatrix} \Omega & 0 \\ 0 & Q \end{pmatrix} \tag{17}$$

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:

$$\begin{pmatrix} B_0 \sim N(\hat{B}_{OLS}, 4 * V(\hat{B}_{OLS}) \\ \Omega \sim IW(I_n, n+1) \\ Q \sim IW(\kappa_Q^2 * \tau * V(\hat{B}_{OLS}), \tau) \end{pmatrix} \tag{18}$$

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 $p = 3$[13].

3.5 Baseline Results

Our baseline results are presented in figure (13), 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

[13] 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.

coefficients following equation (14)[14].

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.

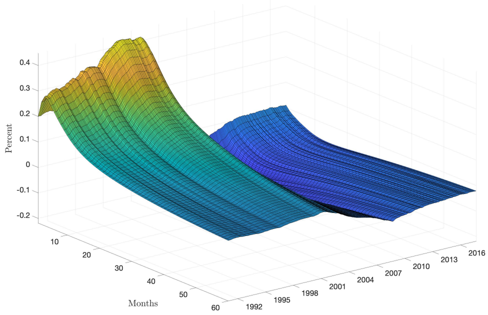
Our study finds fluctuations in the policy rate based on the same shock over time. A shock that led to a 0.2 per cent increase in the FFR in January 1991, moves the FFR by less in more recent years. The effect of the shock in the FFR matches the narrative and is close to zero after 2008 consistently 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.

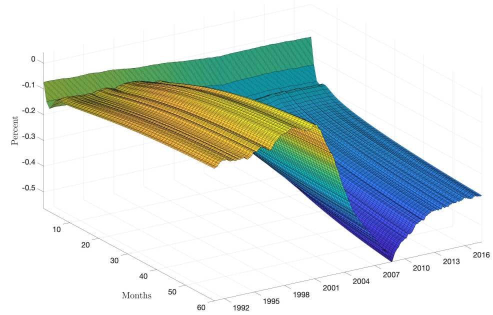
Figure (14) highlights our findings on time variation. The plot shows the impulse response functions from figure (13), 1 year after the shock (blue line) together with the level of the P80/P20 ratio (red line) in a 2-dimensional format along the time axis. Looking at the levels of inequality, the figure 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 finan-

[14]See also appendix (3.12) for clarification.

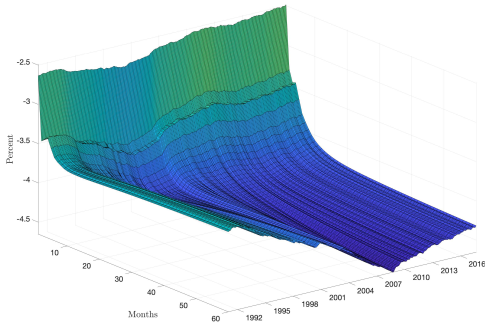
(a) Interest Rate



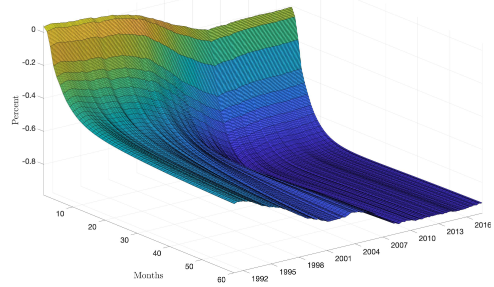
(b) CPI



(c) Shares



(d) Industrial Production



(e) P80/P20

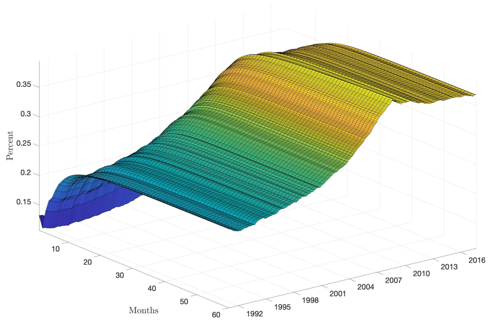


Figure 13: Baseline Results - cumulative IRFs to a contractionary monetary policy shock that lead to an increase of 20 Bps in the FFR in 1991M1. All variables entered the model in log differences except the FFR.

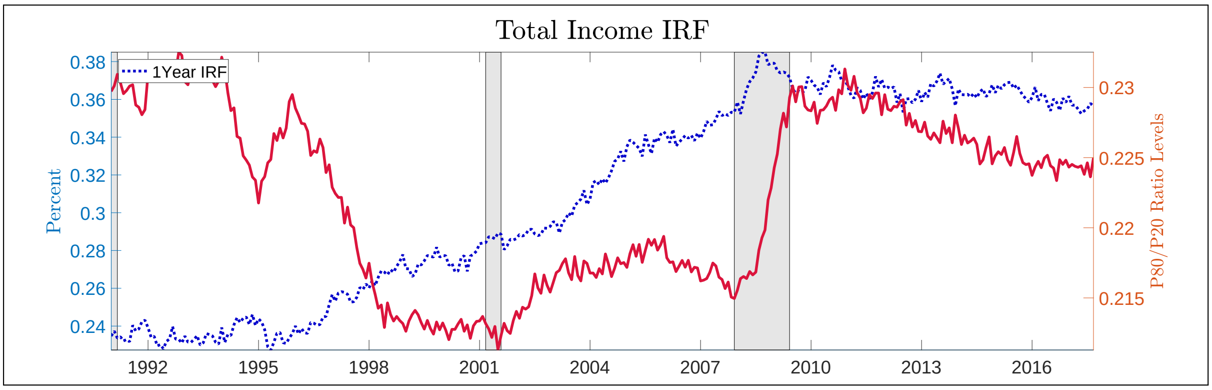


Figure 14: The time-varying effect of monetary policy shocks. The graph displays the median IRF of the posterior distribution, 1 year after the shock along the time axis together with the levels of the P80/P20 ratio of total factor income. The shaded areas display crises.

cial crisis. In the latest observation periods, we observe a stagnating behaviour of high responsiveness, indicating that during the zero lower bound period inequality was highly reactive to monetary policy measures[15].

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 (15) 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 "hump-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 (16), we use the 2-dimensional format to display the time-varying behaviour of the percentile ratios. The upper part of figure (16) 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

[15] Appendix (3.10) provides credibility bands in a similar 2-dimensional format for various horizons of the median responses plotted in figures (13),(14), (15) and (16).

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

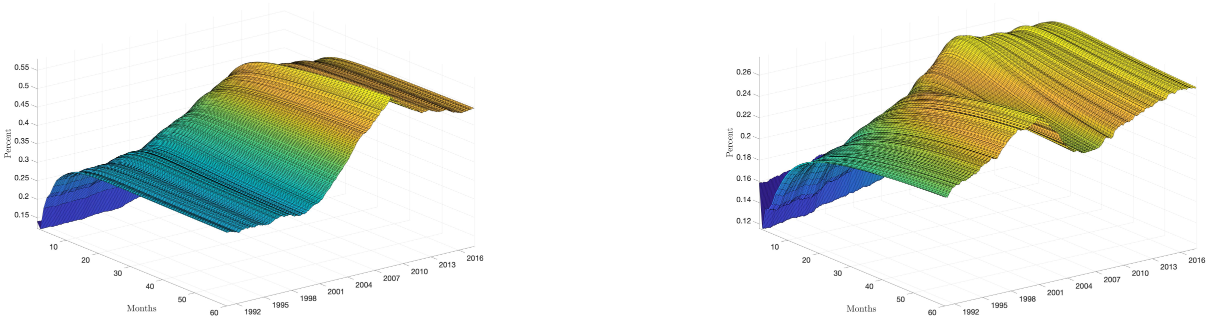


Figure 15: Tails of the income distribution - cumulative IRFs to a contractionary monetary policy shock. All specifications equal the baseline estimation.

in 2007. The financial crisis in 2008 led to an abrupt increase in inequality which gradually decreased in the last years of our observation period. Regarding the responsiveness of the 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 at high levels.

The lower graph in Figure (16) shows the behaviour 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

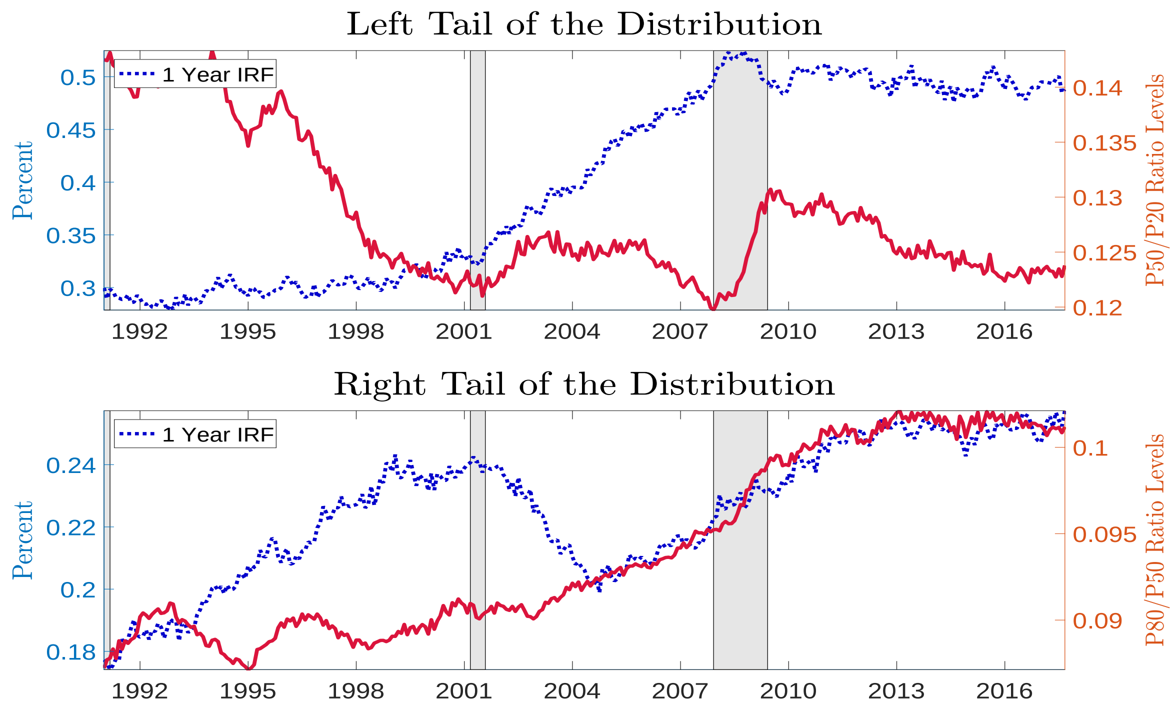


Figure 16: The time-varying effect of monetary policy shocks. The graph displays the median IRF of the posterior distribution, 1 year after the shock along the time axis together with the levels of the percentile ratios. The shaded areas display crises. The upper part of the graph displays the P50/P20 percentile ratio (left tail) while the lower part of the graph displays the P80/P50 percentile ratio (right tail) of the distribution.

distribution, households go through different income reactions.

3.6 The Time-Varying Distributional Channels of Monetary Policy

In figure (17), 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[16]. Our analysis shows that the proportion of labour income decreases 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[17]. 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[18].
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[19]. The income composition channel explains monetary transmission based on all different income components and their reactions to a monetary shock.

Figure (18) 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 peri-

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

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

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

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

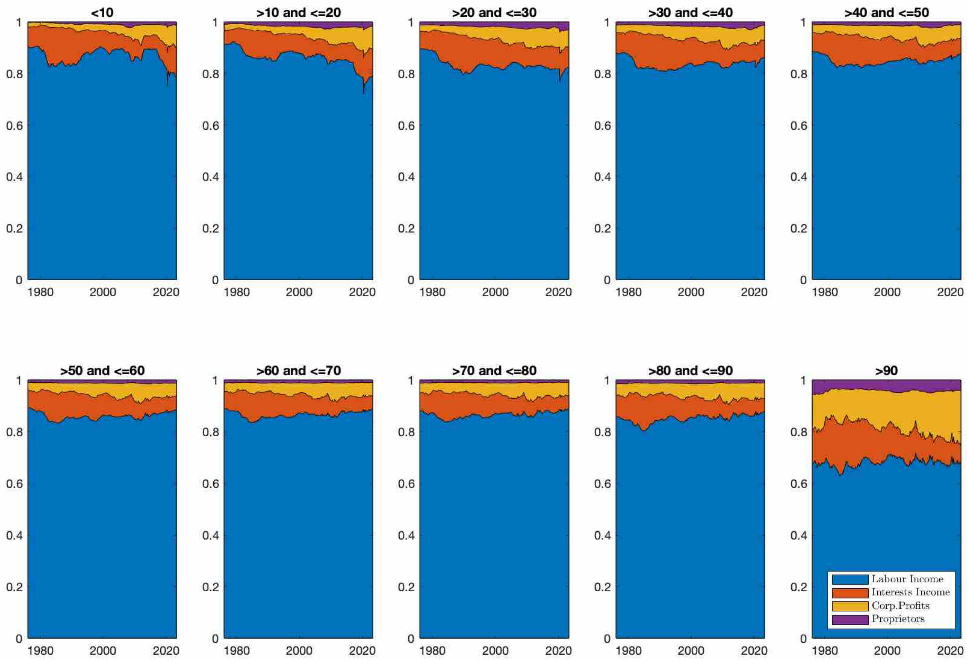


Figure 17: Income decomposition for every decile group of the income distribution. The figure displays real income values. Labour income is defined as the sum between 0.7*proprietors' income and the compensation of employees. Interest income is the total income generated from currency, deposits, and 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.

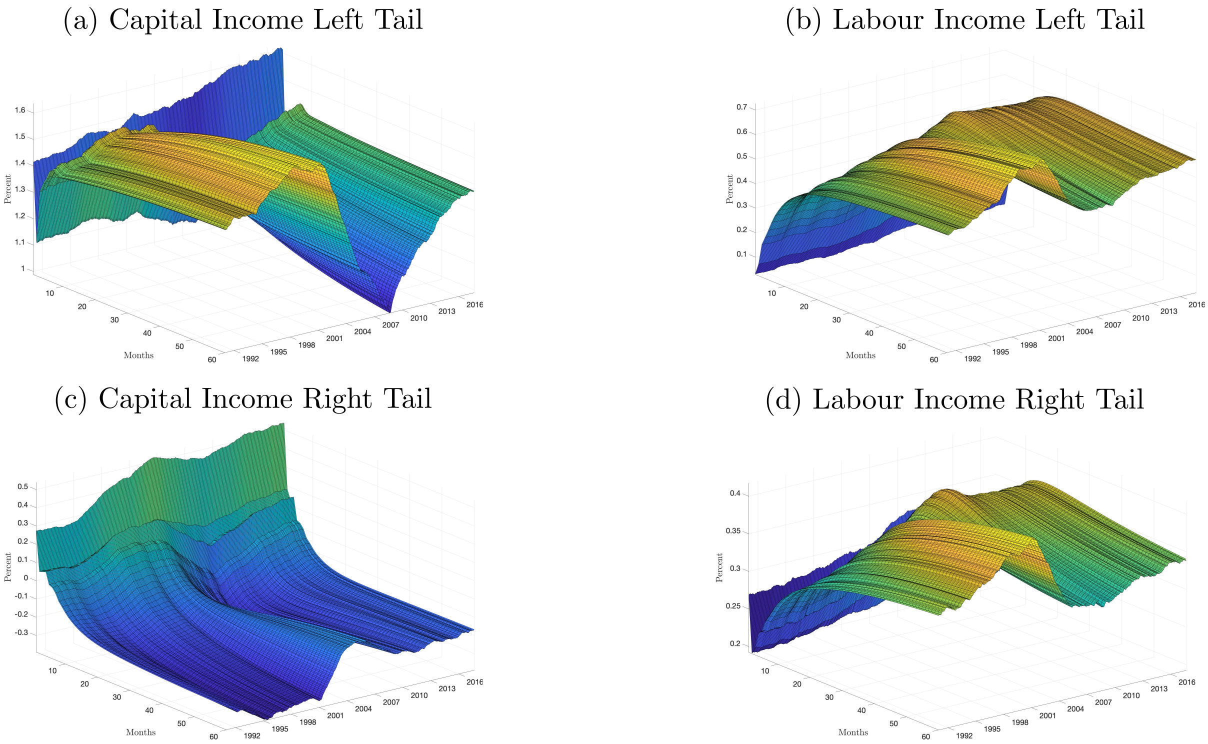


Figure 18: Impulse response functions of the main income components. The figure presents the two tails of the income distribution. All settings of the estimation equal the benchmark specification.

ods. 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.

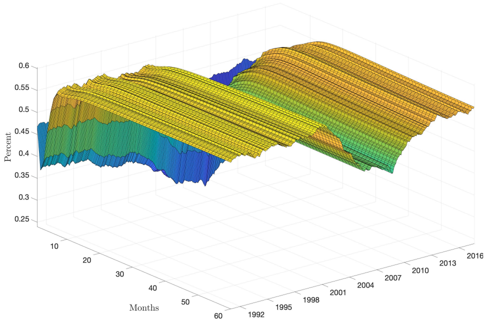
Based on the income decomposition in figure (17), we decomposed capital income into its main components to shed light on the different forces that come from each income component separately after a monetary policy shock. The findings of this exercise are summarised in figure (19). Beginning with corporate profits, the IRFs of the left tail show both high time variation and high responsiveness. The first 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 in inequality indicates that corporate profits at the lower end of the distribution are more vulnerable to such unexpected monetary shocks.

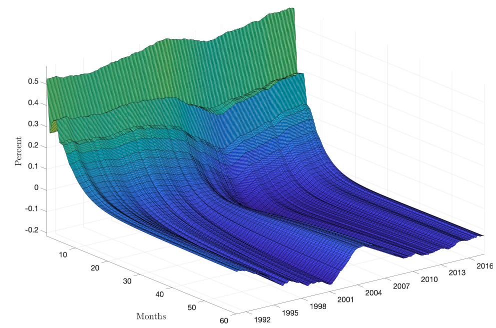
Looking at the response of interest income inequality, we observe that the impact of the shock varies considerably over time. In more recent years, the IRFs indicate both more persistent and more pronounced reactions. The highest point of this increase was reached during the crisis of 2008. After the 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.

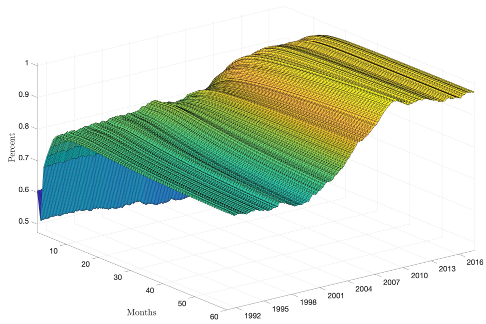
(a) Corp. Profits Left Tail



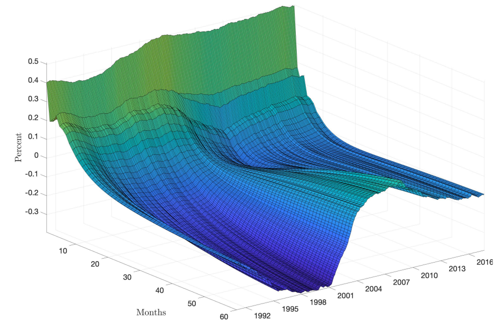
(b) Corp. Profits Right Tail



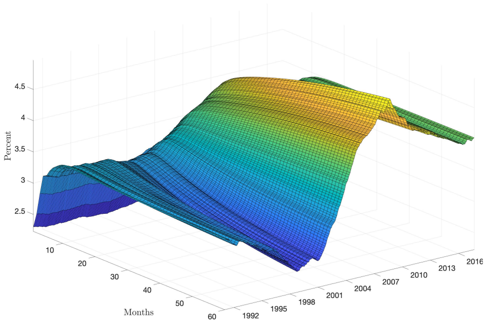
(c) Interest Income Left Tail



(d) Interest Income Right Tail



(e) Proprietors Income Left Tail



(f) Proprietors Income Right Tail

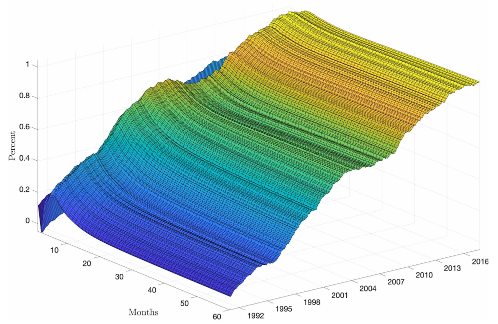


Figure 19: Impulse response functions of the main components of capital income. The figure presents the two tails of the income distribution. All settings of the estimation equal the benchmark specification.

3.7 Robustness

Figure (20) 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 (20) we modified the baseline specification with respect to stochastic volatility. Since the baseline model in section (3.5) assumed constant volatility, the results might be affected by this assumption. Specifically, we allow the main diagonal of the errors' variance-covariance matrix to follow a geometric random walk[20].

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 (20) 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[21].

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[22].

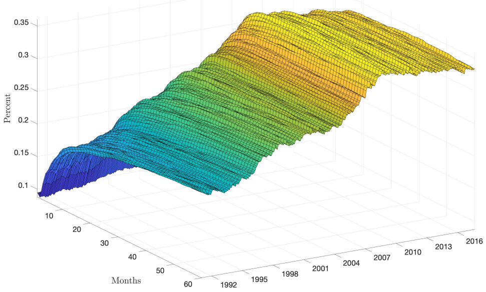
6. The zero lower bound period: As explained in Paul (2020), the effective lower bound during the aftermath of the great financial crisis was characterised by very low volatility in the interest rate. Since our study uses an instrument for shock identification, a period with low information in the data (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.

[20] The exact setup of the model is presented in Appendix (3.11).

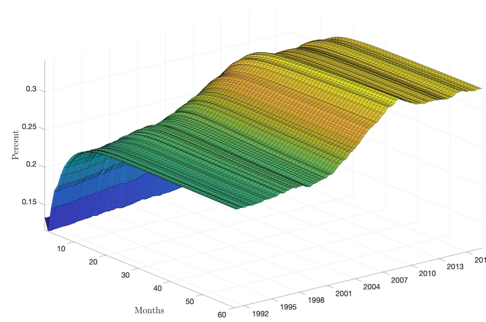
[21] The selection of the pre-sample setting is based on suggestions in Paul (2020). However, the data availability allows only to capture a slightly smaller time span.

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

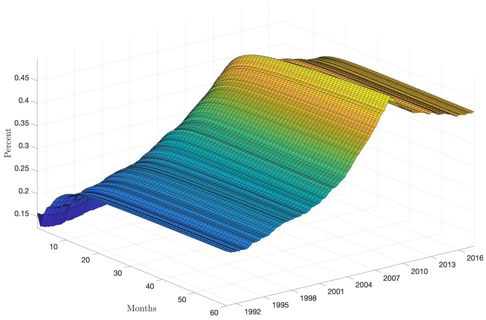
(a) Time-Varying Volatility



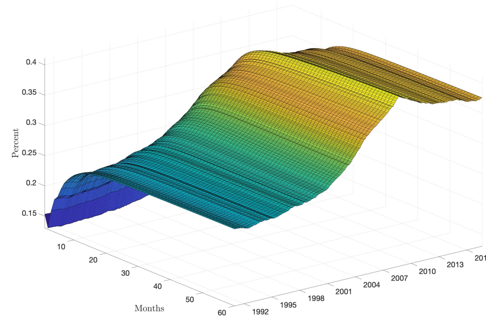
(b) Lower Time-Variation in the Coefficients



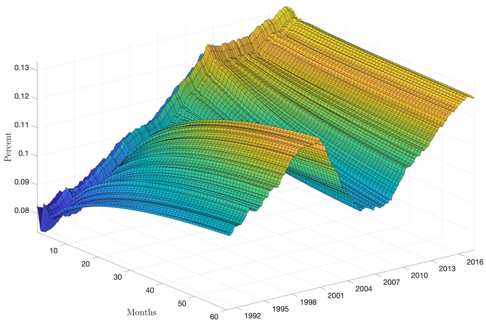
(c) Higher Time-Variation in the Coefficients



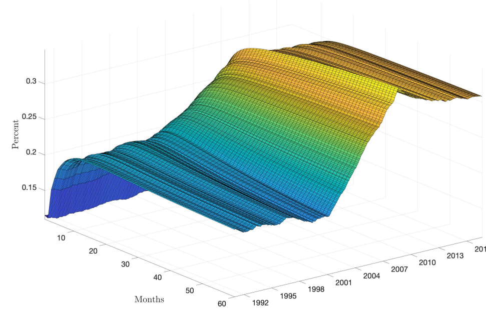
(d) Pre-Sample: Jan. 1976 to Dec. 1990



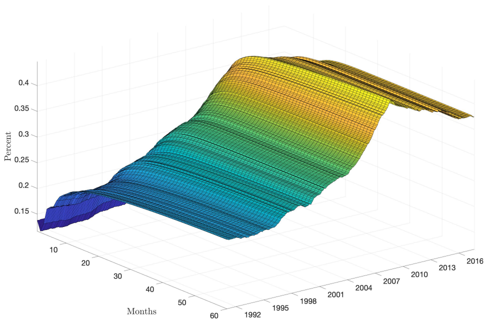
(e) Palma Ratio



(f) 2 Lags in the Baseline Specification



(g) 4 Lags in the Baseline Specification



(h) ZLB Episode Excluded

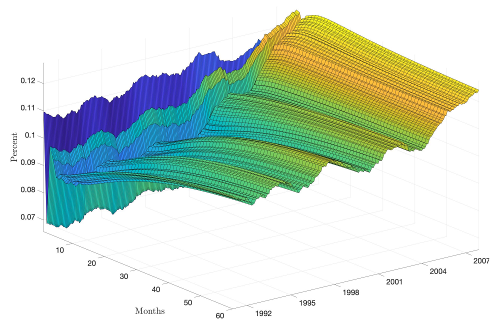


Figure 20: We present the robustness exercises described in the caption of every sub figure. The displayed IRF always shows the P80/P20 ratio of real factor income.

3.8 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 especially the income composition channel became more pronounced during the more recent periods of our investigation.

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

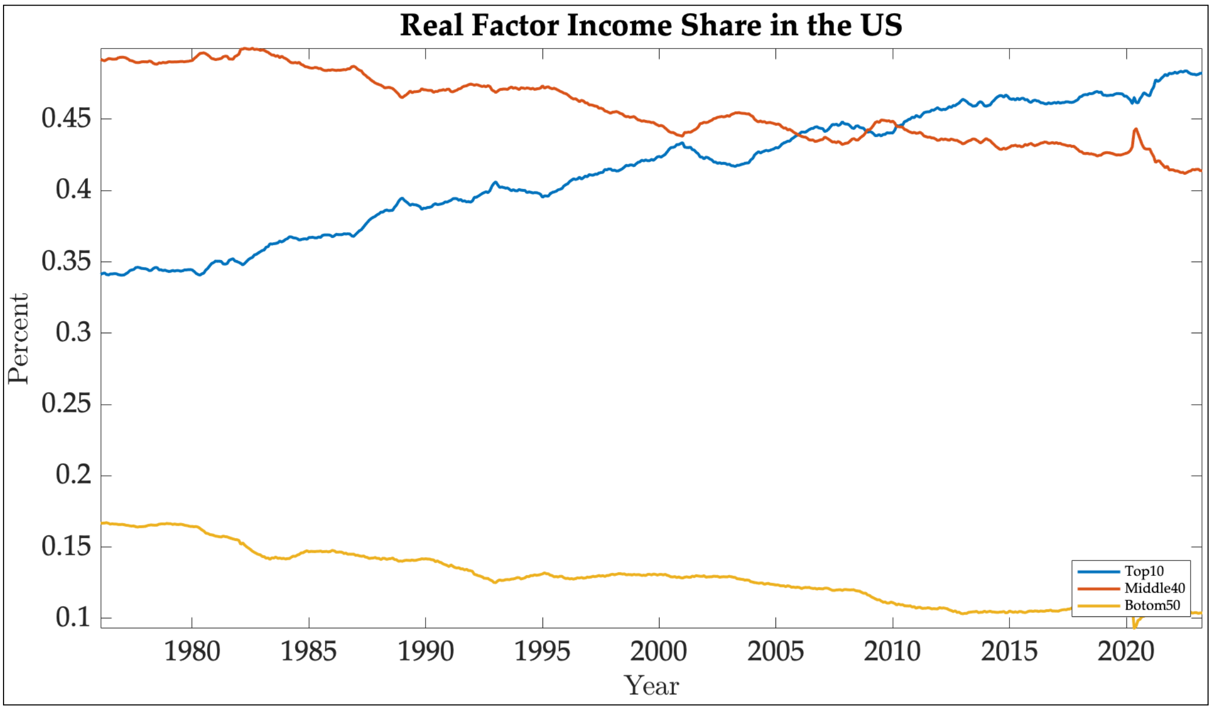


Figure 21: The evolution of real factor income share in the US by the corresponding percentile. Factor income is defined as the sum between labour and capital income and deflated by the GDP deflator. The data is available at the Realtime Inequality Database which can be accessed here.

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

Figure 22: The figure displays the 68% credibility bands of the tails together with the P80/P20 ratio over different horizons and corresponds to figures (13) to (16) in the main text.

3.11 Appendix: Stochastic Volatility Extension - Overall setup and priors

In our robustness check of plot (a) in figure (20), 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 (17) in the main text:

$$\Omega = C^{-1} H_t C^{-1'} \tag{19}$$

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:

$$log(h_t) = log(h_{t-1}) + \sigma_i \psi_t \tag{20}$$

With ψ_t being standard normal and independent of all other shocks in the system. As stated in equation (19), the lower triangular matrix C, which orthogonalizes the residuals is not time-varying. The role of these parameters can be described as:

$$C^{-1} u_t = \epsilon_t \tag{21}$$

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:

$$p(ln(h_{i0})) \sim N(ln(\bar{h_{it}}), 10)) \tag{22}$$

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:

$$p(\sigma_i) = IG(\frac{10}{2}, \frac{1}{2}) \tag{23}$$

For the parameters of the matrix C we define:

$$p(c)) \sim N(0, 10^3 * I_n) \tag{24}$$

3.12 Derivation and Normalisation of IRFs in the Baseline Specification

The approach explained in the baseline specification is based on the contribution of Paul (2020), who shows that a high frequency instrument can be used as an exogenous variable in the VAR equation in order to derive consistent impulse response functions. In general, the estimated IRFs are subject to a bias due to the measurement error in the proxy of the shock. However, once we consider relative IRFs (IRF of the variable of interest divided by the IRF of the shocked variable), the measurement cancels out. This is explained formally in proposition 1 and proposition 3 of Paul (2020) and is the main reason for only considering normalised responses. One consequence of this is that one cannot consider the impact of a one standard deviation shock. However, in the context of TVP models, this has the effect of isolating changes in IRFs that happen because of a change in the transmission of the shock. In other words, by normalising the IRFs we examine the effects of a shock of the same magnitude over time and examine how the transmission evolves.
Specifically, consider the the relationship between the instrument and the structural shock captured by equation (25) in the main text which is replicated here:

$$z_t = \varphi\varepsilon_{1,t} + \eta_t \tag{25}$$

where it is assumed that η_t is orthogonal to all the shocks in the system and $\eta_t \sim N(0, \sigma_\eta^2)$. This relationship defines a fixed signal-to-noise ratio (Caldara and Herbst (2019)). Intuitively, the relationship between the structural shock and the instrument is assumed to be fixed over time. This assumption contrasts with other specifications in the literature where the coefficient φ in equation (15) is allowed to vary over time (see Mumtaz and Petrova (2023) for a direct generalisation of this aspect to the time-varying case). As discussed in in the main text, by fixing the implied variation in z_t to achieve $\bar{z}_t * \bar{a}_{1991M1,1} = 0.2$ one considers same shock sizes over time. Hence, all IRFs displayed in the figures have to be interpreted relative to "a monetary policy shock that led to a 20Bps shock increase in the FFR in January 1991".

4 The Distributional Effects of Oil Supply News shocks

Abstract

This study uses high-frequency data on the distribution of US income to investigate the heterogeneous effects of oil supply news shocks. Using a FAVAR with an external instrument, We show that these shocks have large negative effects on the left and right tail of the distribution. For low-income individuals, the effect is driven by a decline in wages and proprietor's income, while a fall in corporate profits and interest income drives the effect for affluent individuals.

4.1 Introduction

The recent energy crisis has again focused attention on oil prices. A large empirical literature has established the importance of oil shocks for economic fluctuations. Considering the oil market the US belongs to the top producing and consuming oil nations in the World with an oil industry making up about 5.4 per cent of total US employment and 7.6 per cent of the national total GDP[23]. In a recent important contribution, Känzig (2021) uses a narrative approach to identify oil supply news shocks, i.e. unexpected fluctuations in current and future oil supply, and shows that these disturbances have a sizeable effect on US industrial production and CPI inflation. By applying this identification approach, Känzig (2021) builds on a large literature that reaches similar conclusions for oil market disturbances (see e.g. Hamilton (2003), Baumeister and Kilian (2016), Caldara *et al.* (2019)).

One common feature of this literature is the focus on aggregate macroeconomic outcomes. Recent studies find alarming movements of inequality in the US, with a drop in the median income of households and alarming behaviour of the real income share[24].

In this chapter, we exploit high-frequency data on the distribution of income and its components for the US to investigate the distributional effects of oil supply news shocks. We use a factor augmented VAR (FAVAR) to jointly model the oil market, macroeconomic variables and income in deciles of the distribution. The oil supply shock is identified using the external instrument approach of Känzig (2021). The analysis leads to three key findings:

1. While an adverse oil supply shock has the largest effect at the left tail of the income distribution, the income of affluent individuals also declines relative to the median.

[23]These statistics are taken from the U.S. Energy Information Administration (2023) and are accessible here.

[24]See Telford (2019), Semega and Kollar (2022), Guzman and Kollar (2023) and the time series of real factor share provided in the previous section.

2. For individuals at the left tail, the decline in income is driven by a sharp fall in wages and proprietor's income.
3. At the right tail, income declines as the shock pushes down components of capital income such as interest income and corporate profits.

Our study is related to Berisha *et al.* (2021) who examine the impact of oil production and dependency on the annual Gini coefficient for US states in a reduced-form setting. Our analysis is an extension of Berisha *et al.* (2021), as we identify an oil supply shock taking into account the effect of news and examine how the distribution and components of income are affected rather than focusing on one measure of inequality. Our study is also related to Del Canto *et al.* (2023) who examine the effect of oil supply shocks on households with differing levels of educational attainment.
The chapter is organised as follows: Section 4.2 gives an overview of the literature, the data and the empirical model are described in Section 4.3 while Section 4.4 describes the main results.

4.2 Literature

This work contributes to the literature by investigating the distributional effects of oil supply news shocks. Researchers have long studied the transmission of oil shocks. An early investigation by Hamilton (1983) finds that economic crises historically followed oil price increases. Following the author's explanations, this correlation may be due to three reasons: 1. A simple coincidence in the data, 2. Endogeneity of explanatory variables and 3. A causal relationship. The empirical investigation uses Sim's macro model and specifically focuses on the role of oil prices. The paper concludes that the timing, magnitude and/or duration of at least some of the crises would have been different if these oil price increases or energy shortages had not occurred leading to an indication of a causal relationship. One implication emerging from this study is the aim of resynthesizing the demand and supply-oriented interpretation of oil price shocks. So far the empirical literature has treated oil prices as exogenous in the modelling procedure, where an oil price shock mainly had been seen as a supply-side-driven exogenous impulse.

However, recent approaches question this and shift the focus to shocks coming from the demand side of oil. Barsky and Kilian (2001) is an example of a study that argues that oil supply shocks were not that important for explaining the period of stagflation in the 1970s. The authors question to what extent the literature is sure about the importance of oil supply shocks and prove a monetary explanation of the above phenomenon which is in line with microeconomic theory. The central argument is that oil price increases by themselves are not eager to trigger stagflation and that there must be an excess demand in the oil market to reach that point, which flips the way of thinking in the literature. An upcoming work by Kilian (2008a) reviews the literature on energy prices and their transmission on the economy. The author explains that endogeneity is a crucial problem in this sector and departs from previous considerations in Hamilton (2003) stating that the results therein are driven by a weak instrument. Kilian (2008a) highlights the fact that the literature needs to differentiate between energy supply and demand shocks.

The differentiation between oil supply and demand shocks fuelled an ongoing debate in the literature, splitting empirical findings, which is closely related to the identification approach a specific study uses. Over the last 20 years, the research field has been dominated by three identification approaches that provide different results into what is driving an oil price shock (demand vs. supply)[25].

An influential contributor is Kilian (2009), who provides a novel approach by timing restrictions. The starting point of this study is the claim that oil production cannot be adjusted quickly to a change in prices. Keeping this in mind, the author treats oil prices as endogenous in a structural VAR framework and differentiates between three oil price shocks: 1. An aggregate demand shock, 2. An oil supply shock, 3. A precautionary demand shock shows that each of these shocks has different effects on the economy. Identification is achieved by ordering the real price of oil first in a Cholesky identification, which implies a vertical oil supply curve (slow adjustment of oil production and hence, an unresponsive supply curve in the short term). The findings provide evidence that researchers need to rethink how to model the oil market. Especially, when endogenous oil prices are assumed, the focus needs to be on the demand side of the market, which also appeals to monetary policymakers to adopt this way of thinking. In contrast to this, Hamilton (2009) discusses the role of oil price shocks in the 2007 crisis and shares the "conventional" view that oil price shocks are supply-driven and states that these shocks appear to make a material contribution to the financial crisis. Apart from timing restrictions the literature comprises a second line of studies that uses sign and inequality restrictions to identify the oil price shock in a VAR framework. A study that uses sign restrictions is provided by Peersman and Van Robays (2009), who are looking at the transmission of oil price shocks in the EU and the US. The authors find striking differences in the timing of the responses and the transmission mechanism in general when comparing the two economies. Beginning with the US, a direct pass-through channel is observed. The rising energy prices lead to indirect effects of rising production costs. In contrast to that, the EU displays a more sluggish response because of dominant second-round effects that are mainly due to wage increases. All in all, a conventional oil supply shock leads to

[25] Stock and Watson (2016) provide an extensive overview of the techniques used for factor models and vector autoregressions.

a decrease in GDP and an increase in inflation. The trade-off between price stability and output stabilization appears to be more crucial for the US since the European Central Bank is mainly focusing on price stability. At the same time, oil-specific demand shocks may trigger the same effects on GDP but very limited on inflation leading to no conflict of interest neither for the US or the EU policy institution.

Regarding the use of sign restrictions Kilian and Murphy (2012) show that sign-identified VAR models can result in misleading impulse response functions. The authors claim that the set of admissible IRFs has to be narrowed down by other methods than simple summary statistics such as the median. A suggestion of the paper is to impose further inequality restrictions on the elasticity of the oil demand and supply curves. This is achieved by discarding the impulse responses that do not satisfy the elasticity of the demand curve, which in turn is taken from previous considerations in the literature. The advantage of this approach is that even though the model produces admissible impulse response functions, they are not all equally likely and not all match the narrative equally well. Kilian and Murphy (2012) provide a new methodology that contributes to the use of sign-identified VARs. When adapting this method to their investigation the authors report that fluctuations in the real price of oil are mainly driven by oil-demand shocks. Oil supply shocks play a minor role, which places their study next to Kilian (2009). The same methodology is used by an upcoming investigation by Kilian and Murphy (2014), who propose a VAR that includes oil inventory demand and technically enables the authors to identify a speculative "forward-looking" shock. Following the authors, the inclusion of this forward-looking component into the VAR is crucial. The study finds a larger role of oil supply shocks, which comes at the expense of the explanatory power of the speculative demand shocks. Kilian and Murphy (2014) identify three shocks: 1. A flow supply shock, 2. A flow demand shock and 3. A speculative demand shock. Regarding the third shock, the authors claim that any expectation of a future decline in oil supply that is not already captured by the two previous shocks necessarily causes an increase in the real price of oil due to speculative demand.

A recent contribution by Baumeister and Hamilton (2019) directly addresses this methodology introduced based on a fully Bayesian approach. The authors explain that from a Bayesian perspective setting these inequality restrictions is equal to having a very strong prior belief on the elasticity. The study suggests relaxing the dogmatic priors but at the same time tightening the loose priors when there is good reasoning. The overall claim is that studies conducting Bayesian inference should not treat prior information as an "all-or-nothing" method. When doing this, the authors challenge the findings stated by Kilian and Murphy (2012, 2014), showing that oil-supply shocks are more important drivers with limited effects coming from speculative demand.

Our work follows the third line of studies in this research field and uses external data to identify the oil price shock. An early benchmark study is provided by Hamilton (2003), who finds that the effect of energy price disruptions on the economy is nonlinear. Hamilton suggests a quantitative dummy-variable approach for the external instrument of oil price shocks by looking at military conflicts. Additionally, the author finds that when using the external instrument for identification in a linear specification, the results are in line with the nonlinear methodology without an instrument suggesting that the nonlinear specification may be more appropriate to filter exogenous components. Another study making use of external data for identification purposes is Kilian (2008b), which provides a new measure of exogenous oil supply shocks. The author derives direct projections of macroeconomic variables on the exogenous oil supply shock series using counterfactuals. The procedure can be explained in two steps. First, the counterfactual production level of oil-producing countries is derived. This is treated as a time series of exogenous oil production shortfalls in regression to generate the "treatment" effects of the shock on the macroeconomic variables. The study finds that an exogenous oil supply shock decreases GDP and increases inflation. This, however, happens with a time delay rather than immediately. Similarly, Stock and Watson (2012), provide insights from a dynamic factor model with an instrument identification by using the shock series provided by Hamilton (2003) and Kilian (2008b). The authors find that the financial crisis period was characterised by shocks that were experienced in the past but much bigger. Furthermore, the main driving forces of the recession were shocks of financial conditions and uncertainty. However, the role of oil shocks was also nonnegligible. Finally, the slowdown in labour force growth was the main reason for the upcoming slow recovery. A more recent contribution that is closest to our paper is provided by Känzig (2021). Känzig (2021) provides a new series of oil supply news shocks by exploiting high-frequency future prices around OPEC announcements. When using this series for identification in a Proxy-VAR framework, he provides evidence for a strong channel through supply expectations. Negative news leads to price increases, a fall in oil production and an increase in oil inventories. Looking at the US, the author reports a decrease in economic activity, an increase in inflation and a depreciation of the US Dollar.

In contrast to the large number of studies that investigate the impact of oil shocks on the economy, there is little evidence regarding the distributional effects triggered by oil shocks. A recent study that looks at this relationship is provided by Berisha *et al.* (2021). The authors look at the interplay between resource (oil) abundance and inequality in the US based on panel data. The study finds that states with low oil consumption are more vulnerable to higher income inequality. The effects of oil abundance when oil production is low show less inequality if production goes up. When production is high, oil abundance causes higher inequality when production increases further. The results are reversed when looking at oil dependency. A study that investigates the effect of inflationary shocks on heterogenous households was recently provided by Del Canto *et al.* (2023). The authors consider two shocks that can be defined as inflationary shocks, an oil shock and a monetary shock and find that the source of the inflationary shock matters regarding its effects (regressive or progressive). Respectively, oil shocks are found to be regressive. After a 1 standard deviation increase in oil prices households with less than a high school education must receive \$800 more to afford their pre-shock level. Middle-aged college-educated households instead, gain \$833 from the same oil price shock. These findings are derived via a new methodology that uses impulse response functions from a standard empirical model and aggregates them into welfare movements using cross-sectional Data on consumption, labour income and asset holdings.

4.3 Empirical Model and Data

To estimate the impact of oil supply news on income for different groups of the population, we use a factor-augmented VAR (FAVAR) model. An alternative line of research follows Chang *et al.* (2024), who define a functional VAR in order to estimate the effects of shocks along the distribution. While these models are an interesting development and could be used to answer our research question, the current application of the functional VARs focuses on the distribution of a single variable, i.e., income or consumption solely. In contrast to that, our dataset contains not income but all the major components of income. Via PCA analysis the FAVAR provides an efficient dimensionality reduction approach to derive the impulse responses of all these variables simultaneously. It is unclear how to incorporate distributions of multiple variables in functional VARs, which is an interesting extension for future research but as it requires an extensive analysis is beyond the scope of this paper. Consequently, our model is defined by the VAR:

$$Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + u_t \tag{26}$$

where $Y_t = \begin{pmatrix} z_t \\ \hat{F}_t \end{pmatrix}$, where z_t denotes a set of variables about the oil market: the real price of oil, world oil production and world oil inventories. $\hat{F}_t$ represents factors that summarize information in a panel of macroeconomic and financial series and the individual-level data on income and its components, described below. The factors are estimated using the non-stationary factor model of Barigozzi *et al.* (2021). Denote X_t as the $(M \times 1)$ data matrix that contains the panel of macroeconomic and financial series that summarize information about the economy, and also includes income data at the disaggregated level.

The observation equation of the FAVAR is defined as:

$$X_t = c + b\tau + \Lambda F_t + \xi_t \tag{27}$$

where c is an intercept, τ denotes a time-trend, F_t are the R non-stationary factors, Λ is a $M \times R$ matrix of factor loadings, and ξ_t are idiosyncratic components that are allowed to be $I(1)$ or $I(0)$. Note that the idiosyncratic components corresponding to the disaggregated income data can be interpreted as shocks that are specific to those groups and also capture possible measurement errors. The shocks to equation (26) represent macroeconomic or common shocks. It is the response to these common shocks that is relevant to our investigation. This ability to estimate the effect of macroeconomic shocks while taking into account idiosyncratic errors via equation (27) is a key advantage of the FAVAR over a VAR, where these two sources of fluctuations are harder to separate (see De Giorgi and Gambetti (2017) and Cantore *et al.* (2022)). Moreover, by incorporating a large data set, the FAVAR reduces the problem of information deficiency (see e.g. Forni and Gambetti (2014)) and shock deformation (see e.g. Canova and Ferroni (2022)). We follow Banbura *et al.* (2007) and use a Natural Conjugate prior implemented via dummy observations. The priors are implemented by the dummy observations y_D and x_D that are defined as:

$$y_D = \begin{bmatrix} \frac{diag(\gamma_1 s_1 ... \gamma_n s_n)}{\kappa} \\ 0_{N\times(P-1)\times N} \\ diag\,(s_1 ... s_n) \\ .... \\ 0_{EX\times N} \end{bmatrix}, \qquad x_D = \begin{bmatrix} \frac{J_P \otimes diag(s_1 ... s_n)}{\kappa} & 0_{NP\times EX} \\ .... & \\ 0_{N\times(NP)+EX} & \\ .... & \\ 0_{EX\times NP} & I_{EX}\times 1/c \end{bmatrix} \tag{28}$$

where $J_P = diag(1, 2, ..., P)$, γ_1 to γ_n denote the prior mean for the parameters on the first lag obtained by estimating individual AR(1) regressions, s_1 to s_n is an estimate of the variance of the endogenous variables obtained individual AR(1) regressions, κ measures the tightness of the prior on the autoregressive VAR coefficients and c is the tightness of the prior on the remaining regressors. We set $\kappa = 0.2$ and $c = 1000$. We also implement priors on the sum of coefficients (see Banbura *et al.* (2007)). The dummy observations for this prior are defined as:

$$\tilde{y}_D = \frac{diag\,(\gamma_1\mu_1 ... \gamma_n\mu_n)}{\tau}, \tilde{x}_D = \begin{pmatrix} (1_{1\times P}) \otimes \frac{diag(\gamma_1\mu_1 ... \gamma_n\mu_n)}{\tau} & 0_{N\times EX} \end{pmatrix} \tag{29}$$

where μ_i is the sample average of the *ith* variable. As in Banbura *et al.* (2007) we set $\tau = 10\kappa$. The total number of dummy observations is T_D.

4.3.1 Identification of the Oil supply news shock

To identify the oil supply news shock, we use an external instrument approach (see the explanations in section (2.7)). As a reminder we just present the outcome of this exercise. The reader is referred to Stock and Watson (2008) and Mertens and Ravn (2013) for a detailed proof of the methodology. As for the procedure conducted in this chapter, the method of identification follows the same procedure described in the robustness section (2.7).

Denoting the instrument by m_t, the reduced form errors by u_t and the first column of the impulse matrix by a_0, an estimate of $E(m_t u_t') = \begin{pmatrix} E(m_t u_{1t}') \\ E(m_t u_{2t}') \\ . \\ . \\ E(m_t u_{Nt}') \end{pmatrix}'$ can be easily obtained by using a linear regression. However, the correlation between the instrument and the reduced form error is unknown. This parameter can be eliminated by normalising the left and the right hand side by dividing by the first element of $E(m_t u_t')$ and a_0, respectively. Therefore the impulse vector to a unit shock is given by $\tilde{a}_0 = \begin{pmatrix} 1 \\ \frac{E(m_t u_{2t}')}{E(m_t u_{1t}')} \\ . \\ . \\ \frac{E(m_t u_{Nt}')}{E(m_t u_{1t}')} \end{pmatrix}'$.

In our benchmark model, we employ the instrument constructed by Känzig (2021) which is based on the variation in oil futures prices around OPEC announcements. Känzig (2021) provides evidence to suggest that the instrument is relevant and exogenous.

4.3.2 Data and Estimation

As noted above, X includes both aggregate and individual-level data. The aggregate data is taken from the Fred-MD database. This consists of 134 variables covering industrial production, employment, consumer prices, asset prices, interest rates, exchange rates and spreads[26].

The data on individual level income is obtained from the Real Time Inequality database constructed by Blanchet *et al.* (2022), which is introduced in setion (3.3). Reconsidering, Blanchet *et al.* (2022) construct *monthly* distributions of income, wealth and their components by statistically matching the annual distributional national accounts of Piketty *et al.* (2018) with the current population survey and the survey of consumer finances in order to incorporate demographic information. They then construct monthly

[26] A full list of these variables is available on FRED-MD website.

variables by re-scaling each component of income and using information on the distribution of wages from monthly and quarterly survey and administrative data. We use *factor income* as our benchmark income measure. Factor income is the sum of labour and capital income[27].

We define 10 groups based on the deciles of factor income: $P_1, P_2, \ldots, P_{10}$. P_1 includes individuals that fall below the tenth percentile of factor income, P_2 denotes individuals above the tenth percentile but below the twentieth percentile and so on. We construct average factor income, capital and labour income in each of these groups. In addition, we calculate the average of the main components of capital and labour income in each group. All of these income variables are deflated by the national income deflator and included in X. The sample ranges from 1976M1 to 2017M12[28].

The number of factors in the FAVAR model is chosen via the information criteria of Bai and Ng (2002). This procedure suggests the presence of 15 factors. The lag length is set at 12[29]. The parameters of the VAR model in (26) are estimated using a Bayesian approach. We use a Markov chain Monte-Carlo algorithm to approximate the posterior distributions. We employ $11,000$ iterations, retaining every 10^{th} draw after a burn-in period of 1000.

4.4 Empirical Results

Before turning to the effect of the oil supply news shock on the distribution of income, we show the response of selected aggregate variables to this shock in figure (23). These results broadly support the conclusions reached by Känzig (2021). A 10% increase in the oil price leads to an increase in oil inventories and the median response of oil production is negative at medium horizons, albeit with large error bands. The shock depresses both global and US industrial production and leads to an increase in the US unemployment rate and CPI. The shock has a limited effect on short-term interest rates but affects financial conditions adversely, with the BAA spread increasing and the stock market index declining.

4.4.1 Impact on the distribution of income

Figure (24) shows our main result. The left panels of the figure show the median response of total income, labour income and capital income, averaged in each group defined by deciles of total income. The right panels present the response of these variables in

[27]As in Blanchet *et al.* (2022) labour income is defined as the sum of wages and 0.7 times proprietors income. Capital income is the sum of 0.3 times proprietors income, corporate profits, interest income, rental income net of corporate taxes and non-mortgage interest payments.

[28]As discussed in Känzig (2021), the instrument is only available from 1984M4 and the estimation of the A_0 matrix uses this sample.

[29]Our main results are robust to the number of factors and lags.

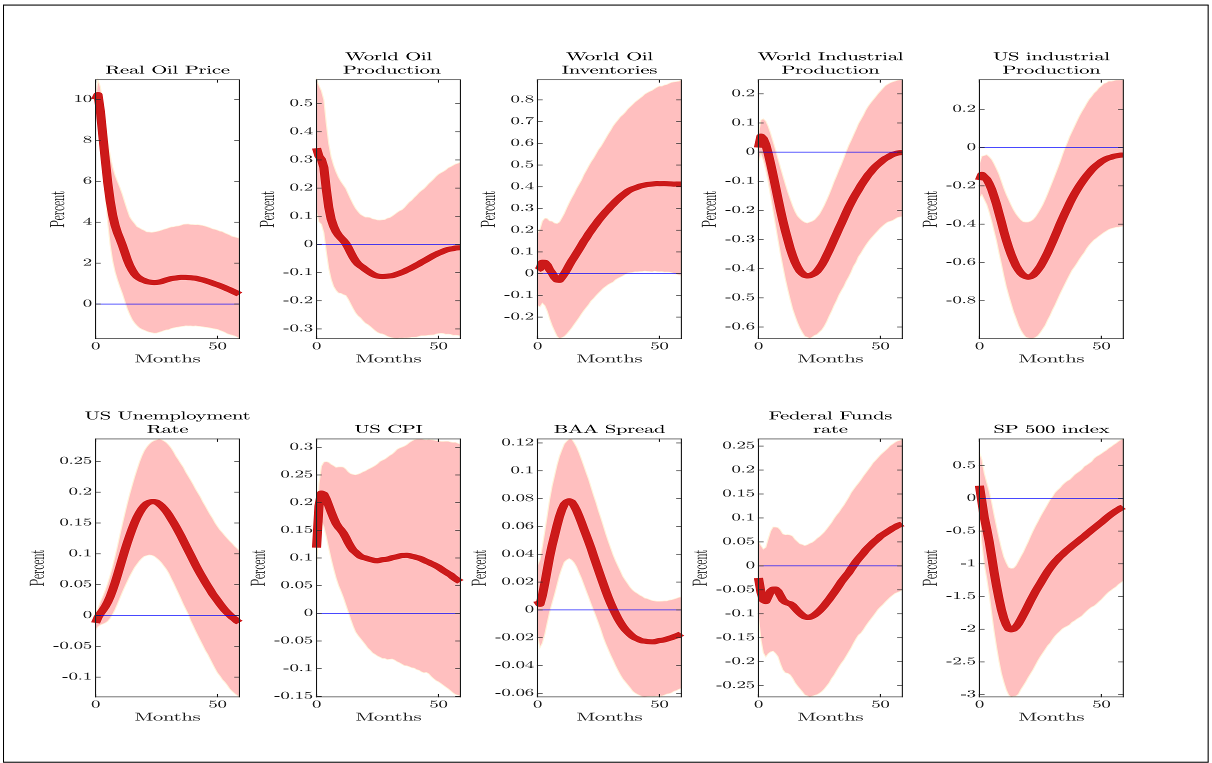


Figure 23: Impulse response functions of selected variables to an oil supply news shock. The shock is normalised to increase the oil price by 10%. The solid lines are the medians while the shaded area represents the 90% error band

each decile group, along with 90% error bands at the 2 year horizon. The top row of the figure shows that the oil supply shock has the largest effect on the income of individuals on the left tail–for the first decile, total income declines by 1% at the 2 year horizon. The impact is smaller towards the centre of the distribution with the income of individuals in groups P_6 and P_7 falling by less than 0.5 %. However, for the top 10 %, the effect of the shock appears to be relatively larger. The second row of the figure shows that the impact on the left tail is driven by the largely negative reaction of labour income. In contrast, capital income, which constitutes a larger proportion of income at the right tail, barely reacts significantly below the median at the 2 year horizon. For high-income individuals, capital income declines substantially driving the larger reaction of total income observed for this group.

In a related paper, Del Canto *et al.* (2023) find that the oil supply news shock has a smaller effect on labour income for households with high educational attainment (bachelor's degree or higher) relative to households where the head has only obtained some college education. However, they report a relatively muted impact of the shock on households with even lower educational attainment. As discussed in their paper, educational attainment is likely to be correlated with the permanent component of income, while the

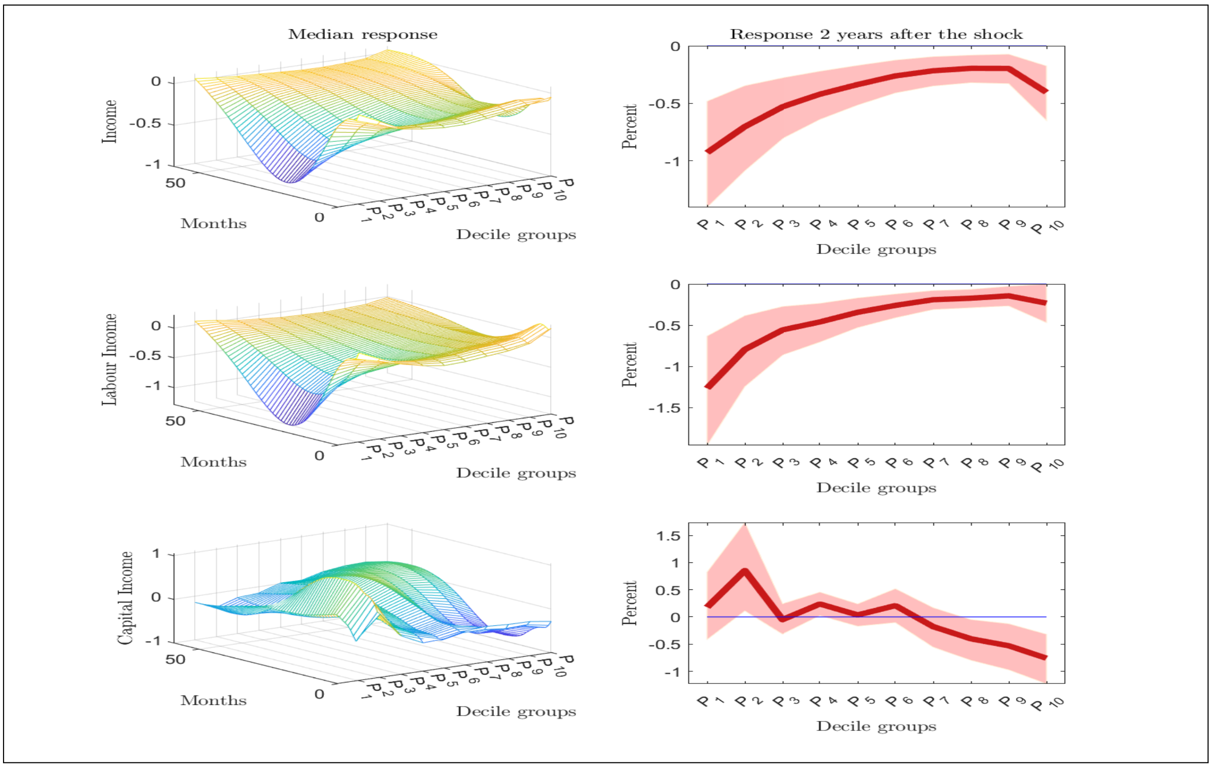


Figure 24: Impulse response functions of total income, labour income and capital income. The shock is normalised to increase the oil price by 10%. The first column shows the median response. The right panel shows the response at the 2 year horizon. The solid lines are the medians while the shaded area represents the 90% error band. $P_1, P_2, \ldots, P_{10}$ denotes the decile groups.

distributions considered in our study pertain to total income[30].

Figure (25) shows the reaction of some of the main components of labour and capital income to the oil shock and suggests two key conclusions[31]. First, the shock leads to a decline in labour income at the left tail as both wages and proprietor's income decline. Second, capital income is adversely affected at the right tail – the shock is associated with a fall in interest income for groups P_7 to P_{10} and corporate profits for the top decile, possibly as a result of the rise in corporate spreads and fall in interest rates.

[30]Del Canto *et al.* (2023) obtain labour income from the Current Population Survey. One crucial advantage of the Blanchet *et al.* (2022) database over the CPS is the fact that it incorporates information from the Survey of Consumer Finances and may provide more accurate estimates of income at the right tail of the distribution.

[31]Note that interest income is defined as income from currency bonds and deposits.

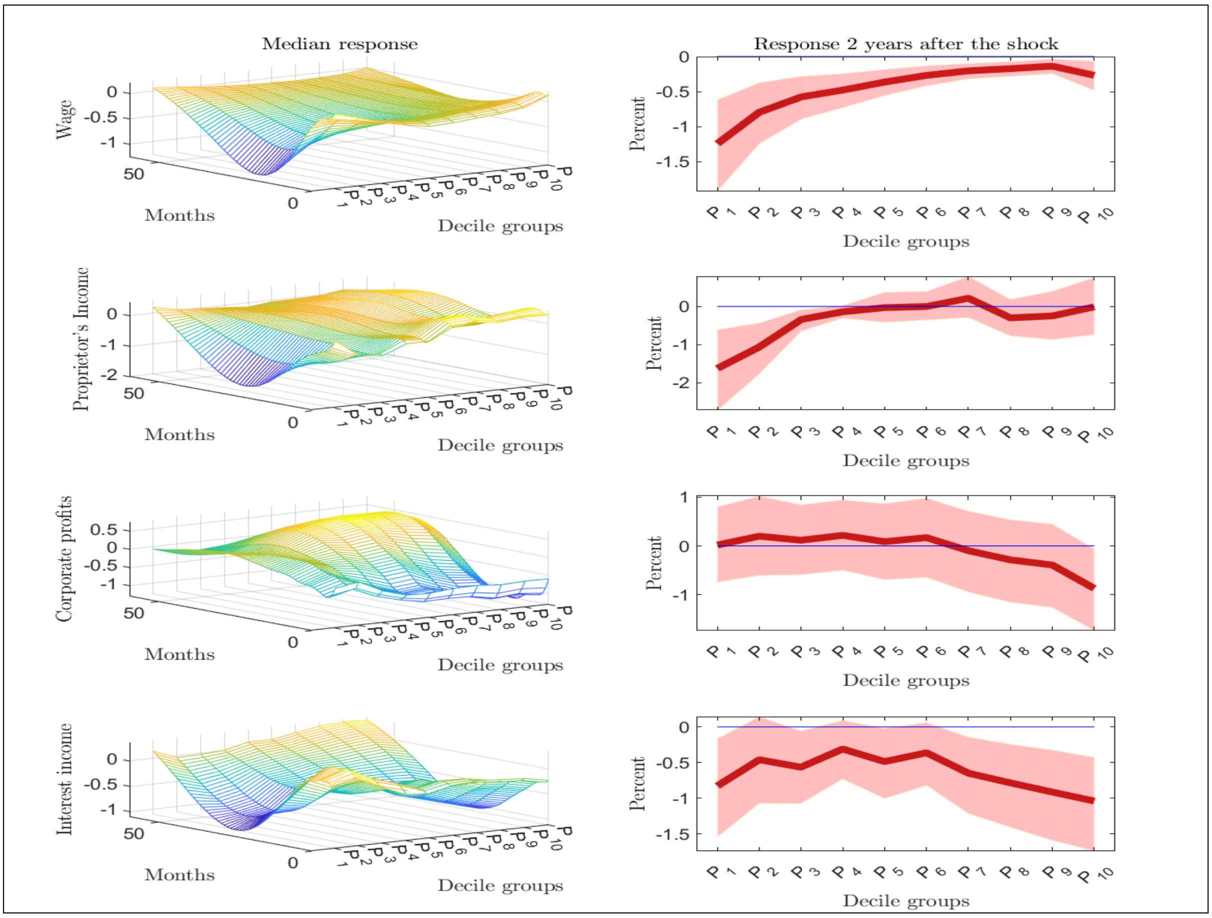


Figure 25: Impulse response functions of the components of labour and capital income The shock is normalised to increase the oil price by 10%. The first column shows the median response. The right panel shows the response at the 2 year horizon. The solid lines are the medians while the shaded area represents the 90% error band. $P_1, P_2, \ldots, P_{10}$ denotes the decile groups.

4.4.2 Robustness

We carry out several robustness checks that are presented in detail in the upcoming section.

Beginning with the underlying identification approach, we follow Känzig (2021) closely. As discussed in Känzig (2021), the oil supply news shock can also be identified under weaker assumptions: i.e. allowing for the possibility that other disturbances occur at the same time as the news shock. One method to accomplish this is identification via heteroscedasticity, which only requires the assumption that the variance of oil supply news shocks increases around OPEC announcements while the variance of other shocks remains unchanged.
The methodology used here closely follows Rigobon and Sack (2004), who introduced this approach to identify monetary policy shocks. Consider splitting the data into two subsamples S and $\tilde{S}$, where S comprises all announcement dates and $\tilde{S}$ all other dates.

Also, assume that these subsamples are comparable in other dimensions. Adopting the conditions stated in Rigobon and Sack (2004) in our approach we assume that the instrument of oil price news shocks is driven by the shock of interest and other shocks according to:

$$m_t = \varepsilon_{1,t} + \sum_{j \neq 1} \varepsilon_{j,t} + v_t \tag{30}$$

Where m_t denotes the external instrument, $\varepsilon_{1,t}$ denotes the oil shock and $\varepsilon_{j,t}$ comprises all other shocks. v_t is assumed to follow a normal distribution $v_t \sim N(0, \sigma_v^2)$. Formally three assumptions need to be satisfied so that identification by heteroscedasticity is suitable:

1. $\sigma_{\varepsilon 1}^{S} > \sigma_{\varepsilon 1}^{\tilde{S}}$
2. $\sigma_{\varepsilon 2:n}^{S} = \sigma_{\varepsilon 2:n}^{\tilde{S}}$
3. $\sigma_{m}^{S} = \sigma_{m}^{\tilde{S}}$

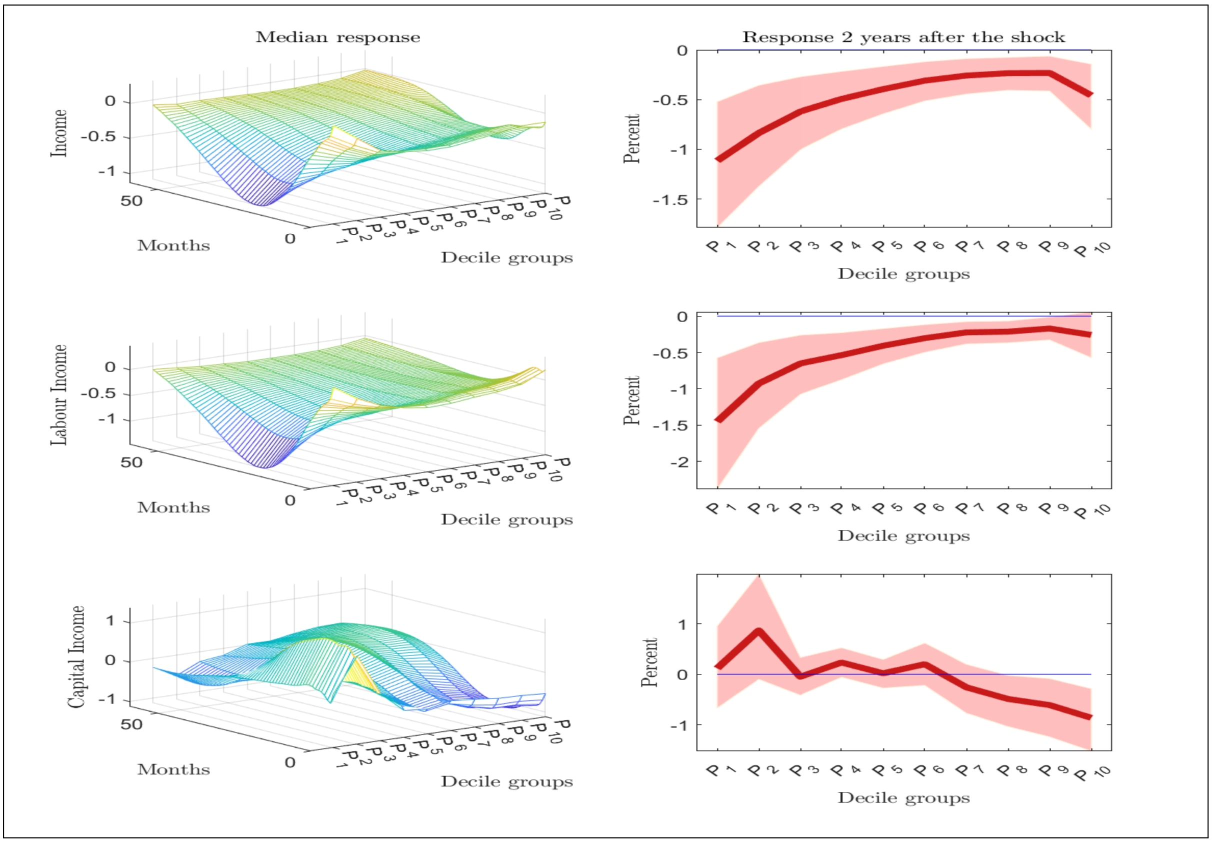
Which mathematically expresses the relatively higher importance of oil shocks during OPEC announcements. Identification is achieved by looking at the difference in the variance-covariance matrix between the two regimes S and $\tilde{S}$. The structural impact coefficient is then defined as the ratio of the differences between the two regimes:

$$\tilde{\alpha}_0 = \frac{E_S[m_t u_t] - E_{\tilde{S}}[m_t u_t]}{E_S[m_t^2] - E_{\tilde{S}}[m_t^2]} \tag{31}$$

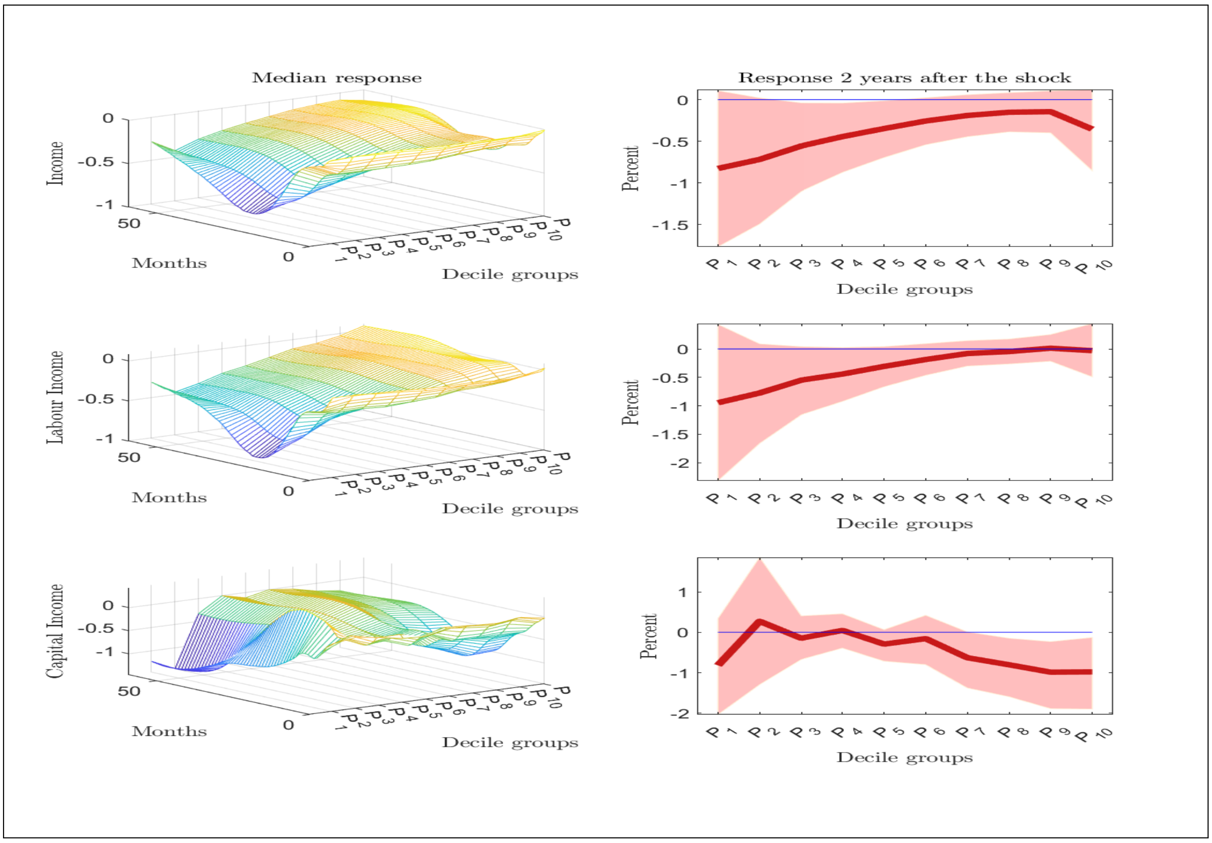
We show in figure (26a) that we obtain very similar results to the benchmark when the oil shock is identified using this approach. In particular, the shock has the largest effect on income at the left tail.

We also use the time series of the oil supply shock from the VAR model of Baumeister and Hamilton (2019) as an alternative instrument. As shown in figure (26b), the impulse responses obtained from this approach are broadly similar to the benchmark case.

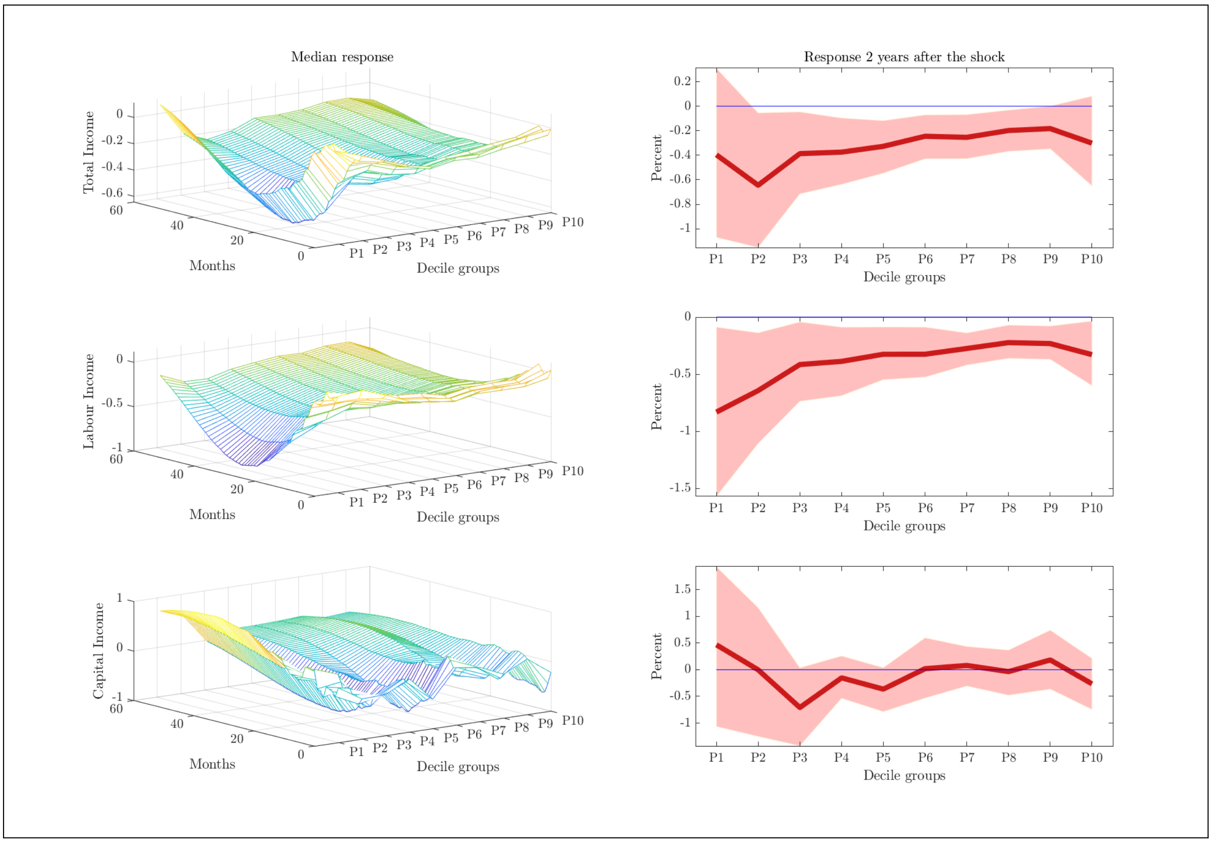
Regarding the specification and the model we can confirm the following: The results are also preserved for FAVAR models with alternative lag lengths and the number of factors. As a further check, we estimate the VAR model of Känzig (2021) adding the deciles of income measures one by one to the original set of endogenous variables. As shown in figures (26c), (26d), (26e) the results from this model support the benchmark conclusions regarding the distributional effects of the shock.



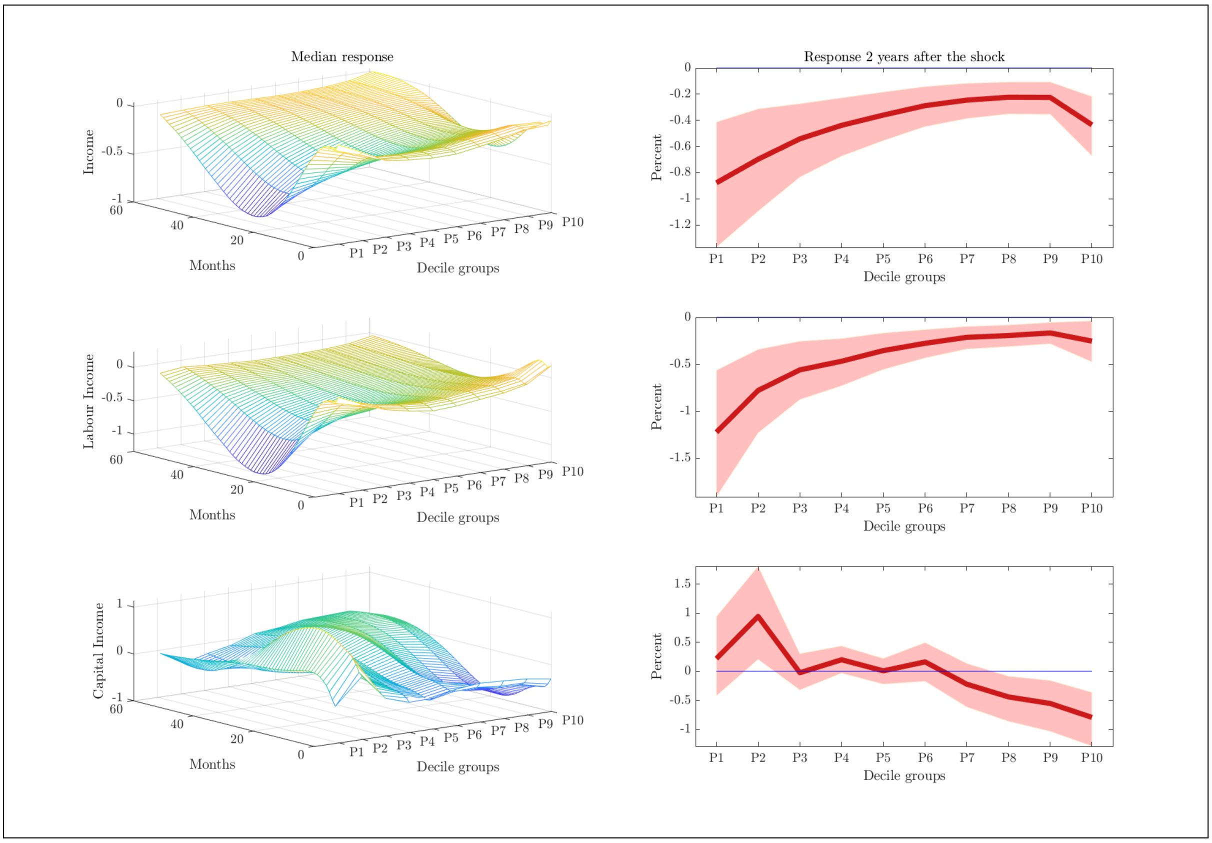
(a) Identification based on Heteroscedasticity



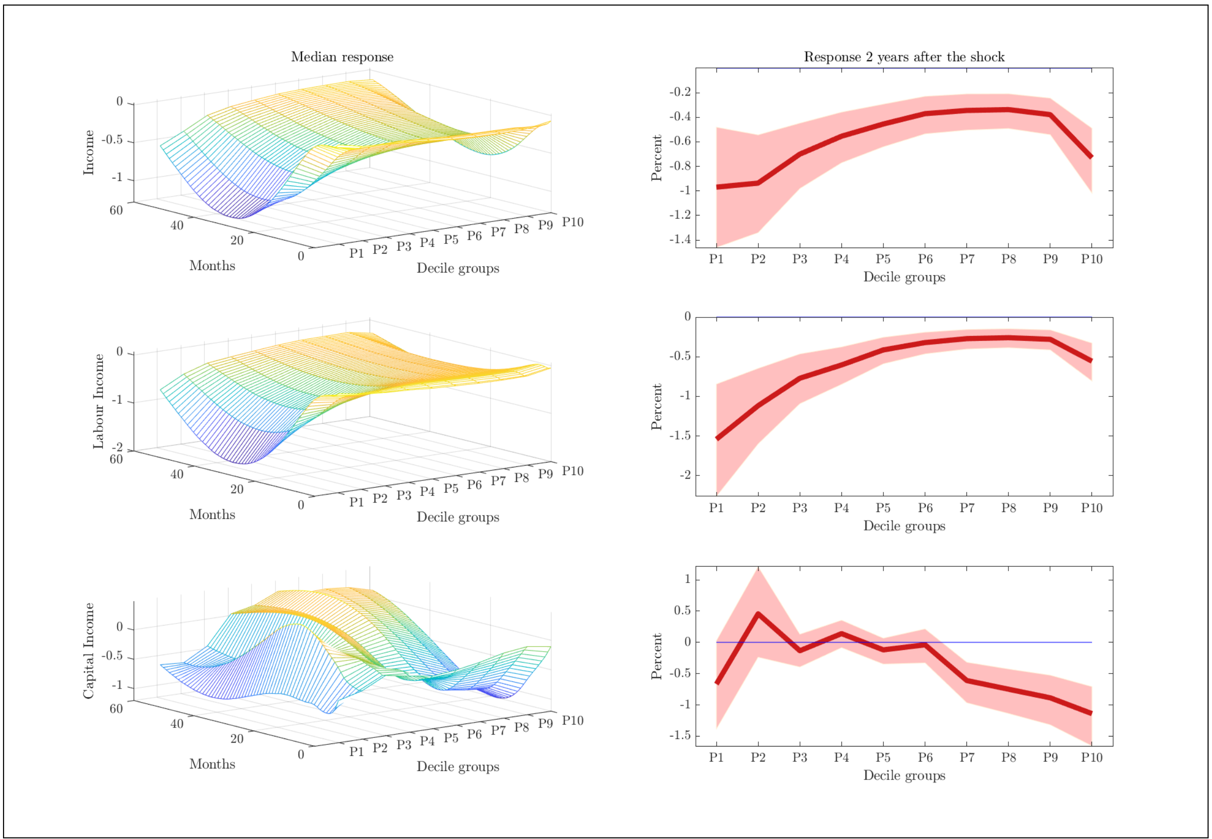
(b) Proxy of Baumeister and Hamilton (2019)



(c) Bayesian proxy-VAR estimation



(d) Estimation with 6 lags



(e) Estimation with 10 factors

Figure 26: Sensitivity checks of the baseline findings. The specific exercise is mentioned in every caption of the figure. All other settings equal the baseline specification.

4.5 Conclusion

This study shows that adverse oil supply news shocks have a heterogeneous effect on the US income distribution using a Factor Augmented VAR (FAVAR) approach. While the impact of the shock is largest at the left tail of the distribution, more affluent individuals are also significantly affected by the shock. An examination of the components of income suggests that these results are driven by a decline in the labour income of the former group and the capital income of the latter. In particular, wages react more strongly for the left tail as does proprietors' income. At the same time, corporate profits and interest income show an inverse behaviour regarding the asymmetry of the effect on the distribution and mainly capture the loss of affluent individuals. These findings appear to be robust for several sensitivity checks such as the model, lag length specification, the number of factors, the identification technique and different shock series considered.

5 Concluding Remarks

By using high-frequency instruments for identification in different macro-econometric models, this thesis investigated the propagation of macroeconomic shocks on the income distribution and highlighted the consequences that these shocks can have, particularly in advanced economies like the United Kingdom and the United States.

Beginning with monetary policy shocks, recent economic studies have shown that monetary policy plays a significant role in influencing inequality. The theoretical side of this research has shifted from the representative agent framework to the use of heterogeneous agent models, as suggested by Kaplan *et al.* (2018) or Gornemann *et al.* (2021). This shift emphasizes the importance of indirect effects, highlighting that household inequality impacts how a monetary policy shock affects the economy. As a result, various distributional channels have emerged, stemming from the interaction of wealth-, income-, and substitution effects. This work focuses on these indirect effects from an empirical perspective.
In this case, empirical studies detect only a few theoretical channels appropriately. For instance, evidence is presented for the income composition channel (Coibion *et al.* (2017), Guerello (2018), Cloyne *et al.* (2018)), the earnings heterogeneity channel (Inui *et al.* (2017), Furceri *et al.* (2018), Theophilopoulou (2022)) or the inflation channel (Romer and Romer (1999), Easterly and Fischer (2001)).

In line with this research, the first chapter investigated the UK income distribution and found that a 25 basis point increase in the policy rate produces a significant rise in income inequality in the short term by 0.22 per cent. The median household and the poor move closer together, whereas the gap between the rich and the median household rises. When decomposing total income into its main components by quintiles, the study highlighted the driving forces of these asymmetric effects. It is mainly due to the change in the main income sources with higher income levels that leads to a higher connection to financial markets and hence, different effects experienced after a monetary tightening. A phenomenon captured by the income composition channel.

The second chapter added another layer of complexity to the understanding of monetary policy shocks and extended these findings concerning time variation when looking at the US. By analysing granular income data from the Realtime Inequality Database introduced in Blanchet *et al.* (2022), the study used income data that sum up to the national account totals. A monetary policy shock was analysed via a high-frequency identification approach in a time-varying VAR setting. The findings confirmed the same distributional channels (income composition and earnings heterogeneity channel) but highlighted the higher responsiveness for more recent periods in the sample. While the earnings heterogeneity channel always remained important for monetary transmission, it is the income composition channel that lead to a more responsive income distribution over time. This time-dependent nature of the impact emphasizes the evolving challenges policymakers face in managing macroeconomic stability.

Apart from this line of research, studies that investigate the macroeconomic effects of oil shocks have established an ongoing debate in 1. how to identify an oil shock (a) time restrictions, b) inequality and sign- restrictions, c) identification using external instruments) and 2. where such an oil shock comes from: demand-side driven (Kilian (2008a), Kilian (2009), Kilian and Murphy (2012, 2014)) or supply-side driven (Hamilton (1983), Hamilton (2009), Baumeister and Hamilton (2019)). It is mainly the studies using external data for identification such as Hamilton (2003) and Känzig (2021), this thesis builds on to contribute to the literature by shedding light on the distributional effects of oil supply news shocks. A research question that the authors find has not attracted a lot of attention in the literature.

With regard to that, the third chapter extended the analysis of the previous chapters by looking at the effects of oil price news shocks on the same US income distribution. Again, identification was achieved via a high-frequency instrument, however, in a FAVAR setting. This model enabled the researchers to include an approximation of the whole income distribution by deciles. The shock produced asymmetric effects along the distribution displaying the higher vulnerability of labour income at the left tail of the distribution, while capital income components mainly drive the losses of households at the right tail.

All in all, macroeconomic shocks (here, monetary and oil price news shocks), hit the income distribution asymmetrically. These effects depend on the main income components of the households. On top of that, there is indication that for more recent periods the US economy became more reactive to contractionary monetary shocks. These findings have important implications for policymakers underlining the potential of re-distributive effects of macroeconomic shocks and calling for a policy design that not only targets macroeconomic objectives but also mitigates the adverse effects on the income distribution.

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