

EFFECTS OF MONETARY POLICY SHOCKS ON  
INEQUALITY:  
A PROXY-SVAR APPROACH

by

Arnaud N. Mertens

#300019919

ECO 6999

Major Research Paper

Supervisor: Professor Lilia Karnizova

Department of Economics

Faculty of Social Sciences

University of Ottawa

September 2018

## Abstract

Inequality has been increasing in the United States over the past three decades. While several avenues have been explored to explain this rise, the role of monetary policy has only recently been considered. Moreover, the overall effects of monetary policy shocks on inequality remain ambiguous both theoretically and empirically. Therefore, I propose a new study of the effects of conventional monetary policy shocks on income inequality in the United States. To do so, I use a structural vector autoregression (SVAR) model with external instruments. It consists of taking series of monetary policy shocks as proxies for structural shocks. First, I provide evidence that contractionary monetary policy shocks significantly increase inequality in the long run. Second, by breaking the income distribution down into different groups, I show that the higher an income group in the distribution is, the more favored it is by contractionary shocks. Third, I find that the increase in income of the top 1% is strikingly symmetric to the decrease of the bottom 10% after a contractionary monetary policy shock. These findings suggest that the Fed's actions play a role in long-term inequality.

*Keywords:* Monetary Policy, Inequality, Proxy SVAR, External Instrument, Shock, Income

### Acknowledgements

It would be bold to claim that writing this research paper was not demanding. Indeed, there were a lot of ups and downs. However, I want to write a few lines to thank the key people who made this possible. First, this work would not have been possible without the precious mentoring by Professor Lilia Karnizova. She always gave me valuable advice. Secondly, I would also like to thank my family, my dog, and especially my pig. Even though they were thousands of miles away, they knew what to say when I needed them the most. Finally, I do not thank Larry Page and Sergey Brin. Indeed, the work may have been completed sooner without their inventions.

# Table of Contents

I.	Introduction.....	5
II.	Monetary Policy and Inequality .....	6
	A. Transmission Channels .....	6
	B. Review of Empirical Evidence.....	8
III.	Methodology .....	11
IV.	Data Sources.....	15
	A. Concepts of Inequality and Measures.....	15
	B. Selected Instruments.....	18
	C. Macroeconomic Variables .....	19
V.	Estimation and Results .....	20
	A. Specification.....	20
	B. Instrument Choice.....	21
	C. Results and Discussion .....	24
	D. Robustness Checks .....	30
VI.	Conclusion .....	31
VII.	References.....	33
I.	Appendix A: Data.....	36
II.	Appendix B: Supplementary Material.....	37

# I. Introduction

Inequality has been rising in the United States in the recent decades. According to Piketty et al. (2016), the average pre-tax national income of the bottom 50%<sup>1</sup> has increased by 23% between 1966 and 2014, while the income of the top 10% has risen by 148%. Whereas Okun (1975) argues that there is a trade-off between efficiency and equality, other studies show that inequality can have serious negative effects. For example, Hsing (2005) finds that high inequality impedes economic growth in the United States. In addition, Rajan (2010) indicates that it can lead to financial crises.

As a result, several authors have been attempting to identify potential factors behind this rise in inequality. However, the role of monetary policy has only recently been considered. As shown in Section 2, Coibion et al. (2017) propose five channels through which monetary policy could affect inequality. Unfortunately, while three channels imply that an expansionary monetary policy leads to an increase in inequality, two others indicate that this same policy leads to a decrease. The theoretical sign of the overall effect of monetary policy shocks on inequality is therefore ambiguous. Consequently, several studies have attempted to empirically assess the impact of monetary policy shocks on inequality. However, there is no consensus. For instance, while Coibion et al. (2017) conclude that a contractionary shock increases inequality in the United States, Davtyan (2017) argues the opposite.

The purpose of this paper is therefore to assess the effects of conventional monetary policy shocks on inequality in the United States. To do so, I use a structural vector autoregression (SVAR) model with external instruments. This approach is a method developed by Stock and Watson (2008, 2012) and Mertens and Ravn (2013). Series of shocks are constructed outside the SVAR model and used in estimating their effects on the variables included in the VAR. In other words, it consists in taking series of shocks as proxies of structural shocks, while previous studies on inequality have used series of shocks as the true structural shocks (e.g., Coibion et al., 2017). In addition, I use data from the World Inequality Database (WID.world). It merges national accounts, fiscal, and survey

---

<sup>1</sup> Adults between the lower end and the 50th percentile of the income distribution

data, capturing the entire income distribution, while previous studies have in most cases used survey data, which means that the top and bottom 1% of the distribution had to be removed to avoid outliers. By contrast, with the WID.world data, it is possible to analyze the effects of shocks on different income groups, including the top 1%.

Taking these points into consideration, I show that contractionary monetary policy shocks significantly increase inequality in the long run. Moreover, by breaking the income distribution down into different groups, I find that contractionary shocks have monotonic effects. More specifically, the higher the group in the income distribution is, the higher its average income rises after contractionary shocks. Finally, I consider the responses of the income shares of the different groups to monetary policy shocks and show that the rise in inequality is mainly driven by the tails of the distribution. My results are robust to several changes in the model and data specifications and are in line with Coibion et al. (2017).

In Section II, I briefly describe the channels through which monetary policy could affect inequality and then discuss the conflicting previous findings. In Section III, I present the methodology. To be more specific, I depict the approach used by Stock and Watson (2008, 2012) and Mertens and Ravn (2013). Then, in Section IV, I show the selected external instruments (called “proxies”) and the inequality variables as well. In Section V, I refine my choice of instruments and discuss my results. Finally, I conclude in Section VI.

## **II. Monetary Policy and Inequality**

### **A. Transmission Channels**

Several different channels have been considered by previous studies. Coibion et al. (2017) describe the following five potential channels.<sup>2</sup> The first one is called the “income composition channel”. The idea is that the main sources of income are not the same among all households: there is some heterogeneity. For example, some receive a significant share of their income from financial or corporate income, whereas a large majority of individuals

---

<sup>2</sup> Nakajima (2015) presents similar channels. His “inflation channel” includes the financial segmentation, the portfolio, and the savings redistribution channels, while the “income channel” encompasses the income composition and the earnings heterogeneity channels.

simply earn a wage. Therefore, those with this significant share of income from financial or corporate income will be better off than others if expansionary monetary policy increases their financial or corporate income more than wages. Also, as stated by Coibion et al. (2017), the “owners” are often among the wealthiest individuals, which means that inequality tends to rise after a negative monetary policy shock. The second channel proposed by Coibion et al. (2017) is the “financial segmentation channel.” While most people are not active in financial markets, some individuals regularly trade, which means that changes in money supply impact them earlier than the others. Therefore, expansionary monetary policy shocks should tend to favor those active in financial markets. Since active individuals in the financial markets often have higher income, this channel should lead to increased income inequality. Theoretical results support this view. For instance, Ledito (2011) creates a model with two agents and demonstrates that the agent closest to the injection of money is ultimately better off while the other one is in a worse situation than they were before. The third channel is called the “portfolio channel”. One commonly accepted fact is that low-income agents usually hold proportionately more cash than high-income agents. As a result, expansionary monetary policy shocks should affect more the low-income agents than those with higher incomes, implying an increase in inequality.

The three channels seen above have effects of the same sign. More specifically, an expansionary monetary policy shock leads to an increase in inequality. However, according to Coibion et al. (2017), there are two other channels that have opposite effects to the previously discussed channels. The first one is called the “earnings heterogeneity channel”. The earnings of low- and high-income agents react in different ways to monetary policy shocks. For example, if low-income individuals have a greater propensity to be unemployed than high-income individuals during recessions, an accommodative monetary policy could reduce earnings inequality by enhancing employment. The second channel is the “savings redistribution channel”. An expansionary monetary policy shock reduces interest rates, which affects negatively the savers and benefits the borrowers. However, borrowers are usually poorer than savers, which means that expansionary monetary policy shocks could decrease inequalities. This view is supported by Doepke and Schneider (2006). The authors conclude that inflation negatively affects wealthy households, while it benefits those belonging to the middle class and having nominal loans.

To conclude, while the first three channels indicate that expansionary shocks increase inequality, the next two channels imply the opposite. Also, the sign of the different channels can be questioned. For example, as proposed by Coibion et al. (2017), one could argue that the income composition channel could lead to a decline in inequality after an expansionary monetary policy shock. In fact, a large share of income of low-income agents is from social transfers. Taking into account that transfers are usually countercyclical, this channel could decrease inequality, which is the opposite of what is said above. Therefore, both the sign and the magnitude of the theoretical effects of monetary policy on inequality are ambiguous and empirical analyzes must be carried out to determine these two elements.

## **B. Review of Empirical Evidence**

The study of possible impacts of monetary policy on inequality is relatively recent. One of the first papers to clearly examine the link between monetary policy and inequality is Romer and Romer (1999). On the one hand, the authors find that expansionary monetary policies are correlated with lower inequality in the United States in the short run. On the other hand, using data from several countries, they find that low inflation is correlated with lower long-term inequality. Their results are therefore opposed, but they conclude that the cyclical impacts of monetary policy are a priori short-lived, which means that low inflation should be prioritized if one wants to reduce inequality.

Inflation is intrinsically linked to monetary policy, as one of the Federal Reserve's objectives is to manage inflation. It is therefore interesting to study the link between inequality and inflation, before looking at the effects of monetary policy. Romer and Romer (1999) is not the only paper to consider the impact of inflation on inequality and there is actually a rather dense literature that traces this link. Laidler and Parkin (1975) indicate that the losers of inflation are usually the rich and the poor. Individuals in the middle-income class seem less affected: the reason is that they have more nominal debts than those belonging to the tails of the distribution. Using cross-country data, Albanesi (2007) finds that income inequality is positively correlated with inflation. Bulir (2001) is in line with this result. Based on the Kuznets model, he demonstrates that price stability reduces income inequality. More specifically, inflation reduction appears to have a large effect in the presence of hyperinflation, significantly reducing inequalities, while this effect becomes

very small at low inflation rates. Again, Li and Zou (2002) exploit panel data across several countries and concludes that inflation is positively correlated with inequality. In other words, high inflation is associated on average with higher inequalities. Also, Li and Zou (2002) conclude that inflation raises the income share of the wealthy. Furthermore, Kang et al. (2013) use data from South Korea and concludes that while inflation seems to have an impact in the short run, it does not affect inequality in the long run. This result supports the idea that monetary policy has only temporary effects. Finally, Galli and van der Hoeven (2001) study the impact of inflation and monetary policy on income inequality. For this purpose, the authors use data including the United States and 15 OECD countries. They find that the effects of inflation depend on the initial level of inflation. Indeed, when the inflation rate is already low, a further decline increases inequality. However, inequality decreases after a drop in inflation when the initial rate is high.

In addition to these papers highlighting the link between inflation and inequality, some papers examine the effects of monetary policy. Although the literature is not very extensive, some papers deserve to be mentioned. Table 1 summarizes the effects of conventional monetary policy shocks on inequality found by previous authors. For instance, Coibion et al. (2017) use US survey data from 1980. The authors construct inequality measures (Gini coefficients, cross-sectional standard deviations, etc.), as well as measures within the distribution (e.g., the average income of the bottom 10%). The great advantage of their research is that they can distinguish several types of inequality (income, earnings, and even consumption inequality), using survey data. This approach contrasts with many other papers studying the impact on inequality with only income Gini indices but not having the possibility to study other kinds of inequality or the effects of monetary policy on precise intervals in the distribution (e.g., the top 10%). However, Coibion et al. (2017) trim the top and bottom 1% of the distribution in order to avoid outliers. This may have important consequences, since several papers show that the top 1% matters (e.g., see Kenworthy and Smeeding (2013) for the United States). Bearing this in mind, using local projections, the authors conclude that contractionary monetary policy shocks permanently increases inequality.

By contrast, using a SVAR model, Villarreal (2014) finds that contractionary monetary policy shocks reduce income inequality in Mexico. Francisco Villarreal argues

that his findings are different from Coibion et al. (2017) because the structure of the economy is not the same. However, using US Gini coefficients, Davtyan (2017) shows that a contractionary shock decreases income inequality, which also contradicts Coibion et al. (2017). Nonetheless, some authors support the findings of Coibion et al. (2017). For instance, Galbraith et al. (2007) create a VAR model with US data excluding the pre-Volcker period. The authors find that a contractionary monetary policy increases earnings inequality. Mumtaz and Theophilopoulou (2017) obtain similar results. More specifically, the authors reproduce an analysis comparable to Coibion et al. (2017). They use survey data for the United Kingdom and construct measures<sup>3</sup> of inequality, finding that tight conventional monetary policy shocks lead to a permanent increase in inequality.

***Table 1: Effects of Conventional Monetary Policy Shocks on Inequality***

Paper	Country	Inequality Data type	Method	Effect on Inequality	
				SR	LR
Coibion et al. (2017)	United States	Survey	Local projections (Narrative identification)	+	+
Villarreal (2014)	Mexico	Survey	Local projections (MP shocks identified with DSGE model)	-	None
Davtyan (2017)	United States	Gini indices	SVAR (contemporaneous and long-run restrictions)	-	-
Mumtaz and Theophilopoulou (2017)	United Kingdom	Survey	SVAR (Sign restrictions)	+	+

Note: SR stands for the short-term effect of tight conventional monetary policy shocks on inequality, while LR is for the long-term effect.

So far, only the effects of conventional monetary policy have been described. There is however a very small literature studying the impact of unconventional monetary policy

<sup>3</sup> They also trim the tails of the distribution.

on inequality. Quantitative easing seems to raise inequality. For instance, Mumtaz and Theophilopoulou (2017) find effects opposite to those of conventional monetary policy. Saiki and Frost (2014) abound in this direction. Using household survey data with a VAR model, they find that unconventional monetary policy tends to boost income inequality in Japan. One of the potential explanations would be the strong influence of the portfolio channel compared to the other channels.

To sum up, the effects of monetary policy on inequality are ambiguous. While differences in results between countries are not unusual, divergent results within a country are questionable. I therefore propose a new analysis to assess the effects of monetary policy shocks on inequality in the United States. To the best of my knowledge, the method described below has never been applied with inequality variables. Moreover, while I briefly discuss the effects of unconventional monetary policy above, I only consider conventional monetary policy in the following analysis.

### III. Methodology

I use a Vector Autoregression model as proposed by Sims (1980) combined with external instruments to analyze the effects of monetary policy shocks on inequalities. Let  $Y_t$  be a vector of  $r$  variables combining a policy indicator, macroeconomic variables, and an inequality variable. Then the reduced form VAR model that I consider is

$$A(L)Y_t = \eta_t, \quad (1)$$

where  $A(L) = I - A_1L - \dots - A_pL^p$  and  $p$  is the lag order. Also,  $\eta_t$  is the vector of the reduced form innovations and can therefore be rewritten as

$$\eta_t = Y_t - E_{t-1}Y_t = A(L)Y_t \quad (2)$$

The reduced form innovations are related to the structural shocks  $\varepsilon_t$  by the relation

$$\eta_t = S\varepsilon_t = [s_1 \dots s_r] \begin{pmatrix} \varepsilon_{1t} \\ \dots \\ \varepsilon_{rt} \end{pmatrix} \quad (3)$$

or, equivalently,

$$\varepsilon_t = S^{-1}\eta_t, \quad (4)$$

where the expected value of  $\varepsilon_t$  is zero (i.e.,  $E[\varepsilon_t] = 0$ ) and  $S$  is a  $rxr$  matrix. The structural shocks are uncorrelated between different periods (i.e.,  $E[\varepsilon_t\varepsilon_s'] = 0$  for  $t \neq s$ ) and

$E[\varepsilon_t \varepsilon_t'] = I$ , the identity matrix. Also, one can easily obtain the variance-covariance matrix of the reduced form model  $\Sigma$ .

$$E[\eta_t \eta_t'] = \Sigma = E[SS'] \quad (5)$$

However, if one wants to calculate the impulse response functions (IRFs) or the forecast error variance decomposition (FEVD), they must identify the structural shocks. To do this, an approach is to obtain the elements of  $S$  in order to identify the structural shocks by using the equation (4). However, with the above relations, it is actually impossible to identify the different shocks. Indeed, the variance-covariance matrix only gives  $r(r + 1)/2$  restrictions on  $S$ , which means that one needs  $r(r - 1)/2$  additional identifying restrictions to obtain all the shocks.

The common approach is to identify shocks using internal VAR restrictions. There are actually several different ways. One can, for example, use zero short-run restrictions (e.g., the well-known Cholesky identification) or sign restrictions. There are also other methods, such as, non-exhaustively, long-run restrictions (also called “Blanchard-Quah” restrictions), or even identification by heteroskedasticity. That being said, such approaches require strong assumptions about the structure of the economy, especially about the relationships between the different shocks. Some of these assumptions become tricky to apply if one uses low frequency variables. Indeed, while the use of the Cholesky identification seems to be trivial, it would be unreasonable, for instance, to think that a monetary policy shock occurring in the year has no contemporaneous effect on GDP, using low frequency variables (e.g., annual frequency).

Therefore, I use another approach to identify the effects of monetary policy shocks. More specifically, I use the approach developed by Stock and Watson (2008, 2012) and Mertens and Ravn (2013). The innovation of the authors is to use constructed series of shocks as “proxies” of the true structural shocks, whereas the literature has so far treated the series as the true structural shocks. By accepting the series as proxies, we consider that they can actually be slightly different from reality. This approach is not incongruous since many series of shocks are constructed either narratively (e.g., Romer and Romer, 2004) or from models (e.g., Smets and Wouters, 2007). This approach is known as “the

identification using external instruments” (also called “Proxy-SVAR”) and are thus thought of as quasi-experiments.

However, I am not interested in computing the impulse responses to all the shocks. Since only the monetary policy shock is crucial in my research, it is not necessary to identify all the elements of  $S$ . More specifically, partition the vector

$$\varepsilon_t = \begin{pmatrix} \varepsilon_t^p \\ \varepsilon_t^{np} \end{pmatrix} \quad (6)$$

where  $\varepsilon_t^p$  is a scalar containing the shock of interest and  $\varepsilon_t^{np}$  is a vector  $(r - 1) \times 1$  containing the other shocks.<sup>4</sup> To compute the impulse responses to the shock of interest, Gertler and Karadi (2015) state that one simply needs to estimate

$$A(L)Y_t = s_1 \varepsilon_t^p \quad (7)$$

where  $s_1$  is the column of the matrix  $S$  coinciding with the effect of  $\varepsilon_t^p$  on each element of  $\eta_t$ . The use of instrumental variables allows the identification of the vector  $s$  in a very simple way. Consider the instrument  $m_t$  (also called “proxy variable”). Following Mertens and Ravn (2013), assume that the expected value of the instrument  $m_t$  is null (i.e.,  $E[m_t] = 0$ ).<sup>5</sup> The authors state that the instrument must satisfy the following three conditions to be a valid instrument:

(1).The instrument must be correlated with the shock of interest (relevance condition).

$$E[m_t \varepsilon_t^{p'}] = \Phi \quad (8)$$

(2).The instrument must be uncorrelated with the other shocks (exogeneity condition).

$$E[m_t \varepsilon_t^{np'}] = 0 \quad (9)$$

(3).The instrument must be uncorrelated with the history  $X_t$  (vector of lagged dependent variables, such that  $X_t = [Y_{t-1}' \dots Y_{t-p}']'$ ).

$$E[m_t X_t'] = 0 \quad (10)$$

---

<sup>4</sup> Mertens and Ravn (2013) and Gertler and Karadi (2015) consider the general case where  $\varepsilon_t^p$  is a vector of shocks of interest. The reasoning does not change: one needs to use an instrument for each shock of interest. Moreover, this case can be extended by using several instruments for a single shock of interest.

<sup>5</sup> If it is not the case, one can simply demean the instrument by subtracting the average of the proxy for each period.

According to the same authors, the third condition can be relaxed. Indeed, if the potential instrument  $\tilde{m}_t$  is correlated with the lagged dependent variables, one should simply use the residuals of the projection of  $m_t$  on the history  $X_t$ . In the next section, I perform several tests and manipulations on the selected instruments to ensure their quality.

Consider now the partition of  $S$ ,

$$S = [s_1 \dots s_r] = [s^p \ S^{np}], \quad (11)$$

where  $s^p$  is the column  $s_1$  and  $S^{np}$  is a matrix containing the remaining columns of  $S$ .<sup>6</sup>

Let partition further such that

$$S = [s^p \ S^{np}] = \begin{bmatrix} s_1^p & S_1^{np} \\ s_2^p & S_2^{np} \end{bmatrix}.^7 \quad (12)$$

Then, Mertens and Ravn (2013) explain that the above equations combined with the three conditions for a valid instrument imply that

$$\Phi s^{p'} = E[m_t \eta_t']. \quad (13)$$

Indeed, this result can easily be obtained since

$$E[m_t \eta_t'] = E[m_t (S \varepsilon_t)'] = E[m_t \varepsilon_t'] S'. \quad (14)$$

However, we know that

$$E[m_t \varepsilon_t'] = [\Phi \ \mathbf{0}], \quad (15)$$

where  $\mathbf{0}$  is a vector  $1 \times (r - 1)$  of zeros, because of the first and the second conditions for a valid instrument. Therefore, it follows immediately that

$$E[m_t \varepsilon_t'] S' = [\Phi \ \mathbf{0}] S' \quad (16)$$

which leads to confirm the result from Mertens and Ravn (2013),

$$\Phi s^{p'} = E[m_t \eta_t']. \quad (17)$$

As stated by these authors, it gives a system of  $r$  equations adding identifying restrictions. However,  $\Phi$  is an unknown scalar, which means that there are actually  $r - 1$  identifying restrictions when we subtract the unknown parameter. Following Mertens and Ravn (2013), when one partitions  $E[m_t \eta_t'] = [E[m_t \eta_{1t}'] \ E[m_t \eta_{2t}']]$ , the restrictions can be rewritten:

$$s_2^p = (E[m_t \eta_{1t}']^{-1} E[m_t \eta_{2t}'])' s_1^p. \quad (18)$$

---

<sup>6</sup>  $s^p$  is a vector  $r \times 1$  while  $S^{np}$  is a matrix  $r \times (r - 1)$ .

<sup>7</sup>  $s_1^p$  is a scalar,  $s_2^p$  a vector  $(r - 1) \times 1$ ,  $s_1^{np}$  a vector  $1 \times (r - 1)$  and  $S_2^{np}$  a matrix  $(r - 1) \times (r - 1)$

The same authors reach the conclusion that these restrictions are actually a set of covariance restrictions because  $E[m_t \eta'_{1t}]^{-1} E[m_t \eta'_{2t}]$  is known. The impulse responses to the shock of interest can thus be estimated. While those manipulations may seem complex, they are actually straightforward to implement. Mertens and Ravn (2013) propose the following three simple steps for the estimation:

- (1). Estimate the reduced form VAR using Ordinary Least Squares (OLS). Keep the estimates of the VAR residuals  $\eta_t$ .
- (2). Regress the estimates of the VAR residuals on the instrument  $m_t$  to estimate  $E[m_t \eta'_{1t}]^{-1} E[m_t \eta'_{2t}]$
- (3). Use  $E[m_t \eta'_{1t}]^{-1} E[m_t \eta'_{2t}]$  in equation (18).<sup>8</sup> The impulse responses can be easily obtained.

## IV. Data Sources

### A. Concepts of Inequality and Measures

One of the biggest challenges in this analysis is finding adequate measures of inequality. Some authors simply use series of Gini coefficients (e.g., Davtyan, 2017). However, this approach has several limitations. For instance, Gini indices are often relative measures, which means that they do not capture absolute differences. Thus, Gini indices could increase while absolute poverty decreases. Also, while two countries have similar Gini indices, it does not imply that their income distributions are similar.

Other authors use survey data. For example, Coibion et al. (2017) exploit the Consumer Expenditures Survey (CEX) to construct inequality measures in the United States. This approach allows to consider a higher frequency than the series of Gini coefficients<sup>9</sup> and other concepts of inequalities than income inequality. For instance, Coibion et al. (2017) analyze the effects of monetary policy on earnings, consumption and

---

<sup>8</sup> Mertens and Ravn (2013) use additional identifying restrictions to obtain the impulse responses to two shocks. They only identify one shock using the instrumental variables, while the other one is identified using common approaches.

<sup>9</sup> Gini coefficients are often available at an annual frequency.

expenditures inequality. Moreover, the use of survey data allows to construct measures to compare the evolution of different income groups (e.g., the top 10%, the bottom 50%, etc.), which is difficult with Gini indices because of the variables and parameters included in the formula. However, this method also involves disadvantages. In particular, it would be quixotic to assume that a survey of 1,500 to 2,500 interviewed households each month is representative of the population. Indeed, surveys are often self-reported, which means that they suffer from biases. Also, surveys are never random samples from the population and some segments of the population are often underrepresented (or, conversely, overrepresented). For instance, Mumtaz and Theophilopoulou (2017) use survey data from the Family Expenditure Survey (FES) to study the impact of monetary policy in the United Kingdom. The authors point out that the FES tends to overrepresent elderly and other categories, while the same survey underrepresents self-employed and younger households. Therefore, surveys often require the inclusion of weights assigned to each demographic category in order to correct sampling biases. Finally, one of the main concerns about the use of these surveys is that the top and bottom 1% of the distribution are not often analyzed, either because the authors trim them in order to avoid measurement errors or because the statistical agencies top-code the top 1% for anonymity issues. However, as shown earlier, the top 1% matters (Kenworthy and Smeeding, 2013).

Therefore, I use data from another source: the World Inequality Database (WID.world). This database provides series of income and wealth inequality measures. One of its great contributions is that it combines survey, fiscal and national accounts data for several countries. The authors can thus construct reliable series as this method exploits different data sources. In addition, the database captures the income distribution while being consistent with macroeconomic aggregates. In other words, it provides measures of average income for each quantile of the distribution. Moreover, the authors use similar computational methods<sup>10</sup> for several countries, which allows a certain comparability with future potential papers. However, a major limitation is that data are available at an annual frequency, which is less attractive than data from surveys that are often available at a

---

<sup>10</sup> Computational methods are deliberately omitted. One can find the details of the methods and concepts used in WID.world in Alvaredo et al. (2016), as well as in Piketty et al. (2016) for the United States.

quarterly or monthly frequency. While some authors attempt to overcome this problem by interpolating data at a higher frequency, I prefer avoiding this method because it artificially reduces data uncertainty but raises several concerns (e.g., the true data generating process is unknown). Therefore, I choose to avoid interpolation and use annual frequency data.

Also, I focus on income inequality, while WID.world provides series of measures of wealth and income inequality, sometimes also distinguishing between men and women. One of the main reasons is that some series span too short periods of time, which raises estimation problems. Furthermore, I consider measures of inequality splitting household income equally between different adults of each household and/or couple. These units are called by Alvarado et al. (2016) the “equal-split adults”. Obviously, as argued by Chiappori and Meghir (2015), income is rarely evenly distributed within a household. However, it is also uncommon for a household earner to keep their income for themselves without sharing it.<sup>11</sup> Finally, I use two main concepts: pre-tax national income and post-tax disposable income. Piketty et al. (2016) define pre-tax national income as “*the sum of all pre-tax personal income flows accruing to the owners of the production factors, labor and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of pension system*” (p. 9), while post-tax disposable income is defined as the pre-tax income plus the Social assistance benefits minus the net taxes on production, income and wealth. The use of data from WID.world may be questioned like any other data source. Some authors criticize the inclusion of certain elements in the concepts mentioned above.<sup>12</sup> However, each database has pros and cons. The measures are valid as long as the authors use a clear methodology and motivate their approach. Also, one should note that the absolute level of inequality is not critical in the analysis that follows. Indeed, since only the percentage change in inequality is of interest, the measures are legitimate forasmuch as they are constructed homogeneously over time and the errors affect all groups equally.

---

<sup>11</sup> As stated by Piketty et al. (2016), this approach would underrepresent the income available to non-working spouses.

<sup>12</sup> For instance, there are differences in level between the Gini indices published by the following organizations: World Bank, CIA, OECD and WID.world.

## B. Selected Instruments

I consider several instruments for monetary policy shocks. More specifically, I use two main series of shocks as instruments:<sup>13</sup>

- The narratively identified monetary policy shocks initially computed by Romer and Romer (2004). The authors derive a series of intended changes in the federal funds rate (FFR). Then, they regress these intended changes on the available information in order to obtain residuals representing shocks that are free of anticipatory actions and endogenous movements.
- The monetary policy shocks identified in Smets and Wouters (2007). The central bank follows a Taylor rule taking into account the output gap and inflation. The monetary policy shock is defined as the residual of the monetary policy reaction function.

The original series of Romer and Romer (2004) has monthly shocks from March 1969 to December 1996, while Smets and Wouters (2007) propose quarterly shocks from 1959:I to 2004:IV. The period of time covered by Smets and Wouters (2007) is longer, but is not fully exploited in this paper since inequality data are only continuously available from 1966. Also, in order to analyze the effects of monetary policy shocks after 1996 with a similar approach to Romer and Romer (2004), I use the re-estimated shocks computed by Wieland and Yang (2016) up to December 2007, instead of the original ones. I also use the series provided by Halperin (2013), to check the correspondence with the series developed by Wieland and Yang (2016). Halperin (2013) follows the same methodology as Romer and Romer (2004).

Since inequality data are annual, some transformations are needed in order to exploit the shocks in a low frequency SVAR. Indeed, the shocks of Romer and Romer (2004) are monthly, while those of Smets and Wouters (2007) are quarterly. Following

---

<sup>13</sup> The money supply shock constructed by Sims-Zha (2006) could be a potential proxy, but is dropped as it requires at least the inclusion of a monetary aggregate as an additional variable in the VAR. Other series are considered, but are not retained because of the small periods they cover when they are aggregated (e.g., Gürkaynak, Sack, and Swanson (2005) cover 15 years), raising concerns about the estimation.

Kilian (2009), I construct series of annual shocks by taking the average<sup>14</sup> of the shocks occurring in each year,

$$m_t = \frac{1}{i} \sum_{j=1}^i \hat{\pi}_{jt}, \quad j = 1, \dots, i \quad (19)$$

where  $i = 12$  if the original constructed shock  $\hat{\pi}_{jt}$  is monthly or  $i = 4$  if it is quarterly,  $m_t$  is the instrument of the year  $t$  and  $\hat{\pi}_{jt}$  is the original proxy shock of the month or quarter  $j$  in the year  $t$ . Undoubtedly, other methods of aggregation are available. For example, a shock occurring at a specific month or quarter could be considered as the annual shock or, in other words,

$$m_t = \hat{\pi}_{jt} \quad (20)$$

where  $j$  is a specific month or quarter. However, this procedure seems to lose a lot of information and depends heavily on the selected month or quarter. For instance, Romer and Romer (2004) regularly report shocks occurring in December (around FOMC dates), while January seems to be often free of shocks. I therefore decide not to use this method.

### C. Macroeconomic Variables

The VAR includes three macroeconomic variables<sup>15</sup>. In my benchmark model, I use the effective federal funds rate (FFR), a measure of the industrial production (IP) and the consumer price index (CPI). In the sensitivity analysis section, I also use other variables. For instance, I replace the industrial production index with either the real gross domestic product or the unemployment rate. I also replace the CPI by either the Producer Price Index (PPI) or the Personal Consumption Expenditures Price Index (PCEPI). Additional details and data source for each variable are reported in Appendix A.

---

<sup>14</sup> It is straightforward that taking the sum would not change the result of the impulse responses.

<sup>15</sup> All time series are seasonally adjusted, except for the federal funds rate. However, this is not a problem because interest rates do not normally have seasonality.

# V. Estimation and Results

## A. Specification

Inequality data are available from 1966 to 2014. However, to avoid non-stationarity concerns (which is likely given that some indicators have been increasing for several years), all variables are taken as percentage changes from the previous year, except the federal funds rate (FFR). More specifically, I do not use an approximation with logarithms, but the following precise formula:

$$\begin{aligned} \text{Percentage change in variable } i_t & \quad (21) \\ &= \frac{\text{variable } i_t - \text{variable } i_{t-1}}{\text{variable } i_{t-1}}. \end{aligned}$$

I avoid the use of logarithms since it only allows a good approximation for small changes. However, using annual data, it is likely that the changes are larger than those obtained with monthly variables. Moreover, I choose not to include the period after 2007. Indeed, the federal funds rate is close to zero during the Great Recession and there is a great use of unconventional monetary policies, which could lead to delicate analyzes. Also, the instruments are available over a period ending either in 2004 or 2007. Furthermore, I follow the approach developed by Gertler and Karadi (2015). To be more specific, the residuals of the reduced-form VAR are estimated over the entire period (i.e., transformed variables are available from 1967 to 2007), whereas they are then regressed on instruments that are available over shorter periods.

Eventually, my benchmark model includes 4 variables, which are the following:

$$Y_t = [FFR_t \quad \text{Industrial production}_t \quad \text{Consumer price index}_t \quad \text{Inequality}_t]'$$

where *Inequality*<sub>*t*</sub> is one of the income inequality measures. I choose to use a lag length of one lag. This choice may seem short, but is mainly motivated by the following two reasons. First, the exploited period does not allow to consider a large number of lags. Indeed, there are only 41 observations between 1967 and 2007, which means that the number of coefficients to be estimated should ideally be limited. Second, this choice is not

incongruous by using a battery of tests<sup>16</sup> to guide my choice. Information criteria propose either one or two lags, depending on the period considered (e.g., 1967–2007 or 1967–2004). Also, they are almost equal in both cases. Furthermore, my results are robust to the use of two and three lags, although the estimates are less precise.

## B. Instrument Choice

Table 2 presents the correlations between the measures of shocks. It can be seen that the correlations between the shocks identified by Smets and Wouters (2007) and those constructed with the Romer and Romer’s (2004) methodology are strong. It seems to indicate that the instruments identify the same shock to a certain extent. Moreover, the instruments computed using the Romer and Romer’s (2004) approach are highly correlated (i.e., the cross-correlations are close to 1), which is consistent since they are constructed in the same way.

*Table 2: Correlations Between Original Instruments*

	<i>SW</i>	<i>RR<sub>original</sub></i>	<i>RR<sub>Halperin</sub></i>	<i>RR<sub>Wieland&amp;Yang</sub></i>
<i>SW</i>	1.00			
<i>RR<sub>original</sub></i>	0.52	1.00		
<i>RR<sub>Halperin</sub></i>	0.60	0.95	1.00	
<i>RR<sub>Wieland&amp;Yang</sub></i>	0.54	0.98	0.97	1.00

Source: Author’s calculations. All instruments are first annualized by following the procedure in Section IV.B. *SW* corresponds to the monetary policy shock series from Smets and Wouters (2007), while *RR<sub>original</sub>*, *RR<sub>Halperin</sub>*, and *RR<sub>Wieland&Yang</sub>* correspond to the shocks computed by Romer and Romer (2004), Halperin (2013), and Wieland and Yang (2016), respectively.

As previously mentioned, instruments must satisfy three conditions to be valid. Mertens and Ravn (2013) propose an approach to ensure that the third condition<sup>17</sup> is met. The authors use F-tests to check whether lagged dependent variables (also called the

<sup>16</sup> Formally, I use the following: LR, AIC, HQIC and SBIC.

<sup>17</sup> Recall: the instrument must be uncorrelated with the history  $X_t$  (vector of lagged dependent variables, such that  $X_t = [Y_{t-1} \dots Y_{t-p}]'$ ), i.e.,  $E[m_t X_t'] = 0$ .

“history”  $X_t$ ) have a predictive power for the instruments. In other words, they regress the instruments on the history  $X_t$  and calculate F-statistics. Ideally, they want to obtain F-statistics that do not allow them to reject  $H_0$ . It is important to emphasize that this approach does not really correspond to a test. Indeed, while the rejection of  $H_0$  makes it possible to conclude that the lagged variables have a predictive power for the instruments, the nonrejection does not allow to conclude whether the history has predictive power or not.

**Table 3: Predictive Power of the Lagged Dependent Variables**

Instrument	(1)		(2)	
	F-statistic	Prob>F	F-statistic	Prob>F
<b><i>SW</i></b>	4.34	<b>0.01</b>	3.30	<b>0.02</b>
<b><i>RR<sub>original</sub></i></b>	1.50	0.24	2.27	<b>0.09</b>
<b><i>RR<sub>Halperin</sub></i></b>	1.00	0.40	1.17	0.34
<b><i>RR<sub>Wieland&amp;Yang</sub></i></b>	0.75	0.53	1.22	0.32

Source: Author’s calculations. In (1), the history is defined as  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI]'$ . In (2), the History is defined as  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI \ L.Post - tax\ disposable\ income\ Gini]'$ .  $L.var$  is the first lag of variable  $var$ . F-statistics are obtained by regressing each instrument on the history.<sup>18</sup>

In Table 3, I follow the approach of Mertens and Ravn (2013) in conducting F-tests. For all the results, I only use one lag of dependent variables due to the length of the data sample. I focus on only two different Histories: (1) includes all variables of  $Y_t$  except the inequality variable, while (2) includes these same variables, adding the post-tax disposable income Gini index as an inequality measure.<sup>19</sup> The null hypothesis of no predictability is rejected at a 5% significance level for both cases using the monetary policy shocks from Smets and Wouters (2007). When the inequality measure is included (i.e., (2)), it becomes possible to reject  $H_0$  at a 10% significance level by using the original

<sup>18</sup> F-statistics are calculated over slightly different periods since the instruments are not available over identical periods.

<sup>19</sup> It would be unfeasible to consider all possible cases since several inequality measures are used in the following analysis. Therefore, I deliberately keep it simple by using a benchmark inequality measure in this section.

shock from Romer and Romer (2004). Therefore, I conclude that some instruments seem to be correlated with their history. To tackle this problem, Mertens and Ravn (2013) propose to regress the instruments on the History  $X_t$ . Then, one should simply use the residuals of these regressions as new instruments. I follow this approach and create a new set of instruments that, by construction, are not predicted by the histories of macroeconomic variables (i.e., either (1) or (2)).

**Table 4: F-Statistics for Testing Instruments Strength**

Instrument	Original		(1)		(2)	
	F1	F2	F1	F2	F1	F2
<b><i>SW</i></b>	<b>11.25</b>	<b>15.21</b>	<b>16.65</b>	<b>23.01</b>	<b>17.02</b>	<b>22.36</b>
<b><i>RR<sub>original</sub></i></b>	1.62	4.11	1.64	4.87	2.07	3.24
<b><i>RR<sub>Halperin</sub></i></b>	2.96	9.01	3.31	<b>10.07</b>	2.97	8.16
<b><i>RR<sub>Wieland&amp;Yang</sub></i></b>	2.71	6.79	2.94	7.32	3.06	5.54

Source: Author's calculations. Three columns are provided : Original, (1) and (2). In Original, I use the original instruments. In (1) and (2), I use instruments corresponding to the residuals of the regression of the original instruments on  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI]'$  and  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI \ L.Post - tax\ disposable\ income\ gini]'$ , respectively. F1 is the F-test from the regression of the instrument on all residuals obtained with the reduced-form VAR, while F2 is the F-test from the regression of the residual of the FFR equation (obtained by estimating the reduced-form VAR) on the instrument.

In addition, Montiel Olea et al. (2012) suggest checking the value of two statistics: F1 and F2. These statistics can be computed as follows: F1 is the F-statistic of the regression of  $m_t$  on  $\eta_t$ , while F2 is the F-statistic of the regression of  $\eta_{1t}$  on  $m_t$ . Here  $\eta_t$  is the vector of residuals obtained with the reduced-form VAR including the variables  $Y_t = [FFR \ Industrial\ production \ CPI]'$ .<sup>20</sup> In Table 4, I present the values of these statistics with the three sets of instruments: the original instruments, as well as the instruments that are the residuals of the regressions of the original instruments on the Histories in cases (1) and (2). Staiger and Stock (1997) propose a rule of thumb in order to

<sup>20</sup> I do not provide the tests with  $Y_t$  including inequality measures since they are similar.

avoid weak instruments. The authors state that F-statistics should be greater than 10:<sup>21</sup> Otherwise, the constructed instruments might be weak. It can be seen in Table 4 that the instruments computed from Smets and Wouters (2007) have F-statistics systematically greater than 10. By contrast, instruments calculated using the Romer and Romer's (2004) approach are lower than 10 in almost all cases, which raises potential problems.

To conclude, the above analysis shows that the lagged dependent variables seem to have predictive power for the original instruments. Therefore, I compute new instruments that are not correlated with these lagged dependent variables. Then, by applying further tests on these variables, I find that the instruments from Smets and Wouters (2007) are not weak, whether they be orthogonal to their History or not. In the following analysis, I use the transformed Smets and Wouters (2007) series of monetary policy shocks (i.e., the series of uncorrelated shocks, in the case (1)). However, I then conduct several robustness checks and show that the results are similar by using untransformed shocks. Finally, I find similar results with the shocks of Romer and Romer (2004).

### C. Results and Discussion

As aforementioned, my benchmark model is estimated over the full-sample period (i.e., from 1967 to 2007) and incorporates the following variables:

$$Y_t = [FFR_t \quad \text{Industrial production}_t \quad \text{Consumer price index}_t \quad \text{Inequality}_t]'$$

where  $\text{Inequality}_t$  is a measure of inequality. In the following analysis, I use different inequality measures. Following Coibion et al. (2017), I begin by considering in Figure 1 two main inequality variables: the post-tax disposable income Gini index in column (A) and the post-tax disposable income difference between the top 10% and the bottom 10% in column (B). Then, I refine my study by analyzing the cumulative impact of monetary policy shocks on distinct income groups in order to capture differences between classes.

Before addressing inequality, I briefly comment on the behavior of the impulse responses<sup>22</sup> of macroeconomic variables. First of all, in Figure 1, it can be seen in both cases

---

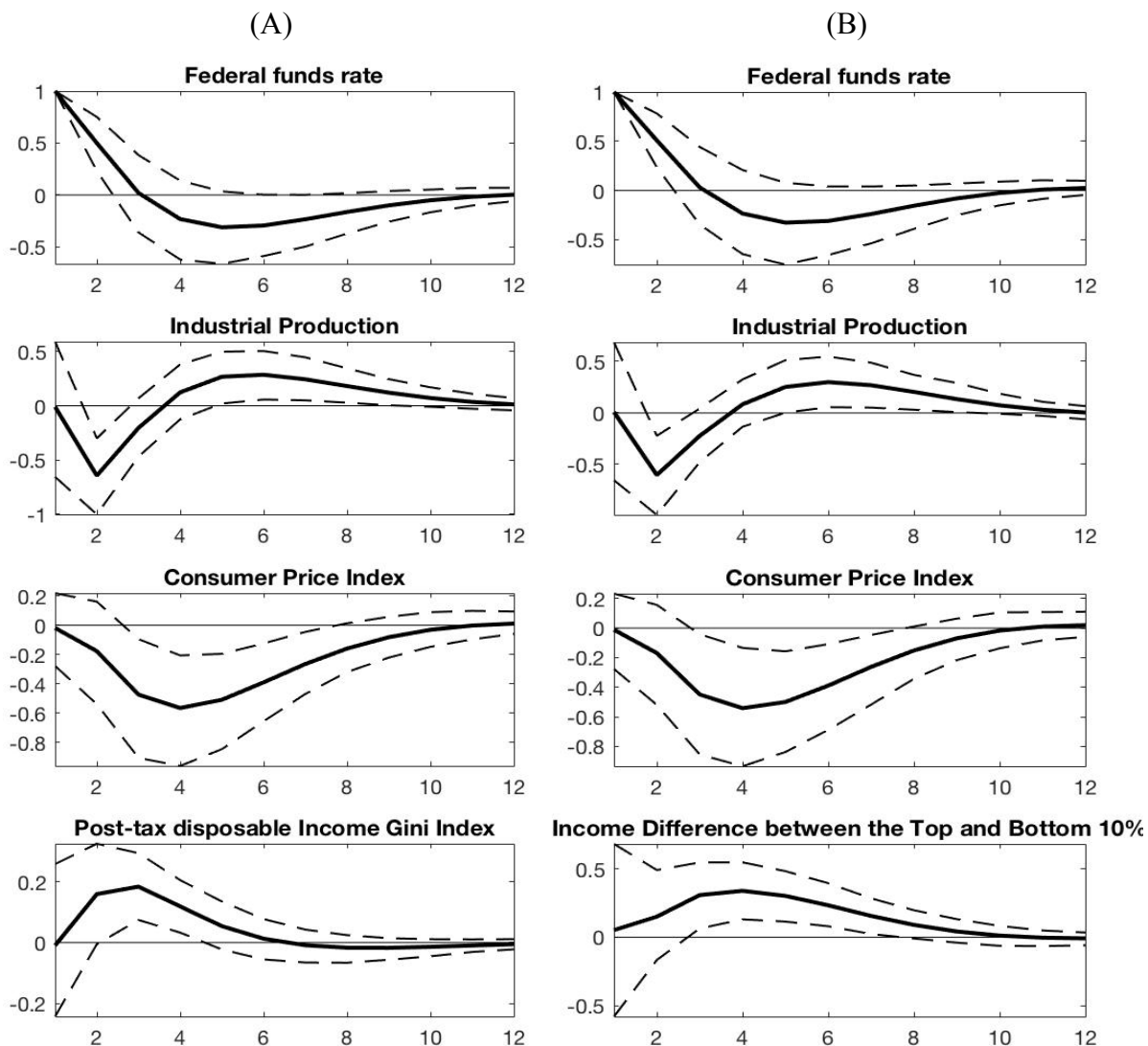
<sup>21</sup> This rule does not imply that instruments with F-statistics lower than 10 are weak.

<sup>22</sup> In Figure 1, I report 68% confidence intervals for impulse responses. I compute these confidence intervals using bootstrapping. The number of iterations is set to 10,000. Also, impulse responses are constructed over a 12-year horizon.

that a 100 basis points (i.e., 1 percentage point) contractionary monetary policy shock leads to a significant decline of the industrial production after 2 years. The industrial production index then increases very slightly during three years. However, the cumulative impulse response is negative, although tending to zero. Also, interestingly, I do not observe a price puzzle. More specifically, the consumer price index (CPI) decreases significantly in a near horizon, which corresponds to the expected behavior. Finally, the federal funds rate rises in the first periods, which is normal since the use of instruments implies an increase in the federal funds rate. More globally, the obtained results of the two models are highly similar and match expectations. In the “Robustness checks” section, I consider several changes to the model, leading to results that are in line with these impulse responses. Also, as I show later, the use of pre-tax variables yields results extremely similar to those obtained with post-tax data. Therefore, to ease the analysis, I focus on after-tax inequality variables.

By analyzing the impact of monetary policy on income inequality, one can observe that inequality measures significantly increase in the early period following a contractionary shock. These results are interesting to compare with some of those previously obtained by different authors. As mentioned earlier, Coibion et al. (2017) show that tight monetary policy shocks lead to higher inequality levels in the United States. By contrast, Davtyan (2017) finds opposite results. Clearly, my findings correspond to those obtained by Coibion et al. (2017). Several factors could explain the differences among the previous findings. For example, the approaches present divergences. Indeed, Coibion et al. (2017) use survey data, while Davtyan (2017) uses Gini indices from the OECD database. Another potential explanation is that the approach used by Davtyan (2017) has some shortcomings. For instance, the author interpolates quarterly variables from annual data, in order to use a Cholesky decomposition. It actually raises several problems (e.g., the data generating process is unknown). By contrast, the approach of Coibion et al. (2017) is robust to many changes, which seems to confirm the validity of the results. Therefore, I consider the results of Coibion et al. (2017) as the benchmark findings in the previous attempts to identify the impact of conventional monetary policy on inequality.

**Figure 1: Impulse Responses of Macroeconomic and Inequality Variables to Contractionary Monetary Policy Shocks**



Sources: Author's calculations. Instrument: Monetary policy shock from Smets and Wouters (2007), orthogonalized to the History  $X_t = [L.FFR \ L.Industrial \ production \ L.CPI]'$ .  $Y_t = [FFR \ Industrial \ production \ CPI \ Post - tax \ disposable \ income \ gini]'$  in (A).  $Y_t = [FFR \ Industrial \ production \ CPI \ Inc. \ Diff. \ between \ top \ 10\% \ and \ bottom \ 10\%]'$  in (B). Percentage values on Y-axis and years on X-axis.

In short, my results are consistent with those of Coibion et al. (2017). In other words, a contractionary monetary policy shock leads to a statistically significant rise in income inequality. Moreover, this increase is persistent over time: a shock is followed by higher long-term inequality levels. Finally, the macroeconomic aggregates of my model adequately respond to contractionary shocks, which supports the chosen methodology.

In the subsequent analysis, I use the same macroeconomic aggregates but add measures to capture changes between income groups. To be more specific, I report the cumulative impulse responses<sup>23</sup> of the average income of different classes. For instance, in Figure 2, the “0—10” class corresponds to the average income of adults<sup>24</sup> between the lower end and the 10<sup>th</sup> percentile of the income distribution. Also, I do not report the impulse responses of macroeconomic aggregates since they are almost identical to those plotted in Figure 1.

First of all, it can be observed that a contractionary monetary policy shock is followed by heterogeneous income responses among the different groups. In particular, while the average income of the bottom 10% (i.e., the “0—10” class) declines, the income of the other groups increases. More strikingly, the increase in income of the top 1% (i.e., the “99—100” class) is accompanied with the decrease of the bottom 10%. Moreover, it can be seen that the higher the income group, the higher the response of its average income. For instance, the accumulated median response of the “90—99” is above the response of the “50—90”. Also, the effects of contractionary monetary policy shocks are highly similar between groups “10—50” (not reported here) and “50—90”. It suggests that inequality is at least partly driven by the tails of the income distribution. Furthermore, although I do not plot confidence intervals in Figure 2, it is important to note that the results are statistically significant at a 68% confidence level in a majority of cases. To be more precise, the decline in income of the “0—10” is significant in the first periods, while the response becomes insignificant after seven years. A similar conclusion can be obtained with the “99—100”.

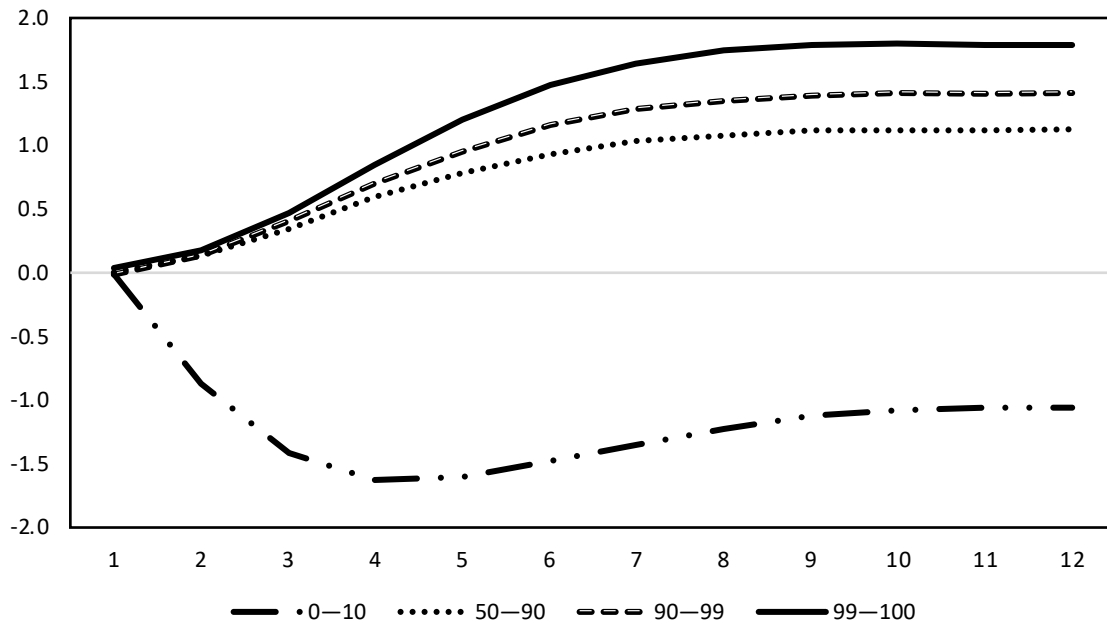
---

<sup>23</sup> I use cumulative responses rather than simple impulse responses in order to make it easier to compare results.

<sup>24</sup> As previously stated, I use “equal-split adults”. In other words, the household income is equally split between the adults of the household. It implies that this method controls for changes in the household composition over time, differences in bargaining power within households, and gender inequality.

By contrast, the rise in the groups “90—99” and “50—90” is statistically significant from the second period to the end of the horizon.<sup>25</sup>

**Figure 2: Distributional Effects of Contractionary Monetary Policy Shocks on Average Income (Post-tax Disposable Income)**



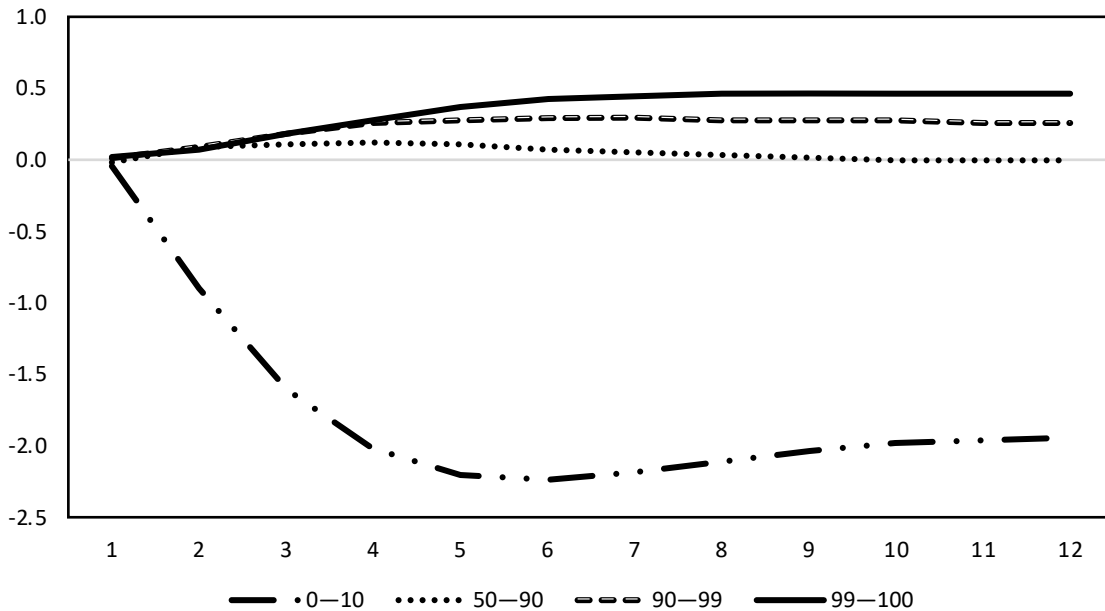
Sources: Author’s calculations. Median responses are reported without confidence intervals. Instrument: Monetary policy shock from Smets and Wouters (2007), orthogonalized to the History  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI]'$ . Only responses of average income are reported.  $Y_t = [FFR \ IP \ CPI \ Average\ income]'$ . Percentage values on Y-axis and years on X-axis.

Another useful measure of inequality to consider is the income share of the different groups. In Figure 3, I plot the impulse responses of these measures for the groups considered above. This measure is reasonable given that the average income of a group might increase after a monetary policy shock, while the income share decreases as the average income of other groups increases more. Again, the measures are taken as percentage changes. The results point to monetary policy shocks having heterogeneous impacts on income inequality. For instance, the income share of the bottom 10% drops more than their average income. It is quite logical since a contractionary monetary policy

<sup>25</sup> The same behavior is observed with the group “10—50”.

shock leads to a significant increase in income in the higher income groups, while the average income of the bottom 10% significantly decreases. It is thus straightforward that their income share falls further. It is also interesting to note that the response of the “50—90” group is not significantly different from zero.<sup>26</sup> Moreover, the median response even indicates a final value very close to zero, although slightly negative. As previously mentioned, the response of the “10—50” (not reported here) is similar to that of the “50—90” group. Therefore, although contractionary monetary shocks lead to an increase in the income of the groups “10—50” and “50—90,” the effect on the income share is around zero, which means that inequality is actually mainly driven by the tails of the distribution.

**Figure 3: Distributional Effects of Contractionary Monetary Policy Shocks on Income Share (Post-tax Disposable Income)**



Sources: Author’s calculations. Median responses are reported without confidence intervals. Instrument: Monetary policy shock from Smets and Wouters (2007), orthogonalized to the History  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI]'$ . Only responses of income share are reported.  $Y_t = [FFR \ IP \ CPI \ Income\ share]'$ . Percentage values on Y-axis and years on X-axis.

<sup>26</sup> Again, I do not report confidence intervals. The bottom 10% decline is permanent and statistically significant at 68%. By contrast, the responses of groups “90—99” and “99—100” lead to significant increases in the first periods, but then become uncertain. Finally, the response of the “50—90” is not statistically different from zero, like that of the “10—50” (not reported).

Briefly summarizing, my results point to contractionary monetary policy shocks leading to monotonic effects on the income distribution. These differences within the distribution have several potential explanations. For instance, one could argue that the income composition is not the same across the distribution. For example, according to CBO (2011), financial income and business income accounted for about 20% of the total income of the top 1% in 2007. However, as reported by the same source, this share decreases over time. By contrast, some income groups rely heavily on labor earnings, which might lead to divergent effects.

## D. Robustness Checks

In this section, I analyze the robustness of the results. Therefore, I consider several small changes in the model to assess whether the conclusions remain unchanged or not. To be more specific, I compare the above results with those obtained with the following modifications:

- **Change in the concept:** I replace the post-tax disposable income by the pre-tax national income. As previously stated, it can be seen in Figure 4 (Appendix B) that the results are highly similar, which leads to draw the conclusion that contractionary monetary policy shocks raise income inequality measures using both concepts. By reproducing the analysis by income group, I also obtain similar results leading to the same conclusions. Thus, I observe monotonic effects such that the higher the income group, the more it will be favored by contractionary shocks.<sup>27</sup>
- **Changes of instrument:** In the previous analysis, I use annualized shocks from Smets and Wouters (2007). However, the series of monetary shocks has been transformed to be orthogonal to the “shortened” History, that is:  $X_t = [L.FFR \quad L.Industrial\ production \quad L.CPI]'$ . As I show in Figure 5 (Appendix B), the results are extremely similar using either the original shocks (i.e., the Smets and Wouters (2007) series which is simply annualized) or the orthogonal shocks to the entire History (i.e., the series which is orthogonal to the History  $X_t =$

---

<sup>27</sup> The statistical significance of the cumulative responses varies slightly across income groups, as does the magnitude of the medians. However, these slight variations do not change the conclusion.

[*L.FFR L.Industrial production L.CPI L.Post – tax disposable income gini*]'). In Figure 6 (Appendix B), my Proxy-SVAR is estimated using the shock series from Halperin (2013) and Wieland and Yang (2016). I only report responses to original annualized shocks. That said, the responses to orthogonal shocks to the two Histories are, again, very similar. On the one hand, it is observed that inequality increases after a monetary policy shock. On the other hand, monetary tightening leads to a price puzzle. Although the Consumer Price Index (CPI) response is counterintuitive, the effect on inequality remains similar, confirming the above findings.

- **Changes in the number of lags:** Given the small number of observations, I cannot reasonably estimate a VAR with a large number of lags. That said, I test two different structures with 2 and 3 lags, respectively. Although the results are more uncertain, I reach the same conclusions.
- **Changes in macroeconomic variables:** In column (A) of Figure 7 (Appendix B), I replace the industrial production index by the unemployment rate. The results are in line with what is expected: the impulse response function of the unemployment rate increases when the impulse response function of the industrial production index decreases. I also use another potential candidate by replacing the industrial production index by a measure of real GDP and obtain results similar to the benchmark findings. Finally, in column (B) of Figure 7, I use a Personal Consumption Expenditures index instead of the CPI and still get similar results.

To conclude, these checks demonstrate that my results are robust to many changes. They lead to the same findings. Obviously, it would be interesting to test whether the chosen period influence the results. Unfortunately, this is impossible as it would significantly reduce the number of observations.

## VI. Conclusion

Over the past three decades, inequality has been rising in the United States. Although several studies have attempted to explain this increase, the potential role of monetary policy has only recently been considered. At least five channels through which

monetary policy could affect inequality have been identified, but the overall theoretical effect remains ambiguous. While three channels indicate that expansionary shocks tend to increase inequality, two other channels imply the opposite. Consequently, a few empirical studies have been carried out to determine the overall effect, but these come to divergent conclusions.

Therefore, I propose an alternative approach to assessing the effects of monetary policy shocks on income inequality in the United States. My contribution is twofold. First, I work with a recently introduced database that has been largely neglected. It allows me to study the impact of monetary policy shocks on different income groups, notably the top 1%. Second, I use a recently introduced method that, to the best of my knowledge, has never been used to assess inequality responses. More specifically, series of shocks are taken as proxies to identify monetary shocks in my SVAR. This approach requires only three hypotheses, which contrasts with the usual methods. Taking these elements into account, I show that contractionary monetary shocks significantly increase long-term inequality. This result is robust to several changes. Furthermore, by breaking the income distribution down into different income groups, I show that the income of the bottom 10% has a symmetrical response to the income of the top 1%. In other words, while the income of the top 1% increases after a contractionary shock, the income of the bottom 10% decreases. Finally, I show that the higher a group in the income distribution, the more it benefits from contractionary shocks. Thus, in the light of my findings, it is clear that the earnings heterogeneity channel and the savings redistribution channel have greater effects than the other channels, provided that the channels are correctly identified.

My findings suggest many opportunities for future research. First, the same analysis could be extended to evaluate the impact of monetary policy shocks on inequality in other countries. It is likely that the results would substantially depend on the choice of the considered countries, in particular because of structural differences. Second, my paper shows promising results using a Proxy-SVAR. However, these results depend on the availability of reliable series of shocks. Special attention should be devoted to the research for reliable instruments, allowing similar analyses to be carried out in Europe, for example. We are only at the beginning of major research advances.

## VII. References

- Albanesi, S., 2007. "Inflation and Inequality," *Journal of Monetary Economics*, Elsevier, vol 54(4), pages 1088-1114.
- Alvaredo F., A. B. Atkinson, L. Chancel, T. Piketty, E. Saez & G. Zucman, 2016. "Distributional National Accounts (DINA) Guidelines: Concepts and Methods used in the World Wealth and Income Database," WID.world Working Paper 2016/2.
- Bulir, A., 2001. "Income Inequality: Does Inflation Matter?" *IMF Staff Papers*, Palgrave Macmillan, vol 48(1), pages 139-159.
- Coibion, O., Y. Gorodnichenko, L. Kueng & J. Silvia, 2017. "Innocent Bystanders? Monetary Policy and Inequality," *Journal of Monetary Economics*, Elsevier, vol 88(c), pages 70-89.
- Congressional Budget Office, 2011. "Trends in the Distribution of Household Income Between 1979 and 2007," Publication 4031, Congress of the United States.
- Chiappori, P.-A. & C. Meghir, 2015. "Intrahousehold Inequality," in A.B. Atkinson and F. Bourguignon (eds.), *Handbook of Income Distribution*, vol 2, pages 1369-1418.
- Davtyan, K., 2017. "The Distributive Effect of Monetary Policy: The Top One Percent Makes the Difference," *Economic Modelling*, Elsevier, vol 65, pages 106-118.
- Doepke, M. & M. Schneider, 2006. "Inflation and the Redistribution of Nominal Wealth," *Journal of Political Economy*, vol 114(6), pages 1069-1097.
- Galbraith, J. K., O. G. Giovannoni & A. J. Russo, 2007. "The Fed's Real Reaction Function Monetary Policy, Inflation, Unemployment, Inequality – and Presidential Politics," *Levy Economics Institute Working Paper* 511.
- Galli, R. & R. van der Hoeven, 2001. "Is Inflation Bad for Income Inequality: the Importance of the Initial Rate of Inflation," *ILO Working Paper* 29, Employment Policy Department, International Labour Organization.
- Gertler, M. & P. Karadi, 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, vol 7(1), pages 44-76.
- Gürkaynak, R. S., B. Sack & E. T. Swanson, 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, vol 1(1), pages 55-93.
- Halperin, B., 2013, December 21. "Updated Romer and Romer (2004) Measure of Monetary Policy Shocks," Retrieved from <http://www.basilhalperin.com/blog/2013/12/updated-romer-and-romer-2004-measure-of-monetary-policy-shocks/>
- Hsing, Y., 2005. "Economic Growth and Income Inequality: the Case of the US," *International Journal of Social Economics*, vol 32(7), pages 639-647.
- Kang, S., Y. Chung & S. Sohn, 2013. "The Effects of Monetary Policy on Individual Welfares," *Korea and the World Economy*, vol 14(1), pages 1-29.

- Kenworthy, L. & T. Smeeding, 2013. "GINI Country Report: Growing Inequalities and their Impacts in the United States," GINI Country Reports.
- Kilian, L., 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, vol 99(3), pages 1053-1069.
- Laidler, D. & M. Parkin, 1975. "Inflation: A Survey," *Economic Journal*, Royal Economic Society, vol 85(340), pages 741-809.
- Ledoit, O., 2011. "The Redistributive Effects of Monetary Policy," Working Paper 44, Department of Economics, University of Zurich.
- Li, H. & H. Zou, 2002. "Inflation, Growth, and Income Distribution: A Cross-Country Study," *Annals of Economics and Finance*, vol 3, pages 85-101.
- Mertens, K. & M. O. Ravn, 2013. "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, vol 103(4), pages 1212-1247.
- Montiel Olea, J. L., J. H. Stock & M. W. Watson, 2012. "Inference in Structural VARs with External Instruments," Presentation Slides, Harvard University.
- Mumtaz, H. & A. Theophilopoulou, 2017. "The Impact of Monetary Policy on Inequality in the UK. An Empirical Analysis," *European Economic Review*, vol 98(c), pages 410-423.
- Nakajima, M., 2015. "The Redistributive Consequences of Monetary Policy," Federal Reserve Bank of Philadelphia, Business Review, Second Quarter, pages 9-16.
- Okun, A. M., 1975. "Equality and Efficiency: the Big Tradeoff," Brookings Institution Press, Washington, D.C.
- Piketty, T., E. Saez & G. Zucman, 2016. "Distributional National Accounts: Methods and Estimates for the United States," *The Quarterly Journal of Economics*, vol 133(2), pages 553-609.
- Rajan, R., 2010. "Fault Lines: How Hidden Fractures Still Threaten the World Economy," First Edition, Princeton University Press.
- Romer, C. & D. Romer, 1999. "Monetary Policy and the Well-Being of the Poor," *Economic Review*, First Quarter, pages 21-49.
- 2004. "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, vol 94(4), pages 1055-1084.
- Saiki, A. & J. Frost, 2014. "Does Unconventional Monetary Policy Affect Inequality? Evidence from Japan," *Applied Economics*, vol 46(36), pages 4445-4454.
- Sims, C. A., 1980. "Macroeconomics and Reality," *Econometrica*, vol 48(1), pages 1-48.
- Sims, C. A. & T. Zha, 2006. "Were There Regime Switches in U.S. Monetary Policy?" *American Economic Review*, vol 96(1), pages 54-81.

- Smets, F. & R. Wouters, 2007. “Shocks and Frictions in the US Business Cycles: A Bayesian DSGE Approach,” *American Economic Review*, vol 97(3), pages 586-606.
- Stock, J. H. & M. W. Watson, 2008. “Lecture 7 – Recent Developments in Structural VAR Modeling,” Presented at the NBER Summer Institute in the Lecture “What’s New in Econometrics: Time Series”.
- 2012. “Disentangling the Channels of the 2007-09 Recession,” *Brookings Papers on Economic Activity*, pages 81-135.
- Villarreal, F., 2014. “Monetary Policy and Inequality in Mexico,” MPRA Paper 57074, University Library of Munich, Germany.
- Wieland, J. F. & M. Yang, 2016. “Financial Dampening,” NBER Working Paper 22141, National Bureau of Economic Research, Cambridge, MA.

## I. Appendix A: Data

Variable/Instrument	Code of DBs	Source	Period	Trans.
Effective Federal Funds Rate	FEDFUNDS	(A)	1967–2007	0
Industrial Production Index	INDPRO	(A)	1967–2007	1
Real Gross Domestic Product	GDPC1	(B)	1967–2007	1
Unemployment rate	LNS14000024	(C)	1967–2007	0
Consumer Price Index	CPIAUCSL	(C)	1967–2007	1
Personal Consumption Expenditures Price Index	PCEPI	(B)	1967–2007	1
Producer Price Index	PPIACO	(C)	1967–2007	1
Inequality measures*	/	(D)	1967–2007	1
Romer and Romer (2004) Monetary Policy Shocks	/	Romer and Romer (2004)	1969–1996	2
— Re-estimated by Wieland and Yang (2016)	/	Wieland and Yang (2016)	1969–2007	2
— Re-estimated by Halperin (2013)	/	Series from Halperin's blog	1969–2007	2
Smets and Wouters (2007) Monetary Policy Shocks	/	King and Watson (2012)	1967–2004	2

\* : Inequality measures are not detailed but details can be obtained on [www.WID.world](http://www.WID.world)

### Sources:

(A): Board of Governors of the Federal Reserve System (US), retrieved from FRED.

(B): U.S. Bureau of Economic Analysis, retrieved from FRED.

(C): U.S. Bureau of Labor Statistics, retrieved from FRED.

(D): Piketty, T., E. Saez & G. Zucman, 2018. "Distributional National Accounts: Methods and Estimates for the United States," *The Quarterly Journal of Economics*, vol 133(2), pages 553-609. [Retrieved from WID.world].

### Transformations:

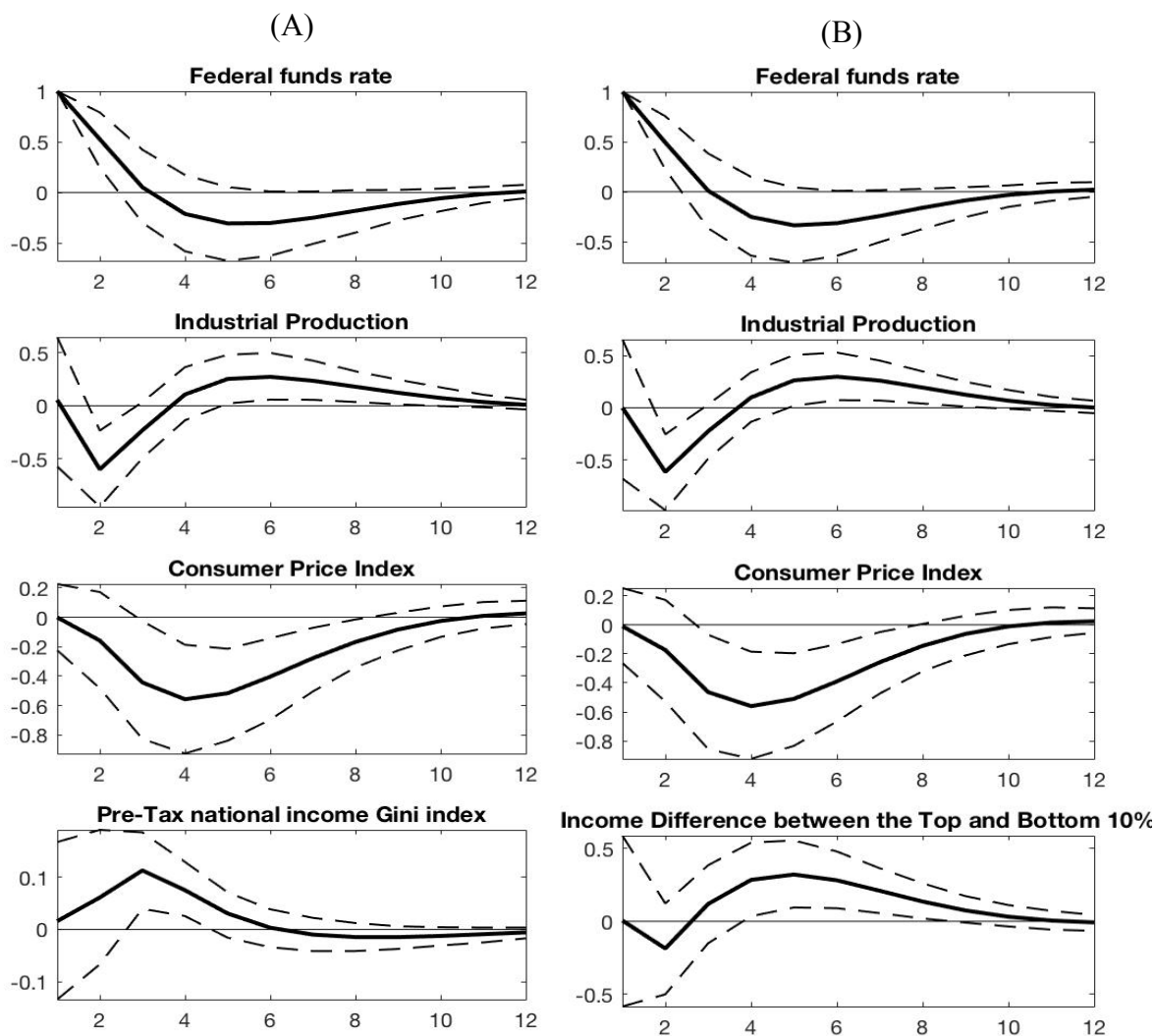
0: None

1: Percentage change

2: Shocks are annualized as discussed in Section IV

## II. Appendix B: Supplementary Material

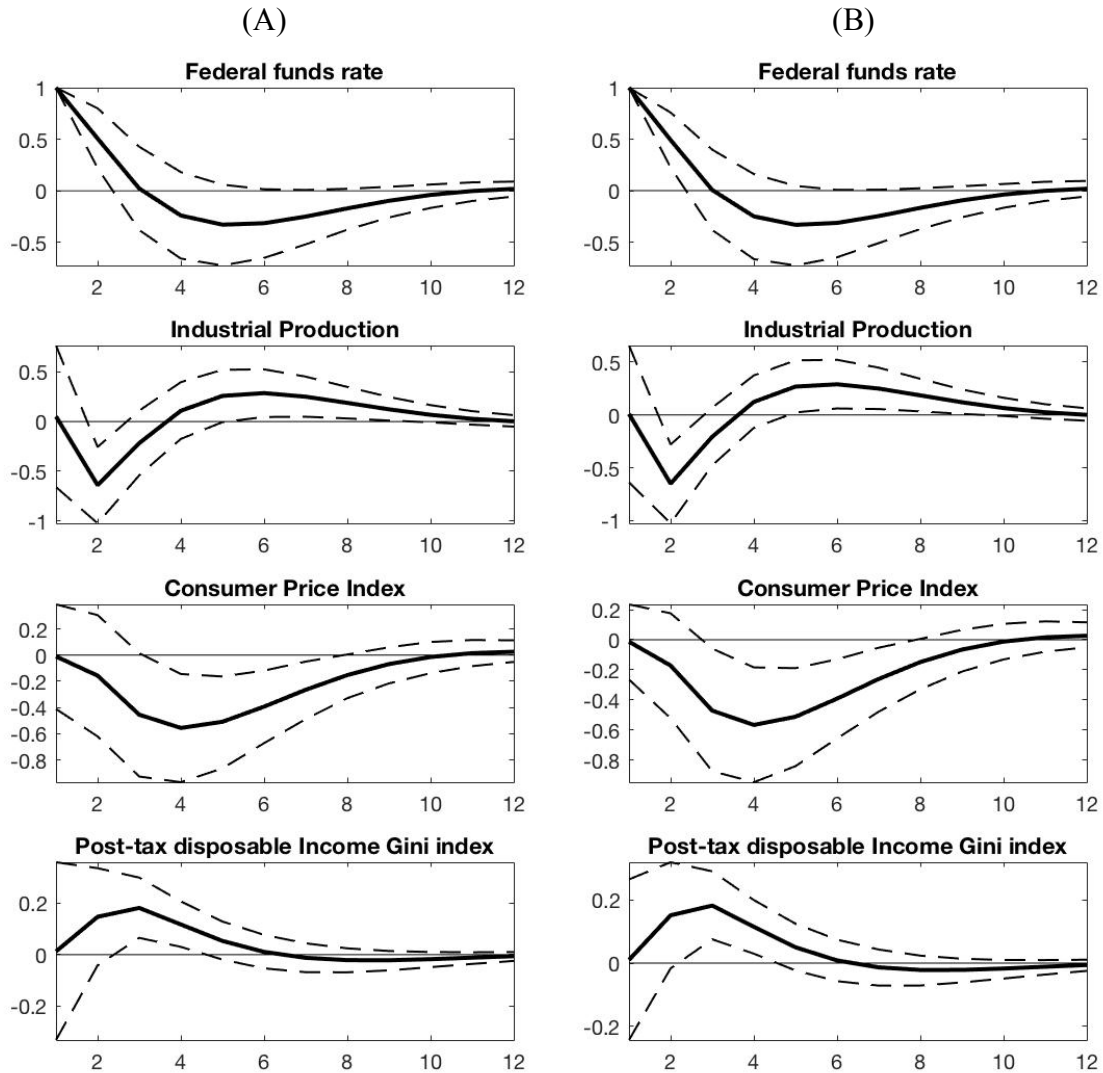
Figure 4: Robustness Checks Using Pre-Tax National Income



Sources: Author's calculations. Instrument: Monetary policy shock from Smets and Wouters (2007), orthogonalized to the History  $X_t = [L.FFR \ L.Industrial \ production \ L.CPI]'$ .  $Y_t = [FFR \ Industrial \ production \ CPI \ Pre-tax \ national \ income \ gini]'$  in (A).  $Y_t = [FFR \ Industrial \ production \ CPI \ Inc. \ Diff. \ between \ top \ 10\% \ and \ bottom \ 10\%]'$  in (B). Pre-tax concepts are used in both cases. Percentage values on Y-axis and years on X-axis.

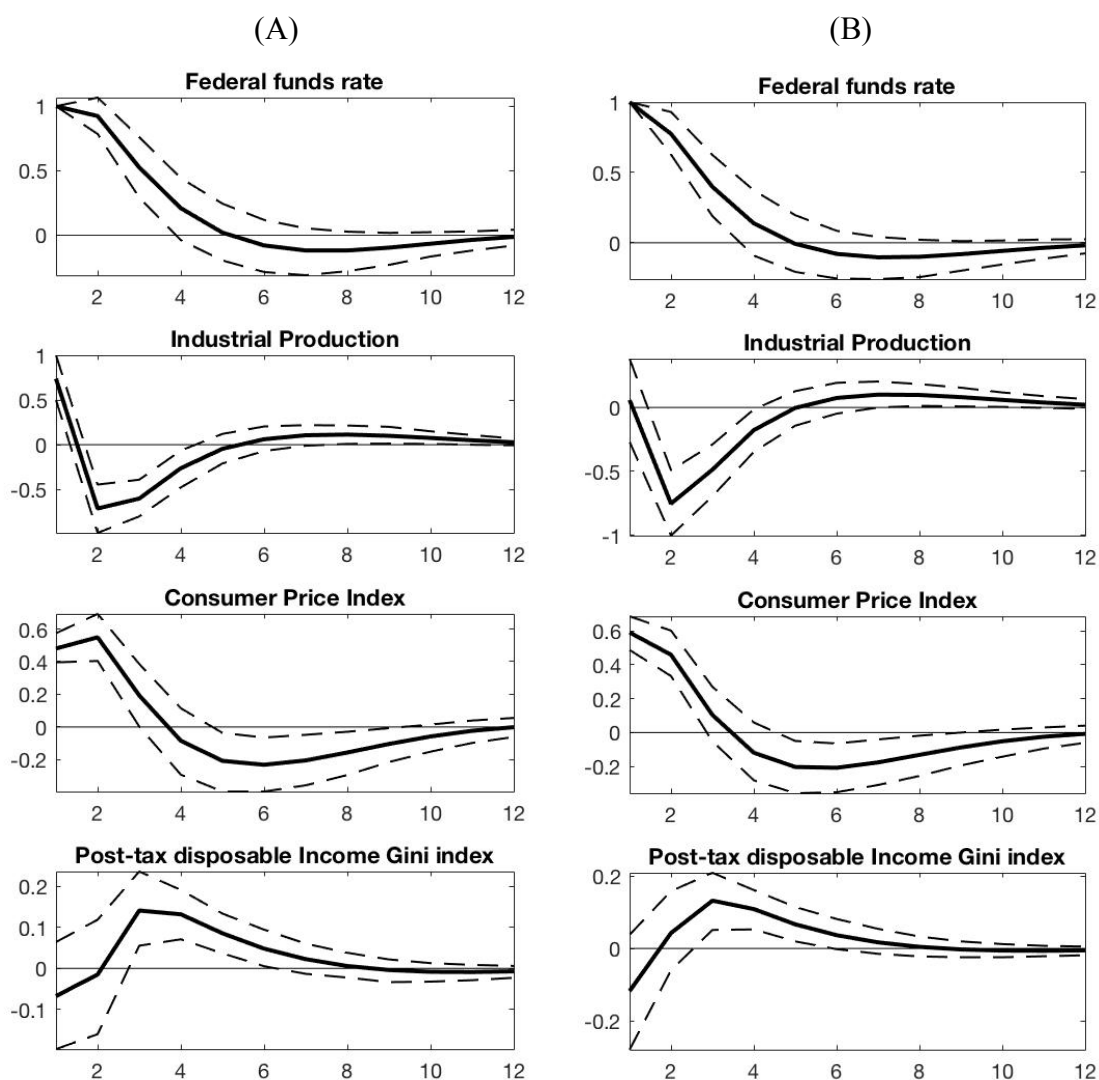
**Figure 5: Robustness Checks Using Smets and Wouters (2007)**

**Instruments**



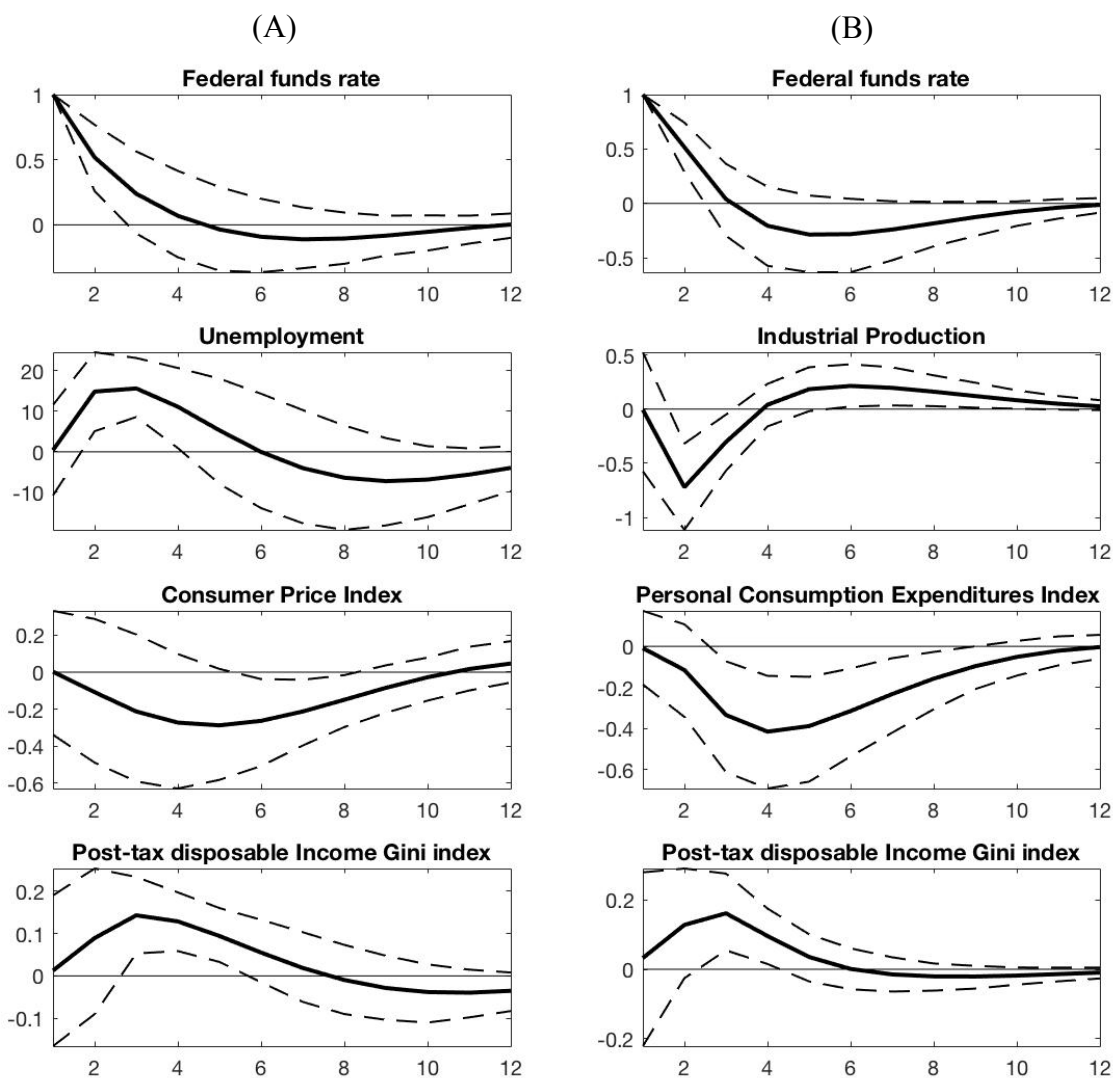
Sources: Author's calculations. In column (A), the original Monetary Policy shock from Smets and Wouters (2007) is used, while the orthogonal shock to  $X_t = [L.FFR \ L.Industrial\ production \ L.CPI \ L.Post - tax\ disposable\ income\ gini]'$  is used in column (B). Also,  $Y_t = [FFR \ Industrial\ production \ CPI \ Post - tax\ disposable\ income\ gini]'$ . Percentage values on Y-axis and years on X-axis.

**Figure 6: Robustness Checks Using Other Instruments**



Sources: Author's calculations. In column (A), the original Monetary Policy shock from Halperin (2013) is used, while the original Monetary Policy shock from Wieland and Yang (2016) is used in column (B). Also,  $Y_t = [FFR \text{ Industrial production} \text{ CPI} \text{ Post-tax disposable income gini}]'$ . Percentage values on Y-axis and years on X-axis.

**Figure 7: Robustness Checks Using Other Macroeconomic Variables**



Sources: Author's calculations. Instrument: Monetary policy shock from Smets and Wouters (2007). In column (A),  $Y_t = [FFR \text{ Unemployment rate } CPI \text{ Post-tax disposable income gini}]'$ . In column (B),  $Y_t = [FFR \text{ Industrial Production } PCEPI \text{ Post-tax disposable income gini}]'$ . Percentage values on Y-axis and years on X-axis.