Monetary policy and income inequality in the US - An empirical investigation

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Resumé

Dette speciale undersøger, hvordan pengepolitiske stød påvirker indkomstuligheden i USA. Undersøgelsen bygger på kvartalsdata fra perioden Q1 1999 til Q4 2023 og benytter to empiriske metoder: Structural Vector Autoregression (SVAR) og Bayesian Vector Autoregression (BVAR). Formålet er at analysere dynamikken mellem pengepolitik og indkomstulighed, samt at belyse hvilke mekanismer der driver denne sammenhæng. Som mål for pengepolitikken anvendes en skyggerente, som tager højde for både konventionelle og ukonventionelle pengepolitiske tiltag. Dette muliggør en konsistent analyse på tværs af perioder med forskellige pengepolitiske regimer, herunder perioder præget af nulrenter og kvantitative lempelser. Indkomstulighed måles ved to forskellige indikatorer: Gini-koefficienten, som indfanger den overordnede indkomstfordeling i samfundet, og S80/S20-ratioen, som måler forholdet mellem den samlede indkomst for de 20% rigeste og de 20% fattigste husholdninger. Ved at inkludere begge mål adresseres potentielle forskelle i, hvordan pengepolitiske stød påvirker forskellige segmenter af befolkningen. Resultaterne viser, at et kontraktivt pengepolitisk stød – defineret som en stigning i skyggerenten på 1 procentpoint – generelt har begrænsede og ofte statistisk insignifikante effekter på indkomstulighed. Dog ses enkelte signifikante resulater hvor Gini-koefficienten stiger, hvilket indikerer en stigning i den overordnede ulighed, mens S80/S20-ratioen falder, hvilket antyder, at forskellen mellem top og bund i indkomstfordelingen reduceres. Disse modsatrettede bevægelser fortolkes som resultatet af, at forskellige transmissionskanaler dominerer alt efter, hvilket ulighedsmål der benyttes. På baggrund af analysen konkluderes det, at faldende pengepolitiske renter i perioden ikke i sig selv har været den afgørende årsag til øget indkomstulighed i USA. I stedet peges der på mere strukturelle forhold, såsom stigende huspriser som en af årsagerne til højere indkomst indkomstulighed.

Contents

1 Introduction

Income inequality has been a growing concern in both academic and policy debates, particularly in the aftermath of the Great Recession of 2008. While fiscal policy has traditionally been the primary tool for addressing income disparities (OECD, 2024, pp. 92–93), the role of monetary policy in influencing inequality has received increasing attention in recent years. Recently, Rangvid (2025) has published a book highlighting how lower interest rates have fundamentally changed the world. One of his key arguments is that, since the 1980s, falling interest rates have contributed to rising income inequality, partly through higher asset prices and lower returns on savings — developments that have particularly disadvantaged lower-income households who rely more heavily on interest income from savings (Rangvid, 2025).

Central banks worldwide, including the Federal Reserve, have implemented unconventional monetary policies such as near-zero interest rates and quantitative easing (QE) to stimulate economic activity. However, these policies may have unintended distributional effects, potentially exacerbating or mitigating income inequality.

Understanding the broader consequences of monetary policy requires considering not only the tools employed, but also the objectives pursued by central banks. While monetary policy has often been considered neutral with respect to income distribution (Creel & Herradi, 2024), the specific mandates under which central banks operate may influence their potential impact on inequality. Whereas the European Central Bank (ECB) operates under a single mandate to ensure price stability, the U.S. Federal Reserve (Fed) has a dual mandate: to maintain stable prices and maximize employment (Froyen, 2013). This distinction raises important questions about the socioeconomic consequences of monetary policy, particularly its distributional effects.

A central mechanism through which monetary policy may influence inequality is the level of interest rates. Since the early 1980s, the effective federal funds rate — the primary instrument of U.S. monetary policy — has exhibited a pronounced downward trend, especially during periods of economic turmoil. Recognizing this trend is crucial, as it defines the macroeconomic environment within which debates about monetary policy and inequality unfold.

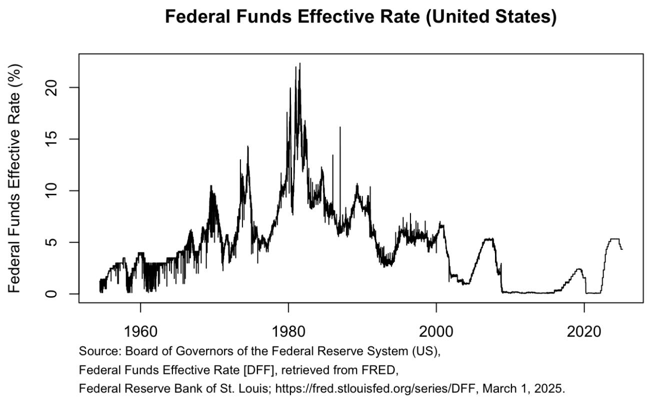

Figure 1: The Federal funds effective rate, source: FRED

As illustrated in Figure 1, the federal funds rate in the United States peaked in December 1980 and has followed a downward trend ever since. After reaching the zero lower bound in December 2008, it remained near zero until January 2016. A brief tightening cycle followed, peaking in April 2019, before rates were once again lowered.

The long-run decline in interest rates reflects several structural developments. In the early 1980s, inflation was brought under control by Federal Reserve Chairman Paul Volcker through aggressive monetary tightening. Since then, a combination of global factors has contributed to the sustained decline in interest rates. Demographic shifts, such as longer life expectancies and aging populations, have increased the overall savings rate. At the same time, lower inflation expectations and rising global demand for U.S. assets, particularly U.S. dollars as international reserves, have exerted further downward pressure on interest rates. This “cocktail” of forces has helped shape the current low-interest-rate environment (Bernanke, 2005; Froyen, 2013; Rangvid, 2025).

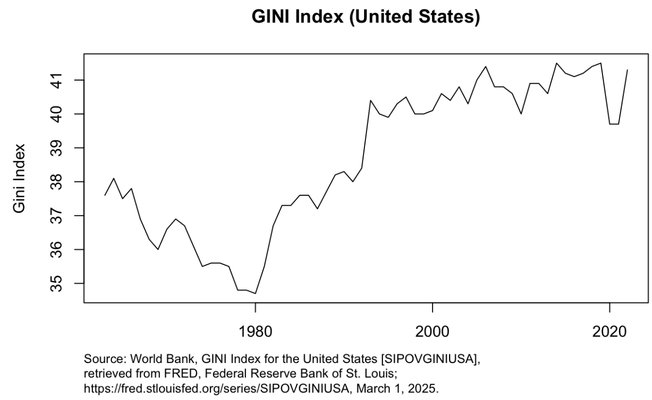

Figure 2: Gini Index for the United States, source: FRED

Figure 2 presents the Gini coefficient for the United States. The Gini coefficient measures the distribution of income across the population, with higher values indicating greater inequality. The figure shows that inequality reached its lowest point around 1980, coinciding with the peak in the federal funds rate. Since then, inequality has generally increased, even as access to credit has expanded. This temporal pattern suggests a potential link between monetary policy and the distribution of income.

One of the main reasons these findings are of interest is that lower interest rates reduce the cost of financing, making it cheaper for both households and firms to borrow. This, in turn, encourages firms to invest and expand, which increases labor demand and leads to more hiring. As employment rises, aggregate consumption increases due to higher income levels. Additionally, lower interest rates facilitate household consumption of credit-financed goods, for example, through lower credit card and mortgage interest rates. As firms expand and the labor market tightens, upward pressure on wages follows, which particularly benefits lower-income households. Consequently, income inequality may decline as a result of these mechanisms (McKay & Wolf, 2023). However the opposite is seen when looking at figure 1 and figure 2, maybe something else is at play. However, this theoretical mechanism appears to contrast with the patterns observed in figure 1 and figure 2, where declining interest rates coincide with rising income inequality. This discrepancy suggests that additional forces may be influencing the distributional effects of monetary policy.

The existing literature on this topic spans both the United States and the euro area, although some studies focus exclusively on one region. This paper aims to analyze the relationship between monetary policy and income inequality in the U.S. context. To achieve this, it will employ Structural VAR (SVAR), and Bayesian VAR (BVAR) models to explore the dynamic interactions between these variables. The methodological framework draws inspiration from *Income Inequality and Monetary Policy in the Euro Area* by Creel and El Herradi (2024), but it is adapted to fit the institutional and macroeconomic characteristics of the United States.

By contributing to the ongoing debate on the distributional effects of monetary policy and the effect on income inequality, this study seeks to provide insights that may inform future policy decisions. The findings could have important implications for central banks, policymakers, and economists aiming to balance macroeconomic stability with social equity.

2 Problem statement

The literature on monetary policy and income inequality has primarily focused on Europe, where several studies have used VAR and BVAR models to examine the relationship between central bank actions and inequality trends (Creel & Herradi, 2024) (Lenza & Slacalek, 2024). Many of these analyses reference earlier research from the United States (Coibion et al., 2017), but similar studies directly applying these methods to U.S. data are more limited.

To address this research gap, this report will analyze how monetary policy in the United States has influenced income inequality over the past 24 years. By employing SVAR, and BVAR models, the report will assess how different monetary policy measures have impacted income distribution over time. Based on this, the following research question is posed:

How has monetary policy affected income inequality in the United States?

3 Method

To analyze the problem statement, the following approach is applied.

The analysis begins by estimating a structural vector autoregressive (SVAR) model, which allows for tracing the transmission channels of monetary policy shocks. The SVAR framework is particularly suitable for this analysis, as it makes it possible to identify how a monetary policy shock propagates through the economy and affects income inequality.

Impulse response functions derived from the SVAR model are then examined. The baseline model, presented in Figure 5, serves as the starting point, followed by an extended model shown in Figure 6, which includes a more detailed specification of U.S. monetary policy. Both models are estimated using an SVAR(8) specification, selected for its empirical stability and compatibility with the Gini coefficient and the S80/S20 ratio. The impulse responses are first evaluated using the Gini coefficient as the inequality measure, after which the analysis is repeated using the S80/S20 ratio, with the inequality variable being the only change.

The same procedure is applied to the extended model: impulse responses are first calculated with the Gini coefficient and then with the S80/S20 ratio. The consistent use of the SVAR(8) specification across both models ensures the comparability of results.

To account for potential structural changes in the monetary policy regime over the sample period, the analysis is replicated using a Bayesian VAR (BVAR) model. In this setting, impulse responses are generated based on 50,000 posterior draws, with a burn-in period of 25,000 iterations. The initial values for the hyperparameters λ, μ, and δ follow the specification in Giannone et al. (2015), and are subsequently re-estimated to optimally fit each model variant. The selected hyperparameters, along with their economic interpretations, are reported and discussed for each case. The lag length is kept constant at 8 lags in all BVAR estimations to ensure consistency with the SVAR analysis.

Across all impulse response analyses, a standardized monetary policy shock of 100 basis points to the shadow rate is simulated, corresponding to a 1% increase. This standardization allows for coherent comparison of monetary policy effects on income inequality across model specifications.

4 Literature review

In this section, a selective review of the literature on income inequality and monetary policy is presented. The focus is on the methodological approaches, the formulation of research questions, and the conclusions drawn in the selected studies. While not exhaustive, the reviewed contributions provide valuable insights into the relationship between monetary policy and its implications for income inequality.

4.1 Innocent Bystanders? Monetary Policy and Inequality in the U.S.

Coibion et al. (2017) aims to estimate the effect of monetary policy on inequality. It uses both consumption and income inequality as measures to understand the heterogeneity of agents and the different transmission channels through which monetary policy impacts inequality.

To analyze the distributional effects of monetary policy, the researchers measure inequality using three approaches: the Gini coefficient, cross-sectional standard deviations of log levels, and differences between the 90th and 10th percentiles. This comprehensive approach enables them to capture various aspects of inequality, including overall distribution, dispersion, and extremes. They focus on pre-tax measures of income but also include after-tax income as a robustness check.

As independent variables, the study considers a wide range of macroeconomic factors influenced by monetary policy, including real GDP, unemployment rates, and house prices. They also examine different components of household income, such as labor earnings, financial income, business income, and transfer income, recognizing that households' income sources vary significantly. By including these components, the study accounts for the heterogeneous effects of monetary policy on different income groups.

The identification of monetary policy shocks is crucial to their analysis. The authors use the Romer and Romer (2004) method, which isolates monetary policy innovations by regressing changes in the federal funds rate on the Federal Reserve's real-time forecasts of GDP growth, inflation, and unemployment. These shocks are then incorporated into a local projection model, allowing the researchers to estimate dynamic impulse responses over different time horizons.

Their findings indicate that contractionary monetary policy leads to higher inequality, affecting both income and consumption inequality. The study suggests that using heterogeneous agents is essential when examining the implications of monetary policy. It also concludes that standard representative agent models significantly underestimate the welfare costs of zero-lower bound interest rates (Coibion et al., 2017).

4.2 Income inequality and monetary policy in the euro area

Creel and Herradi (2024) aim to explore the impact of the ECB's monetary policy between 2000 and 2015 on 10 EU countries. They use quarterly data; however, the inequality measures are either yearly or have missing quarterly observations. To address this issue, they transform the data using a Generalized Least Squares regression.

To perform a Panel-VAR analysis, the researchers use the Gini coefficient, the net Gini coefficient, and the S80/S20 ratio as their dependent variables to analyze income inequality extremes. As independent variables, they include real GDP, the consumption deflator, stock prices, the total employed population, a real house price index, the short-term nominal interest rate, and the shadow rate for the EU developed by Krippner(Krippner, 2020).

The reason for using two different measures of the short-term interest rate is that the nominal interest rate captures only conventional monetary policy, whereas the shadow rate captures both conventional and unconventional monetary policy.

In their analysis, they implement a +100 basis point IRF shock to both the nominal interest rate and the shadow rate to examine how this affects the income inequality measures and the other variables. Their results show that contractionary monetary policy increases income inequality. Although the results are statistically significant, the observed increases are relatively small (Creel & Herradi, 2024).

4.3 How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area

Lenza and Slacalek (2024) investigates the effects of quantitative easing (QE) on income and wealth inequality in the euro area. Their research builds upon a growing body of literature exploring the distributional impacts of monetary policy, particularly unconventional measures such as QE. The authors employ a two-step empirical approach.

First, they estimate the aggregate effects of QE using a multi-country Bayesian vector autoregression (BVAR) model, which includes macroeconomic and financial variables for four major euro area economies—France, Germany, Italy, and Spain. Their model identifies QE shocks via an external instrument approach, capturing the dynamic transmission of policy changes to key economic variables such as unemployment, wages, house prices, and stock prices.

Second, they utilize a reduced-form simulation on micro-level household data from the Household Finance and Consumption Survey (HFCS) to distribute the aggregate effects across individual households. This microsimulation accounts for three key transmission channels: the earnings heterogeneity channel, which captures the impact of employment gains for lower-income households; the income composition channel, which differentiates effects based on income sources (wages vs. financial income); and the portfolio composition channel, which examines the impact of asset price changes on household wealth.

A key finding of the study is that QE contributes to a modest reduction in income inequality. This effect is primarily driven by the earnings heterogeneity channel, as lower-income households experience employment gains, leading to a compression of the income distribution. The Gini coefficient for gross household income declines from 43.15% to 43.09% one year after a QE shock.

However, the study finds that QE has negligible effects on wealth inequality, as gains in stock prices (which favor wealthier households) are largely offset by increases in housing wealth, which is more broadly distributed. The study adds to the existing research by offering a detailed breakdown of how QE affects different household segments, going beyond earlier analyses that primarily examined conventional monetary policy.

While some studies have found that monetary policy can contribute to rising income inequality, others have highlighted varying effects depending on the context and transmission mechanisms. This study builds on these insights by considering both income and wealth dynamics, providing a broader perspective on how QE interacts with household heterogeneity.

While the effects of QE on inequality are found to be temporary, the paper highlights the importance of considering heterogeneity in the transmission of monetary policy. The results suggest that QE can provide short-term support to vulnerable households but is unlikely to be a major driver of long-term inequality trends, which are more influenced by structural factors such as globalization and tax policy (Lenza & Slacalek, 2024).

4.4 CENTRAL BANK POLICIES AND INCOME AND WEALTH INEQUALITY: A SURVEY

Colciago et al. (2019) reviews the literature on the relationship between central bank policy and economic inequality, focusing on both theoretical and empirical contributions. A new paradigm is presented, integrating models with price stickiness, incomplete markets, and household heterogeneity to better understand how inequality influences macroeconomic variables and how macroeconomic shocks and policies affect inequality. The paper outlines different channels through which monetary policy can impact the distribution of income and wealth. Among the most prominent are the income composition channel, where the primary sources of household income play a crucial role; the portfolio composition channel, where differences in asset holdings mean that wealthier households benefit more from rising stock prices; and the earnings heterogeneity channel, where wage and employment effects of monetary policy affect different population groups differently.

The literature does not reach a clear consensus. Some analyses suggest that accommodative monetary policy can reduce income inequality by increasing employment and wages among low-income households. Other findings indicate that expansionary monetary policy exacerbates inequality, primarily through rising stock prices, which disproportionately benefit the wealthiest households. Similarly, there are conflicting results regarding wealth inequality: while some analyses suggest that rising house prices can reduce inequality, others find that stock market gains contribute to a greater concentration of wealth at the top.

The paper highlights that the economic consequences of monetary policy on inequality depend on both transmission channels and economic structures. It emphasizes that future research should focus on general equilibrium models with heterogeneous agents, as these offer better tools for quantifying the exact mechanisms driving the distributional effects of monetary policy. Additionally, it underscores that the cyclical impact of monetary policy on inequality is relatively short-lived, while structural factors such as globalization and tax policy play a more significant role in shaping long-term inequality trends

(Colciago et al., 2019).

4.5 Summary of litterature review

The literature on monetary policy and income inequality does not reach a clear consensus on how central bank actions impact income and wealth distribution. Several analyses find that contractionary monetary policy increases inequality by reducing employment and suppressing wage growth for lower-income groups, while benefiting those with financial assets through higher interest rates. Other findings suggest that expansionary monetary policy can reduce inequality in the short term by boosting employment but may simultaneously increase wealth inequality through rising stock prices.

A key focus in the literature is the role of transmission channels. The earnings heterogeneity channel shows that low-income households are primarily affected through employment changes, while the portfolio composition channel highlights that wealthier households benefit from rising asset prices. Studies use different measures of inequality, including the Gini coefficient and percentile differences, but results vary depending on the methodology and data used.

Several studies find that income inequality declined during periods of accommodative monetary policy. However, there is broad consensus that monetary policy is not the primary driver of long-term inequality trends. Instead, structural factors such as globalization, taxation systems, and labor market institutions are generally considered to play a more substantial role in shaping income distribution over time.

Other studies in this field have reached similar conclusions. Using household data for Denmark covering the period from 1987 to 2014, Andersen et al. (2023) find that easing monetary policy has a substantial effect on income inequality. Samarina and Nguyen (2024) applies a panel VAR and local projection methods to data from 10 euro area countries between 1999 and 2014, and finds that expansionary monetary policy decreases income inequality . Similarly, Aye et al. (2019) use U.S. data from 1980 to 2008 in a local projections framework and conclude that contractionary monetary policy increases income inequality.

Overall, the literature points in different directions depending on the specific aspect of inequality being analyzed and the methods applied. Most studies conclude that monetary policy can have temporary effects on inequality, but long-term developments are primarily shaped by structural factors.

5 Data

To conduct the analyses in this project, data is required. One of the challenges in this regard is that researchers often rely on microeconomic data, as it allows for an examination of how agents are affected at the individual level, which can then be aggregated. However, in the literature review, there is an article that utilizes macroeconomic data for the euro area (Creel & Herradi, 2024). To align with this approach, this paper adopts their variable selection as a foundation for analysis. This choice is further supported by additional studies.

For measuring income inequality, both the Gini coefficient and the S80/S20 ratio are employed. To assess whether monetary policy influences income inequality, the following variables are included: GDP, inflation, unemployment, the monetary policy rate, the shadow rate and stock indices.

In the following sections, each variable and the rationale behind its selection will be described in detail.

Gini and S80/S20

The reason for using the Gini coefficient to analyze income inequality is that it serves as a measure of how evenly income is distributed within a society. Several studies employ this variable as the dependent variable, as it provides an economy-wide assessment of inequality (Coibion et al., 2017; Creel & Herradi, 2024; Lenza & Slacalek, 2024). However, this measure also has its limitations, as it captures inequality only at the aggregate level and does not account for heterogeneity among agents in the economy.

Heterogeneity among economic agents has been estimated for the euro area, and in this paper, this approach is extended to the United States. To better capture differences between high- and low-income groups, the Gini coefficient is supplementet with the S80/S20 ratio, which provides a more detailed perspective on income disparities. It is important to consider multiple measures of income inequality because of fundamental differences in income composition across groups. Lower-income households tend to be more hand-to-mouth and rely primarily on labor income, whereas higher-income households derive a larger share of their income from capital and financial assets.

As a result, lower-income groups are generally more sensitive to the business cycle, since labor income tends to fluctuate more during economic expansions and contractions. This makes these groups particularly vulnerable to monetary policy shocks compared to higher-income households, whose capital income is less directly tied to short-term economic fluctuations. Assessing such heterogeneity in income inequality makes it possible to analyze how different income groups respond differently to changes in monetary policy (Dossche et al., 2021, p. 99) , (McKay & Wolf, 2023).

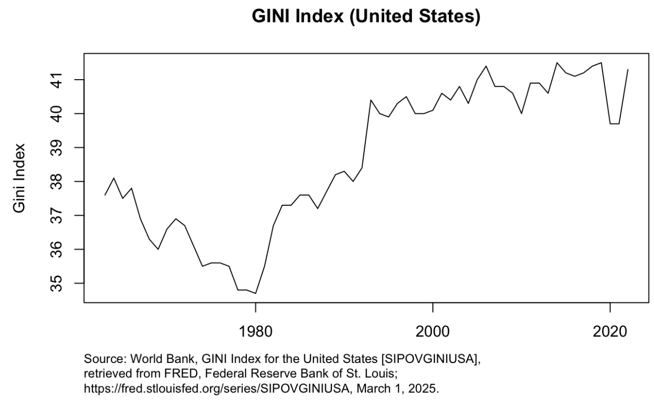

Figure 3: Gini Index for the United States, source: FRED

The Gini coefficient used in this project is obtained from the Federal Reserve Economic Data (FRED). This variable spans from 1963 to 2022 and is available on an annual frequency. However, to maximize the amount of data available, the variable is transformed into quarterly data using the Chow-Lin method. This approach is also applied in *Income Inequality and Monetary Policy in the Euro Area*, where the underlying assumption is that the Gini coefficient is a slow-moving variable over time Creel and Herradi (2024, p. 335).

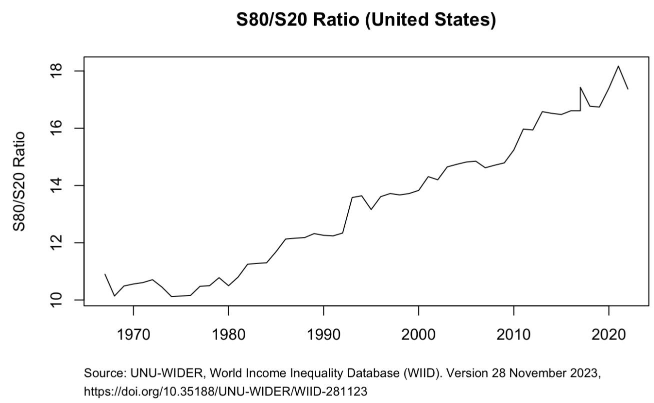

Figure 4: S80/S20 for the United States, source: UNU-WIDER

The variable used in this project to account for heterogeneity among economic agents is the S80/S20 ratio. This variable is obtained from the World

Income Inequality Database and measures the income disparity between the wealthiest 20% and the poorest 20% of the population.

The S80/S20 ratio is also employed to examine whether the effects of monetary policy disproportionately impact different income groups. While financial markets are more effectively utilized by high-income individuals, credit expansion under expansionary monetary policy can provide greater benefits to low-income households (Israel & Latsos, 2019).

Having addressed the measures of inequality, attention now turns to the broader economic indicators that guide monetary policy, beginning with real GDP.

Real GDP

As part of the dataset selection, GDP is incorporated, which represents the overall economic activity within the economy. The chosen time series is on a quarterly basis, measured in chained 2017 billion dollars, and seasonally adjusted. Given that the focus is on assessing how monetary policy influences income inequality, it is essential to include variables that the Federal Reserve considers when determining which monetary policy measures to implement. Among these is economic activity, as the Federal Reserve operates under a dual mandate: ensuring stable inflation and maximizing employment.

The rationale for including this variable in the dataset is also supported by previous research, as GDP is commonly used in related studies(Creel & Herradi, 2024; Lenza & Slacalek, 2024).

In addition to output, price stability is a central objective of the Federal Reserve. Consequently, inflation is appropriately included in the dataset.

Inflation

One of the Federal Reserve's mandates is inflation, which must be kept stable while simultaneously maintaining high employment (Froyen, 2013, p. 358). The measure of inflation used excludes food and energy and is reported as the Consumer Price Index (CPI). The data is quarterly, seasonally adjusted, and aggregated from monthly observations, with the quarterly measurement being the average of the three months within the quarter.

However, this measure differs from the approach used in the literature analyzing Europe, where the GDP deflator is commonly applied (Creel & Herradi, 2024; Lenza & Slacalek, 2024). Nevertheless, since the Federal Reserve considers this specific measure of inflation when setting its interest rate policy, it is used in this analysis instead.

Turning from one mandate to the other, unemployment represents the second pillar of the Federal Reserve's dual mandate. Including a measure of labor market performance is therefore an essential component of the variable selection.

Unemployment

Another mandate of the Federal Reserve is to maximize employment (Froyen, 2013, p. 358). The measure used for employment is the unemployment rate, where a low unemployment rate indicates high employment and vice versa. The selected time series is expressed as a percentage, seasonally adjusted, and aggregated from monthly to quarterly data, with the quarterly value representing the average of the three months.

The unemployment rate is chosen as it is also used in "How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area." In contrast, "Income inequality and monetary policy in the euro area" employs the total number of employed individuals as the measure (Creel & Herradi, 2024; Lenza & Slacalek, 2024).

With both pillars of the Federal Reserve's dual mandate now covered, attention turns to the central monetary policy tool known as the Federal Funds Effective Rate.

Federal Funds Effective Rate

The Federal Reserve—usually just called "the Fed"—sets the Federal Funds Effective Rate. This is a short-term policy rate and, in effect, the rate banks earn when they choose to deposit excess reserves with the Fed. Under its dual mandate, the Fed must strive simultaneously for maximum employment and price stability. Because economic data arrive with a lag, the Committee inevitably looks backward when assessing current conditions. At the same time, it must peer forward, doing its best to judge where the economy is heading. Using that assessment, the Fed adjusts the policy rate to accelerate or slow overall activity through the various monetary-policy transmission channels.

Conventional policy, however, runs into a hard constraint: the zero lower bound. Once the Fed's target rate is pushed all the way down to (or slightly below) zero, it cannot be cut further without triggering distortions in money markets and encouraging people simply to hold cash. In other words, the familiar tool of adjusting the federal funds rate loses traction, forcing policymakers to rely on less conventional measures when additional stimulus—or restraint—becomes necessary (Froyen, 2013).

Understanding how the Federal Funds Effective Rate affects the broader economy requires an examination of the transmission channels through which monetary policy operates.

Transmission Channels — Conventional

It is crucial to consider the monetary policy transmission mechanisms when analyzing interest rate changes, as they determine how monetary policy affects the economy. Expansionary monetary policy, characterized by lower interest rates, negatively impacts savers while benefiting borrowers. A decline in interest rates drives asset prices upward, as lower discount rates increase the present value of future cash flows from assets. This tends to benefit wealthier households, who hold a disproportionate share of financial assets.

At the same time, lower interest rates stimulate economic activity through several reinforcing mechanisms. Reduced borrowing costs encourage firms to invest in capital and expand their operations. This expansion increases labor demand, leading to higher employment levels and tightening labor markets. As firms compete for workers, upward pressure is placed on wages—especially in the lower segments of the income distribution, where slack is typically higher. In parallel, lower interest rates also reduce households' debt servicing costs, making it easier for them to finance consumption, particularly for durable goods. For example, lower credit card or mortgage rates increase disposable income for indebted households, enabling greater consumption.

These dynamics are particularly beneficial for lower-income households, who are generally more dependent on labor income and more likely to be financially constrained. As their employment and income prospects improve, aggregate consumption rises, reinforcing the economic recovery. Consequently, income inequality may decline due to the stronger relative gains experienced by these households. Although inequality is usually measured through income differences, the end goal for agents is utility, which is achieved through consumption. When inequality is reduced, especially for lower-income groups, their consumption possibilities improve (McKay & Wolf, 2023).

The direct effects of lower interest rates include a reduction in interest payments, particularly for those with variable-rate loans, while short-term savings instruments yield lower returns. Additionally, intertemporal substitution occurs, making saving less attractive and consumption more appealing. This leads to heterogeneous effects: individuals with liquid savings can quickly adjust their consumption, while those with illiquid or locked-in assets may respond more slowly.

The indirect effects of lower interest rates manifest through increased household consumption and higher business investment. As output rises, wages and employment increase, triggering a second-round boost to consumption. The size of this effect depends on whether the increased income accrues as wages or business profits, as different groups have different marginal propensities to consume (Dossche et al., 2021). As this example describes the effects of lower interest rates, the opposite mechanisms are at play when interest rates rise.

After having gone through the transmission channels of the Federal Funds Effective Rate, it is important to recognize that this rate is not the only instrument available to the Federal Reserve. In practice, the Fed has several tools at its disposal to conduct monetary policy. Therefore, it is relevant to include the Shadow Short Rate, which serves as an estimate of the overall monetary policy stance—particularly when conventional tools, such as the policy rate, are constrained.

Shadow Short Rate

The shadow rate is an estimated short-term interest rate designed for use during periods of unconventional monetary policy, when the conventional policy rate is constrained by the zero lower bound. It serves to capture the overall monetary policy stance by consolidating the effects of both conventional and unconventional measures into a single indicator.

In this analysis, the shadow rate developed by Krippner is employed. This approach offers consistency with conventional interest rates during normal times while also providing an interpretable equivalent rate under unconventional policy regimes. The measure incorporates various policy rates and reflects the central bank's forward guidance to financial markets (Krippner, 2020).

In order to understand the economic effects of the Shadow Short Rate, it is essential to explore the transmission mechanisms associated with unconventional monetary policy, which this measure is designed to capture.

Transmissionchannels - Unconventional

Unconventional monetary policy refers to measures undertaken by central banks when traditional policy tools, such as short-term interest rates, are constrained—typically by the zero lower bound. One common form of unconventional policy is large-scale asset purchases, also known as quantitative easing (QE), where central banks purchase government and corporate bonds. These interventions lower financing costs for both governments and firms, thereby facilitating more expansive fiscal policy and encouraging private sector investment. In turn, this can support job creation and economic growth.

There are two primary transmission channels through which unconventional monetary policy is believed to affect income inequality, though empirical studies reach conflicting conclusions.

The first is the earnings heterogeneity channel. Here, QE is argued to reduce income inequality by stimulating economic activity, leading to job creation and wage growth, particularly benefiting lower-income households.

The second is the income composition channel. This view holds that QE increases asset prices by lowering interest rates, thereby raising capital income disproportionately for wealthier households who hold a larger share of financial assets. As a result, income inequality rises.

Empirical evidence is mixed regarding which of these channels dominates. In the United States, studies suggest that the income composition channel tends to prevail, leading to an overall increase in inequality (Colciago et al., 2019).

After going through the transmission channels, it is relevant to turn to one of the first segments of the economy that tends to react to monetary policy decisions, namely the stock market. This is captured by the S&P 500 index, which also represents the final variable included in the dataset.

S&P 500

The S&P 500 index is included in the models as a proxy for stock market performance in the United States. It comprises the 500 largest publicly traded companies by market capitalization. The index is included to account for potential capital income received by economic agents through equity holdings. Furthermore, the stock market tends to respond immediately to monetary policy interventions, making it a relevant channel for the transmission of monetary policy shocks (Creel & Herradi, 2024, pp. 336–337).

6 Empirical methodology

Following the presentation of the dataset, this chapter outlines the empirical methodology used to examine the relationship between monetary policy and income inequality. All variables are expressed in log-levels, except for the income inequality measure, the unemployment rate, inflation, and the shadow rate (Creel & Herradi, 2024; Lenza & Slacalek, 2024). Although some of the variables may be integrated of order one (I(1)), differencing is not applied to achieve stationarity. This decision is based on two methodological arguments.

First, two of the variables are theoretical to be cointegrated. For instance, monetary policy systematically responds to inflation and unemployment dynamics, while financial markets, such as the stock market, react almost immediately to changes in monetary policy. Second, the income inequality variable evolves slowly over time, making it less volatile and more persistent by nature. Differencing the variables would remove these long-run relationships and reduce the model's ability to capture meaningful economic dynamics. As a result, working in levels preserves the long-term information embedded in the data, thereby improving the efficiency and interpretability of the estimation (Brooks, 2014; Enders, 2014).

In the constructed model, Krippner's shadow rate is used throughout the entire sample period. This approach captures both conventional and unconventional monetary policy measures within a single interest rate indicator, as the shadow rate reflects the stance of monetary policy even when the nominal policy rate is at or near the zero lower bound.

The model includes the following variables: income inequality (measured by the Gini coefficient and the S80/S20 ratio), real GDP, the unemployment rate, CPI excluding energy and food, the monetary policy rate based on the shadow rate and the S&P 500.

The time period chosen for the model follows the existing literature (Creel & Herradi, 2024; Lenza & Slacalek, 2024). Consequently, the time period for the model is set to Q1 1999 until Q4 2023.

The following sections are structured around three main parts: VAR, SVAR, and BVAR. The fundamentals of VAR are first reviewed, as they provide the necessary foundation for understanding and applying SVAR. This is followed by a presentation of the theoretical framework for SVAR, and subsequently, an introduction to BVAR.

6.1 VAR

To examine the relationship between multiple time series variables, Vector Autoregression (VAR) is commonly used. VAR models analyze how several variables influence each other simultaneously, while also capturing how their historical values affect current outcomes. With n variables, the system consists of n equations, each incorporating a specified number of lags. This is typically denoted as VAR(p), where p represents the number of lags.

When constructing a VAR model, certain assumptions are made—most notably, that the variables are stationary and do not contain deterministic trends. However, there is an ongoing debate regarding whether the variables should be differenced to achieve stationarity, as this can help eliminate long-term trends and external influences. The argument against differencing is that it may remove valuable information about long-run comovements and structural relationships, which are essential to understanding real-world economic dynamics. One of the strengths of estimating a VAR model in levels is precisely its ability to preserve these relationships (Enders, 2014, p. 291).

This thesis follows econometric theory and employs both log-level and level variables, rather than differencing them. As a result, selecting the optimal number of lags using the Akaike Information Criterion (AIC) becomes more complex, given the inclusion of non-stationary variables. In this case, the AIC suggests using 10 lags, which corresponds to 30 months or 2.5 years of data. Considering that the full sample consists of 100 quarters, using 10 lags would mean allocating approximately 10% of the available observations to lag structure, which is considered excessive. Moreover, testing the stability of the model using the roots of the characteristic polynomial reveals that the system is not stable when 10 lags are included.

To address this, and in line with the existing literature, 8 lags are selected instead. At this lag length, the model satisfies the stability condition and maintains the structural relationships without overfitting (Creel & Herradi, 2024).

Furthermore, because a standard VAR(p) model captures only reduced-form dynamics and includes both current and past effects, a Structural Vector Autoregression (SVAR) model is used instead(Enders, 2014).

For the sake of clarity, the VAR models is presented in a general form, which will later be transformed into SVAR models. Since a full reduced-form VAR with eight lags would take up considerable space, an illustrative example using a VAR(1) specification is provided.

The system consists of seven equations with seven endogenous variables. These variables are treated as the unknowns in the system. The notation for each variable is given below:

Table 1: Notation for the endogenous variables in the VAR model

Symbol	**Economic Variable**
y	Log real GDP
π	Inflation
u	Unemployment
r	Short term shadow rate
s	Log S&P 500
q	Income inequality (Gini and S80/S20)

The VAR(1) system is as follows:

$$y_t = \alpha_1 + a_{11}y_{t-1} + a_{12}\pi_{t-1} + a_{13}u_{t-1} + a_{14}r_{t-1} + a_{16}s_{t-1} + a_{17}q_{t-1} + \varepsilon_{1,t}$$
$$\pi_t = \alpha_2 + a_{21}y_{t-1} + a_{22}\pi_{t-1} + a_{23}u_{t-1} + a_{24}r_{t-1} + a_{26}s_{t-1} + a_{27}q_{t-1} + \varepsilon_{2,t}$$
$$u_t = \alpha_3 + a_{31}y_{t-1} + a_{32}\pi_{t-1} + a_{33}u_{t-1} + a_{34}r_{t-1} + a_{36}s_{t-1} + a_{37}q_{t-1} + \varepsilon_{3,t}$$
$$r_t = \alpha_4 + a_{41}y_{t-1} + a_{42}\pi_{t-1} + a_{43}u_{t-1} + a_{44}r_{t-1} + a_{46}s_{t-1} + a_{47}q_{t-1} + \varepsilon_{4,t}$$
$$s_t = \alpha_5 + a_{51}y_{t-1} + a_{52}\pi_{t-1} + a_{53}u_{t-1} + a_{54}r_{t-1} + a_{56}s_{t-1} + a_{57}q_{t-1} + \varepsilon_{5,t}$$
$$q_t = \alpha_6 + a_{61}y_{t-1} + a_{62}\pi_{t-1} + a_{63}u_{t-1} + a_{64}r_{t-1} + a_{66}s_{t-1} + a_{67}q_{t-1} + \varepsilon_{6,t}$$

This system can be equivalently represented in matrix form:

$$\begin{bmatrix} y_t \\ \pi_t \\ u_t \\ r_t \\ s_t \\ q_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} + \Phi_1 \begin{bmatrix} y_{t-1} \\ \pi_{t-1} \\ u_{t-1} \\ r_{t-1} \\ s_{t-1} \\ q_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \end{bmatrix}$$

Where

$$\Phi_1 = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \end{bmatrix}$$

Finally, the model can be represented in the following compact form:

$$\mathbf{Y}_t = \nu_0 + \Phi_1\mathbf{Y}_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{WN}(0, \Sigma_\varepsilon) \tag{1}$$

Where ε_t denotes a vector of structural shocks that are assumed to be independently and identically distributed with zero mean and covariance matrix Σ_ε.

When rewriting this as a VAR(8) model with eight lags, the equation becomes:

$$\mathbf{Y}_t = \nu_0 + \Phi_1\mathbf{Y}_{t-1} + \Phi_2\mathbf{Y}_{t-2} + \Phi_3\mathbf{Y}_{t-3} + \Phi_4\mathbf{Y}_{t-4} + \ldots + \Phi_7\mathbf{Y}_{t-7} + \Phi_8\mathbf{Y}_{t-8} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{WN}(0, \Sigma_\varepsilon) \tag{2}$$

Where eight lags is included for each endogenous variable along with their corresponding coefficient matrices.

6.2 SVAR

While standard VAR models capture dynamic correlations among variables, they are insufficient for isolating economically interpretable structural shocks.

To address this limitation, a Structural Vector Autoregression (SVAR) model is employed. SVAR models allow for contemporaneous relationships between variables to be identified through theoretically motivated restrictions, enabling a structural interpretation of impulse responses (Enders, 2014). These restrictions are introduced by specifying the order in which variables influence each other contemporaneously. To achieve exact identification of the system, it is necessary to impose a sufficient number of restrictions on the contemporaneous impact matrix. The required number of restrictions is determined by the following formula:

$$\frac{n(n-1)}{2} \tag{3}$$

Here, n represents the number of variables. In this case, there are 6 variables, which results in:

$$\frac{6(6-1)}{2} = 15 \tag{4}$$

This means that 15 restrictions are needed to fully identify the system. The identification strategy is typically achieved by imposing unit values (1s) on the diagonal of the impact matrix, which constrains the variables from influencing each other contemporaneously. This setup ensures that each variable only reacts to structural shocks in a predetermined order within the same time period (Enders, 2014).

Cholesky decomposition

The Cholesky decomposition matrix used in this thesis is structured according to the economic interpretation of the variables and in line with existing literature (Creel & Herradi, 2024, p. 342). Since all variables are expressed in log-levels—except for the income inequality measure, the unemployment rate, inflation, and the interest rate—the matrix is constructed accordingly:

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ l_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ l_{31} & l_{32} & 1 & 0 & 0 & 0 & 0 \\ l_{41} & l_{42} & l_{43} & 1 & 0 & 0 & 0 \\ l_{51} & l_{52} & l_{53} & l_{54} & 1 & 0 & 0 \\ l_{61} & l_{62} & l_{63} & l_{64} & l_{65} & 1 & 0 \\ l_{71} & l_{72} & l_{73} & l_{74} & l_{75} & l_{76} & 1 \end{bmatrix} \tag{5}$$

The ordering of the variables in the SVAR model is as follows:

$$\begin{pmatrix} \text{Income Inequality (Level)} \\ \text{Real GDP (Log)} \\ \text{Inflation (Level)} \\ \text{Interest Rate (Level)} \\ \text{S\&P 500 (Log)} \end{pmatrix}$$

Figure 5: The proprosed variable ordering by Creel & Herradi (Creel & Herradi, 2024, p. 336).

In the first Cholesky identification structure, the variable ordering follows the context of the euro area, where the European Central Bank (ECB) operates under a single mandate of price stability. This identification is the basis for the analysis by Creel and El Herradi, who investigate the effects of monetary policy on income inequality in the euro area. Although the United States follows a different monetary policy framework, this ordering is adoptede to ensure academic reproducibility and comparability with existing research. After applying this identification in the SVAR model, the specification is extended as follows:

$$\begin{pmatrix} \text{Income Inequality (Level)} \\ \text{Real GDP (Log)} \\ \text{Unemployment (Level)} \\ \text{Inflation (Level)} \\ \text{Interest Rate (Level)} \\ \text{S\&P 500 (Log)} \end{pmatrix}$$

Figure 6: Expanded with variables accounting for the Federal Reserve's dual mandate.

In this expanded model, the Federal Reserve's dual mandate is incorporated, explicitly including both unemployment and inflation as policy targets.

The identification strategy implies that macroeconomic aggregates such as output (real GDP) and financial markets (S&P 500 index) respond dynamically to monetary policy shocks. The ordering of variables reflects a hypothesized causal structure in the economy.

Real GDP (log) is placed early in the ordering because production typically impacts other economic variables such as employment and prices. Inflation is placed after output, recognizing that output developments influence price dynamics. The short-term interest rate, representing monetary policy, is placed after inflation to allow immediate reactions to economic conditions. The S&P 500 index follows the interest rate because asset prices quickly adjust to monetary policy changes.

Income inequality is placed first in the system. This reflects the assumption that inequality evolves slowly over time relative to other macroeconomic variables (Creel & Herradi, 2024). Thus, while inequality does not react within the same period to shocks in output, inflation, interest rates, and financial markets, it is allowed to adjust in the following periods.

in order to proceed a Cholesky decomposition is applied to identify our Structural VAR (SVAR) model.

$$\mathbf{B}_0 Y_t = w + \mathbf{B}_1 Y_{t-1} + \mathbf{B}_2 Y_{t-2} + \mathbf{B}_3 Y_{t-3} + \mathbf{B}_4 Y_{t-4} + ... + \mathbf{B}_7 Y_{t-7} + \mathbf{B}_8 Y_{t-8} + u_t \tag{6}$$

$$u_t \sim \mathrm{WN}(0, \Sigma_u) \tag{7}$$

The matrices $\mathbf{B}_i$ impose contemporaneous restrictions among the endogenous variables, thereby determining the structural relationships and the transmission of shocks within the same period.

6.3 BVAR

Building on the previously estimated VAR(8) model. The model is challenged by the relatively small sample size of approximately 100 observations, as well as by the fact that both conventional and unconventional monetary policies were conducted during the sample period. To account for the potentially different effects of these monetary policy regimes (Korobilis, 2025, p. 3), multiple samples are drawn. By averaging across these, the model avoids overparameterization and produces estimates that converge more closely to the true underlying parameters (Doan et al., 1984; Kuschnig & Vashold, 2021). A Bayesian VAR (BVAR) model is then estimated:

$$\mathbf{Y}_t = \nu_0 + \Phi_1 \mathbf{Y}_{t-1} + \Phi_2 \mathbf{Y}_{t-2} + \Phi_3 \mathbf{Y}_{t-3} + \Phi_4 \mathbf{Y}_{t-4} + ... + \Phi_7 \mathbf{Y}_{t-7} + \Phi_8 \mathbf{Y}_{t-8} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{WN}(0, \Sigma_\varepsilon). \tag{8}$$

In the BVAR framework, hyperparameters and their associated priors are explicitly specified. The Minnesota prior is employed, assuming that each variable follows a random walk process. The hyperparameters used are λ (tightness of the Minnesota prior), μ (sum-of-coefficients prior), and δ (single-unit-root prior). These are collected in the hyperprior γ, which is treated hierarchically. Specifically, initial values are assumed for these hyperparameters, while the model is allowed to optimize them in response to the data. Following the literature, the initial values for λ, μ, and δ is set to 0.2, 1, and 1 respectively. The corresponding standard deviations are set to 0.4, 1, and 1 (Giannone et al., 2015, p. 440).

To anchor the prior specification in the observed data, Bayes' law is applied:

$$p(\gamma \mid \mathbf{y}) \propto p(\mathbf{y} \mid \boldsymbol{\theta}, \gamma)\, p(\boldsymbol{\theta} \mid \gamma)\, p(\gamma) \tag{9}$$

$$p(\mathbf{y} \mid \gamma) = \int p(\mathbf{y} \mid \boldsymbol{\theta}, \gamma)\, p(\boldsymbol{\theta} \mid \gamma)\, d\boldsymbol{\theta} \tag{10}$$

The first equation expresses the posterior distribution of the hyperparameters γ given the data $\mathbf{y}$, as proportional to three components: the likelihood of the data conditional on the model parameters and hyperparameters $p(\mathbf{y} \mid \boldsymbol{\theta}, \gamma)$, the prior of the model parameters given the hyperparameters $p(\boldsymbol{\theta} \mid \gamma)$, and the prior of the hyperparameters themselves $p(\gamma)$. In other words, the model updates the beliefs about γ using both the observed data and prior assumptions.

The second equation is the marginal likelihood of the data given the hyperparameters γ, obtained by integrating over all possible values of $\boldsymbol{\theta}$. This step makes it possible to find the hyperparameters that best explain the observed data.

The three components of the hyperprior γ — λ, μ, and δ — have the following interpretations: if $\lambda \to 0$, the model places more weight on the prior, and the posterior distribution approaches the prior. Conversely, as $\lambda \to \infty$, more weight is placed on the data, and the influence of the prior diminishes. Regarding μ, if $\mu \to \infty$, the prior becomes uninformative. If $\mu \to 0$, the model is pulled toward a specification with as many unit roots as variables, implying no cointegration. The interpretation of δ is similar: if $\delta \to \infty$, the variables are pulled toward their unconditional mean, while if $\delta \to 0$, the model assumes the presence of at least one unit root and allows for cointegration (Kuschnig & Vashold, 2021).

Having laid this methodological foundation, it is now possible to proceed with the empirical analysis.

7 Empirical Results

This chapter presents the empirical findings from the structural vector autoregressive (SVAR) and Bayesian VAR (BVAR) models used to investigate the effects of monetary policy on income inequality. The analysis begins with the examination of impulse response functions (IRFs) derived from the SVAR model, with a particular focus on the dynamic impact of a contractionary monetary policy shock, specifically, an increase in the shadow rate on income inequality.

Subsequently, the same analysis is conducted within a Bayesian VAR (BVAR) framework. The motivation for this lies in the structural changes in monetary policy observed during the sample period, including a shift from conventional to unconventional tools. The BVAR model, by incorporating prior information and allowing for greater flexibility, is particularly well-suited to account for such regime shifts.

Finally, to ensure the reliability of the results, the empirical findings from both the SVAR and BVAR models are subjected to a series of validation checks. These include stability tests, assessments of residual properties, and Bayesian-specific diagnostics. This step is crucial to verify that the estimated IRFs can be interpreted with confidence.

7.1 SVAR - results

In the following chapter the impulseresponses from the SVAR model will be interpret and analyzed.

The analysis begins with the model presented in Figure 5, followed by an examination of the corresponding impulse responses.

The first scenario involves a 100 basis point shock to the shadow interest rate, and the resulting impulse responses are assessed.

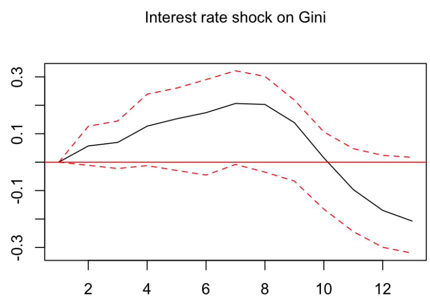

Figure 7: Impulse response of the Gini coefficient to a 100 basis point increase in the shadow interest rate. The solid line shows the point estimate, while dashed red lines represent 90% confidence intervals.

It can be observed from the model that the impulse response is not statistically significant at the 90% confidence level. However, the trajectory of the impulse response indicates that following an initial 1% increase in the shadow rate, the Gini coefficient tends to rise, implying an increase in income inequality. Over time, this effect appears to reverse, with inequality eventually declining after the monetary policy shock. Nevertheless, as the responses are not statistically significant, these patterns should be interpreted with caution.

One possible explanation for the muted response is the Federal Reserve's dual mandate, which requires monetary policy to balance price stability with maximum sustainable employment. Hence, even when interest rates are raised, measures may be taken to prevent substantial increases in unemployment, thereby mitigating effects on inequality.

Overall, based on this impulse response, there is no clear evidence that monetary policy has a significant effect on inequality. Alternatively, the lack of significance may reflect underlying heterogeneity among economic agents, which blurs the aggregate relationship.

To further investigate this, the same impulse response exercise is replicated, but the Gini coefficient is replaced with the S80/S20 ratio as an alternative measure of income inequality.

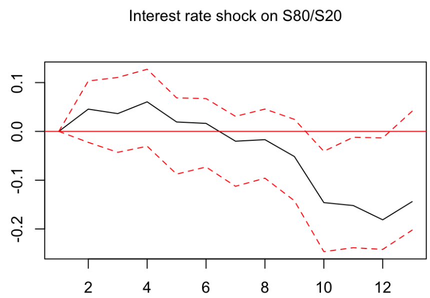

Figure 8: Impulse response of the S80/S20 coefficient to a 100 basis point increase in the shadow interest rate. The solid line shows the point estimate, while dashed red lines represent 90% confidence intervals.

Statistically significant results in the impulse response functions are observed. However, this significance emerges only after 9 to 10 quarters following the initial shock, which is consistent with the notion that income inequality adjusts slowly over time. Before this point, the responses are not statistically significant at the 90% confidence level.

Interestingly, the results after 9–10 quarters indicate an effect that is opposite to what is commonly expected: higher interest rates are typically thought to dampen economic activity, which would normally be associated with increasing inequality. However, considering the transmission mechanisms of monetary policy, it is known that higher interest rates transfer income from borrowers to savers, which could explain the observed decline in inequality. This means that the 20% with lowest income benefit from higher income from fixed income investments. However this means that the income composition channel is stronger than earnings heterogeneity channel, as income inequality lowers.

Nonetheless, it may be necessary to fully integrate the Federal Reserve's dual mandate into the Cholesky decomposition and the broader model to better capture these dynamics.

In order to proceed the Cholesky identification is modified to explicitly account for the Fed's dual mandate as shown in *figure 6*.

Figure 9: Impulse response of the Gini coefficient to a 100 basis point increase in the shadow interest rate. The solid line shows the point estimate, while dashed red lines represent 90% confidence intervals.

An impulse response has been generated using the revised Cholesky ordering. As before, a 1% increase in the shadow interest rate is used as the monetary policy shock, and the analysis examines its effect on income inequality, as measured by the Gini coefficient.

It can be observed that approximately four quarters after the shock, inequality rises, and this increase is statistically significant at the 90% confidence level. However, the significance disappears again before six quarters have passed.

Interestingly, just before 12 quarters have elapsed, inequality declines, and this decrease is also statistically significant at the 90% level. This finding is again contrary to conventional expectations and is the opposite of the effect observed around four quarters after the shock. Moreover, the magnitude of the decline in inequality appears larger than the magnitude of the earlier increase.

To further investigate the role of agent heterogeneity, the Gini coefficient is replaced with the S80/S20 ratio as an alternative measure of inequality.

Figure 10: Impulse response of the S80/S20 coefficient to a 100 basis point increase in the shadow interest rate. The solid line shows the point estimate, while dashed red lines represent 90% confidence intervals.

An impulse response have been generated where the shadow rate is raised by 1% and it id examined how the S80/S20 ratio responds. This time, the picture is somewhat more ambiguous. Once again, the overall trend indicates that an increase in the shadow interest rate leads to a decline in inequality. However, these results are only statistically significant at the 90% confidence level in the 10th and 12th quarters following the initial shock.

Overall, the results from the SVAR analysis point to a conclusion that diverges from much of the recent literature. However, the findings are consistent with the claims made by Rangvid (2025), namely that accommodative monetary policy leads to rising asset prices, which tend to widen income inequality, as financial assets are predominantly held by wealthier households, while lower-income households primarily hold deposits (Rangvid, 2025, p. 107). When monetary conditions tighten and asset prices fall, this effect is reversed. It is observed, both using the Gini coefficient and the S80/S20 ratio, that inequality decreases when the shadow interest rate rises because lower income groups is more reliant on interest income (Rangvid, 2025, p. 96).Overall, the evidence suggests that the income composition channel plays a prevailing role in the transmission of monetary policy to income inequality which is also prevailed in (Colciago et al., 2019, pp. 1212–1213).

It is also important to note that the estimation period for the impulse responses covers several distinct monetary policy regimes, ranging from periods focused on stimulating inflation to periods aimed at suppressing inflation. These structural changes in monetary policy may have influenced the dynamics observed in the model.

Given these findings and the potential impact of time variation in the monetary policy framework, it would be valuable to proceed with a BVAR (Bayesian VAR) analysis. A BVAR could allow for more flexibility in capturing changes over time and offer a robustness check for the results obtained with the SVAR model.

7.2 BVAR

In order to address the presence of different monetary policy regimes over the past approximately 26 years, a BVAR framework is employed, allowing for greater flexibility and robustness in capturing potential time variation in the transmission mechanisms affecting inequality. The model is estimated using a Gibbs sampler with 50,000 draws, discarding the first 25,000 as burn-in to ensure convergence and reduce sensitivity to initial values.

The first model

As a starting point, the initial model is estimated as shown in *figure 5*, and assess its implications for the income inequality indicators.

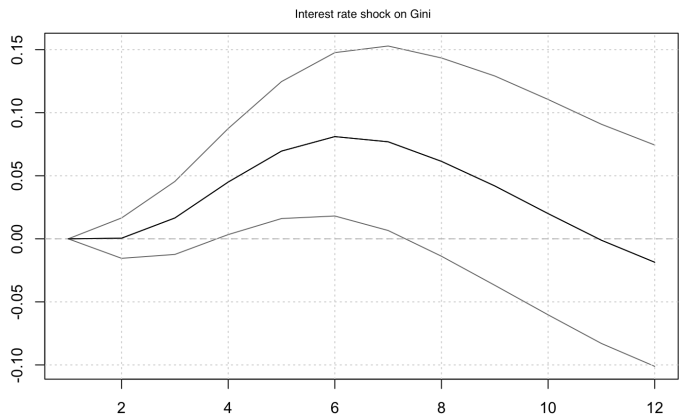

Figure 11: Impulse response of the Gini coefficient to a 100 basis point increase in the shadow interest rate. The solid black line shows the point estimate, while gray lines represent 90% confidence intervals. $\lambda = 0.745, \mu = 0.258$ and $\delta = 0.217$

The first estimation of a 1% increase in the shadow rate on the Gini coefficient is consistent with the existing literature. It shows that, starting from the 4th quarter and lasting until approximately the 7th quarter after the shock, there is a statistically significant effect on the inequality measure. This finding suggests that monetary policy influences income inequality. However, it should be noted that most of the impulse response is not statistically significant.

The observed increase in inequality is also consistent with conventional monetary policy transmission mechanisms, where contractionary monetary policy tends to increase income inequality.

The analysis proceeds by examining income heterogeneity among agents in the economy. Specifically, the Gini coefficient is replaced with the S80/S20 ratio as the measure of inequality, and the impulse response functions are re-estimated accordingly.

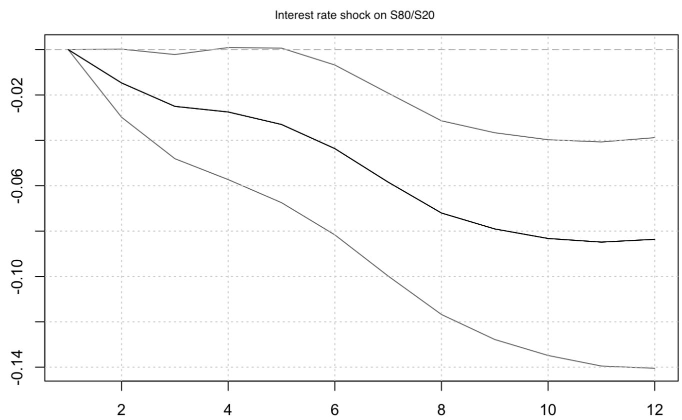

Figure 12: Impulse response of the S80/S20 coefficient to a 100 basis point increase in the shadow interest rate. The solid black line shows the point estimate, while gray lines represent 90% confidence intervals. $\lambda = 0.53769, \mu = 0.25475$ and $\delta = 0.24957$

An impulse response to a 1% increase in the shadow interest rate is estimated, using the S80/S20 ratio as the measure of inequality. The results clearly show that an increase in the shadow rate leads to a decline in income inequality. It can be observed that between the 4th and 6th quarters after the shock, the effect becomes statistically significant, and inequality continues to decrease thereafter.

This finding is different from figure 11, as the previous results using the Gini coefficient indicated that an increase in the shadow rate was associated with rising inequality. This raises an important question: is the observed decline in the S80/S20 ratio driven by rising incomes among the bottom 20%, falling incomes among the top 20%, or a combination of both?

Overall, these results support the claims made by Rangvid (2025).

However, it is important to note that both the impulse responses using the Gini coefficient and the S80/S20 ratio may be difficult to fully interpret, as the unemployment rate is missing from the model. Since unemployment is a key transmission channel for monetary policy to affect income inequality, its exclusion could bias the results or omit important dynamics.

The second model

The analysis now proceeds by estimating the second model, in which the baseline specification is extended to account for the Federal Reserve's dual mandate, as shown in *Figure 6*.

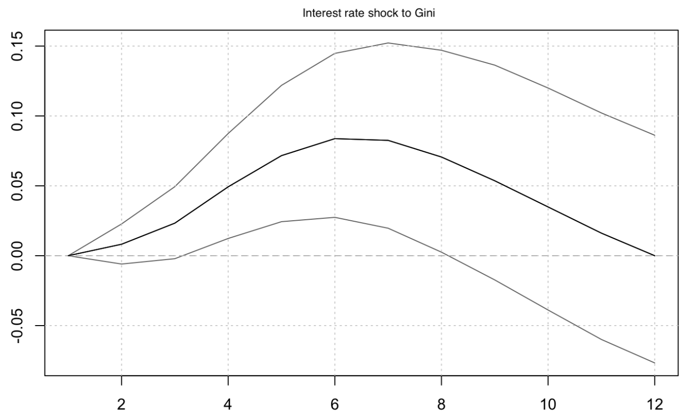

Figure 13: Impulse response of the Gini coefficient to a 100 basis point increase in the shadow interest rate. The solid black line shows the point estimate, while gray lines represent 90% confidence intervals. $\lambda = 0.76132, \mu = 0.31309$ and $\delta = 0.24255$

A 1% increase in the shadow interest rate is implemented to examine its effect on the Gini coefficient. Once again, the impulse response is broadly in line with the mainstream literature: contractionary monetary policy leads to higher income inequality. The effect is statistically significant from just before the 4th quarter and until around the 8th quarter after the shock.

Including the unemployment rate in the model allows for consideration of the Federal Reserve's dual mandate. However, the results still show that inequality increases following a contractionary monetary policy shock. This suggests that, at the aggregate level, the income gap between high- and low-income agents widens when monetary policy tightens, despite potential stabilizing effects on employment.

These findings underline the importance of considering heterogeneity among agents in the economy. To investigate this further, the impulse response of the S80/S20 ratio is estimated, allowing for an assessment of how monetary policy influences the relative income distribution between the highest- and lowest-income segments of the population.

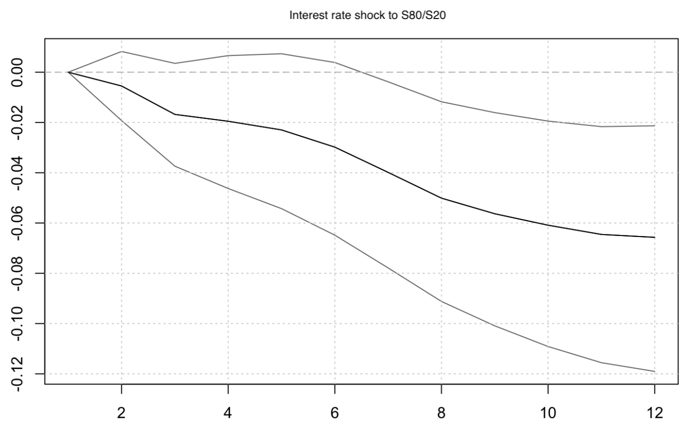

Figure 14: Impulse response of the S80/S20 coefficient to a 100 basis point increase in the shadow interest rate. The solid black line shows the point estimate, while gray lines represent 90% confidence intervals. $\lambda = 0.60928, \mu = 0.2525$ and $\delta = 0.28013$

A 1% increase in the shadow interest rate is introduced, and the impulse response of the S80/S20 ratio is estimated. In this case, the shock remains statistically insignificant until the 6th quarter after the initial impulse. From the 6th quarter onwards, the model indicates that contractionary monetary policy leads to a decrease in income inequality. In other words, the ratio between the top 20% and bottom 20% of income earners declines when monetary policy tightens.

This finding is interesting, as the model includes different monetary policy regimes, and the result stands in contrast to the findings obtained using the Gini coefficient. While the Gini-based results suggest that tighter monetary policy increases inequality, the earnings heterogeniety channel, the S80/S20 ratio implies the opposite.

Overall, the impulse response analyses have produced mixed results, offering valuable insights for reflection and discussion. While the findings based on the Gini coefficient are broadly consistent with the existing literature, the results using the S80/S20 ratio do align with previous research.

8 Validating the Empirical Findings

Before drawing conclusions based on the estimated models, it is essential to assess the reliability and robustness of the empirical results. This chapter presents a set of diagnostic checks to validate the structural vector autoregressive (SVAR) and Bayesian VAR (BVAR) models used in the analysis. By examining properties such as stability, absence of unit roots, heteroskedasticity, and distributional assumptions, it's ensured that the estimated impulse response functions (IRFs) can be interpreted with confidence.

The first section focuses on the SVAR models, evaluating their underlying VAR structures through standard time series diagnostics. The second section addresses the validation of the BVAR models using Bayesian-specific tools, such as effective sample size and Geweke diagnostics. These checks are crucial to establish the credibility of the results and ensure that the models provide meaningful insights into the effects of monetary policy on income inequality.

Detailed results from the diagnostic tests for both the SVAR and BVAR models are reported in Appendix from section 11.2.

8.1 SVAR

The four SVAR models are based on underlying VAR models. All four VAR models are stable in their roots, which means that the models do not exhibit explosive behavior. A roots test is used to check for the presence of unit roots; if a unit root were present, the results would be unreliable, and the corresponding impulse response functions (IRFs) could not be trusted. However, none of the models exhibit unit roots.

Due to the relatively short sample size and the fact that most variables are expressed in logs or levels, several diagnostic tests—such as tests for asymmetry and normality—indicate potential serial correlation, and the normality tests suggest that the residuals are not normally distributed. These results are expected given the nature of macroeconomic time series. However, across all models, ARCH tests indicate no presence of heteroskedasticity.

The results of the stability tests show that all models are stable, as they follow a consistent baseline and the variance does not change over time. Overall, based on these diagnostic checks, it can be assumed that the results produced by the SVAR models are reliable.

8.2 BVAR

Assessing the validity of the Bayesian VAR (BVAR) models requires a different set of diagnostics than those used for classical VAR frameworks, due to the Bayesian estimation approach and the use of prior distributions. Ensuring the reliability of the posterior inference and the resulting impulse response functions (IRFs) is critical for drawing credible conclusions.

First, an Effective Sample Size (ESS) test is performed for each parameter. This diagnostic evaluates how many independent draws the Markov Chain Monte Carlo (MCMC) algorithm effectively provides, after accounting for autocorrelation in the chain. A low ESS may indicate poor mixing or convergence issues. In this case, the ESS values are lower than the total number of posterior draws (25,000), but remain at acceptable levels across all estimated parameters. This suggests that the MCMC algorithm performs reasonably well and provides sufficiently reliable posterior estimates for the purposes of the analysis.

Next, the Geweke convergence diagnostic is applied, which tests whether the mean of the early part of the Markov chain is statistically different from the mean of the later part. All test statistics fall within the acceptable range of a z-score of ±1.96, which suggests that the Markov chains have converged and that the posterior distributions are stable.

Furthermore, a sensitivity analysis is conducted on the prior hyperparameters (λ, μ, and δ) to evaluate the stability of the results. Initially, standard prior values are used, but these are subsequently re-estimated to improve model fit.

In both BVAR models, the estimated hyperparameters indicate a moderate influence of the prior relative to the data. Across specifications, λ ranges between approximately 0.54 and 0.76, suggesting a balanced reliance on prior information and observed data. The values of μ, which lie between 0.25 and 0.31, indicate that the model does not impose strong assumptions about the presence or absence of unit roots, but instead allows for a moderate degree of persistence in the data. Similarly, δ values are consistently below 0.30, which implies that the model permits cointegration relationships and does not excessively shrink variables toward their unconditional means.

These results support the robustness of the BVAR estimation by confirming that the hyperparameters do not unduly distort the data-driven dynamics. The chosen prior structure allows for long-term relationships in the data while maintaining enough flexibility to reflect underlying economic realities.

9 Discussion

This chapter discusses the findings presented in the empirical results chapter, with a particular focus on the distributional effects of monetary policy.

The results from the SVAR and BVAR models present a mixed picture. In the SVAR framework, income inequality—as measured by the Gini coefficient—appears to increase following a rise in the shadow rate. However, over a longer horizon, the effect seems to reverse. For the S80/S20 ratio, the pattern is less ambiguous: an increase in the shadow rate is associated with a reduction in income inequality. These findings provide evidence consistent with both the earnings heterogeneity channel and the income composition channel.

Nonetheless, the main takeaway from both the SVAR and BVAR models is that the estimated effects are relatively small, with many impulse responses failing to reach statistical significance across multiple lags.

To account for changes in monetary regimes over the sample period, the BVAR model is used to provide a more robust analysis. Here, is is observed that the Gini coefficient increases following a contractionary monetary policy shock, while the S80/S20 ratio declines, indicating opposing dynamics depending on the chosen inequality measure. Once again, the results point in both directions, suggesting that more than one transmission channel may influence income inequality.

Several mechanisms may help explain these seemingly contradictory results. The following sections explore two possible explanations: the role of financial markets in shaping inequality through asset income channels, and the implications of the Federal Reserve's dual mandate, which may attenuate the full distributional impact of monetary tightening.

When examining the results, the Gini coefficient indicates that income inequality increases following a contractionary monetary policy shock. This finding aligns with the majority of the studies reviewed in the literature section. In contrast, the S80/S20 ratio shows the opposite effect: inequality appears to decrease in response to a contractionary policy, which contradicts most of the existing literature.

One possible explanation for this divergence is that the income composition channel dominates in the case of the S80/S20 ratio, while the earnings heterogeneity channel plays a more significant role for the broader Gini measure. However, it is important to consider the broader macroeconomic environment in which these studies were conducted. Much of the existing literature is based on periods characterized by accommodative monetary policy and stable inflation. In contrast, the sample used in this study includes periods with inflationary pressures, where interest rate hikes were implemented to counteract inflation—as well as periods with the opposite dynamics.

Therefore, when comparing the findings to the existing literature, the results in this paper suggest that the effects of monetary policy on inequality may vary across different monetary policy regimes. In particular, the observed decline in inequality (as measured by the S80/S20 ratio) following contractionary shocks may reflect relative gains for lower-income households, consistent with the income composition channel. This could help explain why the S80/S20-based results deviate from those found in Gini-based studies, which tend to capture broader earnings-related effects.

Another possible explanation for the observed S80/S20 dynamics is the effect of interest rates on asset prices. When interest rates rise, asset prices tend to fall. Since one of the key differences between the top 20% and the bottom 80% of the income distribution is the share of income derived from financial assets, monetary policy changes can have disproportionate effects on these groups (Dossche et al., 2021).

This may help explain why income inequality has continued to rise during a prolonged period of declining interest rates, because it is then the income composition channel which dominates. As interest rates have fallen, asset prices have increased, benefiting those who already own such assets. Meanwhile, returns on fixed-income investments, such as savings accounts and government bonds, have diminished, disproportionately affecting households that rely on these safer forms of savings. High-income households, who are better equipped to understand and respond to expansionary monetary policy, are able to benefit from falling rates by leveraging low borrowing costs to acquire more income-generating assets (Israel & Latsos, 2019). This dynamic reinforces their wealth position and creates a snowball effect over time.

However, when interest rates eventually rise, these leveraged positions may be unwound. High-income households may then be forced to sell assets to repay debt, reducing their stock of income-producing assets in the short term and shifting the cost burden from savers to borrowers.

In line with the argument put forward by Rangvid (2025), this may indicate that the dominant driver behind rising income inequality during periods of falling interest rates is the income composition channel—where those with greater exposure to capital income benefit more from accommodative monetary policy (Rangvid, 2025, p. 107).

For the broader economy, as captured by the Gini coefficient, the impulse responses appear to reflect the earnings heterogeneity channel. In contrast, when inequality is measured using the S80/S20 ratio—capturing heterogeneity across income groups—the results point towards the income composition channel. However, since the effects are either only briefly statistically significant or emerge with long lags, and the overall impact on inequality remains limited, attention must also be directed towards how the Federal Reserve conducts monetary policy.

The Federal Reserve operates under a dual mandate: to promote both price stability and maximum sustainable employment. This means that when adjusting monetary policy, the Fed must consider the trade-off between controlling inflation and maintaining a healthy labor market. In practice, this constrains the extent to which interest rates can be raised to combat inflation, as doing so too aggressively could lead to a sharp rise in unemployment.

Therefore, the Fed aims to calibrate monetary policy carefully—tightening just enough to reduce inflation without causing a significant deterioration in employment. This balancing act may explain why only a modest increase in the Gini coefficient is observed following a contractionary shock, and why the effect becomes statistically insignificant after a few quarters.

Moreover, stabilizing mechanisms outside of monetary policy may also play a role. Fiscal policy, including unemployment benefits and social safety nets, can provide support to households affected by job losses, thereby dampening the potential inequality-increasing effects of tighter monetary policy.

The preceding sections have explored possible explanations for why the impulse responses are relatively small, point in different directions, and in many cases fail to reach statistical significance throughout the post-shock horizon. This raises a broader question, if monetary policy shocks have only limited and often insignificant short-term effects, what then explains the persistent rise in income inequality during a period of falling interest rates.

An attempt has been made to explain the rise in income inequality through the specified macroeconomic variables. However, additional factors may contribute to the long-term trend of increasing inequality, particularly in the context of persistently low interest rates. As rates decline, asset prices—most notably housing—tend to rise. This dynamic increases both rental costs and house prices, disproportionately affecting low-income households, who must allocate a larger share of their income to housing expenses.

At the same time, imputed rent (the estimated value of living in an owned home) has also been increasing, driven by factors such as easier access to credit, low interest rates, and land-use restrictions. Since imputed rent is included in income measures, rising housing values may contribute to observed changes in income inequality indicators such as the S80/S20 ratio. This could explain why inequality appears to rise when rates fall—lower rates inflate housing prices, which in turn raise imputed rent and affect the measured distribution of income (Cava, 2016).

Moreover, neighborhood effects may amplify these dynamics over time. High-income individuals tend to buy property in desirable areas with better schools, infrastructure, and social networks. Their children benefit from these environments, increasing their own future earning potential. In contrast, low-income households are often concentrated in less advantaged neighborhoods, reinforcing patterns of lower social mobility. These spatial and intergenerational dynamics suggest that the income composition channel—where certain types of income grow faster than others—may play a larger role than previously acknowledged (Ioannides & Ngai, 2025).

As housing prices continue to rise, the barriers to homeownership also increase. Higher property values are typically accompanied by stricter mortgage requirements and larger down payment obligations, further excluding low-income households from the housing market. Those with higher incomes and accumulated wealth are increasingly able to purchase high-value properties, which not only offer better long-term appreciation but also serve as a vehicle for wealth accumulation. Over time, this leads to a feedback loop in which income inequality transforms into wealth inequality, as property ownership becomes concentrated among those already better off.

Furthermore, the process has an intergenerational character, whereby real estate wealth, once acquired, can be passed on to future generations, solidifying economic advantages across time. In this way, wealth accumulation through housing can entrench disparities, contributing to a snowball effect in which inequality becomes self-reinforcing. Taken together, this points to the possibility that income inequality is subject to a form of hysteresis. The prolonged period of low interest rates and unconventional monetary policy may have set in motion structural changes in the economy and housing market, the full consequences of which are still unfolding (Cava, 2016; Ioannides & Ngai, 2025; Israel & Latsos, 2019; Smith et al., 2022).

10 Conclusion

This thesis has examined how monetary policy affects income inequality in the United States, employing an empirical econometric framework as the primary analytical approach. The results present a more nuanced perspective than that found in much of the existing literature. Overall, the estimated effects are limited in magnitude and often statistically insignificant, particularly when using the Gini coefficient as the principal measure of inequality. This indicates that monetary policy cannot be considered a primary explanatory factor for the long-term trend of rising income inequality.

When using the S80/S20 ratio, the analysis suggests a minor reduction in inequality following contractionary monetary policy. Although the effect is small, it may be interpreted as a weak indication that the income composition channel plays a role—whereby lower-income households benefit relatively more during periods of tighter monetary conditions.

Taken together, the findings imply that monetary policy is not a central driver of the persistent increase in inequality over recent decades. Rather, structural factors, such as developments in housing markets and asset prices, are likely to exert a more substantial influence on income distribution.

While monetary policy may have secondary distributional consequences, the responsibility for addressing rising inequality lies with elected policymakers. It is through legislative action that governments can mitigate some of the inequality-enhancing mechanisms embedded in the current economic system. The role of central banks, including the Federal Reserve, remains primarily focused on maintaining price stability and supporting macroeconomic conditions conducive to full employment. Nevertheless, further research is warranted to deepen our understanding of the complex channels through which monetary policy may affect the distribution of income, and to better inform the broader policy debate.

References

Andersen, A. L., Johannesen, N., Jørgensen, M., & Peydró, J.-L. (2023). Monetary policy and inequality. *The Journal of finance (New York)*, *78*(5), 2945–2989. https://doi.org/10.1111/jofi.13262

Aye, G. C., Clance, M. W., & Gupta, R. (2019). The effectiveness of monetary and fiscal policy shocks on u.s. inequality: The role of uncertainty. *Quality & quantity*, *53*(1), 283–295. https://doi.org/10.1007/s11135-018-0752-3

Bernanke, B. (2005). The global saving glut and the u.s. current account deficit.

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge University Press.

Cava, G. L. (2016, May). *Housing prices, mortgage interest rates and the rising share of capital income in the united states* (tech. rep.). Reserve Bank of Australia.

Coibion, O., Gorodnichenko, Y., Kueng, L., & Silvia, J. (2017). Innocent bystanders? monetary policy and inequality. *Journal of Monetary Economics*, *88*, 70–89. https://doi.org/10.1016/j.jmoneco.2017.05.005

Colciago, A., Samarina, A., & Haan, J. (2019). Central bank policies and income and wealth inequality: A survey. *Journal of economic surveys*, *33*(4), 1199–1231. https://doi.org/10.1111/joes.12314

Creel, J., & Herradi, M. E. (2024). Income inequality and monetary policy in the euro area. *International Journal of Finance & Economics*, *29*(1), 332–355. https://doi.org/10.1002/ijfe.2688

Doan, T., Litterman, R., & Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews*, *3*, 1–100. https://doi.org/10.1080/07474938408800053

Dossche, M., Slačálek, J., & Wolswijk, G. (2021). Economic bulletin. *Economic bulletin (European Central Bank), Issue 2/2021*.

Enders, W. (2014). *Applied econometric time series*. Wiley.

Froyen, R. T. (2013). *Macroeconomics* (10. ed., global ed.).

Giannone, D., Lenza, M., & Primiceri, G. E. (2015). Prior selection for vector autoregressions. *The review of economics and statistics*, *97*(2), 436–451. https://doi.org/10.1162/REST_a_00483

Ioannides, Y., & Ngai, L. R. (2025, February). *Dp19907 housing and inequality* (tech. rep. No. Discussion Paper No. 19907). CEPR Press. https://cepr.org/publications/dp19907

Israel, K.-F., & Latsos, S. (2019). The impact of (un)conventional expansionary monetary policy on income inequality - lessons from japan.

Korobilis, D. (2025). Exploring monetary policy shocks with large-scale bayesian vars. https://doi.org/10.48550/arxiv.2505.06649

Krippner, L. (2020, May). Documentation for shadow short rate estimates. https://www.ljkmfa.com/wp-content/uploads/2021/07/Documentation-for-SSR-estimates-29-May-2020.pdf

Kuschnig, N., & Vashold, L. (2021). Bvar : Bayesian vector autoregressions with hierarchical prior selection in r. *Journal of statistical software*, *100*(14), 1–27. https://doi.org/10.18637/jss.v100.i14

Lenza, M., & Slacalek, J. (2024). *How does monetary policy affect income and wealth inequality? evidence from quantitative easing in the euro area* (tech. rep. No. 39). Wiley Periodicals Inc. https://doi.org/10.2866/414435

McKay, A., & Wolf, C. K. (2023). Monetary policy and inequality. *Journal of Economic Perspectives*, *37*(1), 121–44. https://doi.org/10.1257/jep.37.1.121

OECD. (2024). *Society at a glance 2024: Oecd social indicators* (tech. rep.). OECD Publishing. https://doi.org/https://doi.org/10.1787/918d8db3-en

Rangvid, J. (2025). *How low interest rates change the world: Global trends caused by low rates and emerging factors shaping the future of rates*. Oxford University Press. https://doi.org/10.1093/9780198946410.001.0001

Samarina, A., & Nguyen, A. D. M. (2024). Does monetary policy affect income inequality in the euro area? *Journal of Money, Credit and Banking*, *56*(1), 35–80. https://doi.org/10.1111/jmcb.13017

Smith, S. J., Clark, W. A. V., ViforJ, R. O., Wood, G. A., Lisowski, W., & and, N. T. K. T. (2022). Housing and economic inequality in the long run: The retreat of owner occupation. *Economy and Society*, *51*(2), 161–186. https://doi.org/10.1080/03085147.2021.2003086

11 Appendix

11.1 The Macroeconomic Variables

In the following section, the variables used in the analysis are presented graphically, along with information about their sources.

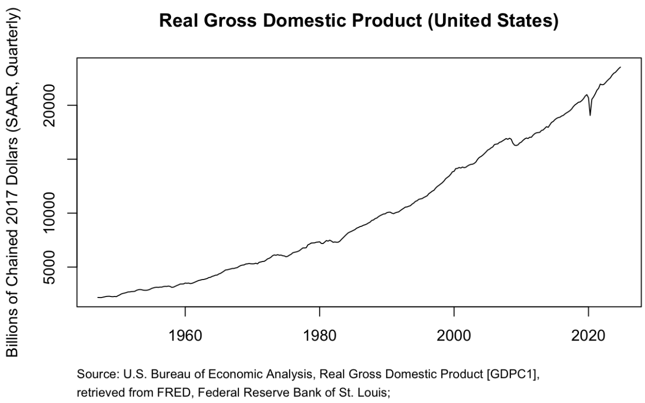

Figure 15: Seasonally adjusted real GDP in 2017 chained dollars, quarterly, source: FRED

This figure shows real GDP for the United States, measured in billions of chained 2017 dollars, seasonally adjusted and reported on a quarterly basis. The data are retrieved from the Federal Reserve Bank of Atlanta via the FRED database.

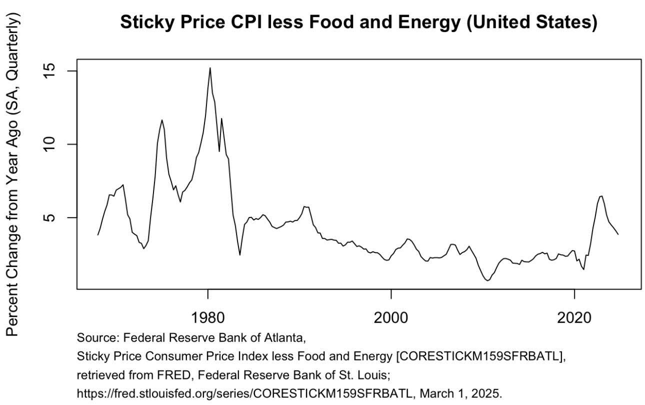

Figure 16: Seasonally adjusted Sticky Price Consumer Price Index less Food and Energy, quarterly, source: FRED

The figure presents the Sticky Price CPI excluding food and energy for the

United States, with seasonal adjustment and quarterly frequency. The data source is the Federal Reserve Bank of Atlanta, accessed through the FRED database.

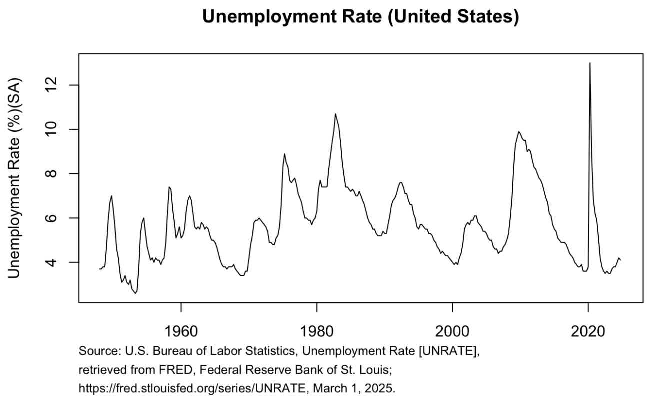

Figure 17: Seasonally adjusted Unemployment Rate, quarterly, source: FRED

The figure presents the Unemployment Rate for the United States, with seasonal adjustment and quarterly frequency. The data source is the Federal Reserve Bank of Atlanta, accessed through the FRED database.

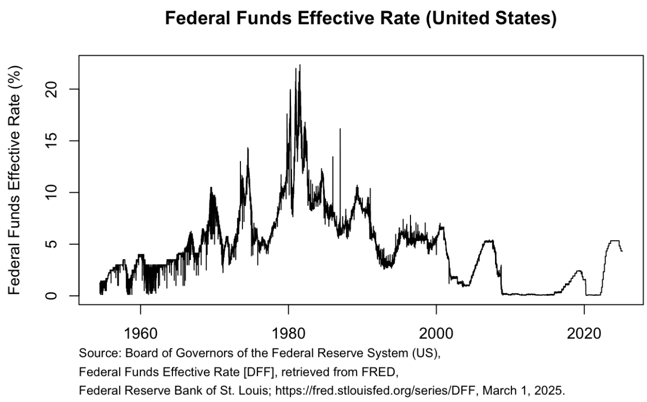

Figure 18: Federal Funds Effective Rate, source: FRED

The figure presents the Unemployment Rate for the United States. The data source is Board of Governors of the Federal Reserve System (US), accessed through the FRED database.

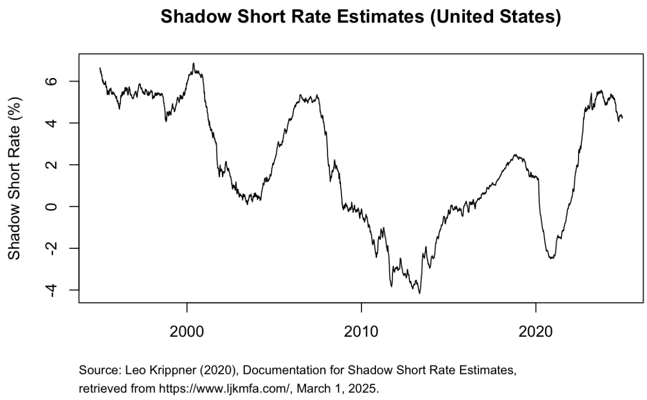

Figure 19: Shadow Short Rate Estimates for the United States, source: ljkmfa

This figure displays the Shadow Short Rate estimates for the United States, compiled by Dr. Leo Krippner and obtained from his official website (www.ljkmfa.com).

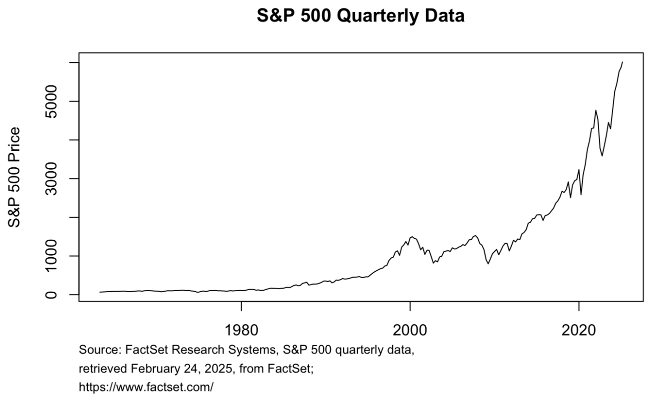

Figure 20: S&P500 Index, quarterly, source: FactSet

The figure presents the stock index S&P 500 for the united States and quarterly frequency. The data source is FactSet, accessed through (www.FactSet.com).

11.2 Diagnostics

In the following section, diagnostic tests for both the SVAR and BVAR models are presented. These are conducted to assess the internal consistency of the models and to determine the degree of confidence that can be placed in the estimated results. The diagnostics focus on key aspects such as model stability and the statistical properties of the residuals.

ADF-test

The following presents the ADF test results for the variables used in the SVAR, and BVAR models.

Variable	ADF Statistic	p-value	Stationary?
`Log(GDP)`	-2.1136	0.5296	No
`Unemp.`	-2.2549	0.4710	No
`Gini`	-3.1840	0.0945	No
`S80/S20`	-2.9941	0.1648	No
`Inflation`	-1.1288	0.9142	No
`Log(S&P 500)`	-2.5646	0.3427	No
`Short term shadow rate`	-3.1088	0.1173	No

Table 2: Results from Augmented Dickey-Fuller (ADF) tests on differenced variables. The null hypothesis of a unit root is rejected at the 5% level if the p-value is below 0.05.

It can be observed that none of the variables listed above are stationary. Typically, these variables would be differenced to achieve stationarity. However, this step is omitted, as the approach followed in the relevant literature does not apply differencing.

Roots test

To assess the stationarity of the system, the characteristic roots of the companion matrix are examined. Table 3 and 4 presents the characteristic polynomial of the VAR(8) model. If all roots lie within the unit circle, the system is considered stable and stationary.

11.3 Roots

Table 3 presents the roots of the VAR(8) model corresponding to the specification shown in Figure 5.

Table 3: Stability Check – Roots of the VAR(8) Models Used for Gini and S80/S20 SVAR Identification

SVAR(8) Gini	**SVAR(8) S80/S20**
0.9828524	0.99740030
0.9828524	0.99740030
0.9775112	0.97554117
0.9775112	0.97554117
0.9524265	0.96922155
0.9524265	0.96922155
0.9492938	0.95825659
0.9492938	0.95825659
0.9439207	0.95526505
0.9439207	0.95526505
0.9417581	0.95130528
0.9417581	0.95130528
0.9389775	0.92757926
0.9389775	0.92757926
0.9244015	0.91969234
0.9244015	0.91969234
0.9008933	0.89382013
0.9008933	0.87340296
0.8952956	0.87340296
0.8952956	0.86731025
0.8650226	0.86731025
0.8650226	0.83736940
0.8364301	0.83736940
0.8364301	0.82866955
0.8349646	0.82866955
0.8100524	0.79776695
0.8100524	0.79776695
0.8034765	0.79279519
0.8034765	0.79279519
0.7979620	0.78594487
0.7979620	0.78594487
0.7744691	0.78340362
0.7744691	0.72442526
0.7464989	0.72442526
0.7464989	0.72227016
0.5477555	0.72227016
0.5477555	0.57056274
0.3391140	0.57056274
0.3391140	0.46285879
0.1156845	0.05896693

The test indicates that all roots lie within the unit root circle, confirming that the VAR(8) model based on the specification in Figure 5 is stable.

Table 4 presents the roots of the VAR(8) model corresponding to the specification shown in Figure 6.

Table 4: Stability Check – Roots of the VAR(8) Models Used for Gini and S80/S20 SVAR Identification

SVAR(8) Gini	SVAR(8) S80/S20
0.9975992	0.9995879
0.9975992	0.9995879
0.9810460	0.9816367
0.9810460	0.9816367
0.9798499	0.9802935
0.9798499	0.9802935
0.9621798	0.9793127
0.9621798	0.9793127
0.9584800	0.9749042
0.9584800	0.9749042
0.9504006	0.9656768
0.9504006	0.9656768
0.9467797	0.9588574
0.9467797	0.9588574
0.9453616	0.9286301
0.9453616	0.9286301
0.9426177	0.9244064
0.9426177	0.9244064
0.9150357	0.9243711
0.9150357	0.9243711
0.9134678	0.8904952
0.9134678	0.8904952
0.9038551	0.8693506
0.9038551	0.8693506
0.8874359	0.8685591
0.8874359	0.8685591
0.8745856	0.8615336
0.8745856	0.8615336
0.8721680	0.8405152
0.8721680	0.8405152
0.8507864	0.8336909
0.8507864	0.8336909
0.8361313	0.7969992
0.8361313	0.7969992
0.8289584	0.7776109
0.8289584	0.7776109
0.8108338	0.7673179
0.8108338	0.7673179
0.7155551	0.7528654
0.7155551	0.7528654
0.6593273	0.7488537
0.6593273	0.7488537
0.6369694	0.7264931
0.6369694	0.7264931
0.4705453	0.7104622
0.4705453	0.7104622
0.3240663	0.2948704
0.3240663	0.2396425

The test indicates that all roots lie within the unit root circle, confirming that the VAR(8) model based on the specification in Figure 6 is stable.

As shown in Tables 3 and 4, all roots lie within the unit circle in both specifications, indicating overall model stability. Based on this, the specification in Figure 6 is selected for further analysis.

11.4 Portmanteau Test

In this chapter, the results of the Portmanteau test are reported in order to assess the presence of autocorrelation in the residuals.

Table 5: Portmanteau Test (asymptotic)

Variable	Chi-squared	df	p-value
Figure 5 Gini	494.59	400	0.00086
Figure 5 S80/S20	476.81	400	0.00491
Figure 6 Gini	704.72	576	0.00018
Figure 6 S80/S20	721.92	576	0.00003

The Portmanteau test indicates the presence of autocorrelation in the residuals. However, this result is expected, as none of the variables were differenced to achieve stationarity.

11.5 ARCH Test

The following section reports the results of the ARCH test, which is used to examine the presence of heteroskedasticity in the residuals.

Table 6: ARCH Test (multivariate)

Variable	Chi-squared	df	p-value
Figure 5 Gini	1020	5400	1
Figure 5 S80/S20	1020	5400	1
Figure 6 Gini	1428	10584	1
Figure 6 S80/S20	1428	10584	1

The results of the ARCH test indicate the absence of heteroskedasticity, with all p-values equal to 1, suggesting that the null hypothesis of homoskedasticity cannot be rejected.

11.6 JB Test

This section presents the Jarque–Bera test results for all models, assessing whether the residuals deviate from the assumption of normality.

Table 7: Jarque–Bera Test (multivariate)

Variable	Chi-squared	df	p-value
Figure 5 Gini	124.90	10	< 2.2e-16
Figure 5 S80/S20	162.69	10	< 2.2e-16
Figure 6 Gini	67.82	12	8.19e-10
Figure 6 S80/S20	45.87	12	7.31e-06

The test results indicate a rejection of the null hypothesis of normality. This is not surprising, as the use of non-stationary variables often leads to non-normal residuals in VAR models.

11.7 Skewness Test

This section presents the results of the multivariate skewness test for all models, assessing whether the residuals exhibit significant asymmetry.

Table 8: Skewness Test (multivariate)

Variable	Chi-squared	df	p-value
Figure 5 Gini	42.78	5	4.09e-08
Figure 5 S80/S20	34.07	5	2.31e-06
Figure 6 Gini	23.62	6	6.12e-04
Figure 6 S80/S20	17.39	6	7.94e-03

The test results suggest that the residuals are significantly skewed in all model specifications. This result supports the rejection of the null hypothesis of symmetry and aligns with expectations, given the inclusion of non-stationary variables.

11.8 Kurtosis Test

This section reports the outcomes of the multivariate kurtosis test, which evaluates whether the residuals exhibit excess kurtosis relative to the normal distribution.

Table 9: Kurtosis Test (multivariate)

Variable	Chi-squared	df	p-value
Figure 5 Gini	82.11	5	3.33e-16
Figure 5 S80/S20	128.62	5	< 2.2e-16
Figure 6 Gini	44.19	6	6.78e-08
Figure 6 S80/S20	28.48	6	7.64e-05

The results indicate strong evidence of excess kurtosis across all specifications, providing further support for rejecting the assumption of normality. As with the skewness and Jarque–Bera tests, this outcome is expected due to the level specification of non-stationary variables.

11.9 Stability test

The following section presents the results of the stability test conducted for all models.

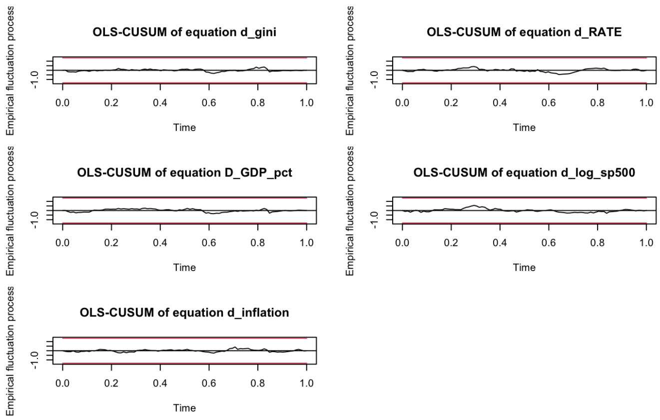

Figure 21: This is the stability for the VAR(8) with Gini coefficient and the variable ordering from figure 5.

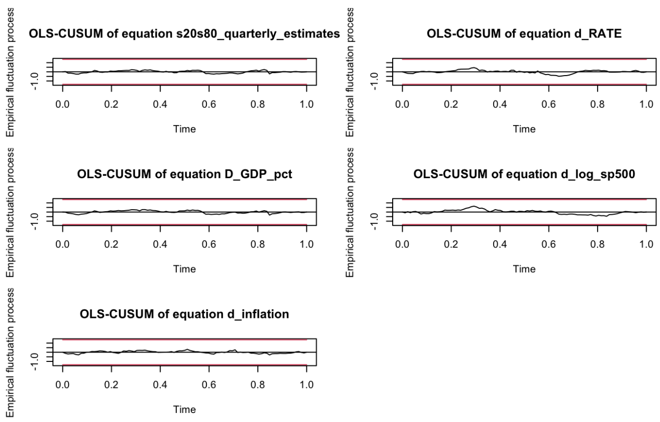

Figure 22: This is the stability for the VAR(8) with S80/S20 and the variable ordering from figure 5.

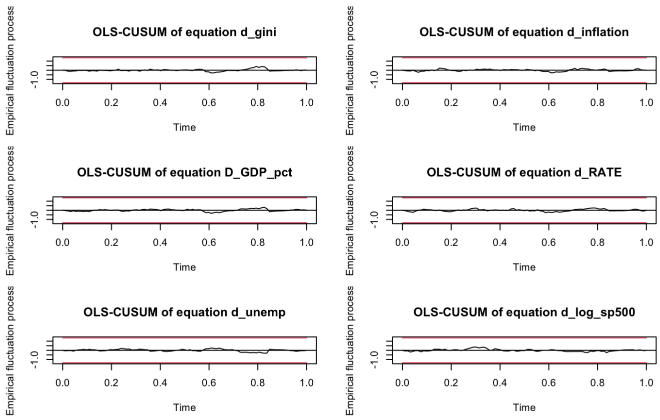

Figure 23: This is the stability for the VAR(8) with Gini coefficient and the variable ordering from figure 6.

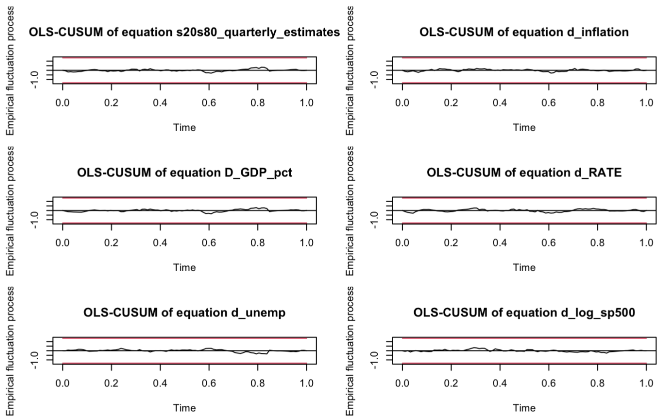

Figure 24: This is the stability for the VAR(8) with S80/S20 and the variable ordering from figure 6.

The stability plots presented above indicate that all estimated models satisfy the stability condition.

11.10 Effective Sample Size

The table below presents the effective sample sizes, which provide an indication of the efficiency and reliability of the MCMC estimates.

Table 10: Effective Sample Size for each dataset and parameter

Variable	`ml`	`lambda`	`soc`	`sur`
Figure 5 Gini	659.08	4273.10	553.99	505.80
Figure 5 S80/S20	383.10	4083.49	378.82	339.06
Figure 6 Gini	1016.61	4243.93	589.56	877.01
Figure 6 S80/S20	791.77	3837.18	832.86	622.31

The effective sample sizes are somewhat limited, given that they are lower than the total number of 25,000 posterior draws, indicating a potential reduction in estimation efficiency.

11.11 Geweke's Diagnostics

The table below presents the z-scores obtained from the Geweke convergence diagnostics.

Table 11: Geweke Z-scores for each dataset and parameter

Variable	`ml`	`lambda`	`soc`	`sur`
Figure 5 Gini	-1.548	1.101	-1.200	1.391
Figure 5 S80/S20	0.142	-0.399	0.609	-1.025
Figure 6 Gini	-1.693	0.234	1.469	0.970
Figure 6 S80/S20	1.510	0.411	-1.796	-1.069

The z-scores are all within the ±1.96 range, indicating that none are statistically significant at the 5% level and can therefore be considered acceptable.