Louvain School of Management

Assessing Monetary Policy Effectiveness in Euro Area: A VAR-SVAR Framework

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Summary

Macroeconomic modelling has proven its crucial importance in understanding today's ever-changing economy. The recent surge in inflation has shed light on the central banks' ability to maintain price stability. Plenty of papers have assessed the monetary policy efficiency, using different models, and leading to various conclusions. No consensus has emerged on which model was performing better, but the literature is perpetually trying to obtain more robust findings.

Knowing this, we provide a thorough study of the intricate dynamics and causal effects involved in the relationship between monetary policy and inflation, through the implementation of two complementary models: a Vector Autoregressive and a Structural Vector Autoregressive model. In this thesis, we opt not to employ theory-based or sign restrictions, instead adopting a recently proposed statistical method. This method relies on a non-Gaussian framework of independent shocks for the purpose of identification.

We use impulse response function to determine the dynamic response of a variable to a one-unit shock in another variable. Doing so, we obtain insights into the magnitude, timing, and persistence of the responses. Interesting results emerge:

- With our modelling, we observe a direct causal link between increase in interest rate and decrease in inflation, with a rather important persistency over time.
- The influence of monetary policy on inflation is not always overpowering, as inflation can be influenced by a myriad of external factors.
- Due to the complexity of transmission mechanisms, the impact of monetary policy actions on inflation is not instantaneous but occur with a delay.
- Our analysis indicates that while monetary policy effectively dampens inflation, it does so without causing undue disruptions to sustainable economic growth.

Three implications emerge for monetary policy: (1) Even though interest rate must remain a key element in the central banks' toolbox, there is a need for central banks to develop their adoption of a more comprehensive and flexible approach to monetary policy; (2) central banks should place greater emphasis on other factors that drive inflation, to better tailor their monetary policy to the real problem; (3) central banks may need to work more closely with other policy institutions, such as fiscal authorities, to coordinate efforts in achieving their inflation targets.

Acknowledgements

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Also, I want to thank my family. My father, for the support, the wise pieces of advice and the countless discussions. My brothers, for being a never-ending source of inspiration. An last but not least, my mother, for the opportunities you provided me, and for helping me in becoming a better person every day.

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1 Introduction

1.1 Context

In 2021-22, economic conjuncture in Europe have been hit by a strong and persistent rise in inflation, which came as a surprise for most analysts and economists after the long period of low inflation we experienced in 2011-2020. Energy and food prices inflation were the main drivers of the rise in headline inflation in the Euro Area (EA), making up around two-thirds of the inflation (as depicted in Figure 1.1). Energy inflation rose mainly due to the Russian invasion of Ukraine, which lead to disruptions in the supply of major commodities in Europe, mostly oil and natural gas, and their direct impact on electricity prices. Core inflation – excluding energy and food inflation – was also on the rise during the past year and a half, mainly because of several factors among which a supply shock due to supply chain bottlenecks following the pandemic mobility restrictions, but also the combination of easy monetary conditions and large fiscal stimulus announced to fight the pandemic that helped fuel the economy and promote a fast post-pandemic recovery (International Monetary Fund, 2022). Because of these unforeseen events and dynamics, most international institutions and private forecasters underestimated the surge in inflation.

To fight against this inflation concerns, central banks' primary objective is to maintain price stability, which is crucial for economic growth, investment, and consumer confidence, as it allows businesses and individuals to make informed decisions and plans for the future. Additionally, monetary stability helps maintain the value of earnings and savings, promotes efficient resource allocation, and enhances a country's international competitiveness[1]. To do so, centrale banks can monetary policy tools such as interest rates or money supply adjustments. For example, by raising interest rates, central banks can make borrowing more expensive, which can reduce spending and slow down economic growth, ultimately leading to lower inflation. Understanding deeply this relation between interest rates and inflation is key for the monetary policies to be efficient.

However, the effectiveness of these tools depends on a variety of factors such as the strength of the economy, the nature of the inflationary pressures, or the degree of independence of the central bank. As explained, the recent rise in inflation was partly driven by global economic

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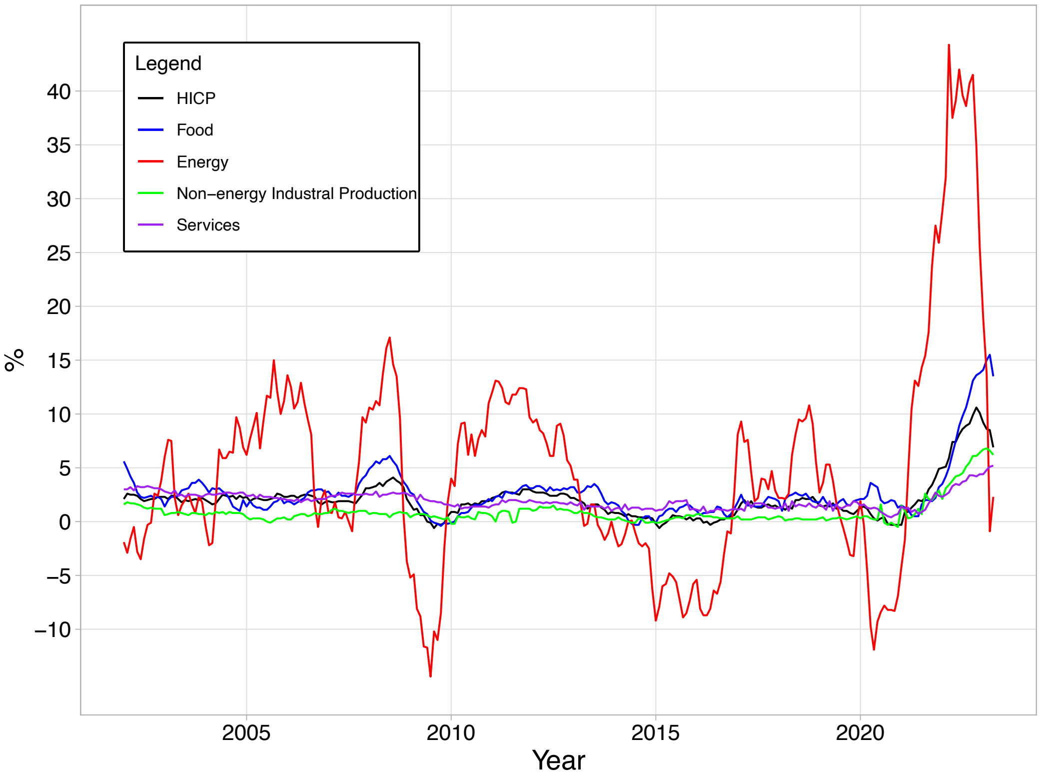
[1] https://www.ecb.europa.eu/mopo/intro/benefits/html/index.en.html

Figure 1.1: Euro Area Inflation and its main components, 2013-2023



Source: Eurostat and author's manipulations.
https://ec.europa.eu/eurostat/databrowser/view/PRC_HICP_MANR__custom_7107603/default/table?lang=en

shocks and exploding energy prices, and these are events in which the central banks have limited control and impact power.

Additionally, the mandate of the ECB has been diversified in 2020, with the addition of support to economic growth and employment to their core missions[2]. Raising interest rates too quickly or aggressively can lead to a recession or economic downturn, which can have negative consequences for individuals and businesses (detailed later in section 2.3.3).

All this said, the economic situation has put in the center of the discussions the question of the ability of central banks to control inflation. Hence, building a thorough understanding of the relationships between the interest rates environment and inflation development appears to be of first-order importance in macroeconomic analysis.

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[2] https://www.ecb.europa.eu/home/search/review/html/ecb.strategyreview_monpol_strategy_overview.en.html

1.2 Research Question and Motivation

Our objective is to conduct a rigorous evaluation of the dynamic connection between essential monetary policy variables and inflationary patterns, through implementation of widely used macroeconomic models. Many different of such models have been developed in the literature, each has its pros and cons and is widely documented. We chose to implement two complementary models, based on the extensive recognition, theoretical characteristics, empirical track record, and practical significance associated with them.

The two models considered are:

1. *Vector Autoregressive (VAR) model:* Multivariate time series model that captures the dynamic relationships among multiple variables simultaneously.
2. *Structural Vector Autoregressive (SVAR):* Extension of the VAR model that aims to identify the underlying structural relationships and shocks in a system.

The literature has proposed different theory-based approach to identify the monetary policy shocks in the VAR framework, mainly the economic restrictions models (Sims, 1980; Blanchard and Quah, 1989) or specific sign restrictions (Uhlig, 2005). These procedures are based on a-priori economic beliefs, which might not always be true in reality, with the increasing complexity of the interactions between economic variables. In this thesis, we adopt a recently developed statistical identification technique that depend on independently distributed structural shocks. Utilizing this statistical approach enables us to compare theoretical insights concerning various monetary policy shocks with information derived from data.

Our scope with this research is to implement traditional models that have proven their robustness using the most recent data on the extreme inflation surge and the most aggressive monetary tightening of the past decades, relying on lately developed data-driven estimation techniques, to assess the efficiency of monetary policies. Implementing this combined VAR/SVAR approach allows to gain comprehensive insights into the intricate dynamics and causal effects involved in the relationship between monetary policy and inflation. Having a deep understanding of these relationships is crucial to policymakers and international institutions to insure an accurate development of monetary policies.

Our focus lies in investigation the impact of variations in the central bank's policy interest rate rather than unconventional measures. While the impact of unconventional measures undoubtedly hold significance on its own, it is probable that interest rates will continue to remain a key policy instrument.

After providing an overview of the context, along with the academic and practical significance of the subject matter and the models we consider, we establish our primary research question as follows:

To what extend can conventional monetary policy measures, such as rising interest rates, effectively mitigate inflationary pressure?

1.3 Summary of Research

Based on Euro Area GDP growth, inflation rate, and year-on-year change in Euribor-3m, the core results discovered through our study are explained below. Given that our study relies on three specific time series centered around Euro Area data, we acknowledge that the findings cannot be automatically extended to a broader context. Instead, our objective is to gain in-depth insights into the effectiveness of monetary policy and to compares our findings with existing literature.

Monetary policy efficiency. Under our modelling, we observe a direct causal link between increase in interest rate and decrease in inflation, with a rather important persistency over time.

Limited impact of interest rate. The influence of monetary policy on inflation is not always overpowering, as inflation can be influenced by a myriad of external factors, such as supply shocks, global economic conditions, and changes in consumer behavior. Thus, while monetary policy plays a significant role in managing the economy, its direct impact on controlling inflation is subject to a range of complex interactions and external dynamics.

Delayed transmission. Due to the complexity of transmission mechanisms, which are even oversimplified in our model, the impact of monetary policy actions on inflation is not instantaneous. This implicates difficulty for policymakers to immediately evaluate the efficiency of their actions.

Economic stability. Our analysis indicates that while monetary policy effectively dampens inflation, it does so without causing undue disruptions to sustainable economic growth.

1.4 Structure of the thesis

Now we introduced the general context of the thesis, the research question and our central results, the subsequent chapters of the master's thesis are organized as follows.

Chapter 2 This chapter reviews elementary economic concepts necessary to follow the rest of the thesis. Mainly, it focusses on the concept of inflation itself along with the different theories of inflation development. This chapter also provides an overview of the central banks' role, monetary policy actions and transmission mechanism.

Chapter 3 In this chapter, we cover the theoretical background of VAR and SVAR modelling. We start with a model comparison to other widely used macroeconomic models. We then provide a (S)VAR model and equations description, before diving deeper into model estimation techniques and model diagnostics.

Chapter 4 Here, we detail the methodology employed to address our research question, we explain the different techniques used to assess the efficiency of monetary policies. We also furnish a description of the utilized data, and stationarity tests.

Chapter 5 This chapter details and discuss our results. Prior to that, we provide a model diagnostic and a straightforward interpretation of our model estimation. The analysis are performed with R.

Chapter 6 The last chapter concludes the master's thesis. We highlight the implications of our results for monetary policy and conclude with recommendations for potential future research directions.

2 Macroeconomic Theory of Inflation

Understanding the causes and effects of inflation is crucial for formulating effective economic policies and managing the stability of economies. This chapter delves into the realm of inflation theory, exploring the multifaceted nature of inflation. Specifically, this chapter examines different theories of inflation, the role of central banks in managing inflation, and the mechanism through which monetary policy is transmitted in the economy. By comprehensively analyzing these aspects, this chapter aims to provide a solid foundation for understanding the complexities and dynamics of inflation and its implications for monetary policy and economic stability.

2.1 Concept Definition

Inflation is an economic concept defined as the general increase in price of goods and services over time. As prices rise, the same amount of currency can buy fewer goods and services, hence it erodes the purchasing power of money over time.

The most common way to estimate inflation is to measure the changes of a Consumer Price Index (CPI). To build this price index, statistical agencies collect the price over time of a large basket of goods and services that is representative of the items consumed by the households. The inflation rate is computed as follow:

$$\pi_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}$$

In Europe, the price index used is the Harmonized Index of Consumer Prices (HICP). The index covers a wide range of goods and services, including food, clothing, housing, transportation, healthcare, education, and recreation. It measures the average price changes of these items over time and expresses them as a percentage change from a base period.

2.2 Theories of Inflation

Totonchi (2011) postulates that inflation results from five categories of explanatory variables interacting with each other: monetary shocks, demand side, supply side shocks, structural and political factors. He proposed a review of competing theories of inflation, to better understand causes of inflation, which are summarized here below:

- **Quantity theory of money:** Changes in the general level of prices is due to changes in the quantity of money circulating.
- **Monetary theory of inflation:** Money supply determines the prices and output in the short term (Friedman, 1963).
- **Demand pull theory:** Aggregate demand, consisting in consumption, investment and government expenditure, is the source of demand-pull inflation. If aggregate demand is above aggregate supply, inflation is rising (Keynes, 1936).
- **Cost push theory:** Increase in production costs (i.e. wages or raw materials) are the cause of higher prices.
- **Structural inflation theory:** Inflation is pushed by structural changes in the modern economies.
- **Rational expectations theory:** In the 1970s, postulates that economic agents are able to build rationale macroeconomic expectations based on past and current available information. In this theory, for example, a fully anticipated change in monetary policy will not have any direct impact in the short run.

In reality, it is really hard to decompose the inflation rate into its monetary, demand-pull, cost-push or structural components. Also, inflation itself can also be a cause of future inflation, and this process is a dynamic process, where the shocks are mixed and difficult to identify separately (Totonchi, 2011).

To accurately fight inflation, the right tools must be used by monetary authorities. Because the factors underlying the inflation surge are different in a cost push inflation and in a demand-pull inflation, the reaction to monetary policies will also be different. In a demand-inflation scenario, when this one is too strong and tests the productive system, a rise in interest rates is effective. But if the problems are on the supply side, a more effective reaction would be to stimulate supply (De Callataÿ, 2022).

2.3 The Role of Central Banks & Monetary Policy

2.3.1 Central Banks

A central bank is defined as a "public institution that manages the currency of a country or group of countries and controls the money supply"[3]. Their operations can be summarized as follow (Williamson, 2020):

- Central banks have objectives.
- Those objectives are achieved through formulation of monetary policy.
- Implementation of those policy rules is made via central banks actions.

However, centrale banks are not totally free in their actions. Indeed, central banks are restricted in their actions by legislations that determine their mandates, sets out the rules and the overall goals.

The European Central Bank (ECB) began to operate in 1998, as the central bank for the eurozone countries (in which were at the time 11 member states), with as primary objective to maintain price stability, initially defined as maintaining inflation rates close to but below 2% over the medium term. Ensuring that the value of money does not deteriorate over time is a key feature to allow sustainable economic growth and well-being of citizens.

Over the years, the world has seen major changes and the ECB was assigned new macro-objectives, because of the growing concerns on the trade-off between price and financial stability. Indeed, the summer of 2021 was marked with a strategy review from the ECB[4]. Their target shifted from a below 2% inflation goal to a symmetric 2% target over the medium term, meaning that they consider equally undesirable to have inflation deviations above or below the target. ECB also serves other objectives, such as balanced economic growth, an economy aiming at full employment and social progress, and a high level of protection and improvement of the quality of the environment, as long as all ECB decisions are without prejudice to the primary objective.

The main instruments used are the ECB policy rates, that determine financing conditions and influence economic development. But setting interest rates is not the only tool of the monetary

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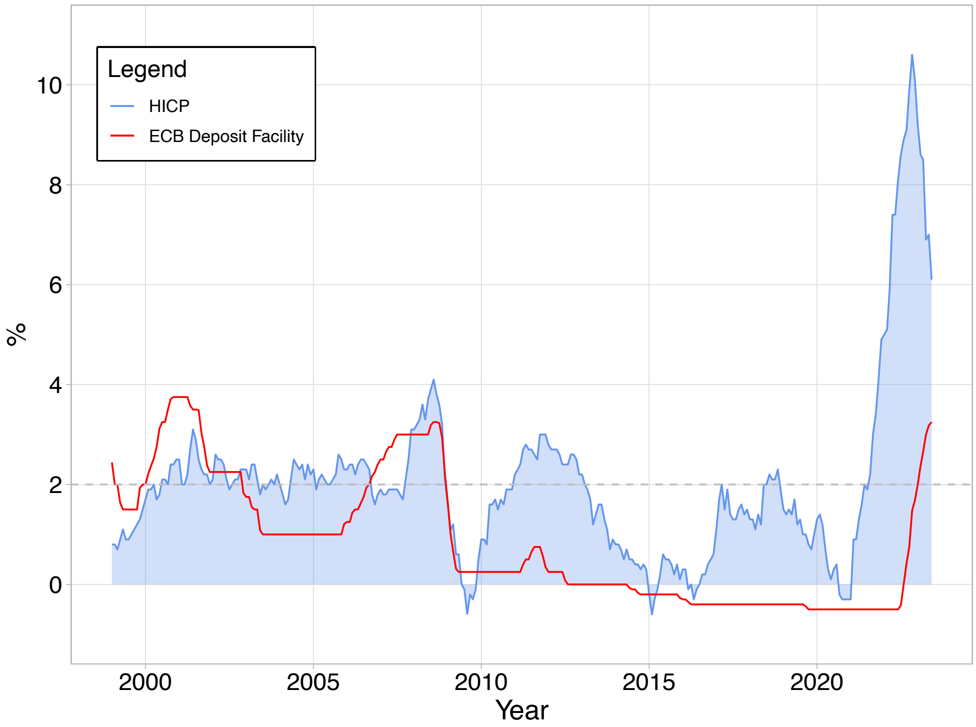
[3] See ECB website : https://www.ecb.europa.eu/ecb/educational/explainers/tell-me/html/what-is-a-central-bank.en.html

[4] See https://www.ecb.europa.eu/home/search/review/html/index.en.html

Figure 2.1: Euro Area Inflation and ECB Deposit Facility, 1999-2023



Source: ECB Data Portal
https://data.ecb.europa.eu/data/datasets/ICP/ICP.M.U2.N.000000.4.ANR

policy: several new instruments have been added to their toolbox to better fight economic changes and challenges, such as minimum reserve requirements.

By raising interest rates, central banks can make borrowing more expensive, which can reduce spending and slow down economic growth, ultimately leading to lower inflation. Similarly, by reducing the money supply, central banks can make it more difficult for individuals and businesses to borrow, which can also reduce spending and inflation.

Figure 2.1 shows the evolution of one of the key rates of the ECB, the deposit facility rate, together with the evolution of headline inflation since 1999. We can observe a correlation between both variables, where inflation decrease after the interest rate increases, for example in 2000, 2008 and recently in 2023.

2.3.2 Policy rule

To determine the appropriate monetary policy, the ECB use various inputs: data analysis, projections from mathematical models, and judgment of policymakers. This very complex process has been famously approximated in a mathematical equation developed by Taylor (1993) aiming at presenting a framework for central banks to determine an appropriate level of interest rates based on prevailing economic conditions.

With the new missions of the ECB, the Taylor-rule that connects short-run interest rate and inflation targets is becoming even more accurate. The Taylor rule can be specified as follow:

$$R_t = r_t^* + \pi_t + \alpha(\pi_t - \pi^*) + \gamma(Y_t - Y^*) \tag{2.1}$$

In this equation, R_t is the central bank's policy interest rates at time t, r_t^* is the equilibrium real interest rate, which is the interest rate consistent with full employment and stable inflation, π_t is the actual inflation rate, π^* is the central bank's inflation target, Y_t is the actual aggregate output and Y^* is a measure of potential output. The coefficients α and γ measure the responsiveness of the central banks to deviations from targets in inflation and potential output.

This rule sets guidance on how central banks should set interest rates to achieve their target in a dual mandate (maintain price stability and support economic activity). Central banks adjust their monetary policy to respond to inflation deviations from the target and economic output divergence from the potential.

In this relation, the coefficients alpha and gamma are typically positive. Hence, in situations where inflation surpasses the target or output exceeds its potential, the central bank should raise interest rates to cool down economic activity and mitigate inflationary pressures. Conversely, when inflation falls below the target or output lags behind its potential, the central bank should lower interest rates to encourage economic growth.

However, it is crucial to acknowledge that the actual implementation of monetary policy is more intricate than the simplified Taylor rule. Central banks take into account a diverse array of economic indicators and factors during their decision-making process.

2.3.3 Monetary policy transmission mechanism

The success of a monetary policy relies on an accurate assessment of the impact and timing of these actions plans on the economy by the authorities. A thorough understanding of the different monetary transmission channels is required to ensure the rights tools are used, in an appropriate way. The objective of the below is to propose an introductory overview of the main transmission mechanisms found in the literature (Mishkin, 1995).

Interest Rate Channel. The most common channel of monetary transmission comes from classic Keynesian theory and is a standard feature since more than 70 years. Also supported by John Taylor (1995), this model states that a monetary policy contraction (*M*) will push short-term interest rate (*i*) up, which will transfer into higher long-term rates through sticky prices and rationale expectations. This situation leads to a decrease in investments (*I*) in business fixed, residential housing, consumer durable goods or inventory, which causes a fall in aggregate output (*Y*). The schematic overview of the mechanism is:

$$M \downarrow \;\Rightarrow\; i \uparrow \;\Rightarrow\; I \downarrow \;\Rightarrow\; Y \downarrow$$

Exchange Rate Channel. With the development of the globalization, the attention has grown for monetary policy effect of net exports (*NX*) through flexible exchange rates fluctuations (Taylor 1995; Obstfeld & Rogoff, 1995). The mechanism also starts with an interest rate effect, because an increase in domestic interest rate will make deposits in the domestic currency more competitive and attract capitals denominated in foreign currency, which will push the value of the local currency relative to other up (*E*). An appreciation of the domestic currency decreases the exports, foreign goods become cheaper than local goods, inducing a decline in net exports, hence output falls. The schematic overview of the mechanism is:

$$M \downarrow \;\Rightarrow\; i \uparrow \;\Rightarrow\; E \uparrow \;\Rightarrow\; NX \downarrow \Rightarrow\; Y \downarrow$$

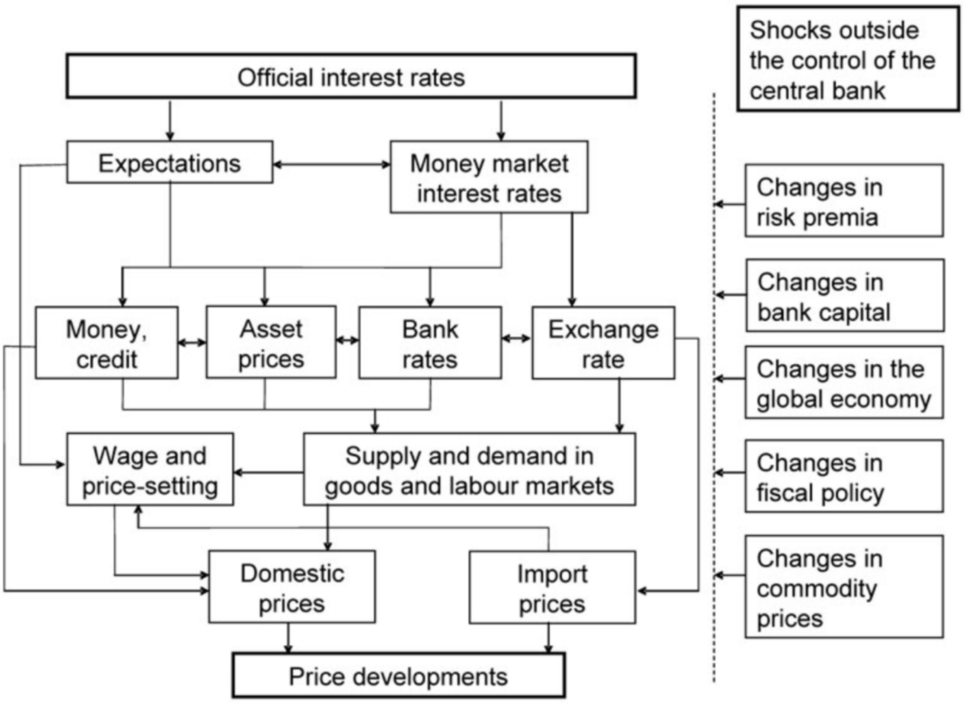
Wealth Effects. Defended by Modigliani (1971), this model explains that the wealth of households determines consumption (C). Indeed, consumers spendings depend in their lifetime resources, such as real capital or financial wealth (stocks). Monetary tightening have a bad effect on the price (*P*) of stocks or land property, which decrease consumers' wealth, leading to a decline in the tendency to consume. The schematic overview of the mechanism is:

$$M \downarrow \;\Rightarrow\; P \downarrow \Rightarrow wealth \downarrow \Rightarrow\; C \downarrow \Rightarrow\; Y \downarrow$$

Credit Channel. The monetary transmission channel includes the role of banks in the financial system. Bernanke and Gertler (1995) raised the importance of this bank lending channel by explaining how a contractionary monetary policy, that reduce the reserves of banks and deposits, will also impact the credit lending market. When banks tend to lend less, then investments also decrease accordingly. The schematic overview of the mechanism is:

$$M \downarrow \;\Rightarrow\; bank\ deposits \downarrow \Rightarrow bank\ loans \downarrow \Rightarrow\; I \downarrow \Rightarrow\; Y \downarrow$$

Figure 2.2: Monetary policy transmission mechanism overview



Source: European Central Bank (see link in the footnote)

All the above monetary policy transmission channels explain how monetary policy decisions affect global economy and price development. Figure 2.2[5], from the European Central Bank, summarizes these mechanisms and adds shock that are not within the control of central banks but that also impact massively global economy.

This schematic representation is interesting to have a better overview of the complexity and interconnections of the different transmission mechanisms.

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[5] https://www.ecb.europa.eu/mopo/intro/transmission/html/index.en.html

3 Empirical Framework

Theory and empirical studies have both proven that monetary policy may have a significant influence on the price level, but also other economic indicators such as unemployment rate, economic activity, public expenditures, etc. Econometrics analysis has a key role, filling the gap between theory and fact, by verifying and testing mathematical relations based on theory to reflect reality.

To understand behavior and interactions of economic variables, assess the efficiency of policy interventions and analyze the impact of shocks on the economy, central banks rely heavily on mathematical econometric modelling.

The most common approaches in the literature for empirical analysis of macroeconomics variable dynamics are the Dynamic Simultaneous Equations Models (DSEM) (see Klein and Goldberger, 1955), the Vector Autoregressive models (VAR) (as in Sims, 1980; Bernanke and Blinder, 1992; Herwartz and Plödt, 2016a) and the Dynamic Stochastic General Equilibrium models (DSGE) (see for example Sbordone, Tambalotti, Rao and Walsh, 2010; Christiano, Trabandt and Walentin, 2010). The different models will be briefly discussed in section 3.1.

In this thesis, we will focus on the implementation of a VAR model, which has proven to be a key tool for macroeconomics and finance modelling since the early 1980s. Particularly, these models are powerful in capturing the properties of the data, and identifying, testing, and quantifying the existence of dynamic relationships between two or more variables.

We will also implement an extension of the previous model, a Structural Vector Autoregressive (SVAR) model, which allows to model unobserved structural shocks that are hidden in the reduced form of the VAR model and to observe the system's reaction to these types of shocks (Lange, Dalheimer, Herwartz and Maxand, 2021). In particular, we will estimate the structural form using statistical properties of the data.

In the following sections, we will introduce the different macroeconomic models cited, explain why we chose to implement a VAR model instead of the others, as well as the theoretical and mathematical background behind autoregressive models. Doing so, we equip the reader with the necessary tools to understand the final analysis.

3.1 Models Comparison

3.1.1 Dynamic Simultaneous Equation Models

Developed in the 1950s by researchers from the Cowles Commission, Dynamic Simultaneous Equations Models were the dominating model in empirical macroeconomics analysis before the rise of VAR models. The primary objective was to build a tool for policymakers by implementing quantitative techniques for Keynes macroeconomic theory.

With DSEM, dynamic interactions between the variables are captured by representing them as a system of equations. Each equation represents a variable as a linear combination of multiple other variables that may impact it. These models usually contain a large number of variables and allow for precise analysis economy reaction to different policy scenarios and alternative path of exogenous variables (Kilian and Lütkepohl, 2017).

The demise of this model started with the widely spread critique of econometric policy evaluation by Lucas (1976), when he explained the invariance of estimated models to different policy scenarios. The force of this critique diminished the use of this model in academic research and induced a rise in interest in alternative models, like DSGE models.

3.1.2 Dynamic Stochastic General Equilibrium Models

DSGE models can also be represented as a system of equation comporting endogenous variables such as output or capital, which are subject to exogenous state variables shocks.

When implementing DSGE models, the user must define the microstructure of the economy, determining the organization of each economic unit, their characteristics and behavior (like rational expectations of agents and utility maximization). This structure is fixed and does not vary when new shocks happen in the economy.

Exogenous shocks can be applied to the model such as technology evolution or other random variations. The dynamic of the endogenous variables subject to random shocks in the model is determined by a (log-linear) structure of agents' behaviors that depend on the variables known to the agents at each time point (Kilian and Lütkepohl, 2017).

Canova and Ciccarelli (2013) identify the main drawback of these models. By construction, a lot of restrictions are imposed on the model structure, which are not always in line with the statistics of underlying data used to calibrate or estimate the model parameters.

3.1.3 Comparison Table

The below table summarize the main strengths and weaknesses of the three methods.

Table 3.1: Macroeconomic models features comparison.

Features	**DSEM**	**DSGE**	**SVAR**
Exogeneity restrictions	Many	Few	None
Dynamic exclusion restrictions	Many	Few	Few
Number of variables	Very large	Large	Small
Number of shocks	Many	Few	Few
Trend treatment	Implicit	Explicit	Explicit
Microstructure required	No	Yes	No

Notes: This table is retrieved from Kilian and Lütkepohl (2017).

In the end, we chose to implement a VAR model for several reasons. First, it is widely recognized in the economic literature as an effective tool to capture dynamic monetary policy effect on other economic indicators. The abundant documentation about this model is crucial to develop a robust model. Then, from the above criteria, the model also stands out for its simplicity which makes it is easy to read and interpret the produced results. Also, this model is very flexible: it is easy try different models, to add or delete a variable, to change the time frame or the number of lags, and to compare the different models with diagnostics tests.

3.2 Autoregressive Time Series Models: Theory

The empirical model employed in this paper falls under the category of autoregressive models. This section serves the purpose of offering readers a comprehensive understanding of the underlying mechanics of the model, along with their respective assumptions and validation procedures.

3.2.1 Autoregressive process (AR)

According to Athanasopoulos and Hyndman (2018), autoregressive processes are useful when future values of a variable of interest depend uniquely on a linear combination of the past values of the variable. Mathematically, a univariate autoregressive process of order p (meaning that we use p past values to explain the variable at a certain time point), noted $AR(p)$, is:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p} + u_t \tag{3.1}$$

Where y_t is a real, a_0 is a constant, $a_i, i = 1, \ldots, p$ are estimated coefficients. u_t represents the stochastic error term (or innovation) and is assumed to be a white noise process with zero mean, constant variance and serial uncorrelation. In other words, $\mathbb{E}(u_t) = 0$, $\mathbb{E}(u_t^2) = \sigma_u^2$ and u_t and u_s are uncorrelated for $t \neq s$.

3.2.2 Vector Autoregressive (VAR)

Vector autoregressive (VAR) models are used to capture the dynamic interactions between multivariate time series. In essence, it is a system of linear regression equations, where each line represents a specific variable. Each variable depends on its own lag values but also past values from the other variables in the model, up to a specific number of lags p, called a $VAR(p)$ model (Kilian and Lütkepohl, 2017).

Let us consider a K-dimensional VAR model of order p

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t \tag{3.2}$$

Where $\boldsymbol{y}_t = [y_{1t}, \ldots, y_{Kt}]'$ is the vector of observable variables, $\boldsymbol{A}_i, i = 1, \ldots, p$ are $(K \times K)$ coefficients matrix, and a constant term vector $\boldsymbol{a}_0$ is added to the model to capture intercept parameters. Like above, the vector $\boldsymbol{u}_t$ consists of reduced-form residuals, which are serially uncorrelated, have zero mean and $Cov(\boldsymbol{u}_t) = \boldsymbol{\Sigma}_{\boldsymbol{u}}$ is the $(K \times K)$ variance-covariance matrix. The diagonal elements of this matrix are the variances of the endogenous variable, and the off-diagonal elements are covariances of the errors.

For example, the mathematical representation of a simple VAR(p) model containing the interest rate (i_t) and the inflation rate (π_t) for $t = 1, \ldots, T$ can be summarized with the following system of equations:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t \tag{3.3}$$

Where

$$\boldsymbol{y}_t = \begin{pmatrix} i_t \\ \pi_t \end{pmatrix}, \quad \boldsymbol{A}_i = \begin{bmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{bmatrix} \; for\; i = 1, .. p \;, \quad \boldsymbol{u}_t = \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

$\boldsymbol{u}_t$ being independent and identically distributed (iid) white noises.

Such a model is qualified as reduced form model, which means that the current values of the data is a linear combination of only its own past values and lagged values from other variables endogenously included in the model. This model estimates contemporaneous and lagged effects among the variables, capturing their interdependencies and interactions over time.

3.2.3 Structural Vector Autoregressive (SVAR)

The SVAR model is an extension of traditional VAR models with the objective of identifying structural relationships and shocks in a system and estimate the causal effects of these structural shocks on the variables.

To do so, additional identification restrictions have been incorporated on the residuals (B-models) or on the coefficients (A-models). We will focus on B-models, where the identification process involves applying restrictions on the VAR residuals to decompose them into structural shocks. SVAR models assume that structural shocks affecting variables can be decomposed into orthogonal or independent component, enabling a more senseful economic interpretation of the error term (Kilian and Lütkepohl, 2017).

From Kilian and Lütkepohl (2017), a B-model takes the form of:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{3.4}$$

- $\boldsymbol{y}_t$ is the $K \times 1$ vector of observed time series variables, $t = 1, \dots, T$
- $\boldsymbol{a}_0$ represent intercept parameters.
- $\boldsymbol{A}_i,\ i = 1, \dots, p$, are $(K \times K)$ matrix of autoregressive coefficients.
- $\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t$ represent the structural shocks, a $K \times 1$ vector of series with zero mean and serially uncorrelated. $Cov(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$ is a diagonal matrix.
- $\boldsymbol{B}$ is a $K \times K$ matrix, the structural impact multiplier matrix, implementing the instantaneous effect of the structural shocks on the variables of the system.

In both above models, fitted coefficients from the regression refer to the estimated values of the endogenous monetary policy actions, which are influenced by the lagged values of the endogenous variables. The residuals $\boldsymbol{u}_t$ represent the portion of the observed policy actions that are not determined by the endogenous variables. They reflect the random or stochastic component of the system and do not have a clear economic interpretation. However, The SVAR model decomposes the reduced-form residuals into structural shocks, which have economic interpretations and can be associated with specific factors or shocks in the system (Kilian and Lütkepohl, 2017).

The implementation of a structural VAR model enables us to consider that the fluctuations in the data are influenced by the combined impacts of economically meaningful structural shocks. The current data observations can be seen as a blend of present and previous structural shocks. This understanding holds significance as it aids researchers in quantifying causal connections in the data that may be concealed in reduced-form VAR analysis (Kilian and Lütkepohl, 2017).

The covariance matrix of the structural shocks, $Cov(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Sigma}_{\varepsilon}$ is a diagonal matrix. This result is important as it ensures the structural shocks are uncorrelated, which is necessary for meaningful impulse response analysis (Lütkepohl, 2005).

One can easily see that the estimation of the reduced form VAR model is the starting point for the subsequent SVAR estimation techniques, that will be based on the reduced form residuals estimates $\boldsymbol{u}_t$ and their covariance matrix. In SVAR analysis, the main challenge is to adequately identify the matrix $\boldsymbol{B}$, known as the identification problem. From Equation 3.2, we retrieved the covariance matrix $Cov(\boldsymbol{u}_t)$ which is a representation of the cross-equation relations of the reduced-form residuals:

$$Cov(\boldsymbol{u}_t) = \boldsymbol{\Sigma}_{\boldsymbol{u}} = \boldsymbol{B}\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}\boldsymbol{B}' \tag{3.5}$$

Straightforward, Equation 3.5 holds for any matrix $\boldsymbol{B}$ that decompose the covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{u}}$. The matrix $\boldsymbol{B}$ is thus non-unique, additional restrictions need to be implemented to ensure unicity (Lange et al., 2021). We will present in section 3.3.2 a few different techniques commonly used to identify the (unique) inversible matrix $\boldsymbol{B}$.

3.3 Model estimation

3.3.1 Lag-Order Selection Procedure

When estimating a VAR model, one must determine the appropriate lag order p to use. In practice, literature agrees that this lag order should be derived from the data used in the model using tools such as information criteria or sequential testing procedures (Kilian and Lütkepohl, 2017).

The *sequential testing procedure* involve a series of hypothesis test that continues until the null hypothesis is rejected. In a top-down method, the starting point is a model with order $p_{\max}$, the largest model, and sequentially reduce the number of lags, using Wald or LR tests for parameter restrictions. Bottom-up sequential tests start from the simplest model and enlarging the model adding lags only when residuals autocorrelation tests show that the dynamic structure of the data is not captured properly by the model. Usual tests for this method are Portmanteau test or LM test (Kilian and Lütkepohl, 2017).

Information criteria methods rely on the trade-off between the accuracy of the model (improved fit to the data when lag order increase) and the parsimony of the model to select the adequate lag order of the VAR model. From the literature, three criteria stand out as the most commonly used: the Akaike Information Criterion (AIC), the Hannan-Quinn Criterion (HQC) and the Schwarz Information Criterion (SIC), or also called Bayesian Information Criterion (BIC) (Kilian and Lütkepohl, 2017). Each criterion is a computed following a mathematical formula of the form:

$$Criterion(m) = \log\left(\det\left(\boldsymbol{\Sigma}_u(m)\right)\right) + c_T\varphi(m) \tag{3.6}$$

Where m is the potential lag order used to compute the criterion, $\boldsymbol{\Sigma}_u(m)$ is the residual covariance matrix of the model, $\varphi(m)$ corresponds to the total number of regressors, and c_T is a sequence of weights that depends on the sample size.

A common rule used to determine the maximum number of lags to implement in a model has been developed by Schwert (1989):

$$p_{max} = [12\, x \left(\frac{T}{100}\right)^{\frac{1}{4}}] \tag{3.7}$$

3.3.2 Model estimation method

Let us consider our VAR and SVAR models again:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t \tag{3.8}$$

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{B}\boldsymbol{\varepsilon}_t$$

The first step is to estimate the coefficients matrix $\boldsymbol{A}_i, i = 1, \dots, p$ of the equation system from the Vector autoregressive model. Estimation of the reduced form VAR is straightforward, using or least squares (LS) or maximum likelihood methods (see, e.g., Lütkepohl 2005). LS method means finding the coefficients matrix such that the sum of squared residuals u_t is minimized.

SVAR estimation is more controversial, and the literature offers different methods to identify the non-unique structural form. Starting with the groundbreaking research by Sims in 1980, scholars have established two primary approaches to identification strategies. One approach, inspired by Sims' original ideas, revolves around incorporating economic theory. These methods employ economic constraints, such as short-run or long-run restrictions (introduced by Sims in 1980 and Blanchard and Quah in 1989, respectively), or specific patterns of signs (as demonstrated by Uhlig in 2005), as a priori assumptions. In these methods, the structural estimation amounts to include in the model prior beliefs of economic theory though the $\boldsymbol{B}$ matrix by imposing restrictions on the coefficients to be estimated, i.e. sign restrictions or forcing some coefficients to be null.

Conversely, Lange et al. (2021) gather in their paper more recent advancements in statistical identification methods that capitalize on the specific characteristics of the data itself, such as heteroskedasticity of structural shocks or the uniqueness of non-Gaussian independent components. Heteroscedasticity of the structural shocks refer to the idea that the variance or covariance of the residuals might be subject to structural and persistent change at a certain point in time. Non-gaussian refers to the non-normal distribution of the reduced-form residuals.

Lange et al. (2021) summarized six different estimation methods within the two above categories, that can be applied in diverse data settings. Our VAR results showed a concordance with the second category, estimating the least dependent innovation under non-gaussian assumption. This estimation technique has been developed by Matteson and Tsay in 2017 and is based on the distance covariance matrix.

Also, we chose this method because Herwartz, Lange, and Maxand (2019) made a large-scale comparative study of the different heteroscedasticity and independence-based models. Evidence from the simulations suggest that identification through independent components offers increased robustness compared to alternative distributional frameworks and heteroskedasticity, as long as the innovations possess non-Gaussian characteristics.

The mathematical explanation of the estimation method is derived from Lange et al. (2021). In the presence of Gaussianity, the decomposition factor of the covariance matrix $\boldsymbol{\Sigma}_u$ lacks uniqueness since Gaussian random vectors maintain their joint distribution when rotated.

However, if we assume that there is no more than one Gaussian-distributed component ε_{it} in $\boldsymbol{\varepsilon}_t$, the structural matrix $\boldsymbol{B}$ can be determined uniquely. To introduce the nonparametric identification scheme, let $\boldsymbol{D}$ represent a lower triangular Cholesky factor of the covariance matrix of the reduced-form errors, $\boldsymbol{\Sigma}_u = \boldsymbol{DD'}$, which establishes a connection between the structural and reduced-form errors through $\boldsymbol{\varepsilon}_t = \boldsymbol{D}^{-1}\boldsymbol{u}_t$. Additional candidate structural shocks can be generated by this approach as

$$\tilde{\boldsymbol{\varepsilon}}_t = \boldsymbol{Q}\boldsymbol{\varepsilon}_t = \boldsymbol{Q}\boldsymbol{D}^{-1}\boldsymbol{u}_t, \tag{3.9}$$

Where $\boldsymbol{Q}$ represents a rotation matrix such that $\boldsymbol{Q} \neq \boldsymbol{I}_K,\ \boldsymbol{QQ'} = \boldsymbol{I}_K$. The parameterization of the rotation matrix can be achieved by utilizing the product of $K(K-1)/2$ unique forms of orthogonal *Givens* rotation matrices. For instance, when $K = 3$, the definition of $\boldsymbol{Q}(\theta)$ is as follows:

$$Q(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_1) & -\sin(\theta_1) \\ 0 & \sin(\theta_1) & \cos(\theta_1) \end{bmatrix} \times \begin{bmatrix} \cos(\theta_2) & 0 & -\sin(\theta_2) \\ 0 & 1 & 0 \\ \sin(\theta_2) & 0 & \cos(\theta_2) \end{bmatrix} \times \begin{bmatrix} \cos(\theta_3) & -\sin(\theta_3) & 0 \\ \sin(\theta_3) & \cos(\theta_3) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

With rotation angles $0 \leq \theta_i \leq \pi,\ i = 1,2,3$. The random vector $\tilde{\varepsilon}_t$ is defined as a rotation of the vector $\boldsymbol{\varepsilon}_t$. The set of potential structural matrices $\boldsymbol{B}(\theta)$, denoted by $\boldsymbol{DQ}(\theta)$, is specified based on the Cholesky factor $\boldsymbol{D}$ and the vector of rotation angles θ for the Givens matrices.

From the various criteria available to measure the degree of dependence between random variables, we decided to use the Székely et al. (2007) distance covariance, denoted as $\mathcal{U}_t(.)$. Matteson and Tsay (2017) developed an Independent Component Analysis (ICA) algorithm that gives a matrix estimate $\widehat{\boldsymbol{B}}$ by minimizing the distance covariance of the respective structural shocks $\tilde{\boldsymbol{\varepsilon}}_t = \widehat{\boldsymbol{B}}^{-1}\widehat{\boldsymbol{u}}_t$, using a gradient algorithm. The definition of potential structural matrices $\boldsymbol{B}(\theta)$ involves the utilization of the Cholesky factors $\boldsymbol{D}$ and the vector of rotation angles θ in $\boldsymbol{Q}(\theta)$. The estimation of the structural matrices $\widehat{\boldsymbol{B}} = \boldsymbol{B}(\tilde{\theta})$ is determined by the rotation angles $\tilde{\theta} = argmin_\theta \mathcal{U}_T\big(\tilde{\boldsymbol{\varepsilon}}_t(\theta)\big)$.

3.3.3 Model Diagnostics

There is a wide array of tools to assess the robustness of estimated VAR models. These tools include informal graphical techniques such as residual plots but also more formal statistical specification tests to evaluate the validity of the model's underlying assumptions (mainly the white noise properties of the residuals).

- **Test for Residual Autocorrelation**

One basis assumption of the VAR models is that the residuals are white noises, hence $\boldsymbol{u}_t$ are assumed to show no serial correlation. To verify that this assumption holds, we use on the residuals a Portmanteau testing method of the absence of serially correlated disturbances. This test evaluates the null hypothesis of $H_0\colon \mathbb{E}(\boldsymbol{u}_t \boldsymbol{u}_{t-i}') = 0, i = 1,2, \ldots$ (Kilian and Lütkepohl, 2017).

- **Test for Heteroscedasticity**

Then, we test the assumption of constant variance in the residuals, or the presence of homoscedasticity. In time series, we name by Auto-Regressive Conditional Heteroskedasticity (ARCH) effect clustered areas of volatility, which can happen during changing economic conditions like crisis. Hence, an ARCH Lagrange Multiplier test can be performed on the residuals to detect time-varying conditional volatility (Kilian and Lütkepohl, 2017).

- **Test for Normality**

Although normality of the residuals is not a mandatory characteristic for the validity of VAR modelling, it can still be an area of interest. Normality of the residuals can be observed via a histogram but in a more formal setup, the most common way to statistically verify normality is via the test developed by Jarque and Bera (1987). The objective of this test is to have a global measure of the skewness and the kurtosis of the residuals and verify these values are similar to those of a normal distribution.

- **Stability of the model**

A crucial assumption in conventional VAR analysis is the time-invariance of the model. A wide array of techniques exists to test the stability over time of a model. One possibility is to implement a Chow test of assessing the null hypothesis of time-invariant parameters throughout the entire sample period in contrast to the possibility of parameter values changing at a specific date. Another possibility for structural change testing, the one we will use in this thesis, is based on fitting models to samples of increasing length and analyzing recursive residuals. More formally, we start from a sample size of T_0 and fit a model to the sample for $t = 1, \ldots, \tau \; with \; \tau \in \{T_0, \ldots, T\}$ using least square and retrieve the recursive residual (the last residual). We then compute the cumulative sum (CUSUM) of recursive residuals and test for stability based on this value. This methodology has been originally developed by Durbin and Evans (1975) for testing structural change in linear regression models.

4 Methodology & Data

4.1 Methodology

The aim of this empirical analysis is to employ a Vector Autoregressive (VAR) and Structural VAR (SVAR) modeling approach to investigate the impact of monetary policy on inflation. By employing these models, we seek to comprehensively assess the dynamic relationship between key monetary policy variables and inflationary trends. The VAR model allows us to capture the interdependencies among multiple variables, whereas the SVAR model enables us to identify and estimate the causal effects of structural monetary policy shocks on inflation.

Several tools have been developed to analyze the relations estimated via VAR and SVAR models, as described in Kilian and Lütkepohl (2017):

Impulse Response Analysis. Describe the dynamic response of a variable to a one-unit shock in another variable (or structural shock), while holding all other variables in the VAR (SVAR) model constant.

Forecast Error Variance Decomposition. Emphasize the individual impact of each shock on the variability of the variable under examination (in SVAR analysis).

Historical Decomposition. Provide further information on the contribution of structural shocks to a variable of interest over time (in SVAR analysis).

This methodology provides a robust framework to analyze the complex interactions and transmission channels involved in the monetary policy-inflation, yielding valuable insights into the effectiveness and implications of monetary policy actions in shaping inflation outcomes.

4.1.1 Impulse Response Function

Kilian and Lütkepohl (2017) explain that IRFs illustrate the dynamic response of a variable to a one-unit shock in another variable, while holding all other variables in the VAR model constant. Doing so, this tool provides insights into the magnitude, timing, and persistence of the responses.

Concretely, the IRF is computed by simulating the VAR model with the impulse at time 0 and let the system evolve using the estimated equations. The responses of the variables are recorded at each time period and can be displayed in a plot. More formally, Pfaff (2008) explains that the evolution of the system for the impulse response function is based on a representation of the VAR(p)-process called Wold Moving Average Decomposition. The effects of shocks in the variables of the system are represented as the following decomposition:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_0 \boldsymbol{u}_t + \boldsymbol{\Phi}_1 \boldsymbol{u}_{t-1} + \boldsymbol{\Phi}_2 \boldsymbol{u}_{t-2} + \cdots, \tag{4.1}$$

With $\boldsymbol{\Phi}_0 = \boldsymbol{I}_K$, and the $\boldsymbol{\Phi}_\mathbf{s}$ are computed reiteratively following:

$$\boldsymbol{\Phi}_\mathrm{s} = \sum_{j=1}^{s} \boldsymbol{\Phi}_{\mathrm{s-j}} \boldsymbol{A}_j \ \ for\ s = 1,2, \ldots and\ \boldsymbol{A}_j = 0\ for\ j > p \tag{4.2}$$

The $(i,j)th$ element of the matrices $\boldsymbol{\Phi}_\mathrm{s}$ can be interpreted as the response of variable $y_{i,t+s}$ to a unit shock in variable y_{jt}, with all other past values of $\boldsymbol{y}_t$ being constant. The change in y_{it} is measured by the innovation u_{it}.

In a SVAR model, impulse response functions show the impact of an unexpected one-time impulse in structural shocks $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Kt})'$ on variables in the system over the next periods (Kilian and Lütkepohl, 2017). From Lütkepohl (2005), Equation 3.4 can be rewritten as

$$\begin{aligned} \boldsymbol{A}(L)\boldsymbol{y}_t &= \boldsymbol{a}_0 + \boldsymbol{B}\boldsymbol{\varepsilon}_t \\ \boldsymbol{y}_t &= \boldsymbol{A}(L)^{-1} a_0 + \boldsymbol{A}(L)^{-1} \boldsymbol{B}\boldsymbol{\varepsilon}_t \\ &= \boldsymbol{v} + \boldsymbol{\Phi}(L)\boldsymbol{B}\boldsymbol{\varepsilon}_t = \boldsymbol{v} + \sum_{i=0}^{\infty} \boldsymbol{\Phi}_\mathrm{i} \boldsymbol{B}\boldsymbol{\varepsilon}_{t-i} = \boldsymbol{v} + \sum_{i=0}^{\infty} \boldsymbol{\Theta}_\mathrm{i} \boldsymbol{\varepsilon}_{t-i} \end{aligned} \tag{4.3}$$

Where $\boldsymbol{v}$ is the unconditional mean of the series, and $\boldsymbol{A}(L) = \boldsymbol{I} - \boldsymbol{A_1 L} - \boldsymbol{A_2 L^2} - \cdots - \boldsymbol{A_p L^p}$. $\boldsymbol{\Theta}_\mathbf{i} = \boldsymbol{\Phi}_\mathbf{i} \boldsymbol{B}$ can also be expressed as

$$\frac{\partial \boldsymbol{y}_{t+i}}{\partial \boldsymbol{\varepsilon}_t{}'} = \boldsymbol{\Theta}_\mathrm{i}, i = 0,1,2, \ldots, H\ where\ \Theta_\mathrm{i}\ is\ a\ K \times K\ matrix$$

The elements of $\boldsymbol{\Theta}_\mathbf{i}$ are interpreted as the response of the system to shocks $\boldsymbol{\varepsilon}_t$.

4.2 Data

4.2.1 Variables Choice

The underlying data for the analysis comports of monthly economic indicators, ranging from January 1999 to June 2023. All data have been retrieved from online public databases like

Eurostat, ECB Statistical Data Warehouse or ECB Data Portal. The year 1999 marks the creation of the ECB, it was thus a natural choice to start our analysis by this year.

Throughout the process, various models have been implemented, a lot of different variables combination have been tried, in order to develop the model that captures the best the sought effect: the impact of monetary policy on inflation developments. It turned out including too many variables was leading the model to overfitting and poor test diagnostics results. In Appendix A, one can find the different tested models and their diagnostic.

During the variable choice, a trade-off has been encountered: balancing between the will to have meaningful variables, that can explain each other and interact with each other accurately, and the assumption of stationarity in the time series when working with VAR models (see more information about that in section 4.2.2). For example, a simple way to transform interest rate, which is not stationary as such, is to differentiate the time series (subtracting the current value of the series from the previous one). Because ECB's key interest rates are sometimes constant over several periods, the resulting differentiated series deviates totally from the original data structure and eliminates the information.

Our final model contains 3 variables: a measure of inflation in the Euro Area, the growth of economic activity and an interest rate. This choice is in line with our assumption that central banks set interest rate following a Taylor-type rule.

Surely, Central Banks respond to more variables than only economic output and inflation, but VAR with too many variables lose in credibility in the VAR estimates, with a greater chance of overfitting. Standard VAR models have difficulties handling more than about 6 variables, and even worse when the sample size is too small (Kilian and Lütkepohl, 2017).

4.2.2 Model Variables Description

The first variable of the model is the inflation rate, $inflation_t$, measured as the percentage change in the Euro Area (EA) Harmonized Index of Consumer Prices (HICP) compared with the same period one year earlier ("year-on-year" or "y-o-y" changes). This variable represents the main target of central banks.

After, general economic activity is included in the model through the annual growth rate of real GDP in EA, gdp_growth_t, which is an indicator of global health of the economy. GDP data is not available on a monthly basis but is published every quarter, hence we used linear interpolation to transform quarterly data into monthly time series.

The last variable is the short-term interest rate. In the beginning, this rate was defined as the central bank monetary policy instrument. The ECB has 3 key interest rates, from which we selected the rate on deposit facility. Deposit facility allows banks to place overnight deposits at national central banks. The deposit rate provides a floor for the overnight interbank market interest rate (like Euribor), thus shapes the whole short-term money market rates. By investing the dynamics of this rate, we figured out this deposit facility rate was not adequate for VAR modelling. Indeed, this rate is fully determined by the ECB, which makes its evolution following a stairs shape, jumping or decreasing by the fixed amount decided in the monetary policy. Hence, we decided to use the Euribor 3-months as the short-term interest rate for the Euro Area. EURIBOR stands for Euro Inter Bank Offering Rate and is a benchmark in the Eurozone. In essence, it is the average interest rate at which Eurozone banks offer unsecured funds to one another in the interbank market for a three-month period. It serves as a reference rate for various financial products. This rate is not directly controlled by central banks, but key interest rates strongly influence the dynamics of interbank rates (see Appendix B for a plot of both Euribor3m and ECB deposit facility to see how similar the dynamics of both rates are). To achieve stationarity, our final variable for the short-term interest rate is the year-to-year change in the Euribor 3-months, called $interest\_rate\_ch_t$.

4.2.3 Data Validation Tests: Stationarity

Working with times series to build vector autoregressive models relies on certain assumptions. The most important one is the *stationarity* of each time series, which ensures reliability of the estimated long-run relationships and accurate short-run dynamics between variables. Stationarity is defined as the property of time series where its statistical properties, such as mean, variance and autocovariance, do not vary over time (Kilian and Lütkepohl, 2017). However, non-stationary series can still be used in the VAR framework, even though less accurate.

The first step into assessing stationarity is to plot the time series to have a general overview of the behavior of the series (Athanasopoulos and Hyndman, 2018). Time series that comports trends or seasonal patterns, are not stationary. The plot of a stationary time series should be approximately horizontal, with a constant variance.

The most common method to transform a non-stationary series to compute the difference between consecutives observations, known as differencing. It helps to remove changes in level, and hence stabilize the mean of a series, reducing trends or seasonality (Athanasopoulos and Hyndman, 2018). More objectively and precisely, one way of determining whether a series is stationary or not is to perform a *unit root test*. We will present two different of these hypothesis tests and perform them to determine if differencing is needed.

The most widespread unit root test is the Augmented Dickey-Fuller (ADF) test, which has as null hypothesis H_o that the time series has one unit root and therefore are stationary. If the p-value of the test is below 0.05 (5%), we reject the null hypothesis of non-stationarity, and the series are stationary. If we fail to reject the null hypothesis, the time series must be transformed to remove the unit root.

Kwiatkowski, Phillips, Schmidt, and Shin (1992) proposed an alternative test, that we will use to verify our ADF test results. Indeed, because the methodology behind the tests is different, they may lead to different results. In the KPSS test, the null hypothesis is the stationarity of the series, and the alternative hypothesis is the unit root existence. In this test, we will look at the test statistic value and compare it with the critical value, which is 0.463 for a 5% significance level. We will reject the null hypothesis of stationarity if the test statistic is above the critical value, i.e. small values of the test statistic indicates there is no unit root.

- **Results**

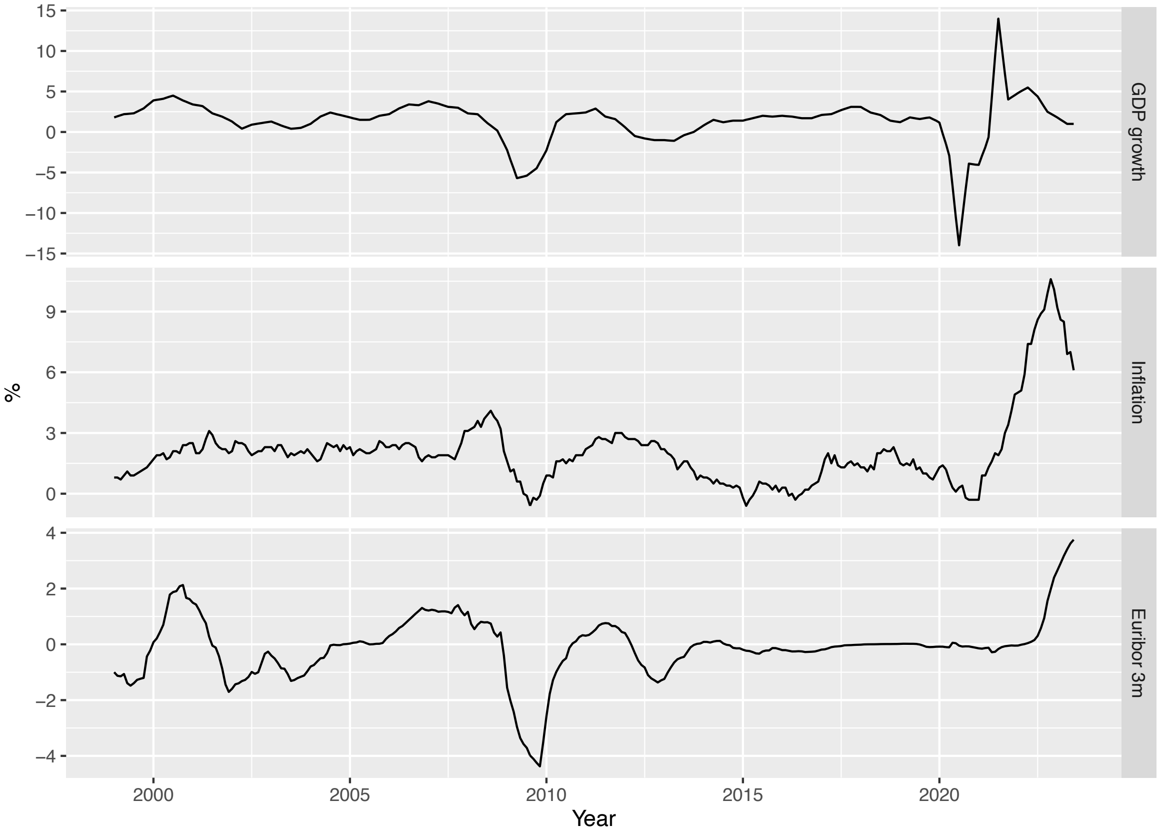
In economy, stationarity is more the exception than the rule. Performing the test on all the variables confirmed this general thought, this is why all our series are expressed in terms of "growth rate" or "change in" rather than index or nominal values. Below, you can see the final results of our unit root tests as well as plots representing our different variables in the model.

Table 4.1: Unit root tests results

	Augmented Dickey-Fuller	**KPSS**
Criteria	***p-value < 0.05***	***t-stat < 0.463***
$inflation_t$	0.03	0.382
gdp_growth_t	0.03	0.182
$interest\_rate\_ch_t$	< 0.01	0.238

Notes: All the tests have been performed with at least 5 lags.

Figure 4.1: Model variables time plot, 1999-2023



Source: Monthly data series retrieved from ECB Data Portal.
https://data.ecb.europa.eu/#dashboard-tab-1

From Table 4.1, the results from our stationarity tests show that all our series are stationary, which respects the underlying assumption of VAR modelling. This has been achieved by using growth rates or change in rates instead of real rate. Figure 4.1 represents a time plot of the different variables used in the model. It is observable that the series are rather horizontal with constant variance but suffer from short time intervals of anormal behaviors that have occurred during crisis periods such as the 2008 Global Financial Crisis, the Covid era or the recent surge in inflation. However, these anomalies in the data are not strong enough to alter the outcome of our ADF and KPSS stationarity tests.

5 Econometric Results

This chapter's aim is to present our estimated models and their main relevant findings for monetary policy assessment. Our goal is to show that the estimated models provide valuable insights into the effectiveness and implications of monetary policy, while highlighting some of their limitations.

5.1 Model Estimation

5.1.1 Reduced-form VAR Model

The starting point of our analysis is a 3-dimensional VAR model of order 12, $VAR(12)$ of the form:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_{12} \boldsymbol{y}_{t-12} + \boldsymbol{u}_t \tag{5.1}$$

We included a constant in the model to represent the baseline level. Economic reasoning let us believe that the variables have a long-run average, the mean of our series being 1.39/2.04/-0.09 for the GDP growth, Inflation and Euribor-3m change respectively. This long-run average will be captured by the constant, estimated at respectively 0.179, 0.129 and -0.042.

The coefficients matrix $\boldsymbol{A}_i, i = 1, \dots, 12$ and the intercept have been estimated using Ordinary Least Square (OLS) per equation, minimizing the sum of squared residuals $\boldsymbol{u}_t$. A straightforward analysis of the coefficients, given their amount and time difference, is complicated. Still, you can find the list of coefficient matrix in Appendix C.

However, what can be analyzed is the estimated variance-covariance matrix of the residuals, as displayed in Table 5.1.

Table 5.1: Variance-Covariance matrix of the VAR residuals

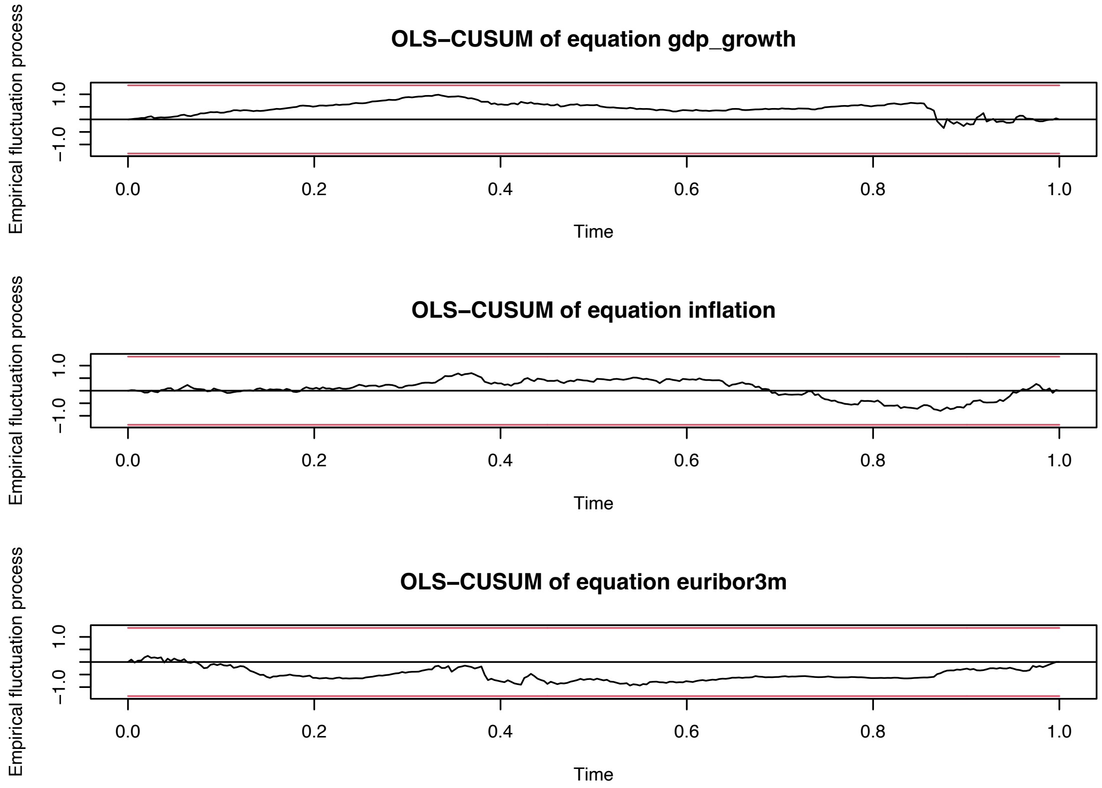
	$\boldsymbol{GDP\ growth}$	$\boldsymbol{Inflation}$	$\boldsymbol{Euribor\ 3m}$
$\boldsymbol{GDP\ growth}$	0.233	0.016	-0.005
$\boldsymbol{Inflation}$	0.016	0.084	0.004
$\boldsymbol{Euribor\ 3m}$	-0.005	0.004	0.016

First, a positive covariance between GDP growth and inflation indicates that periods of higher GDP growth are associated with higher inflation levels and vice-versa, which is consistent with the will to cool down economic activity when ECB tries to control inflation. Then, we observe negative covariance between GDP growth and Euribor-3m changes. This relation shows that periods of lower GDP growth appear when the interest rate increase. This result is in line with the monetary policy transmission mechanisms explained in section 2.3.3. Finally, periods of higher interest rates change are linked to periods of higher inflation, as expected from the economic theory of central bank's monetary policies to fight inflation. Attention that covariance does not imply causality, causation will be analyzed in the next sections.

About the model estimation, the lag order has been chosen using information criteria, and in particular the AIC, but also model diagnostics. AIC was postulating a lag order equal to the lag max, but the model diagnostics were better using 12 lags. Other criteria were proposing a lower number of lags, but studies have shown that AIC was performing better than the other lag order methods explained earlier (Kilian and Lütkepohl, 2017). Moreover, when dealing with monthly data, the application of this criterion's recommendations results in reduced mean squared error (MSE) in the estimation of response points and more precise confidence intervals for impulse response functions. This characteristic holds particular significance for our analysis, as the impulse response function serves as a focal point in our research (Kilian and Ivanov, 2005). This number of lags is in line with previous similar studies (see for example Herwartz and Plödt, 2016a), and sufficient to capture the potential delays in the transmission of changes in one variable to another in the system.

The implementation of the model diagnostics tests explained in section 3.3.3 proved the robustness of our model. The residuals autocorrelation test with $h = 60$ shows a p-value of 0.35, above the threshold of 0.05. We fail to reject the null hypothesis of no serial correlation. For the heteroscedasticity test of the residuals, we obtain a p-value of 0.03, very close to the threshold. We take this value as acceptable for the model (looking at the data plots, this result is certainly driven by the 2 spikes in our data, during the 2008 crises and the recent surge in inflation). We consider it acceptable because it is not a permanent change in the structure of the data, there are just two anormal spikes in the data that impact variance development. The normality test shows non normality of the residuals, which is good for our later estimation of the SVAR model based on non-gaussian residuals. Finally, Figure 5.1 displays the structural stability of the VAR model, where cumulative sum of our recursive estimation residuals stays

Figure 5.1: Stability of the VAR model


OLS−CUSUM of equation gdp_growth

OLS−CUSUM of equation inflation

OLS−CUSUM of equation euribor3m

Notes: Recall from section 3.3.3, the plots display the cumulative sum of recursive residuals for models fitted to samples of increasing length (increasing with time)

within the barriers, showing stability of the model. When the CUSUM significantly deviates from the zero line, it indicates potential lack of structural stability in the underlying model.

Also, Appendix D displays a diagram of fit, a residual plot, the autocorrelation and partial autocorrelation function of the residuals for each equation, which confirm our above diagnostic.

5.1.2 Independence Based Estimation of Structural VAR

As explained before, the structural VAR model in an enhancement of the reduced-form model where a matrix $\boldsymbol{B}$ is estimated to capture the instantaneous effects of the structural shocks on the variable of the system.

Our statistical estimates for the matrix $\boldsymbol{B}$ in our 3-dimension framework, that corresponds to the unique decomposition of the least squares covariance matrix of the reduced form residuals $\boldsymbol{\Sigma}_u$ obtained by minimizing the distance covariance of the respective structural shocks, yields:

$$\widehat{\boldsymbol{B}} = \begin{bmatrix} 0.482 & 0.020 & 0.017 \\ 0.021 & 0.285 & 0.049 \\ -0.015 & -0.06 & 0.127 \end{bmatrix}$$

We obtain a model of the form:

$$\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_{12}\boldsymbol{y}_{t-12} + \tilde{\boldsymbol{\varepsilon}}_t \qquad (5.1)$$

Where $\tilde{\boldsymbol{\varepsilon}}_t = \widehat{\boldsymbol{B}}^{-1}\widehat{\boldsymbol{u}}_t$.

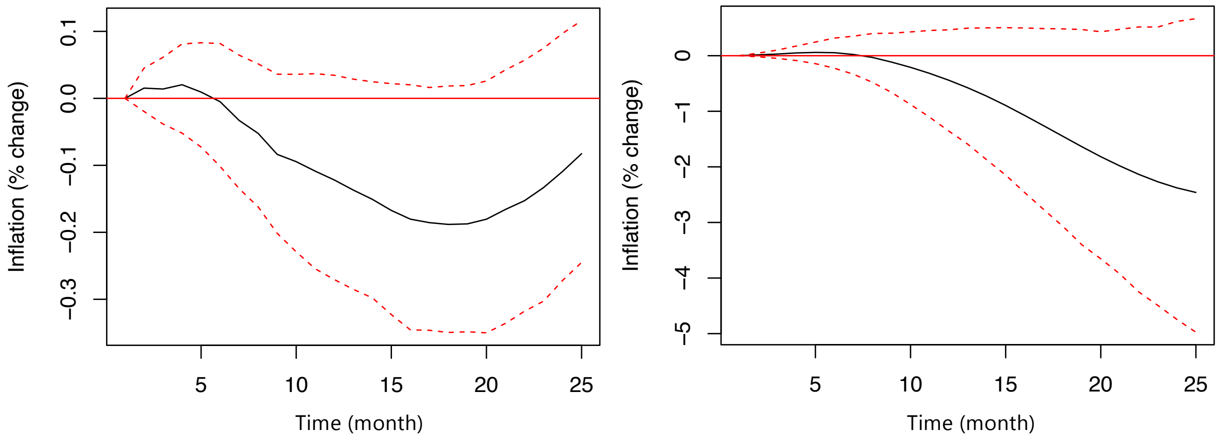
The $\widehat{\boldsymbol{B}}$ matrix must be read as follows: the rows represent the model variables, the first being GDP growth and the last interest rate change, and the columns represent the structural shocks associated with the variables, e.g. the first column is $\varepsilon_{GDP\ growth}$. For example, element (2,1) of the matrix is the contemporaneous impact of the structural shock $\varepsilon_{GDP\ growth}$ on inflation. Our computations corroborate the findings of Herwartz and Plödt (2016b), indicating that the empirical model does not successfully identify a monetary policy shock based on its theoretical effect pattern.

A first observation of the coefficients absolute values allows to understand the strength of the impact: larger absolute values in the $\widehat{\boldsymbol{B}}$ matrix suggest a stronger contemporaneous impact of the shocks on the variables. Hence, the estimation suggests that the structural shocks have a more significant impact on the variables to which they are associated than on the other variables, which makes sense and is in line with our labelling. A focus on the last column, the contemporaneous impact of monetary policy shocks on the variables in the model, we see positive coefficients. This means that, in the short run, our model postulates that monetary policy shocks have a positive relationship with GDP growth and inflation, with a greater influence on inflation than on GDP growth. Even if this result may seem strange, it is a rather frequent observation, called the "price puzzle", that we will discuss later in section 5.2.2.

5.2 Impulse Response Function

In this section, we will discuss the impact of the variation in one particular variable on the other variables in the system and compare our results with the economic theory and previous similar empirical studies.

Figure 5.2: Response (left) and cumulative response (right) of **inflation** to a **shock in interest rate change.**



Notes: Impulse response function of an interest rate change shock on inflation for 24 periods ahead. Generated with our 3-variables VAR model estimated on monthly data from January 1999 to June 2023.

5.2.1 Shocks in the Model Variables

This section is based on our reduced-form VAR model estimation. In Figure 5.2, we observe the impulse response of *inflation* to a one-unit shock in interest rate y-o-y change on the left and the cumulative impulse response on the right (the third variable, GDP growth, remaining unchanged). The dark line represents the average behavior of inflation response to interest rate change according to our model fitted on data from the past two decades. The red dots represent 95% bootstrap error bands computed with 1000 bootstrap runs.

Our primary focus lies in examining the intricate relationship between monetary policy (changes in interest rate) and inflationary pressures, as depicted in the plots. It is noteworthy that a modification in the interest rate manifests a delayed impact, gradually exerting downward pressure on inflation over the course of several months. After reaching his peak decline, the impact is fading towards 0 again. This result lets us think that a single rate hike is not optimal in effectively fighting inflation in the long-term and that repeated monetary policy actions, like ECB did in the past month, would induce more durable effects. On the right, the cumulative response function (CRF) shows the total cumulative change in inflation following the shock, helping to understand the global impact and the persistence of the shock's effect. Our results are in line with similar studies (e.g. Cloyne and Hürtgen, 2016) and align well with economic intuition: contractionary monetary policy shocks lead to a substantial decrease inflation.

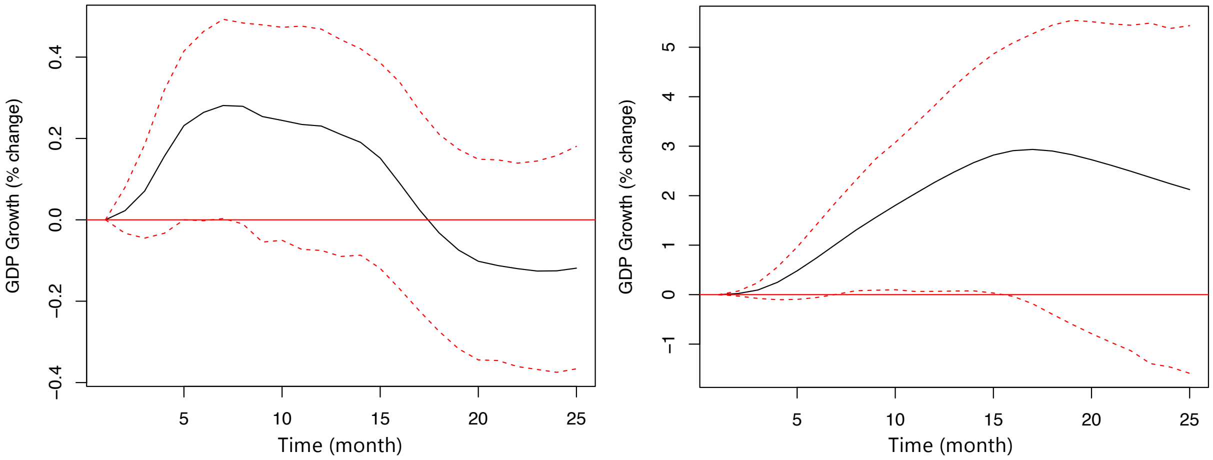
However, the error bands need to be considered. Indeed, within the bounds of the confidence interval, a plausible scenario emerges wherein the response of inflation remains unaffected by fluctuations in the interest rate, suggesting a lack of influence. Still, there is clear evidence that monetary policy is more likely to decrease inflation than not influence it, or even increase it. Furthermore, attention should be directed to the scale of the response impact. According to our model, the analysis on the left demonstrates a limited impact of monetary policy on headline inflation, with inflation decline peaking at -0.2 per cent, which is smaller than other similar analysis, in particular the -1.00 percentage points of Cloyne and Hürtgen (2016) modelling. These numbers are induced by a ceteris paribus shock in interest rate, meaning that this development will only occur in a situation where all other variables in the economy do not change over the two years of evolution forecast, which in practice will not happen. Recall also the above reaction is induced by a one per cent shock, whereas monetary policy often occurs in smaller shocks and repeatedly over time.

The above investigation is a global assessment of the monetary policy efficiency since 1999 and does not advance that ECB's choices regarding the recent rates hikes were efficient. If we put our results in parallel with our previous explanation of the recent surge in inflation, which is cost-pushed and driven by factors that are out of the control of central banks, like energy prices and geopolitical events like the invasion of Ukraine by Russia, etc., we may wonder if the above response analysis will materialize in the next months/years.

This reasoning raises the question of why central banks, despite being aware of the limited effectiveness of their tools in combating the recent inflation surge, have still pursued the most aggressive monetary policy witnessed in decades? De Callataÿ (2022) postulates multiple answers to that question. The first one is straightforward and derives from our above analysis: rate hikes will have a direct impact on inflation developments. Then, the centrale banks must keep their credibility. The Debt Sovereign crisis and the Covid Era are strong examples of the usefulness to have a supranational entity able to control rates. This is also related to sentiment of the public towards international institutions. Every individual is worried about his wallet and hates to see rising prices. The aggressive monetary policy led by ECB was a clear signal that inflation was taken seriously and that vigorous measures have been taken to counteract it.

As for the impulse response of *GDP growth* to a one-unit shock in interest rate y-o-y change, represented in Figure 5.3, the results are not totally in line with our expectations.

Figure 5.3: Response (left) and cumulative response (right) of **GDP growth** to a **shock in interest rate change.**



Notes: Impulse response function of an interest rate change shock on GDP growth for 24 periods ahead. Generated with our 3-variables VAR model estimated on monthly data from January 1999 to June 2023.

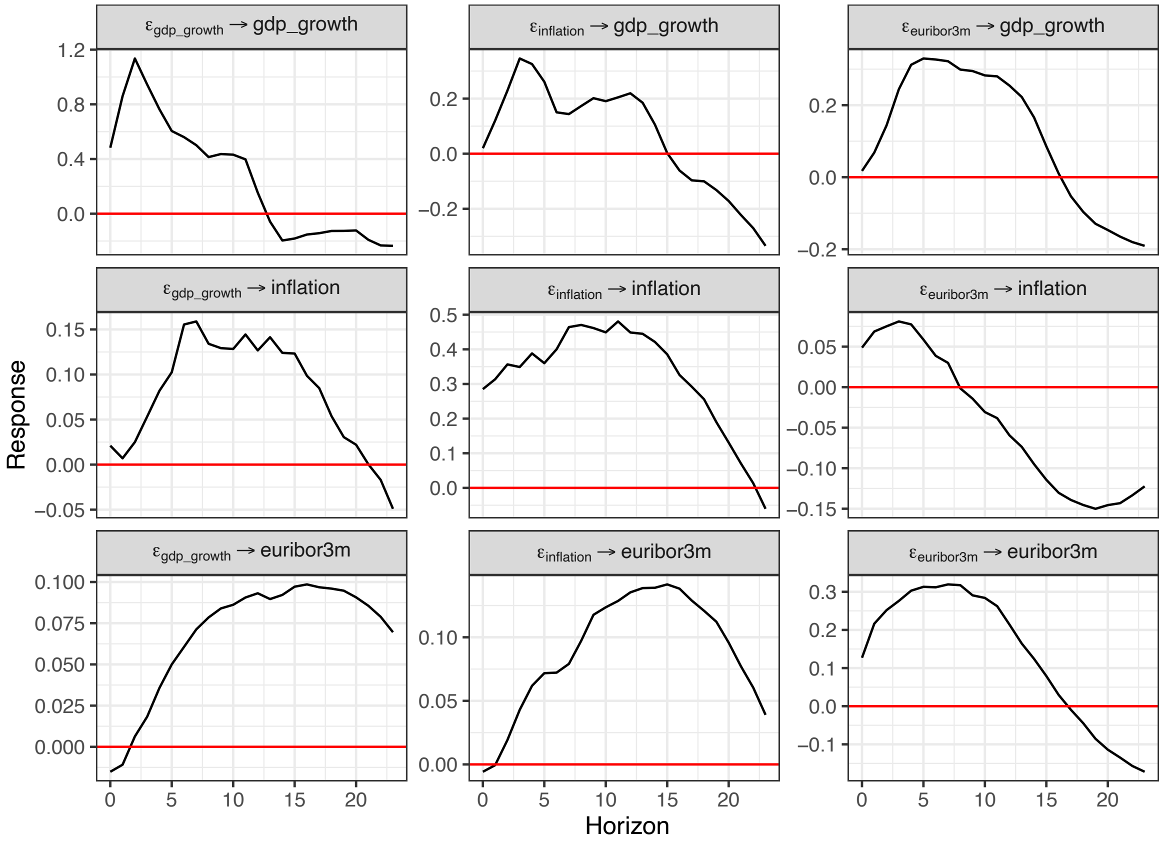
In the short and medium term, we observe that the shock in interest rate engender a rise in the GDP growth. From the interest rate channel explained in section 2.3.3, we have learned that interest rates increase should in theory tend to cool down economic activity by reducing investments and spending. Our VAR model ultimately validates this relationship but only on longer terms. Indeed, there is a considerable delay between the impact of the shock and the resulting decrease in GDP growth.

This result is however interestingly important. It showcases the central bank's ability to strike a balance between inflation control and sustainable economic growth. It indicates that while monetary policy effectively dampens inflation, it does so without causing undue disruptions to other vital economic indicators. This holistic approach contributes to maintaining overall economic stability while achieving the crucial objective of price moderation.

5.2.2 Structural Shocks Introduction

The calculated structural shocks reveal concealed information that is not apparent in the conventional reduced-form VAR model, as discussed earlier. Nevertheless, policymakers may have interest in understanding how the system responds to such isolated shocks. Figure 5.4 illustrates the response of the variables to each structural shock over time. We will focus on the last column of plots, that reveals the variables response to monetary policy unexpected shocks.

Figure 5.4: Response of the SVAR model variables to impulse in the structural shocks.



Notes: Impulse response function of structural shocks variations for 24 periods ahead. Generated with our 3-variables SVAR model estimated on monthly data from January 1999 to June 2023.

As expected from the absolute values of the $\hat{\boldsymbol{B}}$ matrix coefficients, the scale of the impact is rather limited for cross variable relationships, but still worth considering.

Following on the pioneer work of Christiano, Eichenbaum, and Evans (1999), many SVAR studies are built on a recursive assumption with the policy instrument placed last. This identification strategy enables all variables to have simultaneous effects on interest rates, while interest rates have delayed impacts on the other macroeconomic variables, as an intuitive explanation. The aforementioned SVAR studies present similar results regarding the above plot of $\varepsilon_{euribor3m}$ shocks on inflation, the so-called “price puzzle”. First documented by Sims (1992), it can be described as the increase in price level in response to an unanticipated monetary tightening. Unfortunately, our statistical estimation of the $\boldsymbol{B}$ matrix does not help in solving this price puzzle.

Apart from that, conclusions similar to the reduced-form VAR model can be drawn. $\varepsilon_{euribor3m}$ will, with a delay, gradually push inflation dawn until reaching a peak decline (at almost -0.15%) then will fade.

Some other results are also worth noticing. First, an unexpected shock in inflation will, according to the model, result in a gradual increase in interest rate. This relationship is in line with the central bank's monetary policy reaction to surging inflation. Also, inflation shocks are producing an increase in GDP growth in the short term but will ultimately reduce activity in the long term. Indeed, increasing inflation can incentivize consumers to consume now to avoid higher costs in the future, leading to short term increase in activity, but will ultimately erode purchasing power. This erosion will push people to cut spending and investments at longer horizons.

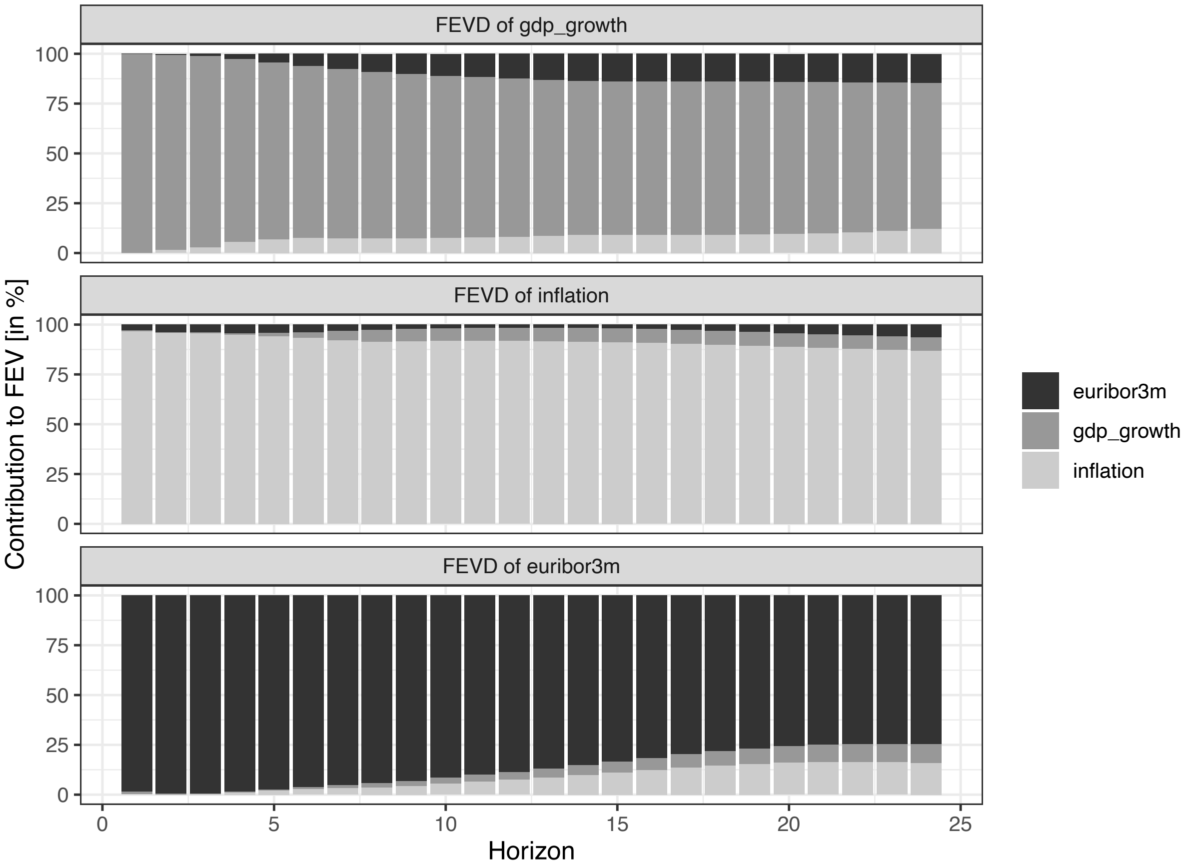
5.3 Variance decomposition

A forecast error variance decomposition (FEVD) allows to understand by how much a structural shock in a variable contributes to the forecast error variance (uncertainty) of the other variables at $\boldsymbol{y}_{t+h}$for horizon $h = 0,1, \ldots, H$. FEVD measure the variability in the forecast of each variable attributable to each structural shock based on the impulse response function simulations (Kilian and Lütkepohl, 2017).

Once again, the absolute values of the off-diagonal $\widehat{\boldsymbol{B}}$ coefficients are rather small, hence the impact of the shocks is limited.

The bar chart demonstrates that at first, structural shocks will not have a considerable impact in the variability of the other variables, but this impact will gently grow to reach significant values. This FEVD analysis can help policymakers understand the limited impact of the different structural shocks on the economy.

Figure 5.5: Forecast error variance decomposition of structural VAR



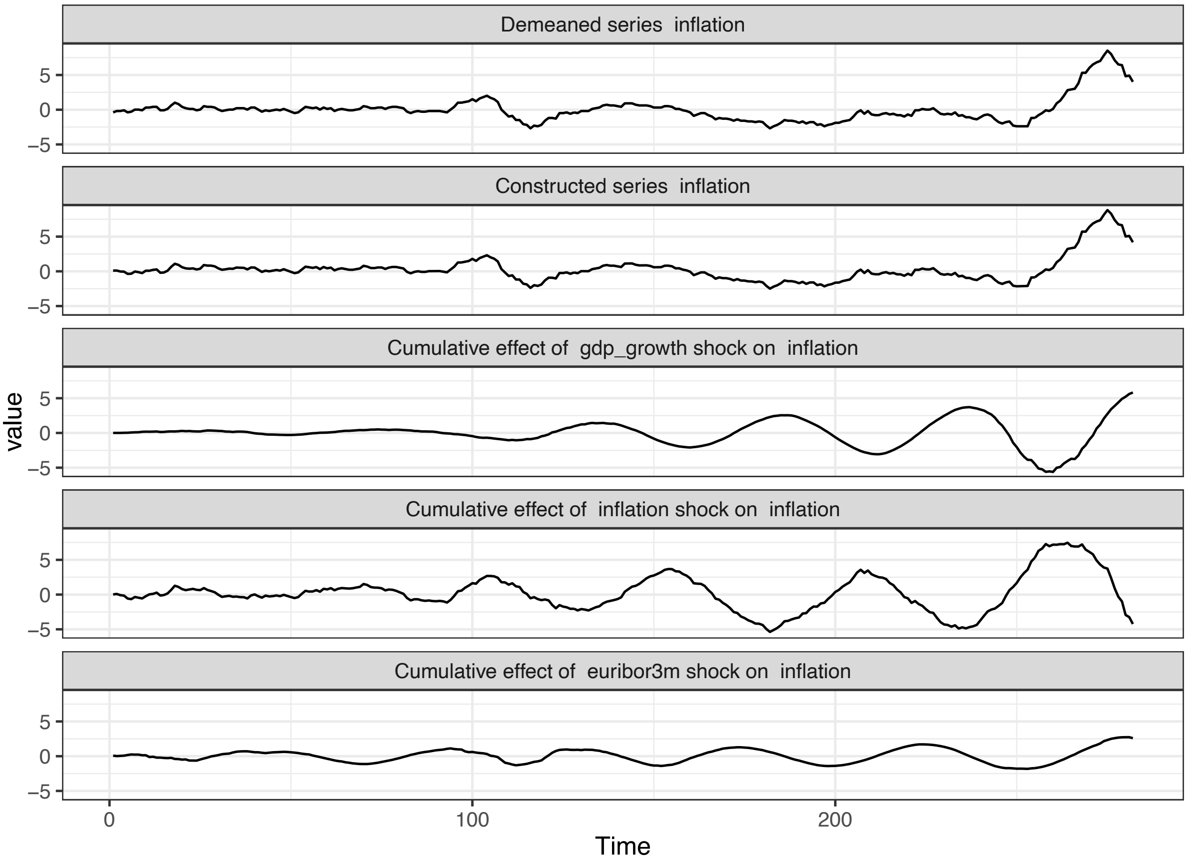
Notes: Forecast Error Variance Decomposition of structural shocks variations for 24 periods ahead. Generated with our 3-variables SVAR model estimated on monthly data from January 1999 to June 2023.

5.4 Historical decomposition

Historical decomposition provides insights on how much a variable's evolution is explained by the cumulative effects of earlier changes in the other variables. In the SVAR framework, Figure 5.6 quantifies the extent to which a specific structural shock accounts for the observed historical variations in the SVAR variables (Kilian and Lütkepohl, 2017).

Figure 5.6 indicates that inflation fluctuations over time are mainly explained by inflation shocks than interest rate shocks. Also, a remarkable pattern to observe is the opposite effect between inflation and GDP growth shocks on inflation. When inflation structural shocks have a positive impact on inflation (inflation increase), then GDP growth structural shocks have a negative impact on inflation and vice-versa.

Figure 5.6: Historical decomposition of inflation's evolution



Notes: Historical Decomposition of Euro Area inflation's evolution due to structural shocks. Generated with our 3-variables SVAR model estimated on monthly data from January 1999 to June 2023. Expressed in percent deviation from the mean.

5.5 Limitations

Even though VAR models have become popular tools for monetary policy assessment, it is crucial to acknowledge that these empirical techniques come with certain limitations.

Firstly, Rudebusch (1998) investigates the intrinsic sense of VAR coefficients. In our study and other similar studies, individual equations of the VAR model are often overlooked. As a matter of fact, the estimated coefficients of the VAR equations are typically omitted from reports, or put in Appendix, which reflect the challenge in interpreting distinctly the VAR equations.

Also, the effectiveness of the models depends on the availability and quality of the underlying data. VAR models are typically estimated a posteriori using past data, which disregard the real-time nature of the decision making for monetary policy. Indeed, central banks develop their policy based on contemporaneous data, not final and revised data. VAR models are thus suitable tools for ex-post analysis but not decision-making. This critique from Rudebusch (1998) has been countered by Bernanke and Boivin (2003). In their study of the real-time data constraints for VAR analysis, they suggest that differentiation between real-time data and ex-post revised data holds limited significance.

A limitation in the model is that centrale banks in practice react to more than only GDP growth and inflation to determine their monetary policies, but VAR models have difficulties to handle a large number of variables. An alternative to overcome this issue and enrich the number of variables would be to consider factor-augmented VAR (FAVAR) methods, such as in Bernanke and Boivin (2003), or large-scale Bayesian VAR (BVAR) models, like in Banbura, Giannone, and Reichlin (2010). In these models, hundreds of time series can be implemented, fitting better to what central banks really monitor. Another rationale for exploring larger VAR models is the desire to investigate the effects of monetary policy shocks at a more detailed level. For instance, policymakers might be curious about not only the reaction of the overall price level to a monetary policy shock but also the response of sub-indices corresponding to specific expenditure components (Kilian and Lütkepohl, 2017).

Furthermore, our analysis ranges on a period of almost 25 years, assuming that central banks and economic reactions are stable over time. Splitting the sample could solve this issue, but smaller samples decrease the accuracy of the estimation, and thus of the subsequent analysis.

A critique of SVAR analysis is that the results are dependent on the identification technique, potentially leading to varying implications. Here, we used a data-driven independence-based identification technique in a non-Gaussian framework. Our model estimates diverge from for example sign restriction models, that force the sign pattern of the matrix estimates according to economic theory (Uhlig, 2005).

To conclude, while VAR models offer valuable insights, careful consideration and robustness checks are necessary to ensure their suitability and reliability for monetary policy analysis.

6 Conclusion

This thesis wished to provide a robust assessment of the monetary policy efficiency in combatting inflationary pressure, through the application of well-known macroeconomic models – the reduced-form and the structural VAR model – each of which provide a different insight on the relationship between economic variables. Our results were focused on the Euro Area with the use of the most recent data on economic activity (GDP growth), inflation (HICP) and interest rate (Euribor-3m), ranging from the creation of the European Central Bank in 1999 until June 2023.

In the introduction, we outlined our base concern and summarized the main results of the thesis. After a review of theoretical background in chapter 2 and 3, chapter 4 detailed our methodology and the following chapter presented and discussed our main results as well as limitations of our study. To conclude the thesis, this final chapter will focus on concrete implications of our results for monetary policy development and recommendations for further research.

6.1 Implications for Monetary Policy

From our analysis, we understand that policy rates must remain a key element in the central banks toolbox to maintain price stability. Our VAR modelling revealed however that interest rates manipulation is not the perfect and powerful tool to achieve price stability, as commonly believed. Realizing this has far-reaching implications in the ongoing efforts to enhance the effectiveness of monetary policy.

Firstly, it emphasized the need for central banks to develop their adoption of a more comprehensive and flexible approach to monetary policy. This could include forward guidance, quantitative easing, or direct intervention in financial markets.

Secondly, central banks might place greater emphasis on other factors that drive inflation, such as supply-side shocks, fiscal policy, or inflation expectations. Understanding and addressing these determinants become crucial for maintaining price stability.

Furthermore, central banks may need to work more closely with other policy institutions, such as fiscal authorities, to coordinate efforts in achieving their inflation targets. Fiscal policy measures can complement monetary policy actions, particularly in situations where interest rates are constrained.

6.2 Recommendations for Future Research

Finally, we close this work with suggestions that we deem interesting to investigate for further research.

First, other models than the ones presented in this thesis are worth considering for monetary policy assessment, or variations of our models. We already discussed in the limitations section 5.6 how Factor Augmented Vector Autoregressive models can solve the limited scope issue of our analysis. Also, depending on the structure of the data, alternative estimations techniques of the impact multiplier matrix $\boldsymbol{B}$ in SVAR could be considered, like identification based on heteroskedasticity of structural shocks. Moreover, as explained in Chapter 3, DSGE models also bear a strong track record in macroeconomic analysis, offering a more precise description of the economy, closer to reality, but less data driven.

Another potential lead would be to deep dive into the use of nonlinear structural VAR models, as discussed by Kilian and Lütkepohl (2017). Exploring potential variations in the influence of monetary policy on inflation or GDP growth under specific thresholds or conditions could provide a more nuanced understanding of policy effectiveness.

Moreover, one could consider investigating a time varying parameters estimation for the VAR model, to examine how the effectiveness of monetary policy varies over different economic conditions or periods could provide deeper insights into the dynamics at play.

Also, I would recommend applying this methodology to different countries. Comparing the results of the model between emerging and developed economies could help identify common patterns or unique characteristics.

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