MASTERARBEIT | MASTER'S THESIS

Titel | Title

Forecasting macroeconomic variables that can influence the European Union Budget Allocation using the VAR model on EU

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Univ.-Prof. i.R. Dipl.-Ing. Dr. Robert Kunst

Acknowledgements

Completing this thesis was one of the most challenging yet rewarding tasks in my education. I would like to express my gratitude to the individuals who helped and supported me.

I would like to extend my deepest gratitude to Prof. Robert Kunst, my supervisor, whose invaluable guidance, boundless support, and profound expertise have been the cornerstone of my thesis journey. Their mentorship has not only shaped my academic endeavors but has also inspired me to strive for excellence. I owe a debt of gratitude for their wisdom, which is inspiring in every way and greatly improved this meaningful pursuit.

In addition, I would like to express thanks to all the faculty members at the University of Vienna, for creating an ideal atmosphere for learning. It was a tough journey, but it was all worth it.

Lastly, I want to thank my family and friends for their unwavering help during my studies. Without their influence, I would not have the dedication to conquer this last years.

Thank you!

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Abstract

This thesis examines the macroeconomic factors that influence the budget allocation of the European Union (EU), with a focus on predicting economy. Using quarterly data from past budget cycles, this study analyzes the relationship between key macroeconomic variables, such as GDP growth, inflation, unemployment and interest rates, and the allocation of funds within the EU budget.

The research methodology involves conducting a quantitative analysis of the macroeconomic data over a certain period and identifying key variables that affect the budget allocation. A VAR model is constructed to predict the important macro variables to help an efficient budget allocation for future years in EU.

The study also evaluates the indirect impact of external factors on the EU budget and the potential effects of other geopolitical factors and shocks, such as changes in trade policy and the growth of emerging economies with the influence of the Russia-Ukraine war and COVID-19 pandemic.

This research aims to contribute to the field of macroeconomics by providing a better understanding of the factors that indirectly influence EU budget allocation and predicting economy which is important for the budget decisions process. This information can be useful for policymakers and economic agents who are involved in the very complex EU budget planning process.

Key words: European Union Budget allocation, European funds, macroeconomic variables, forecasting, VAR model

Zusammenfassung

Diese Masterarbeit untersucht die makroökonomischen Faktoren, die die Budgetzuweisung der Europäischen Union (EU) beeinflussen, mit einem Schwerpunkt auf der Vorhersage der Wirtschaftsentwicklung. Unter Verwendung von quartalsweisen Daten aus vergangenen Haushaltszyklen analysiert diese Studie die Beziehung zwischen wichtigen makroökonomischen Variablen wie dem BIP-Wachstum, der Inflation, der Arbeitslosigkeit und den Zinssätzen sowie der Verteilung von Mitteln innerhalb des EU-Haushalts.

Die Forschungsmethodik beinhaltet die Durchführung einer quantitativen Analyse der makroökonomischen Daten über einen bestimmten Zeitraum und die Identifizierung wichtiger Variablen, die die Budgetzuweisung beeinflussen. Ein VAR-Modell wird konstruiert, um die wichtigen makroökonomischen Variablen vorherzusagen und eine effiziente Budgetzuweisung für zukünftige Jahre in der EU zu unterstützen.

Die Studie bewertet auch die indirekten Auswirkungen externer Faktoren auf den EU-Haushalt und die potenziellen Auswirkungen anderer geopolitischer Faktoren und Schocks, wie Änderungen in der Handelspolitik und das Wachstum aufstrebender Volkswirtschaften mit dem Einfluss des Russland-Ukraine-Krieges und der COVID-19-Pandemie.

Diese Forschung zielt darauf ab, zum Bereich der Makroökonomie beizutragen, indem sie ein besseres Verständnis der Faktoren vermittelt, die die Budgetzuweisung der EU indirekt beeinflussen, und die Wirtschaftsentwicklung vorhersagen, was für den Budgetentscheidungsprozess wichtig ist. Diese Informationen können für politische Entscheidungsträger und Wirtschaftsakteure nützlich sein, die am sehr komplexen Prozess der EU-Budgetplanung beteiligt sind.

Schlüsselwörter: Haushaltszuweisung der Europäischen Union, Europäische Fonds, makroökonomische Variablen, Prognose, VAR-Modell

1. Introduction

In any nation or region, budgeting is an essential component of policy development and accountability. With regards to the European Union, with its special arrangement of establishments and connections between various degrees of government, close attention was being set to present the parts of planning. Showing economic agents that EU resources are being used effectively to achieve results that benefit citizens (Downes et al., 2017).

Over the past few years, there have been remarkable differences in economic activity and business cycles across the European Eurozone. Thanks to the COVID-19 pandemic influence, geopolitical tensions including the Russian-Ukraine conflict, as well as the negative financial impact of Brexit on funds, these external factors have caused a rapidly rising degree of economic integration on a national level and as well EU level.

While there have been studies on the European Union budget and its allocation, the specific focus on forecasting economy that influence budget decisions using macroeconomic analysis is a relatively new and unexplored area of research. Previous studies have primarily focused on overall EU budget's size and composition, as well as its impact on member states and specific policy areas. Few studies have analyzed the relationship between macroeconomic variables and EU budget allocation. Additionally, most of these studies have been descriptive in nature, rather than predictive, and have not attempted to construct a vector autoregressive model to forecast economy which is important for the budget decisions process.

Furthermore, the EU has experienced substantial changes in recent years, as mentioned above, which have added complexity to the budget planning process. These changes make it challenging to accurately predict future budget decisions, and thus there is a need for new research that can take these factors into account.

Therefore, the proposed topic of forecasting economy using macroeconomic analysis with the VAR model is a novel area of research that can contribute to the understanding of the EU budget and its impact on member states and policy areas.

Economic outlook

The economic and budgetary outlook for the EU is set by a considerable degree of uncertainty. During this challenging period, difficulties are expected to arise with slowing growth and gradually easing inflation. Paolo Gentiloni, Commissioner for Economics, highlights the need for precise policy coordination in the EU to address these challenges effectively.

The Russia-Ukraine conflict hasn't stopped, and there's no sign of a peaceful end to it either. Its economic consequences have exceeded expectations far beyond what we have imagined, resulting in ongoing suffering and destruction. Due to its geographical proximity to the conflict and potential changes in reliance on fossil fuel imports, the EU's economy is one of the most vulnerable.

We are now in times where EU economy is still being impacted by the serious damage of the macroeconomic variables such as a sharp rise of inflation, and the pressure on energy costs, food, and other commodity prices thanks to the effect of the pandemic crisis. The pandemic has had a major impact on the building of the EU finance structure resulting in a budgetary package. This tool combines Next Generation EU (NGEU) instrument with the Multiannual Financial Framework (MFF) for the project period 2021 to 2027 (D'Alfonso et al., 2022). Since the MFF is the 7-year performance frame that sets annual ceilings, it primally serves as an investment budget which is grouped under seven main headings (Downes et al., 2017). However, new challenges of the present events pushed the current MFF to its limits in its first years of implementation.

EU budgetary framework – "MFF" sets the limits for EU expenditure over a period of several years. The MFF considers multiple factors including:

- *EU Policies and Priorities* - The MFF is made to help the EU achieve its goals in areas like employment, social cohesion, economic expansion, and environmental sustainability. Every policy area has a budget allocated to it based on its expected impact and importance.
- *EU Programs and Projects:* The MFF finances several EU initiatives, including projects related to agriculture, infrastructure development, regional development, and research and innovation. The budget allocation for each program or project is determined by its objectives and expected outcomes.

- *EU Member States' Contributions:* The MFF is funded by the EU Member States' contributions where the contribution rates are determined through negotiations among the Member States.
- *Economic and Political Conditions:* The MFF considers the economic and political conditions of the EU and its Member States. A country's unemployment rate or economic growth rate, for example, may influence how much money is allocated to the budget.

The MFF's overall goal is to guarantee that the EU budget is utilized effectively and efficiently to accomplish its policy priorities and objectives while also considering the political and economic conditions of the EU and its Member States (Schratzenstaller, 2017).

The EU budget has gained momentum thanks to this new financial architecture, giving it an essential role in the Union's plan to relaunch these affected economies. It is designed to support public investments, agriculture, digital transformation, security, defense, and migration within individual member states of the EU. The joint EU budget and NGEU instrument play a very important role in the recovery strategy to relaunch the economy within that new financial architecture (D'Alfonso, 2020). It is estimated to contribute with €2 018 billion to the EU's role in the world economies (European Union, 2024). Their main priority is to support the green and digital transformations but at the same time concentrate on other objectives, including both traditional and moderate initiatives (D'Alfonso et al., 2023).

Mechanism of the EU funding

Customs duties, payments from national budgets (based on the gross national income (GNI) of each Member State), and contributions from Member States' value added tax (VAT) are the three primary sources of funding for the EU budget. In addition to making contributions to the Union's common budget, EU redistributes a portion of its wealth among its members in order to support its shared policies. The ability of single country to influence the allocation of the contributions to the EU budget depends on its diplomatic skills, strategic alliances, and political leverage within the EU decision-making process. Member states participate in budget negotiations, where they can advocate for their priorities and interests. They can lobby for specific projects or policy areas that they believe deserve funding. including the approval of budget proposals and amendments. Moreover, member states' financial contributions to the EU budget can influence their bargaining power and leverage in budget negotiations - countries that contribute more may seek to ensure that their interests are adequately represented in budget allocations (European Commission, 2021).

In 2022, nine countries (including Germany, Austria, Sweden, Netherlands, Ireland, Denmark, Finland, France, Belgium) were net contributors and remaining 18 were net recipients. Member states usually redistribute financial resources from higher-performing nations to lower-performing nations through the EU budget, where net contributions still correlate with economic performance (Deutsche Bundesbank, 2023).

Expenditure categories of MFF

As Johannes Hahn (European Commissioner for Budget and Administration) says: "The EU budget is really for everybody – businesses, farmers, researchers and students. "

Currently, the EU budget supports 7 main headings or expenditure categories, where each one of them is dedicated for a specific policy area. Several headings are both funded under the MFF and the NGEU instrument (European Commission, 2021).

1. Single Market, Innovation and Digital - Since these sectors is essential to securing future growth through increasing investments, programs under this heading serves in areas like digital transformation, strategic infrastructure, the competitiveness of small and medium-sized businesses and help address common issues like climate change and changes in demographics.
2. Cohesion, Resilience and Values - The goal of the spending under this heading is to make the EU Member States more cohesive and resilient. In order to achieve this, the funding supports sustainable territorial development and reduces disparities within and between Member States as well as between EU regions.
3. Natural Resources and Environment - The EU budget is and will remain a major force behind sustainability, funding environmentally friendly agriculture and marine sectors in addition to battling climate change, protecting the environment, ensuring food security, and promoting rural development.
4. Migration and Border Management - Programs under this category aim to address issues with migration and border management to protect the EU's asylum system.
5. Security and Defence - This heading covers initiatives whose goals are to improve Europe's defense capabilities, increase the security and safety of its citizens, and supply the means by which any Member State can respond to external challenges.

6. Neighborhood and the World - Programs under this heading support the socioeconomic influence of the EU in developing nations, its neighborhood, and the global community. The heading also includes assistance for countries preparing to join the EU.
7. European Public Administration - This heading covers mainly the administrative expenditure of all EU institutions.

Acceptation of the EU budget

The budgetary allocation for the EU is decided upon collaboration of three primary institutions, whereas the negotiation process starts a few years before its actual adoption. The current MFF covers the years 2021–2027 and The European Parliament, the Council, and the Commission all participated in its negotiation. Firstly, the European Commission proposes the initial draft budget, defining spending priorities and limitations. Secondly, the Council of the European Union is the body that negotiates and approves the final budget size on behalf of the member states. Lastly, the European Parliament have a major control over specific allocation since they have the authority to accept or reject the entire budget proposal. Therefore, there is no single entity with the authority to approve anything because the process involves proposals, discussions, and approvals from various institutions (European Union, 2024).

EU 2023 Adopted Budget

The forecast for the months of 2023 was set to lift the outlook for growth with slightly lowering the inflation numbers (European Commission, 2024). It has also secured effective support in addition to assisting in the recovery process from the pandemic. The 2023 budget provided additional funding for several programs and policies intended to assist in coping with the effects of Russia's war of aggression against Ukraine, including the energy crisis. EU Parliament increased funding to address the consequences of the war in Ukraine, but on the other hand also trying to strengthen other priorities of Parliament. This includes tackling the energy crisis, supporting climate and environment policy, defense, and research and innovation (D'Alfonso et al., 2022) and consider the green and digital transition which is in line with the priorities that were set in guidelines for 2023 (PubAffairs Bruxelles, 2022).

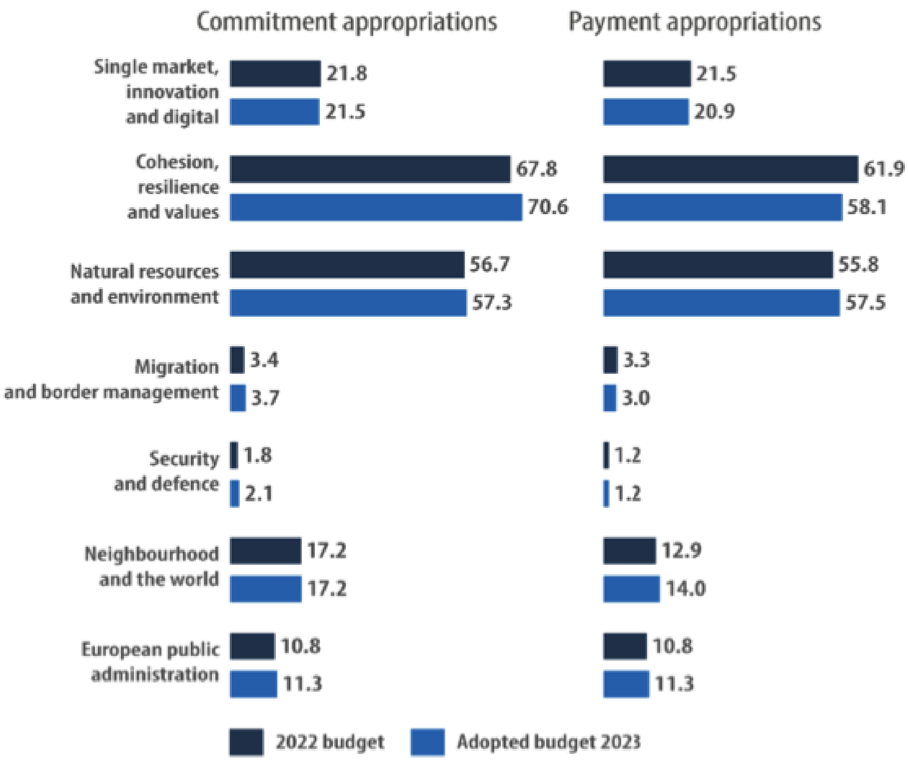

Figure 1 2022 Budget vs 2023 Adopted Budget

Figure 1 highlights the importance of external factors on the budget, and how the indirect effect of macroeconomic variables influences the decision-making process. Parliament underlined the extraordinarily complex challenges facing the EU, while adopting the allocation of needed funds for the new version of budget. Forecasting these challenges could simplify the preparation in planning the redistribution of such matters, which can be meaningful. In general, the EU budget allocation can be influenced by a variety of factors, including political priorities, economic conditions, and member state contributions. Overall, macroeconomic variables can play a role in shaping the EU budget allocation by affecting the well-being of the EU institutions and member states. The influence of these variables is typically indirect but still essential (D'Alfonso et al., 2022).

2. *Literature Overview*

Adarov (2021) focuses on the significance of conducting additional research into the macroeconomic effects of financial cycles during economic changes. The study is closely related to a larger body of research on the importance of financial factors in macroeconomic imbalances which lead to “macroeconomic overheating crises “, that we now face. The paper uses a panel VAR framework to analyze this connection and its effect on the formation, which is crucial for influencing policy discussions.

Neaime and Gaysset (2022) highlight the fundamental impact of macroeconomic shocks on countries' GDP, inflation, and interest rates. Mostly the Covid-19 pandemic and the previous economic collapses have shown that the monetary and fiscal policy tools (currently in use) are ineffective in addressing certain macroeconomic variables, leading to damaging consequences for the economy. This paper applies the stationarity and causality tests derived from a VAR time series model of macro variables. While identifying the exogenous and endogenous shocks that are the root cause of imbalances, they also propose policy recommendations for better monetary implementation in the future.

Capek et al. (2023) evaluate the forecast potentiality of six different dynamic stochastic general equilibrium (DSGE) models for specific core macro variables such as GDP growth, inflation, and the interest rate in the EU area. However, combining forecast from the DSGE models does not consistently result in improvements in macroeconomic predictiveness which may be highly affected by the focus on the euro area economy. They find improvements for specific time periods and variables when using prediction pooling, dynamic model averaging, and combinations of forecasts based on Bayesian predictive synthesis, even though these combinations do not tend to systematically achieve superior forecast performance.

Cronin and McInerney (2023) argue, since the introduction of the euro, that the EU needs to pay close attention to the accuracy of official forecasts. However, econometric analysis reveals that EU fiscal requirements in output variables account for forecast errors in both the headline budget balance and the structural budget balance. This indicates, on either projection, the presence of biases with the influence of political factors. Overall findings show excessive pessimism in official forecasts over the past few years. These errors can result in fiscal policy failing to meet budgetary targets. If they persist, they may also give the public the impression that the EU's fiscal rules are not working as intended.

Wang et al. (2023) state that macroeconomic forecasting has become a new trend for monetary and fiscal authorities all over the world. They compare 2 methods – the factor augment (FA) approach, such as AR and VAR models, and the variable selection approach. The paper investigates the different settings for forecasting several macroeconomic variables.

Dees et al. (2005) have investigated the connections between major economies and regions' international business cycles. This topic has received a lot of attention in the last decades due to notable variations in business cycles and economic activity. In this work, a global VAR (GVAR) is used to investigate the global shock transmission mechanisms providing a quantitative analysis of outputs, prices, inflation, and interest rates. With the specific conditions as the eurozone has (a single exchange rate and short-term interest rate), the euro area is considered as a single economy. Using structural impulse response functions, the effects on the short-term and long-term implications of external shocks are investigated through various simulations. Not only does trade play a role in the transmission of shocks, but financial variables are also impacted, which has a knock-on effect on real variables, which is particularly meaningful. The global economic analysis can be conducted using a complex, but easily understandable, framework provided by the GVAR model.

Panagiotelis et al. (2019) indicate that all the planning for the government budget, central bank policy, and business decisions depends on forecasting the macroeconomic variables, particularly key indicators like GDP growth, inflation, and interest rates. Lagged macroeconomic variables have historically been used as leading indicators in attempts to forecast the business cycle, dating back at least to the 1940s, although it is still questionable how effective these methods can be. It was also demonstrated in the 1970s and 1980s that predictions made using VARs and univariate ARIMA models performed better than structural macroeconomic models. In the early 2000s, as researchers started to create high-dimensional macroeconomic datasets, a dynamic factor modeling (DFM) framework is used with many predictors, predicting forecasts which are more accurate. A comprehensive empirical investigation is conducted utilizing a range of techniques and information sets with an increasing number of predictors to investigate forecasts at different time horizons. The findings indicate that, in contrast to other nations as US economy, it is challenging to predict Australian key macroeconomic variables.

A noteworthy decline in the world's financial markets, and different markets in developed, emerging, and advanced economies are negatively impacted by the pandemic. With additional proof that the European stock markets are the main source of shock waves that spread to other regional stock markets, Belaid et al.'s (2023) unexpected conclusion was that the COVID-19 pandemic led to increasing crisis spillovers between advanced and emerging stock markets. Salisu et al. (2022) provide a global perspective on the effects of the COVID-19 pandemic on financial markets using a multi-country Threshold-Augmented Global Vector Autoregressive Model.

Wieland and Wolters (2013) emphasize that one crucial component to consider is if policymakers adjust their decisions in response to changes in the forecast. Forecasts play a noteworthy and crucial role in the process of economic policy making, but depending on their accuracy, forecasts may or may not be helpful in designing specific policies. Including the interaction between forecasts and policy decisions within a structural model is a potential approach to improve forecast accuracy. Structural models account for additional unobservable components, such as economic shocks. One way to think of shocks is as a significant disruption to the economy. Overall, these shocks show that the model was unable to predict the recession, but they help identify the causes of the unanticipated shortfall and are useful for the recovery process. Although forecasts are a crucial component of many processes used to decide on economic policy, attention should be focused on longer-term projections. Model uncertainty is an important issue in practice.

Thu & Leon-Gonzalez (2021) assert that many developing nations like Vietnam, Thailand, Philippines, Sri Lanka, and Ghana have small, open economies that make them vulnerable to shocks from the global or more powerful economies. The problem of breaks arises when predicting macroeconomic variables because the relationships between them tend to change over time, posing various challenges such as increased forecasting uncertainty, difficulties in policy formulation, and risks of economic instability. Given that developing economies frequently experience more changes to their policy and legal frameworks than advanced economies, it is likely that dynamic models will provide accurate forecasts for both inflation and economic growth.

3. Research questions

With the given topic of this thesis, I tried to understand the importance of current events in the EU economy. While building the model one need to be curious and understand the significance of the below questions that can help to navigate the model through the expected results of this paper.

1. Can macroeconomic variables accurately predict the allocation of the EU budget, and if so, which variables are the most important predictors?
2. How do changes in macroeconomic conditions affect the allocation of the EU budget, and how can policymakers use this information to optimize budget allocation?
3. What is the most accurate forecasting model for predicting EU budget allocation using macroeconomic variables, and how can this model be improved?
4. How does the allocation of the EU budget vary across member states, and what factors explain these differences?
5. What is the impact of external economic shocks on the allocation of the EU budget, and how can policymakers prepare for and respond to these shocks?

I try to answer these questions in the conclusion part of this paper where I also consider their importance and influence on the EU budget.

4. Methodology

International business cycle links between economies and regions have received a lot of attention in recent years due to several developments across some major macroeconomic variables. In my case, I concentrate on the EU economy, which is the main interest of this thesis in using a VAR model (Dées et al., 2005).

The VAR model

It's important to select a model that can accurately capture the dynamics of the EU budget allocation and its relationship to the selected macroeconomic variables. This methodology can help to construct a forecasting model for EU budget allocation using macroeconomic analysis, providing policymakers with valuable insights into future budget decisions – specify factors that have the most significant impact on the EU budget allocation. The effect is somehow indirect; however, it can also help policymakers understand how to allocate funds more efficiently.

The choice of model depends on the characteristics of the data, the complexity of the relationships between the variables, and the forecasting horizon. A vector autoregressive (VAR) model is well-suited for easily capturing the dynamic relationships among multiple time series variables. This allows for interaction between EU budget allocation and selected macroeconomic variables, ultimately leading to more accurate forecasts.

VAR models were introduced to the economics profession by Christopher Sims (1980), about 43 years ago. Sims was criticizing the highly specified macro-models that were based on strong restrictions and assumptions about the dynamic nature of the variables that interact with one another. Thanks to VARs, it became more efficient to allow one to model macroeconomic data accurately, without imposing these forceful conditions. VAR models are bi-directional, enabling variables to influence each other. Essentially, they capture the dynamic nature of variables as a function of past observed values, along with today's shocks (Lütkepohl, 2005).

One criticism of VARs is that they are not theoretical, meaning that the equations are not theoretically structured because they are not based on any economic theory. A direct interpretation of the estimated coefficients is challenging because it is assumed that each variable in the system influences every other variable, yet VAR models still have their uses in a variety of situations.

In my case, I use the VAR model on EU member countries. I want to examine the external and as well internal shocks in one economy – the EU economy model where I try to analyze EU countries as one nation and restrict the analysis to the subset of variables that correspond to the EU countries in the dataset. This can also be taken as a limitation of this thesis because I do not want to concentrate on global economic events that influence each country specifically and independently.

The macroeconomic variables

The subject of the VAR analysis with the forecasting horizon includes the following macro indicators: GDP growth rate, rate of inflation, interest rate and unemployment rate. I have chosen these variables due to their importance for policymakers and economic agents. Obtaining reliable predictions of future changes is an extremely valuable asset for improving economic activity (GACR, 2022).

In practice, this means that in order for a set of variables to be useful for predicting one another, it is necessary to keep the number of variables in a VAR small and, moreover, to ensure that the variables are plausibly related. For instance, the correlation between the unemployment rate, inflation rate, and short-term interest rate, as well as other economic theory findings, indicate that these variables may be useful in predicting one another in a VAR. However, adding an unrelated variable to a VAR reduces forecast accuracy because it introduces estimation error without adding predictive content (Stock & Watson, 2020).

Break – a dummy variable in the VAR model

Restrictions built into VAR model enable us to find causal relationships outside of those found in reduced form of models. These causal connections can be used to predict and model the effects of specific shocks, like changes in policy. In contrast with these properties, a shock to a non-stationary time series process would have a permanent effect on the future values of the process.

Due to a sudden shock in the economy, a series of data can often contain a break. A common way of solving break, as it does not split the data, is to use a dummy variable in the VAR model. The dummy variable consists of 1s and 0s and it can be used to determine the importance of policy actions on the models (Stock & Watson, 2020).

The VAR model used in this thesis incorporates the concept of a break. The global economy, and notably the EU, experienced a significant impact during the onset of the COVID-19 pandemic in March 2020. Introducing a dummy variable enables me to capture and model the influence of this break on macroeconomic variables.

The VAR model with macro variables

Basically, the VAR model implies that each macroeconomic variable depends on all the other variables in the system. Equation (1) depicts this relationship, where four macroeconomic variables are represented along with a break, denoted by the exogenous dummy variable representing the COVID-19 period (Stock & Watson, 2020).

$$\boldsymbol{Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \beta_D D_t + \varepsilon_t} \tag{1}$$

The variables in the equation can be defined as follows:

$\boldsymbol{Y_t}$ – is a column vector of the endogenous macroeconomic variables at time t

$\boldsymbol{\alpha}$ – is a constant term or intercept

$\boldsymbol{\beta_1, \beta_2, \beta_p}$ – are coefficient matrices corresponding to the lagged values (4x4 matrices)

$\boldsymbol{Y_{t-1}},\ \boldsymbol{Y_{t-2}}, \dots ,\ \boldsymbol{Y_{t-p}}$ – are lagged values of the vector of variables up to p-lags

$\boldsymbol{\beta_D}$ – is a coefficient matrix associated with the dummy variable $\boldsymbol{D_t}$ (a 4x1-vector)

$\boldsymbol{D_t}$ – is the dummy variable that takes a value of 1 during the period of the break and 0 otherwise

$\boldsymbol{\varepsilon_t}$ – is a vector of error terms at time t, representing the unexplained or residual variation in the variables

Stationarity in the VAR model

In the most intuitive sense, stationarity means that the statistical properties such as mean, variance, covariance, and standard deviation do not vary over time. It does not mean that the series does not change over time, just that the way it changes is not a function of time (Hyndman, Athanasopoulos, 2018).

Stationary series in Time Series also means series without a trend or seasonal components. In other words, series are easier to analyze, model and predict effectively and precisely and have become a common assumption in many practices in time series. These include trend estimation, forecasting and causal inference, among others. In general, the VAR model can work only if each of the variables in the model is stationary which is a crucial condition to have (Affek, 2019).

1st and 2nd Differencing

A non-stationary time series can be made stationary by calculating the differences between following observations – it is called differencing. Differencing can eliminate/reduce trend and seasonality by stabilizing the mean and therefore remove changes in the level of the time series. However, in certain cases, the differenced data may not seem stationary after 1st difference. To obtain a stationary series, it might be necessary to difference the data twice, so it will have T – 2 values, also it would model the original data's "change in the changes" (Hyndman & Athanasopoulos, 2018).

Augmented Dickey-Fuller (ADF) test

The ADF test is a type of statistical test known as a unit root test. Since models cannot effectively forecast non-stationary time series data, the ADF test is commonly used to determine whether a given time series exhibit stationarity or not (Chang & Park, 2002).

The following assumptions are used when conducting the ADF test:

Null Hypothesis (HO): Series is non-stationary, or series has a unit root.

Alternative Hypothesis (HA): Series is stationary, or series has no unit root.

Auto regressive conditional heteroscedasticity test (ARCH)

The presence of conditional heteroscedasticity in a time series, indicating that the variance of the series varies over time, can be statistically identified using the ARCH test. ARCH test is particularly helpful in forecasting or financial modeling (Engle, 2004).

Serial Auto-Correlation Test

Serial correlation or Autocorrelation is where error terms in a time series transfer from one period to another. In other words, an error for one time period "t" is connected with the error for an upcoming period "t+h". This can lead to problems such as inefficient and inconsistent OLS estimations, T-stat being too large, or a regression coefficient appears to be statistically significant when it is not (Escanciano & Lobato, 2009).

For detecting serial correlations in classical univariate or multivariate time series analysis, Portmanteau test was developed (Bücher et al., 2023).

Granger causality (GC)

The statistical significance of one variable in relation to another is determined by GC statistics. The basic idea is as follows: if knowledge of a second time series improves the prediction of a first time series, then the second time series is said to have a causal influence on the first (Bose et al., 2017).

The GC test tells us whether lagged $\boldsymbol{x_t}$ helps explain $\boldsymbol{y_t}$, and vice versa.
The null hypotheses are:

X does not Granger cause y

Y does not Granger cause x

Impulse response functions (IRF)

The definition of an impulse response is a system's reaction to an outside change. The external change is known as an exogenous shock in the macroeconomic context, and the system is a system of equations that make up a multivariate autoregressive model. Since every variable in the VAR model is dependent upon every other variable, the information provided by individual coefficient estimates about how the system will respond to a shock is restricted. An IRF is quite helpful for policy analysis because it can address such questions as "What will happen to GDP after X periods if a demand shock happens now?" (Chudik & Georgiadis, 2022).

Forecast error variance decompositions (FEVD)

FEVD is part of the structural analysis and is used to check for forecast errors in the IRF. The amount of information that each variable contributes to the autoregression's other variables is shown in this variance decomposition. According to Pesaran & Shin (1998) this decomposition basically determines the proportion of each variable's forecast error variance that can be explained by exogenous shocks to the other variables (Lanne & Nyberg, 2016).

Quality model checks

Generating predictions is one of the main purposes of VAR models. However, because the model needs to be tested it is also important to be interested in quality checks for the forecast outputs. There are several quality checks that can be performed on a forecasting model to ensure it is accurate and reliable. The history of accuracy studies was set in 1969 by Reid and Newbold and Granger who tried to define post-sample forecasting accuracy.

The most common ones are back testing, cross-validation, out-of-sample testing, sensitivity analysis, and error analysis. By performing these quality checks, one can ensure that our forecasting model is robust enough to handle real-world scenarios (Hyndman & Athanasopoulos, 2018).

In my thesis I construct the below types of quality model check:

A. Out-of-sample testing – comparison table with test data and real data
B. Predicting the physical future – forecasting graph

Accuracy of the forecasting model

To make sure that the forecasts are trustworthy and credible, time series forecasting models must have their accuracy assessed. Forecast inaccuracy can result in inadequate decisions choices, which can have serious consequences. A model's reliability can be assessed using several metrics, such as Mean error (ME), Mean absolute error (MAE), Root mean squared error (RMSE) (Medium, 2023).

5. Results

In this section, I analyze the results of the thesis that were obtained in RStudio:

The dataset which was used to determine a relationship between EU expenditures and macroeconomic variables for the correlation matrix in Table 1 and Figure 2 is built on 5 annual variables – total budget expenditures in 7 categories for EU, GDP growth, inflation, interest, and unemployment rates. The dataset covers years from 2000 until 2022, however it is worth mentioning, that the formation of EU and its respective budget had different number of member states during the observed period:

- EU-15 for years 2000 to 2003
- EU-25 for years 2004 to 2006
- EU-27 for years 2007 to 2012
- EU-28 for years 2013 to 2020
- EU-27 for years 2021 to 2022

The correlation matrix in Table 1 was constructed to determine the relationships between EU budget expenditures and macroeconomic variables. The results indicate that the EU budget expenditures tend to decrease as the interest rate rises, according to the strong negative correlation (-0.822) between the two variables. There is also a slight negative correlation (-0.254 and -0.1) between EU Budget expenditures and the unemployment rate or GDP growth, respectively. Surprisingly, there is no significant correlation between the inflation rate and EU budget expenditures.

Correlation matrix					
Variables	*EU Budget expenditures*	*Inflation rate*	*Interest rate*	*Unemployment rate*	*GDP growth*
EU Budget expenditures	1	-0.005	-0.822	-0.254	-0.1
Inflation rate	-0.005	1	0.259	-0.436	0.351
Interest rate	-0.822	0.256	1	0.342	0.039
Unemployment rate	-0.254	-0.436	0.342	1	-0.15
GDP growth	-0.1	0.351	0.039	-0.15	1

Table 1 Results of correlation matrix between given variables

Plotting macroeconomic variables against EU Budget expenditures is illustrated in Figure 2. The figure has four scatter plots where each X-axis represents specific macroeconomic variable, and the Y-axis denotes EU Budget Expenditure for the years 2000 to 2022. It is essential to keep in mind that correlation does not necessarily imply causation. It is not always the case that one variable causes the other, even when two variables seem to be connected. It is possible that one or both of the other two variables are being affected by a third variable.

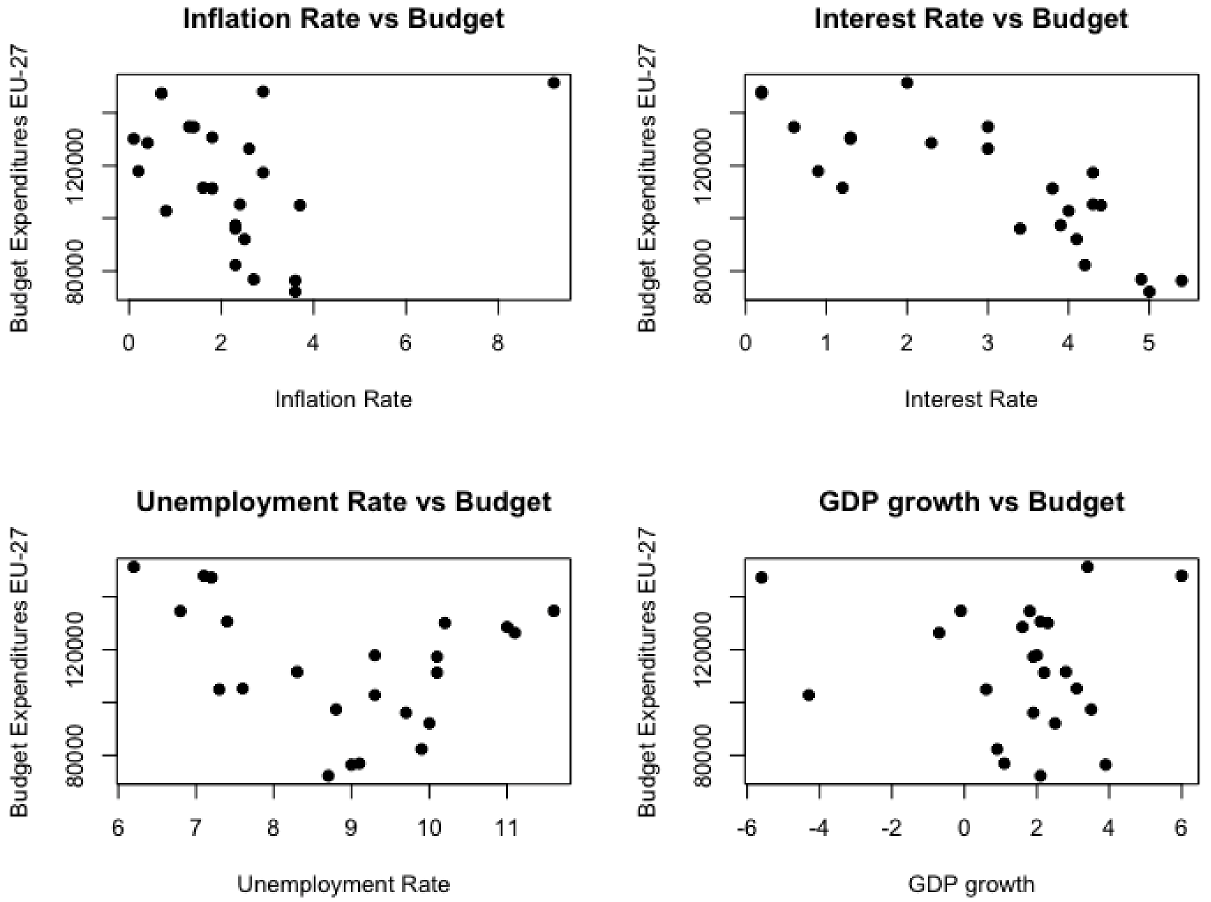

Figure 2 Plots of macro variables against EU Budget Expenditures

The constructed VAR model was then put to the test with a novel dataset that included four important macroeconomic variables in the EU. For variables such as GDP, inflation, and unemployment rate the results were obtained for all member states of the EU 27 countries - Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia. However, for the interest rate, the results were captured only for 19 countries, where the interest rate data was available due to the common currency in the euro area.

The data for the novel dataset were downloaded online from OECD.Stat. This platform includes data for OECD countries and selected non-countries (OECD.Stat, 2020). It covers the period from 2000 Q1 to 2022 Q4 - the number of observations is 92 for each variable. I selected this timeframe considering its relevance to current economic conditions and its implications for the future of the EU.

The quarterly data for GDP is presented in terms of growth rates – expenditure approach which is determined by the summation. The unemployment rate is a percentage of the labor force, which includes both employed and unemployed people. Individuals within the working age demographic who did not hold a job during the reference period but are willing to work and have made efforts to find one are classified as unemployed. The aggregate data for interest rate is calculated as a weighted average of individual country rates. This approach accounts for the varying contributions of each member state (Euro area – 19 countries) to the overall EU economy, ensuring that the aggregated interest rate reflects the collective economic conditions across the EU. The aggregate inflation data for consumer prices is derived from the growth rates of individual country indices, weighted according to each country's contribution to the overall EU economy as was done for interest rate. By calculating a weighted average growth rate over one year, it captures the combined effect of price changes across member states, providing a comprehensive measure of inflation within the EU.

The VAR results

The variables of interest have the below naming convention, which provides a clear understanding of how they are labeled and identified within the context of the model: EU_GDP, EU_INF, EU_RATE, and EU_UNEM.

During the process of making the variables stationary, as it is one of the key assumptions used in VAR model, 3 variables were transformed to achieve stationarity by doing 1st and 2nd difference (taking the difference of the differences) – EU_INF, EU_RATE, and EU_UNEM.

Performing ADF test on four macro variables indicates that after taking the first difference the series becomes stationary, implying that it does not possess a unit root and exhibits a stable mean and variance over time.

Variable	p-value
EU_GDP	0.01
EU_INF (1st diff)	0.049
EU_RATE (1st diff)	0.017

EU_UNEM (2nd diff)	0.01

Table 2 P-value results for ADF test

Table 2 displays the p-values associated with the ADF test, which are less than the conventional significance level of 0.05. The test rejects the null hypothesis of non-stationarity in favor of the alternative hypothesis of stationarity for all data series.

Theoretically, we should include enough lagged values to ensure that the error term exhibits serially uncorrelated behavior. I used 2 lags in the "VAR EU model" because the function 'Varselect' determines the optimal lag order for the model (RDocumentation, -), which is based on the sample size (N=90 quarters in total). This function tries different lag orders and returns the one with the lowest information criteria – such as Akaike information criterion (AIC) or BIC (Stock & Watson, 2020). Notably, for this selection I used AIC.

To construct the model, I created the dummy variable mentioned in section 4 to construct the model with break, considering the start of COVID-19 period that highly influenced the economic well-being. The exogenous variable consists of zeros and ones starting in Q2-2020 (the start of pandemic period).

VAR model tables of the summary statistics are constructed and displayed in the appendix section.

For Appendix Table 1 - EU_GDP equation, the included variables do not collectively explain EU_GDP variations well, based on the p-value 0.33. However, the intercept is statistically meaningful, indicating that the dependent variable has a non-zero value even when all predictors are zero or absent. Among the lagged variables, only the lagged value of EU_GDP (denoted as EU_GDP.l1) is marginally significant suggesting a mild impact on the current EU_GDP. The model's R^2 is 0.02, suggesting that only a small portion of EU_GDP growth variations is explained by the model.

For Appendix Table 2 – EU_INF equation, the model indicates a good collective explanatory power of the included variables. The exogenous dummy variable is extremely significant representing its considerable influence on EU_INF. Specifically, the lagged GDP variables (EU_GDP.l1 and EU_GDP.l2) are marginally significant implying some impact on the endogenous variable. A moderate portion of EU_INF variations is explained by the model with R^2 being 0.43.

For Appendix Table 3 – EU_RATE equation, the model exhibits a good fit based on a p-value of less than 0.05. Both the intercept and the lagged variable EU_RATE.l1 are significant, implying some influence on EU_RATE. The R^2 is 0.15.

For Appendix Table 4 – EU_UNEM equation, the model demonstrates strong collective explanatory power. Specifically, lagged variables - EU_GDP.l1, EU_UNEM.l1 and EU_INF.l2 have impact on EU_UNEM with their p-values being less than 0.05 respectively. The model's R^2 is 0.33, a marginal portion of EU_UNEM variations is explained by the model.

Next, I performed diagnostic testing that includes an ARCH test to investigate potential conditional heteroskedasticity within the time series data. Therefore, based on this test, there is sufficient statistical evidence to reject the null hypothesis, indicating the presence of ARCH effects in the multivariate residuals of the VAR model. The obtained p-value of 0.01 is smaller than the significance level of 0.05. Addressing this heteroskedasticity issue, it is essential to ensure the reliability of the model's predictions.

The Portmanteau test does not reject the null hypothesis with corresponding p-value of 0.87. Based on this test result, there's no strong indication of serial autocorrelation in the errors of the constructed VAR model, which is a favorable outcome.

In the case of GC test, EU_GDP does significantly influence the EU_INF, EU_RATE and EU_UNEM variables with low p-value to reject the null hypothesis. There is strong statistical evidence of instantaneous causality, such as immediate impact between EU_GDP and the three variables. Results are also in favor for EU_INF which does Granger-cause and has an influence on the other variables. This means the past values of EU_GDP contain information that helps predict EU_INF, and vice versa. There's a mutual influence between these variables which might be expected from certain economic circumstances and theories.

On the other hand, EU_RATE and EU_UNEM do not Granger-cause variables in the model because there is not a statistically significant influence of past values of EU_RATE on predicting EU_UNEM or vice versa. The absence of GC might indicate a more complex relationship or other external factors impacting these two variables.

One of the econometric tools conducted in the model analysis involved examining FEVD to test for forecast errors in IRF. This variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. Figure 3 illustrates the 10-period forecast with y-axis ranging from 0 to 1, representing 4 variables of interest. Specifically, the FEVD for EU_GDP shows that an individual shock to GDP primarily affects EU_GDP itself. Reaching almost 40% variations in EU_GDP over a 10-year horizon is attributed to a shock from EU_INF, with the remaining percentage stemming from EU_INF itself. Additionally, EU_INF contributes approximately 20% to the shock in EU_RATE, and EU_GDP exhibits some variations arising in 3rd period. Variable EU_GDP becomes a significant factor in explaining forecast error variance for the shock in EU_UNEM, accounting for 40% of the variations while EU_INF contributes with 10%. The FEVD results, in summary, demonstrate the complex relationships between the variables and the considerable effect that GDP shocks have on both themselves and other variables, particularly EU_INF and EU_UNEM. These results provide insightful information on the dynamic relationships present in the model.

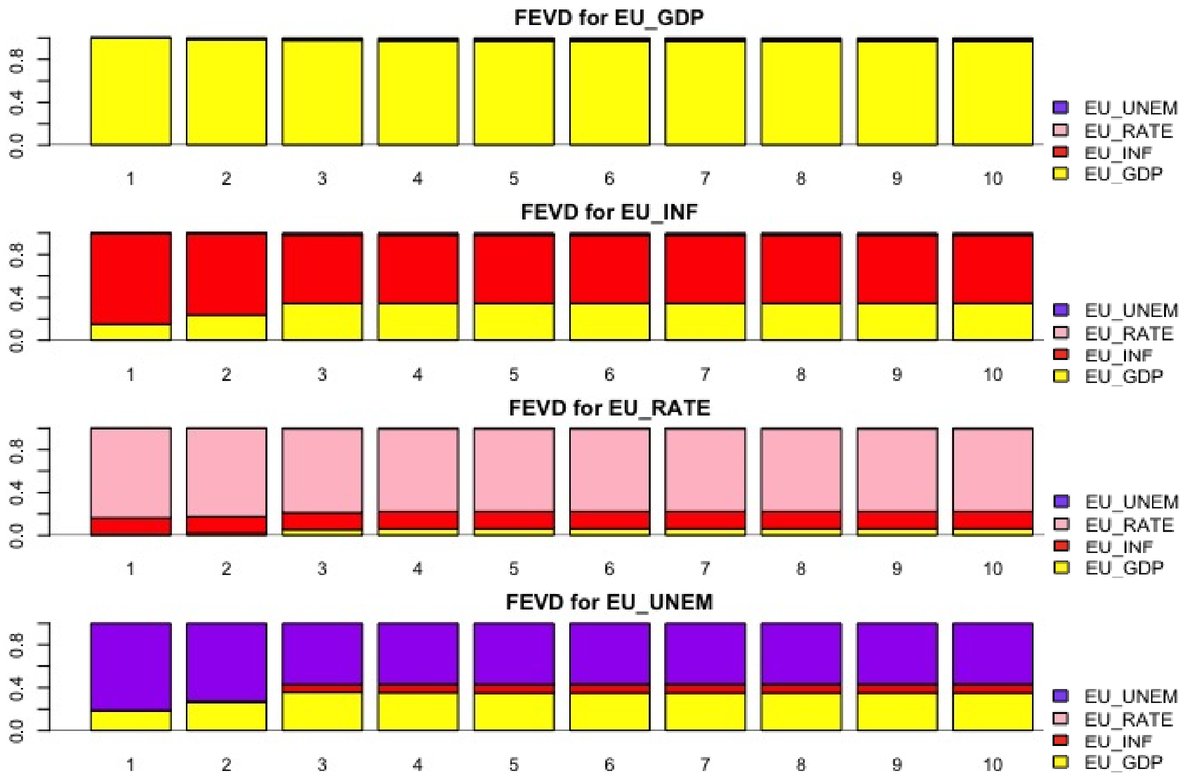

Figure 3 FEVD for specific macroeconomic variable

Another check was the IRF which is used to analyze the dynamic response of the system to a one-unit shock to one of the variables. The next images show the asymptotic standard errors plotted by default at the 5% significance band. Figures 4,5, 6 and 7 are plotted for all four macro variables for 10 lags; in each plot the black line represents the IRF, and the red lines represent the confidence intervals.

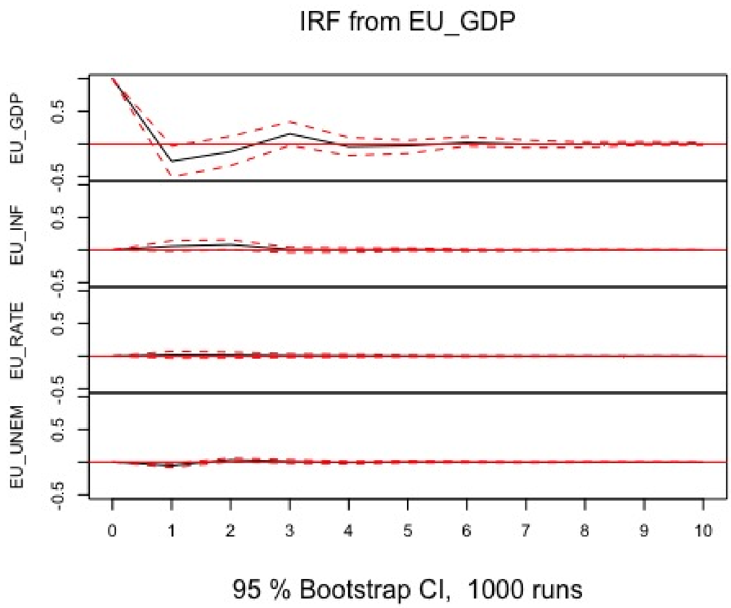

Figure 4 Plot of IRFs of a VAR model built from EU_GDP

Figure 4 depicts a shock from EU_GDP, resulting in a short and hardly significant negative impact on EU_GDP after one time period. The effects of the shock die out in time period 6 where the IRF and confidence intervals converge to zero. Notably, the GDP shock shows no significant effect on the other variables.

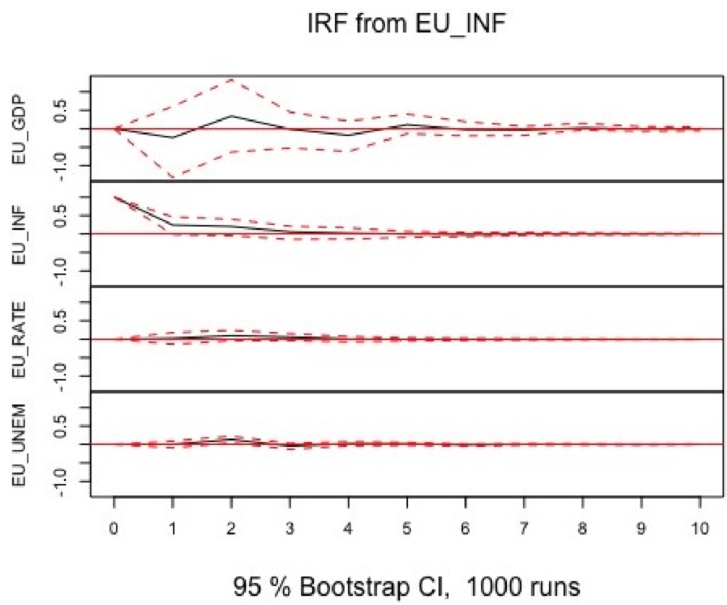

Figure 5 Plot of IRFs of a VAR model built from EU_INF

Figure 5 illustrates the impact of a shock originating from EU_INF. Primarily, it has no significant effect on EU_GDP, but it affects EU_INF itself. For other variables (EU_RATE and EU_UNEM) there are no perceptible effects.

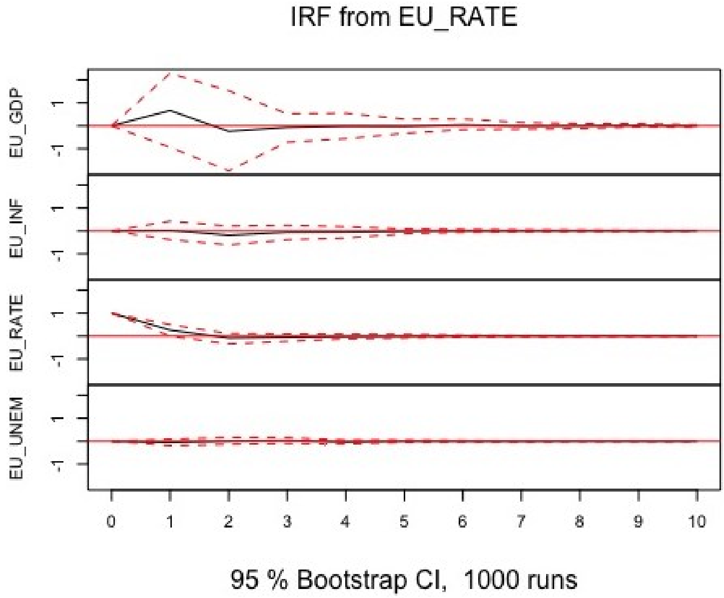

Figure 6 Plot of IRFs of a VAR model built from EU_RATE

Figure 6 analyzes a shock from EU_RATE, which has no significant effect on any variable except itself.

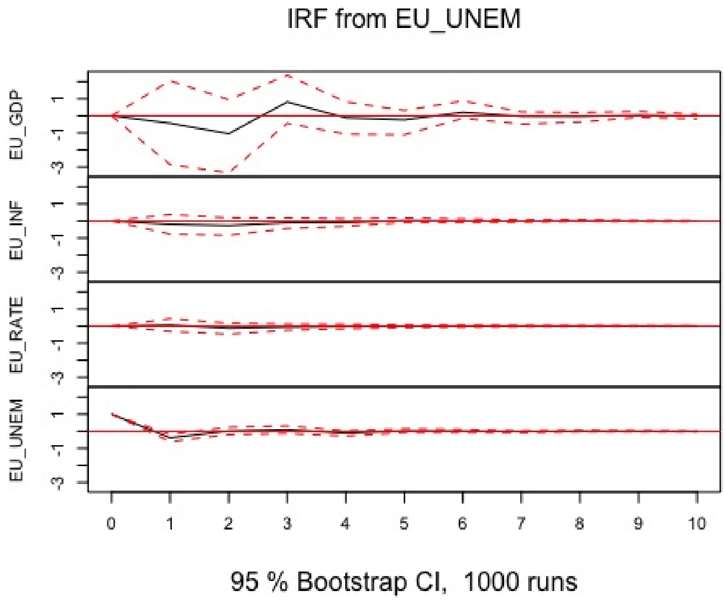

Figure 7 Plot of IRFs of a VAR model built from EU_UNEM

Figure 7 illustrates a shock emerging from EU_UNEM, again resulting in no significant impact on any variable except itself.

Even though IRF does not allow macroeconomic factors to be predicted directly from the model, it is important to highlight how difficult it is to predict macroeconomic outcomes with only four variables. There are many factors that influence these variables in the real world, making the macroeconomic environment very complex. The need for a more thorough approach is further highlighted by considering the variety of shocks that occurred during the observed period, such as the energy crisis, the COVID-19 epidemic, geopolitical tensions including the Russian-Ukraine conflict, each of which had unique political and financial consequences. This implies that the inclusion of additional variables is necessary to obtain accurate understanding of budgetary dynamics. Overall, the IRF does not suggest that there is any meaningful linkage between the analyzed variables. Sometimes, the discovery of absent associations between variables is as important as an opposite situation.

Figure 8 displays the forecasting of macroeconomic variables, and Table 3 depicts their future values.

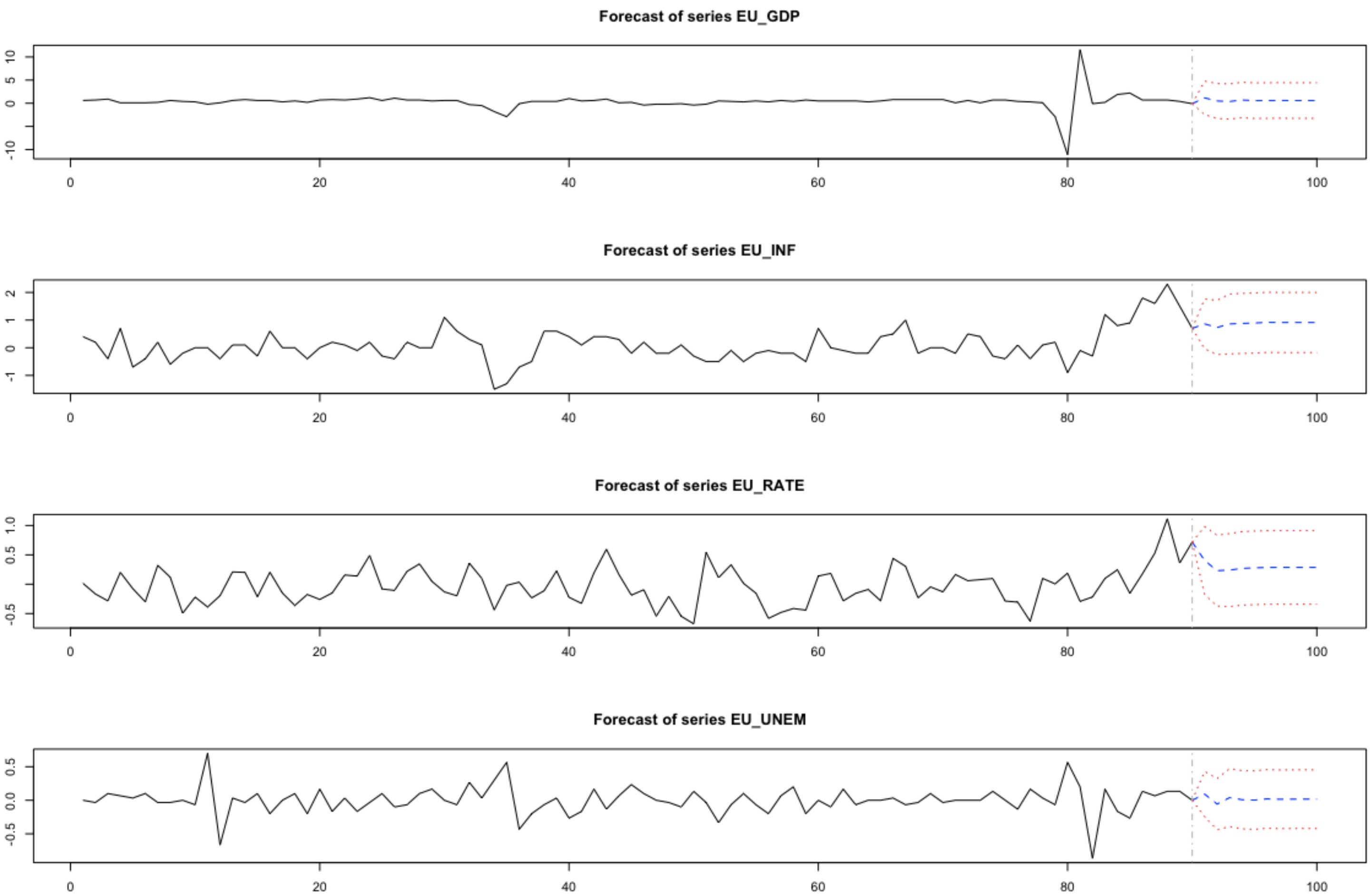

Figure 8 Future forecasting prediction of specific macroeconomic variables

Figure 8 predicts and plots the future trajectories for the next 10 quarters of all four variables accurately. It anticipates that EU_GDP will likely remain stable, EU_INF will experience an upward trend, EU_RATE will initially decline before stabilizing its values, and EU_UNEM will exhibit minor fluctuations but eventually ends up being stable. In summary, the graph presents an in-depth visualization of the expected dynamics for every macroeconomic variable, providing insightful information on how each will behave and react after the break in the model – starts of COVID-19. Figure 8 pictures the overall outlook for the EU's macroeconomic landscape in the coming quarters.

Prediction of physical future				
Period n. head = 10	*EU_GDP*	*EU_INF*	*EU_RATE*	*EU_UNEM*
Q1 - 2023	2.31	1.04	0.46	0.27
Q2 - 2023	-0.70	0.32	0.24	0.01
Q3 - 2023	0.43	0.57	0.31	0.26
Q4 - 2023	0.59	0.76	0.15	-0.07
Q1 - 2024	0.05	0.64	0.11	0.06
Q2 - 2024	0.89	0.95	0.21	0.06
Q3 - 2024	0.66	0.86	0.22	-0.04
Q4 - 2024	0.32	0.9	0.28	0.08
Q1 - 2025	0.71	0.9	0.32	0.04
Q2 - 2025	0.52	0.78	0.30	0.06

Table 3 Prediction of future macroeconomic values

Table 3 provides quarterly predictions for macroeconomic variables, representing the expected changes in GDP, inflation, interest, and unemployment rates for each respective quarter. The column EU_GDP forecasts a fluctuating but generally positive trend, indicating anticipated growth. Inflation, represented by EU_INF, is predicted to exhibit a gradual increase with peaks in the Q1- 2023 and later in Q2 - 2024, suggesting a moderate upward trend in price levels. Changes in EU_RATE show a mixed pattern, with periods of increase and decrease, reflecting potential shifts in monetary policy. Predictions for EU_UNEM indicate a varied trajectory, with some quarters experiencing increases and others showing decreases, reflecting labor market dynamics.

Result for Out-of-sample forecasting

Period h = 10	EU_GDP		EU_INF		EU_RATE		EU_UNEM	
	True value	Predicting value	True value (1st diff)	Predicting value	True value (1st diff)	Predicting value	True value (2nd diff)	Predicting value
Q3 - 2020	11.6	*-22.6*	-0.1	*-3.27*	-0.29	*0.4*	*0.2*	*1.5*
Q4 - 2020	-0.1	*31.21*	-0.3	*2*	-0.22	*-0.77*	*-0.86*	*-3.14*
Q1 - 2021	0.2	*-1.64*	1.2	*0.52*	0.10	*-1.09*	*0.16*	*0.23*
Q2 - 2021	1.9	*1.16*	0.8	*0.64*	0.25	*1*	*-0.16*	*0.54*
Q3 - 2021	2.2	*-2.15*	0.9	*0.12*	-0.16	*-0.02*	*-0.26*	*0.35*
Q4 - 2021	0.7	*2.49*	1.8	*0.83*	0.17	*-0.24*	*0.13*	*-0.28*
Q1 - 2022	0.7	*-0.31*	1.6	*-0.03*	0.53	*0.18*	*0.07*	*0.38*
Q2 - 2022	0.7	*-0.57*	2.3	*-0.02*	1.12	*0.03*	*0.13*	*0.19*
Q3 - 2022	0.4	*-0.31*	1.5	*0.09*	0.36	*0.14*	*0.13*	*-0.01*
Q4 - 2022	- 0.1	*0.02*	*0.7*	*-0.52*	0.72	*-0.21*	*0*	*0.37*

Table 4 Out-of-sample test result in comparison with true values

Table 4 summarizes the out-of-sample testing results for the VAR model over a 10-quarter horizon in comparison with true values. In the case of EU_GDP, the model reveals a consistent pattern of underestimation (Q3-2020, Q3-2021) where the predicted values show high negative deviations, and overestimations (as observed in Q4-2020) between the true values and predicted values. Conversely, for EU_INF, the model generally captures the direction of change, although there are again instances of both overestimation and underestimation. EU_RATE predictions display mixed performance, with some quarters showing accurate forecasting while others exhibit noticeable deviations. Moreover, in Q2-2022, the model struggles to predict the true values for EU_RATE. Lastly, predictions for EU_UNEM are generally accurate, with occasional deviations. The model effectively captures the second order differencing pattern, reflecting a commendable performance in predicting unemployment rates over the out-of-sample period.

Forecasting model's performance

Performance metrics			
Variable	*ME*	*RMSE*	*MAE*

EU_GDP	1.09	14.76	7.73
EU_INF	1.00	1.70	1.46
EU_RATE	0.32	0.72	0.63
EU_UNEM	-0.06	0.90	0.63
Global	0.59	7.45	2.61

Table 5 Performance metrics of model's macroeconomic variables

Performance metrics for the VAR model across all four macroeconomic variables are presented in Table 5. For EU_GDP, the model exhibits a positive ME of 1.09, with relatively high RMSE and MAE values, indicating a considerable degree of prediction error. In contrast, EU_INF shows a near-zero ME, suggesting balanced predictions and low RMSE and MAE, indicating overall accuracy. EU_RATE demonstrates a positive ME, with moderate RMSE and MAE, reflecting reasonable predictive performance. However, EU_UNEM displays a negative ME, implying a tendency to overestimate. The global metrics suggest an overall balanced performance for the VAR model, emphasizing the need for further refinement, particularly in capturing unemployment dynamics.

Limitations of the model

In this sub-chapter, a few limitations of the technique will be outlined and stated. It is necessary to identify all important conditions that might have affected how the results were interpreted.

This thesis only takes EU as one nation (one-size-fits approach), neglecting the diverse economic conditions and landscapes of individual member states, which is the main limitation of this paper. However, it can serve as a benchmark and be used on specified country, for more efficient usability of the EU funds in the 7 categories. The correct allocation of funds is a very crucial process which can take several months of planning to properly negotiate the requirements of each member states. Thus, during time of constant change – the external influence on various aspects of this common economy, can cause a new complication in the process of correctly allocating the reserved funds. The depicted macroeconomic variables serve as a forecasting example how to construct more complex models on individual countries where the results would be more precise.

Other limitations could be the model itself because there are several variants of the VAR. The basic VAR model has various modifications, each with unique changes represented to address the basic model's imperfections. Moreover, in my model I used 2nd difference to make unemployment variable stationary. Overall, some researchers suggest that it is better to use fewer differences in data than more - each time one applies differencing, some information is lost from the data, as seen in the performance metric of the forecasting model for EU_UNEM. This is debated in the forecasting community because some experts say that differencing tends to make forecast models robust (Bårdsen et al., 2012).

Data drifting represents a limitation in the context of forecasting macroeconomic variables using a VAR model. VAR model assumes stationarity in the time series data. However, if the statistical properties of the macroeconomic variables change over time (data drifting), the model's reliability and forecasting accuracy may be compromised (Tonner et al., 2011). This problem was displayed in Table 5 - the results of MPE and MAPE among all variables - high values could be an indication that the model struggles to accurately capture the percentage deviations of predicted values from actual values, highlighting the model's sensitivity to changing data distributions.

Moreover, macroeconomic variables are influenced by various external factors such as policy changes, economic events, and global trends. These external factors can introduce shifts in the data distribution, making it challenging for a dynamic VAR model to adapt. Economic conditions, policies, and global events evolve, and these changes are not always captured adequately by historical data used for training the VAR model. I highlight the importance of regularly updating the model, such as incorporating rolling-window approaches, updating the model with fresh data, or considering more adaptive modeling techniques that account for evolving economic conditions can be useful for policy analysis or decision-making process. Additionally, by acknowledging these challenges, one can explore approaches that are more resilient to shifting data distributions and study this subject in more detail (Shi et al., 2024).

6. Summary

Proper budget allocation and creation for policy makers in the EU is important. With indirect economic shocks that form these predictions, one needs to consider future development of the country and consider several aspects that influence the economy. Most of the budget is currently allocated to boost the European Union's territorial, social, and economic cohesion. The adopted 2023 EU budget helped reducing the negative effects of Russia's war of aggression against Ukraine, not only in the nation but also in its southern neighbors and member states. In addition, future budget will preserve and generate jobs while assisting in the continuous, sustainable recovery from the coronavirus pandemic. A significant portion of the budget is also allocated to innovation, guaranteeing a smooth digital transition, and creating a more resilient and environmentally friendly Europe which several categories of the budget support. The fight against illegal immigration, strengthening border control, and boosting security are additional spending priorities.

Forecasting macroeconomic variables in the time of constant change is also very important to somehow prepare for different economic scenarios and situations. An effective method for capturing the dynamic behavior present in economic time series prediction is the VAR model. It can be used when two or more time series influence each other – in the case of this thesis; four macroeconomic variables, where the relationship is specified as a bi-directional. Often the dynamics that are predicted by the VAR model are more interesting than the actual estimated coefficients. For this reason, I have reported the GC statistics as well as IRF and FEVD analyses, which are helpful in determining the system-wide effects of exogenous shocks to macroeconomic variables in my result section. Moreover, I also performed the correlation matrix between EU budget expenditures in 7 main categories and corresponding macro variables to find a positive or negative correlation relationship.

With respect to the EU budget for 2022 and the adopted 2023 budget that addressed external shocks, the VAR model analysis offers insights that are in line with the novel dataset that covers all 27 EU member states. The period ranges from 2000 Q1 to 2022 Q4, aligning with recent economic developments and the anticipated trajectory of the EU.

The VAR model's results indicate important discoveries such as the EU_GDP equation lacks overall importance and the included variables may not collectively explain EU_GDP variations well, the EU_INF equation's great significance, the EU_RATE equation's important outcomes, and the EU_UNEM equation's being remarkably significant. However, the presence of conditional heteroskedasticity is confirmed by ARCH test and needs to be taken into consideration, to improve forecasts predictions to guarantee the accuracy of policy actions.

Although the Portmanteau test results do not suggest strong serial correlation in the errors, Granger causality tests show that EU_GDP, EU_INF, EU_RATE, and EU_UNEM have immediate effects on one another and exhibit mutual influence. The FEVD analysis emphasizes the complex interactions between variables and the significant influence of GDP shocks on themselves and other variables, particularly EU_INF and EU_UNEM.

Notably, the IRF for EU_GDP shows a gradual reduction in the impact of a shock over time. Similar patterns are observed for EU_INF, EU_RATE, and EU_UNEM, each display non-powerful responses to shocks. Although the model is not perfect at forecasting shock effects, it does highlight the challenges in economy that is always shifting.

On the other hand, the heterogeneity in the model may be the reason why the constructed model did not produce meaningful forecasting results in the out-of-sample analysis. If the model's out-of-sample forecasting performance is worse than a univariate benchmark, Allan and Fildes (2001) suggest first attempting to improve it by adjusting variables, lag structures, or considering nonlinear form. Moreover, forecasting properties are often disappointing even if models fit the data well.

Ultimately, the findings of the VAR model provide insightful information about the dynamic linkages that exist within the macroeconomic environment of the EU, which can help policymakers to make the optimal decisions. The results of the VAR model could shape future policy choices that align with the priorities, especially in the light of the anticipated EU budget 2024. Understanding the connection between GDP events, inflation, interest rates, and unemployment will be crucial for policymakers as they create plans for upcoming years. My research highlights the need for a comprehensive, yet adaptable approach given the EU's dedication to respond to outside shocks like the COVID-19 pandemic, the energy crisis, and the ongoing Russia-Ukraine war conflict. The insights from the VAR model can contribute to the development of a more solid and well-informed EU budget, with the aim of strengthening important priorities, that we nowadays challenge, like the military, research and innovation, and climate and environment policy.

In summary, the results of the VAR model offer a forecast that aligns with the goals and challenges of the EU, giving decision-makers a crucial tool for influencing the fiscal environment of the upcoming years. Unexpectedly, the inflation rate is not correlated with the budget expenditures, highlighting the complex interplay between economic factors and the EU budget, whereas the remaining variables have a negative correlation relationship with the budget. Given the data limitations of the model, we could not achieve satisfactory prediction accuracy. Moreover, the start of pandemic - the break dummy variable in the model, will always somehow damage the growth of the macroeconomic variables. Therefore, for future research I suggest monthly or daily data – higher frequency and more variables for the model. Changing these conditions can lead to meaningful and improved predictions. Being consistent with the above analysis, only parts of model require re-specification after the break part in the model. In fact, since frequent re-modelling is one method of keeping model relevance in such a changing world, I do not consider it to be an issue for macro-forecasting model.

7. *Conclusion*

This thesis examines the effect of macroeconomic variables from external shocks that indirectly impact the EU budget and forecasting the macroeconomic variables for upcoming months with the construction of the VAR model.

In the thesis, I tried to link the economic outlook that is currently happening between EU member states – the fluctuating inflation rate, caused by the COVID-19 pandemic which pushed the common economy to its limits, following the common issues with Russian-Ukraine conflict, and the persistence of a slow economy these past few years.

Understanding the forecasting method's importance is essential, particularly in context of the indirect impact of external shocks on budget itself. This indicates how closely the distribution of funds within the EU budget and macroeconomic dynamics are related with their complex relationship as was shown in the correlation matrix of EU Budget expenditures in 7 categories and the given macro variables.

This thesis aims to provide insights into the interconnectedness of economic factors and their role in shaping budgetary policies, offering a foundation for informed decision-making in navigating uncertain economic landscapes.

The result of my thesis also provides answers to the research questions that were set in section 3.

1. Can macroeconomic variables accurately predict the allocation of the EU budget, and if so, which variables are the most important predictors?

As Panagiotelis et al. (2019) address, all crucial economic decisions depend on key indicators such as GDP growth, inflation, and interest rates. In Table 1, the correlation matrix, the results indicate that the EU budget expenditures tend to decrease as the interest rate rises. This is also the case with unemployment rate and GDP growth, but on the other hand inflation rate cannot be taken as a predictor which correlate with the budget. However, if the modeling framework uses a higher number of predicting variables, the forecast become more accurate at different time horizons. While the model currently includes four important variables, which could be considered as the limitations, expanding the range of regressors could yield various forecasting scenarios. This can be used for future research proposal.

2. How do changes in macroeconomic conditions affect the allocation of the EU budget, and how can policymakers use this information to optimize budget allocation?

Changes in macroeconomic conditions can substantially impact the allocation of the EU budget as it is seen in Figure 1 where the 2023 budget increased funding for specific programs in different categories. During periods of economic downturns or recessions, policymakers might allocate more resources toward stimulus programs aimed at boosting economic growth, employment, and supporting industries that are particularly affected – again the case for new adopted budget of 2023. Conversely, during periods of economic expansion, the budget allocation might shift toward investments in innovation, infrastructure, and sustainable development. Understanding the varying needs of different sectors in response to economic fluctuations allows policymakers to optimize budget allocation strategies. By closely monitoring and adopting the EU budget allocation in response to macroeconomic conditions, policymakers can strive for a more efficient and effective utilization of resources, contributing to the overall stability and prosperity of the EU economy.

3. What is the most accurate forecasting model for predicting EU budget allocation using macroeconomic variables, and how can this model be improved?

In this paper I utilized the VAR model due to its dynamic behavior which would make the suitable candidate for forecasting purposes. The model exhibits several commendable attributes:

- forecasting a collection of related variables
- testing whether one variable is useful in forecasting another (the basis of Granger causality tests)
- IRF analysis, where the response of one variable to a sudden but temporary change in another variable is analyzed
- FEVD, where the proportion of the forecast variance of each variable is attributed to the effects of the other variables.

On the other hand, this thesis does not compare several models or specifications. In the Summary section, I proposed the necessary improvements for this specific model for future purposes.

4. How does the allocation of the EU budget vary across member states, and what factors explain these differences?

As it is explained in the sub-category “Mechanism of the EU funding”, EU redistributes a portion of its wealth among its members to support its shared policies. For example: country that contribute more to the budget may seek to ensure that its interests are adequately represented in the allocations of the country.

Although this question remains partially unaddressed in the thesis due to one-size-fits approach, it stands as a potential avenue for future research. A more comprehensive analysis considering diverse economic settings, with the specific well-being of individual member states and different allocation of 7 categories of budget, would be particularly intriguing and insightful.

5. What is the impact of external economic shocks on the allocation of the EU budget, and how can policymakers prepare for and respond to these shocks?

External changes/shocks are never predictable, and one cannot expect them to happen. Nobody knew how the start of COVID-19 pandemic, or the war conflict against Ukraine, or the new structure of EU zone without United Kingdom would affect the common EU economy and how would it eventually and indirectly change the flow of the budget allocation. However, the impact can be substantial and multifaceted because it can massively disrupt economic conditions. To prepare for such scenarios, policymakers can adopt some strategies like having flexibility in budget allocation, or monitoring economic indicators, or being more coordinated and having collaborative efforts across all member states.

The future potential for this specific model is to address and study it on a global level. However, I would need to extend the EU VAR model to a GVAR model, which may be considered as a future research proposal. This thesis so far investigates only the economy shock mechanisms at the EU level to bridge the gap between purely statistical analyses and conventional modeling strategies. The GVAR is a global modeling framework that is used for analyzing the international macroeconomic transmission of shocks, considering drivers of economic current activity, spillovers between linked countries, and the effects of unobserved and observed common economic factors. The model was originally proposed by Pesaran (2004) and later developed by Dees (2007). It uses time series, panel data, and factor analysis techniques. More recently Chudik et al. (2020) even developed an augmented GVAR model to quantify the global macroeconomic impact of COVID-19. This was also my motivation and inspiration to take this thesis so far on a “local” EU level and not consider expanding it to worldwide selection and influence that is happening between international economies (Mohaddes & Raissi, 2020).

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Appendix

Table 1 – VAR Estimation Result for equation EU_GDP

EU_GDP = const + exo1 + EU_GDP.l1 + EU_INF.l1 + EU_RATE.l1 + EU_UNEM.l1 + EU_GDP.l2 + EU_INF.l2 + EU_RATE.l2 + EU_UNEM.l2				
	Estimate	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	0.5014	0.2324	2.157	0.0341 *
Exo1	0.2106	0.7054	0.298	0.7661
EU_GDP.l1	-0.2666	0.1318	-2.023	0.0465 *
EU_INF.l1	-0.2409	0.5141	-0.469	0.6406
EU_RATE.l1	0.6621	0.7785	0.850	0.3977
EU_UNEM.l1	-0.4364	1.2075	-0.361	0.7188
EU_GDP.l2	-0.2122	0.1450	-1.464	0.1472
EU_INF.l2	0.3221	0.4906	0.657	0.5134
EU_RATE.l2	-0.2547	0.7780	-0.327	0.7442
EU_UNEM.l2	-1.4182	1.0713	-1.324	0.1894
R^2	0.01638			

Table 2 – VAR Estimation Result for equation EU_INF

EU_INF = const + exo1 + EU_GDP.l1 + EU_INF.l1 + EU_RATE.l1 + EU_UNEM.l1 + EU_GDP.l2 + EU_INF.l2 + EU_RATE.l2 + EU_UNEM.l2				
	Estimate	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	-0.08043	0.05799	-1.387	0.169430
Exo1	0.62314	0.17601	3.540	0.000678 ***
EU_GDP.l1	0.05776	0.03287	1.757	0.082856
EU_INF.l1	0.24299	0.12827	1.894	0.061874
EU_RATE.l1	0.02418	0.19425	0.124	0.901271
EU_UNEM.l1	-0.19751	0.30128	-0.656	0.514021
EU_GDP.l2	0.07325	0.03617	2.025	0.046285 *
EU_INF.l2	0.15603	0.12242	1.275	0.206239
EU_RATE.l2	-0.24848	0.19411	-1.280	0.204318
EU_UNEM.l2	-0.27312	0.26731	-1.022	0.310063

R^2	0.425

Table 3 – VAR Estimation Result for equation EU_RATE

EU_RATE = const + exo1 + EU_GDP.l1 + EU_INF.l1 + EU_RATE.l1 + EU_UNEM.l1 + EU_GDP.l2 + EU_INF.l2 + EU_RATE.l2 + EU_UNEM.l2				
	Estimate	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	-0.06935	0.03733	-1.858	0.0670
Exo1	0.20378	0.11330	1.799	0.0760
EU_GDP.l1	0.01997	0.02116	0.944	0.3482
EU_INF.l1	0.02207	0.08257	0.267	0.7899
EU_RATE.l1	0.26062	0.12504	2.084	0.0404 *
EU_UNEM.l1	0.06054	0.19394	0.312	0.7557
EU_GDP.l2	0.01967	0.02329	0.845	0.4009
EU_INF.l2	0.08825	0.07880	1.120	0.2662
EU_RATE.l2	-0.16180	0.12495	-1.295	0.1992
EU_UNEM.l2	-0.10453	0.17207	-0.607	0.5453
R^2	0.1507			

Table 4 – VAR Estimation Result for equation EU_UNEM

EU_UNEM = const + exo1 + EU_GDP.l1 + EU_INF.l1 + EU_RATE.l1 + EU_UNEM.l1 + EU_GDP.l2 + EU_INF.l2 + EU_RATE.l2 + EU_UNEM.l2				
	Estimate	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	0.0221492	0.0216985	1.021	0.310519
Exo1	-0.0735298	0.0658551	-1.117	0.267619
EU_GDP.l1	-0.0531529	0.0123001	-4.321	4.53e-05 ***
EU_INF.l1	0.0009490	0.0479907	0.020	0.984273
EU_RATE.l1	-0.0552020	0.0726787	-0.760	0.449822
EU_UNEM.l1	-0.3857913	0.1127236	-3.422	0.000991 ***
EU_GDP.l2	0.0002854	0.0135343	0.021	0.983231
EU_INF.l2	0.1229191	0.0458030	2.684	0.008889 **
EU_RATE.l2	0.0367200	0.0726275	0.506	0.614568

EU_UNEM.l2	-0.1554303	0.1000137	-1.554	0.124211
R^2	0.3333			