UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

THE IMPACT OF PANDEMIC POLICY MEASURES ON CREDIT ACTIVITY AND THE REAL ECONOMY IN THE EURO AREA DURING THE COVID-19 CRISIS

Ljubljana, September 2023
KLARA ŽBONTAR

AUTHORSHIP STATEMENT

The undersigned **Klara Žbontar**, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title **The Impact of Pandemic Policy Measures on Credit Activity and the Real Economy in the Euro Area During the COVID-19 Crisis**, prepared under supervision of **Professor Igor Masten PhD.**

D E C L A R E

1. this written final work of studies to be based on the results of my own research;
2. the printed form of this written final work of studies to be identical to its electronic form;
3. the text of this written final work of studies to be language-edited and technically in adherence with the SEB LU's Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this written final work of studies in accordance with the SEB LU's Technical Guidelines for Written Works;
4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;
5. to be aware of the consequences a proven plagiarism charge based on the this written final work could have for my status at the SEB LU in accordance with the relevant SEB LU Rules;
6. to have obtained all the necessary permits to use the data and works of other authors which are (in written or graphical form) referred to in this written final work of studies and to have clearly marked them;
7. to have acted in accordance with ethical principles during the preparation of this written final work of studies and to have, where necessary, obtained permission of the Ethics Committee;
8. my consent to use the electronic form of this written final work of studies for the detection of content similarity with other written works, using similarity detection software that is connected with the SEB LU Study Information System;
9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this written final work of studies in the electronic form, the right of its reproduction, as well as the right of making this written final work of studies available to the public on the World Wide Web via the Repository of the University of Ljubljana;
10. my consent to publication of my personal data that are included in this written final work of studies and in this declaration, when this written final work of studies is published.
11. that I have verified the authenticity of the information derived from the records using artificial intelligence tools.

Ljubljana, September 27th 2023 Author's signature: ________________________

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

€STR	Euro short-term rate
APP	Asset Purchase Program
CET1	Common Equity Tier 1
CLI	Composite Leading Indicator
CoCos	Contingent Convertibles
CPPI	Commercial Property Price Index
CRR	Capital Requirement Regulation
DoD	Definition of Default
EA	Euro Area
EBA	European Banking Authority
ECB	European Central Bank
ECL	Expected Credit Losses
EDF	Expected Default Frequencies
EIF	European Investment Fund
EM	Expectation Maximization
EONIA	Euro OverNight Index Average
ESRB	European Systemic Risk Board
EU	European Union
FAVAR	Factor-augmented Vector Autoregression
GDP	Gross Domestic Product
HICP	Harmonized Index of Consumer Prices
IFRS9	International Financial Reporting Standard 9
LCR	Liquid Coverage Ratio

LP	Labor Productivity
LTRO	Longer-term Refinancing Operation
MFI	Monetary Financial Institution
MS	Member State
NFC	Non-financial Corporation
NPL	Non-performing Loans
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PELTRO	Pandemic Emergency Longer-term Refinancing Operations
PEPP	Pandemic Emergency Purchase Program
PPI	Production Price Index
PSG	Public Guarantee Schemes
RPPI	Residential Property Price Index
RWA	Risk-weighted Assets
SME	Small and Medium-sized Enterprises
SURE	Support to mitigate Unemployment Risks in an Emergency
TCR	Total Capital Ratio
TLTRO	Targeted Longer-term Refinancing Operation
ULC	Unit Labor Cost
UTP	Unlikely to Pay
VAR	Vector Autoregression
YC	Yield Curve

INTRODUCTION

The year 2020 will always be remembered and be forever marked as the year of the SARS-CoV-2 outbreak. A disease known by the name COVID-19 has spread around the world, a pandemic has been declared, and a vast majority of countries introduced different forms of quarantine or other containment measures which disrupted many business operations. Containing the virus using lockdowns allowed healthcare to cope with the disease as fewer people needed hospital care which gradually allowed the economic activity to resume. Due to the implementation of quarantines and social distancing which were needed to contain the virus, the world has been put into a lockdown which pushed the world's economies into severe recession. The magnitude of the output fall was unlike anything experienced so far. The COVID-19 crisis affected many areas. Countries with policymakers on top provided support to households, firms, financial markets, and all other areas that suffered due to the virus outbreak. Policymakers had to make sure that people were able to meet their needs and that businesses would be able to continue operations once the pandemic was over. Fiscal and monetary policies introduced large, targeted measures which included credit guarantees, loan forbearances, tax reliefs, enhanced benefits, and expanding liquidity capacity which kept many households and businesses viable during these hard times. A recovery plan was important to bring economies back on track. Coordinated fiscal stimulus across countries had a major beneficial effect on all economies and was thus vital to the global recovery (Gopinath, 2020).

The fast-spreading COVID-19 disrupted mobility and trade in the whole world. Containment measures introduced across the globe significantly impacted the regional and global value chains, as well as sectors, such as tourism and services. This is evident from a sharp fall in economic activity in 2020. The global GDP growth rate had declined by 5.7 percentage points. from 2019 (World Bank, n.d.) while the GDP growth rate in the euro area had decreased by 7.7 percentage points compared to 2019 (Eurostat, n.d.). Due to disrupted business activity, firms experienced a disruption in cash flows and revenues which led to liquidity problems as they were not able to meet their obligations to employees, suppliers, and creditors. On the other hand, increased uncertainty during the time of the great lockdown and risk aversion in financial markets increased funding costs for banks. Banks' bond yields increased significantly. Riskiest bank bond yields (CoCos) increased by 10 percentage points in March 2020. Also, yields of corporate bonds increased. If there had been no countermeasures and no policy response, the market conditions would have just kept worsening and it would have translated to tighter and tighter lending conditions which would have eventually decreased the lending activity. The policy response to the COVID-19 shock was quick and significant which combined monetary policy support, released micro- and macro-prudential requirements, and direct support from national governments and supernational authorities. After the announcement of support packages and the pandemic emergency purchase program (PEPP hereinafter) in March 2020, the rise of bond yields stopped. The policy measures made sure that banks were able to accommodate the increased demand for credit coming from corporations and households that were affected by the crisis. Many companies experienced a sharp drop in their revenues which made it harder for them to pay their obligations. This has led to a significant increase in credit demand which banks were able to match and increase lending due to pandemic support policy measures. From March to May 2020 the banks' lending increased by €250 billion, which could be marked as the highest increase ever recorded in three months. The annual growth rate of loans to firms was 7.3% in May. The increased demand for credit would normally increase the borrowing costs but due to the introduced support measures the lending rates for firms did not increase since the measures prevented the tightening of borrowing conditions (Altavilla, Barbiero, Boucinha & Burlon, 2023).

The whole Europe had come together to help countries recover from the devastating economic impact of the coronavirus outbreak. The EU's long-term budget (€1.211 trillion) has been formed which, together with the Next Generation EU (€806.9 billion), amounts to €2.018 trillion in current prices. This makes it the largest stimulus package ever financed by the EU. The package aims to help repair social and economic damage caused by the pandemic, mitigate the effects on the real economy, and make Europe more sustainable, resilient, and prepared for the upcoming challenges (European Commission, 2020a). The most important and largest part of Next Generation EU represents the temporary recovery instrument called Recovery and Resilience Facility worth €723.8 billion. €338.0 billion is meant to be distributed in the form of grants and €385.8 billion in the form of loans with favorable terms to support investments and reforms in the Member States (European Commission, 2020b).

The effect of tightening credit conditions on economic activity has been a burning question ever since the previous financial crisis of 2008/09 where disruptions in the credit market caused a severe economic downfall. Economists have been eager to prove the connection between the financial markets and business cycles, as well as the transmission mechanism of credit shocks to the real economy. There have been several studies that evaluated the effects of credit shocks on the real economy. My thesis follows a similar mind frame to evaluate the effects of credit shocks on economic activity during the COVID-19 crisis in the euro area. Contrary to most studies, I am trying to evaluate the effects of a positive credit supply shock on economic activity, i.e., in general how the economy reacts to increased bank lending. During the COVID crisis, many pandemic policy measures were introduced. They aimed to increase bank lending and provide access to capital for households and companies that faced liquidity shortages. Policy measures that stimulated bank lending during the COVID crisis can be interpreted as a positive credit stimulus which effects on the real economy I tried to evaluate. The monetary policy introduced the Asset Purchase Program (APP hereinafter) and PEPP programs which helped absorb the shock while long-term liquidity injections into the banking system through programs, such as Longer-term Refinancing Operation (LTRO), Targeted Longer-term Refinancing Operation (TLTRO) III, and Pandemic Emergency Longer-term Refinancing Operations (PELTRO) supported banks and increased lending. European Central Bank (ECB hereinafter) also stimulated bank lending by allowing banks to operate temporarily below the level of capital defined by the Pillar 2 Guidance, the capital conservation buffer, and the liquidity coverage ratio. On the other hand, fiscal stimulus came in the form of public guarantee schemes which transferred some of the risk from banks to governments. All pandemic policies together stimulated bank lending and thus acted as a positive credit supply shock on the economy during the pandemic.

The main idea of my master's thesis is to evaluate how the pandemic policy measures impacted the credit and economic activity in the euro area during the crisis. My methodology relies on the FAVAR approach which was proven to be successful in estimating the effects of structural shocks on different economic and financial indicators. In my analysis, credit easing policy measures, introduced to counter the effects of the COVID-19 crisis, were perceived as a positive credit supply shock. Effects of that shock were observed on key economic and financial variables by analyzing impulse response functions. In an additional analysis, I also evaluated what the economic downfall would have been if policymakers had not intervened. This was done by simulating counterfactual economic conditions which would occur in the absence of pandemic policy measures. This allows me to quantify the effects of pandemic policy measures on different aspects of the economy and economic activity while also evaluating what would the consequences of the COVID-19 crisis be if policy did not intervene.

The euro area is particularly interesting when it comes to modeling the credit shocks as in the euro area bank lending holds a key position. In contrast to the US economy, the banking sector in the euro area plays a critical role when it comes to funding the private sector (Peersman, 2011). This leads me to my first research question which I would like to answer within my thesis:

Q1: How to properly quantify the stimulus (credit shock) provided by the pandemic policy measures in the euro area?

Many economists have modeled the credit shocks on the US economy using corporate credit spreads (the difference in yields between various corporate debt instruments and government securities of comparable maturity). My focus is on pandemic policy measures which were introduced to improve credit conditions and encourage bank lending. So, in other words, to prevent a credit crunch. Therefore, I believe a corporate credit spread is not the way to go but instead proposes to use a measure that captures the improved bank lending. This brings me to my first hypothesis:

H1: Credit spread which is defined as a difference between a long-term bank lending interest rate and risk-free government bond yield of comparable maturity is a proper measure of quantification of the stimulus provided by the pandemic policy measures in the euro area.

There are many possible ways to model credit shocks, which brings me to my next research question:

Q2: How to model credit shocks in the euro area environment properly?

Many models would allow such estimation, for example, standard Vector Autoregression (VAR), structural VAR, Ordinary Least Squares (OLS) regression, FAVAR, and many other alternatives that were used by researchers in their studies to model credit shocks and to evaluate their effects on the real economy. I believe that the most appropriate model for my type of analysis of credit shocks is a factor-augmented vector autoregressive (FAVAR hereinafter) model. Factor models, such as FAVAR, are especially appropriate for such analysis since FAVAR can capture a large number of macroeconomic and financial time series by a small number of unobservable factors. Also, due to a large set of data used in the estimation process, FAVAR is not sensitive to the choice of data that is meant to represent economic activity or financial conditions. My next hypothesis is the following:

H2: Factor-Augmented VAR (FAVAR) model is the appropriate methodology for modeling the impact of credit shocks on the euro-area economy.

My next and most important research question is the following:

Q3: How did the pandemic policy measures focused on boosting credit activity impact the real economy in the euro area during the COVID-19 crisis?

I wanted to analyze how much the pandemic policy measures impacted the real economy. Many researchers have proved that the tightening of credit conditions has negative consequences for the real economy. Many empirical studies (e.g. Boivin, Giannoni and Stevanović (2016), Helbling, Huidrom, Kose and Otrok (2011), Mueller (2009), and Peersman (2011)) provide evidence of the effects of disturbances in credit markets for business cycle dynamics. Many of these examine the relationship between credit cycles and business fluctuations. In addition, the economic theory of financial accelerator developed by Bernanke and Gertler (1989), and Bernanke, Gertler and Gilchrist (1998) suggest a tight link between credit spreads and economic activity. So my third hypothesis is the following:

H3: The pandemic policy measures focused on boosting bank lending and increasing credit activity had a significant positive impact on the real economy in the euro area during the COVID-19 crisis.

My findings suggest that pandemic policy measures focused on credit easing played a significant role in boosting bank lending during the COVID-19 crisis. They managed to stimulate the economy and prevent a much longer recession as they successfully countered the negative effects coming from the containment measures. Without any policy interventions during the pandemic, GDP would be lower by 4% at the end of 2021 and industrial production by 7%, based on my estimation. Policy interventions contributed to a quick and efficient recovery. My analysis of impulse responses to a positive credit shock shows that increased bank lending to non-financial corporations (NFC) leads to increased economic activity. I observed significant and very persistent growth of economic output in the period following the shock. Increased lending also leads consequently to increased inflation which triggers an immediate tightening of the monetary policy. On the other hand, increased lending improves labor market conditions. The initial shock of 1.27% stimulates the credit conditions even further, boosting the lending activity to increase by 10% in the following 2 years, which boosts the GDP and industrial production by 2.8% and 3.7%, respectively.

My master's thesis is structured in the following way. First, I discuss the pandemic policy measures that were adopted during the COVID-19 crisis to counter the negative effects coming from containment measures. Monetary, fiscal, and prudential policy measures introduced during the crisis to boost the economy were described. The next section focuses on the theory of credit shocks in which the connection between the credit shocks and the business cycles is explained. This section also describes the transmission channels of credit shocks to the real economy where the main mechanism is the financial accelerator which relies on the theory of external finance premium. The next section proceeds with examining the past research that has been done to analyze the effects of credit market shocks on the real economy. I present a quick overview of different modeling approaches and identifications of credit shocks that the economists used in their studies. The empirical part of the thesis starts with an overview of the methodology and framework that was used in my analysis. The core part of the thesis is presented in the last section where I present the main findings of my analysis based on the FAVAR model, impulse response functions, and counterfactual analysis.

1 OVERVIEW OF ECONOMIC POLICIES IN THE PANDEMIC

Restrictions set by the government to prevent the spread of the virus have led to a large decrease in economic activity. Demand for non-essential goods and services dropped dramatically during the COVID-19 period. The service sector was highly affected by those measures, particularly services, such as restaurants, accommodation, and travel. There were also disruptions on the supply side due to border closures and a decline in intermediate goods production. A severe supply shock mostly affected companies that are part of the global supply chains. NFCs and households experienced a large decline in income which caused an increased demand for liquidity. Companies with higher liquidity reserves and equity are more resilient to shocks and are more likely to survive the losses in the longer term. Firms that cannot operate normally due to liquidity shortages affect households by reducing wages and firing employees. Due to the risk of losing a job and experiencing a difficult financial situation, households further decrease their demand for unnecessary goods and services. This deepens the initial impact of the crisis on the companies, leading to higher unemployment and a reduction in salaries. This again impacts the households and lowers their desire for unnecessary consumption (ESRB, 2021).

The COVID-19 crisis led to a sharp deterioration of credit conditions since there was a significant decrease in asset values. Companies had decreased cash inflows which led to short-term liquidity problems which could quickly turn into insolvency if those companies lost their access to funding. Fiscal policy measures supported firms facing liquidity and solvency issues while monetary policy stabilized asset prices and kept funding conditions for banks favorable. The financial system was quite resilient at the start of the crisis due to regulatory reforms which were implemented at the end of the previous financial crisis which forced banks to keep high capital buffers and made banks more resilient to shocks. The regulatory measure allowed banks to draw from those buffers so they could keep lending to the real economy (ESRB, 2021).

Another channel of transmission of the shock is the cross-border spillover effect. The negative shock in one country can have spillover effects on another economy. Lowering the demand for imported goods has a negative effect on the companies across the border. On the other hand, measures adopted by one country can have positive externalities and effect on financial stability of another country by stimulating demand for imported goods and services. Increasing production in a firm that is part of the cross-border value chain has a positive spillover effect on aggregate supply. This has a positive effect on the other country's financial stability by lowering defaults of those firms and households across the border. Since lots of European banks lend to foreign entities, the spillover effect also affects the financial stability in the home country where the measure was implemented (ESRB, 2021).

The magnitude of the negative shock that was caused by the COVID-19 crisis on the real economy depends on the following three factors: resilience in terms of vulnerabilities, exposure to the shock in terms of the size of the shock in a particular sector, and effectiveness of policy measure in terms of mitigating the shock. For example, NFC's resilience or vulnerability to a shock depends on the sector of economic activity, funding sources, net worth and liquidity buffers, and of course most importantly access to funding. The magnitude of the shock that is transmitted to the NFC depends on the demand changes due to lockdowns and restrictions, interruption of value chains, and cost of compliance with the COVID-19 measures. Policy measures used to cushion the shock for NFC effectively are measures that protect the company's liquidity and solvency which mostly represent loan moratoria, public guarantee loans, and public loans. For the household, on the other hand, the highest risk presents the loss of employment and a decrease in salary. Policy measures that help households include employment support measures, direct grants to support income, and loan moratoria. The interesting bit is that the mere announcement of the measure helped stabilize bank lending in the early stages of the pandemic (ESRB, 2021).

A wide range of monetary, fiscal, and regulatory support policies and programs were adopted in the spring of 2020 to prevent the long-term consequences of the pandemic on the real economy. Fiscal policies across countries introduced a wide range of aid schemes including government-sponsored job retention programs, grants to firms, public guarantees, moratoria on loan payment, and income support for the self-employed. The overall government pandemic support measures amounted to 14% of GDP in Europe (based on information available up to September 2020). The actualization of these measures was over 700 billion EUR, with more than 400 billion EUR of issued public guaranteed loans and more than 840 billion of loans subject to loan moratoria (Beck, Bruno & Carletti, 2021a). ECB also played a crucial role by implementing many monetary policy measures through asset purchase programs and increasing liquidity to finance new loans through longer-term refinancing operations. Also, many prudential policy measures were introduced to encourage bank lending (Bruno & De Marco, 2021).

The COVID-19 crisis also encouraged the adoption of extraordinary measures to support the economy and maintain the ability of banks to provide credit to the economy. The main objective was to prevent a financial crunch for either people, corporations, sovereigns, or banks. A wide set of monetary, fiscal, regulatory, and supervisory measures were introduced to mitigate the negative effect of the pandemic on the real economy (Beck, Bruno & Carletti, 2021a).

1.1 Monetary pandemic policy measures

The ECB played a crucial role in addressing the tightening of financial conditions caused by the COVID-19 crisis and thus successfully mitigated the impact of the crisis on the real economy. The response of the ECB was quick and sufficient. Effective COVID-19-related policy measure is the one affecting credit allocation as this plays a vital role in stimulating economic growth. Banks played a crucial role in mitigating the negative effects of the COVID-19 crisis as they are the ones that transmit the monetary policy impulses to the real economy. The effectiveness of the implemented measures to support the economy, therefore, largely depends on the response of the banking system. To encourage bank lending and prevent a reduction of credit supply during the crisis, a wide set of monetary policy actions, such as liquidity injections were implemented, as well as relaxation of some prudential and accounting requirements (Bruno & De Marco, 2021).

The support to the euro system was implemented through asset purchase programs of securities issued by governments and corporations (APP and PEPP) which were meant to help the economy to absorb the shock and through injecting long-term liquidity into the banking system to finance new loans and thus support credit for firms and households (LTRO, TLTRO III, and PELTRO). All measures aimed to ensure the flexibility of monetary policy, stabilization of financial markets to ensure the transmission mechanism worked, and to ensure sufficient liquidity especially to maintain bank lending (Aguilar et al., 2020). Between March and December 2020, the key interest rates stayed untouched to complement the refinancing scheme. Main refinancing operations stayed at 0.00%, with a marginal lending facility at 0.25% and a deposit facility at -0.5%, respectively (Rakic, 2021).

1.1.1 Asset purchase programs (APP and PEPP)

The original ECB asset purchase program (APP) of 20 billion EUR net purchases a month has increased by an additional 120 billion EUR, which was meant to be utilized by the end of 2020 (Rakic, 2021). In addition, the ECB introduced a temporary program called the Pandemic Emergency Purchase Program (PEPP) for public and private sector assets purchases which is a non-standard monetary policy measure and it managed to keep the interest rates at historically low levels (Beck, Bruno & Carletti, 2021a). The PEPP was announced on 18 March 2020 with an initial budget of 750 billion EUR and to be terminated by the end of 2020. At the beginning of June, the Governing Council increased the budget by 600 billion EUR and decided to extend the program to the end of June 2021. In December, the PEPP increased again by 500 billion EUR amounting to 1.85 trillion EUR altogether. The period was extended to the end of March 2022. The monthly number of net purchases or type of assets or jurisdictions were not predefined, which allowed for flexibility when it came to the distribution (Rakic, 2021). Till the end of August 2021, the Euro system has purchased 1.35 trillion EUR of which 95% represented public sector assets (Bruno & De Marco, 2021). By purchasing assets, the ECB absorbs a portion of duration risk and thus lowers borrowing yields in government and corporate debt markets. Duration risk happens due to the change in the market price of medium and long-term bonds in their time to maturity. Purchasing bonds from investors frees the investors' ability to acquire new risk and, thus, reduces the risk price which lowers term premium in bond yields. During the pandemic, in addition to duration risk, default risk was also increased. The increased APP diminished the risk when there was a large increase in government debt. Sovereign risk is connected to bank lending as the sovereign yields indirectly affect the bank lending interest rates as the cost of bank lending is linked to the costs of the financing raised by the banks. The announcement of PEPP had a significant positive effect on the sovereign debt yields and the main stock market indices. The increase in PEPP in June also had a positive effect but to a lesser degree. The effect of the announcement of the asset purchase programs is one of the main transmission channels called the stock effect (Aguilar et al., 2020).

1.1.2 Longer-term refinancing operations (LTROs)

To provide banks with liquidity and to prevent any deterioration of money market conditions, the ECB decided to increase LTROs temporarily under a fixed-rate full allotment procedure. The interest rate was the same as the average deposit facility rate. The additional 13 LTROs added 288.9 billion EUR of liquidity to the financial system of the euro area. Targeted longer-term refinancing operations (TLTROs) is a non-standard monetary policy measure that was meant to increase motivation for banks to lend more and thus offer bank credit to firms in times of liquidity shortages associated with the pandemic. In March 2020, the Governing Council eased TLTRO III conditions and lowered the interest rates to a minimum of -0.75% for all operations outstanding during the period from June 2020 to June 2021. At the end of April, the ECB further eased the conditions by reducing applicable interest rates even more to the minimum of -1%. At the end of 2020, the support under TLTRO III was extended by 1 year till June 2022. Loans qualified for TLTRO III are those made to non-financial corporations and households (excluding mortgages) in the euro area (Rakic, 2021). TLTRO III intended to encourage lending to self-employed and small and medium-sized enterprises (SME) which were hit the most and are more dependent on bank lending as they have a harder time gaining financing on the market (Aguilar et al., 2020). Borrowing under TLTRO III amounted to €1.3 trillion in June 2020, which meant this was the largest liquidity operation ever recorded. Overall lending in the euro area increased by €600 billion in net amount since 13th March (Altavilla, Barbiero, Boucinha & Burlon, 2023).

In April 2020, the ECB also launched a new pandemic emergency longer-term refinancing operations (PELTROs) which was meant to be used in exceptional circumstances (Aguilar et al., 2020). The monetary measures provided favorable funding costs which were transmitted to the real economy by lowering lending rates and increasing bank lending (Altavilla, Barbiero, Boucinha & Burlon, 2023).

1.2 Regulatory and prudential pandemic policy measures

Several regulatory and prudential policies were introduced to increase capital and liquidity by allowing banks to operate temporarily below the level of capital defined by the Pillar 2 Guidance, the capital conservation buffer, and the liquidity coverage ratio. Many European countries also decreased the countercyclical capital buffers to zero. Supervisors also relaxed the loan loss classification standards in March 2020 regarding the "Unlikely to pay" (UTP) status of debtors and the specific loan loss provisions when loans were subject to government-initiated payment moratoria. The caveat when it comes to the relaxation of standards is an incentive for banks to keep unviable loans alive, so banks must apply provisions adequately to avoid zombie lending (Beck, Bruno & Carletti, 2021a). To relieve any unnecessary pressure on banks, a more flexible approach to supervisory processes, timelines, and deadlines was introduced. Finally, temporary regulatory changes to the Capital Requirement Regulation (CRR) were established (Bruno & De Marco, 2021). The ECB estimated that capital measures would provide €120 billion of relief in total which would allow up to €1.8 trillion in loans to households and SMEs (Beck, Bruno & Carletti, 2021b).

The European Banking Authority (EBA) and European Commission provided recommendations, clarity, and guidance to the prudential regulatory framework during the pandemic. They were not introducing new rules but merely reminding banks to use the flexibility that is allowed in the banking regulations in response to the COVID-19 shock. There were three main issues which were dealt with:

- the usage of capital and liquidity buffers,
- treatment of bank exposures in accounting and prudential terms, and
- banks dividend pay-out policy.

Prudential policy expects banks to comply with minimum liquidity and capital requirements. Banks need to have a Liquid Coverage Ratio (LCR) equal to or above 100% which is enough liquid assets to cover the net outflows over a 30-day stress period. On the other hand, minimum capital requirements Pillar 1 requires banks to have a minimum Total Capital Ratio (TCR) of 8% and Common Equity Tier 1 (CET1) of 4.5%. Pillar 2 requires additional regulatory buffers which include the capital conservation buffer as well as other macroprudential buffers, such as countercyclical capital buffers, systemic buffers, and other buffers as well. If a bank goes below these buffers, it can trigger restrictions on dividend payments and bonuses. ECB and EBA encouraged banks on 12th March 2020 to use the liquidity and capital buffers to support lending. Banks were allowed to fully use their liquidity and capital buffers and operate below the LCR threshold, Pillar 2 Guidance requirements, and the capital conservation buffer. Some national authorities also changed their countercyclical capital buffer to zero (Bruno & De Marco, 2021).

The EBA introduced flexibility in accounting requirements (IFRS9) and prudential rules and with it affected the banks' risk-weighted assets (RWA), expected credit losses (ECL), and provisions. In spring 2020 banking authorities provided clarifications on how relief measures, such as moratoria or public guarantees should be reported. Moratoria initiated as a response to the COVID-19 crisis will not automatically fall under default or under the definition of forbearance which means that it does not increase the credit risk nor loan loss provisions banks need to set aside. Normally, the definition of default includes borrowers who are more than 90 days late on their payment ("past due" criteria) or if the bank has reasonable doubts that the borrower will not be able to repay the loan ("unlikely to pay" or UTP criteria). In the same manner, for publicly guaranteed loans, the activation of the guarantee does not classify the loan as defaulted. Still, the guaranteed loan can be classified as defaulted. Therefore, banks should still monitor the risk accurately. The new conditions propose a risk of moral hazard and excessive risk-taking on the banks' side. Therefore, EBA introduced additional reporting requirements which made bank balance sheets more transparent (Bruno & De Marco, 2021).

Another intervention of the ECB in the banking sector was limiting the dividend distribution. In March 2020, banks were asked not to distribute profits in the form of dividends or share buybacks until January 2021. This is the only new intervention that was introduced compared to the other regulatory changes. The goal of this measure was to keep the capital available for lending to the real economy until the pandemic has settled. Releasing the capital buffers proposed a risk that banks would rather than increase lending use this opportunity and reward their shareholders. The measure was extended to September 2021 but in an easier form where the dividends had not been banned but the amount of payment was limited to 15% of 2019-20 profits or 20 basis points of the CET1 ratio, whichever was lower (Bruno & De Marco, 2021).

At the end of January 2021, the ECB showed that the use of overall capital buffers was limited. However, CET1 levels in the third quarter of 2020 were below the CET1 requirements before the COVID-19 adjustments to guidance. Although capital buffers are meant to absorb the negative shock, banks were mostly not willing to utilize the capital and liquidity measures, which could be explained by the pressures coming from the financial markets. Investors would rather see dividend payments than usage of capital buffers for excess lending or loss absorption. Investors would rather keep higher capital ratios to reduce default risk and avoid a downgrade rating. In short, banks refrained from using capital buffers as it would lead to increased funding costs. There was also a bit of uncertainty about how and when banks would need to rebuild their capital buffers (Beck, Bruno & Carletti, 2021b).

Using local projection models, Altavilla, Barbiero, Boucinha, and Burlon (2023) concluded that if the monetary pandemic response measures had not been introduced, the banks' lending capacity would have been severely hampered and there would have been a substantial contraction of lending. In the absence of monetary and prudential COVID-19 policies, unemployment would increase by 1.4% or 1 million workers over 2 years, based on their estimates. From 2020 to 2022, the lending to firms would have been 3 percentage points lower if there had been no TLTROs while macroprudential policy measures increased loan growth by 2.2 percentage points (Altavilla, Barbiero, Boucinha & Burlon, 2023).

1.3 Fiscal pandemic policy measures

Europe reacted quickly to the negative COVID-19 pandemic shock and provided aid to their economies. Many government support packages were adopted and together amounted to a nominal value of more than €2,400 billion (measured on 30th September 2020) which represented 14% of GDP. Most measures were introduced to compensate businesses that were constrained by restrictions or lockdowns. The government-sponsored job retention programs allowed firms to adjust working hours and reduce wages. This policy measure kept the unemployment rates down during the pandemic and in times of lockdowns. Government grants were used to cover fixed costs, such as rent or loan interest. These measures mostly helped small companies or self-employed, mostly firms that had significant revenue losses due to lockdowns. Aid was sometimes granted in the form of tax relief or deferrals, mostly for those sectors that were hit the hardest. For strategic firms whose bust would have had a significant impact on the economy, hybrid capital instruments and equity instruments were introduced. National authorities also introduced borrower relief measures, such as public guarantee schemes (PSGs) and moratoria on loan repayments. Those two measures were meant to encourage banks to grant new loans by shifting part of the risk to the public sector (Beck, Bruno & Carletti, 2021b). Records in September 2020 showed an uptake of 4% of GDP. In addition, around 5% of total banks' loans were subject to moratoria. The policy measures accepted in European countries differ when it comes to scope and scale. Out of 31 ESRB member countries, all used public guarantee on loans, 30 used direct grants, 29 used tax deferrals, and 23 used loan moratoria. Loan moratoria and direct grants were identified as the most important measures for firms and households. Public guarantees and tax deferrals were close second (ESRB, 2021).

Public guarantees had the largest announced amount while loan moratoria had the highest uptake. Moratoria applied to both firms and households while public guarantees mostly applied to firms. The size of fiscal measures and the uptake of those depended largely on the severity of the pandemic shock in that country. Countries that experienced a larger negative shock tended to implement larger measures and had larger uptakes of those measures. The type of adopted fiscal measures also depended on the pre-crisis fiscal space of the country. If the country had a limited amount of space, which means it was already in a deficit, it accepted more measures, such as public loans and guarantees, while they did not use as many direct grants and tax measures (ESRB, 2021).

1.3.1 Guarantee schemes

Guarantee schemes for bank loans represented one of the main policy actions to support SMEs and mid-cap companies during the pandemic. The objective was to provide access to bank loans during the pandemic for businesses that were affected by the COVID-19 crisis and to transfer some of the credit risk and potential losses from banks to governments. Public guaranteed loans were meant to mitigate the cost of lending for banks and encourage banks to lend more and, thus, prevent the credit crunch. The demand for bank loans increased to record levels as a consequence of the lockdowns which caused businesses to have liquidity shortages as they lost their capacity to finance their ongoing costs by the operating income. Loans were used to finance workers' salaries and necessary investments. Due to high uncertainty, a lot of firms also sought out cautionary liquidity buffers (Falagiarda, Prapiestis & Rancoita, 2020).

Guarantee schemes in various countries had different features but they all had to comply with the guidelines set by the European Commission. Guarantee schemes were meant to support self-employed and businesses that were affected by the COVID-19 crisis with the condition that they were viable at the end of 2019 before the crisis began. The guarantee was typically applied to new loans with medium- or long-term maturities (an average maturity was around five years). The deadline for applying for the loan was mostly set for the end of 2020. The maximum amount of the loan per borrower was typically set to 25% of the borrower's revenue or twice the salary amount in 2019. The usual share that was guaranteed varied between 70% and 90% of the principal while some countries had also granted 100% guarantees (for smaller loans to SMEs and self-employed). The guarantees in some countries came with limiting conditions on profit distribution, limits on rewards for managers, or even obligations to retain employees. The features of guarantee schemes were meant to mitigate any excessive risk-taking on the side of banks or dismissal of workers on the side of businesses (Falagiarda, Prapiestis & Rancoita, 2020).

The size of the utilization of guarantee schemes mostly depended on whether the country offers alternative fiscal relief measures, the conditions of loan pricing, and the severity of lockdowns. From the firm's perspective, mostly SMEs and self-employed took guarantee loans while large companies abstained from taking such help. Large companies mostly did not have such liquidity shortages or depend as much on bank financing as SMEs. The vast majority of new credit in most countries from April to July was covered by public guarantees. Many companies had taken a guaranteed loan only as a precautionary buffer as only a part of the approved amount had actually been disbursed (Falagiarda, Prapiestis & Rancoita, 2020).

In June 2020, €181 billion in new loans and 1.2% of total loans were covered by public guarantees. The vast majority, 95%, were granted to corporates. Since the PSG transferred risk from banks to governments, it reduced the risk-weighted assets (RWA) of banks. On average, loans subject to public guarantee had an RWA of 18% of the exposure value, which is significantly lower than the RWA of normal corporate loans which is on average 54%.

This increased the regulatory capital ratio since the loan loss provisions decreased (Beck, Bruno & Carletti, 2021b).

Through the European Investment Bank Group, the EU initiated a 25 billion EUR guarantee fund and aimed to mobilize up to 200 billion EUR for European SMEs. The European Investment Fund (EIF) managed a large proportion of this fund. SMEs represent 99.8% of all companies in Europe, 60% of value-added, and 70% of the labor market. They are much more dependent on bank financing and they were also more vulnerable during the COVID-19 crisis (Brault & Signore, 2020).

The important decision when it came to guarantee schemes was timing when it was okay to terminate the schemes. If the termination was too soon, it might trigger bankruptcies of firms due to severe liquidity squeezes, which would also diminish banks' capital. This would have automatically led to a tightening of credit conditions inducing more bankruptcies and obstruction of financing of viable firms. On the other hand, keeping the schemes alive for too long would have led to an enlarged involvement of government in economic outcomes, which means suboptimal allocative efficiency and reduced productivity of the whole euro economy over a long period by keeping non-viable firms alive (Falagiarda, Prapiestis & Rancoita, 2020).

Overall, we can say that the implementation of loan guarantee schemes was essential for supporting firms in their liquidity needs in the early period of the COVID-19 crisis. Guaranteed loans together with other policy measures prevented many companies from going bust. On the other hand, public guarantee schemes also affected the financing conditions because lending rates remained at historically low levels for quite some time (Falagiarda, Prapiestis & Rancoita, 2020).

1.3.2 Moratoria on loan repayments

Moratoria on loan payments was implemented to support and help borrowers face liquidity problems during the pandemic. Moratoria allows borrowers to delay their loan repayments without being marked as default and does not trigger forbearance. This measure aimed to prevent bankruptcy of companies that were otherwise solvent but just temporarily faced liquidity shortages due to the COVID-19 crisis. Many otherwise viable businesses were affected by the lockdowns and other restrictive measures introduced by the national authorities which cut off their cash flows. Providing moratoria to these companies mitigated the liquidity shock and prevented many bankruptcies. On the other hand, moratoria affects banks by decreasing interest profit while prolonged moratoria delays accurate provisioning. Improper provisioning reduces the transparency of the balance sheet and may increase the difficulty for the bank to raise funds in financial markets. This is why provisioning, loan monitoring, and reporting is so important (Bruno & De Marco, 2021).

Moratoria on loans comes in different forms across Member States but it has similar objective and substance. The main objective of moratoria is to postpone payment for borrowers affected by the crisis for a specific period allowing borrowers to repay the loan after the situation goes back to normal. The moratoria are based either on national law (legislative moratoria) or on a non-legislative relief initiated as part of an industry or sector-wide scheme. EBA supported this measure and saw it as an effective approach to supporting short-term liquidity problems of otherwise profitable obligors. Moratoria on loan does not mean that the risk of default should be ignored but banks should still identify and measure risk properly. Banks need to be able to identify borrowers whose liquidity problems are not short-term due to containment measures but will eventually go bankrupt. Such cases should be marked properly and banks' financial statements should reflect the true quality of their portfolios (EBA, 2020).

Moratoria is not marked as forbearance if it was granted in response to the COVID-19 crisis. The timeline for this type of moratoria was only until 31 March 2021. The conditions to apply for moratoria needed to be general and not applied to specific financial obligations or specific borrowers. The moratoria were not automatic but the obligor had to apply to get moratoria on its loan. In the request obligor needed to present the facts of how it was affected by the pandemic. The conditions for the application of moratoria were standardized and available to all borrowers affected by the crisis. Conditions usually included the loss of employment for individual borrowers or closing business operations due to the COVID-19 crisis for SMEs. The moratoria could only affect the timeline of payments while other loan conditions stayed the same. The moratoria could only be applied to loans that were issued before the COVID-19 outbreak. Therefore, new loans granted after the COVID-19 crisis were not subject to such moratoria. The maximum period of moratoria was limited to 9 months to limit the risk for banks coming from unknown insolvency issues faced by the obligor. General payment moratoria does not remove the obligation for banks to identify UTPs for the definition of default (DoD). Such a process should continue through the moratoria period. Banks should still check firms' financial statements and look for potential obligors for UTPs (EBA, 2020).

In June 2020, more than €870 billion of loans were subject to moratoria on loan repayments (around 6% of total loans from European banks). Most moratoria were granted to SMEs. Moratoria mitigated the default risk but, on the other hand, reduced interest revenues of banks. The moratoria are only temporarily deferred payment that still needs to be repaid in the future. This means that there is a risk of a sudden increase in non-performing loans (NPLs) once the moratoria period is over (Beck, Bruno & Carletti, 2021b).

1.3.3 SURE

Another temporary measure adopted on the EU level to fight the negative economic and social effects of the COVID-19 crisis was called SURE (Support to Mitigate Unemployment Risks in an Emergency). SURE's objective was to protect the people and mitigate the negative socio-economic consequences of the COVID-19 virus in addition to national job retention schemes. The budget for SURE was €100 billion for affected Member States (MS) to preserve employment and protect employees (also self-employed) against losing their jobs and personal income. SURE was meant to protect short-time work schemes. Loans given under the SURE instrument were dependent on voluntary guarantees from member states. Each state contributed a guaranteed amount relative to its share of the total gross national income of the EU (based on 2020 data). The overall amount of loans distributed through SURE amounted to €98.4 billion. The final disbursement happened on 14th December 2022. All 19 MS that asked for support have received the amount they asked for. The funds raised by social bonds were transferred to Member States in the form of loans with favorable terms. The Commission analyzed the effect SURE had on the real economy and employment and discovered that SURE had covered around 31.5 million people and 2.5 million firms in 2020. Policy measures supported by the SURE instrument saved around 1.5 million people from unemployment in 2020. SURE mostly benefited small and medium enterprises (SMEs) in sectors like accommodation and food services, manufacturing, and retail trading which were affected by the COVID-19 measures the most (European Commission, 2023).

The main objective of all these measures described in this section was to create a positive relationship between businesses, households, and banks and consequently avoid a credit crunch, as well as to keep risk premiums at low levels and overall help the economy absorb the shock of the crisis. These support measures were adopted mostly to protect firms and households that were affected by the pandemic and total lockdowns. The economic background supporting these measures is simple. The COVID-19 crisis represents a risk that the severe economic downturn with the accompanying high unemployment rates will result in high long-term structural unemployment rates. This would hinder economic recovery and result in overall lower growth rates. Supporting households and corporations was thus a high priority while, at the same time, the pressure on banks was relieved Beck, Bruno & Carletti, 2021a).

2 THEORY OF CREDIT MARKET SHOCKS

The real question, which is also the main research question of my master's thesis, is how the pandemic policy measures focused on credit activity impacted the real economy in the euro area and how the economic output would look like if those measures didn't take place. Pandemic policy measures could be interpreted as a positive credit shock. Many researchers have proved that the tightening of credit conditions (credit shock) has negative consequences for the real economy. Many empirical studies (e.g. Boivin, Giannoni and Stevanović (2013), Helbling, Huidrom, Kose and Otrok (2011) and Peersman (2012)) provide evidence of the effects that disturbances in credit markets have on business cycle dynamics. Many of these examine the procyclical nature of credit cycles and business fluctuations. In addition, the economic theory of financial accelerator developed by Bernanke and Gertler (1989) and Bernanke, Gertler and Gilchrist (1998) suggest a tight link between credit spreads and economic activity. This section focuses on how credit shocks are transmitted to the real economy and how researchers modeled credit shocks in the past.

A question that many economists tried to answer is the following: “Do credit market shocks affect the real economy and drive business fluctuations?” The previous financial crisis of 2008/2009 caused a great economic downturn which has renewed interest in the connection between the real economy and credit markets and has also triggered an intense debate about whether shocks emerging in financial markets impact the business cycles. The tightening in the credit conditions in the US in 2008 and 2009 had serious macroeconomic consequences which suggests that the credit conditions significantly impact the real economy. However, the relevance and transmission mechanism of disruptions in credit conditions to the real economy is still uncertain. Many studies have identified different credit and loan shocks and have come to the same conclusion that a credit shock significantly impacts real economic activity (Boivin, Giannoni & Stevanović, 2013). Understanding the effects that disturbances in financial markets have on the real economy is essential for policymakers, as well as for modelers who try to improve the construction of theoretical models which include financial intermediaries (Peersman, 2011).

The early literature already noted the relationship between financial markets and real economy but has been forgotten. Fisher (1933) and Keynes emphasized the effect of credit markets on the economic outcome during the Great Depression. Other research mostly focused on the role of money and the hypothesis of efficient financial markets which has drawn attention away from the credit shock effects on the real economy Helbling, Huidrom, Kose & Otrok, 2011). They have paid little attention to financial systems or the role of credit conditions in economic growth. After World War II economists constructed general equilibrium models which included complete markets while transaction costs or imperfect information were not recognized. Based on the Modigliani-Miller theorem, it is equivalent if the firm borrows by issuing equity or acquires debt. In such a theory, financial markets play no role. Under the assumption of complete markets, there is no effect coming from the financial markets as frictions/imperfections do not exist. Financial markets only play a role in the real economy when financial imperfections exist. Joseph Stiglitz, Michael Spence, and George Karloff emphasized the importance of financial markets for the real economy in the 1970s. They worked on asymmetric information and principal-agent theory. Asymmetric information stands for the theory which can be interpreted as an example of the difference in the information that the borrower and lender have about the repayment prospects (Bernanke, 2007). Spence (1973) demonstrated that well-informed agents can signal their information to those who do not have much information. On the other hand, Stiglitz (1975) showed that through screening an agent is able to acquire additional information on the better-informed agent. Different insurance policy is a simple example of screening where insurance can learn more about the client by offering different policies. The basic economic theory now states that under the assumption of complete markets, the real economy and financial markets interact through wealth and substitution. The asset prices that represent the financial markets affect household wealth and consequently their consumption. On the other hand, asset prices also affect investment decisions by influencing a firm’s net worth and its market value. Increased asset prices increase the firm’s net worth which consequently increases the firm's ability to invest and borrow, which only increases the asset price even more. Credit shocks largely emerge through the financial accelerator and other mechanisms that form a relationship between firms, households, and countries and their balance sheets (Helbling, Huidrom, Kose & Otrok, 2011). A decrease in the supply of credit, which can be caused by an increase in the excess bond premium, causes a reduction in asset prices and a downfall of economic activity through the work of the financial accelerator mechanism which was emphasized by Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), and Hall (2011).

2.1 Transmission of credit shocks to the real economy

Growth and prosperity in the economy are mainly created by "real" factors like labor productivity, excess of capital, land, technical knowledge, and creativity. However, financial factors also play a crucial role when it comes to acquiring the starting capital which makes it possible for an entrepreneur to realize his business idea. Financial markets make expanding a firm's production or employment possible. Healthy financial markets have a positive effect on the economy as they help realize its full potential by effectively allocating funds. This also means that faulty financial markets prevent economic growth. The banking sector with lots of nonperforming loans and insufficient capital requirements hampers economic growth. Financial markets and credit conditions also have long-term effects on the economy and business cycles (Bernanke, 2007).

There are two channels through which credit conditions affect the real economy. The first channel is the balance sheet channel which is based on the firm's external finance premium. The cyclical movements in borrowers' balance sheets amplify the business cycles. It works through a deterioration of the firm's net worth which increases the firm's external finance premium which consequently causes a reduction in investment, employment, production, and prices. This consequently affects the demand for credit. The second channel is the bank lending channel which indicates a deterioration of the financial intermediaries' external finance premium which tightens the supply of loans and consequently triggers a decline in economic activity (Bernanke & Gertler, 1995).

The first channel can be interpreted as the relationship between credit spread and real activity which can be explained by the financial accelerator mechanism. The theory was developed by Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1996, 1999). A key concept of the theory is external finance premium which represents a difference between the cost of raising funds externally and the opportunity cost of capital raised internally (Mueller, 2009). The external finance premium is usually positive as external sources of funds are always more expensive. This is due to the lender's cost of monitoring the borrower and estimating the risks and benefits of the loan. The external finance premium depends on the strength of the borrower's financial position. If the borrower is highly liquid, has great net worth, and expects big cash flows, it means that the cost of borrowing from external sources will be lower. Such borrowers make better investment decisions and business action to ensure a positive outcome which is why the lender's monitoring and evaluation is less intense. Such borrowers pay lower external finance premiums. The connection between the external finance premium and the financial position of the borrower forms a channel that creates a long-lasting effect of otherwise short shocks (Bernanke, 2007). If the borrower has a large net worth (strong financial position) it means that it will have a lower external finance premium. If the borrower has a lower net worth, the lender expects to be compensated more by a larger premium for higher agency costs. The lender feels more comfortable lending to a borrower knowing it meets certain requirements for financial ratios which can give greater collateral and that can make regular down payments. The borrower's financial position thus affects their borrowing conditions. The fluctuation in the quality of the borrower's balance sheet also affects the borrower's investment and spending decisions (Bernanke & Gertler, 1995). If external premium increases, it makes it harder for firms to borrow externally, which reduces spending and production which has a negative effect on the real activity. A change in the premium can be motivated by a productivity shock, monetary shock, or even problems in financial markets. For example, the productivity shock which is a real shock affects the financial conditions, which results in persistent fluctuations in the economy. The key mechanism is the external finance premium or financial accelerator. A positive shock on productivity improves the firm's balance sheet which lowers its external finance premium and makes it easier and cheaper for the firm to borrow which is why a firm can invest more and over a longer period even after the initial shock has already worn off as the financial position of the firm improved. The financial accelerator mechanism applies to any shock that improves the borrower's financial position. The financial accelerator can, thus, help explain the persistence and amplitude of business fluctuations and cycles (Bernanke, 2007).

If the business conditions are good, the borrowers tend to improve their net worth, which consequently lowers agency costs and increases investment which amplifies the business conditions. Just the opposite can be observed for the economic downturn. Shocks that affect the borrowers' net worth can trigger business fluctuation. Many economists suggested that the firm's balance sheets which can also be viewed as solvency or creditworthiness can have a significant impact on macroeconomic activity. Agency costs can be interpreted as deadweight losses in financial contracts whenever an asymmetry of information between lenders and borrowers is present. Those costs represent higher costs of external compared to internal financing. The higher net worth of the borrower correlates to lower agency costs. The relationship between agency costs and borrower's net worth has two relevant implications. The first implication can be linked to procyclicality. A borrower's net worth is procyclical, which means that in good times the borrower has a higher net worth while in a recession it is more likely that it will have lower net worth. This also means that the agency costs have a procyclical movement – higher in recessions and lower in expansions. This procyclical movement also induces investment fluctuation and persistence of cyclical movement which can be interpreted as the accelerator effect. Secondly, a shock to net worth (independent of business cycles) will start the real fluctuations. A good example of an independent shock is an unexpected price decrease which reduces the value of the borrower's collateral which consequently reduces the borrower's net worth and increases agency costs (Bernanke & Gertler, 1989).

Financial accelerator does not only work through firms but also through households. Their external finance premium is also inversely correlated with their financial position. A large part of their net worth represents house equity. It can serve as collateral which affects the terms and conditions of their loans. Changes in the value of their home affect their borrowing and spending as the external finance premium reflects their cost of borrowing. This also indicates an interesting theory where the effect of a decline in house prices on household consumption is greater if there are more people with relatively low home equity. Another theory implies that flexible mortgage rates have a quick effect on household cash flows which also affects their spending (Bernanke, 2007).

A similar accelerated effect can also be observed in the transmission of monetary policy on spending, investing, and borrowing choices. This can be explained by supplementary channels, such as the credit channel. The credit channel can be split into 2 parts: the balance-sheet and the bank-lending channel. The balance-sheet channel relates to the financial accelerator. The interest rates set by the monetary policy affect the asset prices and potential cash flows which consequently set their creditworthiness and external finance premium. A contractional monetary policy increases the risk-free rates, which decreases the value of assets and liquidity which makes lending harder. The effect of the policy decision is larger than the difference in the interest rate because of the accelerator effect. The bank-lending channel works through the supply of loans which is affected by the interest rate set by the monetary policy. In the 1960s and 1970s, in the USA, monetary policy had a large impact on the bank loan supply by applying reserve requirements and regulation Q. Reserves were higher than they are today, and interest payable was capped on deposits. Banks did not have as many options for funding except deposits. This is why monetary policy had quite a large effect on the balance sheets of banks and issued loans. The reserve requirements are much lower in the USA today, as well as regulation Q is gone. On the other hand, financial markets are much more developed and easily accessible than in the past. This is why the bank-lending channel plays a much smaller role in the USA than it used to while in Europe where most economies are still pretty much bank-dependent, the bank-lending channel is still very much relevant. While banks do not rely on deposits as much as they used to, it is important to mention that non-deposit funds are more expensive. The cost of funding thus relies on the creditworthiness of the bank itself. Here, we can again recognize the external finance premium paid by banks which is reflected in the cost and availability of loans. This view of the bank lending channel matches the view of a financial accelerator based on external finance premiums and balance sheets. The only difference is the type of borrowers to which the mechanism applies. On one hand, it refers to firms and households, as well as to banks and other financial intermediaries. The bank channel will have a bigger impact on the economy if borrowers rely on bank lending mostly and have few alternative sources of funding or if other funding is more expensive. This is mostly true for small firms and households (Bernanke, 2007).

The principal-agent friction was also largely used in the past in macroeconomic models to evaluate the effect of financial frictions on the real economy (output and unemployment). Many models analyzing the 2008 crisis have used the friction in the relationship between the principal and the agent. In that case, an intermediary and the suppliers of funds. There is a difference between the intermediaries' lending rate and the interest rate that supplies receive. This difference can also be indicated as a spread. A spread will be larger for a leveraged intermediary than for a well-capitalized one. If a crisis occurs, it lowers the asset values which widens the spread and increases financial frictions. Another source that causes financial friction is debt overhang. If a firm already has a debt, it makes it harder for it to borrow as new debt adds additional assets which also raise the value of the existing debt. The financial crisis also worsens the overhang. Kiyotaki and Moore (2019) also considered liquidity as financial friction. There is a known bottleneck when it comes to investing which is the rate at which a firm can raise funding. To be ready to seize an investment opportunity, a company keeps money on hand. This presents a wedge between the return on investment and the cost of outside capital where holding money presents additional costs and widens the spread (Hall, 2011).

2.2 Modeling credit shocks

Many economists tried to explain the reason behind the 2008/2009 financial crisis. The shock in the credit market was highlighted as one of the main drivers of the 2008/2009 crisis. Researchers have proved that a credit shock can cause a significant deterioration in economic activity and increase unemployment. Most economists have identified the credit shock as a widening of the credit spread which can be used as a proxy for tightening of the credit conditions. Using different modeling approaches they all came to the same conclusion that middle credit-quality corporate bond spread at longer maturities works best as a proxy for credit shock. Their results suggest that the worsening of credit conditions leads to a significant and long-lasting fall in economic output. Credit spread has proven to work in the US economy. Conversely, the banking sector in the euro area plays a much bigger role when it comes to funding the private sector, especially SMEs, which is why bank lending shocks have significant effects on the euro area economy.

Worsening on the financial markets usually leads to a long period of economic downfall. During such periods asset prices, which are forward-looking in nature, can serve as important information on the relation between the real economy and financial market. Changes in asset prices can be seen as early-warning signs of a recession and can be used to observe the degree of stress on financial markets. Many researchers, among others Stock and Watson (1989), Friedman and Kuttner (1998), Duca (1999), Emery (1996), Gertler and Lown (1999), Ewing, Lynch and Payne (2003), Mody and Taylor (2004), Meeks (2009), Gilchrist, Yankov and Zakrajšek (2009), and Mueller (2009), touch the subject of asset prices and forecasting economic conditions. Information on default risk indicators has been emphasized to have predictive power of economic activity, especially corporate credit spreads which describe the difference in yields between corporate debt instruments and government securities of comparable maturity (Gilchrist, Yankov & Zakrajšek, 2009). The credit spread can be divided into three components: expected default rate, the difference in financial risk, and financial frictions. During the crisis of 2008, all three components increased (Hall, 2011). Amato and Remolona (2003) also divided total credit spreads into different components which relate to the probability of default, financial risk, and other determinants. They showed that the probability of default represents only a small part in non-crisis years, especially for low-risk bonds which are highly rated. In normal times a fair amount of the spread can be explained by the fact that corporate bonds are taxed while government bonds are not and taxes do not rise in crisis times. While credit spreads are observed as a difference between private and public (government) borrowing interest rates, a term spread represents the difference between long and short-term government borrowing interest rates which also holds significant predictive power for future employment and output (Hall, 2011). Philippon (2009) explains a theoretical framework where an increase in corporate bond spreads causes a general decline in economic activity which happens due to a reduction in the present value of corporate cash flow which occurs before the output falls. Increased credit spreads can also result from a decreased supply of credit due to the worsening of the corporate balance sheet or due to the worsening of the health of suppliers of credit (financial intermediaries), the mechanism called financial accelerator. If credit supply decreases, it causes asset values to fall, which increases the incentive to default resulting in the widening of yield spreads as lenders demand higher compensation for the expected increase in defaults. It is also emphasized that different spread measures in different time periods have different predictive power. For example, the paper-bill spread (difference in yield between non-financial commercial paper and Treasury bills of comparable maturity) has lost its predictive power in the period after 1990. This is not surprising as financial markets have evolved and the information about specific financial assets has changed (Gilchrist, Yankov & Zakrajšek, 2009). Gilchrist and Zakrajšek (2012) pointed out that in the US during the financial crisis in 2007 and 2009, credit spread served as a key benchmark for the stress level in the financial system. The interest in credit spreads appeared once the theories that focused on the relationship between the quality of borrower's balance sheets and external finance premiums were developed. Credit spreads also influence the supply of funds provided by financial intermediaries, which increases the importance of credit spread in relation to business fluctuations.

Hall (2011) studied the relationship between financial frictions and economic activity. He has discovered a strong connection between frictions in financial markets and economic activity. Financial frictions can explain the difference between the return received by providers of the capital and the cost paid by the users of the capital. So, in other words, a difference between the interest rate received by households and the rate paid by firms. The providers are usually consumers while the users are mostly businesses but can also be consumers as well. Financial frictions can also explain a wedge between savings and investments. Hall showed that an increase in financial frictions caused by a crisis relates to increased unemployment and decreased output. He analyzed the effects and significance of these frictions in a dynamic general-equilibrium model. The model confirmed that in the financial crisis of 2008 and 2009, an increase in financial frictions led to a dramatic fall in economic activity. Financial frictions lead to output fall but, on the other hand, increase the spread between the interest rates of private businesses and households that borrow the capital and the interest rate received by the government. To measure the spreads, Hall used the spreads between BAA- and AAA-rated corporate bonds and 20-year Treasury bonds. The excess spread (December 2008 compared to their normal values for 20 years) was 3.65 percentage points for BAA bonds and 1.08 points for AAA bonds. Hall took credit spreads as the driving force as it also affects the term spread where the short-term government rates are much more affected by the financial shock than the long-term rates (Hall, 2011).

Meeks (2009) showed that shocks to spreads on corporate credit markets cause significant macroeconomic fluctuations. His methodology relies on a structural VAR model of bond spread and sign restriction on impulse response functions on credit shocks. He showed that credit shock in the bond market results in output fall, price decrease, and fall in policy rates. The credit shock he identified is not related to innovations in the monetary policy of bond market liquidity but is mostly related to risk compensation. His results also showed that during a crisis, the effect of the credit shock is larger than in normal times while in normal times it still has a non-zero effect on economic activity. This is because non-financial firms can offset shocks in credit markets by borrowing from alternative sources like bank credit lines or they can use their retained revenues. Also, firms mostly borrow over the long-term which means that a shock in the bond market will not have an immediate effect on the economic activity. Meeks built on the work done by Gertler and Lown (1999) and Balke (2000), who studied the financial accelerator mechanism, and Friedman and Kuttner (1998), who used a VAR and the paper-bill spread as a shock. Meeks identified credit shocks by identifying explicit economic assumptions. The assumption that was used is that the variables in the VAR can be arranged in a Wold causal chain with bond spreads ordered last. The causal ordering was broadly used by Friedman and Kuttner (1998), Gertler and Lown (1999) and Balke (2000). It implies that all macroeconomic variables react to the credit conditions within a month but not the other way around. He excluded the default component from the changes in the bond spreads and used that as credit market shocks. He was able to separate shocks that produce movements of expected default from credit market shocks by forcing sign restrictions on impulse response functions of spreads. However, he did not impose restrictions on output, monetary policy, or prices. His finding suggests that output reacts immediately and significantly and not with a delay. His study also suggests that credit shock played an important role in 2001 and 2008/09 recession. What is more, the credit shock that drove up the spreads happened before the start of the recession. Credit market shocks can contribute to 15% of the variance of output. The contribution is similar even if he did not account for the last recession. Bernanke and Gertler (1995) argued that the credit channel is usually not an independent factor causing business fluctuations but rather works as an endogenous factor that produces a dynamic response of the economy to the shifts in monetary policy. With his research, Meeks opposed Bernanke and Gertler by proving that credit shock did play an independent role in the financial crisis of 2008/09 and it also appears to be significant in normal times, not only in a crisis (Meeks, 2009).

Similar research has been done by Gilchrist, Yankov, and Zakrajsek (2009). They came to similar conclusions as Meeks. If a credit market shock occurs, it results in output fall and lower interest rates. They researched the role of asset prices in business fluctuations which focused mostly on various corporate credit spreads. They constructed multiple credit spreads based on about 900 US bond prices of senior unsecured corporate debt of non-financial entities traded in the secondary market over the 1990 – 2008 period. Unsecured bond spreads capture information about several business fluctuations. Using this ground-up approach allowed them to analyze the information hidden in bond spreads which is orthogonal to information in stock prices and other macroeconomic variables capturing economic activity, inflation, interest rates, and others. Their credit spreads proved to hold substantial predictive power of economic activity and perform better than typical default-risk indicators. Their results also indicate that credit spread on senior unsecured corporate debt instruments has better forecasting performance for economic output relative to other credit spreads used in the past, such as paper bills or high-yield credit spreads. Their credit spreads which are based on EDF (expected default frequencies) bond portfolios are similar at shorter horizons and predictive power compared to standard credit spread indexes based on default risk while at longer horizons outperform them in in-sample and out-of-sample forecasting. They have proved predictive power comes from the middle of the credit-quality bonds. They also observed higher predictive power of spreads at longer maturities. Similar predictive power can be observed for corporate bond spread indexes with BBB – AA ratings. These results imply that credit spreads of longer maturity bonds issued by firms that have a low to medium probability of default hold relevant information about future economic conditions. The same was also proved by Mueller (2009), who was testing the predictive power of corporate bond spreads in different ratings. They constructed a structural factor-augmented vector autoregression which showed that a shock in bond spreads causes large and persistent output fall. They identified credit market shocks as corporate bond spreads which are orthogonal to real economic activity, inflation, and real interest rates, as well as to other financial indicators. The worsening of credit conditions is observed through the widening of the credit spreads. Their results suggest that the worsening of credit conditions leads to a significant and long-lasting fall in output. The decomposition of the forecast error variance showed that credit shocks account on average for more than 30% of the business activity variation over the 2–4-year period (which was measured by the industrial production index). Their results indicate that the disruptions in credit markets account for a significant portion of the US business cycles from 1990 to 2008. A shock to the corporate bond spread translates to a relatively high variation in economic activity and interest rates. These results prove that if credit conditions worsen, it will have a long-lasting effect on the real economy, which was also the case in the past. To explain their results, they offer two alternative explanations. Their first argument relies on the empirical and theoretical asset pricing literature being unable to explain both, the level and movements in credit spreads by using structural models of default (Collin – Dufresne, Goldstein & Martin, 2001). This study provides an explanation of variation in credit spreads through macroeconomic factors, mostly liquidity and risk premiums. Investors in the corporate bond market are mostly banks, other financial intermediaries, or insurance companies. The risk the investor is willing or able to bear is reflected in the risk attitude of the investor. When the financial market conditions worsen, the premium on the risk of default rises, which reduces investing and consequently economic activity. This argument is also aligned with Philippon (2009) who discovered that corporate bond spreads can predict the business fixed investments. In their second argument, Gilchrist, Yankov, and Zakrajšek relied on the linkages between the banking sector and other non-banking-related financial activity to explain their results. Nonfinancial corporations rely on back-up lines of credit from banks to finance their short-term liquidity needs. If monetary policy tightens or financial conditions in the banking sector worsen, banks are forced to decrease their line of credit. This increases liquidity risks for corporates, which may also result in insolvency if the conditions worsen severely enough. Shock in the financial markets results in increase of the cost of credit. This argument is aligned with the findings discovered by Gertler and Lown (1999) and Mueller (2009) who present a close relationship between bank lending standards and conditions in the credit market (Gilchrist, Yankov & Zakrajšek, 2009).

Gilchrist and Zakrajšek (2012) measured credit spread with the corporate bond spread they constructed themselves. They constructed a credit spread index called GZ credit spread which includes micro-level data. That proved to be a good predictive variable for the business activity over the 1973-2010 period. Their approach relies on the study done by Gilchrist, Yankov, and Zakrajšek (2009) in which they constructed an indicator from the prices of individual corporate bonds on the secondary market. Their indicator proved to have much higher predictive power compared to the ordinary BAA-AAA corporate bond credit spread. Their GZ credit spread can be divided into two components. The first captures cyclicality through expected defaults and the second captures cyclicality reflected in the relationship between default risk and credit spread called excess bond premium. The division can be explained by the »credit spread puzzle« which shows that less than a half of the variation in corporate bond spreads is explained by the financial health of the issuers, and the unexplained bit is due to time-varying liquidity premium, tax treatment, and default-risk factor. The default risk factor includes the compensation demanded by investors which can be above expected losses. Quite a large share of information that the GZ credit spread holds for business outlook can be explained by the variation in prices relative to the default risk of the issuer. Their methodology includes an identified VAR framework. They analyzed the effect of excess bond premium shock on output, consumption, and investment. The shock is orthogonal to the current economic state but produces negative movement in output, consumption, and investment. The shock also leads to expansionary monetary policy. An increase in excess bond premium causes a reduction in risk appetite, and this results in a decreased supply of credit. Reduced credit supply causes significant adverse consequences on economic activity. With a forecasting regression estimated by the ordinary least squares

(OLS) methodology, they have compared three default-risk indicators which are paper-bill spread, BAA-AAA credit spread, and GZ credit spread. Their baseline OLS contains the term spread (slope of the Treasury yield curve – the difference between 3-month maturity yield and 10-year maturity yield), real federal funds rate (FFR), and lags of economic conditions. They introduced three different measures that account for economic conditions: the growth of private payroll employment, the change in the civilian unemployment rate, and the growth of industrial production (manufacturing). To the baseline specification, all three default risk indicators were added separately to test the predictive power of each indicator individually. The paper-bill spread and the BAA-AAA credit spread seems to do very little as their contribution to the prediction accuracy is quite modest. Nevertheless, they are significant predictors of economic activity. On the other hand, the GZ credit spread turned out to have much higher predictive power and significance of economic activity based on all three measures. The coefficient is also of larger magnitude which implies a negative relation between credit spread and future economic outcome. A 100 basis points increase in GZ credit spread results in a 3 percentage point reduction in the growth rate of industrial production over the next 3 months. In further analysis, they have also proved that the information coming from credit spreads for the economic outlook is captured in fluctuations in the nondefault component of credit spreads and not from expected defaults. The nondefault component was explained by the excess bond premium (Gilchrist & Zakrajšek, 2012).

Muller (2009) also explored the effects of credit conditions and their transmission into the real economy in the US. He analyzed the ability of the term structure of credit spreads to predict GDP growth. He was modeling credit shocks using a macro-finance term structure model. He identified credit spread as a difference between corporate and Treasury yields. He found out that credit factor is highly correlated with the index of tighter loan standards which is why it can be used as a proxy for credit conditions. Credit spread can be divided into two parts: expectations and a term premium. Both were found important when predicting GDP growth. Muller was able to prove the existence of the transmission channel by having such strong predictions. A shock in the credit factor of one standard deviation has a negative effect on the GDP of 0.6% in 1 year. Using the crisis period he was able to predict the economic conditions accurately by using credit spreads which can be interpreted as tight credit conditions during this period (Mueller, 2009).

Helbling, Huidrom, Kose, and Otrok (2011) have researched the significance of shocks on the credit market and their impact on business cycles on a global scale. Their main objective was to prove that credit shocks matter in the global economy. They estimated a series of VAR models to see what role credit market shocks play in the economy. Their research confirmed that credit shocks do play an important role when it comes to global business cycles, especially in the financial crisis in 2008/2009. Not only that but they were also able to show that the US credit shocks have a significant impact on the global growth of the economy in the last period. They analyzed the effect that credit shocks have on business cycles in G-7 countries. Their approach includes the estimation of common components in macro and financial factors and the estimation of several VAR models as the second step. They also used a factor-augmented VAR (FAVAR) to study how the credit shocks that emerge in the US markets are transmitted to the global economy. Their study is the first that analyzes the global effects of credit shocks. They do not use only the traditional measures of credit shock, such as credit spread, but also the volume of credit. The database that they use is a quarterly series of many macro factors of the G-7 countries throughout 1988-2009 which was used to construct global factors for each variable. Their approach to the identification of shocks is based on applying intuitive sign restrictions. Their hypothesis was based on the economic theory of financials imperfections/frictions which largely occur through the financial accelerator. Their study closely relates to some other studies that have researched the importance of credit shock using a VAR approach, such as Meeks (2009). His findings suggest that credit shocks do have a relatively large role during a crisis period while they have a much smaller effect otherwise. Gilchrist, Yankov and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012) have proved that credit shocks do affect the business cycles in the U.S. from 1990 to 2008. In contrast to these studies Helbling, Huidrom, Kose and Otrok (2011) studied the impact of credit shocks on the global scale and in addition to the credit spread measure, they also researched the importance of the volume of loans.

Boivin, Giannoni, and Stevanović (2013) have used a Factor-Augmented VAR model (FAVAR) in a data-rich environment to show that an adverse credit shock results in an increased credit spread which causes a large and persistent economic downturn. They have identified the credit shock as an increase in the 10-year B-spread (a difference in yield between a B-rated bond and a U.S. treasury bond). They used a large panel of U.S. monthly and quarterly data and assumed that all financial and economic indicators can be composed into an aggregate component driven by a small number of common factors. These factors were able to capture a great part of the business cycle movements and were able to explain a significant share of the variability of observed variables. The shock is seen as a sudden increase in external finance premiums. They have allowed all measures of economic activity to respond to the shock immediately while inflation, unemployment rate, and federal funds rate respond with a lag. The credit shock also affects the labor market, expectations of future economic conditions, and price indexes and causes a decrease in short and long-term risk-free interest rates. By simulating the conditions of the recession, they also managed to prove that the jump in credit spreads in 2008 was responsible for a dramatic fall in economic activity. The increase in credit spread in 2009 decreased industrial production by 20% and employment by 7%, respectively (Boivin, Giannoni & Stevanović, 2013).

On the other hand, Greenstone, Mas, and Nguyen (2014) used comprehensive data to research the effects of credit market shocks in the form of bank lending on the real US economy. They emphasized that banks are a key determinant of economic activity. Bank lending is especially important for small and medium-sized companies who do not have a substitute for bank lending but are on the other hand important contributors to economic development and growth. They also acknowledged the connection between the banks' health and business fluctuations. They researched the importance of bank lending by measuring the effects of shocks on small businesses during the period of recession (2007 – 2009) and the normal economic period (1997 – 2009). Their methodology mostly relied on the least squares regressions (2SLS). Their analysis also showed that either during the Great Recession or during normal business activity the shocks do not cause changes in small business or overall employment. The overall conclusion of their research suggests that bank lending is not important for small business or county-level business activity during either the Great Recession or normal times which contradicted their first belief and raised many questions about the benefits of policies that increase credit supply (Greenstone, Mas & Nguyen, 2014).

In contrast to the US economy, the banking sector in the euro area plays a key role when it comes to funding the private sector, which was also proved by Peersman (2011) who documented the impact of bank lending shocks in the euro area economy. The lending supply shocks are mostly triggered by innovations which are represented by the risk-taking appetite of banks. Banks tend to issue riskier loans when the long-term interest rate or the term spread is low. Banks increase the supply of loans to the private sector when the long-term government bond yield drops which indicates low returns on risk-free bonds which creates an incentive for banks to search for higher yields in riskier loans. This monetary transmission channel is called the risk-taking channel. This results in increased economic activity, inflation, and short-term interest rates. In the second step, banks' liabilities increase which also increases bank lending, GDP, and inflation. Policymakers then react by tightening the monetary policy. This means that a term spread could predict economic activity. In his study, Peersman estimates the impact of different types of bank lending shocks on the euro area economy. He identifies three types of bank lending shocks:

- exogenous lending demand shocks,
- monetary policy shifts, and
- lending supply disturbances – "lending multiplier shock" (independent of policy).

For instance, exogenous loan demand shocks represent changes when it comes to access to alternative financing options or any changes that lead to shifts in lending. This shock is identified by a positive connection between the volume of bank loans and lending rate innovations. If the connection is negative, it is considered a supply-side shock. Monetary policy shock can affect lending conditions. An expansionary shock increases the bank loan supply. The transmission mechanism suggests that lowering policy rates reduces bond and other yields, which stimulates bank lending. Lending multiplier shock is independent of monetary policy which provides additional credit supply. A lending multiplier shock is, for example, an innovation that makes it easier for banks to sell their loans on the secondary market, which increases their ability to supply new loans. Another example of lending multiplier shocks are instruments that transfer the risk (for instance, the credit default swap market). The lending multiplier represents the amount of bank lending to non-monetary and financial institutions that is generated from central bank money by the financial sector. The lending multiplier can be calculated as a difference between the bank loans and the monetary base. The innovations could also be captured by changes in the allocated volume of liquidity in the ECB's longer-term refinancing operations which is independent of ECB’s main policy rate. Innovations to the multiplier caused many macroeconomic fluctuations in the past. Innovations can be represented by changes in the risk-taking of banks, securitization activities, and developments in the intermediation process. Peersman (2011) proved that all three bank lending shocks have a significant impact on economic output and prices. Positive innovations to the supply side caused by lending multiplier and monetary policy have a significant positive impact on economic activity and inflation while innovations in the demand side have just the opposite effects. The euro area reacts to the increased loan supply with a policy tightening which lasts around 2 years. The reduction of the term spread leads to a decreased loan supply because it makes lending less profitable by reducing the net interest margin. If the long-term interest rate declines, banks increase lending to the private sector instead of investing in government bonds to increase interest margins. The increase in loan supply induces a boost in economic activity.

Peersman (2011) estimated his structural vector autoregressive (SVAR) model on monthly data using the Bayesian approach. Output measure was represented by the index of industrial production while inflation was represented by HICP. ECB mostly steers its monetary policy through the EONIA. This is why Peersman used EONIA as the policy rate in estimation. For the volume of bank loans, he used an index of Monetary Financial Institution (MFI) loans to the private sector adjusted for sales and securitization. To measure the interest rate on bank lending he constructed a lending rate as a weighted average of interest rates charged by MFIs on new loans to households and non-financial corporations. To capture bank funding conditions (a proxy for term spread), he used the difference between the 10-year government bond yield and EONIA. As a proxy for the interest rate margin, he uses the spread between the lending rate and the EONIA. He discovered that the shocks at the supply and demand side of the banking sector have significant effects on the real economy. His research suggests that bank lending shocks account for more than half of GDP variation and up to 75 percent of long-term price variation in the euro area. One-third of GDP variation, as well as most of inflation variability, can be explained by the shocks to the lending multiplier. A positive shock to the multiplier has a boosting effect on the economy while a negative shock contributes to the recession. The innovations in bank loan supply can explain a large portion of output growth between 2005 and 2007 while negative loan supply shocks have significantly contributed to the recession in 2008 and 2009. After a closer inspection, Peersman discovered that disturbances to the economy are mostly caused by the change in the risk appetite of banks. When long-term interest declines, government bonds become less profitable which is why banks turn to riskier, more profitable lending to the private sector. This then increases economic activity and inflation and stimulates monetary policy tightening (Peersman, 2011).

A more recent study that evaluated the impact of credit supply shocks in the euro area was done by Barauskaitė, Nguyen, Rousová, and Cappiello in 2022. They used a Bayesian VAR framework with sign and inequality restrictions to estimate the effects of two different credit supply shocks. They evaluated the importance of bank loans and market-based finance supply shocks on economic activity in the euro area. Their findings suggest that both shocks have a significant impact on the EA economy as both shocks hold similar explanatory power for GDP growth. Their research suggests that the two credit shocks explained quite a large percent of the output fall during the global financial crisis where bank loan supply shocks are a bit more significant than the market-based financing shock. The importance and explanatory power of market-based finance shocks varies between countries as it depends on how those markets are developed. If the market is well-developed as in Germany or France, the market-based finance supply shock holds more power than the loans supply shock (Barauskaitė, Nguyen, Rousová & Cappiello, 2022).

3 FRAMEWORK AND METHODOLOGY

A recent trend in economic research methodology has been based on using as much data as you have available. Instead of working in an environment where the number of variables is much lower than the number of time periods, it has become popular to use a large number of variables without sacrificing any information (McCracken, 2016). Bernanke and Boivin (2003) were one of the first ones to perform an analysis in a data-rich environment where both, the number of observations (T) and the number of variables (N), are large. A large data set is considered when the number of data series exceeds the number of observations (N > T). This presented a breakthrough in modeling. Estimation of factor models of large dimensions, such as multivariate factor-augmented models for the use of macroeconomic policy analysis or forecasting purposes has become popular. Factor-augmented models have been proven to perform better when it comes to impulse response functions and forecasting than most methods which are based on a small number of predicting variables (McCracken, 2016). This was also proven by Stock and Watson (2002) in their study where they compared the forecast results of a dynamic factor model, univariate regression, small vector regression, and leading indicator models. In a simulated forecasting exercise, the dynamic factor model with its factors outperformed other mentioned models (Bernanke, Boivin & Eliasz, 2005).

A factor-augmented model that has proven to work in a data-rich environment has been a factor-augmented vector autoregression (FAVAR) model. Bernanke and Boivin (2003), Bernanke, Boivin and Eliasz (2005), and Stock and Watson (2005) all used a FAVAR model to observe the application of monetary policy shock to the macroeconomic environment. On the other hand, Gilchrist, Yankov, and Zakrajšek (2009) and Boivin, Giannoni, and Stevanović (2013) also used a FAVAR framework to test the effects of credit shocks on economic activity. This is why I believe using the FAVAR methodology is the correct approach to research the impact of the pandemic policy measures interpreted as a positive credit shock on the economic activity in the euro area.

Pandemic policy measures can be viewed as a positive shock on the credit market and by using the FAVAR methodology, I tried to evaluate the effect that this positive shock had on the real economy. COVID-19 measures which increased the amount of bank loans (credit easing measures) can be perceived as the source of the credit shock. On the monetary policy side, the source of credit shock can be observed through the APP and PEPP programs and through LTRO, TLTRO III, and PELTRO liquidity injections which absorbed the COVID-19 shock and helped the banking system to finance new loans and thus support credit for firms and households. On the other side, fiscal policy introduced public guarantee schemes which transferred some of the credit risk and potential losses from banks to governments and with it encouraged banks to lend more. Moreover, prudential policy measures increased bank lending by allowing banks to operate temporarily below the level of capital defined by the Pillar 2 Guidance, the capital conservation buffer, and the liquidity coverage ratio, as well as increased lending through relaxation of the loan loss classification standards.

To apply the FAVAR methodology to my question, the measure of credit conditions and credit shock needs to be identified. Many economists have identified the credit shock as a widening of the credit spread which can be used as a proxy for tightening of the credit conditions. Credit spread describes the difference in the yield between a mid-quality corporate bond and a Treasury risk-free bond of comparable maturity. Credit spread was proven to work in the US economy while in the euro area banking sector plays a key role when it comes to funding the private sector, which was also pointed out by Peersman (2011). Since I am evaluating the effects of credit easing measures, it also makes sense to measure the credit shock as an increase in bank lending. Since most counter-COVID measures were introduced to increase loans to SMEs, I thought it would be best to measure the size of the credit shock as an increase in bank loans to non-financial corporations. I believe this is the measure that most likely captures the credit conditions and credit shock in the euro area during the pandemic.

A large panel of monthly and quarterly data was acquired in the process of estimation mostly from ECB Statistical Data Warehouse or Eurostat database. As Stock and Watson (2005) emphasized, acquiring a good dataset is an important part of the research as data needs to be informative of the economic conditions we try to explain or predict. In factor-augmented models collecting the data is a time-consuming process because between 100 and 150 series need to be collected (McCracken, 2016). My dataset consists of 154 time series.

By estimating the FAVAR model, I was able to analyze the impulse responses of key economic variables to a credit shock, such as GDP components and price indexes. This allows me to see to what extent the credit shock impacts the real economy. Finally, I also simulated the counterfactual economic conditions that would occur in the absence of credit shock if no pandemic credit easing measures were adopted. This allowed me to answer the most important question of my thesis which is how effective the supporting pandemic policy measures were in boosting real economic activity and what would be the consequences of the COVID-19 crisis if policy had not interfered. This evaluation was done by comparing the actual economic conditions with counterfactual conditions when credit shock is set to zero.

This chapter discusses in detail the methodology and framework that I used to evaluate the impact of pandemic policy measures on credit activity and the real economy in the euro area during the COVID-19 crisis.

3.1 FAVAR methodology

The main idea of a FAVAR model is to use a small number of factors to summarize the information contained in a large spectrum of time series. Those unobserved factors are first estimated and then used as inputs in the VAR model along with the observed factors. The observed factors need to contain a variable to which you apply the shock (Bernanke & Boivin, 2003). In my case, this will be a variable that presents the credit conditions since I will be applying a credit shock.

The FAVAR approach has many advantages over the standard VAR methodology. FAVAR allows you to use a large spectrum of information by summarizing the dynamics by a relatively low number of estimated factors. In contrast, the VAR approach is a small model that has its advantages, mostly simplicity, but it ignores a possible dimension of the economic environment and is, thus, less reliable and informative. In practice, a shock works in a data-rich environment that a low-dimensional VAR model cannot capture. FAVAR methodology minimizes the risk of omitted variable bias. A VAR on the other hand – due to its limited degrees of freedom – rarely includes more than eight variables. Such a small number of variables is unlikely to capture the full set of information that the central banks or financial market participants work with. This causes the estimates and responses to shocks to be biased which can result in misleading conclusions (Bernanke & Boivin, 2003). A typical example is the "price puzzle" where a contractionary monetary policy shock increases the price levels, which is contrary to economic logic as they should decrease (Bernanke, Boivin & Eliasz, 2005). A huge benefit of the FAVAR methodology compared to the VAR is that it allows us to estimate the impulse responses to shocks not only for the variables that are included in the VAR but for basically any variable in the dataset. This is because all variables can be observed as a linear combination of the estimated factors (Bernanke & Boivin, 2003). For the analyst, observing a lengthy list of variables also helps validate the model and makes it easier to understand the shock better as researchers like to observe the effects of the shock on multiple variables, such as total factor productivity, wages, different price levels, investment, consumption, profits, and many others. This is also beneficial due to a complex general concept of economic activity or financial conditions that cannot be captured by a single variable. No single variable can describe the economic activity in full. Even real GDP and industrial production do not completely describe the economic conditions as unemployment, prices, and interests are not captured with it. These are all reasons why the FAVAR model is a better approach compared to the simple VAR (Bernanke, Boivin & Eliasz, 2005).

The FAVAR methodology is based on the standard structural VAR methodology but adjusted to work in a data-rich environment. This is done by combining the standard VAR with factor analysis. The factor analysis relies on the research of dynamic factor models which suggest that a relatively small number of estimated factors can summarize information coming from a large number of time series. Since a small number of factors can efficiently and properly summarize the economic conditions, it makes sense to augment the VAR with such estimated factors. This solves the problem of the degrees of freedom in VAR analysis (Bernanke, Boivin & Eliasz, 2005).

The estimation of the FAVAR model is performed by using a two-step estimation method. In the first step, factors are estimated by principal components while the second step consists of an estimation of the factor-augmented VAR. Let Y_t, a $M \times 1$ vector, denote observable economic variables that have significant effects that spread throughout the entire economy. There is additional information that is relevant for the modeling dynamics of these variables, which is not fully captured by Y_t. This additional information can be summarized by unobserved factors, F_t, a $K \times 1$ vector, where K is relatively small. Unobserved factors represent complex concepts, such as economic activity or credit conditions which cannot simply be explained or represented by a single data series but are rather embedded into multiple variables. The joint dynamics of factor variables (Y_t and F_t) can be expressed with the following FAVAR equation (Bernanke, Boivin & Eliasz, 2005):

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t. \tag{1}$$

where:

- $\Phi(L)$ represents a conformable lag polynomial of finite order d which can include a priori restrictions (similar to the structural VAR methodology),
- ν_t stands for the error term which has a zero mean and a covariance matrix Q.

The equation above represents a VAR model in (Y_t, F_t). This system can be viewed as a standard VAR in Y_t if the elements of $\Phi(L)$ are all zero. If there are non-zero elements, the system is referred to as factor-augmented vector autoregression or FAVAR. Using this method allows us to evaluate the marginal contribution of the additional information summarized by estimated factors F_t. If, however, the standard VAR in Y_t was estimated without including the factors, it would generate biased estimates of the VAR coefficients, as well as impulse response functions. Since F_t are unobserved factors and equation (1) cannot be directly estimated. Factors can be interpreted as conditions that affect many economic variables. This means that we can assume something about these factors from a variety of economic and financial time series. The available "informational" macroeconomic and financial time series can be denoted as X_t, which is a $N \times 1$ vector. It contains economic and financial indicators. Since this is a data-rich environment, the number of time series N is large, which means that the number of series N is greater than the number of time periods T (N > T). The number of series is also much larger than the number of factors (N >> K + M).

The informational time series X_t can be explained by the unobserved factors F_t and the observed factors Y_t by the following equation (Bernanke, Boivin & Eliasz, 2005):

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + e_t'. \tag{2}$$

where:

- Λ^f represents an $N \times K$ matrix of factor loadings,
- Λ^y is an $N \times M$ matrix of loadings on Y_t factors,
- e_t is a $N \times 1$ vector of error terms that have a zero mean and are assumed to be weakly correlated.

Equation (2) represents the idea that both Y_t and F_t have persistent effects on the dynamics of X_t. Conditional on Y_t, the X_t informational time series are basically noisy measures of unobserved factors, F_t. The two-step principal components approach provides a non-parametric way of uncovering the space spanned by the common components, $C_t = (F_t$', $Y_t')'$ (Bernanke, Boivin & Eliasz, 2005).

The estimation of the FAVAR model (equations 1 and 2) is based on a two-step principal components procedure where unobserved factors are estimated in the first step while in the second step, the estimated unobserved factors are included as regressors in the VAR model. Factors can be obtained by a Principal Components Analysis (PCA) estimator. The two-step approach starts with the estimation of the common components, C_t, by using the first $K + M$ principal components of X_t. The first step does not take advantage of the effect that Y_t is observed. When the number of informational time series is large and the number of principal components used is at least the size of the true number of factors, principal components recover the space spanned by F_t and Y_t. The space covered by $\hat{C}_t$, which is not covered by Y_t, represents $\hat{F}_t$. The second step includes the standard estimation of the FAVAR (equation 1) where F_t is replaced by the estimated $\hat{F}_t$.

Restrictions need to be specified to identify the factors and factor loadings uniquely. Factors are acquired from the estimation of equation (2) where the identification of the factors is standard. The identification can be done by restricting loadings ($\frac{\Lambda^{f'}\Lambda^f}{N} = I$) or by restricting the factors ($\frac{F'F}{T} = I$). Both approaches lead to the same common component $F\Lambda^{f'}$ and same factor space. By restricting the factors, $\hat{F} = \sqrt{T}\hat{Z}$ is obtained where $\hat{Z}$ stands for the eigenvectors relating to the K largest eigenvalues of XX' sorted from the largest to the smallest. This approach identifies the factors against any rotations (Bernanke, Boivin & Eliasz, 2005).

This procedure is simple and easy to implement and not computationally extensive. It also allows for some degree of cross-correlation in the idiosyncratic error term (e_t). However, the approach brings uncertainty in the estimation due to the generated regressors bias in the second step. This is why a bootstrap procedure is implemented to obtain confidence intervals of the impulse response functions that account for this uncertainty (Bernanke, Boivin & Eliasz, 2005).

3.2 Identification of credit shocks

The identification of the model must be specified. In my case, credit shocks need to be identified. A simple recursive ordering is used. To identify credit shocks in the VAR part of the model, a contemporaneous timing restrictions procedure needs to be applied. This process identifies credit shocks by restricting only the response of a few selected economic indicators. The idea is to identify credit shocks with the estimated innovations to a variable or linear combination of variables in the VAR. This means that unobserved factors will not respond to a credit shock within the period. By imposing a small number of restrictions, it is unlikely that the model is misspecified. Once the identification scheme is set, the dynamic effects of credit shocks can be measured in the form of impulse response functions (Boivin, Giannoni & Stevanović, 2013).

To implement this identification scheme, time series need to be sorted into two categories: "slow-moving" and "fast-moving" variables. A "slow-moving" variable is assumed to be pre-determined while a "fast-moving" variable is highly sensitive to contemporaneous credit shocks. The classification of each variable is provided in Appendix 2.

This identification first needs to control for the part of $\widehat{C_t}$, which corresponds to the credit conditions. This is achieved by first estimating the »slow-moving« factors F_t^s by estimating the principal components of the »slow-moving« variables. Then, the following regression is estimated:

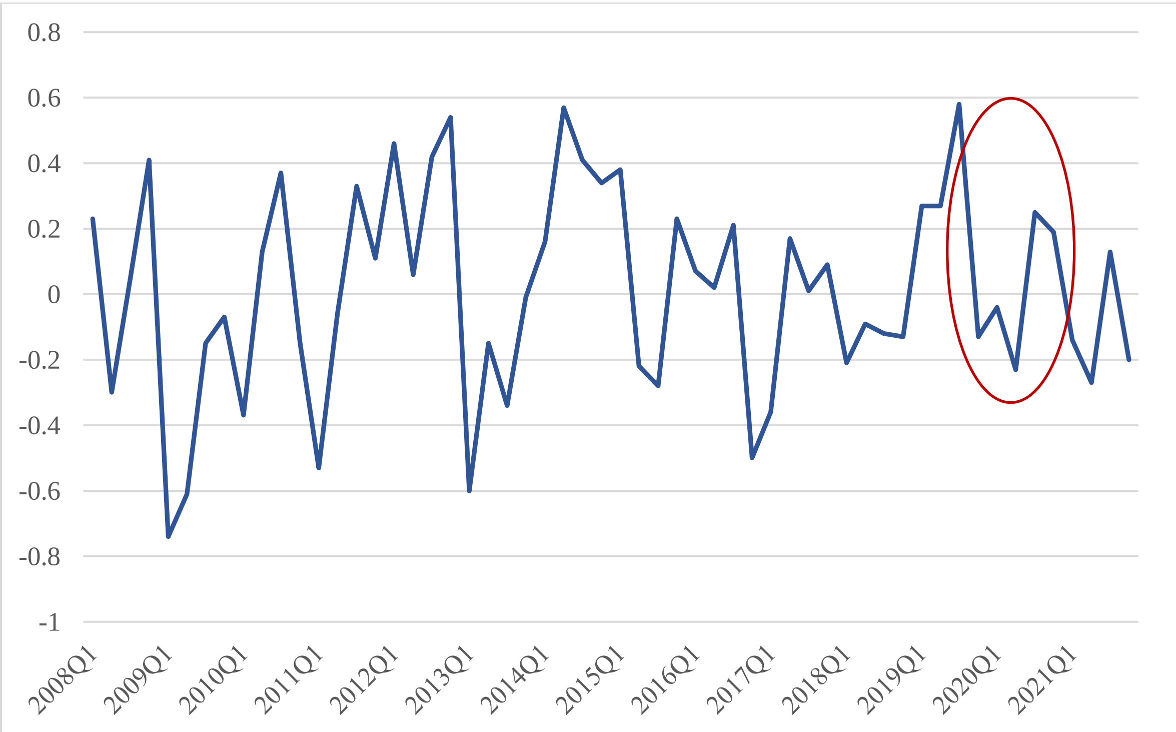
$$\widehat{C_t} = b_{F^s}\widehat{F_t^s} + b_Y Y_t + e_t. \qquad (3)$$

From this equation, $\widehat{F_t}$ is constructed from $\widehat{C_t} - \widehat{b_Y}Y_t$. If $\widehat{F_t^s}$ is correlated with Y_t, so is $\widehat{F_t}$. In equation (2), a specific element of $\Lambda^y{}_i$ equals to 0 if the X'_{ti} is a slow-moving variable, and a non-zero value if it is a fast-moving variable. Finally, the VAR in $\widehat{F_t}$ and Y_t is estimated and identified recursively using this ordering. This is done by expressing the FAVAR's reduced form residuals as a product of a lower triangular matrix of the Cholesky decomposed residual variance-covariance matrix Q and the matrix of structural innovations.

In my specification of FAVAR, I include two variables into Y_t, which represents observable factors. The two observable factors in my specifications are policy rate and credit conditions. The policy rate is interpreted as the monetary policy instrument. This specification distinguishes between monetary policy shocks and credit shocks. The policy rate in my model is captured by EONIA corrected for the euro short-term rate (€STR hereinafter). As Peersman (2011) mentioned in his study, the ECB mostly steers its monetary policy through EONIA. This is why EONIA can be used as a proxy variable for the policy rate in the euro area. Because EONIA was replaced by €STR on 3 January 2022 and was based on the €STR since October 2019 (Bank of Slovenia, n.d.), however, I corrected the EONIA by €STR for the last few periods.

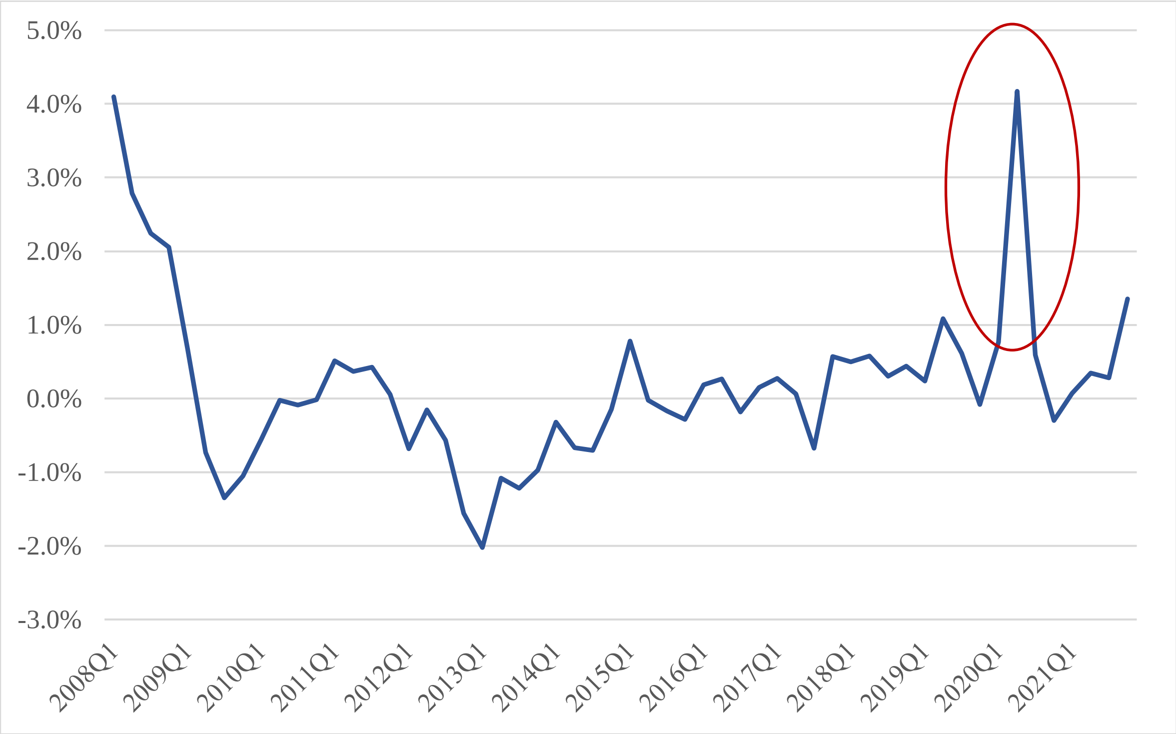
The more controversial question was how to capture credit conditions and credit shocks. Since many US economists used credit spread to capture credit conditions, my first idea was to use a sort of credit spread with a focus on the banking sector as I was trying to capture the positive effect of pandemic policy measures on bank lending and the real economy. I was searching for a credit spread to capture such improvement. Therefore, I tried to use the credit spread defined as a difference between a long-term bank lending interest rate to non-financial corporations and a risk-free government bond yield of 10-year maturity. Figure 1 below presents a quarter-on-quarter percentage point difference in the defined credit spread. As one can observe, there was little movement in the COVID-19 period. The spread decreased only by 0.23 percentage points in the second quarter of 2020 and even increased for the following two quarters. This is why I decided to go with an alternative measure. I noticed that in studies done on the euro area economy, credit shocks are mostly identified through bank loans, such as in a study by Peersman (2011) and even in a recent study by Barauskaitė, Nguyen, Rousová, and Cappiello (2022). Figure 2 shows that there was, in fact, a large increase in bank loans to NFC during the COVID-19 crisis, which can be attributed to policy-induced credit stimulus. From the first to the second quarter of 2020, bank loans to NFC increased by 4.2% and by 7.4% till the end of 2021, which can be interpreted as a positive credit shock. Credit conditions in my model are therefore represented by the total amount of bank loans approved to NFC.

Figure 1: Percentage point difference in credit spread in period 2008 – 2021



Source: Own work.

Figure 2: Relative difference in bank loans to NFC in period 2008 – 2021



Source: Own work.

The credit conditions are assumed to have persistent effects on the whole economy, which is represented in the model by X_t and includes 152 data series in total. The latent factors represent the real activity and general price movements. Bank loans which are used to describe credit conditions are ordered last and their innovations are treated as credit shocks in a standard way. This way of ordering implies that latent factors do not respond to the credit shock within the quarter.

3.3 Data preparation

For the empirical analysis, I constructed a modeling dataset that covers 154 economic and financial data series for the euro area. I considered 114 monthly and 40 quarterly indicators. The time series included in the analysis covers different segments of the euro area economy. They can be classified into the following categories: real output and income, prices, labor market, financial market, money aggregates, interest rates, exchange rates, balance of payment, banking sector, stock market indices, survey data, and foreign economic indicators. All data series were collected from a set of publicly available databases including the Eurostat Database, ECB Statistical Data Warehouse (SDW), OECD Database, Yahoo Finance, and others. Appendix 2 presents the full list of variables included in the analysis with corresponding information about frequency, transformation, and source.

The analysis is performed on a quarterly frequency which spans from Q1 2000 through Q4 2021. Altogether, 88 observations were used. Since not all variables are available on a monthly frequency, I decided to model on a quarterly frequency instead. Therefore, all variables sourced on a monthly frequency had to be aggregated onto a quarterly frequency. Once I had constructed a full dataset on a quarterly frequency, the data was seasonally adjusted and transformed to induce stationarity. Since not all data series were available from 2000 onwards, an interpolation of missing values was done by using the expectation-maximization (EM) algorithm to acquire a balanced panel of data.

3.3.1 Seasonal adjustment

In a time series, one can observe a trend, a seasonal, a cyclical, and an irregular component. The trending behavior represents the long-term behavior of the series. The cyclical component represents regular periodic movements while the irregular component is stochastic which the researcher wants to estimate or forecast (Enders, 2014). Since I am performing a time series analysis, seasonal effect, and calendar effect need to be excluded. In a time series, a seasonal effect is often present since people are driven by natural and social patterns. Also, calendar effects are noticed in a series as they include the working day effect, the leap-year effect, the holiday effect, and others. If seasonal and calendar effects are eliminated from the series, we talk about the seasonally adjusted time series. The procedure that does that is called seasonal adjustment. Seasonally adjusted data is simplified and it can be interpreted better than original actual data as seasonal fluctuations can cloud important movements or features of the series. Seasonal and calendar effects can obstruct the true movements in data related to business cycles or non-seasonal events, such as disruptions in production. Excluding the seasonal patterns from the series makes a time series more meaningful for evaluating changes in economic conditions over time. The seasonal adjustment can be done by different methods (SURS, 2019).

Since many of the time series were not available as seasonally adjusted at the source, I performed seasonal filtering myself. I did that by using a seasonal adjustment function called »seas« which is an alternative, simplified approach to the X-13ARMA-SEATS program of the Census Bureau. The seasonal adjustment is performed by the following 4 steps:

1. Use a smoothing approach to create a trend (TR) from the time series.
2. Calculate the deviation of the actual data from the trend (SI) – 4 series are made since the time series are quarterly observations. The same smoothing algorithm is used on these 4 series separately. These smoothed series are called seasonal factors (SF).
3. Calculate the difference between the actual data and seasonal factors. This will be the seasonally adjusted series (SA).
4. Calculate the difference between the trend and seasonally adjusted series will represent the irregular series (IR).

Trend contains the low-frequency component (long-term variation), seasonal factors contain the medium, and irregular series hold the high-frequency components. The decomposition of the series is the following:

$$Orginal\ series = Trend\ component + \ Seasonal\ component + Irregular\ component$$

For each time series, a separate model is estimated, and each time series is seasonally adjusted independently of other time series (Lengwiler, 2023).

3.3.2 Preparing a balanced panel

Since not all time series are available from 2000 onwards as they only started tracking it later on, the data for such series had to be extended backward in time or, in other words, backcasted for the missing periods. To do this, I used an algorithm developed by Michael W. McCracken. The algorithm transforms each series to be stationary, removes outliers, estimates factors, and computes the R-squared from the estimated factors and factor loadings (McCracken, 2016).

The first step is achieving stationarity of all time series. The stationarity of the time series is achieved by applying an appropriate transformation to the data series. Appendix 2 holds the information about the transformation of each series. Most series that are not stationary were transformed by using the first difference of the logarithm of the series (Δln). Since a difference is applied, one quarter of data is lost, and the data now starts in Q2 2000. A feature of the McCracken algorithm is the removal of outliers. This means that each time series is checked for outliers and each value that drifts from the data median by more than 10 times the interquartile range is considered an outlier. The interquartile range is defined as the difference between the 75th and the 25th percentile of the sample. Outliers are removed and treated the same as missing values. Once the data is stationary and cleansed of outliers, a set of factors can be estimated by using the principal component analysis. Missing values are handled by using an iterative expectation-maximization algorithm (McCracken, 2016).

The static principal component analysis (PCA) is based on the EM algorithm of Stock and Watson (2002). The least squares estimators of Λ and F are considered in the following way:

$$X_t = \Lambda F_t + e_t. \tag{4}$$

The objective function of the balanced panel is the following:

$$V(F,\Lambda) = \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i{}' F_t)^2 \tag{5}$$

where λ_i represents the i-th row of Λ. The objective function can be minimized by calculating the eigenvalues where $\widehat{F_t}$ represent the principal components of X_t. When the panel is unbalanced, least squares need to be calculated using the following objective function:

$$V^{\dagger}(F,\Lambda) = \sum_{i=1}^{N} \sum_{t=1}^{T} I_{it}(X_{it} - \lambda_i{}' F_t)^2 \tag{6}$$

where $I_{it} = 1$ if X_{it} is available and 0 otherwise. Minimization of such an objective function requires iterative methods (Stock & Watson, 2002).

In the first step, all missing values are set to 0 which is the unconditional mean of the demeaned and standardized sample of non-missing values. This re-balanced panel is then used to estimate a $T \times r$ matrix of factors $F = (f_1, \dots, f_T)'$ and $N \times r$ matrix of loadings

$\lambda = (\lambda_1, \dots, \lambda_N)'$ using the following normalization, $\frac{\lambda'\lambda}{N} = I_r$. N stands for the number of variables, T represents the number of observations, and r is the number of factors. The missing values for series i at time t get a value of $\widehat{\lambda}_i'\widehat{f}_t$ which replaces the zero. To de-standardize, this value is multiplied by the standard deviation and the mean of the series is added back. This value is now treated the same as the rest of the values, which means that the mean and the standard deviation of the sample are re-calculated using the newly added values of what were initially considered missing values. This is used to again standardize and demean the sample which is used to re-estimate the factors and loadings using the updated data. The process is repeated as many times as it is needed for the factor estimates to stop changing (McCracken, 2016).

The next step consists of selecting the number of significant factors. The PC_p criteria used for the factor-selection procedure was developed by Bai and Ng (2002) where they used the generalized Mallow's $C_p$criteria for large dimensional panels. The number of factors is selected by minimizing the sum of squared residuals without hurting the model too much. The PC_p penalty is the following:

$$\frac{\log(\min(N,T))}{\min(N,T)}. \tag{7}$$

It differs from the standard BIC criteria because here, the factors are estimated on a two-dimensional panel. Variations of penalty can be obtained due to the following fact:

$$\min(N,T)^{-1} \approx \frac{N+T}{NT}, \quad N,T \to \infty \tag{8}$$

The penalty referred to as PC_{p2} in Bai and Ng (2002) study is the following:

$$\frac{N+T}{NT}\log(\min(N,T)). \tag{9}$$

It has a better finite sample property which is why also McCracken used it in his algorithm (McCracken, 2016).

After the factor estimation, a regression of the i -th series on a set of r factors is performed. For each factor k = 1,…, r an R-square $R_i^2(k)$ is estimated separately for each time series i. The incremental explanatory power or the marginal R-square of a factor k is equal to:

$$mR_i{}^2(k) = R_i^2(k) - R_i^2(k-1) \tag{10}$$

where $k = 2, \dots, r$ and $mR_i{}^2(1) = R_i^2(1)$. The average power of the k-th factor is (McCracken, 2016):

$$mR^2(k) = \frac{1}{N}\sum_{i=1}^{N} mR_i^2(k). \tag{11}$$

Table 1: Marginal R-squared for each factor

Factor 1 - $mR^2(1)$	**0.317**	**Factor 2 - $mR^2(2)$**	**0.213**	**Factor 3 - $mR^2(3)$**	**0.103**	**Factor 4 - $mR^2(4)$**	**0.065**
Yield Curve spot 6Y	0.978	Exports of goods and services	0.794	Deflator GDP	0.437	HICP – Health – CT	0.442
Yield Curve spot 7Y	0.977	Industrial production – total	0.762	Deflator final consumption	0.411	Loans – NFC – 1Y to 5Y maturity	0.404
Yield Curve spot 5Y	0.976	Imports of goods	0.761	HICP – All items	0.402	M3	0.399
Yield Curve spot 8Y	0.974	Exports of goods	0.755	HICP – Goods	0.389	Loans – NFC – Total maturity	0.309
Yield Curve spot 4Y	0.971	GDP total (million EUR)	0.753	IPPI – domestic	0.369	Employment – Construction	0.302
Yield Curve spot 9Y	0.970	Imports of goods and services	0.734	HICP – Goods -CT	0.365	M2	0.290
Bank int rate – Corporations – Over 5Y maturity	0.968	Industrial production – durable consumer goods	0.723	HICP – All-items – CT	0.358	Unemployment rate	0.277
Yield Curve spot 10Y	0.966	Industrial production – intermediate goods	0.720	PPI – Industry	0.351	Consumer confidence indicator	0.265
Bank int rate – Corporations – Total maturity	0.965	Industrial production – Manufacturing	0.709	ULC – Construction	0.301	Deposits from Households	0.253
Yield Curve spot 11Y	0.962	Employment – Total	0.662	ULC – Total	0.299	RPPI	0.212
Factor 5 - $mR^2(5)$	**0.045**	**Factor 6 - $mR^2(6)$**	**0.032**	**Factor 7 - $mR^2(7)$**	**0.026**	**Factor 8 - $mR^2(8)$**	**0.020**
LP – Total	0.393	HICP – Overall index (excluding energy food alcohol and tobacco) – CT	0.274	Real EER	0.523	VIX	0.224
CPPI	0.300	Employment – Industry	0.252	USD/EUR	0.510	Real EER	0.197
STOXX Industrials	0.286	HICP - Services – CT	0.225	GBP/EUR	0.280	USD/EUR	0.148
STOXX Oil and gas	0.286	M1	0.219	CHF/EUR	0.189	CHF/EUR	0.138
DE DAX	0.283	OECD Composite Leading Indicator (CLI)	0.196	HICP – Non-energy industrial goods	0.178	M1	0.106
STOXX 50	0.266	M2	0.184	Brent Crude Oil Prices	0.160	LP – Industry	0.098
STOXX Financials	0.264	Industrial confidence indicator	0.173	HICP – Overall index (excluding energy food alcohol and tobacco)	0.156	CPI – total non-energy	0.084
VIX	0.254	HICP - Non-energy industrial goods – CT	0.167	STOXX Healthcare	0.144	Employment – Public	0.082
STOXX Healthcare	0.232	Economic Sentiment Indicator	0.162	HICP US	0.131	OECD CLI	0.068
HICP – Non-energy industrial goods – CT	0.230	LP – Construction	0.142	HICP – Overall index (excluding energy food alcohol and tobacco) – CT	0.131	LP – Public	0.067

Source: Own work.

In my dataset of 154 time series ($N = 154$) and 87 time periods ($T = 87$), the iterative expectation-maximization process had to be repeated 59 times to achieve constant factor estimates. The PC_{p2} criteria selected 8 significant factors ($r = 8$). Table 1 represents the list of the ten series that load most heavily on the eight factors along with the corresponding marginal R-squares. The first factor has a marginal R-square of 0.317, which means that 0.317 of the variation in the whole data can be explained by the first factor. Factor 1 can be interpreted as the euro area yield curve (which can be described as the term structure of interest rates of AAA-rated EA central government bonds) or bank interest rates to corporations. The first factor's marginal R^2 associated to yield curves and bank interest rates to corporations is on average 0.97. Factor 2 explains 0.213 of the total variation of the data and is heavily associated with the real output variables, such as exports/imports, industrial production, GDP, and even employment with marginal R^2 ranging from 0.66 to 0.79. Third factor contributes 0.103 of the variation and is related mostly to price variables which means it can be interpreted as an inflation factor. Factor 4 is a mix of different segments, such as the banking sector, housing market, and labor market. Factor 5 mostly represents the stock market. Factor 6 is a combination of money supply, price indices, labor market, and survey data while factor 7 holds the most explanatory power for the foreign exchange market. The stock market variables together with foreign exchange variables concentrate on the 8th factor. These eight factors together explain 0.821 of the total variation in all time series data.

4 RESULTS OF THE ANALYSIS

A FAVAR model was estimated using 5 unobserved and 2 observed factors while using a 1-quarter lag. Altogether, the FAVAR model includes 7 factors. The following recursive identification scheme was used:

$$Y_t = [\text{EONIA, Bank loans to NFC}]. \tag{12}$$

Credit conditions are ordered last and monetary policy rate is ordered second to last. This identification scheme assures that the policy rate represented by EONIA does not respond to the credit shock in the same quarter. The appropriateness of the FAVAR specification was tested on a wide range of key macroeconomic indicators representing all segments of real economic activity. Table 2 represents the portion of the variation that the unobserved estimated factors explain measured with R^2. Most selected macro variables have R^2 above 0.60 whereas 80% of the variables in the whole dataset have an R^2 above 0.60. For variables with lower R^2, we need to have lower confidence in the accuracy of impulse responses of such variables. Those variables are, for example, money supply M1 and real effective exchange rate (EER). Since a large portion of variation for most variables can be explained by the estimated factors, indicated by high R^2, it confirms that 5 unobserved factors are enough to summarize the information contained in my dataset of 152 time series.

Table 2: R^2 of selected variables of the estimated FAVAR model

Variable	$\mathbf{R^2}$
Industrial production – Total	0.9071
GDP	0.9740
Investments	0.5989
Private consumption	0.8783
OECD Composite Leading Indicator	0.6426
HICP – All Items	0.9500
Production Price Index – Consumer Goods	0.6338
Unemployment rate	0.6420
Employment	0.8907
Compensation per employee	0.6980
3-month EURIBOR	0.9928
10-year government bond yield	0.9762
Real EER	0.0918
M1	0.2939
M2	0.6881
Banks' interest rate to NFC	0.9881
Cost of borrowing	0.9818
Industrial confidence	0.7694
Consumer confidence	0.7015
New orders – Manufacturing	0.8245

Source: Own work.

Table 3: R^2 of selected variables based on different FAVAR specifications

Variable/Number of factors	**0 – factors**	**1 – factors**	**2 – factors**	**3 – factors**	**5 – factors**
Industrial production – total	0.03	0.18	0.80	0.90	0.91
GDP total (million EUR)	0.03	0.21	0.79	0.95	0.97
HICP – All items	0.13	0.14	0.50	0.91	0.95
PPI – consumer goods	0.10	0.12	0.38	0.62	0.63
Unemployment rate	0.52	0.55	0.55	0.59	0.64
Euribor 3M	0.98	0.99	0.99	0.99	0.99
EA GOVY10	0.82	0.96	0.97	0.97	0.98
M1	0.08	0.08	0.18	0.22	0.29
M2	0.55	0.59	0.68	0.68	0.69
Industrial confidence indicator	0.14	0.26	0.52	0.62	0.77
Consumer confidence indicator	0.11	0.31	0.37	0.39	0.70

Source: Own work.

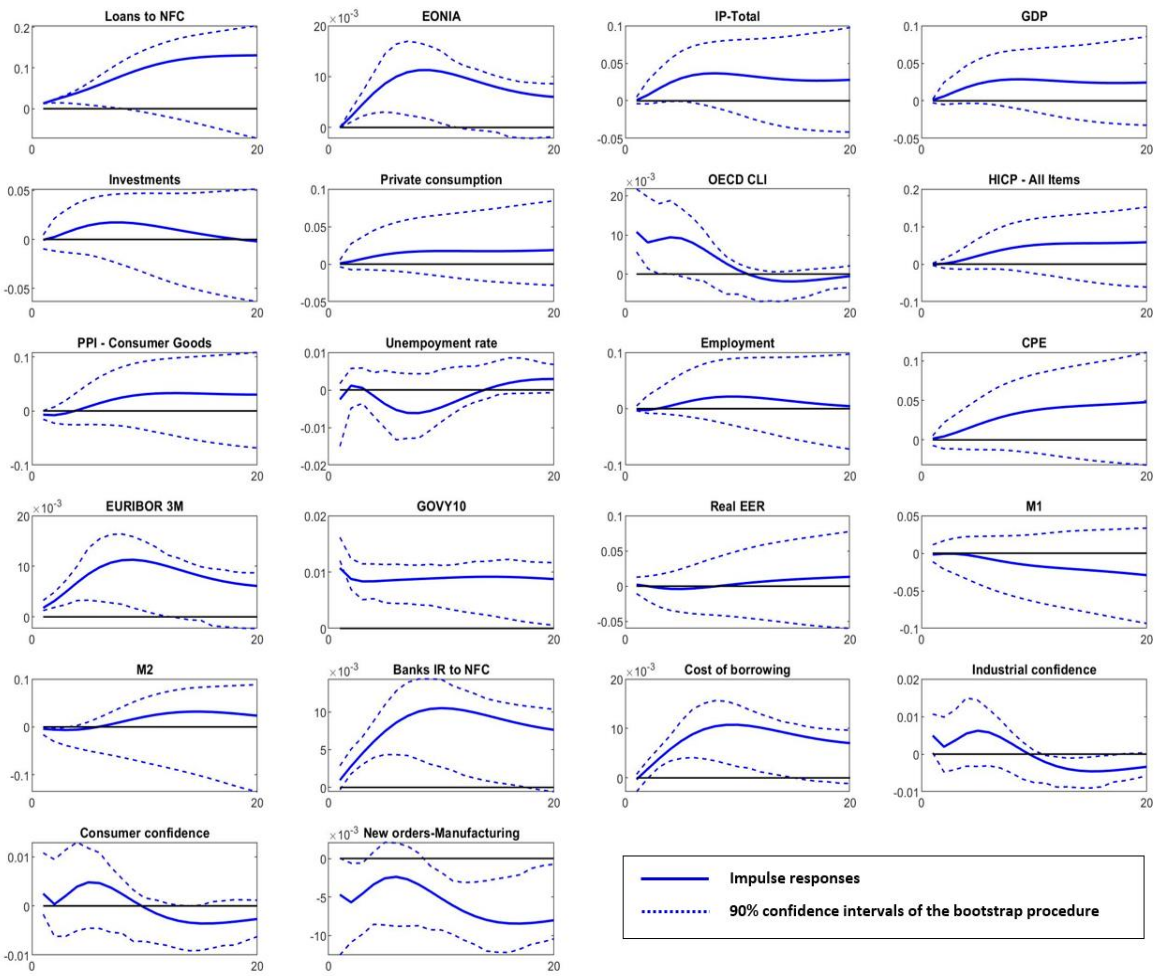
The preferred number of unobserved factors in the FAVAR specification is justified by the portion of variation that the unobserved estimated factors explain for the main macroeconomic variables based on equation (2). Table 3 shows how the R^2 increases by adding additional factors to the model. Based on the R^2 most variables already seem to have a high enough variation explained already by using 3 latent factors. However, industrial and consumer confidence indicators still improve a lot when choosing a 5-factor FAVAR model. This again proves that the 5-factor specification is the appropriate one. Further justification of the number of selected latent factors is provided in the next section by analyzing the impulse response functions.

4.1 Impulse response functions

Figure 3 shows the impulse responses of key macroeconomic variables to the credit shock. Impulse responses also include 90% confidence intervals of a bootstrap procedure repeated 1000 times. The time horizon of the impulse responses is 20 quarters or 5 years. Impulse responses were estimated to a one standard deviation innovation to the credit conditions. A positive credit shock of one standard deviation, equal to 1.27%, was applied. The credit shock is represented by an exogenous increase in loans to NFC. It generates significant and persistent growth of economic activity in the period following the shock. The responses are in line with the economic logic and transmission channels of credit shocks discussed in previous sections. Increased lending boosts real economic activity which can be observed in increased industrial production and GDP. Expanded economic activity is also captured in significant and persistent increases in investments and private consumption which are both components of the GDP. Even conditions in the labor market improve as can be observed in labor market indicators, such as decreased unemployment rate, increased total employment, and even increased compensation per employee (CPE). On the other hand, improved credit conditions and increased output also increase inflation, which can be observed in increased price indices, such as the harmonized index of consumer prices (HICP) of all items and the production price index (PPI) of consumer goods. Increased inflation triggers an immediate monetary policy response in the form of tightening of the monetary policy rate which is represented by an increase in EONIA. The contractionary monetary policy also increases all other interest rates, such as government bond yields, 3-month EURIBOR, bank interest rates to companies, and the overall cost of borrowing. The leading indicators, such as consumer confidence and industrial confidence both react positively, which means the confidence of consumers and industries increases for at least 2 years. Most variables respond slowly as they only reach the maximum effect after 2 years. The only variable that reacts contrary to economic logic is the indicator for new orders, which decreases when it should increase. This response is relatively small but still controversial and would need to be investigated further as the R^2 for it is 0.82, which means factors explain a good proportion of its variation. Note that here, I only display responses of 22 variables whereas I have in total 152 variables available which could in principle be investigated as well.

The monetary policy rate (EONIA) does not react on impact, by assumption, but it increases in the following periods while reaching the maximum level of about 1 basis points two years after the shock. EURIBOR and government bond yield on the other hand are not restricted and react immediately when the shock occurs. Even though the interest rates increase and thereby contrast the positive effect of the shock, economic activity keeps expanding, thus pointing to very persistent and significant responses to increased bank lending which could be the result of financial accelerator. The initial shock of 1.27% stimulates the bank lending even further boosting the lending activity to increase by 10% in the following 2 years, which boosts the GDP and industrial production by 2.8% and 3.7%, respectively.

Figure 3: Impulse responses of selected variables to credit shock



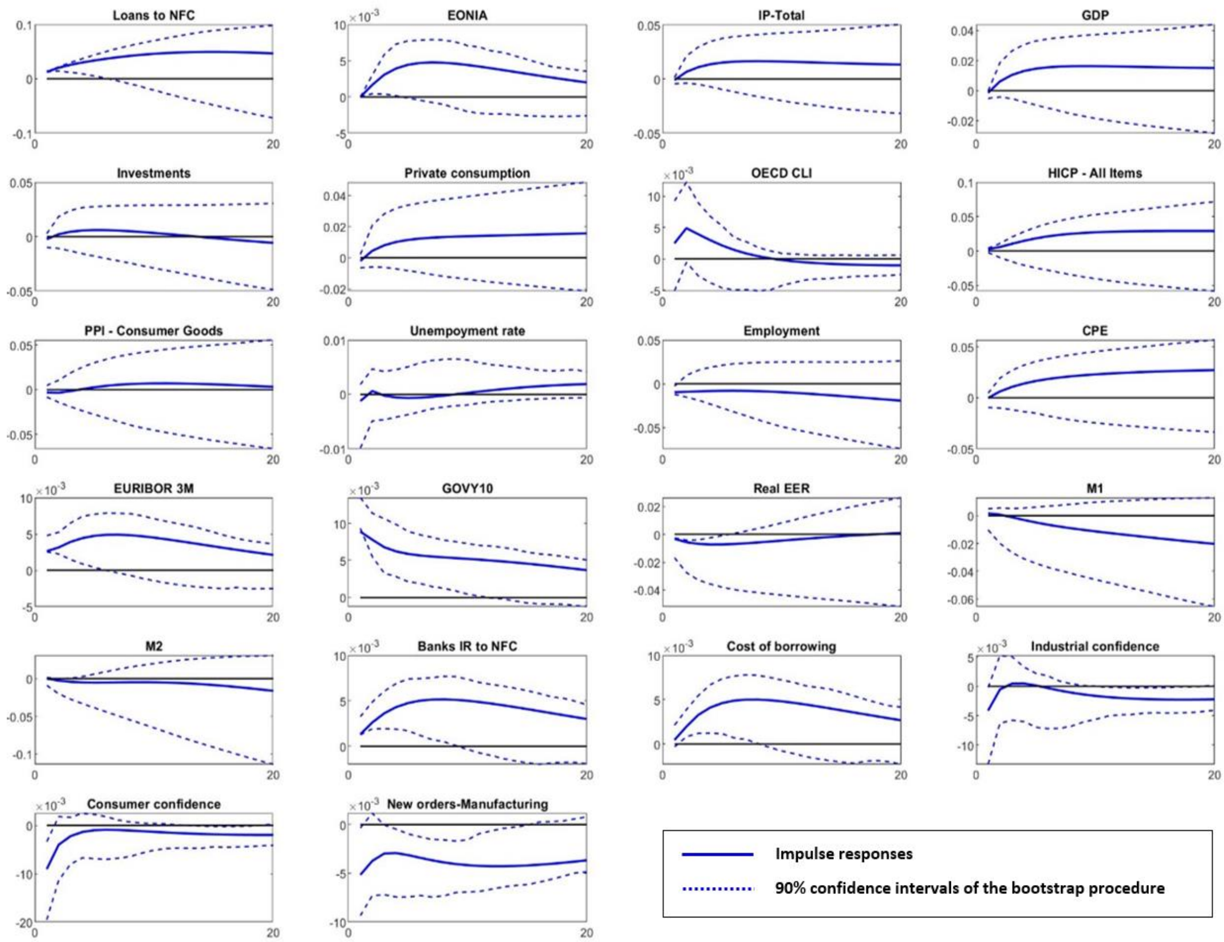
Source: Own work.

Compared to the study of credit shocks on the euro area economy done by Peersman (2011), impulse responses in my analysis move in the same direction for the main macroeconomic variables, such as output, prices, volume of bank loans, policy rate (EONIA), and monetary base. Comparing Peersman's analysis of the effect of lending multiplier shock on the volume of bank loans with my results, both responses show a persistent trend of increased bank lending. The prices also react in a similar persistent manner compared to Peersman's impulse responses. The biggest difference in the analysis is for the output which has a more persistent response on my end compared to the one in Peersman analysis. Overall, a similar movement of macro variables to credit shock can be observed. Another study of credit shocks in the euro area economy was done by Barauskaitė, Nguyen, Rousová, and Cappiello (2022), which produced impulse responses of variables to a negative loan supply shock, instead of a positive shock as in my analysis. Compared to my analysis, their analysis shows the movement of variables in the opposite direction, which again validates my responses as I observe the reaction of variables to a positive shock and they observe it to a negative shock. Their analysis shows a persistent downward trend of price levels as well as a drop in output which is less persistent than in my case. Still, the direction of the variable reaction confirms my results. Both studies validate my results as the direction of the movement of the main macroeconomic variables is the same. The size of the effect is hard to compare as the credit shock was applied using a different approach and was of a different magnitude.

An important question to ask, when modeling using a FAVAR methodology, is how many latent unobserved factors are needed to capture the full range of economic and financial information. The number of selected factors affects the results of the impulse responses notably. To explore the effect of the number of factors on impulse responses to credit shocks, I also considered an alternative specification with 3 latent factors. Impulse responses estimated with 3 latent factors are presented in Figure 4. The biggest difference from the original specification with 5 unobserved factors is that the employment and unemployment rates react controversially, as well as industrial and consumer confidence, which means additional factors are needed to capture the information about the labor market and confidence indicators. Also, other variables, presenting the real economy, have smaller reactions. Most reactions were cut in half. Similar responses are acquired by using 4 unobserved factors. In that respect, the most successful specification, in terms of economic logic, appears to be the approach with 5 unobserved factors, reported in Figure 3. In the case of 5 factors, the FAVAR model appears successful in capturing relevant information. The responses are generally of the expected sign and magnitude where following a positive credit shock, real activity measures increase and prices follow while monetary policy tightens.

The responses generated by my identification of FAVAR with 5 unobserved and 2 observed factors, altogether 7 factors, seem to show a realistic picture of the effect of a positive credit shock on the real economy and provide valuable information about the transmission mechanism of this shock. Increasing bank lending leads to significant and long-lasting positive effects on economic activity. Overall, these results seem to provide a consistent and sensible measure of the effect of improved credit conditions.

Figure 4: Impulse responses of selected variables to credit shock – alternative specification of FAVAR with 3 latent factors



Source: Own work.

4.2 Counterfactual experiment – the impact of pandemic policy measures on the real economy during the COVID-19 crisis

In this section, I try to quantify the effects that the pandemic policy measures had on the economic output during the COVID-19 crisis. From the start of the crisis in March 2020, the ECB introduced several non-standard programs, including increased APP and PEPP, as well as additional liquidity in the form of LTRO, TLTRO III, and PELTRO. ECB even relaxed some capital and liquidity conservation buffers. On the other hand, national governments proposed to cover the banks' losses in the form of public guarantees. All those policy measures combined motivated banks to increase lending and by doing so helped the economy recover faster. To measure the impact of those programs, I implemented an approach following the Wu and Xia (2016) framework which relies on historical decomposition. The main idea is that each macroeconomic variable can be decomposed into its initial deterministic component and a stochastic component which incorporates the sum of all past shocks (Wu & Xia, 2016).

The VAR equation can also be rewritten in the following terms:

$$\begin{bmatrix} f_t{}^m \\ y_t{}^o \end{bmatrix} = \begin{bmatrix} \mu^x \\ \mu^y \end{bmatrix} + \rho^m \begin{bmatrix} F_{t-1}^m \\ Y_{t-1}^m \end{bmatrix} + \Sigma^m \begin{bmatrix} \varepsilon_t{}^m \\ \varepsilon_t{}^{CS} \end{bmatrix}, \tag{13}$$

$$\begin{bmatrix} \varepsilon_t{}^m \\ \varepsilon_t{}^{CS} \end{bmatrix} \sim N(0, I) \tag{14}$$

where:

- μ^x and μ^y are intercepts,
- ρ^m is the autoregressive matrix,
- Σ^m is the Cholesky decomposition of the covariance matrix, and
- $\varepsilon_t{}^{CS}$ represents the credit shock.

The contribution of the credit shocks to an individual macroeconomic variable $X_t^{m,i}$ can be summarized by:

$$\sum_{\tau=t_1}^{\max(t,t_2)} \Psi_{t-\tau}^{CS,i} \; \varepsilon_\tau^{CS} \tag{15}$$

where $\Psi_j^{CS,i}$ represents the impulse response function to a one unit credit shock (ε_t^{CS}) for a variable i after j periods:

$$\Psi_{t-\tau}^{CS,i} = \frac{\partial X_{t+j}^{m,i}}{\partial \varepsilon_t^{CS}} = b_{x,i} \frac{\partial f_{t+j}^m}{\partial \varepsilon_t^{CS}} + b_{x,i} \frac{\partial y_{t+j}^o}{\partial \varepsilon_t^{CS}} \tag{16}$$

The derivatives on the right-hand side of the equation (16) represent the impulse responses coming from a standard VAR (Wu & Xia, 2016).

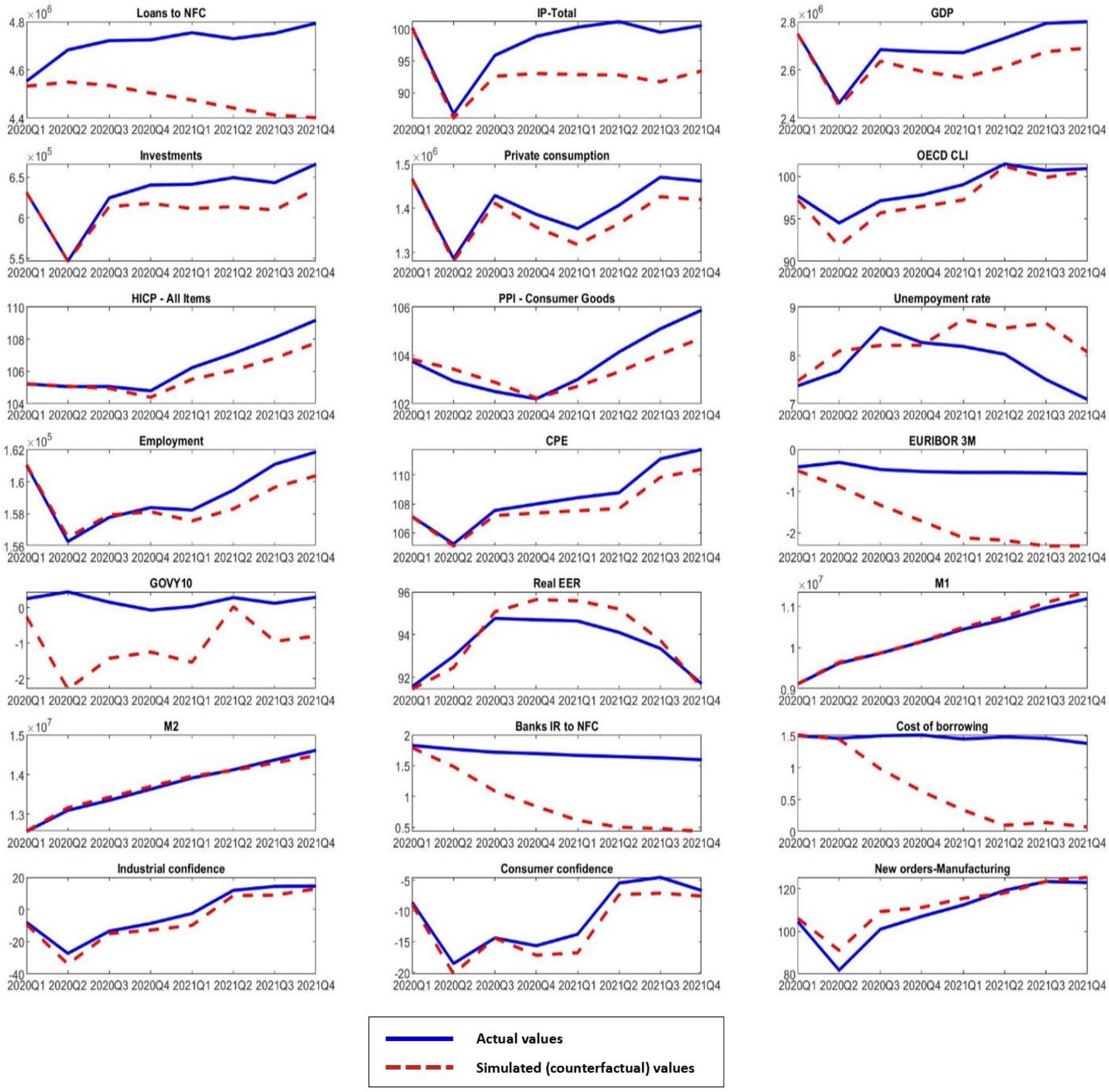
Hence, by setting contributions of the credit shock to zero, I can observe how the real economy would have behaved in artificial conditions where the pandemic policy measures had not been introduced. The observation period for which the contribution of the shock is set to zero covers the time period between 2020Q1 and 2021Q4. This period of 2 years represents the time when the effects of the credit easing measures were the largest, mostly at the beginning of the COVID-19 crisis.

The results of the counterfactual analysis for selected variables are presented in Figure 5. The solid blue line represents the actual values of macroeconomic variables while the dotted red line stands for the realizations that would occur in the absence of the pandemic policy measures (counterfactual paths). The top left figure shows the amount of loans banks would have given to the companies if there had been no interference from the policies. If banks had not been encouraged to increase lending, the amount of loans would have slowly decreased due to the worsened conditions in the financial market caused by the crisis. If banks had not stimulated the economy by lending to those companies that were solvent but were just currently facing liquidity shortages due to the COVID-19 crisis, a much bigger recession would have taken place. The economic activity would have been lower by 4% in relative terms over 2 years, based on the trajectory of the simulated GDP. A similar negative impact would have also been observed for the two GDP components, investments, and private consumption. During the recession in the second quarter of 2020, production took a hard blow as the industrial production index decreased from 100% to 87%. In the artificial world with no policy intervention, the industrial production index would have remained at 93% after two years whereas in reality, the production recovered fairly quickly as it was back at 100 after a good year. Since there would have been a deeper recession it also makes sense that inflation would have been smaller in the case of no credit easing, a 1% relative difference can be observed based on the simulated values. A significant impact can be observed even in the labor market. The unemployment rate would have been higher by 1 percentage point (8.1% instead of 7.1%). Since the economy would have slowed down and taken a hit, interest rates would also have decreased to compensate for the drop in economic output.

The simulated series show persistent and significantly worse economic conditions compared to the actual conditions during the COVID-19 crisis in 2020 and 2021. One can notice that artificial data series show long-lasting negative effects which can also be observed in impulse responses. The artificial data series, which show the economy in an alternative universe where no policy measure was introduced to support bank lending never reaches the level of realized economic conditions. This could be explained by a mechanism called financial accelerator which is also extensively explained in Section 2. Since business and economic conditions worsened due to the COVID-19 shock and containment measures, banks would have decreased their lending since it would have been riskier to borrow as there would have been a higher probability that obligors would have defaulted. If there had been no measures that transferred some of that risk away from the banks, banks would have lent less. Since companies would not have had access to lending, they would have reduced spending, investments, and production which would have had a negative effect on the real activity (GDP and production index). Companies would have slowed down their business activity or would have even gone bankrupt. Thus, they would have started laying off employees, which would have also increased the unemployment rate. All these effects would have just deepened the crisis, which can also be observed in the simulated series as the downward trend keeps persisting.

Increased uncertainty during the time of the crisis would have increased funding costs for banks. If there had been no policy response, the funding costs for banks would have just kept worsening and it would have translated to tighter and tighter lending conditions which would have eventually decreased the lending activity as can be observed in the top figure on the left in Figure 5 where red dotted line shows a negative trend. The policy measures made sure that banks were able to increase lending to match the increased demand for credit coming from corporations and households that were affected by the crisis. Many companies and households were experiencing liquidity problems which made it harder for them to pay their obligations. This led to a significant increase in credit demand which banks were able to accommodate due to pandemic support policy measures. This can be observed by the positive trend in the blue line which shows that the actual lending increased by quite a lot in the following years which had a positive impact on all aspects of the economic activity.

Figure 5: Counterfactual analysis of selected variables to credit shock



Source: Own work.

Research done by Nelimarkka and Laine (2021) evaluated the impact of the ECB's pandemic monetary policy measures on economic activity. Their findings rely on the counterfactual analysis produced by a structural VAR conditional on the simulated interest rates. Their findings suggest that asset purchase programs increased GDP growth by 2 percentage points and inflation by 0.5 percentage points in the crisis period of 2020 and 2021. A similar study was also done by Aguilar, Arce, Hurtado, Martínez-Martín, Nuño, and Thomas (2020) who assessed the impact of PEPP adopted by the ECB during the COVID-19 crisis. Their structural VAR and DSGE simulations show that real GDP in EA would be lower by 1.3% and inflation by 1.3 percentage points. An interesting study done by Valla and Miguet (2022) produced a counterfactual analysis for some major economies, such as France, Spain, Germany, the United Kingdom, and Italy. They produced a simulated GDP series for each country separately, which shows what the GDP would be in the absence of pandemic policy measures. Their results suggest that at the end of 2021, GDP would be lower by more than 10% for all selected countries if no policy actions were taken. Compared to my simulations their findings suggest a much bigger impact of pandemic policy measures but just as well persistent because their simulations never reach the actual GDP but stay persistently below for multiple years. Due to different estimation methodologies and different evaluations of policy stimulus, it is hard to compare the results from the studies described above with my analysis. Still, we can all agree that pandemic policy measures significantly improved the economic conditions during the COVID-19 crisis.

Overall, my simulation shows meaningful results. The main finding of the counterfactual experiment is that policy interventions and credit-easing measures during the COVID-19 crisis achieved their goal of stimulating the economy as otherwise there would have been a much longer recession and COVID-19 would have had a much bigger negative effect on the real economy. Instead, a positive credit shock triggered by the pandemic policy measures contributed significantly to a quick and efficient recovery.

CONCLUSION

The global financial crisis of 2008/09 sparked interest in financial markets and the effects of credit market shocks on economic activity. Several studies tried to evaluate the impact of credit shocks on business cycles and the real economy. On the other hand, the COVID-19 crisis also proposes an interesting phenomenon that would need to be studied more. I try to combine both in my master's thesis by modeling credit shocks to evaluate the impact of pandemic policy measures in the COVID-19 crisis in the euro area. The most important questions that got me thinking were how effective were the policy measures in boosting lending and stimulating the economy during the COVID-19 crisis and what would the impact of the COVID-19 crisis be if there were no policy interventions to limit its negative effects?

The main findings of my thesis can be summarized in the context of the research questions and hypothesis posed in the Introduction:

Q1: How to properly quantify the stimulus (credit shock) provided by the pandemic policy measures in the euro area?

The policymakers reacted to the COVID-19 crisis in a quick and efficient manner by stimulating the economy through monetary, prudential, and fiscal policy measures. Pandemic policy measures can be interpreted in the modeling sense as a positive shock on the credit market. Policy measures that increased the amount of bank loans (credit easing measures) can be perceived as the source of the credit shock. Monetary policy introduced programs, such as APP, PEPP, and operations LTRO, TLTRO III, and PELTRO, which absorbed the COVID-19 shock and helped banks increase lending to firms and households. On the other hand, fiscal policy measures included a program that transferred some of the credit risk and potential losses from banks to governments through public guarantees and stimulated bank lending with it. Even prudential policy measures increased bank lending by relaxing restrictions on the capital conservation buffer, the liquidity coverage ratio, and loan loss classification standards. The best way of quantifying the stimulus is by measuring the amount of bank loans to NFC during the COVID-19 crisis. From the start of 2020 till the end of 2021 when the COVID-19 crisis had significant impacts, bank lending to NFC increased by 7.4%. By measuring the stimulus with the amount of bank loans, I reject my first hypothesis which is the following: "Credit spread which is defined as a difference between a long-term bank lending interest rate and risk-free government bond yield of comparable maturity is a proper measure of quantification of the stimulus provided by the pandemic policy measures in the euro area.*"* I first tried to use this credit spread as proposed in the hypothesis but it did not show much improvement during the crisis, which means it did not capture the stimulus of policy measures accurately.

Q2: How to model credit shocks in the euro area environment properly?

There are many frameworks and different methodologies when it comes to modeling credit shocks. Many economists have used a VAR approach in their studies to capture the effects of credit shocks on the real economy. For modeling on the euro area data, mostly Bayesian VAR was used (example: Peersman (2011), Barauskaitė, Nguyen, Rousová, and Cappiello (2022)) but on the US data, FAVAR framework was used as well. I decided to go with the FAVAR framework. Using a FAVAR model in a data-rich environment I modeled credit shocks and their effects on the real economy in the euro area. A nice feature of a FAVAR model is that it allows you to summarize a broad range of information by a low number of estimated factors. This way no information gets sacrificed and it minimizes the risk of omitted variable bias. Compared to classic VAR, FAVAR uses a lot more information and is thus more reliable and informative. Another benefit of using the FAVAR model is a broad set of variables for which one can produce impulse responses and observe the effects of the shock. This way a model gets validated easier and also shows the effect of the shock on the full range of macro variables which can capture the general concept of economic activity. My FAVAR model included 2 observed variables, EONIA as a proxy for policy rate and loans to NFC for credit conditions, as well as 5 unobserved factors. FAVAR was estimated on 152 data series using 1 lag. I limited the analysis of impulse responses to 22 macro variables which represent all segments of the real economy. Impulse responses show a plausible picture of the economy's response to a positive credit shock. Overall, variables react in a consistent and sensible manner to improved credit conditions. Output and GDP improve significantly and persistently, which pushes prices and overall inflation to increase as well. Conditions in the labor market improve as expected. Increased inflation also pushes the policy rate to increase which represents a tightening of the monetary policy. Overall results of the FAVAR model make sense which points me to believe that a FAVAR model is an appropriate methodology for modeling the impact of credit shocks on the EA economy. With this, I can confirm my second hypothesis ("Factor-Augmented VAR (FAVAR) model is the appropriate methodology for modeling the impact of credit shocks on the euro-area economy.")

Q3: How did the pandemic policy measures focused on boosting credit activity impact the real economy in the euro area during the COVID-19 crisis?

The last research question also led me to the main finding of my master's thesis. To quantify the effect of the pandemic policy measures on economic activity during the COVID-19 crisis, I performed a counterfactual analysis. The stimulus of the policy measures could be viewed as a positive credit shock as policies stimulated bank lending. Therefore, to measure the impact of the pandemic policy measures on the economic activity, I simply set the credit shock to 0. This allows me to observe artificial economic conditions where there is no stimulus coming for the pandemic programs. I observed the real economy through several key macro variables for the period from 2020Q1 to 2021Q4. In the absence of policy intervention during the pandemic, the EA economy would have taken a much larger hit as there would have been a longer recession. The simulated data series show that without the intervention of policies, bank loans to NFC would be lower by 8% after the 2-year COVID-19 period. Without any stimulus coming from the banking sector, GDP would be lower by 4% at the end of 2021 whereas industrial production would be lower by 7% compared to actual numbers. Similar negative effects could also be observed in the labor market where unemployment would increase by 1 percentage point. Overall, in the absence of policy measures during the COVID-19 crisis, the real economy would be hit much harder. This means that the pandemic policy measures which were focused on boosting bank lending and increasing credit activity had a significant positive impact on the real output and economic activity in the euro area during the COVID-19 crisis. Hence, I can confirm my third and last hypothesis.

My analysis of credit shocks in the COVID-19 crisis opens a door for further research. The analysis could be improved and extended by testing many different FAVAR specifications that could be used instead of the selected one. Another identification scheme that could be considered here is to include an inflation index and investments as observable factors as well (similar was done in Boivin, Giannoni, and Stevanović's (2013) study). A different approach could be used to evaluate the effects of pandemic policy measures, such as Bayesian VAR. Moreover, each pandemic policy/program could be evaluated separately to see how big the impact on the credit activity and real economy of each policy measure was separately.

REFERENCE LIST

1. Aguilar, P., Arce, Ó., Hurtado, S., Martínez-Martín, J., Nuño, G., & Thomas, C. (2020). The ECB monetary policy response to the COVID-19 crisis. *Occasional Papers*, Article 2026.
2. Altavilla, C., Barbiero, F., Boucinha, M., & Burlon, L. (2023). The Great Lockdown: Pandemic response policies and bank lending conditions. *European Economic Review*, *156*, 104478.
3. Amato, J. D., & Remolona, E. M. (2003). *The Credit Spread Puzzle*. Retrieved 17. June 2023 from https://www.bsi.si/en/statistics/interest-rates/euro-short-term-rate-eustr
4. Bai, J., & Ng, S. (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica*, *70*(1), 191–221.
5. Balke, N. S. (2000). Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks. *The Review of Economics and Statistics*, *82*(2), 344–349.
6. Bank of Slovenia. (n. d.). *Euro short-term rate (€STR)*. Retrieved 17. September 2023 from https://www.bsi.si/en/statistics/interest-rates/euro-short-term-rate-eustr
7. Barauskaitė, K., Nguyen, A. D. M., Rousová, L., & Cappiello, L. (2022). The impact of credit supply shocks in the euro area: Market-based financing versus loans. *Working Paper Series*, Article 2673.
8. Beck, T., Bruno, B., & Carletti, E. (2021a). *When and how to unwind COVID-support measures to the banking system?* Retrieved 28 May 2023 from https://www.europarl.europa.eu/RegData/etudes/IDAN/2021/659646/IPOL_IDA(2021)659646_EN.pdf
9. Beck, T., Bruno, B., & Carletti, E. (2021b). *Unwinding COVID support measures for banks.* Retrieved 20 May 2023 from https://cepr.org/voxeu/columns/unwinding-covid-support-measures-banks
10. Bernanke, B. (2007). *The financial accelerator and the credit channel*. Retrieved 20 July 2023 from https://www.federalreserve.gov/newsevents/speech/bernanke20070615a.htm
11. Bernanke, B. S., & Boivin, J. (2003). Monetary policy in a data-rich environment. *Journal of Monetary Economics*, *50*(3), 525–546.
12. Bernanke, B. S., & Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *The Journal of Economic Perspectives*, *9*(4), 27–48.
13. Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach*. *The Quarterly Journal of Economics*, *120*(1), 387–422.
14. Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). Chapter 21 The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics. 1*, 1341–1393.
15. Bernanke, B., & Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *The American Economic Review*, *79*(1), 14–31.

16. Boivin, J., Giannoni, M., & Stevanović, D. (2013). Dynamic Effects of Credit Shocks in a Data-Rich Environment. *CEPR Discussion Papers, 2013,* Article 9470.
17. Brault, J., & Signore, S. (2020). Credit Guarantees in the COVID-19 crisis – Relevance and Economic Impact, *SUERF Policy Note*, *2020*(No 176).
18. Bruno, B., & De Marco, F. (2021). *European Banks' Response to COVID-19 "Quick Fix" Regulation and Other Measures.* Retrieved March 21, 2023, from https://www.europarl.europa.eu/RegData/etudes/STUD/2021/695460/IPOL_STU(2021)695460_EN.pdf
19. Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The Determinants of Credit Spread Changes. *The Journal of Finance*, *56*(6), 2177–2207.
20. Duca, J. V. (1999). What credit market indicators tell us. *Economic and Financial Policy Review*, *Q III*, 2–13.
21. Emery, K. M. (1996). The information content of the paper-bill spread. *Journal of Economics and Business*, *48*(1), 1–10.
22. Enders, W. (2014). Applied Econometric Time Series. (4th ed.). New York: John Wiley.
23. European Commission (2021a). *Recovery and Resilience Facility*. Retrieved 23 May 2023 from https://commission.europa.eu/business-economy-euro/economic-recovery/recovery-and-resilience-facility_en
24. European Commission (2021b). *Recovery plan for Europe*. Retrieved 27 July 2022 from https://commission.europa.eu/strategy-and-policy/recovery-plan-europe_en
25. European Commission (2023). *SURE*. Retrieved 11 October 2022 from https://economy-finance.ec.europa.eu/eu-financial-assistance/sure_en
26. European Systemic Risk Board. (2021). *Financial stability implications of support measures to protect the real economy from the COVID-19 pandemic.* Retrieved 28 May 2021 from https://www.esrb.europa.eu/pub/pdf/reports/esrb.reports210216_FSI_COVID19~cf3d32ae66.en.pdf
27. *Eurostat*. (n.d.). *Real GDP growth rate – volume,* Retrieved 19 March 2023 from https://ec.europa.eu/eurostat/databrowser/view/tec00115/default/table?lang=en
28. Ewing, B. T., Lynch, G. J., & Payne, J. E. (2003). The paper-bill spread and real output: What matters more, a change in the paper rate or a change in the bill rate? *Review of Financial Economics, 12*(3), 233–246.
29. Falagiarda, M., Prapiestis, A., & Rancoita, E. (2020). *Public loan guarantees and bank lending in the COVID-19 period*. Retrieved May 28, 2021, from https://www.ecb.europa.eu/pub/economic-bulletin/focus/2020/html/ecb.ebbox202006_07~5a3b3d1f8f.en.html
30. Fisher, I. (1933). The Debt-Deflation Theory of Great Depressions. *Econometrica*, *1*(4), 337–357.
31. Friedman, B. M., & Kuttner, K. N. (1998). Indicator Properties of the Paper-Bill Spread: Lessons from Recent Experience. *The Review of Economics and Statistics*, *80*(1), 34–44.

32. Gertler, M., & Lown, C. S. (1999). The Information in the High-Yield Bond Spread for the Business Cycle: Evidence and Some Implications. *Oxford Review of Economic Policy*, *15*(3), 132–150.
33. Gilchrist, S., & Zakrajsek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, *102*(4), 1692–1720.
34. Gilchrist, S., Yankov, V., & Zakrajšek, E. (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of Monetary Economics*, *56*(4), 471–493.
35. Gopinath, G. (2020). *The Great Lockdown: Worst Economic Downturn Since the Great Depression*. IMF. Retrieved 4 January 2023 from https://www.imf.org/en/Blogs/Articles/2020/04/14/blog-weo-the-great-lockdown-worst-economic-downturn-since-the-great-depression
36. Greenstone, M., Mas, A., & Nguyen, H.-L. (2014). Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times. *NBER Working Papers*, Article 20704.
37. Hall, R. E. (2011). The High Sensitivity of Economic Activity to Financial Frictions. *The Economic Journal*, *121*(552), 351–378.
38. Helbling, T., Huidrom, R., Kose, M. A., & Otrok, C. (2011). Do credit shocks matter? A global perspective. *European Economic Review*, *55*(3), 340–353.
39. Kanngiesser, D., Martin, R., Maurin, L., & Moccero, D. (2017). Estimating the impact of shocks to bank capital in the euro area. *Working Paper Series*, Article 2077.
40. Kiyotaki, N., & Moore, J. (1997). Credit Cycles. *Journal of Political Economy*, *105*(2), 211–248.
41. Kiyotaki, N., & Moore, J. (2019). Liquidity, Business Cycles, and Monetary Policy. *Journal of Political Economy*, *127*(6), 2926–2966.
42. Lengwiler, Y. (2023). *X-13 Toolbox for Seasonal Filtering*. Retrieved 23 May 2023 from https://uk.mathworks.com/matlabcentral/fileexchange/49120-x-13-toolbox-for-seasonal-filtering
43. McCracken, M. W., & Ng, S. (2016). FRED-MD: A Monthly Database for Macroeconomic Research. *Journal of Business & Economic Statistics*, *34*(4), 574–589.
44. Meeks, R. (2009). Credit market shocks: Evidence from corporate spreads and defaults. *Working Papers*, Article 0906.
45. Mody, A., & Taylor, M. P. (2004). Financial predictors of real activity and the financial accelerator. *Economics Letters*, *82*(2), 167–172.
46. Mueller, P. (2009). *Credit Spreads and Real Activity*. Retrieved 17 June 2023 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1105728
47. Nelimarkka, J., & Laine, O.-M. (2021). The effects of the ECB's pandemic-related monetary policy measures. *BoF Economics Review*, Article 4/2021.
48. Peersman, G. (2011). Bank Lending Shocks and the Euro Area Business Cycle. *Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium*, Article 11/766.

49. Philippon, T. (2009). The Bond Market's q. *The Quarterly Journal of Economics*, *124*(3), 1011–1056.
50. Rakic, D. (2021). *The ECB's Monetary Policy Response to the COVID-19 Crisis*. Retrieved 27 April 2022 from https://www.europarl.europa.eu/thinktank/en/document/IPOL_BRI(2020)648787
51. Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374.
52. Stiglitz, J. E. (1975). The Theory of „Screening," Education, and the Distribution of Income. *The American Economic Review*, *65*(3), 283–300.
53. Stock, J. H., & Watson, M. W. (2002). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business & Economic Statistics*, *20*(2), 147–162.
54. Stock, J. H., & Watson, M. W. (2005). Implications of Dynamic Factor Models for VAR Analysis. *NBER Working Papers*, Article 11467.
55. Stock, J., & Watson, M. (1989). New Indexes of Coincident and Leading Economic Indicators. *National Bureau of Economic Research, Volume 4,* 351-409.
56. SURS (2019). *Seasonal adjustment of time series*. Retrieved 15 June 2023 from https://www.stat.si/dokument/5301/SeasonalAdjustmentOfTimeSeries_MEgeneral.pdf
57. Valla, N., & Miguet, F. (2022). *How have major economies responded to the COVID-19 pandemic?* Retrieved 28 June 2023 from https://www.europarl.europa.eu/RegData/etudes/STUD/2022/699531/IPOL_STU(2022)699531_EN.pdf
58. World Bank (n. d.). *GDP growth (annual %)*. Retrieved 17 April 2023 from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG
59. Wu, J. C., & Xia, F. D. (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking*, *48*(2–3), 253–291.

APPENDICES

Appendix 1: Povzetek v slovenskem jeziku (Summary in Slovene language)

VPLIV UKREPOV EKONOMSKE POLITIKE NA KREDITNO AKTIVNOST IN REALNO GOSPODARSTVO EVRO OBMOČJA V COVID-19 KRIZI

Leto 2020 si bomo za vedno zapomnili kot leto izbruha koronavirusa. Bolezen, znana pod imenom COVID-19, se je razširila po celem svetu, razglašena je bila pandemija in velika večina držav je uvedla različne oblike karantene ali druge zajezitvene ukrepe, ki so povzročili težave v številnih podjetjih. Zajezitev virusa s karantenami je omogočila zdravstvu, da se je spopadlo z boleznijo, saj je manj ljudi potrebovalo bolnišnično oskrbo, kar je postopoma omogočilo nadaljevanje gospodarske dejavnosti. Izvajanje karanten in socialnega distanciranja, ki sta bila potrebna za zajezitev virusa, je svetovno gospodarstvo pahnilo v hudo recesijo. Padec proizvodnje je bil večji kot kadarkoli prej. Korona kriza je prizadela številna področja, kot so zdravstvo, finančno premoženje, cene surovin in pravzaprav večino gospodarstva.

Zajezitveni ukrepi, uvedeni po celem svetu, so močno vplivali tudi na regijske in globalne vrednostne verige. To je razvidno iz močnega padca gospodarske aktivnosti v letu 2020. Stopnja rasti svetovnega BDP se je zmanjšala za 5,7 % glede na leto 2019 (Svetovna banka, b.d.), medtem ko se je stopnja rasti BDP v euro območju znižala za 7,7 % v primerjavi z letom 2019 (Eurostat, b.d.). Zaradi motenega poslovanja so imela podjetja težave pridobivati denarne tokove in prihodke, kar je povzročilo likvidnostne težave, saj niso bila sposobna poravnati svojih obveznosti do zaposlenih, dobaviteljev in upnikov. Na drugi strani je povečana negotovost in nenaklonjenost tveganju na finančnih trgih povečala stroške financiranja bank. Če ne bi bilo protiukrepov in političnega odziva, bi se razmere na trgu le še poslabšale kar bi pomenilo zaostritev posojilnih pogojev, ki bi sčasoma zmanjšali kreditno aktivnost. Številnim podjetjem so močno upadli prihodki, zaradi česar so težje odplačevala svoje obveznosti. To je privedlo do občutnega povečanja povpraševanja po kreditih, ki so ga banke zaradi ukrepov v času pandemije uspele zadostiti. Povečano povpraševanje po kreditih bi običajno povečalo stroške zadolževanja, vendar se zaradi uvedenih podpornih ukrepov posojilne obrestne mere za podjetja niso zvišale, saj so ukrepi preprečili zaostrovanje pogojev zadolževanja.

Države so z ukrepi zagotovile podporo gospodinjstvom, podjetjem, finančnim trgom in vsem drugim področjem, ki so trpela zaradi izbruha virusa. Snovalci politik so morali zagotoviti, da bodo ljudje lahko zadovoljili svoje potrebe in da bodo podjetja lahko nadaljevala s poslovanjem, ko bo pandemije enkrat konec. Spomladi 2020 je bila sprejeta široka paleta ukrepov in programov monetarne, fiskalne in regulativne podpore, da bi preprečili dolgoročne posledice pandemije na realno gospodarstvo. Fiskalna in denarna politika sta uvedli obsežne, ciljno usmerjene ukrepe, ki so vključevali kreditne garancije, prestrukturiranje posojil, davčne olajšave, povečane ugodnosti, povečanje likvidnostnih zmogljivosti, ki so v teh težkih časih ohranili številna gospodinjstva in podjetja operativna. Denarna politika je uvedla programa nakupa vrednostnih papirjev APP in PEPP, ki sta pomagala ublažiti šok, medtem ko so dolgoročne likvidnostne injekcije v bančni sistem prek operacij dolgoročnejšega refinanciranja, kot so LTRO, TLTRO III in PELTRO, podprle banke in stimulirale posojila. ECB je spodbujala bančno posojanje tudi tako, da je bankam dovolila, da začasno poslujejo pod ravnjo kapitala, ki jo določajo regulacije za kapitalske rezerve in pod nivojem likvidnostnega kritja. Na drugi strani je fiskalna spodbuda prišla v obliki javnega jamstva, ki je del tveganja neplačila prenesla z bank na državo. Vsi protikoronski ukrepi skupaj so spodbudili bančno kreditiranje in tako delovali kot pozitiven ponudbeni kreditni šok na gospodarstvo med pandemijo. Zaradi sprejetih ukrepov so banke uspele zadovoljiti povečano povpraševanje po kreditih s strani podjetij in gospodinjstev, ki jih je kriza prizadela.

Vpliv zaostrovanja kreditnih pogojev na gospodarsko aktivnost je pereče vprašanje že od prejšnje finančne krize leta 2008/09, ko so motnje na kreditnem trgu povzročile hudo gospodarsko krizo. Ekonomisti so želeli dokazati povezavo med finančnimi trgi in poslovnimi cikli ter na drugi strani razumeti mehanizem prenosa kreditnih šokov na realno gospodarstvo. Obstajajo številne študije, ki so ocenjevale učinke kreditnih šokov na realno gospodarstvo. Moje magistrsko delo sledi podobnemu miselnemu okviru, saj želim oceniti učinke kreditnih šokov na gospodarsko aktivnost med COVID-19 krizo v evro območju. V nasprotju z večino študij poskušam ovrednotiti učinke pozitivnih kreditnih šokov v obliki povečane ponudbe posojil na gospodarsko aktivnost. Torej, če povzamem, želim preveriti kakšen je odziv gospodarstva na povečano posojilno aktivnost bank. Med korona krizo so bili uvedeni številni ukrepi, katerih cilj je bil povečati bančno kreditiranje in zagotoviti dostop do kapitala gospodinjstvom in podjetjem, ki so se soočala z likvidnostnimi primanjkljaji. Ukrepe ekonomskih politik, ki so spodbudili bančno posojanje med korona krizo, je mogoče razlagati tudi kot pozitiven kreditni šok, katerega učinke na realno gospodarstvo sem poskušala ovrednotiti.

Glavna ideja mojega magistrskega dela je oceniti, kako so protikoronski ukrepi v pandemiji vplivali na kreditno in gospodarsko aktivnost v evro območju. Moja metodologija temelji na FAVAR pristopu, ki se je izkazal kot uspešen način ocenjevanja učinkov strukturnih šokov na različne ekonomske in finančne kazalnike. V moji analizi so bili ukrepi kreditnega sproščanja, uvedeni kot obramba proti negativnim učinkom korona krize, interpretirani kot pozitiven šok na strani ponudbe kreditov. Učinki tega šoka na ključne gospodarske in finančne kazalnike pa so bili opazovani v obliki analize funkcij impulznih odzivov. V nadaljnji analizi sem ocenila tudi, kakšen bi bil upad gospodarstva , če ukrepi ne bi bili sprejeti. To je bilo narejeno s simulacijo hipotetičnih gospodarskih pogojev, ki bi se zgodili v primeru, da ukrepov v času pandemije ne bi bilo. To mi omogoča, da kvantitativno ocenim učinke protikoronskih ukrepov na različne vidike gospodarske dejavnosti, hkrati pa ocenim, kakšne bi bile posledice korona krize, če države in snovalci politik ne bi ustrezno ukrepali.

Glavne ugotovitve mojega magistrskega dela lahko povzamem v kontekstu raziskovalnih vprašanj in hipotez:

V1: Kako pravilno količinsko opredeliti kreditno spodbudo (kreditni šok), ki so jo zagotovili protikoronski ukrepi v času pandemije v evroobmočju?

Snovalci ukrepov so se na COVID krizo odzvali hitro in učinkovito s spodbujanjem gospodarstva z ukrepi denarne, bonitetne in fiskalne politike. Ukrepe si lahko v okviru modeliranja razlagamo kot pozitiven šok na kreditnem trgu. Kot vir kreditnega šoka lahko vidimo ukrepe, ki so povečali obseg bančnih posojil (ukrepi kreditnega sproščanja). Denarna politika je uvedla programe, kot so APP, PEPP in operacije LTRO, TLTRO III in PELTRO, ki so ublažili COVID-19 šok in pomagali bankam povečati obseg posojil podjetjem in gospodinjstvom. Ukrepi fiskalne politike pa so vključevali javne garancije, katere so prenesle del kreditnega tveganja in potencialne izgube z bank na države in s tem spodbudile bančno kreditiranje. Tudi ukrepi bonitetne politike so povečali bančno posojanje z omilitvijo omejitev kapitalnih rezerv, likvidnostnega kritja in standardov za klasifikacijo izgub pri posojilih. Najboljši način, kako oceniti količino kreditnega stimulusa z naslova ukrepov, je merjenje višine bančnih posojil nefinančnim podjetjem v času korona krize. Od začetka leta 2020 do konca leta 2021, ko je bil vpliv korona krize največji, se je bančno posojanje nefinančnim podjetjem povečalo za 7,4 %. S tem zavračam svojo prvo hipotezo, ki je naslednja: »Kreditni razmik, ki je opredeljen kot razlika med bančno dolgoročno posojilno obrestno mero in donosom netvegane državne obveznice primerljive zapadlosti, je ustrezno merilo kreditne spodbude, ki so jo zagotovili protikoronski ukrepi v evroobmočju v času korona krize.« Najprej sem poskušala uporabiti ta kreditni razmik, kot je predlagano v hipotezi, vendar se med krizo ni veliko izboljšal, kar pomeni, da ni natančno zajel kreditne spodbude s strani protikoronskih ukrepov.

V2: Kako pravilno modelirati kreditne šoke v evro območju?

Obstaja veliko pristopov in različnih metodologij, ko gre za modeliranje kreditnih šokov. Mnogi ekonomisti so v svojih študijah uporabili VAR pristop, da bi zajeli učinke kreditnih šokov na realno gospodarstvo. Za modeliranje na podatkih evroobmočja je bil večinoma uporabljen Bayesianski VAR (Primer: (Peersman (2011); Barauskaitė, Nguyen, Rousová in Cappiello (2022)), na ameriških podatkih pa sem zasledila tudi uporabo FAVAR pristopa. Odločila sem se za uporabo FAVAR pristopa. Z uporabo FAVAR modela v okolju, bogatem s podatki, sem modelirala kreditne šoke in njihove učinke na realno gospodarstvo v evroobmočju. Lepa značilnost FAVAR modela je, da omogoča, da se širok nabor informacij povzame z relativno malo faktorji. Na ta način nobena informacija ni žrtvovana in tako se zmanjša tveganje pristranskosti opuščene spremenljivke. V primerjavi s klasičnim VAR FAVAR uporablja veliko več informacij, zato je bolj zanesljiv in informativen. Druga prednost uporabe FAVAR modela je širok nabor spremenljivk, za katere je mogoče ustvariti impulzne odzive in opazovati učinke šoka. Na ta način se model lažje validira in prikaže učinek šoka na celoten obseg makro spremenljivk, ki lahko zajamejo splošni koncept gospodarske aktivnosti. Moj FAVAR model vključuje 2 opazovani spremenljivki, EONIA kot približek obrestne mere in posojila nefinančnim podjetjem za opis kreditnih pogojev, ter 5 neopazovanih ocenjenih faktorjev. FAVAR je bil ocenjen na 152 serijah podatkov z uporabo 1 zamika podatkov. Analizo impulznih odzivov sem omejila na 22 makro spremenljivk, ki predstavljajo vse segmente realnega gospodarstva. Impulzni odzivi prikazujejo verodostojno sliko odziva gospodarstva na pozitiven kreditni šok. Spremenljivke se dosledno in logično odzivajo na izboljšane kreditne pogoje. Proizvodnja in BDP se povečata, zaradi česar se cene in splošna inflacija prav tako dvignejo. Razmere na trgu dela se pričakovano izboljšajo. Povečana inflacija prav tako spodbudi obrestno mero k zvišanju, kar predstavlja zaostrovanje denarne politike. Na splošno lahko rečem, da so rezultati FAVAR modela smiselni, kar me vodi k prepričanju, da je FAVAR model ustrezen pristop za modeliranje vpliva kreditnih šokov na gospodarstvo v evroobmočju. S tem lahko potrdim svojo drugo hipotezo ("FAVAR model je ustrezen pristop za modeliranje vpliva kreditnih šokov na gospodarstvo v euro območju.")

V3: Kako so ukrepi, osredotočeni na spodbujanje kreditne aktivnosti, vplivali na realno gospodarstvo v evroobmočju v času pandemije?

Zadnje raziskovalno vprašanje me je pripeljalo tudi do glavne ugotovitve mojega magistrskega dela. Za oceno vpliva ukrepov na gospodarsko aktivnost v času korona krize sem izvedla protidejstveno analizo. Ukrepe lahko interpretiramo kot pozitiven kreditni šok, saj so ukrepi spodbudili bančna posojila. Zato sem za merjenje učinka ukrepov preprosto nastavila kreditni šok na 0. To mi omogoča opazovanje umetnih gospodarskih pogojev, v katerih do spodbud v obliki pandemičnih programov ni prišlo. Realno gospodarstvo sem opazovala skozi več ključnih makro spremenljivk v obdobju od 2020Q1 do 2021Q4. Če med pandemijo ne bi bilo posredovanja ekonomskih politik, bi evropsko gospodarstvo utrpelo veliko večji udarec, saj bi prišlo do daljše recesije. Simulirane podatkovne serije kažejo, da bi bila brez posredovanja politik bančna posojila nefinančnim podjetjem po 2-letnem obdobju korona krize nižja za 8 %. Brez spodbud iz bančnega sektorja bi bil BDP ob koncu leta 2021 nižji za 4 %, industrijska proizvodnja pa za 7 % v primerjavi z dejanskimi podatki. Podobne negativne učinke bi lahko opazili tudi na trgu dela, kjer bi se brezposelnost povečala za 1 odstotno točko. Na splošno lahko rečem, da bi bilo brez ukrepov ekonomskih politik med COVID-19 krizo realno gospodarstvo veliko bolj prizadeto. To pomeni, da so ukrepi v času pandemije, ki so bili usmerjeni v spodbujanje bančnega kreditiranja in povečanje kreditne aktivnosti, pomembno pozitivno vplivali na realno proizvodnjo in gospodarsko aktivnost v evro območju v času korona krize. Tako lahko potrdim svojo tretjo in zadnjo hipotezo ("Ukrepi ekonomskih politik, osredotočeni na spodbujanje bančnega kreditiranja in povečanje kreditne aktivnosti, so med korona krizo pomembno pozitivno vplivali na realno gospodarstvo v euro območju.")

Appendix 2: Variable list and transformations

Variable	Frequency	Transformation	Source
Real output and income			
Industrial production – Total*	Monthly	Δln	ECB SDW
Industrial production - Consumer goods*	Monthly	Δln	Eurostat
Industrial production - Construction*	Monthly	Δln	Eurostat
Industrial production - Manufacturing*	Monthly	Δln	Eurostat
Industrial production - Capital goods*	Monthly	Δln	Eurostat
Industrial production - Durable consumer goods*	Monthly	Δln	Eurostat
Industrial production - Intermediate goods*	Monthly	Δln	Eurostat
Industrial production - Non-durable consumer goods*	Monthly	Δln	Eurostat
Industrial production - Energy *	Monthly	Δln	Eurostat
GDP total (million EUR) *	Quarterly	Δln	Eurostat
Investments - Gross fixed capital formation*	Quarterly	Δln	Eurostat
Government final consumption*	Quarterly	Δln	Eurostat
Private final consumption*	Quarterly	Δln	Eurostat
OECD Composite leading indicator*	Monthly	None	OECD
Prices			
HICP - All items*	Monthly	Δln	Eurostat
HICP - Health*	Monthly	Δln	Eurostat
HICP - Transport*	Monthly	Δln	Eurostat
HICP - Unprocessed food*	Monthly	Δln	Eurostat
HICP - Processed food including alcohol and tobacco*	Monthly	Δln	Eurostat
HICP - Goods*	Monthly	Δln	Eurostat
HICP - Non-energy industrial goods*	Monthly	Δln	Eurostat
HICP - Energy*	Monthly	Δln	Eurostat
HICP - Services*	Monthly	Δln	Eurostat
HICP - Overall index (excluding energy food alcohol and tobacco) *	Monthly	Δln	Eurostat
HICP - All-items - CT*	Monthly	Δln	Eurostat
HICP - Health -CT*	Monthly	Δln	Eurostat
HICP - Transport -CT*	Monthly	Δln	Eurostat
HICP - Unprocessed food - CT*	Monthly	Δln	Eurostat
HICP - Processed food including alcohol and tobacco -CT*	Monthly	Δln	Eurostat
HICP - Goods -CT*	Monthly	Δln	Eurostat
HICP - Non-energy industrial goods - CT*	Monthly	Δln	Eurostat
HICP - Energy - CT*	Monthly	Δln	Eurostat
HICP - Services - CT*	Monthly	Δln	Eurostat
HICP - Overall index (excluding energy food alcohol and tobacco) - CT*	Monthly	Δln	Eurostat

Variable	Frequency	Transformation	Source
PPI - Industry*	Monthly	Δln	Eurostat
PPI - consumer goods*	Monthly	Δln	Eurostat
PPI - energy*	Monthly	Δln	Eurostat
CPI- total non-energy*	Monthly	Δln	ECB SDW
CPI- oil*	Monthly	Δln	ECB SDW
Brent Crude Oil Prices*	Monthly	Δln	Investing
BFOE Crude Oil Spot Price*	Monthly	Δln	ECB SDW
IPPI - domestic*	Monthly	Δln	Eurostat
IPPI - nondomestic*	Monthly	Δln	Eurostat
Residential property price index*	Quarterly	Δln	ECB SDW
House price index*	Quarterly	Δln	Eurostat
Commercial property price index*	Quarterly	Δln	ECB SDW
Price deflator GDP*	Quarterly	Δln	Eurostat
Price deflator final consumption*	Quarterly	Δln	Eurostat
Price deflator Gross fixed capital formation*	Quarterly	Δln	Eurostat
Price deflator Exports*	Quarterly	Δln	Eurostat
Price deflator Imports*	Quarterly	Δln	Eurostat
Labor market			
Unemployment rate*	Monthly	None	ECB SDW
Employment - Total*	Quarterly	Δln	ECB SDW
Employment - Industry*	Quarterly	Δln	ECB SDW
Employment - Construction*	Quarterly	Δln	ECB SDW
Employment - Wholesale*	Quarterly	Δln	ECB SDW
Employment - Public*	Quarterly	Δln	ECB SDW
Labor productivity - Total*	Quarterly	Δln	ECB SDW
Labor productivity - Industry*	Quarterly	Δln	ECB SDW
Labor productivity - Construction*	Quarterly	Δln	ECB SDW
Labor productivity - Wholesale*	Quarterly	Δln	ECB SDW
Labor productivity - Public*	Quarterly	Δln	ECB SDW
Unit labor cost - Total*	Quarterly	Δln	ECB SDW
Unit labor cost - Industry*	Quarterly	Δln	ECB SDW
Unit labor cost - Construction*	Quarterly	Δln	ECB SDW
Unit labor cost - Wholesale*	Quarterly	Δln	ECB SDW
Unit labor cost - Public*	Quarterly	Δln	ECB SDW
Compensation per employee - Total*	Quarterly	Δln	ECB SDW
Compensation per employee - Industry*	Quarterly	Δln	ECB SDW
Compensation per employee - Construction*	Quarterly	Δln	ECB SDW
Compensation per employee - Wholesale*	Quarterly	Δln	ECB SDW
Compensation per employee - Public*	Quarterly	Δln	ECB SDW

Variable	Frequency	Transformation	Source
Interest rates			
ECB - Deposit facility	Monthly	None	ECB SDW
ECB - Marginal lending facility	Monthly	None	ECB SDW
Euribor 1-Month	Monthly	None	ECB SDW
Euribor 3-Months	Monthly	None	ECB SDW
Euribor 6-Months	Monthly	None	ECB SDW
Euribor 1-Year	Monthly	None	ECB SDW
Shadow short rate	Monthly	None	Wu and Xia database
EA government bond yield curve spot (2- to 30-years)	Monthly	None	Eurostat
EA government benchmark bond yield 10-year	Monthly	None	ECB SDW
EONIA	Monthly	None	ECB SDW
€STR	Daily	None	ECB SDW
Foreign market			
GDP UK*	Quarterly	$\Delta\ln$	Eurostat
GDP US*	Quarterly	$\Delta\ln$	Eurostat
HICP UK*	Monthly	$\Delta\ln$	Eurostat
HICP US*	Monthly	$\Delta\ln$	Eurostat
Exchange rates			
GBP/EUR	Monthly	$\Delta\ln$	Eurostat
CHF/EUR	Monthly	$\Delta\ln$	Eurostat
USD/EUR	Monthly	$\Delta\ln$	Eurostat
Real Effective Exchange rate	Monthly	$\Delta\ln$	ECB SDW
Stock market			
Dow Jones Euro STOXX 50	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Industrials	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Technology	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Oil and gas	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Consumer goods	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Healthcare	Monthly	$\Delta\ln$	ECB SDW
Dow Jones Euro STOXX Financials	Monthly	$\Delta\ln$	ECB SDW
VIX Volatility Index	Monthly	None	Yahoo Finance
DE DAX	Monthly	$\Delta\ln$	Yahoo Finance
Money aggregates			
M1	Monthly	$\Delta\ln$	ECB SDW
M2	Monthly	$\Delta\ln$	ECB SDW
M3	Monthly	$\Delta\ln$	ECB SDW
Banking sector			
Loans - NFC - Total maturity	Monthly	$\Delta\ln$	ECB SDW

Variable	Frequency	Transformation	Source
Loans - NFC - Up to 1Y maturity	Monthly	Δln	ECB SDW
Loans - NFC - 1Y to 5Y maturity	Monthly	Δln	ECB SDW
Loans - NFC - Over 5Y maturity	Monthly	Δln	ECB SDW
Bank int rate - Corporations - Total maturity	Monthly	None	ECB SDW
Bank int rate - Corporations - Up to 1Y maturity	Monthly	None	ECB SDW
Bank int rate - Corporations - 1Y to 5Y maturity	Monthly	None	ECB SDW
Bank int rate - Corporations - Over 5Y maturity	Monthly	None	ECB SDW
Bank int rate - Corporations - Total - IFR over 10 years	Monthly	None	ECB SDW
Deposits from Corporations	Monthly	Δln	ECB SDW
Deposits from Households	Monthly	Δln	ECB SDW
Cost of borrowing	Monthly	None	ECB SDW
Survey data			
Economic Sentiment Indicator	Monthly	None	ECB SDW
Industrial confidence indicator	Monthly	None	ECB SDW
Consumer confidence indicator	Monthly	None	ECB SDW
Real inventories and orders			
New orders - Manufacturing	Monthly	None	Eurostat
New orders - Capital goods	Monthly	None	Eurostat
New orders - Consumer goods	Monthly	None	Eurostat
Balance of payments			
Exports of goods and services*	Quarterly	Δln	Eurostat
Imports of goods and services*	Quarterly	Δln	Eurostat
Exports of goods*	Quarterly	Δln	Eurostat
Exports of services*	Quarterly	Δln	Eurostat
Imports of goods*	Quarterly	Δln	Eurostat
Imports of services*	Quarterly	Δln	Eurostat

Source: Own work.

Appendix 2 presents the whole data items list that was used in FAVAR model estimation. For each data series a source and frequency is reported as well as the stationarity transformation. An asterisk, '*', next to the variable denotes a slow-moving variable in the estimation.