UNIVERSITY OF COPENHAGEN
FACULTY OF SOCIAL SCIENCES

Bachelor Thesis

Monetary policy during Covid-19

A SVAR analysis with an event study

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Submitted: November 24, 2022

Approximate character count with spaces: 56000

Abstract

This paper examines the effects of an expansionary shock to the European Central Bank's balance sheet before and during the Covid-19 pandemic starting March 2020. When the ECB buys assets, their balance sheet will increase, which is known as unconventional monetary policy or quantitative easing. We model the effects from the ECB purchasing assets by structural vector autoregressive models with an exogenous variable. We follow the empirical approaches of Uhlig (2005) and Boeckx et al. (2017) to study the effects by imposing sign restrictions on some of the impulse responses. We find quantitative easing from the ECB reduced stress in the financial markets at the cost of inflation. Furthermore, we estimate no statistical significant effect on GDP from asset purchasing. Our analysis imply that the ECB can stabilize the financial markets through policy even during extraordinary events.

Purchasing assets such as bonds increase the price and decrease the yields of the bonds. As agents are considered forward looking, there will also be an effect from the ECB's quantitative easing announcements before the bonds are actually purchased. Therefore, we make an event study to examine the effects of quantitative easing on daily government bond yields in the euro area. We find a positive impact on bond yields from quantitative easing announcements like Jensen et al. (2017) but contrary to Krishnamurthy and Vissing-Jorgensen (2011). Our results could be explained by the ECB's announcements being of smaller scale than expected by the markets, which could result in higher yields on the bonds

Contributions:

- **Both:** Abstract, 1. Introduction, 7. Conclusion
- **Carl Buan:** 2.1, 3.1, 3.3, 5.1, 6
- **Peter Ravn:** 2.2, 3.2, 4, 5.2, 5.3, 6.1

Contents

1 Introduction

The Covid-19 pandemic crashed the economy and the financial markets in the spring of 2020. Many central banks introduced policies to help and secure financial institutions at risk from Covid-19. One of the goals of the European Central Bank (ECB) is to secure the European banking system. Therefore, we wish to ask the question: How did the ECB respond to the pandemic and what effect did it have on the euro area?
Central banks have previously preferred to change the interest rate in times of need, which is defined as conventional monetary policy. Generally, as the deposit rate has been close to or below zero in recent times, it has been difficult to lower the deposit rate even further. Instead, a new monetary policy tool has widely been used called quantitative easing (QE). The idea behind QE is for central banks to buy longer term bonds, which raises the price of the bond, and lowers the interest rates.
This paper aims to assess the impact of the ECB's monetary policy during the Covid-19 crisis on key macroeconomic variables in the euro area. Of interest is the effect on GDP, inflation (HICP), and financial stress denoted by the Composite Indicator of Systemic Stress (CISS). We also consider the main refinancing operations (MRO) as the ECB's policy rate, and the spread between the Euro OverNight Index Average (EONIA) and MRO, which describes the excess of liquidity in the markets. These variables describe the effects of the ECB's response to the Covid-19 pandemic. To combat the crisis, the ECB launched the pandemic emergency purchase programme[1]. A total of €1,850 billion was marked for purchasing private and public sector securities to stabilize the economies of the euro area. For comparison, the ECB's total amount of assets at the beginning of March 2020 was approximately €4,660 billions.

We proceed with a Structural Vector Autoregressive (SVAR) model, as Bernanke and Blinder (1992) and Peersman and Smets (2001) show that SVAR models can assess the effects from monetary policy. We estimate the effects from asset purchasing by the ECB from 2015 to 2021 and find a negative effect on GDP. The result is counter intuitive, so we are cautious about the impulse response functions of our SVAR analysis. This result can be caused by one of two things: Either our model is identified correctly and thus QE decreases GDP. Or, our model is not identified correctly, which could be caused by a wrong causal ordering, or no recursive causal ordering at all. Since we cannot be certain what is correct, we instead identify our model by following the sign restriction approaches of Uhlig (2005) and Boeckx et al. (2017). The idea behind sign restrictions is to mimic a shock to the economy,

[1]Reference: ECB (2022d)

where we only accept impulse response functions that have a correct sign. I.e., if we impose weakly negative sign restrictions on CISS we only consider impulse responses, which are negative or zero. Per Uhlig (2017), we should only apply restrictions on the impulse responses that we are certain of would happen following a shock. We construct these signs from previous results and studies in econometrics to mimic a QE shock.

Boeckx et al. (2017) show that QE from the ECB increased inflation and GDP, while decreasing financial stress during the financial crisis. Uhlig (2005) on the other hand found no clear effect on GDP from conventional monetary policy in the USA. Since the effects of monetary policy is ambiguous regarding GDP, we do not impose restrictions on the response of real GDP. Additionally, one month of the Covid-19 period has been implemented as an exogenous dummy variable, due to it being an outlier. Therefore, we estimate a SVAR model with an exogenous variable (SVARX).

The shock from QE is characterized by an increase in ECB's total assets by up to 1% and fades out after approximately a year. We find GDP slightly increases by 0.1%, but it is not statistically significant. Financial stress decreases by approximately 1%, but quickly returns to zero after 5 months. Inflation increases by 0.1% for approximately a year. The shock from our analysis disappears faster compared to earlier studies examining effects from quantitative easing. During the Covid-19 shock, GDP decreased sharply and returned to normal quickly[2]. Therefore, it seems reasonable that the shocks in our analysis disappear fast. For comparison, the crisis in 2008 had long lasting effects on GDP. Finally, QE does not only affect the economy at the time of purchasing, but it also affects the economy on the day of announcements since markets are forward looking.

To examine the timing of the announcements, we use that central banks announce their purchasing plans prior to the actual launch. These announcements can affect the economy through many channels explored by Krishnamurthy and Vissing-Jorgensen (2011). We specifically analyse the signaling effect since it is closely related to output, so we apply an event study inspired by Jensen et al. (2017). We study the effects of four specific announcement days on daily government bond yield curves of the Euro area. We expect a negative dynamic since bond yields depend negatively on the bond price. However, we find a positive dynamic, which could indicate that the announcements had a smaller effect on bond yields than expected. This result is in accordance with Jensen et al. (2017), but it is not with other event studies like Krishnamurthy and Vissing-Jorgensen (2011). It is possible that the response from the ECB was smaller than the market expected, which would cause the yields to go up.

[2]As we can see in Figure 6 in the appendix

2 Monetary policy by the ECB

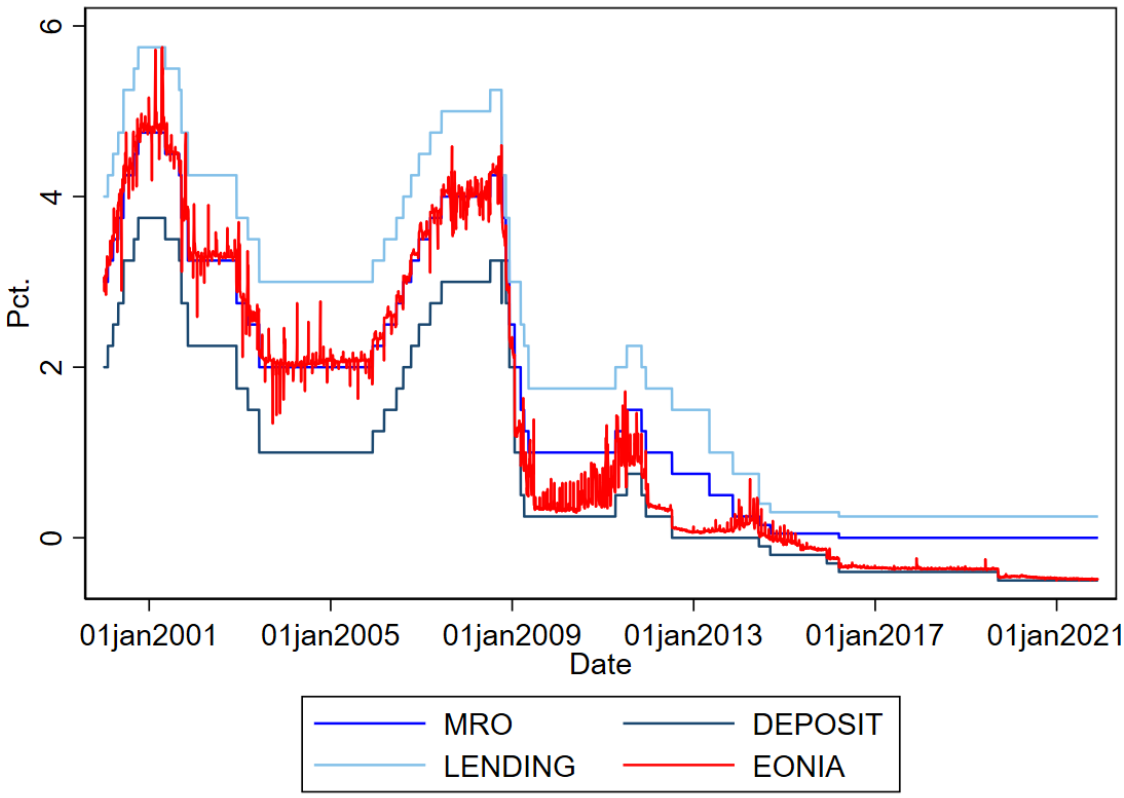
2.1 Conventional policy

One of the most important tools for any central bank is the ability to change their nominal interest rate. This is commonly known as conventional monetary policy. The ECB mainly operates with three different kinds of interest rates: The main refinancing operations (MRO), the deposit facility rate, and the marginal lending facility rate. The deposit and lending rates define the interest rates that banks respectively receive and pay when lending and borrowing money overnight. The MRO defines the rate banks pay to borrow money for one week. Banks can also provide loans to each other outside of the central bank. This interest rate is called the Euro OverNight Index Average (EONIA). Up until the financial crisis in 2008, the EONIA closely followed the MRO as seen in Figure 1. This was a period when the general interest rate fluctuated between 2 and 5 percent. After the financial crisis, the ECB lowered all three interest rates substantially and they even lowered the deposit facility rate below zero from 2014 to 2022. The spread between EONIA and MRO is largely caused by a deficit or an excess of liquidity, according to Linzert and Schmidt (2008). As the spread shows how the ECB's liquidity management matches with the demand from the market, we are interested in assessing it. MRO, which provide the bulk of liquidity to the banking sector per the ECB[3], cannot be negative as institutions would then earn money from borrowing from the ECB. We examine the MRO to account for effects from the ECB's main policy rate.

When EONIA is close to the deposit facility rate, there is an excess of liquidity in the financial markets. EONIA can never be below the deposit facility rate, and when the rate is close to or even below zero, it is naturally difficult for the central bank to lower the interest rates even more: If the deposit facility rate is negative, agents lose money by depositing money and thus might consider withdrawing their money. Having a negative interest rate can be a tool for the ECB to force liquidity into the markets. However, there is a lower bound for the tool to be effective[4]. Therefore, setting the interest rate lower would have little to no effect. The deposit facility rate has only been lowered by 10 basis points thrice from 2015 to 2021, which is unusual compared to earlier period. Therefore, the opportunity for using conventional monetary policy had been restricted and the use of unconventional monetary policy had a greater appeal.

[3]Reference: ECB (2022b)
[4]Reference: ECB (2021)

Figure 1: Official Interest Rates of the ECB and EONIA



Source: ECB statistical data warehouse

2.2 Unconventional policy

Central banks can also aim to stabilize the economy by buying assets such as bonds and securities from public and private institutions. Per Sørensen and Jacobsen (2022), central banks can print their own money to buy bonds to provide liquidity to banks in need. The returns on these assets are known as seigniorage. Furthermore, this leads to an increase in the demand for bonds, which in turn lower the bonds' interest rates. Lowering interest rates by buying assets is defined as quantitative easing (QE) or unconventional monetary policy. A byproduct of QE is that price levels might increase, which is known as the monetary transmission mechanism. When the ECB buys assets, their balance sheet will increase, and the demand for the given assets will increase. This in turn increases the price of the assets, and investors will become richer. Therefore, the demand of non-financial goods and services will increase, and their prices will increase too. This results in increased inflation. Increased inflation can be beneficial for the central bank, when inflation becomes less than

2%, which is the desired inflation target of the ECB[5]. Too low inflation could result in deflation, which is undesirable. Major asset purchasing programs started as an unconventional tool for central banks to conduct monetary policy. The practice was widely used during the financial crisis in 2008 but has been used several times since. This is firstly, because the effects of conventional monetary policy have been regarded as weak, due to the low interest rates. Secondly, QE offers the central bank a quick way to provide liquidity and stabilize the economy. Thirdly, it allows the central bank to target specific areas of interest, whether private or public institutions and bonds or securities. The ECB purchased assets multiple times during the last decade and has since 2015 prioritized purchasing assets instead of lowering the interest rate[6]. The main reason was to raise inflation, as inflation was below the desired target. Between 2020 and 2022, the ECB purchased a large amounts of assets to counter the negative effects of the Covid-19 economic crisis. Overall, QE provided flexibility for the ECB to lower bond interest rates and achieve its stabilization goals.

In Figure 2, the yearly change in the ECB's assets and the stress of the financial markets in euro area (CISS) is depicted from 2015M1 to 2021M12. The CISS-indicator is a summary of financial stress in euro area money, bond, equity, and foreign exchange markets, and financial intermediaries constructed by Hollo et al. (2012)[7]. We use it to separate the exogenous changes in the central bank's assets from their endogenous response to financial stress. During financial stress, European financial institutions can borrow money from the ECB to secure short term liquidity. Unlimited access to liquidity was established by the ECB during the financial crisis, but it only applies if the institution has sufficient collateral. Thus, the ECB's balance sheet also changes independently from QE. This disentanglement of exogenous changes in the balance sheet has earlier been applied in Boeckx et al. (2017). If the endogenous response from the ECB to financial stress is not accounted for, it is possible that the estimation results become biased per Gambacorta et al. (2014)[8]. During the Covid-19 crisis, output fell, and financial institutions needed liquidity, which they could borrow from the ECB. This resulted in the ECB's balance sheet to increase. If financial stress is not accounted for, we would have omitted-variable bias. From Figure 2, we notice that the ECB's asset purchasing increases as a response to financial stress. The positive dynamic between GDP and CISS indicates the endogenous response. We know that after 2019, the major increase in assets is also due to QE. Therefore, Figure 2 illustrates both the

[5]Reference: ECB (2022c)

[6]Reference: ECB (2022a)

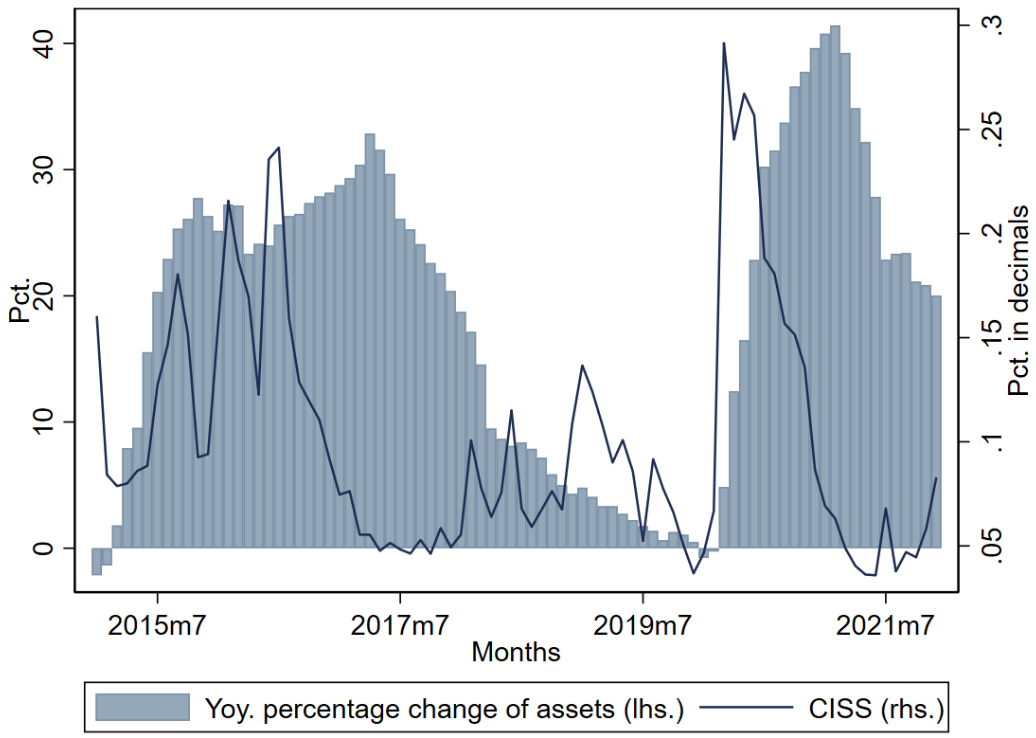
[7]CISS is described further in the appendix

[8]They use the stock markets expected volatility wrt. S&P500 index options VIX, while we use the indicator CISS

endogenous and exogenous response from the ECB. Furthermore, financial stress decreases following expansionary shocks in the ECB's balance. We define a shock as following three characteristics per Ramey (2016): First, the shocks need to be exogenous with respect to the other current and lagged variables in a model. Second, the shocks should be uncorrelated with other exogenous shocks in a given period. Third, the shocks should represent either unanticipated movements in the exogenous variables or news about future movements in the exogenous variables. It can be argued whether QE is exogenous or not, since central banks respond to general trends in the economy. The ECB is independent and can choose exactly what trends in the economy, they will respond to. Therefore, we can consider QE as exogenous. Furthermore, the ECB announce their QE plans prior to purchasing assets, and it could be argued that the asset purchases themselves are not unanticipated movements. QE is only credible, if the central bank actually follows through and buys assets. Asset purchasing might not be unanticipated, but it does bring news about the credibility of the ECB.

Therefore, we consider both QE announcement and asset purchasing as exogenous shocks. To study the effects from unconventional monetary policy on the euro area 19 and the financial markets, we construct structural vector autoregressive models.

Figure 2: The ECB asset purchases and financial market stress



Source: ECB statistical data warehouse

3 Econometric theory

3.1 The Structural VAR model

The use of structural vector autoregressive (SVAR) models to estimate macroeconomics effects from monetary policy is well documented by Bernanke and Blinder (1992), Peersman and Smets (2001), and Uhlig (2005). This is the approach we consider to estimate the macroeconomic effects in the euro area from the ECB's use of QE. Furthermore, we allow for an exogenous variable in our SVAR model due to the assumption that the financial shock from the COVID-19 pandemic is independent from the ECB's use of monetary policy. Lenza and Primiceri (2020) suggest modelling March, April and May of 2020 as a decreasing step-function to adjust for the increased volatility from Covid-19. The idea is to let the function be smaller for each month, so the March has less impact than May. They found that if one is only analysing previous effect, applying exogenous dummies for Covid-19 is not a problem. We choose to only include one dummy for April, since our sample is small, and we want to include as much data as possible. Thus, we consider a SVAR model of p lags with exogenous variables (SVARX), which can be written in the following way, where only the endogenous variables are allowed lags, as the exogenous variable in our model is only contemporaneous:

$$B_0 y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + CX_t + w_t \tag{3.1}$$

where y_t is a $K \times 1$ vector consisting of K endogenous variables, X_t is a $M \times 1$ vector with M exogenous variables, p is the number of lags in the model, and C is a $K \times M$ matrix. C is not allowed any lags to minimize the effect from the exogenous variable. The dimension of the matrix B_i, for $i = 0$ up to p lags, is given by $K \times K$. The $K \times 1$ vector w_t is interpreted as white noise in the model. Furthermore, the elements in the error term are mutually uncorrelated and independent of the deterministic exogenous variable.
If we multiply both sides of the above equation with B_0^{-1}, this yields the reduced SVARX model:

$$\begin{aligned} y_t &= \underbrace{B_0^{-1}B_1}_{A_1} y_{t-1} + ... + \underbrace{B_0^{-1}B_p}_{A_p} y_{t-p} + \underbrace{B_0^{-1}C}_{\beta} X_t + \underbrace{B_0^{-1}w_t}_{u_t} \Leftrightarrow \\ y_t &= A_1 y_{t-1} + ... + A_p y_{t-p} + \beta X_t + u_t \end{aligned} \tag{3.2}$$

We assumed w_t as white noise before, which means the same must hold for u_t in the reduced form model. We know the reduced form of the covariance matrix must be:

$$E\left(u_t, u_t^{'}\right) = \Sigma_u = B_0^{-1} B_0^{-1'} \tag{3.3}$$

We can also describe our reduced form VAR Model as:

$$A\left(L\right) y_t = \beta X_t + u_t \tag{3.4}$$

where $A\left(L\right) = I_K - A_1 L - ... - A_p L^p$ is the lag operator and I_K is a $K \times K$ identity matrix. We know from Kilian and Lütkepohl (2017) that a VAR process with p lags will be stable if all roots of the determinantal polynomial of the VAR operator are outside the complex unit circle, i.e., if the below equation holds:

$$\det\left(A\left(z\right)\right) = det\left(I_K - A_1 z - ... - A_p z^p\right) \neq 0, |z| \leq 1 \tag{3.5}$$

where z denotes a complex number. If the above holds, then we have a stable and invertible VAR process, which allows us to interpret the impulse response functions and analyse the effect from a shock of one variable in a system of endogenous variables. The statement is equivalent to stating that all eigenvalues of the matrix A must be less than modulus 1. The matrix A is also called the companion matrix. A stable model converges to its unconditional mean, and the effect from the shocks will dissipate over time.

3.2 Identification and restrictions

There exist several identification schemes for monetary policy, so there is no universal answer on how to determine the effects. According to Kilian and Lütkepohl (2017), a commonly used way to recover the structural innovations w_t from the reduced form u_t is to orthogonalize the reduced-form errors, by making the errors mutually uncorrelated. The model will then be identified through recursiveness. The variables in a recursive model can affect each other at time t by a given causal ordering. Therefore, a recursive model will have contemporaneous effects following the order. Recursiveness can be achieved by defining the lower-triangular $K \times K$ matrix P with a positive diagonal such that $PP' = \Sigma_u$, where P is commonly known as the lower-triangular Cholesky decomposition of the residuals[9]. Then it follows that B_0^{-1} is a candidate solution from equation 3.3, as we have $PP' = B_0^{-1} B_0^{-1'}$

When identifying a SVAR model through recursiveness, a causal ordering is required. The causal ordering influences the results, so one has to argue properly for the chosen order as a SVAR model of n variables has $n!$ possible orderings. Another way to identify a SVAR

[9]See appendix for more information under Cholesky decomposition

model is using sign restrictions proposed by Uhlig (2005). The idea is to impose economic beliefs and intuition to the shocks of the model to exploit prior beliefs about effects of the variables. Instead of examining a shock to assets, we construct beliefs of multiple shocks, which mimic shocks from QE.

To implement sign restrictions, we first consider our SVAR model from equation 3.1:

$$B_0 y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + w_t$$

We have not included our exogenous variable, as it is not imposed any restrictions. The structural error term w_t has the normalized variance-covariance matrix from equation 3.3. We define $u_t = P\eta_t$, where P is the lower triangular Cholesky decomposition of Σ_u and u_t is the reduced form of the innovations. Then by definition, the shocks, η_t, will be mutually uncorrelated with unit variance. If we compute a large set of combinations of η_t, this allow us to obtain candidate truths denoted by w_t^* for unknown structural shocks, w_t, such that:

$$w_t^* = Q^{'} \eta_t$$

where $Q^{'}$ is defined by a square orthogonal matrix $Q^{'}Q = QQ^{'} = I_K$ and $u_t = PQQ^{'}\eta_t = PQw_t^*$, which makes each possible solution consist of uncorrelated shocks with unit variance. We only keep solutions where the multiplier matrix PQ satisfies the sign restriction on B_0^{-1}. We draw large numbers of possible matrices Q from a set of any random orthogonal matrices[10]. Imposing prior beliefs for our parameters is called a Bayesian approach, in which we also assume each impulse vector that passes, to be considered equally likely.

The sign restrictions are thus imposed numerically by performing N replications of the following four steps[11]:

1. We draw a random orthogonal matrix Q
2. Determine $B_0^{-1} = PQ$, where P is the Cholesky decomposition of the reduced form of the residuals denoted by Σ_u
3. Determine the impact of the shocks wrt. B_0^{-1}
4. If the sign restriction is satisfied then the effect of B_0^{-1} is stored.

Our model is only identified for a number of different B_0^{-1} equal to the number of model repetitions, N. We choose to proceed with $N = 10000$, to be cautious, but the analysis is robust for $N > 500$ and imply the same results.

[10] This set is defined $\mathcal{O}(K) \equiv \left\{ Q | QQ^{'} = I_K \right\}$. For more information see Kilian and Lütkepohl (2017)

[11] We use the following VAR toolbox from Ambrogio Cesa-Bianchi: https://sites.google.com/site/ambropo/MatlabCodes?pli=1

3.3 Structural Impulse Response Functions

We interpret the estimates of the SVARX model using structural impulse response functions (IRF), which illustrates how the endogenous variables in the model react to structural shocks. These structural IRF allow us to easier interpret the estimated parameters, as they show effects from shocks in the system of endogenous variables in a clear way.

Kilian and Lütkepohl (2017) show that if a VAR model with p lags is stable, then it is possible to write it in a multivariate moving-average form such:

$$y_t = \sum_{t=0}^{\infty} \Phi_i u_{t-i}, \quad \Phi_0 \equiv I_K$$

where Φ_i is the coefficient matrix for a period i. This matrix has the response of a given j^{th} variable of y_t, after a shock in a k^{th} variable of u_t after i periods. These impulse responses have to be rewritten to show the mutually uncorrelated structural shocks instead of the reduced form errors u_t, which are correlated with each other. Notice that this is also the case for stable SVARX models, as the exogenous variable is ignored.

We use that $w_t = B_0 u_t$, so we can then write the mutually uncorrelated shocks as:

$$y_t = \sum_{t=0}^{\infty} \Phi_i u_{t-i} = \sum_{t=0}^{\infty} B_0 B_0^{-1} \Phi_i u_{t-i} = \sum_{t=0}^{\infty} \Theta_i w_{t-i}, \qquad \Theta_i = B_0^{-1} \Phi_i$$

where Θ_i is chosen as the Cholesky decomposition of residuals Σ_u. Then it contains impulse responses for each of the endogenous variables $y_t = (y_{1t}, .., y_{Kt})^{'}$ from a one time shock in $w_t = (w_{1t}, .., w_{Kt})^{'}$. So:

$$\frac{\partial y_{t+i}}{\partial w_t^{'}} = \Theta_i, \quad i = 0, 1, 2, ..., H$$

where H is the maximum propagation horizon of the shocks. Then we can simply determine the responses for every period $i = 0, ..., H$ by multiplying Φ_i with B_0^{-1}:

$$\begin{aligned}
\Theta_0 &= \Phi_0 B_0^{-1} = I_K B_0^{-1} \\
\Theta_1 &= \Phi_1 B_0^{-1} \\
&\cdots \\
\Theta_i &= \Phi_i B_0^{-1}
\end{aligned}$$

It should be noted that the structural impulse responses must dissipate and approximate zero as $i \to \infty$ for the model to be stable.

4 Data

We use monthly data from 2015M1 to 2021M12 to estimate our model. We start in 2015M1 to minimize impacts from the European debt crisis which lasted from 2009 to mid-2010's. One could also consider only using data from 2020M1 and onward, but we found the sample size too small. We choose the cut-off month to be 2021M12 because the ECB decided to discontinue the pandemic emergency purchasing programme in December 2021 and we wanted to avoid impacts from the war in Ukraine starting in February 2022.

We transform the data for ECB's assets, real GDP indexed to 2015, and inflation in the euro area by taking the logarithm to it. Most of the data contain some form of unit root and seem to be trending. However, this is not necessarily a problem, if the estimated VAR process is stable per Sims et al. (1990). Therefore, we choose to estimate our VAR model in levels and log-levels. All variables are multiplied with 100 to show the IRF in percent on the y-axis.

To perform the analysis, we use the following six macroeconomic variables:

- log_MONTHLY_GDP: The log of monthly GDP in the euro area. GDP is only measured every quarter, so we decompose it into monthly data using a Chow-Lin disaggregation. This was done by using the Industrial Production in the euro area which includes monthly data. GDP and Industrial Production follow each other closely, so we can in short extract the high frequency data from the Industrial Production and apply it to the GDP per Sax and Steiner (2013). Both time series are chain-linked and seasonally adjusted.

- CISS: The Composite Indicator of Systemic Stress which indicates the financial stress on the euro area market.

- log_ASSETS: The log of ECB's total assets with all currencies combined and seasonally adjusted.

- EONIA_MRO_SPREAD: The spread between the EONIA and the MRO.

- log_HICP: The log Harmonised Index of Consumer Prices, which is used to measure the consumer price index in the euro area. It is seasonally adjusted.

- MRO: The main refinancing operations is the interest rate at which the banks borrow money from the ECB for a 1-week period. We consider MRO to disentangle ECB's conventional monetary policy from its unconventional, i.e., changes in the interest rate from QE. However, MRO has been constant through most of our sample period, so it behaves like a dummy variable.

These variables can be seen in Figure 7 in the appendix. The data was downloaded from ECB Statistical Data Warehouse. Most of the data from ECB's statistical warehouse had to be transformed from either daily or weekly data to monthly data. This was done by taking the average daily or weekly value in a given month, which is in line with the transformations that ECB uses.

5 Empirical analysis

5.1 VAR Study

We estimate two different SVARX Models over the sample period 2015M1-2021M12. The Akaike Information Criteria was used to determine the lag-length selection, thus resulting in two lags for the models, but the models are also robust to other lag specifications. Our two different model estimations are a SVAR model, which is identified by a standard Cholesky decomposition, and a SVAR model with sign restrictions following the method from Uhlig (2005). We impose an exogenous variable for the corona month of 2020m4, since that month is a large outlier due to the major financial shocks from Covid-19. With this specification, our model passes the stability condition of having an absolute maximum eigenvalue of less than 1.0. It should be noted that different decompositions does not change the stability condition.

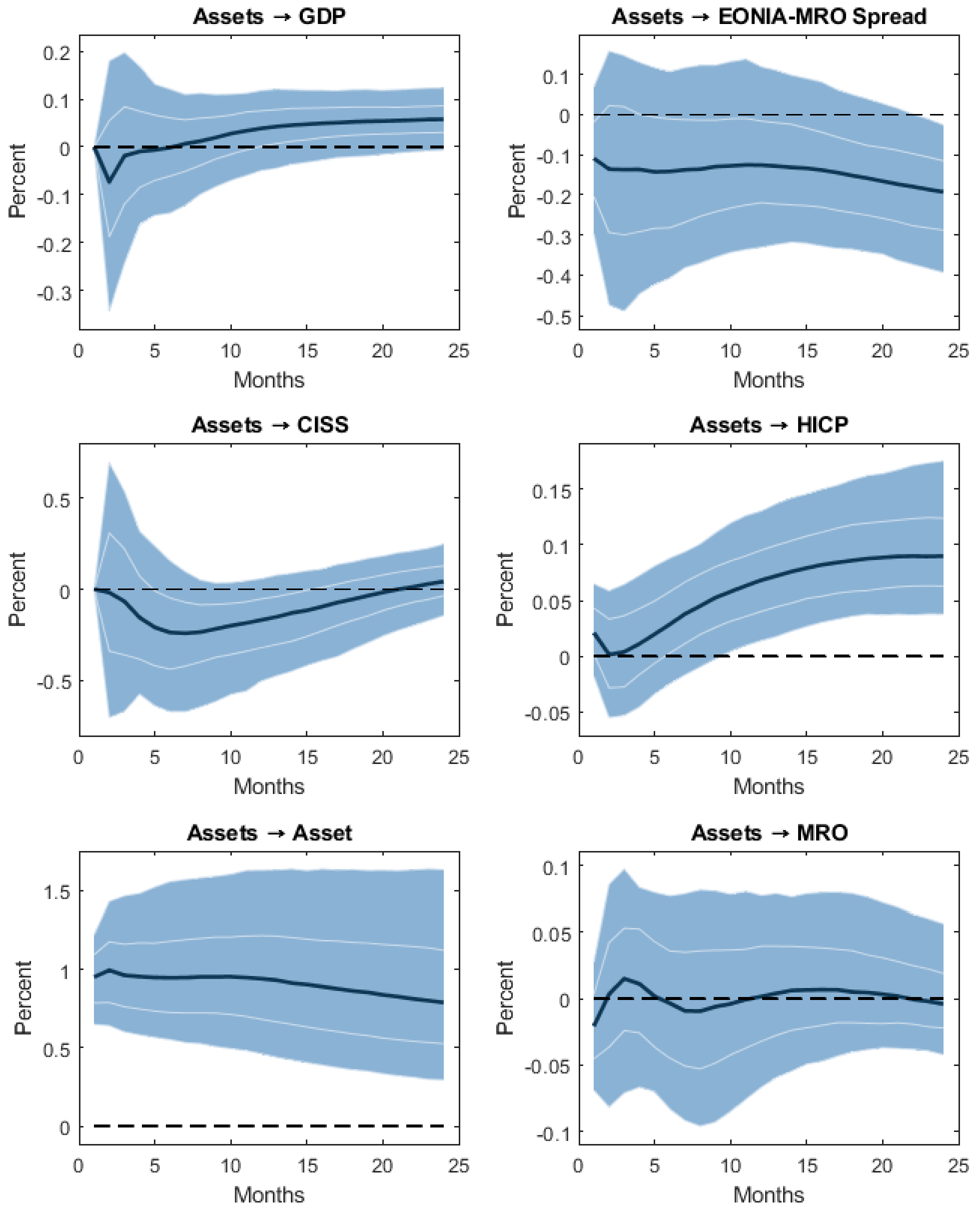
To estimate a SVAR model, we need to determine a causal ordering. We argue that GDP reacts with a lagged effect but likely impacts the other variables. Therefore, we assume that GDP is the first in the causal chain, and it will not have any contemporaneous effects from a shock to assets. Examining assets in Figure 2 show that CISS appeared to lag behind, so we put it just before assets in the causal chain. We also estimate a ordering, where CISS and HICP are swapped, as CISS is a financial variable and thus should be moving faster than HICP. However, this does not change the results significantly as can be seen in Figure 8 in the appendix. We assume assets has contemporaneous effects on the remaining three variables, since financial markets often react quickly. The ordering of the last three variables do not change the results significantly. One could argue to disregard MRO as it only changed once with 5 basis points in our sample, but we choose to keep it to compare our results with those of Boeckx et al. (2017). Furthermore, the IRF did not change significantly without MRO. The above ordering is not necessarily the correct identification for the model, as we cannot be certain of the causal dynamics. One can argue to test each possible model against each other, i.e., to test each causal ordering against

another. This can be problematic according to Kilian and Lütkepohl (2017). Firstly, we assume that the ordering is recursive, but the model is not necessarily recursive. Secondly if the model is recursive, we do not know the order in which the variables are recursive. Thirdly, a Cholesky decomposition with six variables can be written in 720 different ways. It would be an extremely time-consuming task to test if all the variations are robust to each other, which is not necessarily advantageous, when we do not actually know, if the model is recursive in the first place.
We therefore give the following model based on economic intuition following a slow-fast approach by Uhlig (2017):

$$\text{GDP} \rightarrow \text{CISS} \rightarrow \text{ASSETS} \rightarrow \text{EONIA-MRO Spread} \rightarrow \text{HICP} \rightarrow \text{MRO}$$

The estimation results from the SVAR model can be seen in Figure 3. The outer blue bars show the two standard deviations confidence interval of 95%, the white lines show one standard deviation of 68% and the black line represents the median impulse responses. We estimate the confidence-intervals with a nonparametric bootstrap method and analyse the 95% confidence bands. The idea is to randomly resample the data, which provides an estimator without the need for a specific distribution. From Figure 3, we see an initial negative, but insignificant, response from GDP to a shock in the ECB's assets. This is counter intuitive, hence making us unsure about interpreting the results from the IRFs. However, we do notice that HICP increases following a shock in assets, which was expected due to the monetary transmission mechanism.
One could argue that the negative response of GDP is due to the random noise from Covid-19, but this does not seem plausible for two reasons. Firstly, asset purchasing from the ECB was at its lowest in recent years, as is clearly depicted in Figure 2. Secondly, the ECB announced QE after the Covid-19 crisis hit. This imply that both assets and GDP should increase following Covid-19: GDP returns to normal due to an economic recovery and assets increase as the ECB launched QE. Ceteris paribus, Covid-19 should not yield a negative dynamic between GDP and assets in our model. Additionally, we did model one month of the initial Covid-19 shock as a dummy.

Figure 3: Structural impulse responses to a shock in assets, estimated by a Cholesky decomposition with assets being third in the chain. Outer confidence bands show the 95% and the inner white lines show 68%. The black line represents the median.



Instead of using a specific Cholesky decomposition, we follow an approach inspired by Uhlig (2005) and Boeckx et al. (2017). We apply sign restrictions to estimate the effects from QE on the euro area and the financial markets. The idea behind sign restrictions is to only consider shocks that are theoretically and empirically plausible due to QE. We choose to impose several sign restrictions denoted in Table 1:

Table 1: Table of imposed sign restrictions

GDP	CISS	ASSETS	EONIA-MRO Spread	HICP	MRO
-	≤ 0	≥ 0	≤ 0	≥ 0	-

We impose no sign restriction on GDP. This is not trivial since empirical studies show different effects of monetary policy on GDP. Peersman (2011) and Boeckx et al. (2017) show that QE increased GDP following the financial crisis of 2008. Earlier papers studying the Fed Fund Interest rates like Uhlig (2005) do not find a clear conclusion regarding the effect of conventional monetary policy on GDP. Therefore, we end up not imposing any sign restrictions on GDP.

We assume that shocks from unconventional monetary policy, i.e., QE will not increase the financial stress in the markets in the euro area according to Gambacorta et al. (2014). This restriction is to separate the exogenous innovations in the ECB's balance sheet from the endogenous with regards to financial stress as discussed in section 2. Furthermore, the ECB announces major asset purchasing programs, when there is high financial stress, to provide certainty in the markets. We also noticed in Figure 2 that increases in CISS were followed by increases in assets, which in turn seem to decrease CISS.

We assume that the EONIA-MRO spread does not increase by expansionary balance sheet shocks. Figure 1 showed that the EONIA-MRO spread was close to the deposit facility rate, which indicated that there was excess liquidity. When the ECB announces changes to the balance sheet, there will be an even larger amount of excess liquidity in the markets, which lowers the EONIA further, and in turn lowers the EONIA-MRO Spread.

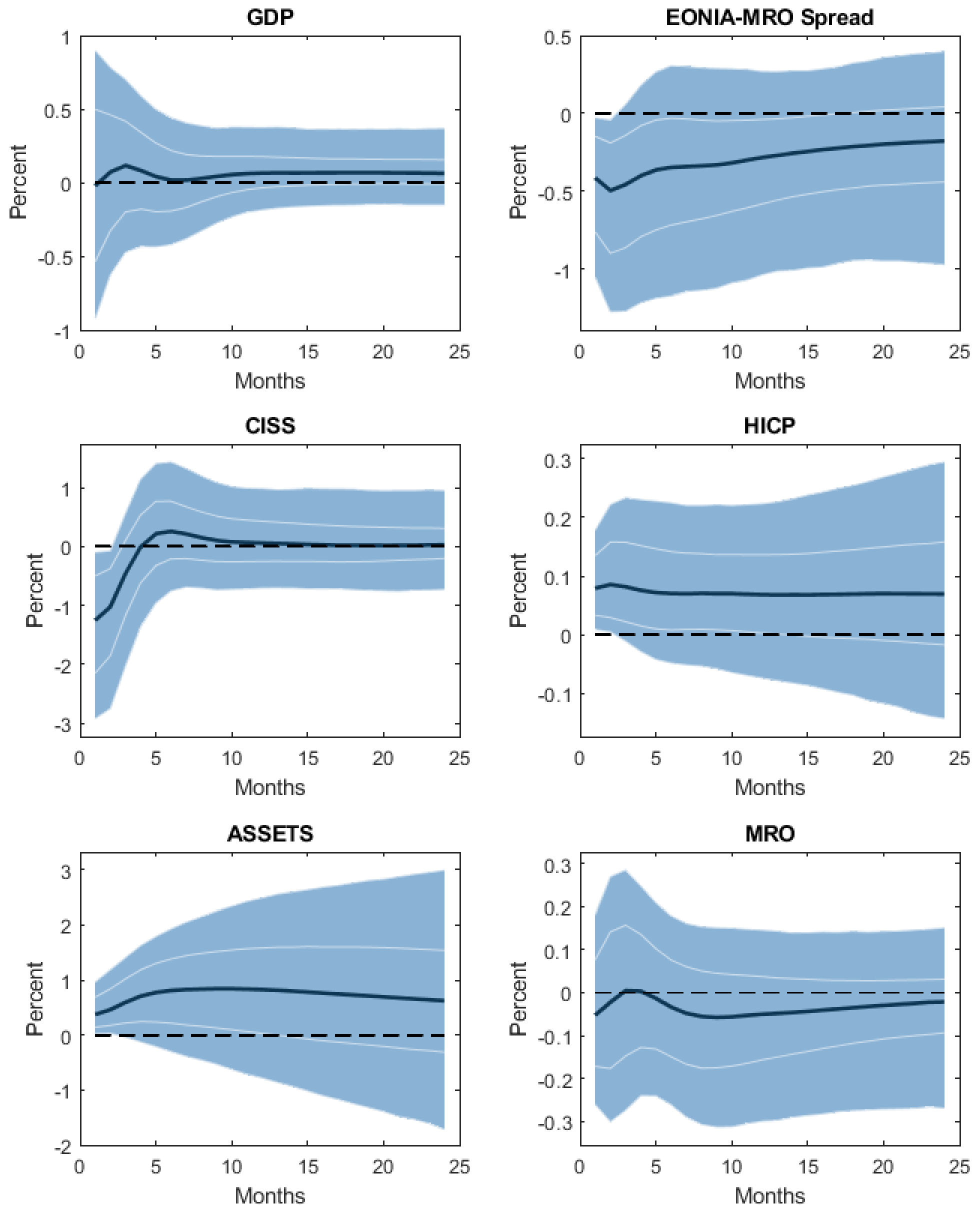
The shock to assets is restricted to being weakly positive, since we are only considering expansionary shocks in the ECB's balance sheet. Peersman (2011) and Boeckx et al. (2017) both assume that inflation does not decrease following QE. When the ECB buys up assets, inflation will increase as described by the monetary transmission mechanism mentioned earlier. Therefore, we impose a weakly positive sign restriction on HICP.

Finally, MRO is not imposed any restrictions, as we are examining only shocks in assets combined with MRO being zero for the majority of the estimated period.

We impose the sign restrictions for $k = 2$ periods, where the contemporaneous shock is $k = 1$. This guarantees that the restrictions only happen in a short time frame to prevent the risks of misspecified identification. Furthermore, we consider one standard deviation of 68% for the confidence interval to follow Uhlig (2005) approach, however, it is often applied in many macroeconometric analyses such as Boeckx et al. (2017). The choice of confidence bands is discussed further in section 6.1.

Figure 4 shows the sign restricted IRF of our SVARX model.

Figure 4: Structural impulse responses to an expansionary monetary policy shock from quantitative easing, estimated by sign restrictions. Outer confidence bands show the 95% and the inner white lines show 68%. The black line represents the median.



The impulse responses show the following:

- The shock to the variables is characterized by an increase in total assets for the ECB around 0.8%, which fades out slowly after approximately a year.
- The median of GDP increases during the first couple of months, but it seems to revert back to zero after a period of 6 months. The confidence intervals are large and go

from -0.5 to +0.5%. Therefore, the effect on GDP is not significant. Because of this, it does not seem like there is a clear conclusion whether an expansionary monetary policy shock affects GDP positively or negatively.

- We notice that a shock in assets imply a major sudden decrease in CISS by approximately 1%, but similarly to GDP, it quickly converges after a few months.
- The spread between EONIA and MRO decreases by 0.5% and slowly converges to zero after a year.
- HICP increases by less than 0.1%, but rather slowly converges to its unconditional mean with still lingering effects after a year.
- The MRO is close to zero and not statistically significant, which is likely due to the MRO only changing once. The impulse response mostly shows white noise in the process.

Our results indicate a slightly positive but insignificant response from GDP following QE. This reveals a similar dynamic as Uhlig (2005), who also left the response from GDP unrestricted. He considered the federal funds rate and contractionary monetary policy shocks in the USA, while we examine QE and expansionary monetary policy shocks in the euro area. He also found no clear result on GDP from monetary policy. Therefore, our results could indicate that unconventional monetary policy does not have a clear effect on GDP during extraordinary financial crisis. This result is contrary to Boeckx et al. (2017), who found a clear positive response from GDP during the financial crisis in 2008. All in all, it does not necessarily hold that monetary policy can increase GDP.

Inflation reacts slowly, which could be caused by rigidness in prices, as inflation is expected and observed to react slowly in macroeconomic theory and in practice. Agents want to be certain of the trend of inflation before increasing prices. Agents also face menu costs when increasing prices, which makes them hesitant to increase their own prices.

We observe that financial stress decreases with great effect immediately, as the ECB reacts to uncertainty in the markets by QE. We notice that the response shows the same result as in Figure 2. Intuitively, financial markets and institutions can react the fastest to unconventional monetary policy, as the ECB announces policy in advance, which the agents can choose to react to immediately.

As mentioned earlier, a negative spread between EONIA and MRO indicates an excess of liquidity. A positive shock to ECB's balance sheet will increase the money supply and there will be an even larger excess in liquidity. From the IRF, we see that the shock from the balance sheet starts to disappear after approximately a year.

It holds that QE has a stabilizing effect on the financial markets on the short run during Covid-19. QE increases the amount of liquidity in the market, as seen by the decreasing spread of the EONIA and MRO. The surplus of liquidity will also increase inflation for up to a year. For all variables, the shock is disappearing after approximately a year. Thus, monetary policy does not have an effect on the long run.

5.2 VAR Robustness checks

Choosing a correct sample period can be difficult. If we choose a sample period that is too short, there is too much uncertainty in our model, so we cannot interpret it. This is especially true during times of extreme volatility, such as the Covid-19 crisis. To study the effects of QE during the Covid-19 crisis, a sample period from 2020M1 to 2021M12 would seem ideal. However, testing this sample results in a SVAR model which is not stable and has no interpretable impulse responses. Therefore, we opt for including a larger sample in our analysis. When we include the period before the crisis, our analysis will also include effects from QE that was not announced as a response to Covid-19. This is not inherently a problem, but our results will not only reflect effects from Covid-19. As seen in Figure 2, the ECB's balance sheet increased before Covid-19, so these effects are also included in our analysis. If we only estimate the period before the crisis (2015M1-2020M2) with the same causal ordering as Figure 3, we find that the effects from a shock to ECB's balance sheet to be mostly similar: For HICP and EONIA-MRO Spread, the impulse responses only become smaller and less significant, while the effect on GDP increases but still not significant. This indicates that QE only impacts inflation and the spread between EONIA and MRO more in the Covid-19 crisis compared to before the crisis. Furthermore, this indicates that the small and insignificant effect on GDP is not caused by the pre Covid-19 period.

When estimating a VAR model, one can test for normality and autocorrelation in the standard errors. We reject the null hypothesis that the standard errors are normally distributed. Kilian and Lütkepohl (2017) state that there is only small gains when specifying the true distribution for macroeconomic models with small samples, i.e., the model is only slightly worse if we model the error term as a normal distribution, even if it were actually a uniform distribution. When we estimate our SVARX models in MATLAB, we obtain our results using nonparametric bootstrap. According to Kilian (1998), nonparametric bootstrapping is the better approach, even if we do not have normality problems. Nonparametric estimation does not assume any specific distribution, thus making the actual distribution irrelevant for the estimation results. Therefore, our estimates should still be interpretable, since our confidence intervals are robust. We reject the null hypothesis of no autocorrelation when testing our model with two lags. However, if we test the model with three lags, we do not reject the hypothesis of no autocorrelation. This could lead us to expand the model with another lag, however the impulse response functions show the same properties, which indicates the model is robust.

Many economists are often weary of estimating VAR models in levels, i.e., non-detrended variables. This is a valid concern since two trending series often are spuriously correlated. This is a problem when the main aim of the analysis is to study misspecification and Granger-Causality tests according to simulation studies like Ashley and Verbrugge (2009), in which differencing the variables is needed. However, if the main aim of the analysis is to study the impulse response functions, estimating the models in levels yields robust results. This is in accordance with our results. Detrending the clearly trending variables for assets, GDP, and inflation into year-over-year change does not give any significantly different results. Ashley and Verbrugge (2009) also suggest the use of a trend term to capture the trending variables. The time trend is modelled by including a new variable that takes the values $1, 2, ..., T$, where T is the sample size. The trend variable will model the trend from the trending variables and avoid spurious correlation. This specification is unlike most other studies mentioned in this paper and adding a trend term does not change the results of our estimation significantly. Another common way to detrend a time series is to use the Hodrick-Prescott (HP) Filter. The use of the HP Filter is widely discussed in econometric literature and there seems to be no consensus of the usefulness of the filter. According to Hamilton (2017), the HP filter can cause spurious correlations, while other authors like Drehmann and Yetman (2018) find that the filter can be used in certain cases. We test the HP-filter and apply a fitting λ value and find closely similar IRF[12]. Therefore, as there is also no clear consensus, we chose not to base our analysis on the HP filter.

5.3 Event Study

Quantitative easing has three ways of affecting the financial markets: Firstly, there is a direct effect from purchasing assets and thus supplying liquidity to financial institutions. Secondly, when the ECB purchase assets from investors, the investors can choose to rein-

[12] λ=129,600 for monthly data, https://www.stata.com/manuals/tstsfilterhp.pdf

vest the received funds to rebalance their portfolios. This is known as the portfolio rebalancing mechanism and can stimulate the economy and increase the demand for assets. Thirdly, due to the ECB announcing purchasing plans prior to buying assets, the markets will respond accordingly. Financial institutions are considered forward looking agents in the macroeconomic and financial theory, hence why they should react immediately to announcements of asset purchasing by the ECB. If the ECB announces bond purchasing, the markets will expect the price of the bond to go up, and thus they will buy bonds in anticipation of the ECB's plans. The VAR analysis done above examined the direct effect of purchasing assets. The effects from portfolio rebalancing by private and public investors is hard to measure and is not the aim of this paper. Therefore, we want to study the third way QE can affect the financial markets. This is done by making an event study, which examines four different QE announcement dates.

The first announcement date was a relaunch of QE in September 2019 by the ECB, which aimed to increase inflation in the euro area to 2%. The rest of the dates consider the three biggest announcements during the Covid-19 period, which was named the pandemic emergency purchase programme (PEPP). The aim of this program was to decrease long-term bond yields to decrease the interest rates, which would make liquidity cheaper for financial institutions. Furthermore, the ECB announced on March 18. 2020 that they had observed high bond yield volatility in the German Bund market. High yields were likely caused by the fiscal policy of many governments, which led to an increase in the government bond yields[13]. The governments' initiatives would result in expectations of an increased supply of government bonds, which cause the yields to increase.
When central banks announce non-traditional monetary policy, QE, it can help lower the long-term bond yields. This only happens if the policy is seen as a credible commitment to not raise interest rates after the economy recovers. Such a commitment can be made by the central bank purchasing long duration assets. If the interest rate on the long-term assets go up, the central bank will lose money, if they commit. A large part of the assets acquired after 2019 by the ECB were longer-term refinancing operations, in which they showed they were willing to keep the interest rates low. This signalling channel will affect all bond market interest rates, so we would expect the yield curves to lower during one of the event dates in this study.

We examine four of the biggest announcements of asset purchasing from 2019 to 2021, which consisted of one standard asset purchasing programme (APP) and three PEPP. This

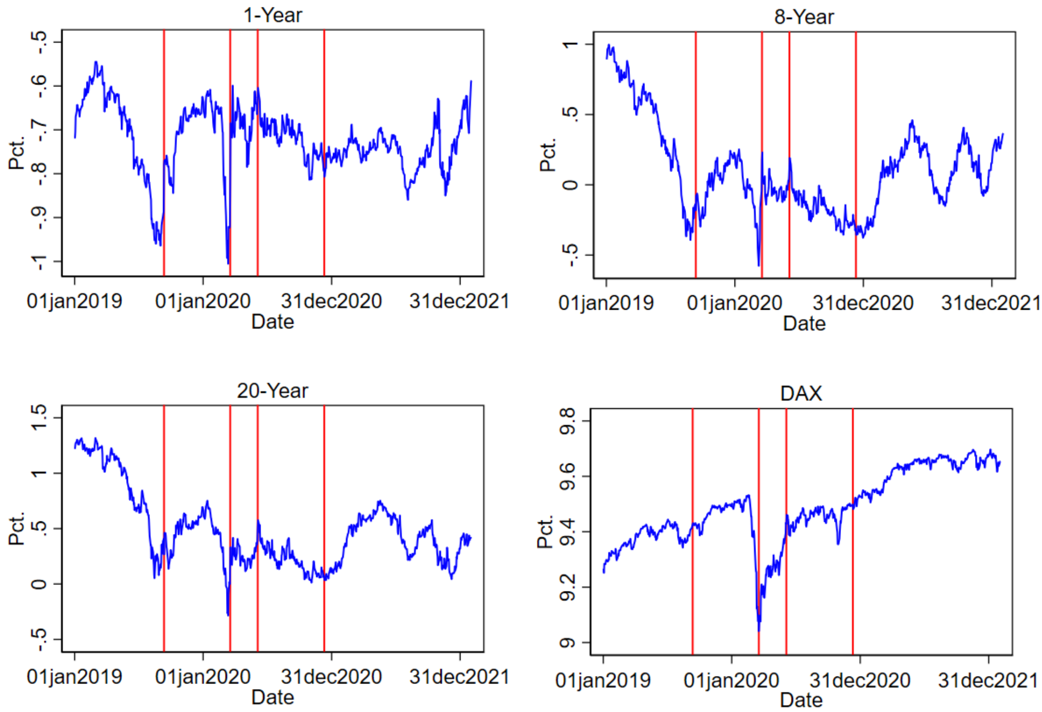
[13]Reference: ECB (2020)

is done to compare effects from announced QE during normal times with that of announcements during crisis:

- On the 12. September 2019, the ECB announced plans to restart their APP, in which they announced plans to buy assets for €20 billion monthly from the 1. November. Furthermore, they decreased their deposit facility rate by 10 basis points. The aim was to increase inflation in the euro area.
- On the 18. Marts 2020, the ECB announced the PEPP as a response to the Covid-19 pandemic. In total, the ECB announced plans to buy assets for €750 billion during 2020.
- On the 4. June 2020 the ECB announced an expansion of the PEPP by another €600 billion.
- On the 10. December 2020, the ECB announced an expansion of the PEPP by another €500 billion.

These dates can be seen as the four vertical lines in Figure 5 in which we also plot the yield curves, which is a measurement for the interest rate of government bonds in the euro area. We have chosen bond maturity times of 1 year, 8 years, and 20 years since we want a short, medium, and long time period. We also plot DAX to measure expectations in the market, since it is the stock market index for the 40 most traded German stocks.

Figure 5: Yield curves and event dates. Red vertical lines indicate the four announcement dates.



Source: ECB statistical data warehouse

The bond yields plotted in Figure 5 can be calculated in a simple way as:

$$\text{Current Yield} = \frac{\text{Annual Coupon Payment}}{\sum_{t-1}^{T} \frac{\text{Cash Flows}_t}{(1+\text{Yield to maturity})^2}} \tag{5.1}$$

where the denominator is the price of the bond. The ECB yield curves are more complex as seen in the appendix under event study, but the general idea behind it is the same. When bonds are bought up in large quantities, the demand for the bond will increase, the bond price will increase, and the yield will in turn decrease. When a central bank announces QE, the economy can be affected in many different ways. Krishnamurthy and Vissing-Jorgensen (2011) mention seven different transmission channels in which non-traditional monetary policy can affect the economy. We will only focus on one of them which is the signalling channel. The signalling channel affects all bond yields, which the ECB tried to lower during the pandemic.

To do an event study analysis, we take inspiration from Jensen et al. (2017). First, we define an event as a day in which we expect the markets to react due to an announcement from ECB. In particular, we examine the four events above. The general idea behind an event study analysis is to examine the abnormal changes in the returns of a time series. In our case, we study if the daily yield returns during the event dates are statistically significant compared to the fluctuations in the markets from the start of 2019 to the end of 2021. The returns during an event day is captured in δ_1 in the following model:

$$\Delta Y_t = \alpha + \delta_1 D_t + u_t \tag{5.2}$$

In this case, $\Delta Y_t = Y_t - Y_{t-1}$, is the daily change in yield curves of 1-, 8- and 20-years, and it is also the log of daily returns of the index DAX. D_t is dummy variables that takes the value 1 if the date is an announcement date, while u_t is white noise. If the coefficient, δ_1, is large enough compared to the error term, it is statistically significant. The ECB announces their purchasing plans at different times of day. Some plans are announced close to the market closure, so certain investors might not be able to react at the announcement date. Therefore, we do the analysis both on the day of the announcement and in a two-day event window. We only include the one-day event window seen in Table 2 below, as the results are only slightly lower in the two-day event window. This estimation can be seen in Table 3 in appendix under event study.

Table 2: Event study results for one announcement day

	(1)	(2)	(3)	(4)
	1-Year	8-Years	20-Years	DAX
12 September 2019	0.109***	-0.042	-0.138***	0.003
18 Marts 2020	0.092***	0.224***	0.219***	-0.058***
4 June 2020	0.014	0.071*	0.116***	-0.005
10 December 2020	0.005	-0.007	-0.010	-0.004
Constant	-0.0001	-0.002	-0.003*	0.001
Sum	0.220***	0.246***	0.187**	-0.063**
N	604	604	604	597

* p<0.10, ** p<0.05, *** p<0.01

Source: ECB statistical data warehouse and own calculations

We use 604 different dates for the yield curves but only 597 days for DAX, which is due to market holidays in Germany.

As can be seen in the above table, there is a mixed response from the yield curves to an announcement from the ECB. We notice that the 1-year maturity bond yields for the first announcement increase by 10.9 basis points, while the decrease in the deposit facility rate was 10 basis points the same day. This indicates that short term maturity yields react to an interest rate decrease. Furthermore, the 20-year maturity bonds instead decrease by 13.8 basis points, which could be caused by QE announcement. Looking at the second announcement, we see that the 20-year maturity yields increase by 21.9 basis points when the ECB announces asset purchases. for the third announcement date, the 20-year maturity yields increase by 11.6 basis points. This is contrary to the economic theory of bond yields, in which we expected them to decrease during an announcement. When looking at the dates of the second and third announcements, it seems like other events might have influenced the yields. Several governments across the euro area announced and launched lockdowns and restrictions due to Covid-19. One of these could be the Covid-19 announcement by Angela Merkel at the second event date, but other factors might also affect the results. This result does not correspond to Krishnamurthy and Vissing-Jorgensen (2011), who find a negative impact of QE announcement on yields. But it does correspond more to the results of Jensen et al. (2017), who found positive effects. They suggest that the ECB's announcements in their analysis was of smaller scale than expected by the markets, which could result in higher yields. The same explanation could also apply to this result. However, this is beyond the scope of this paper, but could be interesting for further study.

6 Discussion

SVAR models offer a simple way to estimate the effects of central banks' monetary policy on macroeconomic variables through the use of IRFs. However, there are several main issues to consider and address regarding their usage as listed by Bernanke et al. (2004). Our model estimates the effects from the ECB's monetary policy by using only six endogenous variables, while central banks and policy makers consider far more variables and larger data sets, when making decisions. Furthermore, our chosen variables may not necessarily represent the actual economy: HICP is just one method of determining the price level and not necessarily the ”true” inflation. An alternative approach to make more use of the large supply of data is to use factor augmented VAR (FAVAR) models as suggested by Bernanke et al. (2004). FAVAR utilizes large amount of data available to construct factors or indexes over large time series data sets to describe common dynamics. If the data can be usefully summarized in factors, some studies show that the factors outperform small VAR models. Including more data in the model is not inherently the correct decision and require much consideration, as variables can be influenced by a lot of different circumstances. This is especially true when considering the Covid-19 period, where consumption would have been lower no matter the ECB's use of monetary policy, as there were lockdowns. This approach would require extensive research and work to include these factors, which is beyond this paper.

We avoid some of the traditional problems associated with estimation by recursiveness, where the results depend on the ordering of the VAR model, due to the use of sign restrictions. Our method leads to another question: can sign restrictions be verified? We explain our sign restrictions through economic intuition and earlier studies, however, that does not necessarily imply the correct or optimal sign restrictions. Fry and Pagan (2011) state "*we do feel that sign restrictions have provided a useful technique for quantitative analysis [...] In other situations such as isolating monetary policy, it seems more likely that using institutional knowledge to provide parametric restriction would be a better way to proceed*". Thus, some authors argue that there are better methods of identification for monetary policy than our chosen sign restrictions, but they do not find that there is always a better option than sign restrictions. For further analysis, it would be interesting to test sign restrictions against other methods.
Krishnamurthy and Vissing-Jorgensen (2011) showed that there are many different transmission channels by which to estimate monetary policy. Our SVAR analysis indicated QE increases inflation, which imply that it would be appealing to examine the inflation channel to determine transmissions effects.

6.1 Finals remarks and further model expansions

The exogenous shocks of Covid-19 can be modelled in many different ways. We chose to only model the exogenous shock from April 2020 as a dummy, but we could extend the exogenous shocks to also cover March and May 2020. Modelling these months as exogenous shocks does not yield significantly different results. This paper's main focus is not to find the optimal approach to modelling Covid-19, but we do find one possible stable model. One way to estimate a VAR model after March 2020 is to look at the standard deviation of the prior distributions per Lenza and Primiceri (2020). If the standard deviation of the priors after March 2020 matches the deviation of the period before, the SVAR model appears to be robust. Looking at the standard deviations of the prior distributions is theoretically difficult and is therefore beyond the scope of this paper. More sophisticated approaches of modelling Covid-19 are not included in any freely available MATLAB toolboxes or common statistical programs. Thus, we do not test or compare this approach to our own but could be studied for further analysis.

We found statistically significant results after switching identification to sign restrictions, where we also applied a one standard deviation confidence bands, 68%. The original SVARX analysis with recursive identification used two standard deviation confidence bands, 95%. It is easier to obtain significant results when allowing for more uncertainty in the model by choosing lower confidence intervals, but this is not by itself the wrong approach. Identification by sign restrictions is inherently uncertain, which is why most studies like Uhlig (2005) and Boeckx et al. (2017) use the one standard deviation confidence bands to arrive at a statistically significant result. Using 68% confidence bands are also chosen for other VAR analyses such as Lenza and Primiceri (2020), where identification is not by sign restrictions. Furthermore, Sims and Zha (1995) state that 68% confidence bands does have its merits: ”*Also, for characterizing likelihood shape, bands that correspond to 50% or 68% posterior probability are often more useful than 95% or 99% bands,*”. Therefore, lower confidence bands can often be better for describing the likelihood function as compared to stricter confidence bands. It is not the aim of this paper to discuss the appropriate amount of confidence interval, but the choice of using 68% confidence bands, when applying sign restrictions, should be noted.

7 Conclusion

We found that asset purchasing by the ECB can reduce financial stress at the cost of inflation even in times of extreme uncertainty as during the Covid-19 pandemic. We estimated no clear effect on GDP, following the approaches of Uhlig (2005) and Boeckx et al. (2017). If the ECB wants to stabilize the financial markets, then quantitative easing is the proper tool, but if they wish to increase output, quantitative easing is not necessarily the correct method. We also found evidence of the possibility for using quantitative easing to increase inflation, as the ECB did before the Covid-19 pandemic. Furthermore, we found a positive effect of asset purchasing announcements on bond yields contrary to Krishnamurthy and Vissing-Jorgensen (2011). However, this aligns with Jensen et al. (2017), who proposed that bond yields increased due to the response of the ECB being smaller than the markets expected.

8 Appendix

Code

The code to produce the graph and data can be found at: https://github.com/peterlravn/Code-for-Monetary-policy-during-Covid-19-

- Python code for downloading and transforming the data: https://github.com/peterlravn/Code-for-Monetary-policy-during-Covid-19-/tree/main/PYTHON%20code
- Stata code for testing models: https://github.com/peterlravn/Code-for-Monetary-policy-during-Covid-19-/tree/main/STATA%20code
- MATLAB code to SVAR models and impose sign restrictions: https://github.com/peterlravn/Code-for-Monetary-policy-during-Covid-19-/tree/main/MATLAB%20code

Aditional info on CISS

CISS was constructed by Hollo et al. (2012) as an composite indicator for stress in the financial markets. CISS includes 15 raw mainly market-based financial stress measures, which are split equally into five categories:

1. Financial intermediaries sector
2. Money markets
3. Equity markets
4. Bond markets
5. Foreign exchange markets

CISS attempts to measure contemporaneous systemic stress by using standard definitions of systemic risk at its core. CISS assigns more weight to a given situation, when multiple markets contain stress, to encapsulate the idea that financial stress is systemic and thus a greater problem for the economy.

Cholesky decomposition definition

From Lütkepohl (2005) the Cholesky decomposition of a positive definite matrix A, which is $m \times m$ matrix, then there exists a lower triangular matrix P, which have the positive main diagonal:

$$A = PP'$$

A lower triangular matrix is a matrix, P, where all values above the diagonal is zero and the reverse holds for the upper triangular matrix, P'. To achieve a recursive structure, we identify the Cholesky matrix as being all ones:

$$PP' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Further details for the event study

Two day event window is estimated as:

$$\Delta Y_t = \alpha + \delta_1 D_t + \delta_2 D_{t-1} + u_t$$

The results can be seen below:

Table 3: Event study results for the two day announcement event window

	(1)	(2)	(3)	(4)
	1-Year	8-Years	20-Years	DAX
12 September 2019	0.060***	0.032	0.03	0.004
18 Marts 2020	0.119***	0.140***	0.170***	-0.019**
4 June 2020	0.014	0.071*	0.116***	-0.005
10 December	0.006	-0.006	-0.009	-0.004
Constant	-0.0004	-0.003	-0.004**	0.0005
Sum	0.189***	0.160*	0.182*	-0.023
N	604	604	604	597

* p<0.10, ** p<0.05, *** p<0.01

Source: ECB statistical data warehouse and own calculations

The bond yields can be found by optimizing for y in the following:

$$P = v^{f_1} \cdot \left(k + \sum_{i=1}^{n-1} \frac{g}{h} \cdot v^i \right) + \left(C + \frac{g}{h} \cdot f_2 \right) \cdot v^{n+f_1+f_2-1} \tag{8.1}$$

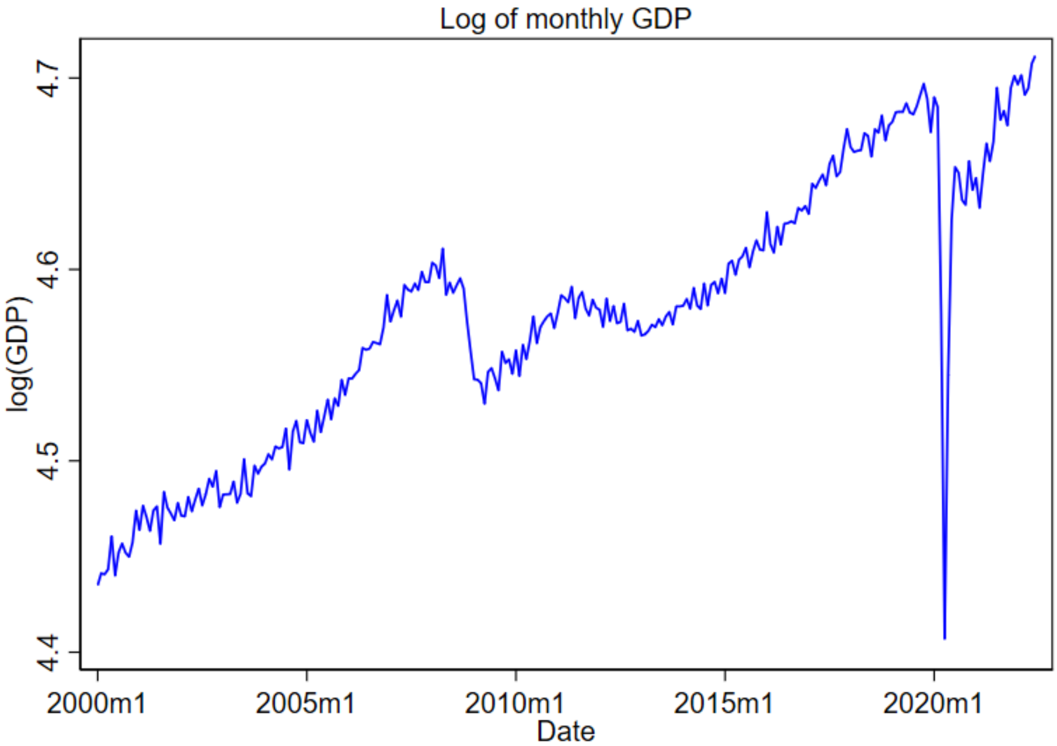
where

- P = gross price of the bond at the close of the previous business day
- g = annual coupon interest rate as a percentage
- k = first/next coupon payment as a percentage
- h = number of coupon payments a year
- n = number of coupon payments to redemption
- f_1 = fraction of the number of calendar days from value date to the first/next interest payment
- f_2 = fraction of the number of calendar days from the last normal coupon date to redemption
- C = redemption value
- v = discount factor, $v = \frac{1}{1+y}$, and y = required redemption yield compounded h times per annum.

For further information, see the following paper from the ECB: https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_area_yield_curves/html/technical_notes.pdf

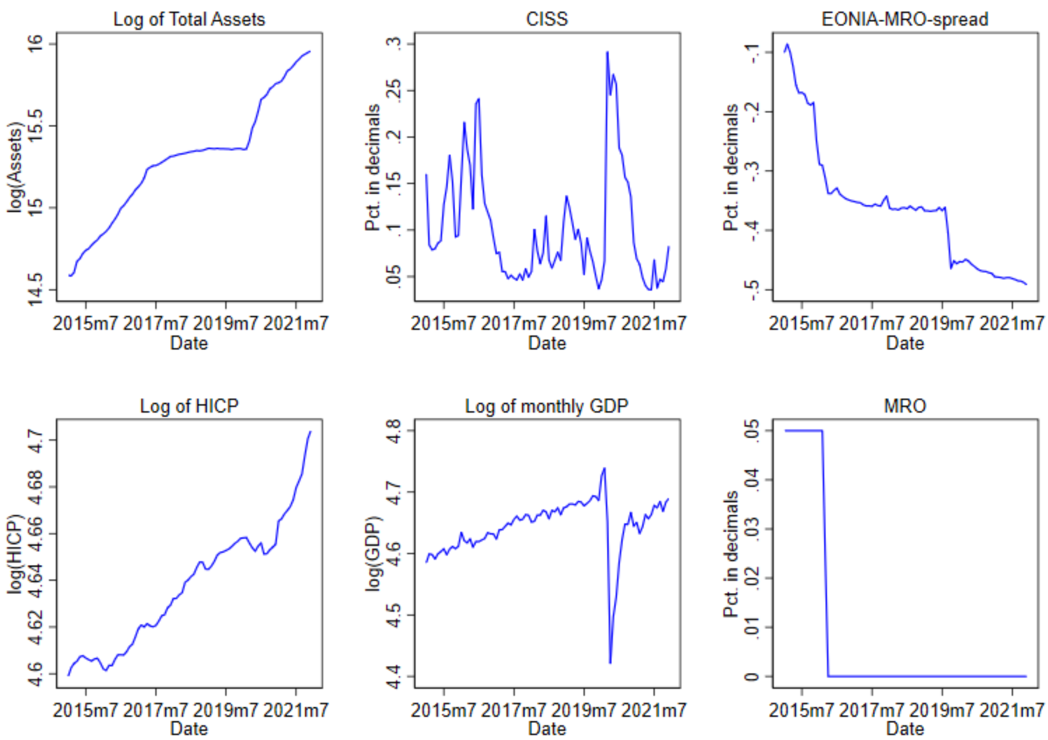
Additional figures

Figure 6: Log of GDP monthly from 2000



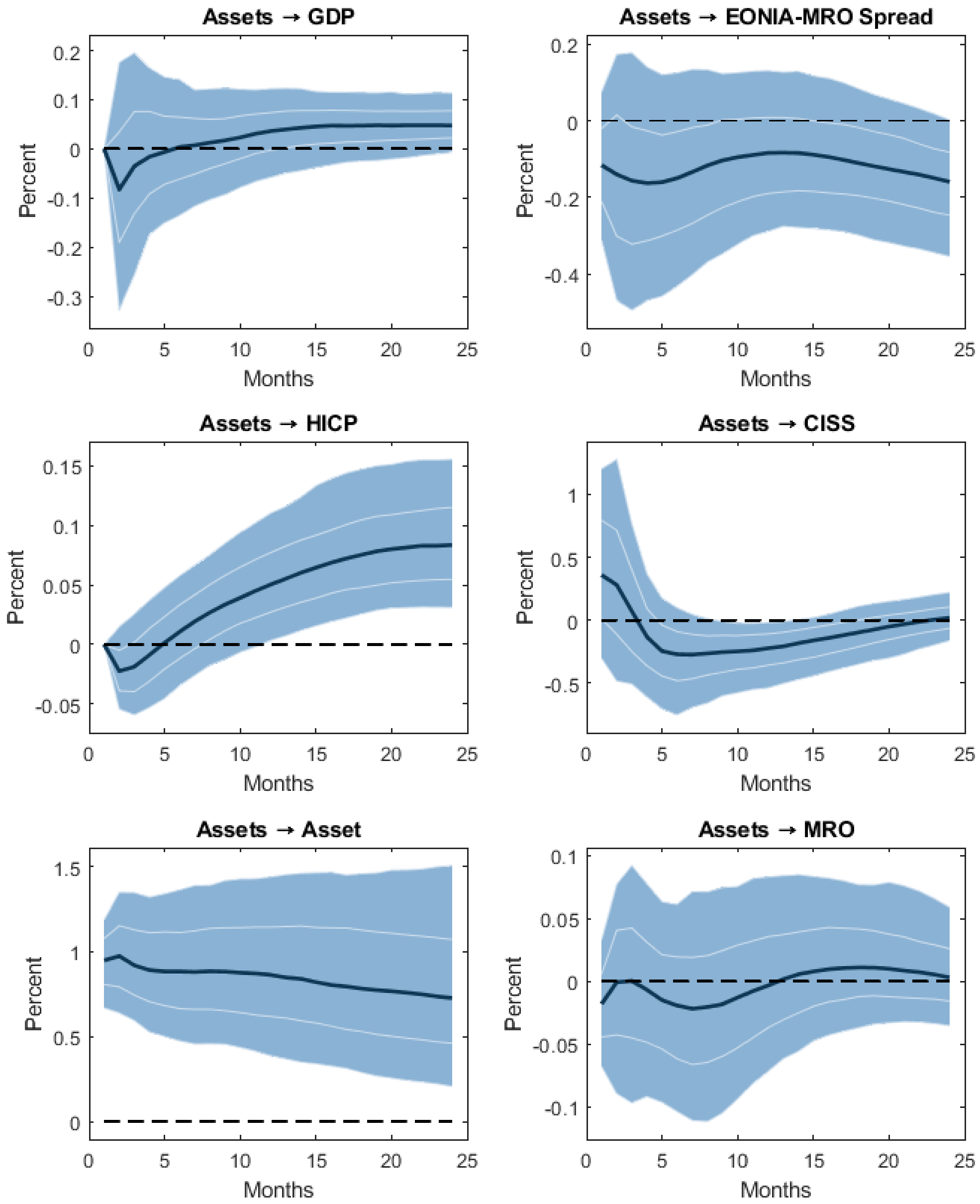
Source: ECB statistical data warehouse

Figure 7: The variables of the model during our sample period



Source: ECB statistical data warehouse

Figure 8: Structural impulse response functions like figure 3 with HICP and CISS switched in the causal order. Outer confidence bands show the 95% and the inner white lines show 68%. The black line represents the median.



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