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Financial Shocks and Economic Fluctuations: Evidence form Norway

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Abstract

In this paper, we evaluate the importance of shocks originating in the financial sector on the Norwegian macroeconomic variables. We estimate demand, supply, monetary policy, investment, and financial shocks in a Bayesian VAR model with sign restrictions. We run three different setups. Firstly, the baseline model is estimated where we find that financial shocks are an important driver for investment and stock prices in the short-run and for the interest rate in the long-run. Moreover, financial shocks explain a limited share of the fluctuations in output and prices across all horizons. Surprisingly, monetary policy shocks are an important driver across all variables. By disentangling the financial shock into a credit and housing shock, we find that housing shocks have a dominant role in explaining the fluctuations in the variables, while the credit shocks are negligible. Lastly, the exchange rate model is estimated, where we look at how shocks from the baseline model can explain the fluctuations in the exchange rate. The results show that monetary policy shocks are the main driver for explaining the short-term fluctuations, while investment shocks become the main driver in the long run.

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1. Introduction

In 2008 the world economy experienced a major financial crisis which affected the global economy. The rate of decline in output, stock markets and trade were higher than during the Great Depression (Eichengreen & O'Rourke, 2009). The financial crisis in 2008 was largely due to the build-up of financial imbalances in the global economy. This was outlined through peaking business cycles, falling real estate markets and little faith in the credit sector. The results were crashes in both real estate and stock markets. The financial crisis also affected Norway, resulting in a stock market collapse at Oslo Stock Exchange with an estimated 64 percent decline over six months. Furthermore, the nominal house prices fell 14 percent between August 2007 and December 2008. During the same period, the fall in real house prices were recorded to 18 percent (Grytten & Hunnes, 2010).

In the aftermath of the global financial crisis there has been extensive research on the relationship between financial and macroeconomic variables. Previous research on the importance of shocks originating in the financial sector have been conducted using dynamic stochastic general equilibrium (DSGE) models, where the results show that financial variables are important for business cycle fluctuations (Justiniano, Primiceri & Tambalotti, 2010; Christiano, Motto & Rostagno, 2010; Christiano, Motto & Rostagno, 2014). Another popular approach has been the use of vector autoregression (VAR) models, in which macroeconomic and financial variables are combined in one model to investigate the response to financial shocks (Jermann & Quadrini, 2012; Fornari & Stracca, 2013; Furlanetto, Ravazollo & Sarferaz, 2017).

Investigating the importance of financial shocks on economic fluctuations has been extended to shocks originating in the housing and credit markets. Gilchrist and Zakrajsek (2012) show that shocks to the excess bond premium leads to a significant decline in consumption, output, and investment. Furthermore, housing shocks have been found to be important for economic fluctuations. Walentin (2014) shows that the mortgage market affects the fluctuation in the business cycle while Prieto, Eickmeier and Mercellino (2016) report that house price shocks were an important factor for explaining the Great Recession.

The main objective of the paper is to identify the importance of financial shocks on the economic fluctuations in Norway. Studies conducted on the relationship between financial and macroeconomic variables have previously been concentrated around the US and Euro data, and the research on how financial shocks explain the economic fluctuations in Norway is largely unknown.

Our paper is based on the work of Furlanetto et al. (2017) "Identification of financial factors in economic fluctuations". In the paper they use a Bayesian VAR model with sign restrictions to quantify the importance of shocks originating in the financial sector. While their paper used data on the US, which is a different economy than Norway, the authors argued that applying the model to a small open economy would be interesting.

In this thesis, we employ a VAR model with sign restrictions using Bayesian methods. The baseline model includes a single financial shock determined by the stock prices, as given by the Oslo Stock Exchange Benchmark Index (OSEBX). The index comprises the most traded shares listed on Oslo Stock Exchange. We define a financial shock as a shock that creates an investment and a stock market boom. To disentangle the supply, demand, and the monetary policy shocks, we use New Keynesian (NK) theory. The demand, investment, and financial shocks move output, prices, and interest rate in the same direction. We separate the demand shocks from the investment shocks by constructing an investment to output ratio. We impose that a positive investment shock contemporaneously increases the ratio while a positive demand shock decreases the ratio[1]. To separate the investment shock from the financial shock, we impose that positive investment shocks have a negative effect on stock prices, while positive financial shocks have a positive effect on stock prices[2]. We find that financial shocks are an important

[1] We consider the demand shock as a non-investment demand shock where it is only a shock to fiscal policy, consumption or increase in foreign demand.
[2] The price of capital can be seen as a proxy of stock market value. A positive investment shock increases the supply of capital which imply a negative relationship with the price of capital. On the

driver for investment and stock prices in the short-run and for the interest rate in the long-run. Moreover, financial shocks explain a limited share of the fluctuations in output and prices across all horizons. For output and prices, supply shocks and monetary policy shocks are the main drivers across all horizons. Blanchard and Quah (1989) also report an important role for supply shocks on output. A puzzling result is the overall large importance of monetary policy shocks. It poses as an important driver across all variables. This is contradicting with the findings of Mountford (2005) and Lindé (2003), who find that monetary policy shocks have limited importance for macroeconomic variables.

In the next set up, we remove the monetary policy shock and separate the financial shock into housing and credit shocks. We disentangle the two shocks by adding a variable called credit to real estate ratio. The ratio consists of the total credit to private non-financial sector, divided by the total value of existing dwellings in Norway. We then impose that positive credit shocks increase the ratio while positive housing shocks decrease the ratio. This restriction only holds on impact. We report an important role for housing shocks on output, while the importance of credit shocks is negligible. The large importance of housing shocks is in line with Leamer (2007) who argued that housing is the business cycle. Iacoviello and Neri (2010) show that the housing sector is one of the driving forces of business cycle fluctuations. Furthermore, Prieto et al. (2016) also report an important role of housing shocks on business cycle fluctuations in the US.

The US economy is a large economy which is largely affected by domestic shocks compared to Norway, as it is a small open economy. This implies that the exchange rate is a key variable for economic development in Norway. Therefore, we deviate from Furlanetto et al. (2017) by extending the model to include the exchange rate. We investigate how the shocks used in the baseline model can explain the fluctuations in the exchange rate. As a measure for the exchange rate, we use the real effective exchange rate which is the weighted average of a country's currency compared to another country's basket of goods. Ideally, we

other hand, financial shocks are shocks to the demand of capital and imply a positive relationship with the price of capital.

would add an exchange rate shock. However, as the exchange rate shock and the demand shock move the variables in the same direction, we are not able uniquely identify the shocks. We therefore add a residual shock to obtain the same number of variables and shocks. The residual shock is supposed to only capture the residual dynamics in the system. It is interpreted as a supply shock that moves output and stock prices in opposite directions. The results show that in the short-run, monetary policy shocks are the main contributor to the fluctuations in the exchange rate. This is consistent with Bjørnland (2008), who reports a significant dependency between monetary policy shocks and the exchange rate. On the other hand, in the long run investment shocks are the main driver for the exchange rate fluctuations. A consistent finding from our results is the importance of monetary policy shocks for all variables. Further, we find financial shocks to explain 23 to 24 percent of the total variation in the exchange rate, across all horizons.

The paper is structured as follows: In Section 2, we present an overview of the literature on financial shocks, credit and demand shocks and the impact of shocks on the exchange rate fluctuations. Section 3 presents the research design, the VAR methodology and description of the data. In Section 4, 5 and 6, we present the results from our models in the following order: The baseline model, housing and credit model, and the exchange rate model. In Section 7, we discuss some limitations connected to the model and our approaches. Lastly, our concluding remarks are presented in Section 8.

2. Literature Review

Furlanetto et al. (2017) employ a Bayesian VAR model with sign restrictions to evaluate the importance of financial shocks in explaining economic fluctuations in the US. The paper can be divided into two steps. In the first step, a single financial shock that is consistent with creating an investment and a stock market boom is introduced. The endogenous variables included are output, prices, interest rate, investment, stock prices and a spread[3]. In the second step, the financial shock is

[3] Credit spread is the difference in yield between two securities at same maturity, but different credit quality. In the first set up they measure the spread as the difference between Baa corporate bonds and federal funds rate.

disentangled into separate components, to investigate whether the shocks originate in the credit markets, the housing sector, or if it captures the significance of uncertainty shocks. They disentangle the financial shock into credit and housing shocks with the endogenous variables output, prices, investment, stock prices and credit to real estate ratio. To investigate if the credit shock was containing uncertainty, they introduced the Chicago Board Options Exchange Volatility (VIX) index as a measure of uncertainty[4]. To differentiate uncertainty shocks from credit shocks they introduced the ratio of excess bond premium over the VIX index. Lastly, the authors investigated the importance of credit demand and credit supply shocks in the same set up by disentangling the financial shock into housing, credit supply and credit demand shocks. The introduction of mortgage rates separates the credit supply from credit demand. The main contribution was that financial shocks pose as an important driver for economic fluctuations in the US, by explaining a large share of the fluctuations in output and investment. Further, their findings suggest that financial shocks have limited impact on inflation. Disentangling the financial shock into housing and credit shocks show that housing shocks absorbed the importance of the financial shock.

2.1 Financial Shocks

In addition to the study of Furlanetto et al. (2017) the role of financial shocks in explaining economic fluctuations have received growing attention in the last decades, and especially after the 2008 financial crisis. The importance of the financial shocks has been studied in models such as DSGE and VAR models. The earlier work on the subject focused on using DSGE models and further implement an investment shock to the model. Justiniano et al. (2010) show using a DSGE model with shocks to the marginal efficiency of investment, that investment shocks are a key driver for movement in output, hours worked, and investment throughout the cycle. However, it has been pointed out by Christiano et al. (2014) that it is imperative to include financial variables in the DSGE model to capture the importance of financial shocks and importantly, to be able to distinguish the financial shocks from traditional investment shocks. This has previously been

[4] VIX index is a measure of stock volatility, based on the S&P 500 index options.

done by Christiano et al. (2010) who augmented a standard DSGE model to include the financial markets and the banking sector. They fit this model to US data and the euro area and find that financial factors are important for business cycle fluctuations as well as being a trigger for the financial crisis in 2008. However, they argue that for the DSGE model to be functional in terms of answering a more variety of financial questions, it must be expanded.

Jermann and Quadrini (2012) enrich the literature by looking at the effect of financial shocks on macroeconomic variables. The authors develop a model which includes firm's financial flow associated with the firm's debt and equity financing. Central for the model is the firm's preference for debt over equity. The firm's ability to borrow is limited by an enforcement constraint which is exposed to random disturbances. The authors define these random disturbances as financial shocks as they affect the firm's ability to borrow. They use two methodological approaches. First, a time series for financial shocks based on the enforcement is constructed. A methodology similar to the construction of productivity shocks as residuals in the Solow model, is used. The authors use data for debt, capital, and output to construct the residual shock (financial shock) based on the enforcement constraint. The results suggest that financial shocks are important for the financial flow, but also for labor. Furthermore, the model shows that the worsening of firms' ability to borrow in 2008–2009 is synonym with a sharp economic downturn. Secondly, they look at the importance for financial shocks on macroeconomic variables using Bayesian methods to estimate the structural parameters. The method allows them to include more shocks and assess the contribution of financial shocks relative to other shocks in the model. From the variance decomposition the results show that financial shocks contribute to almost 50 percent of the volatility in output and about 30 percent to the working hours volatility.

Fornari and Stracca (2013) estimate a panel VAR model for 21 advanced countries with quarterly data between year 1985 and 2011. The structural shocks are identified through sign restrictions. The financial shocks are identified through a restriction on the response of the ratio between the relative share price of the financial sector to the share price from the composite stock market. The results show that financial shocks explain 12 percent of the variation in output. Furthermore, they find that the importance of financial shocks holds in normal times, and thus not constrained by only periods of crisis.

2.2. Housing and credit shocks

How financial shocks affect economic fluctuations have been extended to looking at the importance of shocks originating in the credit and housing market. Through a DSGE model, Iacoviello and Neri (2010) investigated if the housing sector is one of the driving forces of business cycle fluctuations. They wanted to find the nature of shocks hitting the house market by studying a combination of shocks and frictions which can help explain the dynamics of residential investment and housing. Further, the spillover effect from the housing market to the rest of the economy in the US was measured. The authors used quarterly data from year 1965 to 2006, meaning the analysis did not include the Great Recession in 2008. The results indicate that the main shocks driving the housing market at business cycle frequency are housing demand shocks and housing technology shocks. These shocks account for approximately 25 percent each of the cyclical volatility of housing investment and housing prices. In terms of the spillover effect their results show that it is significant, although it is concentrated on consumption rather than business investments.

A study conducted by Gilchrist and Zakrajsek (2012) used US data to examine the relationship between a credit spread and economic activity through a VAR model. Using a credit spread builds on the theory that when financial markets suffer from frictions, it will affect the distance between the spread of two bonds. Wider spread between bonds of different risk rating is a result of the market factoring more risk of default on lower grade bonds where a narrow spread indicates lower default risk. The fluctuations in the spread can come from a reduction in supply of credit due to financial intermediates having worse capital position. This leads to increasing cost of debt and wider spread which gives a reduction in spending and production. As a result, the spread can be viewed as a good measure for the wellbeing of the economy. A measure of credit spread was constructed, the GZ spread, which is based on senior unsecured corporate bonds issued by non-financial institutions. The results suggest that the GZ spread is a better predictor that outshines the more commonly used default to risk indicators spreads for future economic activity, such as the Baa-Aaa and the “paper bill”. The predictive power of the GZ spread is due to fluctuations in the excess bond premium, where shocks to the excess bond premium leads to significant decline in consumption, output, and investment[5].

Walentin (2014) studied the spread between the average interest rate of newly issued mortgages and the government bond rate of equal maturity. Using a VAR model with quarterly data for US, UK, and Sweden, he investigated how the business cycle was affected by shocks to the mortgage spread. He imposed sign restrictions on the first two quarters. This was successfully done by imposing house prices to move in an opposite direction of the mortgage spread. To ensure that the monetary policy shock would not be included in a shock to the mortgage spread, opposite sign on the policy rate compared to mortgage spread was imposed. The main result was that financial frictions in the mortgage market affected fluctuations in the business cycle, where a one percentage decrease in the mortgage spread yielded a two-percentage increase in output.

Prieto et al. (2016) analysed the impact of shocks to the credit spread, house prices, and stock prices have on the US economy. The authors use a VAR model, with quarterly data from year 1958 to 2012 and consider that the relationship between financial indicators and macroeconomy possibly could vary with time. Therefore, they allow for continuous changes in the shock volatility, the autoregressive coefficients, and the contemporaneous relationship between the variables. The authors were able to capture different changes in the connection between financial indicators and the macroeconomy, in terms of whether the change was gradual or long-lasting. The VAR model included six variables: output growth, GDP deflator, house price inflation, spread of corporate bonds, stock price inflation and the federal funds rate. The main findings were that financial shocks account for 20 percent of the variation in output in normal times,

[5] Fluctuations in excess bond premium is due to cyclical changes in the relationship between measured default risk and credit spreads.

but during the Great Recession the variation was over 50 percent. One of the most important shocks for explaining the Great Recession were house price shocks, which explained around 2/3 of the total contribution from the financial sector in that period. In the aftermath of the financial crisis the recovery was both slow and weak, which can be attributed to negative developments in the housing market, due to households being credit constrained.

2.3 Importance of shocks on the exchange rate fluctuation

Most of the studies conducted to analyse the importance of shocks in explaining exchange rate fluctuations have employed VAR models. Even though most of the previous research use VAR methodology, different approaches are used to identify the structural shocks. The researchers also arrive at different conclusions about what determines the exchange rate fluctuations.

In a seminal paper, Clarida and Gali (1994) study the importance of nominal shocks in explaining the importance of exchange rate fluctuations using an open economy model. Their identification procedure is based on the long-run triangular identification scheme developed by Blanchard and Quah (1989)[6]. The assumption is that nominal shocks do not affect the real exchange rate or the real output in the long run. They find that demand shocks, to national saving and investment explain the lion's share of the variation in real exchange rate, while supply shocks explain a limited share of the variation in the exchange rate. The result is consistent with the findings from Chadha and Prasad (1997) and Funke (2000). Using the same methodological approach as Clarida and Gali (1994) with data for United Kingdom, EU, and Japan, both papers find that demand shocks largely drive the fluctuations in the exchange rate. However, Chadha and Prasad (1997) also state that the effects of supply shocks are non-negligible. Canzoneri, Valles, and Vinals (1996) estimated a VAR model with long-run restrictions for EU countries. The authors compared the shocks driving the variation in output and the exchange rate. The results reveal that aggregate supply and demand shocks explain over 90 percent of the variation in output but explained a negligible part of the variation in

[6] Blanchard and Quah introduce restrictions on the systems long-run properties of the shocks where the restrictions was on the sums of the coefficients.

exchange rates. On the contrary, Artis and Ehrmann (2000) estimate a VAR model with short-run restrictions as the identification approach and assume that all nominal shocks have no immediate effect on output. The results show that the exchange rate is largely driven by shocks originating in the exchange rate market itself.

Farrant and Peersman (2006) enrich the literature by using sign restrictions to identify the structural shocks in the VAR model. By using the same open economy model as developed by Clarida and Gali (1994), they introduce sign restrictions based on the short-run dynamics of the model. This is argued to be valid also in a larger class of theoretical models. They find that a large part of the variation in the real exchange rate is attributed to demand shocks. Further, monetary policy shocks have a significant impact on the path of the exchange rate, while supply shocks have no effect in the short or long-run.

Bjørnland (2004) investigate whether the exchange rate is a shock absorber or a source of shocks itself using Norwegian data. The article builds on Norway being a small open economy and likely to be affected by idiosyncratic (country specific) shocks, and further that Norwegian business fluctuations are asymmetric with respect to the European business cycles. She applies a structural VAR (SVAR) model with the variables output, unemployment, the real wage, and the real exchange rate. The structural shocks are identified using long-run restrictions [7]. Her findings give contradicting answers dependent on the shocks. The shocks that determine the fluctuations in output were labour supply and nominal shocks. These shocks have little explanatory power for the fluctuations in the real exchange rate where demand shocks dominated. On the other hand, productivity shocks seem to be important to both real output and real exchange rate variation.

[7] The key identifying assumption here is used to distinguish between demand and supply shocks, asserting that in the long run the level of real output will be determined by supply side factors only. Also, all shocks but the nominal shock can potentially have a long-run effect on the real exchange rate.

3. Methodology & Data

The VAR methodology is based on the work of Thorsrud and Bjørnland (2015) and Furlanetto et al. (2017). The part on sign restrictions is based on the work of Kilian and Lütkepohl (2017). To study effect of shocks generated from the financial sector on the economic fluctuation in Norway, we will employ a Bayesian VAR model with sign restrictions. Lastly, the MatLab code is based on the code from Furlanetto et al. (2017).

3.1. Bayesian VAR model

We estimate the VAR model using Bayesian methods and variables in levels. For theory on Bayesian estimation, see appendix E.2. Bayesian methods are based on a few elementary rules in probability theory, for more discussion on Bayesian probability theory and inference see appendix E.1. We argue that using the Bayesian VAR model is appropriate for our case as we have a limited data set compared to variables and this might solve the problem of over-parameterization (Koop & Korobilis, 2009). One important aspect with the Bayesian VAR is the specification of the prior for our parameters of interest. In many cases, one tries to specify a prior such that the posterior analysis is simplified[8]. According to Kilian and Lütkepohl (2017) it is convenient to specify the prior such that the posterior is from a known family of distributions. To obtain a dominant likelihood, we specify diffuse priors. These priors lead to a Normal-Wishart posterior with mean and variance parameters corresponding to ordinary least squares (OLS) estimates.

3.2. Structural Autoregressive (SVAR) model

The structural autoregressive (SVAR) model was introduced by Sims (1980) and has later become important to study causal relations in macroeconomics. The method allows us to identify the structural shocks such that they can match their theoretical counterparts. The usefulness of the model comes from the fact that it allows us to construct uncorrelated error terms. We consider the standard SVAR model.

[8] The prior is used to shrink the unrestricted model, and as a result reduce parameter uncertainty and improve the accuracy of forecasts.

$$B_0 y_t = b + \sum_{j=1}^{p} B_j y_{t-j} + \varepsilon_t , \quad \varepsilon_t \sim N(0, I) \tag{1}$$

Where K is the number of variables within the system and p is the number of lags. y_t is a $(K \times 1)$ vector of variables, and b contains a $(K \times 1)$ vector of constants. B_0 and B_j are $(K \times K)$ matrices, and ε_t is a $(K \times 1)$ vector of structural shocks with properties $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] \equiv \sum_\varepsilon = I_N$. This means that the covariance matrix for the structural shocks are assumed to be an identity matrix with zeros on the diagonal, where the shocks are uncorrelated. To estimate the effect of structural shocks in the model it is imperative that we obtain the same number of structural shocks as variables, otherwise the system is not identified. The difference between B_0 and B_j is that B_0 shows the contemporaneous effect of the shocks on the variables, as opposed to B_j which shows the lagged response.

3.3. Vector Autoregressive model (VAR)

A problem that occurs when estimating the SVAR model is simultaneity. That is, the variables contained in y_t are simultaneously affected by the structural shocks, results in inconsistent OLS estimators. A way to solve this issue is by deriving the reduced form VAR from the SVAR model and recover the structural shocks through this process.

We consider a $(K \times 1)$ vector of y_t containing all K endogenous variables.

$$y_t = (y_{1,t}, \ldots, y_{K,t})'$$

By multiplying both sides of equation (1) by B_0^{-1}, we can then write the reduced form VAR as follows:

$$y_t = \mu + \sum_{j=1}^{p} A_j y_{t-j} + e_t \tag{2}$$

Where $A_j = B_0^{-1} B_j$, $\mu = B_0^{-1} b$, and $e_t = \varepsilon_t B_0^{-1}$. y_t is a $(K \times 1)$ vector containing observations on K time series variables for t = 1,2,...,T. μ denotes a $(K \times 1)$

vector containing intercepts and A_j is a $(K \times K)$ matrix of coefficients with p as the maximum number of lag. e_t is a $(K \times 1)$ vector of error terms that now is a linear combination of the structural shocks with the following properties:

1. $E[e_t] = 0$
2. $E[e_t, e_s'] = \sum_e$ for t = s
3. $E[e_t, e_s']$ = 0, otherwise

Within the reduced form errors, we have only three unique elements as the correlation of [e_t, e_s'] = correlation of [e_s', e_t].

3.3. Identification of structural parameters

By OLS, we can estimate all the reduced form parameters from equation (2) and further compute the covariance matrix. However, without restrictions the covariance matrix will not be a diagonal matrix and the reduced form errors are likely to be correlated. This makes us unable to identify the structural parameters from the structural VAR and use them for structural analysis.

For the identification procedure we use the fact that the error term, e_t from the VAR model can be written as a linear combination of the structural shocks from the SVAR.

$$e_t = B_0^{-1}\varepsilon_t \tag{3}$$

Where ε_t is $N(0, I)$ and B_0^{-1} is the inverse impact matrix. From equation (3), we can see that knowledge of B_0^{-1} will help us identify the structural shocks ε_t. The variance-covariance matrix is positive definite and symmetric which enables us to factorize it as follows:

$$\sum_e = E[e_t e_t'] = B_0^{-1}E[\varepsilon_t \varepsilon_t']B_0^{-1'} = B_0^{-1}\sum_\varepsilon B_0^{-1'} = B_0^{-1} I B_0^{-1'} = B_0^{-1}B_0^{-1'}$$

Where $\sum_\varepsilon = I$ by definition. As the variance covariance matrix is symmetric it contains $K(K+1)/2$ unique elements. On the contrary, the impact matrix has K^2 unique elements. Thus, we need to restrict the impact matrix by $K^2 - K(K+1)/2$ elements to identify B_0^{-1}. It is imperative that we restrict the impact matrix to have the same number of unique parameters as the covariance matrix. This because the covariance matrix determines the number of unique parameters that can be identified from $\sum_e$. The most common way of imposing restrictions on the impact matrix is using the Cholesky decomposition. This form of identification scheme includes restricting $B_0^{-1} = \mathrm{P}$ to be a lower triangular matrix and then use recursive substitution. Even though the recursive identification scheme is efficient from a computational point of view, we assert that it is not appropriate from a theoretical perspective.

In our study we include fast-moving variables such as the interest rate, stock prices and other financial variables[9]. Keeping in line with Bernanke et al. (2005), we define fast-moving variables such as interest rate and stock prices to react within the same time-period as the shock occurs. The recursive identification scheme relies upon the assumption that variables ordered ahead react with one lag to the shocks ordered after. As we include both the interest rate and stock prices in our model, using recursive identification and setting interest rate ahead of stock prices will mean that the interest will react with one lag to stock price shocks while stock prices will react contemporaneously to monetary policy shocks[10]. This has been argued by Bjørnland and Leitemo (2005) who reports a simultaneous interaction between interest rate setting and shocks to real stock prices. As a result, recursive identification will not be an adequate approach to account for this simultaneous interaction. We then argue that sign restriction as an identification scheme is appropriate as we then restrict the shape of the impulse i.e., we restrict how the variables should react contemporaneously to each shock in the model.

3.4. Sign Restrictions

Sign restrictions as an identification approach can be dated back to Faust (1998), Canova and Nicoló (2002) and Uhlig (2005). The idea is to impose a restriction on the contemporaneous impact matrix, B_0^{-1}, in order to achieve identification.

[9] Killian and Lutkepohl (2017) argue that it is questionable assumption if one assume that none of the observed variables reacts to a monetary policy shock within the same time-period as the shock occurs, especially if fast-moving variables are included in the model.

[10] Recursive identification scheme is a common approach when investigating the interaction between monetary policy and asset prices where they order monetary policy ahead of stock prices, see for example Thorbecke (1997); Millard and Wells (2003); Neri (2004).

We define a $(K \times K)$ lower-triangular matrix with positive elements along the diagonal, P, with the property $PP' = \sum_e$. This is the lower-triangular Cholesky factor.

We now consider $e_t = Pv_t$, where e_t is the reduced form VAR innovations and where v_t is uncorrelated shocks with unit variance by construction. It is important to note that $v_t \neq \varepsilon_t$. Thus, v_t shocks should not be consistent with economically interpretable structural shocks. Since we do not know the solution of the structural shocks ε_t, we can search for candidate solutions in the estimated ε_t^* through constructing large number of combinations, of the shocks v_t, of the form $\varepsilon_t^* = Q'v_t$. By definition, a square matrix $(K \times K)$ Q is orthogonal if $Q' = Q^{-1}$. This implies $QQ' = Q'Q = I$, and we get:

$$e_t = Pv_t = PIv_t = PQQ'v_t = PQ\varepsilon_t^* \tag{4}$$

How we determine whether a candidate solution ε_t^* is a valid solution for the unknown structural shock ε_t, given the vector of reduced form parameters, will depend if the implied structural impact matrix PQ satisfies the supported sign restrictions on B_0^{-1} or not. We keep every solution that satisfies the restrictions and discard the rest. This procedure is repeated and enables us to characterize the set of structural models that are consistent with the maintained sign restrictions and the reduced form parameters. Further, the knowledge of PQ allows us to construct all implied structural impulse response coefficients of interest from the estimates of the reduced form parameters (Kilian & Lutkepohl, 2017).

In order to construct suitable impact multiplier matrices, Q, we use the householder transformation, which was proposed by Rubio-Ramirez, Waggoner and Zha (2010). This builds on the idea that any real square matrix W can be factorized to a QR decomposition, where Q has the same properties as previously, and R is an upper triangular matrix. They provide an algorithm which enables us to draw a random column of the $(K \times K)$ matrix W at random, where $W \sim N(0,1)$, and then apply the QR decomposition for each draw. This algorithm further generates a large amount of candidate solutions for B_0^{-1} as PQ, where Q is obtained from the random draw of W. If the impulse response generated does not satisfy the imposed sign restrictions, we must make another draw of W until they are satisfied. The code from Rubio-Ramirez et al. (2010) acknowledge the fact that instead of generating a new draw one can simply multiply the orthogonal matrix Q by -1 which results in another orthogonal matrix. We then reverse the imposed sign restriction and check if the generated impulse responses satisfy the sign restrictions. If not, we make a new draw. A problem with this approach, is the issue of the shocks having the same sign pattern, leading to two or more shocks having equal effect on impact, and thus not being able to differentiate the shocks from each other. However, we argue that this will not be a problem as we have a distinct set of sign restrictions on the shocks. This will be more discussed later in this paper.

3.5. Data

In this section we present the data used for each model. It is desirable to have the largest dataset as possible to ensure a big sample size, however limitations occur as some data have not been recorded until recent date.

3.5.1 The Baseline model

In the baseline model we use quarterly data with a sample period from year 1991Q1 to 2019Q3. The model includes five variables: output, prices, interest rate, investment, and stock prices. All the variables are domestic, expressed in real terms and are seasonally adjusted to ensure that the variation is non-seasonal. We log every variable except interest rate to stabilize the variance of the series. The measure of output is the real mainland GDP. Prices are a measure of inflation, where we have used a GDP deflator based on the difference between nominal and real output[11]. However, as a robustness check we also estimated the model with CPI. As a measure for the interest rate we use the 3-month Norwegian InterBank Offered Rate (NIBOR), for more in-depth reasoning see appendix A.1. Investment is the real gross domestic private investments for Norway, and we use the Oslo Stock Exchange Benchmark Index, OSEBX as a measure of stock prices. While one could use OBX which is the 25 most traded stocks within the OSEBX, we

[11] The GDP deflator is a measure of the prices of all domestic goods and services while CPI includes both domestic and foreign goods and only measure the goods bought by the consumer. We then use the GDP deflator as we argue that it is a better measure for the domestic prices.

argue the latter gives a better indication of stock prices. Using OBX might not give a clear picture of the total stock market, while OSEBX represent a larger amount of stocks traded in the market.

3.5.2 The Housing and Credit model

In the credit and housing model the data is quarterly with a sample period from year 1992Q1 to 2019Q2. The model includes five variables: output, prices, investment, stock prices and credit to real estate ratio. The first four variables are the same as in the baseline model, and we introduce a credit-to-real estate ratio which consists of credit and house value variables. For credit we use a total credit to private non-financial sector indexed for 2015=100, however we do note that this is not seasonally adjusted but adjusted for breaks[12]. For the real estate value, we use an index on Norwegian dwellings which is seasonally adjusted and where 2015=100 is the basis year. We then log the ratio of credit to real estate.

3.5.3 The Exchange Rate model

In the exchange rate model, we use seasonally adjusted and quarterly data from year 1991Q1 to 2019Q3. The model includes six variables: output, prices, investment, interest rate and real exchange rate. All the variables are in log except for the interest rate. The variables are the same as in the baseline model except for the real exchange rate. The real effective exchange rate is a weighted average of a country's currency compared to another country's basket of goods. It is defined such that an increase in the exchange rate is associated with a depreciation of the Norwegian currency. For more discussion on the choice of exchange rate see appendix A.2.

[12] Break adjusted data accounts for changes or discontinuities in source of data or changes in methodology. It is imperative to exclude the effect of such breaks as they are not representative for the real movements in outstanding consumer credit.

4. The Baseline model

4.1. Our identification approach for the Baseline model

We use sign restrictions as the identification approach, and these will be similar to the ones used by Furlanetto et al. (2017). As previously discussed, we argue that sign restrictions are appropriate as we include fast moving variables such as the interest rate, stock prices and other financial variables. We follow the recommendations from Fry and Pagan (2011) and use DSGE models as economic reasoning behind the sign restrictions, a common approach applied by among Peersman and Straub (2006) and Canova and Paustian (2011). The reason is that DSGE models are based on economic theory. However, as pointed out by Fry and Pagan (2011) the sign information is very weak, and it is imperative that we assign the appropriate amount of sign restrictions to separate the different shocks. Canova and Paustian (2011) demonstrate that VAR models with sign restrictions based on DSGE models are improved when more shocks are identified. However, they also argue that it is sufficient to have fewer identified restrictions as the sign patterns of the shocks are not the same. The latter case has also been mentioned by Peersman and Straub (2006). We follow these suggestions with caution when imposing sign restrictions.

For identifying supply, demand, and monetary policy shocks, we use the economic interpretation from the basic three equations NK model. The advantage with the NK model is that it enables us to uniquely identify the mentioned shocks in a simple way. From the model we can use the fact that it states expansionary monetary policy shocks decrease the interest rate, while positive demand shocks increase the interest rate. The model disentangles the supply shocks from the other shocks by implying that inflation decreases as a result of supply shocks, while inflation increases as a result of monetary policy and demand shocks. It is more difficult to uniquely disentangle demand, investment, and financial shocks as they move output and inflation in the same direction. We consider demand shocks to be non-investment demand shocks when disentangling it from investment shocks. In other words, a demand shock is only a shock to fiscal policy, consumption or increase in foreign demand[13]. Positive shocks to demand and investment move output, prices, and interest rate in the same direction. Therefore, we cannot determine whether the effects on the variable originated from an investment or demand shock. As a result, we need to search for other ways to distinguish them to be able to identify the shocks in the model. One proposed method by Furlanetto et al. (2017) implies a ratio between investment and output. We restrict the investment over output ratio, which enables us to uniquely identify the demand shock from an investment shock. We assume that a positive demand shock will contemporaneously increase output more than investment. On the contrary, a positive investment shock will contemporaneously increase investment more than output and increase the ratio. This is consistent with the findings from Justiniano et al. (2010), who show in a DSGE model that an investment shock has a larger contemporaneous impact on investment and will create an investment boom.

Disentangling the financial shock from an investment shock builds on the paper from Christiano et al. (2014). By including financial frictions in a DSGE model they argue that the marginal efficiency of investment shocks affects the supply of capital, while the financial shocks (risk shock) influence the demand of capital. Furthermore, the price of capital is an important determinant of firm value. We use this notion to state that investment shocks increase the supply of capital, and thus decrease the price of capital and that positive financial shocks increase the demand of capital. As the price of capital is a proxy for the stock value of the firm, we can disentangle the two shocks by imposing sign restrictions on the effect of the shocks on the stock market[14]. The complete set of sign restrictions are summarized in Table 1.

[13] It is important to note that monetary, investment and financial shocks can be characterized as demand shocks as they move output and prices in the same direction.
[14] A higher stock price will induce higher cost of capital. The increase in the cost of capital is reflective of the higher return we get from the higher stock price.

	Supply	Demand	Monetary	Investment	Financial
GDP	+	+	+	+	+
Prices	-	+	+	+	+
Interest rate	NA	+	-	+	+
Investment/output	NA	-	NA	+	+
Stock prices	NA	NA	NA	-	+

Table 1: Restrictions in the Baseline model.

Note: The Table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR model. NA indicates that the response of the variable is left unrestricted.

4.2. Results for the Baseline model

In this section we present the results of the baseline model. The model includes one lag and is estimated with Norwegian data in levels from year 1991Q1 to 2019Q3. For lag selection we used AIC, BIC, and the Hannan-Quinn criterion tests, where both BIC and Hannan-Quinn suggested one lag. For estimation see appendix C.1.1. An important assumption in VAR theory is that the residuals are white noise. To ensure that this holds, we plotted them, which can be found in appendix D.2.2.1. The variables included in the baseline model are output, prices, interest rate, investment, and stock prices. All variables are in log apart from interest rate. The model has five identified shocks: supply, demand, monetary, investment and financial. As mentioned previously, we consider a financial shock to create an investment and stock market boom.

In Table 2, we report the contribution of the five identified shocks in the baseline model to the forecast error variance of the variables at three different horizons, i.e. the amount of variance in the variable that can be explained by the shocks at given horizons. For more in-depth explanation of the forecast error variance decomposition, see appendix D.6. The model is estimated such that it creates a median impulse response based on 1000 draws, and this also applies to the variance decomposition of the model. Hence, each horizon shows the median draw that satisfies the imposed sign restrictions. We define the horizon in quarters. We see that financial shocks are the second driver for explaining the variation in interest rate in the long-run and investment and stock prices in the short-run. One interesting finding is the overall low explanatory power financial shocks have on output and prices.

	Horizon	Supply	Demand	Monetary	Investment	Financial
GDP	1	0,5929	0,0666	0,2131	0,0603	0,0670
	5	0,4050	0,0195	0,4236	0,0176	0,1344
	20	0,1837	0,0219	0,7333	0,0174	0,0437
Prices	1	0,5963	0,0942	0,1758	0,0664	0,0672
	5	0,3070	0,1991	0,3666	0,0424	0,0849
	20	0,0783	0,0695	0,7707	0,0172	0,0643
Interest rate	1	0,0013	0,1399	0,6768	0,0982	0,0839
	5	0,0066	0,1181	0,6199	0,0510	0,2045
	20	0,0125	0,0950	0,5234	0,1384	0,2307
Investment	1	0,0132	0,4120	0,0062	0,2699	0,2987
	5	0,3215	0,2640	0,1036	0,1196	0,1913
	20	0,2942	0,1905	0,3503	0,0663	0,0988
Stock prices	1	0,1376	0,0560	0,0439	0,5359	0,2265
	5	0,1177	0,1039	0,1869	0,4617	0,1298
	20	0,0946	0,1091	0,3330	0,3553	0,1080

Table 2: Median Forecast Error Variance Decompositions for the Baseline model.

The relevance of financial shocks can also be shown in Figure 1, which is the median impulse response function. It is important to note that our sign restrictions state the direction of our variables on impact, hence it has no interpretation. As a result, what we can interpret is the effects following the restricted first period. We observe a hump shaped effect on all the variables except prices which experience a steadier decline. The persistency of financial shocks on output, stock prices and investment are rather short-lived as they decline within the first few quarters. On the contrary, interest rate shows a moderate persistency in response to financial shocks, even though we only impose that it should go up on impact. Prices experience a somewhat large response to financial shocks. This is a contradiction to the findings of Furlanetto et al. (2017) who report a small inflation response to financial shocks. This is also the case with the findings of Christiano et al. (2010), who found inflation being low during stock market booms. While our specifications imply a stock price increase on impact, we see that stock prices rapidly declines afterwards. One would also expect that the response to the investment would be more persistent after the initial shock. Another finding across all the variables is that periods following a boom, the variables decline to a level below their starting point before returning to their initial level. A similar result was found by Mian et al. (2017) where after the initial shock to household debt is dying out, the decline in output is large enough to bring it down to a level below its starting point before returning back to initial level.

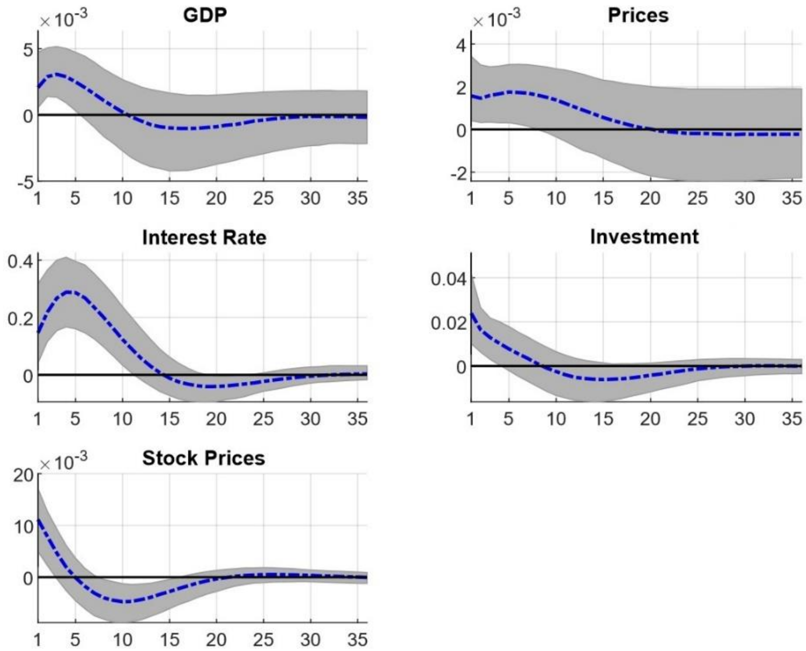

Figure 1: Median Impulse Response of a one standard deviation financial shock in the Baseline model.

Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

As the financial shocks provide little explanation of the variation in the macroeconomic variables, we look at the other shocks in the model. In Figure 2, we present the median impulse responses for each variable together with all the corresponding shocks. Looking at the forecast variance decomposition, there are two shocks that stands out in explaining most of the fluctuations in the variables: monetary policy and supply shocks. For output one can see that supply shocks are the main driver in shorter horizon, but this decreases in the long run, where monetary policy shocks become the important driver. Blanchard and Quah (1989) report an important role for supply shocks on output. However, their results differ in that the importance of supply shocks increases over time. Supply shocks are also an important driver for prices in the shorter horizon and investment as the horizon increases. The importance of supply shocks on output and investment can be explained by the traditional technology shocks in the DSGE, where technology shocks lead to an increase in output and investment. It is interesting to note that supply shocks drive output and prices in different directions and that the supply shocks might be induced by cost push shocks[15]. The importance of investment and demand shocks are limited, except for in stock prices where investment acts as the main driver over all horizons. The low explanatory power of investment shocks is rather puzzling. One would expect investment shocks to account for a larger share of the variation in the macroeconomic variables. Justiniano et al. (2010) found that investment shocks through the marginal efficiency of investment shocks are an important driver for movement in output, investment and hours worked. One possible explanation could be that the inclusion of financial shocks crowds out the effect of investment shocks, as argued by Christiano et al. (2014).

A somewhat surprising and puzzling result is the large importance of monetary policy shocks[16]. It poses as a main driver for interest rate and prices as the horizon increases and further a second driver for output and stock prices. This is contradicting to standard theory on neutrality of money. The theory hypothesizes that lowering the interest rate and increasing the money supply will only have a profound effect on nominal variables such as prices and wages. That is, an increase in the supply of money will be offset by a proportional rise in wages and prices, and thus have no impact on real variables such as real output and investment. From the VAR approach the effect of monetary policy shocks appears to account for a limited share of the fluctuations in real economy. Mountford

[15] A Cost push shock drives output and prices in different directions due to higher costs in production. This can be caused by price mark-up shocks and shocks originating in the labour market, such as labour supply, wage mark-up and matching efficiency shocks.
[16] Romer and Romer (2004) reveal a much larger effect of monetary policy shocks on output and prices. They construct monetary policy shocks from a historical time series of interest rate changes decided upon meetings of the Federal open market committee where innovations are the changes not made in response to forecasts of inflation and real growth. Further, Canova and de Nicolo (2002) shows that monetary policy shocks are an important driver for macroeconomic fluctuations in three out of seven G-7 countries.

(2005) finds evidence that monetary policy shocks explain little of the total variation in the macroeconomic variables. Li et al. (2010) tested the impact of monetary policy shocks on stock prices for Canada and the US. While the effect on the US was relatively large, they find that the immediate response in Canada is small. This is consistent with the findings of Lindé (2003), where the effect of a monetary policy shock had limited importance on Swedish macroeconomic variables. As this is not the case in the baseline model, we estimated the model using CPI as a price measure to see if the result still holds. The result shows that the baseline model is robust to different price measures as it does not change significantly by using CPI. The result is presented in appendix F.4. This leads us to believe that the monetary policy shock contains shocks that are outside the model.

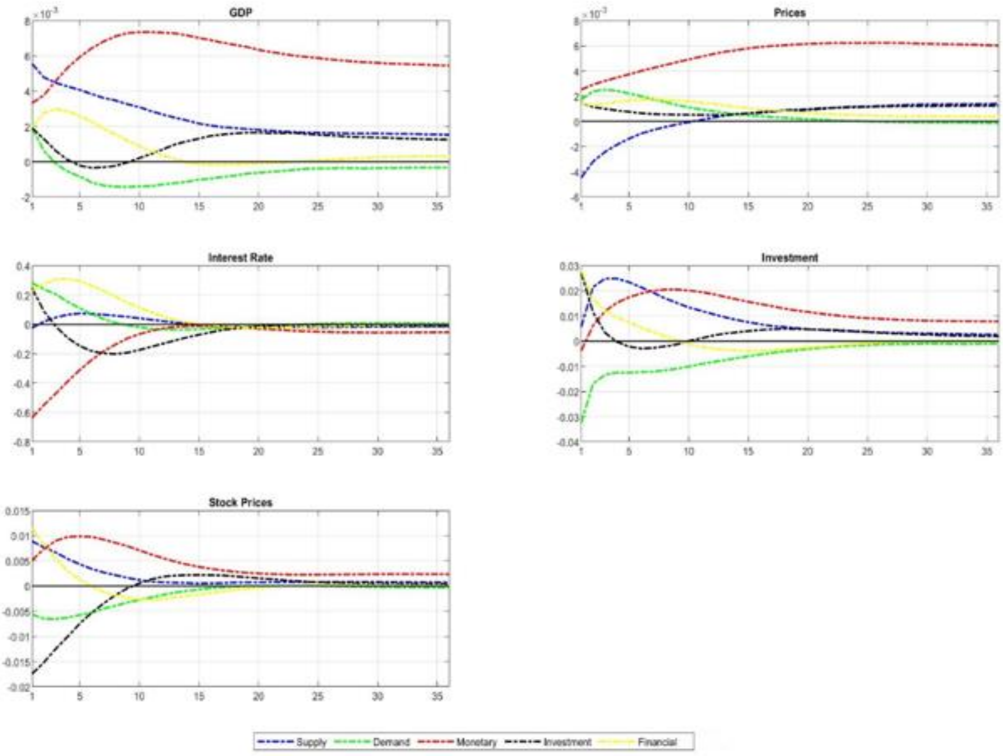

Figure 2: Median Impulse Responses for the Baseline model to a one-standard-deviation supply, demand, monetary, investment and financial Shock.

It is worth noting that Norway exports a large amount of oil and is largely affected by the oil price. It is plausible that monetary policy shocks are contaminated and that we attribute the effects of shocks outside the model to the monetary policy shock[17]. As the interest rate includes such puzzling results, we estimated the model with the policy rate as measure of interest rate without any different results. The results are shown in appendix F.5.

4.3 Sensitivity analysis for the Baseline model

To verify the robustness of our results, we conduct sensitivity analysis by using median target and the modal model as new measures of central tendency of the impulse response functions. Furthermore, we re-estimate the model with five lags as used by Furlanetto et al. (2017).

In the baseline model we used a pointwise posterior median as the measure of central tendency of the impulse response functions and pointwise 68 percent posterior error bands. Meaning that we compute the median of the impulse responses for each horizon. This approach suffers from two distinct shortcomings. First, the multiple shocks problem. The vector of a median impulse response function is not compatible with any of the admissible models unless the posterior median of all impulse response coefficients in the VAR system comes from the same structural model, which arguably is very unlikely. In this case, the pointwise posterior median responses will have no structural economic interpretation. The first shortcoming was postulated by Fry and Pagan (2011), who proposed the median target method as an alternative way of measuring the central tendency[18]. The method consists of searching for the model with the impulse response closest to the median response. This will ensure that the impulse response function comes from the same model with corresponding shocks being orthogonal[19].

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[17] The model could suffer from underspecification i.e. omitting variables that belongs in the true model. This causes omitted variable bias which is attributing the effect of the omitted variables to the estimated effects of the included variables.

[18] Fry and Pagan (2011) show that strong differences between the MT impulse responses and the median responses indicate that the standard model inference will be biased and misleading. Kilian and Murphy (2013) show that some structural models that are admissible based on pure sign restrictions suggest a large instantaneous jump in global oil production in response to positive oil demand shocks. However, this goes against literature that the short-run elasticity of oil supply is low and the inclusion of such models in the construction of median responses distorts the results.

[19] Rather than presenting the median across 1000 draws corresponding to our sign restrictions, we present the draw that was closest to the median across 1000 draws corresponding to our sign restrictions.

The second shortcoming was suggested by Inoue and Kilian (2013). They argue that the median impulse response function is not an adequate statistical representation of the set of admissible impulse response functions. Utilizing vectors of medians as a measure of the central tendency of the impulse response function is inappropriate because the vector of medians is not the same as median of vector. Inoue and Kilian (2013) propose another measure of central tendency, the modal model. The modal model builds on characterizing the most admissible model within the set of structural VAR models that satisfy the sign restrictions. Modal model is by construction then the admissible model that maximizes the posterior density of the sign-identified structural impulse responses. By finding the mode of the posterior they neutralized the two shortcomings associated with the median impulse response vector[20].

In Table 3, we present the results for alternative measures of central tendency and the baseline model estimated with five lags. The full table can be found in appendix F.1. We observe that using different measures of central tendency, neither the modal model nor median target changes the result notably. However, by using five lags, we see a substantial increase in the importance of the financial shock. Remarkably, in horizon five the increase is almost 20 percent.

Horizon	Median target	Modal model	Five lags
1	0,0810	0,0299	0,0755
5	0,0758	0,1114	0,3252
20	0,0237	0,0423	0,1777

Table 3: Fraction of variance explained by financial shocks in the forecast error of output under alternative measures of central tendency and the model estimated with five lags.

We note that the baseline model is considering Norway as a closed economy, as we only include domestic shocks. As seen from the variance decomposition, the importance of financial shocks has limited explanatory power for most of the variables. One possible reason could be that the model specifications are not entirely equal to the Norwegian economy. The model is specified such that we

[20] In the code we proceed as follows. We keep the draw that satisfies the sign restriction and compute the posterior density of the impulse responses. Otherwise discard the draw. We repeat this 1000 times and find a set of the response functions of the modal model that maximizes the posterior density of the impulse responses and construct the 68 percent credible sets.

generate domestic shocks, hence we do not take foreign factors into consideration. It has been argued by Georgiadis (2015) that the global financial cycle is largely driven by financial conditions in the US. Norges Bank mentions in the financial stability report, that small open economies like Norway are especially affected by global turbulence and uncertainty as the financial system operates across borders (Norges Bank, 2019). Another possibility could be that stock prices might not be of importance for the Norwegian economy. Therefore, having financial shocks given by the stock prices may attribute to the limited importance of financial shocks on the macroeconomic variables. Two very prominent financial factors to investigate are the credit sector and the housing sector. In the financial stability report Norges Bank raise concerns that the high household debt and house prices are some of the key vulnerabilities in the financial system. They further consider the negative outcomes of sharp and sudden movements in variables such as interest rate and house prices.

5. The Housing and Credit model

In the first extension we separate the financial shock into two components: housing and credit shocks. Disentangling the financial shock will result in an additional shock and we need to remove one of the existing shocks to obtain an equal amount of shocks and variables. Including more shocks and variables into the model will lead to more difficulties from a computational point of view, but it will also be more difficult to obtain distinct set of sign restrictions. The results from the baseline model suggests that monetary policy accounts for a large part of the fluctuations in our variables. However, we decide to remove it in this extension as our objective is to follow Furlanetto et al. (2017).

Housing and credit shocks are subject to multiple economic interpretations. In the standard macroeconomic models aggregate housing demand shocks are proxied by shifts in consumer preferences for housing services (Liu, Pengfei, & Zha, 2019). It can also be seen as housing bubbles that stems from an increase in housing demand, which is further accelerated by low interest rates and easy access to credit. The credit shock can be viewed as an exogenous decrease in the interest rate, relaxations in debt to income ratios or the change in financial liberalization.

For a narrower view of housing shocks, we turn to Iacoviello and Neri (2010), who use a DSGE model to look at a housing preference shock. They also call this shock a house demand shock as it increases the house prices and returns on housing investments. The housing preference shock captures the variation in the availability of resources needed to purchase a house relative to other goods, and institutional changes that shifts demand towards housing.

A common way of looking at credit shocks are in the form of a shock to the loan to value ratio. Through a DSGE model Gerali, Neri, Sessa and Signoretti (2009) introduces a shock to the ratio between loan and value, which is interpreted as a disturbance that affects credit availability. Another example of a credit shock is the one introduced by Justiniano et al. (2015), who look at credit supply shock as a relaxation of the lending constraint. The literature provides multiple ways of looking at housing and credit shocks, and that these financial shocks lead to an increase in investment and the stock market. However, the main question becomes how to disentangle the two shocks.

5.1. Our identification approach for the Housing and Credit model

A promising way is to look at the credit to real estate value ratio. This is a measure of the total credit of the households and firms, to the total value of the housing stock. We then impose sign restrictions on the magnitude of the response of the credit shock and the housing shock on the ratio. That is, an expansionary credit shock increases the ratio on impact while a housing shock decreases the ratio on impact. The reasoning is the following: Most housing purchases in Norway and in general are financed by credit. A positive credit shock, from example a relaxation in the lending constraint, will increase the supply of credit. This will in turn affect the housing prices and thus increase the value of the housing stock. The only restriction we impose is that the increase in credit is higher than the value of the housing stock on impact. On the other hand, a housing shock caused by change in housing preferences will increase the house prices and value of the housing stock. This in turn is likely to increase the total credit as people now have higher borrowing capacity. As before, the only restriction is that on impact the total value of the housing stock must increase more than the credit stock, which implies that the ratio decreases. The set of sign restriction used is summarized in Table 4.

	Supply	Demand	Investment	Housing	Credit
GDP	+	+	+	+	+
Prices	-	+	+	+	+
Investment/output	NA	-	+	+	+
Stock prices	NA	NA	-	+	+
Credit/ real estate value	NA	NA	NA	-	+

Table 4: Sign restrictions in the Housing and Credit model.

Note: The Table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR model. NA indicates that the response of the variable is left unrestricted.

5.2 Results for the Housing and Credit Model

We now present the results from the housing and credit model. The model includes one lag and is estimated with Norwegian data in levels from year 1992Q1 to 2019Q2. The lag selection is determined by the AIC, BIC, and the Hannan-Quinn criterion tests. For estimation see appendix C.1.2. We plotted the residuals to ensure that they are white noise, which can be found in appendix D.2.2.2. The results are represented in Table 5, where the forecast error variance decomposition reports the contribution of each shock.

Looking at the decomposed financial shock, we see that it has been largely consumed by housing shocks as opposed to credit shocks, and this holds for almost all variables at all horizons. Credit shocks are important for the credit to real estate ratio in the shorter horizon and for stock prices where the fluctuations explained lies around 15 percent. However, it is important to note the limited explanatory power credit shocks have on the other variables. Housing shocks are the main driver for fluctuations in output, prices, and investment as the horizon increases and the main driver for fluctuations in credit to real estate at all horizons. Further, it is an important second driver for the fluctuations in stock prices. A closer look at the other shocks in the model show that supply shocks are important for output and investment. Demand shocks are an important second driver for output and investment in the shorter horizon and for prices at all horizons. As in the baseline model investment shocks are the main driver for stock prices at all horizons and further the importance of investment shocks on the fluctuations in output is still low. Investment shocks pose as a second driver for the credit to real estate ratio in the long run. One possible explanation is that we only restrict the ratio to increase on impact, but in reality, the ratio will not face an increase. In other words, it might well be that an increase in the amount of credit will have contemporaneous effect on house prices of the same magnitude which leads to the ratio being unaffected. This can explain why investment shocks are better at explaining the variation in the credit to real estate ratio.

	Horizon	Supply	Demand	Investment	Housing	Credit
GDP	1	0,5944	0,1686	0,0817	0,0710	0,0843
	5	0,2927	0,0767	0,0575	0,4246	0,1485
	20	0,0732	0,0519	0,2082	0,5520	0,1147
Prices	1	0,6296	0,1812	0,1818	0,0542	0,0531
	5	0,3501	0,3686	0,0646	0,1217	0,0950
	20	0,0868	0,2454	0,0737	0,4369	0,1572
Investment	1	0,0034	0,5492	0,1848	0,1340	0,1286
	5	0,1830	0,2777	0,1394	0,3294	0,0705
	20	0,1057	0,1229	0,3015	0,4337	0,0362
Stock prices	1	0,1421	0,0019	0,5378	0,1784	0,1399
	5	0,1113	0,0029	0,5309	0,1996	0,1553
	20	0,0934	0,0047	0,5125	0,2169	0,1725
Credit/real estate	1	0,0134	0	0,0336	0,6455	0,3076
	5	0,0041	0	0,1646	0,6671	0,1642
	20	0,0023	0,0066	0,2945	0,6260	0,0707

Table 5: *Median Forecast Error Variance Decomposition for Housing and Credit shocks.*

To give further explanation of the importance of housing and credit shocks, we look at the impulse response function presented in Figure 3 and 4. We see that the effect of housing shocks is very persistent for all the included variables, even when only restricted on impact. This is also the case for credit shocks with the only exception being investment where we can detect a rapid decline after impact. This is presented in Figure 4.

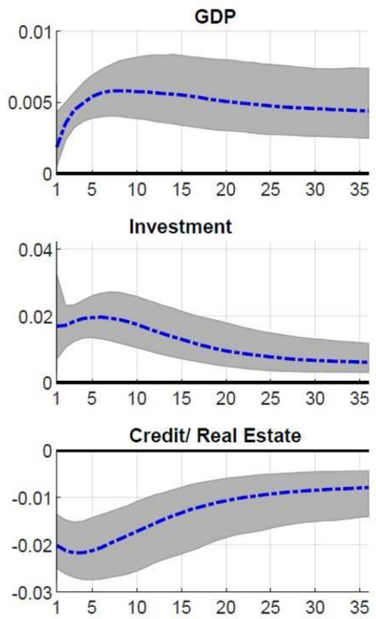

Figure 3: Median Impulse Response of a one standard deviation housing shock in the Housing and Credit model.

Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

We now address a possible reason for the lack of explanation credit shocks have in the model. The credit variable consists of the total credit in the market, and most of the credit in the market is long-term contracts that is not refinanced every quarter. This raises the question whether credit shocks increase total credit more than the real estate value on impact, which we argued to be true when we made the sign restriction. An efficient way of addressing this problem is to take the first difference of the credit variable and restrict the ratio of first difference of credit to real estate value. The reasoning behind the first difference is that we now only look at the new loans issued in the periods as opposed to the total credit in the market. By taking the first difference we can see from Table 6 that credit shocks now explain a higher amount of the variation in output in the long run. The high explanatory power for housing shocks still prevail for output, particularly in the long run.

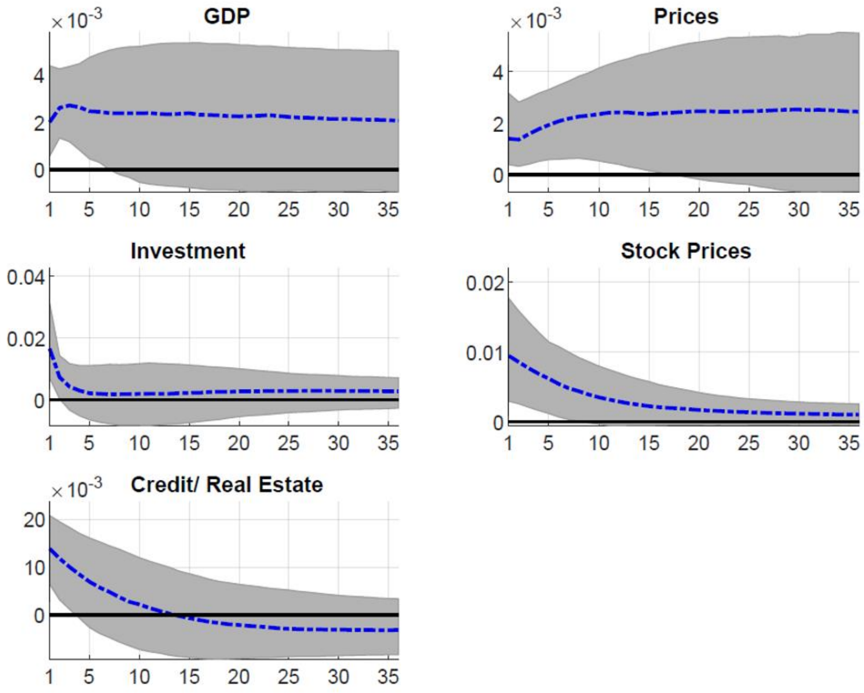

Figure 4: Median Impulse Response of a one standard deviation credit shock in the Housing and Credit model.

Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

5.3 Sensitivity analysis for the Housing and Credit model

As in our baseline model we conduct sensitivity analysis to verify our results. We conduct three different experiments: First, we use different measures of central tendency of the impulse response functions: modal model and median target. For more in-depth discussion of the methods, see section 4.3. Secondly, we re-estimate the model with five lags. Lastly, we estimate the model using credit in difference as opposed to levels. The results are presented in Table 6 and the full table can be seen in appendix F.2.

The results change substantially when we use different measures of central tendency. Credit shocks become more important for the variation in output with median target, but the importance increases remarkably by using the modal model approach. It now poses as an important driver for the variation in output. As credit shocks dominate with modal model, we see that housing shocks become almost insignificant as opposed to using a pointwise posterior median as the measure of central tendency. For the median target, housing shocks explain more in the first horizon, while for horizon five and 20, the results are almost the same as under the pointwise posterior median of central tendency. When estimating the housing and credit model with five lags, credit shocks become more important in the long-run, and housing shocks become less important compared to when we estimated the model with one lag.

Horizon	Median target	Modal model	Five lags	Credit in difference
Credit				
1	0,1990	0,3837	0,0932	0,0709
5	0,2351	0,5857	0,1763	0,1989
20	0,1431	0,6589	0,2669	0,2041
Housing				
1	0,2847	0,0113	0,0944	0,0900
5	0,5347	0,0691	0,4892	0,3690
20	0,6392	0,0362	0,4831	0,4735

Table 6: Fraction of variance explained by credit and housing shocks in the forecast error of output under alternative measures of central tendency, model estimated with five lags and credit in difference.

There is a concern that the removal of monetary policy shocks from the housing and credit model may result in one of the other shocks absorbing it. To address this concern, we looked at the median impulse response of monetary policy shocks in the baseline model to see if it had similar patterns with housing shocks. By eyeballing the graphs, monetary policy shocks and housing shocks induce the same effect on the included variables, just in opposite direction. This leads us to believe that housing shocks are capturing the importance of monetary policy shocks i.e. that we have the same shock with different names.

6. The Exchange Rate model

Norway is a small open economy and is the 36th largest export economy in the world (OEC, NA). Crude Petroleum, non-fillet fresh fish and refined petroleum stand out as some of the biggest products for export. Norway has a lot of imports as well, but the net-export is still positive (OEC). Since 1990, 25 to 45 percent of GDP have subjected for exportation (theglobaleconomy, 2020). The exchange rate has a lot of influence on the Norwegian economy. As mentioned by Bjørnland

(2008), the exchange plays a central role in relationship with monetary policy, through mechanisms such as price levels.

Our approach involves looking at how the fluctuations in the exchange rate can be explained by the same shocks as in the baseline model. From the literature review, it is apparent the shocks in the baseline model affect the exchange rate. It has been conducted extensive research on the relationship between the stock prices and the exchange rate. As the financial shock is given by stock prices, we use theory of the portfolio balance approach. It hypothesizes a causality between stock prices and exchange rate, i.e. changes in the stock prices lead to a change in the exchange rate. This raises the question of how much financial shocks can explain the fluctuations in the exchange rate or whether the other shocks in the model have larger explanatory power of the fluctuations in the exchange rate[21].

In order to look at the importance of the exchange rate for the fluctuations in Norwegian macroeconomic variables, it would be feasible to include an exchange rate shock induced by data on the exchange rate. This would be an interesting approach and arguably the best way to include the exchange rate. However, the methodology of using sign restrictions to identify the structural shocks in the model, results in computational issues with the proposed approach. As argued previously, it is imperative that we obtain a distinct and unique set of sign restrictions in order to distinguish the shocks in the model. By including the exchange rate shock, we are not able to uniquely identify the demand shock from the exchange rate shock, as both shocks move the variables in the same direction. As a result, we are not able to investigate the importance of an exchange rate shock due to methodological limitations. Even though we cannot include an

[21] The two main models explaining the linkages between stock prices and the exchange rate are the flow-oriented model and the portfolio-based approaches. The flow-oriented model was developed by Dornbusch and Fischer (1980) and the model states that changes in exchange rate leads to changes in stock price movements due to the stock prices largely being affected by firm's cash flow which in turn is affected by the real economy and the countries trade position. The stock oriented or portfolio balance approaches (Branson, 1983) postulates opposite causality between stock prices and exchange rate, i.e. that stock prices affect the exchange rate. According to the portfolio balance approach the exchange rate is like other commodities in which it is determined market mechanisms (supply-demand). This implies that a thriving stock market will attract more capital flows from the foreign investors, and this will result in a decrease for the demand of the country's currency and vice versa.

exchange rate shock in the model, it is still evident that the exchange rate is an interesting variable to look at due to its importance for the Norwegian economy.

6.1 Our identification approach for the Exchange Rate model

We investigate the importance of demand, supply, monetary policy, investment, and financial shocks on exchange rate fluctuations. In the baseline model monetary policy shocks had a remarkably high explanatory power. This result is rather puzzling and not consistent with previous research. However, Bjørnland (2008) investigates the monetary policy and exchange rate interactions in a small open economy. Using a VAR model with long-run neutrality restriction, she finds that there is an interdependence between monetary policy and the exchange rate. Although, monetary policy shocks explain a small, but non negligible proportion of the fluctuation in the exchange rate. Excluding monetary policy shocks could as previously mentioned induce omitted variable bias.

The model will consist of the same shocks and variables as in the baseline model and the sign restrictions for the variables are interpreted using the same theory as previously. As we include the exchange rate into the system, we need to have an additional shock to obtain an identified system with equal number of variables and shocks. As we cannot include an exchange rate shock, we rely on a simple yet efficient trick to create a residual shock. We put exchange rate as an unrestricted variable and create a residual shock where we restrict stock prices to increase in response to the supply shock. Furthermore, we impose output and prices to go up and stock prices to go down in response to the residual shock. The residual shock is supposed to only capture the residual dynamics in the system. This restriction allows us to identify a residual shock with an economic interpretation, i.e. a supply shock that moves output and the stock market in different directions. The imposed sign restrictions are summarized in Table 7.

	Supply	Demand	Monetary	Investment	Financial	Residual
GDP	+	+	+	+	+	+
Prices	-	+	+	+	+	-
Interest rate	NA	+	-	+	+	NA
Investment/output	NA	-	NA	+	+	NA
Stock prices	+	NA	NA	-	+	-
Exchange rate	NA	NA	NA	NA	NA	NA

Table 7: Sign restrictions in the Exchange Rate model.
Note: The Table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR model. NA indicates that the response of the variable is left unrestricted.

6.2 Results for the Exchange Rate model

We now present the results from the exchange rate model. The model is estimated with one lag using Norwegian data in levels from year 1992Q1 to 2019Q2. The lag selection is determined by the AIC, BIC, and the Hannan-Quinn criterion tests. For estimation see appendix C.1.3. We have plotted the residuals to ensure that they are white noise. The results are in appendix D.2.2.3. We use the same variables as in the baseline model: however, we have now extended the model by adding an exchange rate variable and a residual shock. All variables are expressed in log, except for the interest rate. In this extension the focus is to look at the importance of the included shocks for the fluctuations in the exchange rate.

The results are presented in Table 8, where the forecast error variance decomposition reports the contribution of the shocks. For the exchange rate, we first notice how it is affected by the different shocks. Overall, financial shocks explain the exchange rate rather consistently across all horizons, by 23 to 24 percent. We further see that across horizon one and 20, financial shocks are an important driver for the overall fluctuations in the exchange rate. This is consistent with a paper from Hatemi–J and Irandoust (2002), who investigates the causality between stock prices and the exchange rate using Swedish data. By employing a VAR model with a Granger non-causality testing procedure, the authors find a uni-directional relationship running from stock prices to the exchange rate. An increase in the Swedish stock prices is associated with an appreciation of the Swedish currency. There is also evidence that the causal relationship depends on operating conditions of the markets.

The main driver for fluctuations in the exchange rate for the first two horizons are monetary policy shocks. However, it shrinks as the horizon increases where the role of investment shocks becomes more important. The importance of monetary policy shocks on the exchange rate is consistent with the findings form Bjørnland (2008). She found a significant dependency between monetary policy shocks and the exchange rate, where the exchange rate immediately appreciates after a contractionary monetary policy shock. In the long-run, investment shocks turn to become the main driver for the fluctuations in exchange rate. Supply shocks play an almost insignificant role for the variation in the exchange rate. This is consistent with the findings of Bjørnland (2004), who found that supply shocks were important for output, but not for the exchange rate. However, she found that demand shocks were important for the exchange rate, which is not the case in the exchange rate model. Residual shocks explain a minor part of the fluctuations in the exchange rate.

	Horizon	Supply	Demand	Monetary	Investment	Financial	Residual
GDP	1	0,4655	0,0574	0,1847	0,0394	0,0961	0,1568
	5	0,3778	0,0249	0,3118	0,0139	0,2319	0,0397
	20	0,1926	0,0425	0,6256	0,0083	0,1029	0,0282
Prices	1	0,4053	0,0874	0,1257	0,1135	0,0438	0,2244
	5	0,1940	0,1427	0,3142	0,0749	0,0889	0,1852
	20	0,0632	0,0426	0,6602	0,0265	0,0994	0,1080
Interest rate	1	0,0432	0,1040	0,5859	0,1284	0,0951	0,0433
	5	0,0296	0,1063	0,5822	0,0578	0,2007	0,0234
	20	0,0770	0,0882	0,5123	0,0883	0,2124	0,0218
Investment	1	0,0066	0,3562	0,0134	0,3002	0,3085	0,0151
	5	0,3170	0,2305	0,0648	0,1207	0,2271	0,0398
	20	0,3035	0,1985	0,2717	0,0746	0,1307	0,0211
Stock prices	1	0,4041	0,0379	0,0368	0,3278	0,1458	0,0477
	5	0,3539	0,0695	0,1518	0,2956	0,0765	0,0526
	20	0,2857	0,0791	0,2787	0,2414	0,0702	0,0448
Exchange rate	1	0,0002	0,0044	0,5167	0,1675	0,2312	0,0800
	5	0,0061	0,0510	0,3366	0,3038	0,2342	0,0683
	20	0,0775	0,1286	0,2304	0,2413	0,2385	0,0836

Table 8: Median Forecast Error Variance Decomposition for Exchange Rate model.

The importance of financial shocks on the exchange rate can also be shown in Figure 5, where we present the median impulse response function. Here, the shocks are only restricted on impact, but as seen from the table, we have left the exchange rate unrestricted in response to all shocks. From the impulse response we see that financial shocks have a marginal effect on the exchange rate. In Figure 6, we present the median impulse responses for each variable together with the corresponding shocks.

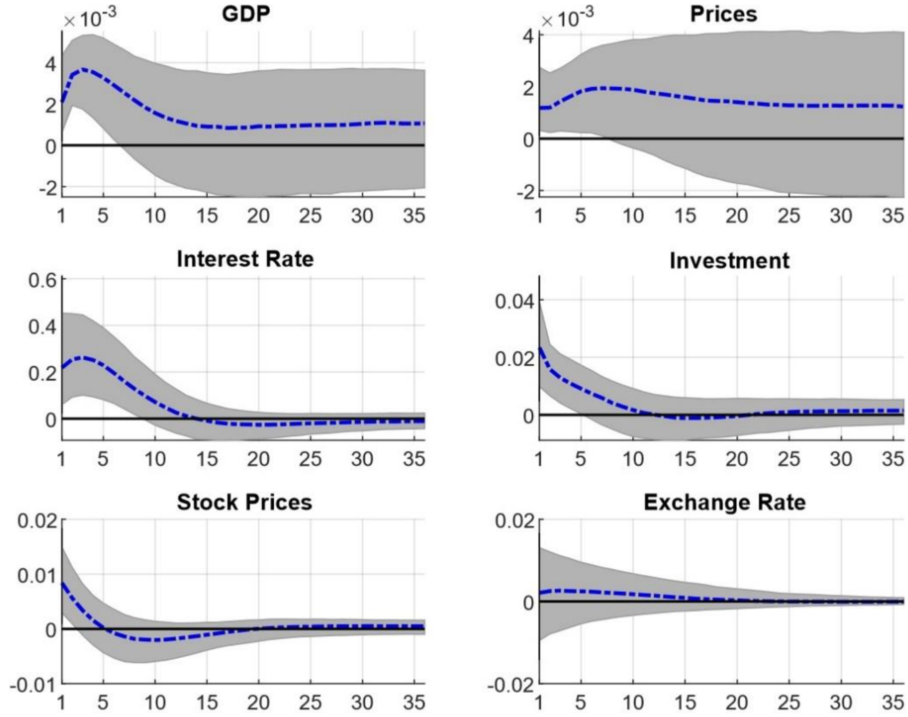

Figure 5: Median Impulse Response of a one standard deviation financial shock in the Exchange Rate model.

Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

Normally one would expect the exchange rate to depreciate when the interest rate goes down and vice versa, but this is not the case in the exchange rate model. There could be different reasons for this, although that does not mean it is necessarily wrong. Firstly, our model uses a simple setup, where we leave the exchange rate unrestricted in any scenario, and this may generate results deviating from the standard view of exchange rate and interest rate mechanisms. Second, we do not include other variables that have an importance for the fluctuations in the exchange rate, such as the oil price. It is evident that the exchange rate of oil exporting countries appreciates when oil prices increase and depreciate when they fall. In the exchange rate model, we saw that expansionary monetary policy shocks led to an appreciation in the exchange rate. This leads us to believe that the monetary policy shocks are contaminated by the oil price.

Our hypothesis is then: The reduction in the interest rate as a result of monetary policy shocks is of less magnitude than the increase in the oil price, which gives an appreciation of the exchange rate. Golub (1983) argues that oil prices affect the exchange rate through wealth effects. An increase in the oil price will give the oil exporting countries more wealth and the oil importing countries less wealth through the country's current account. If the demand of a currency from oil exporting countries surpass the fall in demand from oil importing countries, there will be an excess currency supply in the foreign-exchange rate market, and the currency will then tend to depreciate[22]. Akram (2002) investigate the relationship between the oil and exchange rate using Norwegian data. He finds a negative relationship between the oil price and the Norwegian exchange rate and that this relationship is stronger for oil prices that are below 14 dollars and falling. Furthermore, Usama Al-mulali (2010) investigated the impact of oil prices on the exchange rate and growth in Norway. Using a VAR model with Norwegian data from year 1975 to 2008, his results suggest that the oil price is an important factor for explaining both the exchange rate as well as the growth in output. He finds that an increase of one percent in the oil price will cause the real exchange rate to depreciate by 0.22 percent, which will make exports more feasible. Another paper by Fratzscher, Schneider and Van Robays (2014) examines the relationship between the US dollar, oil prices and asset prices. Some of their findings show that a 10 percent increase in the oil price leads to a 0.28 percent depreciation of the US dollar effective exchange rate on impact. Also, a reduction in the US dollar by one percent causes the oil price to increase by 0.73 percent.

[22] It is important to note that the relationship is the opposite way, as oil is a homogenous and international traded commodity priced in US dollar. A depreciation in US dollar lowers the oil price to foreigners relative to the price of their commodities in foreign currency. They will then push up the demand for oi which in turn push up the oil price in USD (Bloomberg and Harris, 1995).

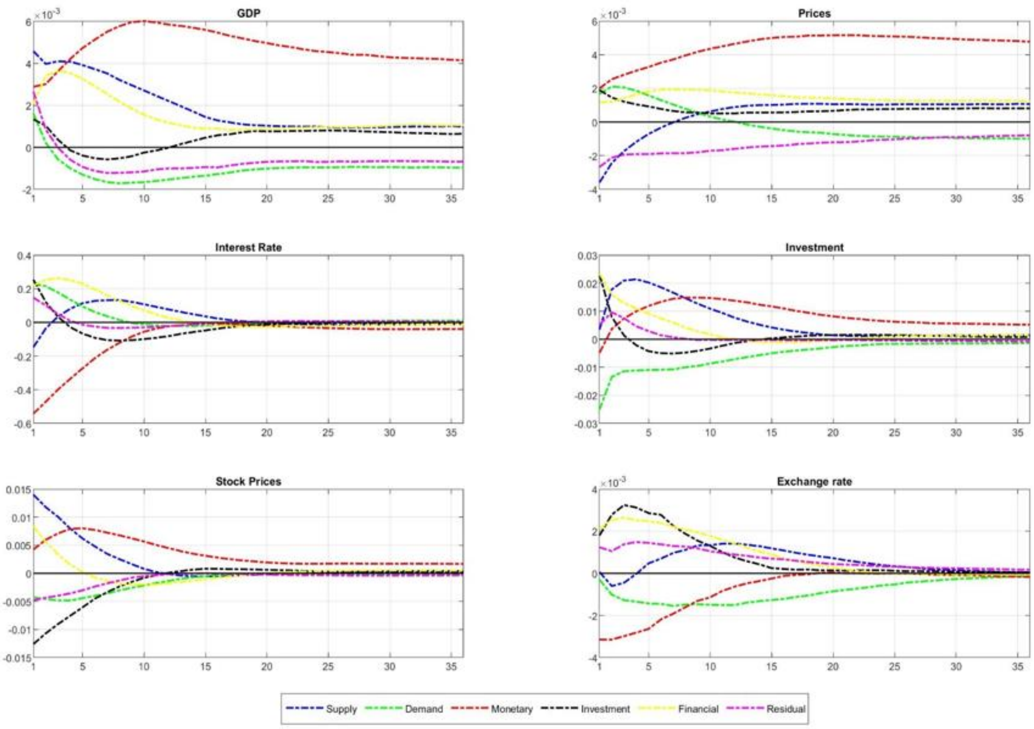

Figure 6: Median Impulse Responses for the Exchange Rate model to a one-standard-deviation supply, demand, monetary, investment, financial and residual shock.

6.3 Sensitivity analysis for the Exchange Rate model

Similar to the previous models, we conduct sensitivity analysis to verify our results. We conduct one experiment by using different measures of central tendency of the impulse response functions: modal model and median target. For more in-depth discussion of the methods see section 4.3. In the previous sensitivity analysis, we also estimated the model with five lags, but time difficulties limit the possibility as the model uses significantly longer time when we include a sixth variable and shock with corresponding sign restrictions. The result of the sensitivity analysis is presented in Table 9. We now look at the variance in the exchange rate explained by financial shocks. With the pointwise posterior median, we saw that financial shocks accommodated for around 20 percent of the variation in the exchange rate across all horizons. As we use median target and modal model the results change substantially. Financial shocks now accommodate for around 50 percent of the variation in exchange rate under both measures of central tendency. The full table can be found in appendix F.3.

Horizon	Median target	Modal model
1	0,4179	0,5231
5	0,5064	0,5156
20	0,5182	0,5184

Table 9: Fraction of variance explained by financial shocks in the forecast error of the exchange rate under alternative measures of central tendency.

7. Discussion

From our point of view, there are several limitations connected to what we have been investigating. The first one is the limitation of adding more variables and shocks. As we need to be able to disentangle every shock we add to the model, it becomes tricky as we add more variables and shocks. Certain features such as looking at an exchange rate shock would be hard with the variables in use as we cannot see whether it is a shock to exchange rate, or a demand shock. This is also connected to time limitations that occur. The model is specified to draw 1000 impulse responses that satisfy the restrictions, and this is a time-consuming process. As we then add more variables and shocks with further restrictions, the time of the computational process is significantly increased, and we do not facilitate high end equipment to speed this process. As a result, we had to go for “simpler” models, especially in the exchange rate model, where instead of looking at an exchange rate shock we rather look at how our existing shocks affect the exchange rate. This leads to the problem that certain variables may be contaminated by effects of other variables not included in the model.

In addition, one could argue the model specifications are not representative for the Norwegian economy, especially if one considers our findings of the large importance for monetary policy shocks. According to the neutrality of money hypothesis, lowering the interest rate and increasing the money stock will only affect nominal variables such as prices and wages, and not have a profound effect on the real economy. The hypothesis states that an increase in the supply of money will be offset by a proportional rise in wages and prices. As for Norway, Serletis and Koustas (1998) found that the null hypothesis of long-run neutrality cannot be rejected.

Problems concerning model specifications are further highlighted in our robustness tests, where we see that changing the measure of central tendency from pointwise posterior median to modal model and median target changes the results. This indicates that some of our results may be driven more by the model rather than the data. As we are using a Bayesian model, we must take into consideration our prior distribution. This is important for the model specification, where we used a diffuse prior. A possible contribution that could have strengthened the model would be to use different priors, such as the Minnesota prior, to find a model that might be more appropriate[23].

The model we have used is a domestic model, however if we were to add the possibility of foreign shocks it would pose as a difficult task from a computational view. Alternatively, one could use the methodology of local projections (Jorda, 2005). The methodology is another approach to derive the impulse response function, where one estimates a local projection at every horizon. One of the advantages is that it is a rather simple setup, as it can be estimated with standard regression. These projections are also more robust to misspecifications compared to the VAR models.

[23] One of most adopted prior for the BVAR models, the Minnesota prior, was developed by Litterman (1980). The belief that is expressed in this prior is that each variable in the system follows an independent random-walk. The Minnesota prior is not motivated by economic theory but is meant to capture common beliefs about how economic time series behave (Ricco & Miranda-Agrippino, 2018), and thus computationally convenient.

8. Concluding remarks

The objective of this master thesis is to assess the importance of shocks originating in the financial sector, and how they explain economic fluctuations in Norway. To investigate this, we employ a Bayesian VAR model with sign restrictions. The results were sensitive to model specifications and should be treated with caution. We proceeded in three steps. In the first step, we run the baseline model with a single financial shock given by stock prices, specified such that it creates an investment and stock prices boom. We find evidence that financial shocks are important for investment and stock prices in the short run but plays a minor role in explaining the fluctuations in output, prices, and interest rate. However, we see that monetary policy shocks surprisingly explain a lion's share of the fluctuation in the variables. This proves to be consistent across various robustness tests, but we do see that the importance of financial shocks increases when re-estimating the baseline model with five lags. It is also interesting to note that investment shocks account for a limited share of fluctuations in output.

In the second step, we disentangle the financial shock into credit and housing shocks. We see that housing shocks absorb the financial shock, where they explain a large share of the fluctuations for all the variables across all horizons. Meanwhile, the effect of credit shocks is limited. The high importance of housing shocks is consistent with Leamer (2007), who states that housing is the business cycle. We address the concern of low explanation credit shocks provide, by taking the first difference rather than using the total amount of credit. The results suggest that credit shocks in difference explain a larger share of the variation in output, although this is the case for longer horizons. We find that our results are sensitive to different robustness tests, as changing the measure of central tendency induces a quite different result for housing and credit shocks. Using the modal model, credit shocks become the main driver while the importance of housing shocks become negligible.

Lastly, we explore how supply, demand, monetary policy, investment, and financial shocks explain the fluctuations in the exchange rate. Financial shocks explain a consistent amount of 23 to 24 percent of the variation in the exchange rate. However, it is not a main driver across any horizon. We find that in the short-run, monetary policy shocks explain the largest share of the fluctuations in the exchange rate, and in the long-run the importance of investment shocks increase. The large importance of monetary policy shocks also prevails in this model for the other variables. By changing the measure of central tendency from pointwise posterior median to modal model and median target, we see that financial shocks accommodate for around 50 percent of the fluctuation in the exchange rate across all horizons and is now the main driver.

Our analysis concludes that financial shocks overall are trivial for the Norwegian economy. However, we find monetary policy shocks to be of high importance in all the estimations it is included in. This would need further testing in order to verify the results. By extending the model to control for more variables and shocks, such as the oil price and exchange rate shocks, one could further test whether the results hold. So far, monetary policy shocks have been assumed to be of negligible importance for the economy, which is why our result is rather puzzling. If it is the case that models with alternative specifications show the same importance of monetary policy shocks and financial shocks, then it is an important finding and needs to be interpreted further.

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Appendix

A. Data

We use quarterly data for Norway. The data and its sources are reported in Table 10.

Variable	Description	Source
GDP	Log of real GDP	SSB
GDP deflator	Log of deflator	SSB
Interest rate	3-month NIBOR	Norges Bank & OSE
Interest rate (1)	Policy rate	Norges Bank
Investment	Log of real domestic investment	SSB
Stock Prices	Log of OSEBX	Finance Yahoo
Total credit	Total credit to non-financial sector	FRED
Real estate value	Price of existing dwellings	SSB
CPI	Log of CPI	SSB
Exchange rate	Log of real effective exchange rate	FRED
Exchange rate (1)	Log of the I-44, Import-weighted krone exchange	Norges Bank

Table 10: Quarterly data. Mainland Norway when applicable.

A.1 Theoretical discussion on the interest rate

For interest rate we had two different choices, whether to use the policy rate or the NIBOR. The policy rate is the overnight interest rate the banks receive on deposits in the Norwegian central bank. The Norwegian Interbank Offered Rate (NIBOR) is referred to as the money market interest rate at different maturities. NIBOR is decomposed by the average expected policy rate for the next three months and an added risk premium. It is central for the bank's financial costs as a higher NIBOR will result in higher cost for the banks, but also the fact that the interest rate consumers and firms get on the loan form banks is the NIBOR with an additional premium. In total it reflects the amount of interest rate a bank requires to lend unsecured money to another bank in Norwegian currency. The policy rate and NIBOR follows each other as can be seen from the plots, where the NIBOR is at a higher level due to the added risk premium. We use the NIBOR as it better indicates the credit in the market due to the policy rate only reflecting the interest rate that the banks get on deposits into the central bank.

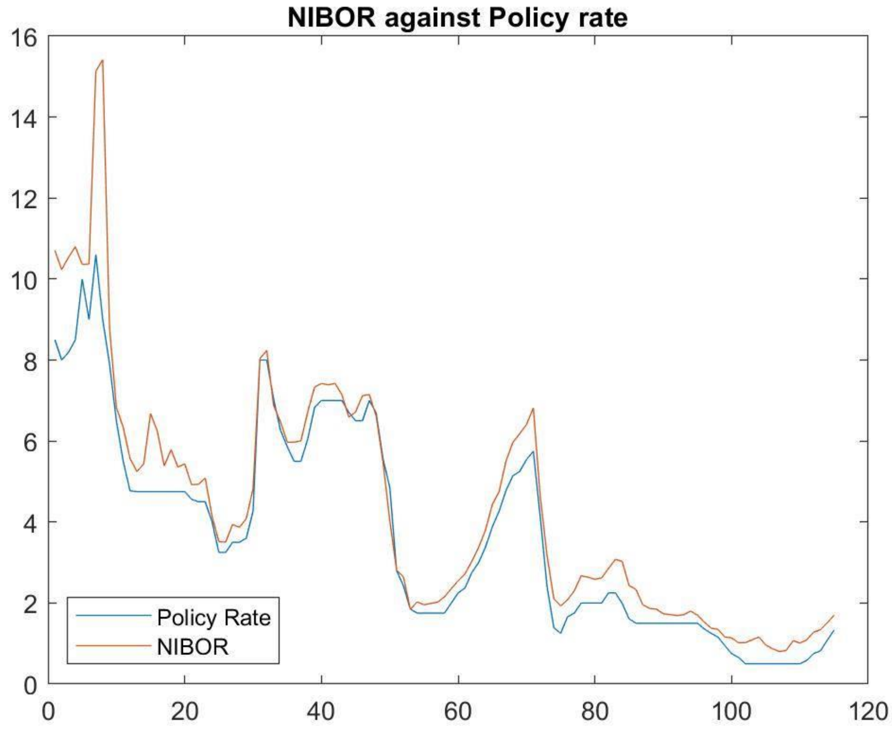

Figure 7: Plot of the NIBOR interest rate against the policy rate.

A.2. Theoretical discussion on the exchange rate

The exchange rate is seen as the value of one currency relative to another currency. It is determined by market mechanisms i.e. supply and demand for the currency. The question was whether to use the trade weighted exchange rate (TWI) or the real effective exchange rate. The calculation of TWI is based on the geometric weighted average of the exchange rates of 25 countries. It is a nominal effective exchange rate index based on NOK exchange rate measured against the currencies of Norway's most important trading partners. It is constructed such that an increase in the exchange rate is synonym with a depreciation in the Norwegian currency. The index is set to 1990=100. The real effective exchange rate is a weighted average of a country's currency compared to another country's basket of goods. By comparing the relative trade balance of a country's currency with another country's currency within the index, one can determine the weight. In short, it is used to measure the value of a currency against an average group of currencies. The exchange rate is specified so that an increase implies a depreciation.

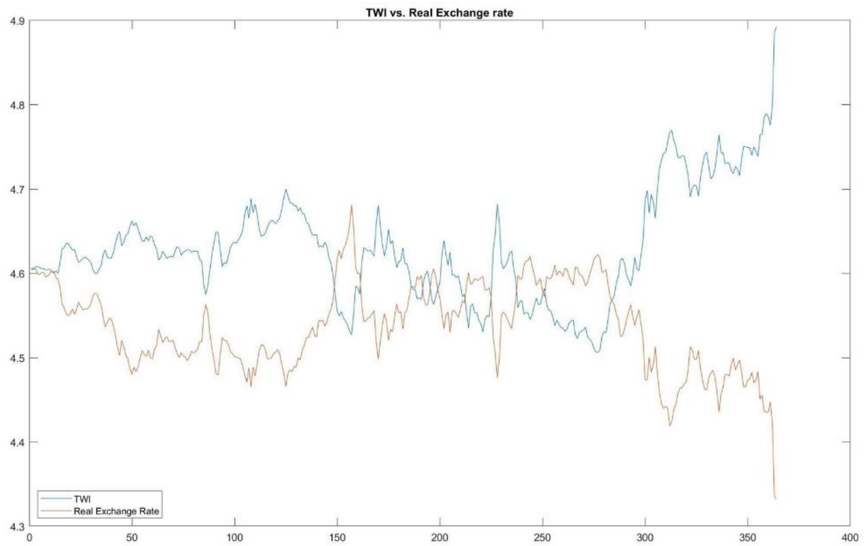

Figure 8: Plot of the Trade weighted exchange rate (TWI) against the real effective exchange rate.

B. Indicators

B.1. Summary statistics

	Mean	Median	Std.dev	CoV	Min	Max
GDP	13,1758	13,2015	0,22	0,0484	12,7712	13,5029
Prices	4,2786	4,2675	0,2371	0,0562	3,8935	4,6399
Interest rate	4,1394	3,4407	2,8098	7,8951	0,8	15,4195
Investment	11,2727	11,3681	0,3522	0,1241	10,3264	11,7468
Stock prices	1,3038	1,3038	0,1125	0,0127	0,9998	1,4803
Total credit	3,9613	4,0146	0,5774	0,3334	2,8792	4,7766
Real estate value	4,3895	4,3498	0,1859	0,0346	4,0834	4,6941
Exchange rate	4,6752	4,6741	0,0481	0,0023	4,5730	4,7869

Table 11: Summary statistics of all variables.

B.2. Lagged Correlations (1992-2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP (1)	1	0,9916	-0,7601	0,9555	0,8979	-0,9962	0,9297	0,0296
Prices (2)	0,9916	1	-0,7576	0,9213	0,8599	0,9909	0,9569	0,0159
Interest rate (3)	-0,7601	-0,7576	1	-0,7039	-0,7572	-0,7492	0,6671	0,1153
Investment (4)	0,9555	0,9213	-0,7039	1	0,9046	0,9516	0,8159	0,0461
Stock prices (5)	0,8979	0,8599	-0,7572	0,9046	1	0,8827	0,7509	-0,1207
Total credit (6)	-0,9962	0,9909	-0,7492	0,9516	0,8827	1	0,9313	0,0329
Real estate value (7)	0,9297	0,9569	-0,6671	0,8159	0,7509	0,9313	1	0,0507
Exchange rate (8)	0,0296	0,0159	0,1153	0,0461	-0,1207	0,0329	0,0507	1

Table 12: Lagged correlations (1992-2019)

Note: We computed the lagged correlation with GDP being one period ahead.

C. Models

C.1. Lag length

To determine the optimal lag length, we use AIC, BIC, and the Hannan-Quinn criterion. The tables below represent the values obtained from AIC, BIC, and the Hannan-Quinn criterion, with the corresponding ranking from best to worst. Ranking is in descending order. For more theory see appendix D.1.

C.1.1. Lag selection for the Baseline model

Lag	logL	AIC	BIC	HQ
1	1085.64	-2.1013	-2.0055	-2.0624
2	1113.01	-2.1060	-1.9424	-2.0396
3	1127.03	-2.0841	-1.8530	-1.9903
4	1162.07	-2.1041	-1.8061	-1.9832
5	1198.87	-2.1277	-1.7632	-1.9799
6	1208.94	-2.0979	-1.6673	-1.9232
7	1250.44	-2.1309	-1.6347	-1.9297
8	1279.73	-2.1395	-1.5782	-1.9119
9	1307.87	-2.1457	-1.5198	-1.8921
10	1341.04	-2.1621	-1.4720	-1.8825

Table 13: Lag length selection for the Baseline model suggested by AIC, BIC, and the Hannan-Quinn.

Note: The optimal lag is the one with the lowest value.

Rank	AIC	BIC	HQ
1	10	1	1
2	9	2	2
3	8	3	3
4	7	4	4
5	5	5	5
6	2	6	7
7	4	7	6
8	1	8	8
9	6	9	9
10	3	10	10

Table 14: Ranking of the lag orders.

Note: Ranking from best to worst and the ranking is in descending order.

C.1.2. Lag selection for the Housing and Credit model

Lag	logL	AIC	BIC	HQ
1	1706.43	-3.3429	-3.2487	-3.3047
2	1729.62	-3.3392	-3.1783	-3.2740
3	1758.65	-3.3473	-3.1201	-3.2552
4	1767.31	-3.3146	-3.0216	-3.1959
5	1784.46	-3.2989	-2.9406	-3.1537
6	1796.19	-3.2724	-2.8493	-3.1010
7	1795.21	-3.2204	-2.7330	-3.0230
8	1832.2	-3.2444	-2.6932	-3.0212
9	1846.2	-3.2224	-2.6078	-2.9736
10	1850.63	-3.1813	-2.5039	-2.9071

Table 15: Lag length selection for the Housing and Credit model suggested by AIC, BIC, and the Hannan-Quinn.

Note: The optimal lag is the one with the lowest value.

Rank	AIC	BIC	HQ
1	3	1	1
2	1	2	2
3	2	3	3
4	4	4	4
5	5	5	5
6	6	6	6
7	8	7	7
8	9	8	8
9	7	9	9
10	10	10	10

Table 16: Ranking of the lag orders.
Note: Ranking from best to worst and the ranking is in descending order

C.1.3 Lag selection for the Exchange Rate model

Lag	logL	AIC	BIC	HQ
1	1327.34	-2.5587	-2.4295	-2.5063
2	1371.44	-2.5749	-2.3496	-2.4835
3	1426.93	-2.6139	-2.2931	-2.4838
4	1459.88	-2.6078	-2.1923	-2.4394
5	1500.89	-2.6178	-2.1082	-2.4113
6	1517.66	-2.5793	-1.9764	-2.3351
7	1555.17	-2.5823	-1.8868	-2.3006
8	1596.69	-2.5934	-1.8059	-2.2745
9	1622.29	-2.5726	-1.6939	-2.2169
10	1650.32	-2.5566	-1.5875	-2.1644

Table 17: Lag length selection for the Exchange Rate model suggested by AIC, BIC, and the Hannan-Quinn.

Note: The optimal lag is the one with the lowest value.

Rank	AIC	BIC	HQ
1	5	1	1
2	3	2	2
3	4	3	3
4	8	4	4
5	7	5	5
6	6	6	6
7	2	7	7
8	9	8	8
9	1	9	9
10	10	10	10

Table 18: Ranking of the lag orders.

Note: Ranking from best to worst and the ranking is in descending order

D. VAR and SVAR theory

D.1. Lag length

It is imperative that one include the appropriate number of lags in order obtain the best possible model. As we do not know the true data generating process, we are not able to point out the correct lag length to include in the model. A too short lag length will indicate a misspecified model as we might omit valuable information and obtain residuals that are autocorrelated. Then, everything not included as an independent regressor will end up in the residuals which ultimately gives biased OLS estimators. If we on the other hand include too many lags, we introduce additional estimation error in the model as we estimate more coefficients than necessary. As a result, the parameter estimates become more uncertain with a larger variance (Bjørnland & Thorsrud, 2015). In large time series data, the method for determining appropriate lag length is based on minimizing the information criterion. Information criteria is based on the premise that there is a trade-off between increased model fit as the number of lags increase, and the increasing parameter uncertainty as the model becomes larger by including more lags.

The information criteria used in a VAR lag-order selection have the general form:

$$C(p) = \log\left(\frac{SSR(p)}{T}\right) + c_T \Phi(p)$$

Where SSR(p) = $\sum_{t=1}^{T} \hat{e}_t \hat{e}_t$ is the estimated residual covariance matrix from the reduced form VAR of order p based on the least square residuals $\hat{e}_t$. p is the candidate lag order in which the criterion is evaluated, $\Phi(p)$ is a function of order p that penalizes large lag orders, and c_T is a sequence of weights that may depend on the sample size. The first term of the equation represents the model fit and this will increase as more lags are added to the model. The latter term represents the penalty for higher p and will decrease with more lags. The method essentially amounts to finding the lag(p) that balances the objective of model fit and parsimony (Kilian & Lutkpohl, 2017).

In order to determine the appropriate number of lags we have utilized the following three methods: Akaike information criterion (AIC), Bayesian information criterion (BIC) and the Hannan-Quinn information criterion (HQC). We used the following Matlab code: [aic,bic] = aicbic(logL,numParam,numObs) and made the proper modifications in order to include the HQC. The following three equations were used:

D.1.1. Akaike information criterion (AIC)

$$AIC(P) = -2(logL) + 2(numParam)$$

where, logL = optimized loglikelihood values and numParam = number of estimated parameters.

D.1.2. Bayesian information criterion (BIC)

$$\text{BIC(P)} = -2(\text{logL}) + numParam * \log(numObs)$$

where, logL = optimized loglikelihood values, numParam = number of estimated parameters and numObs = sample size.

D.1.3. Hannan-Quinn information criterion (HQC)

$$\text{HCQ(P)} = -2(\text{logL}) + 2 * numParam * \log(\log(\text{numObs}))$$

where, logL = optimized loglikelihood values, numParam = number of estimated parameters and numObs = sample size.

D.2. Model diagnostics

D.2.1. Stability

Stationarity is an important concept in time series as many statistical methods rely on it. A stochastic process y_t is said to be covariance stationary if neither the first nor the second order moments depend on time. That is, the mean is constant and autocovariance does not depend on time, but rather the distance between the observations. In other words, the series does change over time, but the change must be equal. For a VAR model to be covariance stationary, the effect of the shocks e_t must eventually die out, otherwise the impulse response functions will not converge towards zero and the shock will have a permanent effect on the variables. Lutkepohl (2005) state that a stable process is stationary. We use this premise to test if the process is stationary through a stability test of the VAR model. The model is stable if the eigenvalues of the companion form matrix is less than one in absolute value $\lfloor \Gamma_1 - \lambda I \rfloor = 0$. We estimate the model using logarithms and not levels on all variables except for interest rate. The use of logarithms in estimating the model have become common practise due to the advantages it brings. Firstly, the log transformation is natural for many economic variables as one is often interested in the growth rates of the variables (Bårdsen & Lutkepohl, 2011). Secondly, using log- transformed data reduces the impact of outliers and it often reduces the increasing variance in trending series (Arino & Frances, 2000). We argue that the latter argument makes the use of log-transformation appropriate for our model as we include series that are trending. In the case of obtaining an unstable model we could difference the time series to achieve stationarity. This means one looks at the difference between a variables value and its value in the previous period.

The eigenvalues of the companion form matrix show that the eigenvalues are less than one in absolute value and we can conclude that the model is stable and further covariance stationary. As our model is stable there is no reason to first difference the data. We present the eigenvalues for the different models in Table 19.

Baseline model	Housing and Credit model	Exchange Rate model
0.2996	0.2118	0.2161
0.8452	0.9268	0.8577
0.8452	0.9268	0.8577
0.9248	0.7885	0.9329
0.9248	0.7885	0.7463
NA	NA	0.8333

Table 19: Eigenvalues for the Baseline model, Housing and Credit model, and Exchange Rate model

D.2.2. Residuals

One important assumption when running a vector autoregressive model is that the error terms e_t are white noise. This means there should be no serial correlation within the error terms e_t (Kilian & Lütkepohl, 2017). To approximately satisfy this, one chooses the lag order that fit the model best.

We provide the plot of the residuals for the different models and by eyeballing the plots, we conclude that the residuals are white noise due to the absence of persistent trends or patterns in the plots

D.2.2.1. Plot of Residuals for the Baseline Model

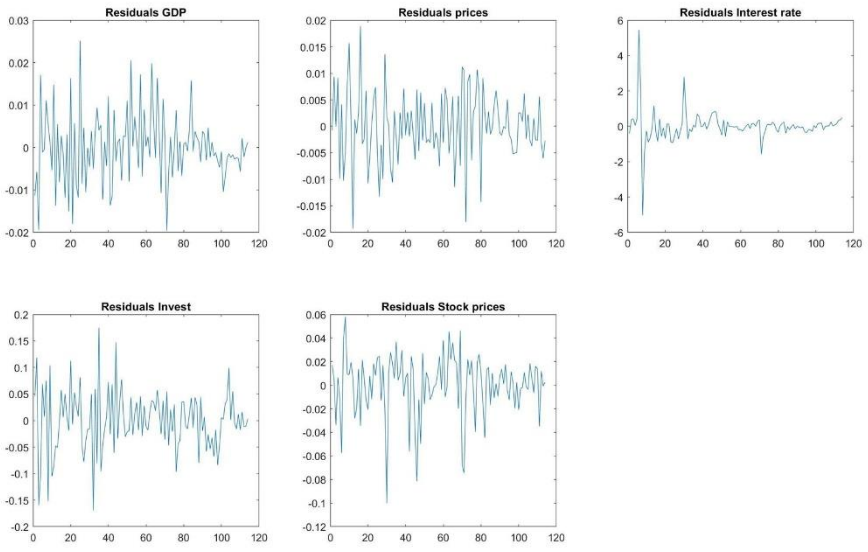

Figure 9: Plot of residuals for the Baseline Model.

D.2.2.2. Plot of Residuals for the Housing and Credit Model

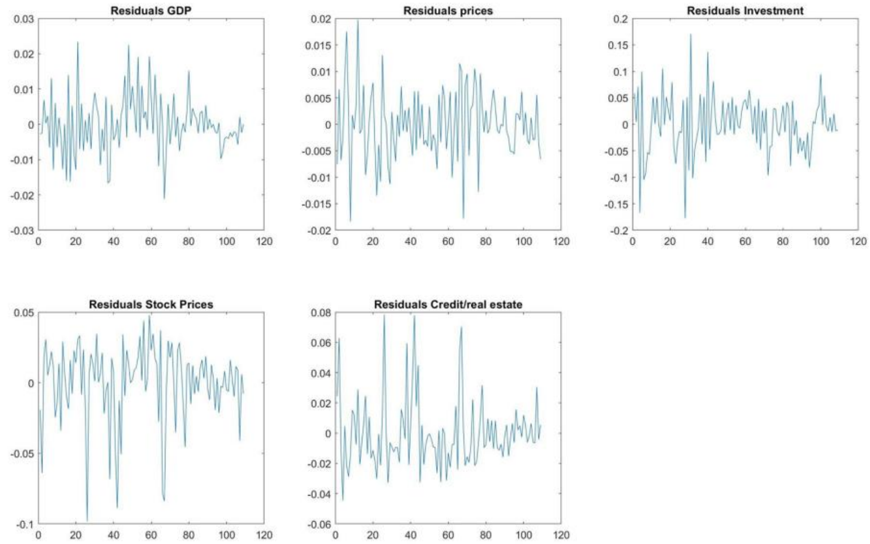

Figure 10: Plot of Residuals for the Housing and Credit Model.

D.2.2.3. Plot of Residuals for the Exchange Rate Model

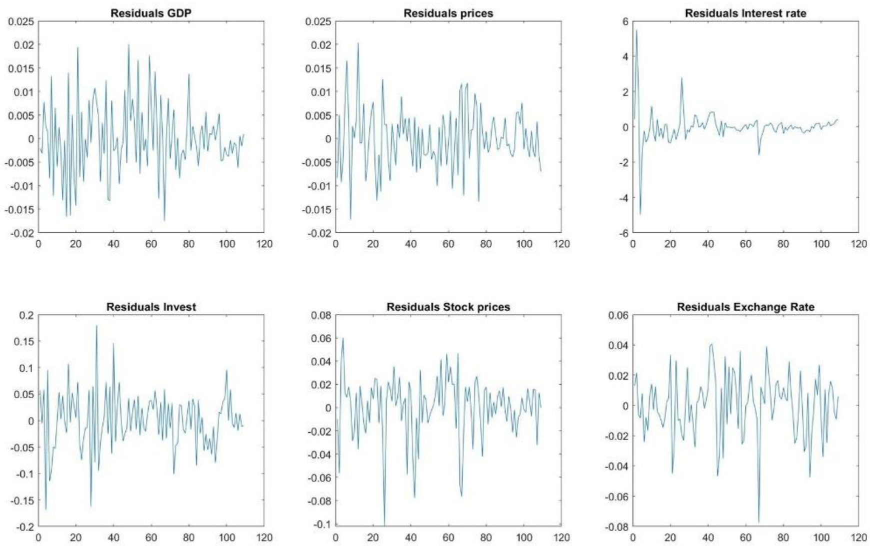

Figure 11: Plot of Residuals for the Exchange Rate Model.

D.3. Companion form

Any VAR (p) model can be rewritten as a VAR (1) model. This is helpful in practical situations and for technical derivations. The reformulation is done by expressing the VAR (p) model in the companion form. This is done by stacking the vectors $y_t, y_{t-1}, \ . \ . \ ., y_{t-p}$ in the Kp × 1 vector. Consider the following companion form model:

$$Z_t = \Gamma_0 + \Gamma_1 Z_{t-1} + v_t \tag{5}$$

where we have defined:

$$Z_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \cdot \\ \cdot \\ y_{t-p+1} \end{bmatrix}, \quad \Gamma_0 = \begin{bmatrix} \mu \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad v_t = \begin{bmatrix} e_t \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad \Gamma_1 =$$

$$\begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & \cdots & I & 0 \end{bmatrix}$$

The dimensions of the vectors Z_t, Γ_0 and v_t are Kp × 1. The coefficient matrix, A_j for J = 1, ...,p will be of the dimension K × K and Γ_1 is Kp × Kp, where Γ_1 is the companion form matrix.

D.4. Moving average

If the VAR(p) is stable which means it is covariance-stationary, we can derive its infinite moving average representation by using recursive substitution. Further, we can write any VAR(p) model as a VAR (1) using the companion form. Starting with

$$y_t = \mu + A_1 y_{t-1} + e_t \tag{6}$$

And using recursive substitution, we obtain the following:

$$y_t = \left(1 + A_1 + A_1^2 + \cdots + A_1^j\right)\mu + A_1^{j+1} y_{t-(j+1)} + e_t + A_1 e_{t-1} + A_1^2 e_{t-2} + \cdots + A_1^j e_{t-j}$$

where $A_1^0 = I$. When the process is stable, $\left(I + A_1 + \cdots + A_1^j\right)\mu \longrightarrow (I - A_1)^{-1}\mu$ as $j \longrightarrow \infty$ Further, $A_1^{j+1} y_{t-j-s} \longrightarrow 0$ as $j \longrightarrow \infty$. This means that the equation reduces to:

$$y_t = v + \sum_{j=0}^{\infty} A_1^j \, e_{t-j} \tag{7}$$

where $v = (I - A_1)^{-1}\mu$. Equation (7) is called the moving average representation of the VAR and we can then write it in terms of moving average coefficients.

$$y_t = v + \sum_{j=0}^{\infty} B_j \, e_{t-j} \tag{8}$$

D.5. Impulse response

D.5.1. Structural analysis

Recall that the covariance matrix of the structural shocks $E(\varepsilon_t \varepsilon_t') = \sum_\varepsilon = I$ and the reduced form errors is $E(u_t u_t') = \sum_u = B_0^{-1} B_0^{-1\prime}$. Deriving the SVAR to reduced form VAR we obtain the reduced form errors as a linear combination of the structural shocks, such that: $u_t = B_0^{-1}\varepsilon_t$. Further, since the covariance matrix is positive semidefinite it can be factorized as $PP' = \sum_e$. We then set $P = B_0^{-1}$, and use that P is invertible to be able to recover the structural shocks since: $e_t = P\varepsilon_t$ => $\varepsilon_t = P^{-1} e_t$. We can use this to investigate how the shocks impact the variables through computing the impulse response function and the forecast error variance decomposition.

D.5.2. Impulse response functions (IRF)

Having identified the structural impact matrix P^{-1} we use MA(∞) representation to derive the impulse response function and see how the variables y_t respond to a shock ε_t from date t to t + s. We start with the MA (∞):

$$Y_{t+s} = v + \sum_{j=0}^{\infty} B_j e_{t+s-j}$$

Recall that: $PP^{-1} = I$

$$Y_{t+s} = v + \sum_{j=0}^{\infty} B_j P P^{-1} e_{t+s-j}$$

where $B_j P = \Theta_j$ and $P^{-1} e_{t+s-j} = \varepsilon_{t+s-j}$

$$Y_{t+s} = v + \sum_{j=0}^{\infty} \Theta_j \varepsilon_{t+s-j}$$

The effect of a shock at date y_{t+s} is $\frac{dy_{t+s}}{d\varepsilon_t} = \Theta_s$. The dynamic multiplier Θ_s only depend on the time separating the shock and the value of y_t, at time t + s and we can then find out how the shock ε_t will impact the level of y in t + s.

D.6. Forecast error variance decomposition

The FEVD explains the proportion of the forecast error variance at date t + s that is explained by the variability in the structural shocks, given at time t. This is useful information as it describes how much of the variance in the endogenous variables that is explained by the structural shocks. The FEVD of a given variable $y_{i,t}$ to the shock $\varepsilon_{l,t}$ at horizon s is given by:

$$FEVD_{ils} = \frac{MSE_{ils}}{MSE_{is}}$$

where the numerator is the mean square error of $y_{i,t}$ attributed to the shock $\varepsilon_{l,t}$ at date t + s. The denominator is the total MSE of $y_{i,t}$ at time t + s. i.e. FEVD shows the ratio of the variance in $y_{i,t}$ caused by the shock $\varepsilon_{l,t}$ to the total variance in $y_{i,t}$ at different horizons.

E. Bayesian estimation theory

E.1. Bayesian inference

Consider the VAR model described above in equation (6). Bayesian inference treats the data $y_t = (y_1, \dots, y_t)$ as given and the parameters of interest A and $\sum$ as unknown. The standard routine is to apply the OLS method to estimate the unknown coefficients A and $\sum$. To improve the estimates of the parameters the Bayesian VAR incorporates prior information i.e. researcher's subjective belief about how the parameters look like. The prior information is assumed to be available in form of a prior density function $g(A, \Sigma)$. The probability distribution function for the data Y given the parameters is given by $g = (Y|A, \Sigma)$. This is the likelihood function which measures how good the data fit the model for a given value on the parameters. Applying Bayes theorem, we obtain the posterior distribution.

$$g(A,\Sigma) = \frac{g(Y|A,\Sigma)g(A,\Sigma)}{g(Y)}$$

$$g(A,\Sigma) = \frac{g(Y|A,\Sigma)g(A,\Sigma)}{g(Y)}$$

$$\longrightarrow \; g(A,\Sigma) \; \propto \; l(Y|A,\sum)g(A,\Sigma) \tag{9}$$

The posterior: $g(A,\Sigma)$ shown in equation (9) contains all information we have on the parameters after we have updated our prior beliefs by looking at the data. The posterior probability distribution is the basis of estimation and inference.

E.2. Bayesian estimation

We estimate the reduced form VAR model using Bayesian methods. The VAR can be rewritten in a compact form as follows:

$$\boldsymbol{Y} = \boldsymbol{XA} + \boldsymbol{U} \tag{10}$$

Where $\boldsymbol{Y} = [y_1, \dots, y_T]'$, $\boldsymbol{U} = [e_1, \dots, e_T]'$, $\boldsymbol{A} = \left[\mu\, A_1, \dots, A_p\right]'$,

$\boldsymbol{X} = [X_1, \dots, X_T]'$,$X_t = \left[y'_{t-1}, y'_{t-2}, \dots, y'_{t-p}\right]'$

Vectorizing (10) leads to:

$$y = (I_N \otimes X)\beta \; + u$$

Where $y = vec(\boldsymbol{Y}), u = vec(\boldsymbol{U})\ and\ \beta = vec(\boldsymbol{B})$ and vec() denote the column wise vectorization. Further, we have that the $u \sim N(0, \Sigma \otimes \mathrm{I})$ because $e_t = iid. N(0,\Sigma)$

The likelihood function can then be written as the following:

$$L(\boldsymbol{B},\boldsymbol{\Sigma}) \; \propto \; |\Sigma|^{-\frac{T}{2}} exp\left[-\frac{1}{2}\left(\beta - \hat{\beta}\right)'(\Sigma^{-1}) \otimes X'X)(\beta - \widehat{\beta)}\right] exp\left[-\frac{1}{2}tr(\Sigma^{-1}S)\right] \tag{11}$$

Where S is the matrix of sum of squared residuals given by: $S = (Y - X\widehat{B)}'\left(Y - X\hat{B}\right)$ and $\hat{\beta} = vec\left(\hat{B}\right)$ where is the maximum likelihood estimator(MLE) given by: $\hat{B} = (X'X)^{-1}X'Y$

The likelihood function in equation (11) is used to update the prior information regarding the VAR parameters. By using diffuse priors for the parameters that is proportional to $|\Sigma|^{-\frac{n+1}{2}}$ the posterior is:

$$L(\boldsymbol{B},\boldsymbol{\Sigma}) \propto |\Sigma|^{-\frac{T+n+1}{2}} exp\left[-\frac{1}{2}\left(\beta-\hat{\beta}\right)'(\Sigma^{-1})\otimes X'X)(\beta - \widehat{\beta)}\right] exp\left[-\frac{1}{2}tr(\Sigma^{-1}S)\right]$$

We then draw the parameters from the posterior distribution and the posterior distribution is the basis for estimating and inference on the parameters.

F. Sensitivity analysis

F.1. Sensitivity analysis for the Baseline model

One of the main results in the baseline model was the little explanatory power of financial shocks on output and the surprisingly high explanation from monetary policy shocks on output. We now test if this result holds under different assumptions. We first apply different measures of central tendency to the baseline model. For more discussion on the methodology behind the different measures see section 4.3. The first experiment consists of using the median target method proposed by Fry and Pagan (2011). From Table 20 the results show that the importance of monetary policy shocks still prevails. In the shorter horizon the explanatory power of monetary policy shocks increases substantially with around 20 percent, while financial shocks still account for little of the variation in output. In our second experiment, we use the modal model proposed by Inoue and Kilian (2013). The result yields limited difference in the variation of output explained by financial shocks. On the contrary, monetary policy shocks now have a limited effect on output, where supply shocks account for almost the entire variation in output, especially in the short run. We also estimate the baseline model with the standard practise of five lags for quarterly data. The result attributes a large proportion of the variation in output to financial shocks, especially in the medium and the long horizon.

	Horizon	Supply	Demand	Investment	Housing
Median target					
GDP	1	0,3197	0,0908	0,1058	0,2847
	5	0,1433	0,0299	0,0570	0,5347
	20	0,0344	0,0290	0,1533	0,6401
Prices	1	0,7028	0,1107	0,1438	0,0389
	5	0,4127	0,2303	0,0800	0,1880
	20	0,1077	0,1267	0,0448	0,4798
Modal model					
GDP	1	0,5195	0,0821	0,0034	0,0113
	5	0,1908	0,0303	0,1248	0,0691
	20	0,0449	0,0081	0,2519	0,0362
Prices	1	0,3952	0,5293	0,0237	0,0518
	5	0,1785	0,7073	0,0145	0,0590
	20	0,0393	0,2562	0,1797	0,0525
Five lags					
GDP	1	0,5491	0,1838	0,0795	0,0944
	5	0,2278	0,0816	0,0251	0,4892
	20	0,1573	0,0468	0,0459	0,4831
Prices	1	0,6290	0,1761	0,0798	0,0584
	5	0,4902	0,2027	0,0976	0,0937
	20	0,1368	0,2293	0,0557	0,3528
Credit in difference					
GDP	1	0,5902	0,1685	0,0803	0,0900
	5	0,3426	0,0574	0,0321	0,3690
	20	0,1360	0,0571	0,1293	0,4735
Prices	1	0,6374	0,1512	0,1091	0,0573
	5	0,3304	0,3551	0,0814	0,1941
	20	0,0843	0,2624	0,0498	0,4629

Table 20: Forecast error variance decompositions for GDP and Prices at each horizon for different measures of central tendency of the model and model estimated with five lags for Baseline model.

F.2. Sensitivity analysis for the Housing and Credit model

We follow the robustness test conducted in the baseline model to the housing and credit model. The importance of housing shocks prevails by using the median target method for central tendency measure and estimating the model with five lags. The importance of credit shocks on output increases in both mentioned tests. For median target, the increase is in the short horizon, but estimating with give lags it is in the long run. On the contrary, the modal model suggests that housing shocks are almost negligible compared to pointwise posterior median and the importance of credit shocks now dominate, especially as the horizon increases.

Lastly, we measure with credit in difference where the importance of credit shocks increase. For more discussion see section 4.3.

	Horizon	Supply	Demand	Investment	Housing
Median target					
GDP	1	0,3197	0,0908	0,1058	0,2847
	5	0,1433	0,0299	0,0570	0,5347
	20	0,0344	0,0290	0,1533	0,6401
Prices	1	0,7028	0,1107	0,1438	0,0389
	5	0,4127	0,2303	0,0800	0,1880
	20	0,1077	0,1267	0,0448	0,4798
Modal model					
GDP	1	0,5195	0,0821	0,0034	0,0113
	5	0,1908	0,0303	0,1248	0,0691
	20	0,0449	0,0081	0,2519	0,0362
Prices	1	0,3952	0,5293	0,0237	0,0518
	5	0,1785	0,7073	0,0145	0,0590
	20	0,0393	0,2562	0,1797	0,0525
Five lags					
GDP	1	0,5491	0,1838	0,0795	0,0944
	5	0,2278	0,0816	0,0251	0,4892
	20	0,1573	0,0468	0,0459	0,4831
Prices	1	0,6290	0,1761	0,0798	0,0584
	5	0,4902	0,2027	0,0976	0,0937
	20	0,1368	0,2293	0,0557	0,3528
Credit in difference					
GDP	1	0,5902	0,1685	0,0803	0,0900
	5	0,3426	0,0574	0,0321	0,3690
	20	0,1360	0,0571	0,1293	0,4735
Prices	1	0,6374	0,1512	0,1091	0,0573
	5	0,3304	0,3551	0,0814	0,1941
	20	0,0843	0,2624	0,0498	0,4629

Table 21: Forecast error variance decompositions for GDP and Prices at each horizon for different measures of central tendency of the model, model estimated with five lags including and credit in difference for Housing and Credit model.

F.3. Sensitivity analysis for the Exchange Rate model

In the robustness check for the last extension, we diverge from the previous sensitivity analysis in one aspect by not re-estimating the model with five lags. As explained previously the inclusion of an addition variable and shock with the corresponding sign restrictions give computational difficulties. As a result, we only provide robustness with different measures of central tendency. Under both tests the importance of financial shocks on exchange rate is magnified where it now accounts for approximately 50 percent of the variation in exchange rate across all horizons. Interestingly, the importance of monetary policy shocks is now negligible compared to using pointwise posterior median as a measure of central tendency. Residual shock now accounts for more of the variation in the exchange rate.

	Horizon	Supply	Demand	Monetary	Investment	Financial	Residual
Median target							
GDP	1	0,4448	0,0031	0,4669	0,0124	0,0404	0,0324
	5	0,3595	0,0442	0,4069	0,0160	0,1481	0,0252
	20	0,2011	0,0945	0,5007	0,0108	0,1250	0,0678
Exchange rate	1	0,2368	0,0200	0,0370	0,0234	0,4179	0,2650
	5	0,1775	0,0250	0,0141	0,0095	0,5064	0,2675
	20	0,1464	0,0476	0,0119	0,0076	0,5182	0,2682
Modal model							
GDP	1	0,4846	0,1783	0,1600	0,0230	0,1504	0,0037
	5	0,3831	0,0448	0,3062	0,0262	0,2374	0,0024
	20	0,1890	0,0168	0,5203	0,0236	0,2048	0,0454
Exchange rate	1	0,0082	0,0014	0,0698	0,0284	0,5231	0,3692
	5	0,0125	0,0007	0,0611	0,0100	0,5156	0,4000
	20	0,0091	0,0014	0,0568	0,0094	0,5184	0,4049

Table 22: Forecast error variance decompositions for GDP and Exchange rate at each horizon for different measures of central tendency for Exchange Rate model.

F.4. The Baseline model with CPI as a price measure

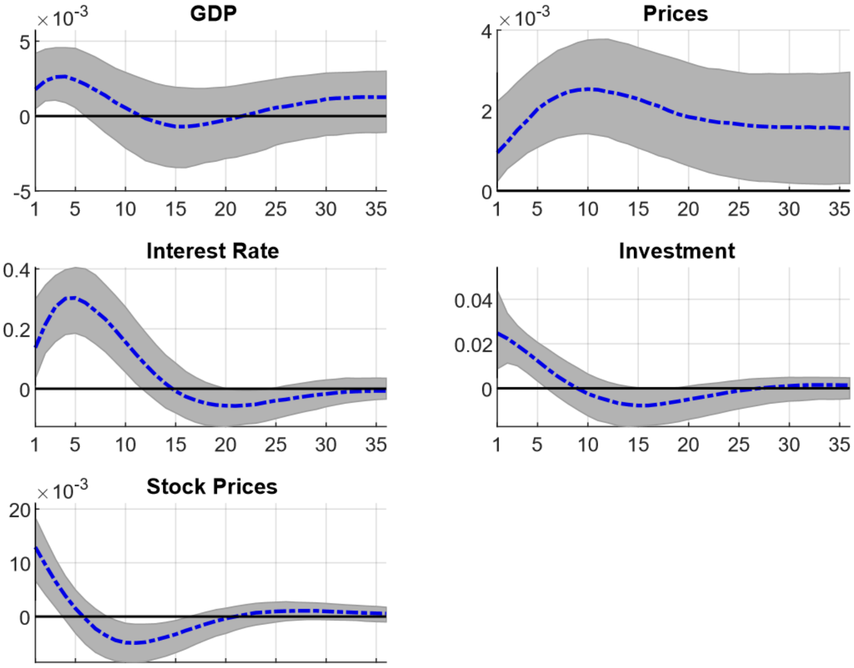

Figure 12: Baseline model with CPI as a price measure.
Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

	Horizon	Monetary policy	Financial
GDP	1	0,1432	0,0536
	5	0,3194	0,1021
	20	0,6322	0,0447
Prices	1	0,1307	0,0510
	5	0,1228	0,1474
	20	0,2631	0,2973

Table 23: Forecast Error Variance Decomposition in the Baseline model with CPI

F.5. The Baseline model with the policy rate as measure of interest

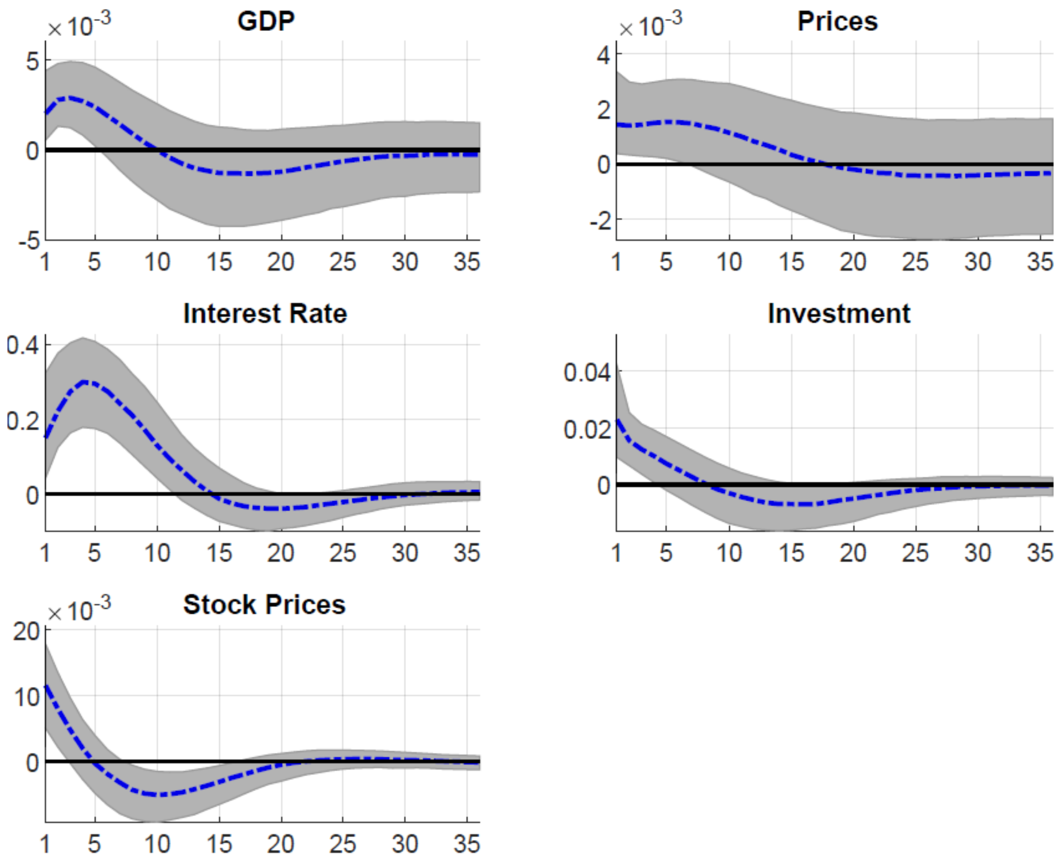

Figure 13: The Baseline model with the policy rate as measure of interest rate.

Note: The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.