The Dynamic Effects of Monetary Policy
Shocks on the Norwegian Macroeconomy

Evidence from Proxy SVAR Models

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Abstract

In this master thesis, the dynamic effects of monetary policy shocks on the Norwegian macroeconomy are examined and compared between two different types of vector autoregressive (VAR) models. The first type is the common Cholesky identified VAR, which imposes a recursive structural ordering. The second type is the proxy structural VAR (proxy SVAR) model, in which the short-run restrictions are partially identified through external instruments for monetary policy shocks. Two feedback rules, which approximate the expected part in the monetary policy of Norges Bank, are utilised to identify monetary policy shocks. But they are merely weak external instruments to identify short-run restrictions in proxy SVARs and thus, the proxy SVAR results pose the risk of a strong bias. Moreover, a financial market variable is utilised for a high frequency identification of monetary policy shocks. This method produces a sufficiently strong external instrument to identify short-run restrictions in a proxy SVAR and hence, these proxy SVAR results can be considered as reliable. In contrast to the Cholesky identified VAR, the proxy SVAR results are mostly in line with literature that evaluates monetary policy shocks in the US. These suggest monetary policy shocks lead to sluggish decreases in inflation, GDP and industrial production, and an initial strong increase in the real effective exchange rate index.¹

¹Stata codes for the empirical analysis are available on request to felix.kapfhammer@me.com.
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Contents

1 Introduction 1

2 Proxy SVAR methodology 4
  2.1 VAR and SVAR model 4
    2.1.1 Reduced-form VAR 4
    2.1.2 Cholesky identification 6
    2.1.3 Identification of the SVAR system 7
    2.1.4 Exogenous variables 8
  2.2 Proxy SVAR model 8

3 External identification of monetary policy shocks 11
  3.1 Forward looking feedback rule identification 11
  3.2 Outlook based feedback rule identification 14
  3.3 High frequency identification 15
  3.4 Alternative identification methods 19
  3.5 Critique of identification methods 20

4 Data 22

5 Model calibration 25

6 Empirical results 28
  6.1 Cholesky VAR 29
  6.2 FLFR proxy SVAR 31
    6.2.1 FLFR instrument conditions 31
    6.2.2 FLFR proxy SVAR results 34
  6.3 OBFR proxy SVAR 34
    6.3.1 Relevance of OBFR instrument 35
    6.3.2 OBFR proxy SVAR results 35
  6.4 HFI proxy SVAR 37
    6.4.1 Relevance of HFI instruments 37
    6.4.2 HFI proxy SVAR results 39

7 Robustness 43
8 Potential extensions

9 Conclusion

References

Appendix A Data sources and descriptive figures

Appendix B Robustness test figures and tables
List of Tables

1  Relevance of FLFR instruments 32
2  Relevance of the OBFR instrument 35
3  Relevance of HFI instruments 38
4  Forecast error variance decomposition of the HFI proxy SVAR 42
5  Information about endogenous and exogenous variables 54
6  Information about underlying variables of instruments 55
7  Robustness test: Relevance of FLFR instruments including polynomials 59
8  Robustness test: Relevance of OBFR instruments including polynomials 60
9  Robustness test: Relevance of HFI instruments including polynomials 61
10 Robustness test: Relevance of collapsed NIBOR instruments 62
# List of Figures

1. Monthly Cholesky VAR vs. quarterly Cholesky VAR \hspace{1cm} 30
2. Cholesky VAR vs. FLFR proxy SVAR \hspace{1cm} 33
3. Cholesky VAR vs. OBFR proxy SVAR \hspace{1cm} 36
4. Graphical heteroskedasticity check in first stage regression \hspace{1cm} 39
5. Cholesky VAR vs. HFI proxy SVAR \hspace{1cm} 40
6. Quarterly GDP and industrial production \hspace{1cm} 56
7. Quarterly Norges Bank sight deposit rate \hspace{1cm} 56
8. Quarterly REER index and Brent spot price \hspace{1cm} 57
9. Monthly consumer price index and industrial production index \hspace{1cm} 57
10. Quarterly FLFR and OBFR instruments \hspace{1cm} 58
11. Monthly HFI instruments \hspace{1cm} 58
12. Robustness test: HFI proxy SVAR with 6M NIBOR instrument vs. HFI proxy SVAR with 1W NIBOR instrument. \hspace{1cm} 63
13. Robustness test: Cholesky VAR vs. HFI proxy SVAR with CPI ordered prior to IP \hspace{1cm} 64
14. Robustness test: Cholesky VAR vs. HFI proxy SVAR with control for ECB’s facility deposit rate \hspace{1cm} 65
15. Robustness test: Cholesky VAR vs. HFI proxy SVAR (pre-crisis sample) \hspace{1cm} 66
16. Robustness test: Cholesky VAR vs. HFI proxy SVAR (post-crisis sample) \hspace{1cm} 67
17. Cholesky VAR and proxy SVAR IRFs for the US from Gertler and Karadi (2015) \hspace{1cm} 68
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1 Introduction

Officially since 2001, Norges Bank has followed the trend and adopted the inflation targeting regime. In particular, the Norwegian government conferred a mandate to Norges Bank to keep inflation stable at 2.5% and to stabilise output and employment. The Norwegian central bank governs the economy mainly through altering the key policy rate, which sets economic variables in motion and creates a new equilibrium in the Norwegian economy. In general, the ability of central banks to control inflation and output through monetary policy is much discussed in literature and most researchers agree that monetary tightening sluggishly decreases inflation and output. However, the extent to which monetary policy eventually influences the macroeconomy remains much debated.

Measuring the effect of monetary policy on macroeconomic variables is not trivial due to strong simultaneity issues. Bernanke and Kuttner (2005) remark the economy updates its expectations about monetary policy constantly and not only at the moment the central bank publishes a new decision. In the Norwegian setting, this means the Norwegian economy partly anticipates changes in Norges Bank’s key policy rate and adjusts accordingly. But simultaneously, Norges Bank adjusts the key policy rate to the state of the economy. Hence, ordinary regressions of inflation and output on the key policy rate will not reveal the true effect of monetary policy. Macroeconomic literature solves this issue by using only the unanticipated monetary policy shocks, which are deviations from the economy’s expectation. As these shocks are a surprise for the economy, it only reacts to them at the time it realises these shocks, which allows to identify a clear causal relationship: Monetary policy shocks are exogenous and cause adjustments in the economy. The aim of this master thesis is twofold: Firstly, the monetary policy shocks induced by Norges Bank are measured through different approaches and secondly, the dynamic responses of the Norwegian macroeconomy on monetary policy shocks is examined.

Macroeconomists developed many different strategies to extract monetary policy shocks. Taylor (1993) formed the basis for a set of feedback rules, which approximate the expected part of monetary policy through the inflation gap and the output gap. Consequently, deviations of the key policy rate from this rule are considered as the monetary policy shocks. Stock and Watson (2001) modified such a feedback rule and considered forecasted values instead of the usual past values in the estimation of the rule. This approach is followed in
the first external identification, where monetary policy shocks are approximated through deviations of the key policy rate from weighted forecasts about the output gap and the inflation gap. The second external identification is also based on a feedback rule, in which economic agents take the forecast of the key policy rate as given and adjust this outlook by their expectation based on observed changes in output and inflation. The third and last external identification approach follows Kuttner (2001), who identified monetary policy shocks through changes in a high frequency financial market variable right after the announcement of a monetary policy decision.

Monetary policy shocks are also often calculated through multi-equational vector autoregressions (VARs). To be precise, one of the equations in the VAR system usually explains the short-term interest rate or the key policy rate in dependence of output, inflation and further variables, which gets close to some sort of feedback rule. The structural shocks of this equation are considered as the monetary policy shocks, which are often identified together with the structural shocks of the other equations through a Cholesky decomposition that imposes a recursive structural ordering on the dependent variables. Another possibility to identify these structural shocks are more specific restrictions of contemporaneous relationships in the VAR system. Sims (1986), Christiano et al. (1994), Christiano et al. (1998), Stock and Watson (2001), Llaudes (2007) and Bjørnland (2008) provide examples for the use of Cholesky identified VARs and structural VARs (SVARs). Identifying the restrictions on contemporaneous effects in SVARs is controversially discussed among researchers since it can strongly influence the identification and consequently also the effect of monetary policy shocks. Stock and Watson (2012), and Mertens and Ravn (2013) developed recently a new method to identify these restrictions through external instruments. This so-called proxy SVAR model offers two opportunities. The SVAR model gets precisely identified through exact restrictions and the monetary policy shocks get closer to the true values. Besides Stock and Watson (2012), and Mertens and Ravn (2013), the proxy SVAR model was also applied by Gertler and Karadi (2015), Montiel-Olea et al. (2016), and Stock and Watson (2016) for example.

In this master thesis, the proxy SVAR model serves as the main tool to evaluate the dynamic effects of monetary policy shocks on the Norwegian macroeconomy since it considers several econometric issues of endogeneity and offers convenient opportunities to
present the dynamic effects.

The master thesis begins with the explanation of the general SVAR methodology and the proxy SVAR extension in section 2. Section 3 introduces concepts of the external identification of monetary policy shocks through three approaches: a forward looking feedback rule, an outlook based feedback rule and the identification through high frequency financial market variables. The sections 4 and 5 provide information on the data and the calibration of the vector autoregressive models that are used to evaluate the dynamic effects of monetary policy shocks.

The core of this master thesis is the estimation of the dynamic effects of monetary policy shocks on the Norwegian macroeconomy in section 6. Before the external instruments are used to identify the proxy SVAR model, the exogeneity and relevance condition of instruments is examined. Finding relevant instruments for monetary policy shocks in Norway turned out to be difficult. The monetary policy shocks from the forward looking feedback rule and the the outlook based feedback are only weak instruments to identify short-run restrictions from the proxy SVAR. The reasons are presumably manifold, whereas the strongest issues might be missing data and the general lack of these rules to reveal monetary policy shocks. Despite the weak instruments, the two proxy SVAR models from the two feedback rules are briefly discussed. In contrary to the latter, the external instrument for monetary policy shocks that is identified from high frequency financial variables is sufficiently strong to identify the proxy SVAR and to provide reliable results with a low potential asymptotic bias. In comparison to the commonly used Cholesky VAR, which serves as comparison, the proxy SVAR provides results that are mostly in line with economic theory and with literature for the US: Monetary tightening leads to a strong and significant increase in the short term in Norges Bank’s sight deposit rate and in the real effective exchange rate index. The consumer price index, GDP and industrial production decrease sluggishly, but mostly not significantly.

After the empirical analysis, the high frequency identified proxy SVAR and the Cholesky VAR undergo robustness tests in section 7. Before the concluding summary in section 9, possible extensions of this master thesis are briefly described in section 8.

This master thesis seeks to complement the Norwegian macroeconomic literature. It provides three new external instruments for monetary policy shocks in Norway, which are
estimated through two feedback rules on a quarterly basis and a high frequency identification on a monthly basis. These external instruments identify, to my best knowledge, the short-run restrictions of the first estimated proxy SVAR models for Norway, whereas the high frequency identified proxy SVAR provides plausible results as well as the opportunity for many extensions.

2 Proxy SVAR methodology

VAR models are widely used for evaluating macroeconomic shocks since they consider several econometric issues like simultaneous movements of macroeconomic variables and the importance of past values to explain the current state of the macroeconomy. Moreover, VARs do not require a large theoretical construct. Christiano et al. (1998), Stock and Watson (2001), Llaudes (2007), Bjørnland (2008), Gertler and Karadi (2015) and many more use either recursive VARs or SVARs since they offer a convenient method to examine and to present the impact of monetary policy on the economy.

At first, the steps from a reduced-form VAR to a SVAR model are explained thoroughly. Subsequently, an extension, the proxy SVAR, is presented.

2.1 VAR and SVAR model

The most important methodology for the VAR and SVAR models are explained based on Lütkepohl and Krätzig (2004), Bagliano and Favero (1998), Christiano et al. (1998) and Schenck (2016).

2.1.1 Reduced-form VAR

In general, the SVAR system can be written as a combination of several simple autoregressive equations:

\[ Ay_t = A_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t \]  (1)
where $y_t$ denotes a $(k \times 1)$ vector of the dependent variables in the equation system, $A_0$ is a time constant $(k \times 1)$ vector containing the intercepts, $A_1$ labels a $(k \times k)$ coefficient matrix of the first lag of the dependent variables $y_{t-1}$ and $A_p$ denotes a $(k \times k)$ coefficient matrix of the $p$-th lag of the dependent variables $y_{t-p}$. The remaining unexplained part of $y_t$ is captured in the structural shocks, which are represented by the $(k \times 1)$ vector $\epsilon_t$ and are assumed to be independent. The matrix $B$ is a restriction matrix and allows for contemporaneous influences of structural shocks on dependent variables. The matrix $A$ is a further restriction matrix which controls the mutual contemporaneous relationships of dependent variables.

As it can be seen in equation (1), each dependent variable of $y_t$ is explained by its own lags, the current values of the other dependent variables as well as their lags and the structural shocks. Note, that it is not possible to estimate the SVAR model directly with conventional estimation techniques since each dependent variable in $y_t$ depends on all other dependent variables and on all structural shocks $\epsilon_t$ simultaneously.

Equation (1) can be rewritten as

$$y_t = C_0 + C_1 y_{t-1} + \ldots + C_p y_{t-p} + \epsilon_t$$

(2)

where

$$C_0 = A^{-1} A_0, \quad C_1 = A^{-1} A_1, \quad C_p = A^{-1} A_p \quad \text{and} \quad \epsilon_t = A^{-1} B \epsilon_t.$$

Equation (2) is the so-called reduced-form VAR model. The error terms of the reduced-form version $\epsilon_t$ consist of compositions of the structural shocks $\epsilon_t$, i.e. matrix $B$ and the inverted matrix $A$ determine how the error terms are decomposed of the structural shocks. Note that $\epsilon_t$ possesses still a zero mean since the structural shocks $\epsilon_t$ have a zero mean on average. But each variance of the reduced-form error terms $\epsilon_t$ depends on all shocks and not only the shocks of the own variable. The variance/covariance matrix $\Sigma_e$ contains all covariances in the upper and the lower triangle and all variance of $\epsilon_t$ on the diagonal.
The variance/covariance matrix indicates that a structural shock in one dependent variable will affect the other dependent variables as well.

### 2.1.2 Cholesky identification

In contrast to equation (1), equation (2) can be estimated with conventional estimation techniques. Thus, the coefficients of $C_0, C_1, \ldots, C_p$ can be estimated as well as $\Sigma_e$. But it is impossible to identify the SVAR system given the information from the estimation of the reduced-form VAR system due to an underidentification of parameters in the SVAR system. In other words, there are many different combinations of $A$ and $B$ possible, which identify $\Sigma_e$. As the lower triangle of $\Sigma_e$ contains the same information as the upper triangle (since $\sigma_{12} = \sigma_{21}$ etc.) the variance/covariance matrix must be symmetric and consequently, less parameters in $A$ and $B$ are needed to identify $\Sigma_e$. Thus, some parameters in the SVAR system have to be restricted. Most commonly, the Cholesky decomposition of $\Sigma_e$ is used to identify the SVAR system, which sets $A$ to a matrix with parameters on the diagonal and $B$ to a lower-triangular matrix such that $A^{-1}BB'A^{-1}' = \Sigma_e$. It should be noted that the order of dependent variables in the system is not important in case of the reduced-form VAR model, but it plays a very important role for Cholesky identified VARs. The ordering of the variables decides which variables are contemporaneously affected by the shocks of other variables. Economic theory is normally used to identify the ordering.

\[
\Sigma_e = \begin{bmatrix}
\sigma_1 & \sigma_{12} & \ldots & \sigma_{1k} \\
\sigma_{21} & \sigma_2 & \ldots & \sigma_{2k} \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{k1} & \sigma_{k2} & \ldots & \sigma_k
\end{bmatrix}
\]

The Cholesky decomposition assures the structural shocks $\epsilon_t$ are uncorrelated across equations, in contrast to the reduced-form error terms $e_t$. The imposed restrictions also ensure
that not every dependent variable in the SVAR model depends on the contemporaneous
values of the other dependent variables and thus, not on every structural shock. In a
Cholesky identification, the first endogenous variable in the recursive VAR, $y_{1,t}$, depends
solely on lagged values of all variables, but not on current values of other variables and
therefore, it is only exposed to the structural shocks of its own variable, $\epsilon_{1,t}$. The second
endogenous variable $y_{2,t}$ depends on lagged values of all variables and it is exposed to
structural shocks of its own variable $\epsilon_{2,t}$ and to structural shocks of the first dependent
variable $\epsilon_{1,t}$, which means it depends indirectly on the $y_{1,t}$ as well. Finally, the $k$-th
endogenous variable $y_{k,t}$ depends on lagged values of all variables and it is exposed to
structural shocks of all variables, $\epsilon_{1,t}, ..., \epsilon_{k,t}$.

In case of $k$ variables in the equation system, the Cholesky decomposition restricts the
least necessary amount of parameters, $(k^2 - k)/2$, in matrix $B$ to enable an identification
of the remaining parameters. According to Ramey (2016), the Cholesky VAR is the most
common approach to evaluate monetary policy shocks. These shocks are represented by
the structural shock $\epsilon_t$ from one of the equation in the system. To be precise the monetary
policy shocks are represented by the structural shocks $\epsilon_R^t$ of the equation where the key
policy rate is the dependent variable. In this master thesis, the common Cholesky VAR
is taken as a baseline comparison to the proxy SVARs.

2.1.3 Identification of the SVAR system

The step from a Cholesky identified VAR model to a SVAR model is small. Parameters
in matrix $B$ can be restricted manually, e.g., $\beta_{k1} = \beta_{k2} = 0$. The manual restriction still
needs to assure a recursive ordering to avoid simultaneity. It is also possible to replace
parameters in the restriction matrix with other constants than zero. The stated exam-
ple would ensure that the structural shocks from the first and second equation do not
temporaneously affect the dependent variable of the $k$-th equation. SVAR systems
will be considered as overidentified, if more restrictions than necessary are imposed on
parameters to estimate the SVAR model.
2.1.4 Exogenous variables

The general SVAR model from equation (1) can be extended through adding weakly exoge-
nous variables to the model, which can be helpful when controlling for further influences
is necessary:

\[ Ay_t = A_0 + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \Omega c_t + B \epsilon_t \]  

(3)

In addition to the general SVAR model, the \((l \times 1)\) vector \(c_t\) is added which contains
\(l\) exogenous variables. The \((k \times l)\) coefficient matrix \(\Omega\) contains the parameters which
capture the effect of the vector \(c_t\) on the dependent variables. These exogenous variables
appear only on the RHS of the equation and never as dependent variables on the LHS of
the equation. Note, that only the contemporaneous values of the exogenous variables \(c_t\)
are incorporated in the SVAR system, but not their lags.

2.2 Proxy SVAR model

Stock and Watson (2012) as well as Mertens and Ravn (2013) developed independently
from each other the proxy SVAR model, which utilises external instruments (gained from
outside the VAR/SVAR model) to identify parameters in matrix \(B\) of the SVAR model.
Stock and Watson (2012) developed the method to generally incorporate shocks from var-
ious external series into the VAR model, while Mertens and Ravn (2013)\(^2\) concentrated
on instrumenting tax shocks in the SVAR model with a narratively identified shock series.
Ramey (2016) calls this “a promising new approach for incorporating external series for
identification.”

Let the external series \(\eta_t\) be an instrument to identify parameters in \(B\). In the following,
the case of a SVAR model with four dependent variables is considered to simplify the
notation and with regard to the application later. In this example, the structural shock
\(\epsilon_{3,t}\) is considered as endogenous and will get instrumented. Like all instruments, \(\eta_t\) has to

\(^2\)The conception of Mertens and Ravn (2013) is followed in this setting, if not indicated otherwise.
fulfil the two essential conditions of instrument variables:

Relevance condition: \( E[\eta_t \epsilon_{3,t}] \neq 0 \)

Exogeneity condition: \( E[\eta_t \epsilon_{i,t}] = 0, \text{ for } i = 1, 2, 4 \)

The relevance condition states the instrument \( \eta_t \) has to be contemporaneously correlated with the structural shock \( \epsilon_{3,t} \) and the exogeneity conditions assures that the instrument is not contemporaneously correlated with any other structural shock \( \epsilon_{i,t} \) than \( \epsilon_{3,t} \).

Following Mertens and Ravn (2013), the proxy SVAR model can be obtained in two steps:

(1) The reduced-form VAR version of the SVAR model (see equation (2)) must be estimated to obtain the residuals, which were called reduced-form errors terms \( e_t \) above. It is important to recall that \( e_t = A^{-1}B\epsilon_t \). Remember that the reduced-form error terms \( e_t \) can always be estimated, while the structural shocks \( \epsilon_t \) can only be estimated if enough restrictions are imposed on the matrices \( A \) and \( B \).

(2) In the second step, the reduced-form error terms \( e_{i,t} \) for \( i = 1, 2, 4 \) have to be regressed on \( e_{3,t} \) using \( \eta_t \) as an instrument.

\[
\begin{align*}
\hat{e}_{3,t} & = \tau_0 + \tau_3 \eta_t + v_{3,t} \\
\hat{e}_{3,t} & = \beta_0 + \beta_{33} \hat{e}_{3,t} + v_{i,t}
\end{align*}
\]

Equation (4) denotes the first stage and equation (5) the second stage of the instrument variable regression. \( \hat{e}_{3,t} \) are the fitted values of equation (4), \( \beta_{33} \) represents its estimates and \( v_{i,t} \) are the error terms in the second stage. The estimates provide the effect of the instrumented reduced-form error term \( e_{3,t} \) on the other error terms \( e_{i,t} \). In other words, \( \hat{e}_{3,t} \) is the exogenous part of the endogenous error term \( e_{3,t} \) which is not correlated with any other structural shock than \( \epsilon_{3,t} \) and hence, it allows to estimate the effect of \( \epsilon_{3,t} \) on \( e_{i,t} \). Therefore, the three \( \beta_{33} \) must equal parameters from the third column in the restriction matrix \( B \), which enables an accurate identification of the SVAR model.
The exogenous instrument \( \eta_t \) improves the precision of the SVAR model through identifying the three bold printed parameters in matrix \( B \). Otherwise, the two identified parameters in the upper triangle would be restricted to zero in the most common identification methods.

\[
B = \begin{bmatrix}
1 & \beta_{12} & \beta_{13} & \beta_{14} \\
\beta_{21} & 1 & \beta_{23} & \beta_{24} \\
\beta_{31} & \beta_{32} & 1 & \beta_{34} \\
\beta_{41} & \beta_{42} & \beta_{43} & 1
\end{bmatrix}
\]

Following the depicted example with four endogenous variables in the SVAR model (i.e. \( k = 4 \)), six restrictions have to be imposed on matrix \( B \) to fulfil the recursive condition from the Cholesky decomposition, if no instrument variable is used. The instrument variable identifies three parameters of the matrix, but Christiano et al. (1998) state a matrix like above still does not satisfy the recursive rank condition, which saves from simultaneity issues. Thus, four further restrictions on \( \beta_{12}, \beta_{14}, \beta_{24} \) and \( \beta_{34} \) need to be imposed after using the proxy variable to avoid simultaneity issues. These additional restrictions will be discussed in section 5.\(^3\)

The use of external instruments has a further strong advantage. If more than one reduced-form error could be instrumented, even more parameters of matrix \( B \) could be identified, which would enable an even more precise identification of the SVAR model. Furthermore, several proxies could instrument a structural shock together to combine information sets.

A proxy SVAR model can only be estimated, if suitable instruments \( \eta_t \) for monetary policy shocks can be found which fulfil the exogeneity and the relevance condition. In the following section, three different kinds of externally identified monetary policy shock series are elaborated. The words \textit{externally identified} define in this context that the monetary policy shock series is not identified through any VAR model.

\(^3\)Note that one more restricted parameter in \( B \) could be identified, if the third and the fourth dependent variable changed positions. However, this is explicitly not conducted in this thesis, as a direct comparison of the proxy SVAR to the VAR identified through the Cholesky decomposition (in which the causal order is not arbitrary between the third and the fourth variable) is desired.
3 External identification of monetary policy shocks

As explained in the introduction, changes in monetary policy can be distinguished in expected changes and unexpected changes, i.e. monetary policy shocks. Both changes are not directly observable, but they can be approximated. Feedback rules, narrative approaches, high frequency identifications and dynamic stochastic general equilibrium models are further approaches to approximate monetary policy shocks besides the identification through all kinds of vector autoregressive models. Subsequently, economic literature on the identification of monetary policy shocks is reviewed and shocks are identified with three different approaches.

3.1 Forward looking feedback rule identification

The first monetary policy shock series is derived through a linear monetary feedback rule, which is developed by Taylor (1993) in the 90s. This rule describes the setting of the Fed funds rate by the Federal Reserve in dependence of the output gap and the inflation gap. In general, feedback rules are more of an approximation to describe monetary policy than an actual rule which the central bank follows. In the past two and a half decades, modified versions from Taylor’s feedback rule were often used to approximate the expected part of monetary policy. Deviations from these rules are considered as monetary policy shocks consequently. Bjørnland (2008) states that also the Norwegian monetary policy is “following close to some kind of Taylor rule from 1993.”

The initial feedback rule from Taylor (1993) is originally calibrated in a backward looking manner, meaning it considers only past values. But Batini and Haldane (1999) describe monetary policy must be set in a forward looking manner to be successful in keeping inflation stable and in smoothing business cycles. Clarida et al. (1998) find big central banks set their base rate indeed with a forward looking perspective. The equation in the VAR model that explains the key policy rate in dependence of the other variables and in dependence of lagged values can be considered as some sort of backward looking feedback rule. Thus, it is likely that the monetary policy shocks from the key policy rate equation in an ordinarily estimated Cholesky VAR (which serves as comparison later) do not reflect the true shocks.
\[ R_t = r^* + \Psi((\pi^f_{t+i} - \pi^*), (g^f_{t+i} - g^f_{t+i}^*)) + \eta_{t}^{FLFR} \] (6)

Equation (6) describes a \textit{forward looking feedback rule} (FLFR) which considers, as the name reveals, forward looking values. \( R_t \) denotes the key policy rate which depends on the desired long-run nominal interest rate \( r^* \) and on some function of the inflation gap \( (\pi^f_{t+i} - \pi^*) \), \( i \) periods ahead of the current period \( t \), and the output gap \( (g^f_{t+i} - g^f_{t+i}^*) \), also \( i \) periods ahead of \( t \). The inflation target \( \pi^* \) is set to 2.5\% in accordance to the inflation goal of Norges Bank.\(^4\) Everything that is not explained in the FLFR is captured in the error term \( \eta_{t}^{FLFR} \), which is considered as the monetary policy shock. In Stock and Watson (2001), the function \( \Psi \) consists of the output gap and the inflation gap averaged over the current quarter and three quarters ahead, i.e. \( i = 0, \ldots, 3 \). However, there might be different approaches to incorporate the nowcast\(^5\) \((i = 0)\) and the forecast for the seven periods ahead \((i = 1, \ldots, 7)\), which are available. Thus, four different FLFRs are created.

The monetary policy shocks can be extracted through rearranging equation (6):

\[ \eta_{t}^{FLFR} = R_t - r^* - \Psi((\pi^f_{t+i} - \pi^*), (g^f_{t+i} - g^f_{t+i}^*)) \] (7)

The different monetary policy shocks from the FLFRs are identified through the following four equations:

\[ \eta_{t}^{FLFR1} = R_t - r^* - \gamma \left( \frac{1}{4} \sum_{i=0}^{3} (\pi^f_{t+i} - \pi^*) \right) - \lambda \left( \frac{1}{4} \sum_{i=0}^{3} (g^f_{t+i} - g^f_{t+i}^*) \right) \] (8)

\(^4\)E.g., see Norges Bank’s Monetary Policy Report 1/12, page 6.

\(^5\)Nowcasts are the predictions of current values as some economic aggregates like GDP are not available right after the realised period.
The monetary policy shocks $\eta_{FLFR1}^t$ in equation (8) are the residuals from the FLFR where the average of the nowcast and the forecasts up to three quarters ahead is taken. $\eta_{FLFR2}^t$ in equation (9) is even more forward looking and considers in a separate term the average of the forecasts four to seven periods ahead in addition. $\eta_{FLFR3}^t$ in equation (10) considers the average of the nowcast and the forecasts up to seven quarters ahead. $\eta_{FLFR4}^t$ in equation (11) considers individually the non-averaged nowcast and forecasts up to seven quarters ahead.

The expected future values of inflation, output and potential output would have to be forecasted, if Norges Bank did not publish future values for the inflation gap and the output gap for the upcoming years in their *Monetary Policy Reports*. Norges Bank’s nowcasts and forecasts are preferred over own forecasts as it is nearly impossible to get closer to the true future values for the Norwegian economy than Norges Bank with its extensive forecasts. Thus, the nowcasted current value and the seven upcoming future values for $(\pi_{t+i}^f - \pi^*)$ and $(g_{t+i}^f - g_{t+i}^*)$ are extracted from the Monetary Policy Reports. Note that the current value (i.e. $i = 0$) of the inflation and especially the output gap are *nowcasted* values, i.e. not the revised, final values. All future values ($i = 1, \ldots, 7$) are forecasted values.

In contrary to the monetary policy shocks from multi-equation VAR models, the shocks from the FLFRs are estimated with simple OLS regressions. The exogeneity and the relevance condition of $\eta_{FLFR1}^t$, $\eta_{FLFR2}^t$, $\eta_{FLFR3}^t$ and $\eta_{FLFR4}^t$ are discussed and tested in
After their inspection, only the most relevant of the four external instruments is taken to identify the SVAR model.

### 3.2 Outlook based feedback rule identification

The third identification approach is based on Norges Bank’s outlook for the forecasted key policy rate, inflation and output as well as expectation adjustments towards this outlook. Assuming the economy would be perfectly predictable, economic agents could fully trust the forecasts of Norges Bank and expect that the forecasted key policy rate $R^f_t$, made in the last period for the current period $t$, becomes reality. However, this assumption is likely to fail as events that happened since the forecast of the key policy rate one period ahead will influence the eventually realised rate in $t$. In particular, economic agents will observe current information like movements in inflation and economic growth and adjust their expectations towards the forecast $R^f_t$ from the last period.

$$R_t = R^f_t + \left[ \gamma((\pi^f_t - \pi^*) - (\pi_t - \pi^*)) + \lambda((g^f_t - g^f_*) - (g_t - g^*)) \right] + \eta_t^{OBFR} \quad (12)$$

The concept of the outlook based feedback rule (OBFR) is structurally different from the concept of the FLFR. While the latter considers solely nowcasted and forecasted values for output and inflation gap, the OBFR consists of three different components: The first is the previously explained forecasted key policy rate $R^f_t$ for the current period $t$. The second component is the adjustment of expectation for events that happened since the previous period, when the forecast was conducted. To be precise, the forecasted inflation gap ($\pi^f_t - \pi^*$) is adjusted by the current observations of the inflation gap ($\pi_t - \pi^*$). The difference between the forecasted inflation gap and the observed inflation gap is called inflation adjustment. Inflation is published every month, so economic agents will have the possibility to adjust their expectations within one quarter accordingly. Furthermore, the forecasted output gap ($g^f_t - g^f_*$) is adjusted by the current observation for the output gap ($g_t - g^*$). The difference between the forecasted value and the current observation is called output adjustment. In contrast to inflation, GDP is published only every quarter, but economic agents will have the possibility to update their beliefs about the growth through information from news, indices or GDP substitutes like industrial production.
To get closer to the reality, the unrevised first release of GDP is used for the current value of GDP $g_t$ instead of the revised and final GDP. The total adjustment of the of forecasted key policy rate through the best belief of economic agents, indicated by the big squared parentheses, consists of the inflation adjustment, weighted by $\gamma$, as well as the output adjustment, weighted by $\lambda$. The third component are the monetary policy shocks $\eta_t^{OBFR}$ which capture everything the economic agents did not anticipate when updating their beliefs about the key policy rate. Assuming that Norges Bank did not systematically deviate from the inflation target of $\pi^* = 2.5\%$, equation (12) can be simplified. For simplicity reasons, it is further assumed that the potential output remains the same, $g^*_t = g^*_t$, even though slight differences from quarter to quarter are realistic:

$$R_t = R^*_t + \gamma(\pi_t^f - \pi_t^r) + \lambda(g_t^f - g_t) + \eta_t^{OBFR}$$  \hspace{1cm} (13)$$

The monetary policy shocks $\eta_t^{OBFR}$ can be obtained through rearranging the OBFR:

$$\eta_t^{OBFR} = R_t - R^*_t - \gamma(\pi_t^f - \pi_t^r) - \lambda(g_t^f - g_t)$$  \hspace{1cm} (14)$$

As in the case of the FLFR shocks, the forecasts for the key policy rate, inflation and output are obtained from Norges Bank’s Monetary Policy Reports. The exogeneity and the relevance condition of $\eta_t^{OBFR}$ will be discussed and tested before it is used as an external instrument to identify the proxy SVAR model in section 6.

### 3.3 High frequency identification

The last approach to identify monetary policy shocks is based on the change in high frequency financial market variables after the announcement of monetary policy decisions, which is referred to as high frequency identification (HFI) in the following. Krueger and

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6Ole-Petter Moe Hansen provided the first release of GDP growth rates from SSB for the period 2005 Q1 - 2014 Q4. The missing values before 2005 and after 2014 are replaced by final GDP values in the analysis.
Kuttner (1996) find the Fed funds future market anticipates the month-to-month changes in the Fed funds rate relatively well. They argue all relevant information is priced in the future rate, which means the future rate contains the economy’s expectation regarding the Fed funds rate. In this circumstance, Kuttner (2001) examines the responses of US treasury bills and bonds to changes in the Fed funds rate. The adjustment in the money market rates that takes place immediately after a change in the target rate identifies the reaction towards the unexpected part of monetary policy, i.e. the monetary policy shocks. Kuttner (2001) remarks that not all financial market variables react well on monetary policy shocks. He finds especially the 3-months and 6-months bill rates are sensitive to changes in the target rate, while 30-year bonds barely react as they are set in a long-dated forward looking manner.

The method applied by Kuttner (2001) to identify monetary policy shocks through the Fed funds future rate is not directly transferable to other economies as there is often no such future rate. For the case of the UK, Gregoriou et al. (2009) identify monetary policy shocks through changes in the LIBOR future contract with a maturity of 3-months, which denotes the de facto short-run domestic nominal interest rate. For Norway, Bjørnland (2008) uses the NIBOR\(^7\) with a maturity of 3-months to gauge the effect of monetary policy shocks on changes in the Norwegian weighted exchange rate. In this analysis, three different NIBOR series are considered to evaluate monetary policy shocks: the 1-week NIBOR, the 3-months NIBOR and the 6-months NIBOR.

As Kuttner (2001) notes, the extraction of monetary policy shocks from the Fed funds future rate is rather complicated since the rates are provided as monthly averages. In contrast, the NIBOR is provided in daily (not averaged) values, which eases the identification of monetary policy shocks. Tafjord (2015) states that the NIBOR is composed of the expectations about the key policy rate \(E[R_d | i]\) in dependence of the remaining

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\(^7\)The Norwegian Interbank Offered Rate (NIBOR) captures Norwegian money market rates for maturities between one week and six months. A panel of leading banks in Norway indicates at which rate they would lend money to another leading Norwegian bank. The NIBOR is the simple average of these inter-bank lending rates, omitting the lowest and the highest rate from the panel. The NIBOR was connected to the USD LIBOR before the Lehman bankruptcy in 2008 and is currently connected to the Kliem USD rate. For detailed information on the NIBOR see Tafjord (2015).
days $i$ to the next key policy rate decision, plus a premium $\alpha_d$. Furthermore, $u_d$, which captures the random noise, is added:

$$NIBOR_d = \alpha_d + E[R_d | i] + u_d$$

whereas the subscript $d$ denotes the day. The expectation about the key policy rate captures the expected part of the monetary policy. When Norges Bank publishes a new key policy rate, the NIBOR moves according to the surprises, i.e. the monetary policy shock. To stay consistent and allow the NIBOR enough time to efficiently adjust to the news about the key policy rate, the daily monetary policy shock $\zeta_d^{HFI}$ is identified through the difference of the NIBOR at the end of the day of the key policy rate decision $NIBOR_d$ and the NIBOR the day before the decision $NIBOR_{d-1}$:8

$$\zeta_d^{HFI} = \Theta_d (NIBOR_d - NIBOR_{d-1})$$

where $\Theta_d$ denotes a dummy variable which takes 1, if a key policy rate decision is published by Norges Bank that day. For equation (16) to hold, it must be assumed that no other shocks influence the NIBOR during the day of the key policy rate decision. The risk that other shocks than the monetary policy shocks influence the identification is increasing in the time span between the two measurements. On the other hand, considering too narrow time windows poses the risk to miss the effective adjustment of the NIBOR

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8In fact, the calculation of the monetary policy shocks is not that simple. In a phone call, Oslo Børs, which publishes the NIBOR series, stated that observations for the daily values are taken at noon, 12m. Between 1999 Q1 and 2003 Q1, it is not clear at which times Norges Bank published its key policy rate decisions. In this period, the monetary policy shock is calculated by the NIBOR the day after the decision minus the NIBOR the day before the decision. Between 2004 Q1 and 2012 Q4, Norges Bank published the key policy rate at 2pm. For this period, the monetary policy shock is calculated by the NIBOR the day after minus the NIBOR the day of the decision. Since 2013 Q1, the decision is always published at 10am. Hence, the monetary policy shocks are calculated by the NIBOR the day of the decision minus the NIBOR the day before the decision. The times of the key policy rate decisions are identified through the publication times of Norges Bank's Monetary Policy Reports.
to the realised key policy rate.

The highest frequency of macroeconomic data are months as the frequency is restricted by variables such as the industrial production index, which serves as substitute for the quarterly available GDP. The conversion of the monetary policy shock $\zeta_d^{HFI}$ series from a daily to a monthly series is not as trivial as it might seem. The impact of monetary policy shocks on macroeconomic variables depends on the days that are left in the month, e.g., shocks in the beginning of the month will have more time to affect macroeconomic variables than shocks at the end of the month. Hence, taking the simple average of shocks across all days of the month might distort their impact. Romer and Romer (2004), Barakchian and Crowe (2013) and Gertler and Karadi (2015) solve this conversion issue by accumulating for each day all monetary policy shocks that occurred in the past 31 days and take the average for every calendar month afterwards. Romer and Romer (2004) and Barakchian and Crowe (2013) take additionally the first difference of this series. However, a slightly different formula is applied in the following which gets close to the previously explained transformation, but it accounts for the fact that not every month has 31 days and the shocks keep their original scale:

$$\eta^{HFI}_t = \sum_{d_m=1}^{D_m} \Theta_{d_m} \left( (NIBOR_{d_m} - NIBOR_{(d-1)m}) \left( 1 - \frac{d_m - 1}{D_m} \right) \right)$$

$$+ \sum_{d_{(m-1)}=1}^{D_{(m-1)}} \Theta_{d_{(m-1)}} \left( (NIBOR_{d_{(m-1)}} - NIBOR_{(d-1)(m-1)}) \left( \frac{d_{(m-1)} - 1}{D_{(m-1)}} \right) \right)$$

The monthly monetary policy shock $\eta^{HFI}_t$ can be decomposed into two components: Firstly, the cumulated shocks from the first day in the the current month $d_m$ to the last day in the current month $D_m$ are weighted with the remaining days of the current month after the shock occurred. Secondly, the cumulated shocks from the first day in the the past month $d_{(m-1)}$ to the last day in the past month $D_{(m-1)}$ are weighted as well with the remaining days of the past month after the shock occurred. The consideration of the remainders from the shocks in the past month is crucial. The shocks for the 1-week NIBOR $\eta^{HFI-N1W}_t$, the 3-months NIBOR $\eta^{HFI-N3M}_t$ and the 6-months NIBOR $\eta^{HFI-N6M}_t$ are all estimated in the same manner.
The examples of Bagliano and Favero (1999), Faust et al. (2003) and Bernanke and Kuttner (2005) show that using high frequency identified monetary policy shocks as an exogenous or endogenous variable in VARs is not uncommon, but taking them as instruments in single or multi equation models with a theoretical background like Bjørnland (2008), Gregoriou et al. (2009) and especially Nakamura and Steinsson (2017) became conventional in the recent years. In contrast, Gertler and Karadi (2015) employ high frequency identified monetary policy shocks as an external instrument to identify a SVAR (as in this thesis). The claim of Barakchian and Crowe (2013), to be the first to use the high frequency identification method to evaluate the impact of monetary policy shocks on macroeconomic - and not financial - variables, indicates that this approach is relatively new to evaluate macroeconomics responses.

### 3.4 Alternative identification methods

Ramey (2016) and Stock and Watson (2016) summarise different identification methods of monetary policy shocks. The identification methods are split in three categories for a better overview: identification through VAR models, external identification and identification through (more) theoretical models.

**Identification through VARs.** As explained before, VAR models contain some sort of incorporated feedback rule in form of the key policy rate equation. However, the identification of the structural shocks of this equation, which are considered as the monetary policy shocks, is much debated among economists. Besides the presented Cholesky identification and the short-run restrictions in matrix $B$, long-run restrictions, developed by Blanchard and Quah (1988), can be used to identify the SVAR model instead. Defenders of long-run restrictions argue that plausible short-run restrictions are often difficult to find. However, short-run restrictions seem to be more popular in monetary policy literature as the method of identifying structural shocks is clear compared to the method with long-run restrictions, which often varies among literature. Faust (1998) used sign restrictions to identify shocks, another possibility that became more popular in the 2000s. While the previous methods are rather interchangeable and usually chosen on the best belief of the researcher, the following method seems to provide improvements in terms of considered information. Bernanke et al. (2005) developed a factor augmented VAR
(FAVAR) model, a combination of a SVAR model with a factor analysis that includes more than a hundred variables. They argue the identification of shocks gets closer to the true shocks as the FAVAR model includes more relevant information that central banks consider in their decision process. However, the identification of the VAR is based on short-term restrictions through a Cholesky decomposition as well.

**External identification.** Besides the three presented identification methods that fall in this category, the narrative approach of Romer and Romer (2004) received much attention in the past. They identified monetary policy shocks narratively through evaluating Federal Open Market Committee (FOMC) minutes.

**Identification through theoretical concepts.** Besides the more empirical identifications methods discussed above, there exist applied methods which require a solid theoretical construct. For example, the dynamic stochastic general equilibrium model (DSGE), as applied by Smets and Wouters (2003) to the Euro area, and later also to the US in Smets and Wouters (2007), are based on New Keynesian frameworks considering imperfect markets.

### 3.5 Critique of identification methods

The previously discussed identification methods in the sections 3.1 - 3.3 feature several advantages as well as disadvantages.

The feedback rule based identifications FLFR and OBFR as well as the Cholesky identification are simple to implement and do not require a strong theoretical construct. But their simplicity poses risks at the same time. The magnitude of monetary policy shocks could be over- or underestimated, if the feedback rule did not reflect the expectation of economic agents about the key policy rate. Central banks are usually considering more macroeconomic variables than just inflation and output gap. All three types of feedback

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9 It should be noted that the identification of FLFR and OBFR shocks could also be assigned to the first category if these series are used as an endogenous variable in the VAR model. For the case of the FLFR see Stock and Watson (2001).
rules cope with a very limited information set and are linear constructs, which means they underly the risk of omitted variables and functional misspecification, which might hurt the assumptions of an OLS estimation. Barakchian and Crowe (2013) even write about the “failure of conventional identification schemes”, where they refer especially to the Cholesky identification. They provide evidence that backward looking feedback rules lead to plausible results for periods until the mid-1990s, but not for a period post-1998 sample. Barakchian and Crowe (2013) indicate that central banks set their key policy rate in a forward looking manner since several decades and use forecasted values. They even state that disregarding future values when identifying monetary policy shocks leads to misspecification. Thus, the FLFR and the OBFR are likely to obtain monetary policy shocks that are at least closer to the true shocks compared to the Cholesky identification. Another potential threat is described by Qureshi (2015). A change in the inflation target can mistakenly be considered as an exogenous shock, even though it results from an endogenous change.10 Luckily, Norges Bank did not change the inflation target during the considered period, but it changed its loss function in 2012 through adding terms which capture financial stability. This change is likely to pose a structural break in the shocks as the loss function changes, but the approximative feedback rule to quantify shocks remains the same. A further concern are time consistent measures of monetary policy shocks. Shocks during recessions might be perceived differently than shocks during euphoria or in other words, shocks might have time inconsistent estimates. After all, monetary policy shocks identified through feedback rules and the Cholesky decomposition might not be as exogenous as they seem and should be taken carefully.

Romer and Romer (2004) developed the narrative approach where they identify shocks in a more forward looking manner through FOMC minutes by arguing that recursive backward looking identification methods, as in the Cholesky decomposition, are not able to capture the expected part of monetary policy. However, Barakchian and Crowe (2013) show that even the narrative approach does not lead to plausible results in more recent periods. Finally, they choose a high frequency identification of monetary policy shocks as finding a feedback rule that considers the appropriate set of information and the right functional

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10Qureshi (2015) shows that seemingly exogenous monetary policy shocks in the US extracted from a Taylor type rule can be partially explained by time-varying inflation targets.
form is simply difficult. Rudebusch (1998) also criticises that the identification through a VAR model is likely to not reveal the true monetary policy shocks. He compares the VAR shocks with orthogonalised Fed fund future rates and follows Krueger and Kuttner (1996) who argue Fed fund future rates should get close to the true monetary policy shocks as economic agents consider all relevant information when trading futures. Additionally to the right set of information, the HFI method should capture time inconsistencies in the expectation about monetary policy, which are not captured in any macroeconomic variable. Even though the HFI method sounds promising so far, it contains weaknesses as well. In recent literature about the HFI method, it is doubted that the extraction of shocks from treasury bills with a short maturity can capture the forward guidance which central banks started to take up in their toolkit since the past financial crisis. To solve this issue, Nakamura and Steinsson (2017) include government bonds with a long maturity in the HFI method to capture the forward guidance. As stated previously, when identifying monetary policy shocks from financial market variables, it is difficult to decide about the time-window around the decision of the central bank. If it was too short, irrational, psychology-based fluctuations could lead to biased shocks and if it was too long, the risk would increase that other shocks distort the measure. Lastly, the transformation from daily to monthly data is arbitrary. However, it should be cherished that the HFI struggles with much fewer and less severe issues than the feedback rules.

4 Data

Four dependent variables are considered in the empirical SVAR model for Norway: the key policy rate (R), the consumer price index (CPI), the gross-domestic product (GDP) and the real effective exchange rate index (REER). There are two different data frequencies required for the SVAR model, quarterly and monthly data. The monetary policy shocks based on the FLFR and OBFR are identified on quarterly basis since the main components of the externally identified shocks are obtained from Norges Bank’s Monetary Policy Reports, which appear usually every quarter. In contrast, the HFI shocks are available on a daily basis. However, as the most frequent macroeconomic variables are available on a monthly basis, a second model with monthly data is considered. Even though Norges Bank started officially in 2001 with inflation targeting, the considered period starts al-
ready in 1999 with the de facto implementation of inflation targeting. Kleivset et al. (2012) outline Norges Bank’s regime change according to which Norges Bank abandoned fixed exchange rates in 1992, but the actual transition towards inflation targeting took some more years. Gjedrem (1999), the governor of Norges Bank at the time, stated at the annual address in February 1999 that the transition was completed and inflation targeting adopted. Thus, the considered time period starts with the year 1999. The last observation is restricted by the availability of the most recent data, which is the second quarter in 2017 for the quarterly data and September 2017 for the monthly data. The data is obtained from Norges Bank’s Monetary Policy Reports and from Macrobond, which in turn obtains the data mainly from SSB, Norges Bank and Oslo Børs.

Regarding the dependent variables, the CPI adjusted for taxes and energy prices CPI-ATE is considered since Norges Bank seems to put much weight on this particular CPI in their Monetary Policy Reports since the first quarter in 2001. However, the earliest CPI-ATE series starts in December 2002. Thus, until November 2002 or the fourth quarter 2002, the CPI adjusted only for energy prices CPI-AE is considered, which seemed to be more important than the unadjusted CPI in the Monetary Policy Reports before 2001. The exclusion of volatile energy prices in the CPI should provide more stable inflation. Furthermore, a high proportion of the energy prices are exogenously given for Norway since it is a small open economy and consequently, a price-taker. The seasonal adjusted GDP for mainland Norway in constant prices is used for the quarterly model, while the seasonal adjusted and smoothed industrial production index (IP) is used as a substitute for GDP in the monthly model. The third endogenous variable in the VAR model is Norges Bank’s sight deposit rate (R), previously referred to as key policy rate. The sight deposit rate displays the interest rate which commercial banks receive for depositing money at the central bank. The REER provided from the European Commission is trade weighted to a group of 37 industrial states with double weights on export and adjusted for relative prices or cost deflators. The exchange rate of a small open economy

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11Svein Gjedrem, former governor of Norges Bank, confirmed in a personal communication on 6 November 2017 at the Norwegian School of Economics that Norges Bank is mainly considering the consumer price index adjusted for taxes and energy prices.

12Note that merging the CPI-ATE and CPI-AE series will produce a small break.
will contain important information, if the trading sector is of a relevant size. In economic downturns and upturns, the floating exchange rate can provide a stabilising mechanism for the economy. On the other hand, currencies of small economies are often subject to fluctuations due to periodical investments or speculations on financial markets. According to Svein Gjedrem,\textsuperscript{13} Norges Bank is not targeting the exchange rate explicitly, but it is incorporating it’s effects on output and inflation in their calculation of the sight deposit rate R. This statement is supported by Røisland and Sveen (2017), who consider the real exchange rate in their theoretical model for an open economy as well, but not as an explicit target. Thus, the real effective NOK exchange rate index might contain important information for the analysis of monetary policy shocks.

Besides the dependent variables of the equations in the SVAR system, one exogenous variable is used in the SVAR model. The crude oil Brent price index (Brent) from Intercontinental Exchange is employed to control for the development of the oil price in the analysis. Even though the oil sector is excluded from the Norwegian mainland GDP, the oil price is strongly influencing the Norwegian mainland economy as seen in the most recent oil price drop. Furthermore, controlling for the oil price might dampen the appearance of a price puzzle in the SVAR analysis. The deposit facility rate of the ECB is used as an additional exogenous variable in a robustness test in section 7, but not in the main analysis. All endogenous and exogenous variables, their source and use in the quarterly or / and monthly model can be found in Table 5 in Appendix A.

In addition to the data used in the SVAR model, some more data is required for the external identification of monetary policy shocks. Regarding the FLFR and the OBFR, quarterly forecasts of inflation and the inflation gap, output and the output gap as well as the forecasted sight deposit rate are obtained from Norges Bank’s Monetary Policy Reports\textsuperscript{14} from March 1999 until September 2017. As much information about the forecasts

\textsuperscript{13}Explained to the author in a personal communication on 6 November 2017 at the Norwegian School of Economics.

\textsuperscript{14}Norges Bank provided from 2001 until 2012 only reports for the first and the second quarter and one more in either October or November. Furthermore, the reports from Q3 2001 and Q3 2003 are not available. The missing values are replaced through weighted averages of forecasts from the consecutive quarter and forecasts, current or realised values from the previous quarter. This issue lowers the quality
as possible is obtained from Norges Bank since it is hardly possible to beat its extensive forecasts. For the high frequency identification of monetary policy shocks, the daily series of the 1-week NIBOR, the 3-months NIBOR and the 6-months NIBOR are obtained. Lastly, the dates of announcements of monetary policy decisions can be found on Norges Bank’s homepage. An overview for the variables taken to construct instruments and their use in the quarterly or / and monthly model can be found in Table 6 in Appendix A.

A descriptive overview of the variables used as endogenous and exogenous variables in the SVAR models can be found in Appendix A. In the following section, the calibration of the VAR models and potential issues with the transformation of the variables are discussed.

5 Model calibration

It is often discussed whether variables in vector autoregressive models should be processed or not. The primary reason is the non-stationary of variables which might lead to spurious results in analyses. A series is called integrated of order zero, if it is stationary without any transformation. But most time series are not integrated of order zero and need to be differenced to remove unit roots and trends and make the series stationary, i.e. integrated of order one. Dickey-Fuller tests can help to determine whether the processed and unprocessed variables are stationary. When conducting tests on the quarterly and monthly series, R, GDP, IP, REER and Brent are integrated of order one, while CPI is borderline with MacKinnon approximated p-values around 10%.15 It is common to use growth rates, i.e. the first difference of the natural logarithm transformation, instead of the level series as they are more likely to be stationary. For example, Stock and Watson of the FLFR and the OBFR identified monetary policy shocks and is picked up again in section 6.2. In total, 1824 values were taken from reports and 448 missing values were compounded manually in addition. The 448 values include the manually calculated output gap with an HP-Filter since the values were only reported from Q1 2003 on in the Monetary Policy Reports.

15The maximum number of lags in the Dickey-Fuller tests for both frequencies are the conventional four quarters or 12 months. The number of lags is reduced in the test until the last one is significant to a 5% confidence level. Trends are never included, constants only if economically meaningful and if significant to a 5% confidence level.
(2001), Bjørnland (2008), Lunsford (2015) and Montiel-Olea et al. (2016) use growth rates in their VARs.

However, Stock and Watson (2016) and Gospodinov et al. (2013) note differencing the series might not only remove unit roots and trends, but also important information like low-frequency co-movements. Sims et al. (1990) argue interrelationships are most interesting for VAR models and not their correct estimates. However, the variables should be cointegrated when using them in a reduced-form VAR to ensure an unbiased empirical analysis. For the following tests, a reduced-form VAR model is estimated with R in levels and natural logarithm transformed GDP, IP, Brent, REER and CPI to get rid of the exponential growth in the series. Transformed Engle-Granger tests are applied to determine whether cointegration is given in every equation of the system. To be precise, the residual of every reduced-form VAR equation is tested on a unit root with a Dickey-Fuller test.\textsuperscript{16} In all cases, cointegration is given to a 1\% confidence level. In addition to the Dickey-Fuller tests on the single equations, a Johansen test is conducted which tests for joint cointegration in the VAR equation system. For both, the quarterly and the monthly reduced-form VAR, cointegration is given.\textsuperscript{17} Based on the results of these two kinds of tests, the approach of Gertler and Karadi (2015) is followed and the VAR is specified in levels, just as the reduced-form VAR which was tested. GDP in the quarterly VAR and IP in the monthly VAR are seasonally adjusted, while CPI is not. The seasonal adjustments are only conducted if necessary to get rid of strong fluctuations in the impulse reaction functions in section 6.

Besides the decision to process variables or not, their ordering in the Cholesky identification plays an important role. In general, the macroeconomic variables GDP/IP and CPI are ordered first since they are not as responsive as the financial variables R and REER. The ordering of GDP/IP and CPI is arguable and differs among literature (e.g., Stock and Watson (2001) vs. Gertler and Karadi (2015)). In this analysis, GDP/IP is ordered

\textsuperscript{16}The maximum number of lags depends on the frequency of the data as above. Neither constants nor trends are allowed for in the Dickey-Fuller test as the mean of the error terms should be zero on average.

\textsuperscript{17}Four lags are used in the Johansen test for the quarterly VAR and 12 lags are used in Johansen test for monthly VAR. The null hypothesis of no autocorrelation could not be rejected to a 5\% confidence level in both cases.
prior to CPI, but the reverse order will be tested in the robustness section. The sight deposit rate is ordered prior to the real effective exchange rate index since exchange rates react immediately on changes in the sight deposit rate, but not vice versa.

The number of lags is an essential parameter in vector autoregressive models. Regarding the model with quarterly data, AIC suggests three lags, while HQIC and SBIC suggest two lags. However, four lags are chosen against the suggestion of the information criteria as it is considered more important to control for potential seasonal effects by including the fourth lag. Regarding the model with the monthly data, AIC suggests 11 lags, HQIC three lags and SBIC just one. Once again against the recommendation of the information criteria, 12 lags are chosen to control for potential seasonal effects.

Based on equation (3), the empirical SVAR model can be obtained with $p=4$ for the quarterly models:

$$
A \begin{bmatrix} GDP_t \\ CPI_t \\ R_t \\ REER_t \end{bmatrix} = A_0 + A_1 \begin{bmatrix} GDP_{t-1} \\ CPI_{t-1} \\ R_{t-1} \\ REER_{t-1} \end{bmatrix} + ... + A_4 \begin{bmatrix} GDP_{t-4} \\ CPI_{t-4} \\ R_{t-4} \\ REER_{t-4} \end{bmatrix} + \Omega Brent_t + B \begin{bmatrix} \epsilon_t^{GDP} \\ \epsilon_t^{CPI} \\ \epsilon_t^R \\ \epsilon_t^{REER} \end{bmatrix}
$$

(18)

and with $p=12$ for the monthly empirical SVAR model:

$$
A \begin{bmatrix} IP_t \\ CPI_t \\ R_t \\ REER_t \end{bmatrix} = A_0 + A_1 \begin{bmatrix} IP_{t-1} \\ CPI_{t-1} \\ R_{t-1} \\ REER_{t-1} \end{bmatrix} + ... + A_{12} \begin{bmatrix} IP_{t-12} \\ CPI_{t-12} \\ R_{t-12} \\ REER_{t-12} \end{bmatrix} + \Omega Brent_t + B \begin{bmatrix} \epsilon_t^{IP} \\ \epsilon_t^{CPI} \\ \epsilon_t^R \\ \epsilon_t^{REER} \end{bmatrix}
$$

(19)
The externally obtained monetary policy shocks in section 3 are used as instruments to identify parameters in matrix $B$ of the SVAR model. The subscripts FLFR1, FLFR2, FLFR3, FLFR4, OBFR, HFI-N1W, HFI-N3M and HFI-N6M for the external instrument $\eta_t$ from section 2.2 indicate which shock is used. After running the reduced-form VAR of the SVAR model in equation (18) and (19), the reduced-form residuals $e_{t}^{GDP}$, $e_{t}^{IP}$, $e_{t}^{CPI}$, $e_{t}^{R}$ and $e_{t}^{REER}$ are obtained, whereas $e_{t}^{R}$ is the endogenous reduced-form error term that gets instrumented. Through the instrument variable regression from equation (5), the three bold printed parameters of matrix $B$ are obtained. The remaining four parameters in the upper triangle $\beta_{12}$, $\beta_{14}$, $\beta_{24}$ and $\beta_{34}$ are restricted to zero to fulfil the recursive condition and to avoid simultaneity issues. The four zero restrictions indicate that CPI and REER have no contemporaneous effects on GDP or IP. Furthermore, REER has no contemporaneous effects on CPI and R.

$$
B = \begin{bmatrix}
1 & 0 & \beta_{13} & 0 \\
\beta_{21} & 1 & \beta_{23} & 0 \\
\beta_{31} & \beta_{32} & 1 & 0 \\
\beta_{41} & \beta_{42} & \beta_{43} & 1 \\
\end{bmatrix}
$$

Subsequently, the presented SVAR models are estimated and their results discussed and compared in four subsections.

### 6 Empirical results

In this thesis, the impulse response functions (IRFs) calculated from the estimated (structural) vector autoregressive models are in the focus of this analysis as they are easy to interpret on the one hand and they provide a summary of the most important information on the other hand.\(^{18}\)

\(^{18}\)To my best knowledge, there exists neither an implemented, nor any manually programmed code for the proxy SVAR model in Stata. Solely Matlab code is available, e.g., from the analysis of Gertler and Karadi (2015). Thus, I coded the proxy SVAR model in Stata on my own. The different notation of SVAR models in the literature and the notation underlying the Stata SVAR command complicated creating the proxy SVAR model in Stata. I cross-checked mainly to the theory in Mertens and Ravn
6.1 Cholesky VAR

In this approach, no external instruments are used to identify parameters in the restriction matrix but the monetary policy shocks are identified through a Cholesky decomposition of the VAR model. This model is referred to as Cholesky VAR in the following and it serves as basis for comparisons to the proxy SVARs, in which restriction parameters in matrix $B$ are identified through FLFR, OBFR and HFI instruments. As a result of the use of monthly and quarterly data frequency, there are two different Cholesky VARs.

The IRFs in Figure 1 are read in the following way: The title of each IRF denotes which variable responses to a monetary policy shock. The size of the shock is one standard deviation of the residuals of the Norges Bank sight deposit rate. The percentage change in the variable can be read on the $y$-axis and the months or quarters on the $x$-axis. Five years are shown for quarterly models and four years for monthly models. It should be noted that the magnitude of the responses of the same variables cannot be directly compared across models as the underlying shocks might have different sizes.

You can see in Figure 1 that the endogenous variables in the monthly Cholesky VAR (left column) do not always respond with similar movements to shocks in the Norges Bank sight deposit rate as the variables in the quarterly Cholesky VAR (right column). Furthermore, the confidence intervals for the Cholesky VAR with monthly data are much tighter around the IRFs since the monthly VAR model contains more than 200 observations while the quarterly VAR model contains merely 70. When comparing the IRFs of the two models it should be kept in mind that the quarterly GDP is substituted with the monthly IP. The sight deposit rates increase immediately due to a monetary policy shock with 0.2% and 0.4% respectively, but the increases get lower and become insignificant after about one and a half years. The response of the sight deposit rate seems reasonable and shows common behaviour when compared to other literature. Both IRFs of the CPI in the second row suggest a mainly positive and partially even significant change in inflation as a
Figure 1: Monthly Cholesky VAR vs. quarterly Cholesky VAR

The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the quarterly Cholesky VAR. The grey dashed lines illustrate the 95% confidence interval.
reaction to a tightening in monetary policy, which is generally referred to as price puzzle in economic literature (see e.g. Christiano et al. (1994)). These results contradict theory as well as empirical findings of various other researchers. In the case of monthly data, IP fluctuates around zero and does not change much. Literature rather suggests a development as seen in GDP for the quarterly data: A small price puzzle in the short term but in general a sluggish decrease of GDP over time, which recovers in the long term. The REER responds with a slight increase of about 0.4% for monthly data in the short term, while the REER for quarterly data responds strongly and significantly positive to a shock in the deposit rate in the medium and long run. The REER is expected to appreciate fast after a contractionary monetary policy shock in Norway and lose its power soon after (see Bjørnland (2008)).

To briefly summarise, CPI, IP and REER with monthly frequency do not show the expected behaviour, while the sight deposit rate does. For the quarterly data, CPI and REER do not follow the common pattern. The different proxy SVAR estimations are expected to improve the results from the Cholesky VARs.

6.2 FLFR proxy SVAR

In the firstly presented proxy SVAR model, the endogenous reduced-form error of the key policy rate is instrumented with monetary policy shocks that are identified through the FLFR. Before the proxy SVAR can be estimated, the two crucial conditions for instrument variables need to be checked.

6.2.1 FLFR instrument conditions

The exogeneity condition requires that the external instrument is uncorrelated with other structural shocks than the structural shock of Norges Bank’s sight deposit rate. This condition can only be discussed, but not formally tested. Structural shocks of GDP or IP can be of various nature, e.g., bad weather conditions, commodity price socks, natural disasters, diseases or war. The FLFR instruments are assumed to be uncorrelated with these structural shocks of GDP since they represent solely monetary policy shocks, which affect GDP only through the sight deposit rate. The same is assumed for IP. A structural
Table 1: Relevance of FLFR instruments

<table>
<thead>
<tr>
<th></th>
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<th>(4)</th>
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<td>$\hat{e}_t^R$</td>
<td>$\hat{e}_t^R$</td>
<td>$\hat{e}_t^R$</td>
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<td>FLFR1</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.103)</td>
<td></td>
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<td></td>
</tr>
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<td>FLFR2</td>
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<td></td>
<td>(0.026)</td>
<td>(0.151)</td>
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<td></td>
</tr>
<tr>
<td>FLFR3</td>
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<td>-0.007</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.174)</td>
<td></td>
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</tr>
<tr>
<td>FLFR4</td>
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<td>-0.096</td>
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<td></td>
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<td>(0.027)</td>
<td>(0.085)</td>
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<td>Constant</td>
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<td>0.003</td>
<td>0.004</td>
<td>0.001</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.038)</td>
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<tr>
<td>F-statistic</td>
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<td>0.63</td>
<td>0.88</td>
<td>0.15</td>
<td>0.81</td>
</tr>
<tr>
<td>F-statistic (robust)</td>
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<td>0.56</td>
<td>0.74</td>
<td>0.15</td>
<td>0.53</td>
</tr>
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<td>70</td>
<td>70</td>
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<td>70</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A shock in the REER can mainly be considered as exogenous shocks from other economies which should not be correlated with the FLFR instruments. Structural shocks of the CPI are difficult to enumerate, but are assumed to be uncorrelated with the instruments. The discussion about the exogeneity condition is the same for the other instruments in the subsequent sections and will not be repeated.

In contrast to the exogeneity condition, the relevance condition can be tested when estimating the first stage of the instrument variable regression. Staiger and Stock (1994) suggest as a basic rule that instruments will be sufficiently strong, if the F-statistic of the first stage regression is larger than ten. Following this thought, instruments in Table 1 should be considered as very weak instruments. FLFR1 is the strongest instrument with a F-statistic of only 1.29. All other instrument alone or all together have values
The left column shows the IRFs of the quarterly Cholesky VAR. The right column shows the IRFs of the quarterly FLFR proxy SVAR. The x-axis labels denote quarters. The grey dashed lines illustrate the 95% confidence interval.
below one. Robust first stage estimations, which allow for heteroskedasticity, lead to even lower F-statistics. For the case of proxy SVAR models, Lunsford (2015) finds that the estimator of weak instruments is inconsistent and asymptotically biased. The weakness of the instruments could result from the incomplete dataset, which is extracted from Norges Bank’s Monetary Policy Reports, but it might also results from a weak conception of the feedback rule. Recalling the numerous negative critique for feedback rules in section 3.5, the weakness should not surprise. As mentioned before, one and sometimes even two of the quarterly Monetary Policy Reports from Norges Bank were left out or were not available in some years. These gaps in the datasets, which are bridged through weighted averages of previous and successive values, might be responsible for a big part of the weakness of the instruments. Nonetheless, the proxy SVAR model is weakly identified through the strongest of the above instruments, FLFR1, and briefly compared to the Cholesky VAR simply to give an impression of the changes, but very strong biases can be expected.

6.2.2 FLFR proxy SVAR results

In Figure 2, the panels in the right column view the IRFs of the quarterly FLFR proxy SVAR and the panels in the left column view the IRFs of the quarterly Cholesky VAR from the previous section. All IRFs change drastically. The IRF of the sight deposit rate in the proxy SVAR suggests a decrease instead of an expected increase as a consequence to a positive monetary policy shock. Just by viewing this result, it should get clear that this model contradicts any suggestions from economic theory and literature. In general, the IRFs worsen compared to the Cholesky VAR, which is not the expected development. But again, the results are not trustworthy due to the very weak instruments.

6.3 OBFR proxy SVAR

In the secondly presented proxy SVAR model, the endogenous reduced-form error of the key policy rate is instrumented with monetary policy shocks that are identified through the OBFR. Before the proxy SVAR can be presented, the relevance condition needs to be checked.
### 6.3.1 Relevance of OBFR instrument

In Table 2 the first stage results of the instrument variable regression is shown. The F-statistic of 14.08 indicates that the residuals of the OBFR are a strong instrument for the reduced-form error of the sight deposit rate. However, a Breusch-Pagan test on the first stage regression indicates the presence of heteroskedasticity. Consequently, the F-statistic with robust standard errors needs to be considered which means the OBFR instrument is weak as well, when applying the rule of thumb that $F > 10$ for strong instruments. Lunsford (2015) provides a table with F-statistic values in dependence of the level of asymptotic bias and statistical significance for proxy SVAR models. Accordingly, the OBFR instrument would provide results with a maximum asymptotic bias of 20% to a 10% confidence level, which means the instrument should be considered as rather weak. The IRFs of the OBFR proxy SVAR should be more reliable than the results of the FLFR proxy SVAR, but they still need to be viewed critically due to a high potential asymptotical bias.

### 6.3.2 OBFR proxy SVAR results

In Figure 3, the IRFs of the quarterly Cholesky VAR are shown in the left column and the IRFs of the quarterly OBFR proxy SVAR are shown in the right column. In the proxy...
Figure 3: Cholesky VAR vs. OBFR proxy SVAR

The left column show the IRFs of the quarterly Cholesky VAR. The right column shows the IRFs of the quarterly OBFR proxy SVAR. The x-axis labels denote quarters. The grey dashed lines illustrate the 95% confidence interval.
SVAR, the monetary policy shock leads to an immediate significant increase of about 0.7% in the sight deposit rate. After half a year, the initial sight deposit rate increase starts to diminish and becomes insignificant after one year. The CPI improves slightly compared to the Cholesky VAR, but it still exhibits some unexpected increase in the medium term. Only after about two and a half years, the CPI begins to fall, but except for the initial jump, all movements are insignificant. GDP improves as well and significantly decreases in the medium term by about 0.5%. The REER strongly increases immediately after the monetary policy shock by 4%. This significant increase vanishes after a short time. To sum up, the responses of the variables in the OBFR proxy SVAR model improve compared to the Cholesky VAR and show mainly expected behaviour, except for the insignificant increase in the CPI in the medium term. However, most movements in the IRFs are insignificant, which can probably be attributed to the small sample of only 70 observations. But also these presented results should be taken with a grain of salt due to the relatively weak instrument.

6.4 HFI proxy SVAR

In contrast to the previous FLFR and OBFR proxy SVARs with quarterly data, monthly data is used in the HFI proxy SVAR analysis which allows for a three times as large sample size. The reduced-form errors of the sight deposit rate are instrumented with the high frequency identified shocks derived from the NIBOR rates. The discussion in section 3.5 suggests the HFI is the most promising approach as it should get the closest to the true monetary policy shocks. In the first step, the relevance of the 1-week NIBOR, 3-months NIBOR and 6-months NIBOR instruments are evaluated. In the second step, the IRFs and a forecast error variance decomposition of the HFI proxy SVAR are discussed.

6.4.1 Relevance of HFI instruments

The first stage regression results for the HFI instruments are presented in Table 3. The F-statistic of the 1-week NIBOR instrument is the lowest with 0.55, followed by all three instruments together with 10.65 and the 3-months NIBOR instrument with 19.47. The 6-months NIBOR is by far the best instrument according to the F-statistic of 30.21. But as in the case of the OBFR instrument, a Breusch-Pagan test indicates heteroskedasticity
Table 3: Relevance of HFI instruments

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
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</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\varepsilon}_t^R )</td>
<td>( \hat{\varepsilon}_t^R )</td>
<td>( \hat{\varepsilon}_t^R )</td>
<td>( \hat{\varepsilon}_t^R )</td>
<td></td>
</tr>
<tr>
<td>1-week NIBOR</td>
<td>0.080</td>
<td></td>
<td>-0.197</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td></td>
<td>(0.149)</td>
<td></td>
</tr>
<tr>
<td>3-months NIBOR</td>
<td>0.694***</td>
<td></td>
<td>0.368</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td></td>
<td>(0.376)</td>
<td></td>
</tr>
<tr>
<td>6-months NIBOR</td>
<td></td>
<td>0.852***</td>
<td>0.641*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.155)</td>
<td>(0.307)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>0.000</td>
<td>0.003</td>
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</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>F-statistic</td>
<td>0.55</td>
<td>19.47</td>
<td>30.21</td>
<td>10.65</td>
</tr>
<tr>
<td>F-statistic (robust)</td>
<td>0.09</td>
<td>5.12</td>
<td>8.55</td>
<td>3.21</td>
</tr>
<tr>
<td>N</td>
<td>213</td>
<td>213</td>
<td>213</td>
<td>213</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

in the error term of the first stage regression. Thus, the F-statistic of the robust first stage regression must be considered, in which the 6-months NIBOR is still the strongest instrument, but yields only a F-statistic of 8.55. According to Lunsford (2015), the asymptotic bias, when using the 6-months NIBOR as instrument, would be maximum 10% with a confidence level of less than 5%. Hence, the HFI instrument can be considered as sufficiently strong and should produce reliable results. Nonetheless, it should be questioned why the first stage regressions contain heteroskedastic residuals and why the instruments are so much weaker when considering the F-statistic corrected for heteroskedasticity. Figure 4 reveals the heteroskedastic residuals result mostly from volatile periods like the recent financial crisis. The stronger the heteroskedasticity in the first stage regression, the higher the standard errors of the estimates and the lower the F-statistic of the robust estimation. In the monetary policy literature, it is not uncommon to end the sample directly before or start the sample directly after volatile periods. This approach is covered in the robustness section.
Figure 4: Graphical heteroskedasticity check in first stage regression

Note: Squared residuals from the regression of the error term $R$ on the 6-months NIBOR instrument.

6.4.2 HFI proxy SVAR results

In Figure 5, the IRFs of the monthly Cholesky VAR are illustrated in the left column of the panels and the IRFs of the HFI proxy SVAR in the right column of the panels. In the HFI proxy SVAR, the sight deposit rate jumps due to the monetary policy shock by approximately 0.7% and peaks around 0.9% in month three. After about one year, the sight deposit rate increase diminishes and becomes insignificant for the rest of the period. The CPI is most times below zero which indicates a lower inflation due to monetary tightening induced by Norges Bank. The magnitude of the change in the CPI is between -0.25% and 0%, but it is constantly insignificant, with the exception of the second month where it reaches its trough. Especially between the months 6 and 24 after the monetary policy shock, the CPI fluctuates closely around zero. The behaviour of the response in the HFI proxy SVAR model improves massively compared to the Cholesky VAR, where the IRFs
Figure 5: Cholesky VAR vs. HFI proxy SVAR

The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the monthly HFI proxy SVAR. The x-axis labels denote months. The grey dashed lines illustrate the 95% confidence interval.
suggest a significant increase in the CPI in the medium term, i.e. a price puzzle. The movement of IP improves strongly as well. While it fluctuates around zero with a very limited magnitude in the Cholesky VAR, IP decreases on average by about 0.5% in the proxy SVAR throughout the four years, whereas the trough is reached after ten months with a decline of 1.1%. But the decrease in IP is also insignificant, with the exception of the second month. The REER jumps significantly by about 5% immediately after the monetary policy shock, but it loses quickly its power and the initial increase diminishes to an roughly 2% increase after six months. After reaching a second peak in the ninth month, the IRF of the REER is heading towards zero and remains insignificant for the rest of the considered period. Magnitude and movements seems also here much more realistic than in the Cholesky VAR. The IRFs of the HFI proxy SVAR suggest Norges Bank could guide CPI and IP only with a limited magnitude in the desired direction, but it should be noted that the influence is mostly insignificant. The significance of the results would presumably increase with a larger sample size.

Barakchian and Crowe (2013) summarise the dynamic effects of monetary policy shocks on the US economy from the empirical analysis of Christiano et al. (1998) as follows:

“After a contractionary monetary policy shock, short term interest rates rise, aggregate output, employment, profits and various monetary aggregates fall, the aggregate price level responds very slowly [. . .]. In addition, there is agreement that monetary policy shocks account for only a very modest percentage of the volatility of aggregate output; they account for even less of the movements in the aggregate price level.”

The empirical findings by Christiano et al. (1998) and the description of Barakchian and Crowe (2013) can also be projected on the Norwegian economy. The description of “very modest” magnitudes in the responses of CPI and IP could be supported for the Norwegian case. However, the words offer scope for interpretation.

As the instruments are reliable and the IRFs of the HFI proxy SVAR model are mostly in line with literature, e.g. they are close to the results from Gertler and Karadi (2015) for
Table 4: Forecast error variance decomposition of the HFI proxy SVAR

<table>
<thead>
<tr>
<th>Time horizon</th>
<th>R</th>
<th>CPI</th>
<th>IP</th>
<th>REER</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>99.8%</td>
<td>0.0%</td>
<td>0.7%</td>
<td>94.0%</td>
</tr>
<tr>
<td>6 months</td>
<td>99.5%</td>
<td>47.8%</td>
<td>34.7%</td>
<td>90.7%</td>
</tr>
<tr>
<td>12 months</td>
<td>98.2%</td>
<td>43.8%</td>
<td>47.8%</td>
<td>89.9%</td>
</tr>
<tr>
<td>18 months</td>
<td>96.1%</td>
<td>34.7%</td>
<td>51.3%</td>
<td>89.7%</td>
</tr>
<tr>
<td>24 months</td>
<td>93.6%</td>
<td>27.7%</td>
<td>54.3%</td>
<td>89.4%</td>
</tr>
<tr>
<td>36 months</td>
<td>91.4%</td>
<td>22.0%</td>
<td>60.1%</td>
<td>88.9%</td>
</tr>
<tr>
<td>48 months</td>
<td>88.3%</td>
<td>20.6%</td>
<td>61.2%</td>
<td>88.5%</td>
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</tbody>
</table>

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

Percentage explained in forecast error variance by an impulse in R.

The results of the HFI proxy SVAR for the US from Gertler and Karadi (2015) and the HFI proxy SVAR for Norway are compared in the subsequent section 7.
is explained initially, 34.7% after six months, 60.1% after 36 months and 61.2% after 48 months. However, merely the explained proportion of the forecast error variation after 36 and 48 months is significant to a 5% confidence level. To sum up, the monetary policy shock significantly explains large parts in the forecast error variance of CPI in the short term and large parts of IP in the long term.

The reliability of the presented empirical results depends on many factors, of which the most important ones are discussed in the subsequent section.

7 Robustness

In the following, merely the robustness of the HFI proxy SVAR model is evaluated as it would be pointless to evaluate the robustness of the unreliable FLFR and OBFR proxy SVAR.

Model risk. At first, it should be questioned how effectively a SVAR model can evaluate monetary policy shocks. Stock and Watson (2001) point out that the alternatives to a SVAR model cope also with many issues. They emphasise the toolkit to evaluate monetary policy shocks is generally limited since credible experiments are not feasible, in contrast to other economic areas like labour economics. Moreover, the restrictions in SVARs are difficult to identify, they cope only with a limited set of variables and they cannot handle non-linearities. The two researchers conclude that SVARs based on economic reasoning together with well-founded identifications can provide good results. In 2012, Stock and Watson improved the identification of restrictions by using instruments, which set the foundation for the applied proxy SVAR model. A direct robustness check across different models in the VAR model category has already been included previously through the comparison of the proxy SVAR to the Cholesky VAR.

Instruments. The key for obtaining a reliable proxy SVAR model is the prudent choice of instruments. In contrast to the many potential instruments for identifying monetary policy shocks in a big open economy like the US, where futures on all kinds of bonds, key rates and exchange rates are available since a fairly long time, much fewer potential
instruments are available for identifying monetary policy shocks in a small open economy like Norway. Of all tested instruments for monetary policy shocks in Norway, solely the HFI-N6M instrument can be considered as strong enough to make reliable inferences. Like conventional regressions, instrument variable regression might be subject to functional misspecification. It could be non-linearities play a role in the first stage regression. Therefore, squared and cubed values of every instrument are included in the first stage regression in addition to the linear values in a robustness test. The robust and non-robust F-statistics for the FLFR instruments in Table 7 in Appendix B do not change noticeably. The non-robust F-statistic of the OBFR instrument halves itself, while the robust F-statistic increases only slightly (see Table 8 in Appendix B). Moreover, none of the variables was significant in the first stage regression with FLFR and OBFR instruments. In the case of the HFI first stage regressions, the linear and the squared NIBOR instruments are significant at least to a 5% significance level, but the cubed values are insignificant in all regressions (see Table 9 in Appendix B). However, when omitting cubed values, the robust F-statistics drop substantially. The non-robust F-statistic increases only for the 1-week NIBOR up to 15.61 compared to the first stage regression with merely linear values and its robust F-statistic even jumps to 34.34. According to the table of Lunsford (2015), such a strong instrument would have only a 5% asymptotic bias at maximum with a confidence level of less than 1%. As this sounds promising, the IRFs of the HFI proxy SVAR with the linear 6-months NIBOR as instrument are compared to the IRFs of the HFI proxy SVAR with the 1-week NIBOR polynomials as instruments. Figure 12 in Appendix B views that the IRFs are quite similar. The monetary policy shock for the proxy SVAR with the 1-week NIBOR polynomials as instruments is a bit smaller which evolves a smaller response in the variables and slightly tighter confidence intervals. Furthermore, the response of CPI slightly improves compared to the 6-months NIBOR as instrument. However, it should be kept in mind that using polynomials as instruments bears a potential overidentification issue.

When including all ordinary instruments of one identification type in the first stage (e.g., all three NIBOR instruments), the F-statistic becomes lower in the first stage of the instrument variable regressions. A likely reason behind this behaviour is multicollinearity of the instruments. To avoid multicollinearity but combine information from all available linear instruments, the different NIBOR instruments are collapsed through simple averages. The first stage regressions with the collapsed NIBOR instruments F-statistics
can be found in Table 10 in Appendix B. The F-statistics do not improve compared to the linear 6-months NIBOR as instrument or the polynomials of the 1-week NIBOR as instruments, neither when taking the average of pairs, nor when averaging all three instruments. However, it should be emphasised, that the single 6-months NIBOR is already a relatively strong instrument which should produce reliable results.

**Model calibration.** The causal order of variables and controlling for influences of other variables are two further key elements in the empirical analysis with SVAR models. As mentioned before, the arbitrary ordering of CPI and IP should be checked on robustness. Hence, the order is reversed in a test with CPI ordered prior to IP. The reordering changes the IRFs of the HFI proxy SVAR not at all (see Figure 13 in Appendix B). As a second robustness test for model specification, the ECB deposit facility rate is included as exogenous variable in addition to the Brent. Controlling for this ECB key policy rate should check whether Norges Bank is shadow targeting monetary policy decisions of the ECB as 62% of the Norwegian imports origin from the EU and 78% of the Norwegian exports went to the EU in 2016.20 Thus, Norges Bank might have interest to follow the ECB’s decisions to avoid anticipated changes in the trading sector. The IRFs of the HFI proxy SVAR change a bit in magnitude and form (see Figure 14 in Appendix B). The IRF of the sight deposit rate does not change at all and the IRF of the REER changes only slightly. But the changes in the IRFs of CPI and IP are more visible. It can be concluded with the examples of the two robustness test from above that the HFI proxy SVAR is robust against changes in the ordering of CPI and IP, but less robust against adding other potentially important influences like the ECB deposit facility rate.

**Time-sensitivity.** Barakchian and Crowe (2013) find that the effect of monetary policy shocks in the US economy is time-sensitive. In the following, it is checked whether this is also the case for the Norwegian economy. The sample is split into two subsamples: a pre-crisis sample from January 1999 to November 2007 and a post-crisis sample from July 2009 to September 2017. The crisis dates are chosen in accordance to the dates of the recent financial crisis published by the Fed. The pre-crisis period is characterised by

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20See SSB on [www.ssb.no](http://www.ssb.no), table: 08804: External trade in goods, main figures, by country/trade region/continent (NOK million).
the dot-com bubble and the overheating of the economy, while the post-crisis period is mainly characterised by low interest rates, stagnation of European growth and the strong oil price drop. The IRFs of the HFI proxy SVAR change strongly in form and magnitude (see Figures 15 and 16 in Appendix B) and therefore, it can be concluded that the effect of monetary policy shocks on the Norwegian economy is time-sensitive as well. On the other hand, Ramey (2016) summarises literature that finds monetary policy has different effects on the economy in times of economic crisis and in times of economic prosperity. Hence, it might be necessary to consider at least one complete business cycle when evaluating monetary policy shocks. Furthermore, it should be kept in mind that the SVAR models cope with the limited information of only five variables, which might not be able to capture time-specific punctual influences of omitted variables.

**Idiosyncratic analysis risk.** The reliability and validity of empirical results increases through similar findings suggested by literature. It might be researchers make individual mistakes in their analyses, but it is unlikely that the same mistakes occur to all researchers. Therefore, the results of the HFI proxy SVAR are compared to the results from Gertler and Karadi (2015) (GK), which can be found in Figure 17 in Appendix B. GK use also HFI instruments to identify the SVAR model for the US. The transformation of variables, their order and the lag length are the same, but GK use the one-year US government bond rate instead of a key policy rate from the Fed. Furthermore, instead of the REER, they use an indicator for the health of the US economy, the excess bond premium, which display the difference of government and corporate bonds with the same maturity. Considering the different sizes of the monetary policy shocks, the magnitude as well as the movements of the responses in the one year bond rate and Norges Banks sight deposit rate, the CPIs and the IPs are remarkably close, especially keeping in mind that the dynamic effects in a small open economy are compared to the dynamic effects in a big open economy. In contrast to GK’s results, the small price puzzle in IP could possibly be prevented in the HFI proxy SVAR for Norway through controlling for the Brent oil prices. The tighter confidence intervals of the IRFs in GK’s proxy SVAR can be ascribed to the almost twice as large sample size and potentially also to more noise in the HFI proxy SVAR for Norway, since the Norwegian economy should be more influenced by other economies compared to the US. With this comparison, the ability of Norges Bank to significantly influence its targets, the inflation gap and the output gap, seems even more realistic than before.
8 Potential extensions

Needless to say, there are many possibilities to extend the presented proxy SVAR model for Norway. In the light of the results from the empirical analysis, it is advisable to build up on the monthly HFI proxy SVAR model as it provides the strongest instruments, it is a relatively robust model, it gets the closest to the true expectations from the theoretical point of view and it receives the best critique.

**Dependent variables.** The HFI proxy SVAR could be taken as a baseline model to evaluate the response of other variables on monetary policy shocks. Gertler and Karadi (2015) add step by step different dependent variables to their proxy SVAR model, which is a mixture of a macroeconomic SVAR and a financial SVAR. This offers them the opportunity to examine the dynamic effects of monetary policy shocks on mortgage spreads and government bonds for example.

**HFI instruments.** A common critique of the basic HFI approach is that an instrument derived from financial variables with short maturities does not capture the forward guidance by central banks, which has become more important since the recent financial crisis. Nakamura and Steinsson (2017) provide a simple solution by deriving instruments from government bonds with long maturities in addition. The same approach could be applied to this model.

**Further external instrument identifications.** Another extension possibility to the proxy SVAR model is the use of more external instruments to identify further short-run restrictions. Weather conditions, natural disasters, diseases, wars and commodity price shocks could be used as instruments to identify structural shocks in GDP and IP for example. Further external instruments would identify more parameters in the matrix $B$ and enable a more precise estimation of the SVAR model.

**FAVAR model.** As mentioned before, one of the biggest limitations for SVAR models is their small information set. Bernanke et al. (2005) pioneered the factor augmented vector autoregressive model, which is the combination of a dynamic factor model and a vector autoregressive model. It offers the opportunity to include compressed information from several hundred variables in a VAR.
9 Conclusion

In this master thesis, the dynamic effects of monetary policy shocks on Norwegian macroeconomic key variables are evaluated with the recently developed proxy SVAR model. In contrast to a common SVAR model, the short-run restrictions in the proxy SVAR model are identified through external instruments for monetary policy shocks, which are derived from a forward looking feedback rule, an outlook based feedback rule and one high frequency financial variable with different maturities.

The forward looking feedback rule identifies monetary policy shocks in Norway with forecasted values of the output gap and the inflation gap, while the outlook based feedback rule derives monetary policy shocks from forecasts about the key policy rate adjusted for changes in the expectation of the economy. Both feedback rules provide merely weak instruments which pose the risk of a high asymptotic bias. The reason behind the weakness is presumably manifold, whereas incomplete data from Norges Bank’s Monetary Policy Reports and the general lack of feedback rules to capture the expected part of monetary policy might have the strongest impact. Proxy SVAR models identified through the two feedback rules are presented, but their results are not reliable. Consequently, they are not helpful to evaluate the dynamic effects of monetary policy shocks on the Norwegian macroeconomy.

The identification of monetary policy shocks through high frequency financial market variables receives the best critique in literature and should get the closest to the true shocks from a theoretical point of view. This approach delivers indeed solid external instruments which are derived from the 6-months NIBOR series. The impulse response functions of the monthly proxy SVAR, identified through this instrument, improve strongly compared to the commonly used Cholesky VAR. Moreover, the proxy SVAR results are relatively robust against changes in the model calibration, but not against changes in the considered time period. The proxy SVAR suggests that Norges Bank’s sight deposit rate and the Norwegian real effective exchange rate index respond on a monetary policy shock with a strong and significant increase in the short term. The consumer price index and the industrial production decrease sluggishly, but mostly insignificant. The results are in line with macroeconomic theory and with literature for the US economy, except for the in-
significance of the responses of the consumer price index and the industrial production. In a comparison to the results from Gertler and Karadi (2015), who use also a high frequency identification for their external instrument and comparable settings in their proxy SVAR for the US economy, the responses on a monetary tightening are relatively similar, but more significant. The difference in the significance can presumably be explained in large parts by the double sample size of Gertler and Karadi (2015).
References


Lunsford, K. G. (2015), ‘Identifying Structural VARs with a Proxy Variable and a Test for a Weak Proxy’.


Qureshi, I. (2015), ‘What are monetary policy shocks?’.


### Appendix A  Data sources and descriptive figures

#### Table 5: Information about endogenous and exogenous variables

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<th>Variable</th>
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<th>Source</th>
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<th>Used in monthly model</th>
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* Only used in a robustness test.
Table 6: Information about underlying variables of instruments

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<td>6-months NIBOR</td>
<td>N6W</td>
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Figure 6: Quarterly GDP and industrial production

Figure 7: Quarterly Norges Bank sight deposit rate
Figure 8: Quarterly REER index and Brent spot price

Figure 9: Monthly consumer price index and industrial production index
Figure 10: Quarterly FLFR and OBFR instruments

Figure 11: Monthly HFI instruments
Appendix B  Robustness test figures and tables

Table 7: Robustness test: Relevance of FLFR instruments including polynomials

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Standard errors not shown. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First stage regressions including squared and cubed values.
Table 8: Robustness test: Relevance of OBFR instruments including polynomials

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Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First stage regressions including squared and cubed values in addition.
Table 9: Robustness test: Relevance of HFI instruments including polynomials

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Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First stage regressions including squared and cubed values in addition.
Table 10: Robustness test: Relevance of collapsed NIBOR instruments

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<td></td>
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<td>Avg(1W &amp; 3M &amp; 6M NIBOR)</td>
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Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
First stage regressions with collapsed NIBORs.
Figure 12: Robustness test: HFI proxy SVAR with 6M NIBOR instrument vs. HFI proxy SVAR with 1W NIBOR instrument.

The left column shows the IRFs of the HFI proxy SVAR with the 6-months NIBOR as instrument. The right column shows the IRFs of the HFI proxy SVAR with the 1-week NIBOR as instrument. The x-axis labels denote months. The grey dashed lines illustrate the 95% confidence intervals.
Figure 13: Robustness test: Cholesky VAR vs. HFI proxy SVAR with CPI ordered prior to IP

The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the monthly HFI proxy SVAR. The $x$-axis labels denote months. The grey dashed lines illustrate the 95% confidence intervals.
Figure 14: Robustness test: Cholesky VAR vs. HFI proxy SVAR with control for ECB’s facility deposit rate

The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the monthly HFI proxy SVAR. The x-axis labels denote months. The grey dashed lines illustrate the 95% confidence intervals.
Figure 15: Robustness test: Cholesky VAR vs. HFI proxy SVAR (pre-crisis sample)

Considered period: January 1999 to November 2007. The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the monthly HFI proxy SVAR. The x-axis labels denote months. The grey dashed lines illustrate the 95% confidence intervals.
Considered period: July 2009 to September 2017. The left column shows the IRFs of the monthly Cholesky VAR. The right column shows the IRFs of the monthly HFI proxy SVAR. The $x$-axis labels denote months. The grey dashed lines illustrate the 95% confidence intervals.
Figure 17: Cholesky VAR and proxy SVAR IRFs for the US from Gertler and Karadi (2015)

The figure is obtained from Gertler and Karadi (2015) on page 61. The IRFs are calculated with Matlab. Note that the 95% confidence intervals are calculated with bootstrapping. The x-axis labels denote months.