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The Impact of Monetary Policy on Unemployment: A Comparison of Local Projections and SVAR Analyses from Norway

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Please note that conclusions drawn are the author's own and do not necessarily reflect the view of the institution or the examiners.

Abstract

This thesis concerns the transmission of monetary policy shocks on the unemployment rate in Norway over the past 20 years. The study compares impulse response functions from local projections - estimated through OLS and IV regressions - and SVAR methodologies - identified with short-term restrictions and external instruments. While touching upon the identification problem, this study contributes to existing literature by providing a comparison framework for how identification strategies affect model results.

I note a delayed response of the unemployment rate to normalized policy shocks through both methodologies. Peak impact is observed after a period of 10 quarters, while quantitatively the response is of a small size. The response is similar for a local projection specified as in Jordà (2005) and for a two-variable SVAR model specified as in Sims (1980). The use of external instruments amplifies the response in local projections, but causes a loss of statistical significance in the SVAR responses. I extend the model to consider dependencies of the impact of monetary policy changes on the current level of interest rates or unemployment rates. As a measure of robustness, I provide estimates for polynomial local projections, and a five-variable SVAR model that includes GDP, the implicit price deflator, and exchange rates - allowing for various lag selections and variable ordering.

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1 Introduction

Variations in the level of unemployment, a defining measure of real economic activity, are a pressing concern for policy making institutions, with both the Federal Reserve and Norges Bank noting price stability and high-and-stable employment as main objectives of their mandates (Federal Reserve, 2023; Norges Bank, 2022, p.3). Labor market fluctuations during the Covid-19 pandemic have also brought increased attention to the potential effectiveness of monetary policy in targeting unemployment and stimulating economic growth. To empirically test this effectiveness, I make use of Norwegian data from the last 20 years to quantify the presence, or lack thereof, of a causal relation between a normalized monetary policy shock and unemployment rates. The research question is posited as follows:

What is the dynamic effect of a normalized monetary policy shock on unemployment rates in Norway?

A possible concern when modeling the variation in the level of unemployment, as a response to the variation in monetary policy, is endogeneity. Formally defined, endogenity is present in cases when the independent variable is correlated with the residual variation of the dependent variable, leading to biased model results (Hill et al., 2020, p.105). One cause of endogeneity, encountered when both the independent and dependent variable are codependent, can be simultaneity. In this case, unemployment and monetary policy might respond to the same driving forces - in particular the economic outlook. Moreover, since monetary policy is likely to respond to expected future unemployment growth, the causality runs both ways.

To speak for the case of endogeneity in this thesis, I note the results of two seminal papers that have analysed the relation of unemployment and macroeconomic indicators of interest. For instance, Phillips (1958) analyzes a timespan of 100 years of UK data, arguing for a negative correlation between unemployment and inflation rates. Importantly, the author highlights the presence of simultaneity in the two variables (p.283). The results of the paper indicate a trade-off between stabilizing unemployment and stabilizing inflation for policymakers.

In regard to the one-sided impact of unemployment on policy rates, Taylor (1993) estimates the relation between short-term interest rates, inflation, and measures of real economic activity - such as output or unemployment, in deviation from their respective potential levels. The empirical results suggest that the short-term interest rate rises by half a percentage point for every percentage point that the output gap and inflation gap widen (p.202). These observations indicate that changes in the monetary policy rate are systematic and closely tied to fluctuations in the macroeconomic environment. The two examples help shift focus on the inter-dependency of macroeconomic series, and serve as useful guidelines for methodology selection.

A methodology that specifically allows modeling of endogenous variables is the structural vector autoregression model (SVAR hereafter), presented initially in Sims (1980). A SVAR model explicitly permits contemporaneous effects while providing an alternative to large scale models that require a priori assumptions and exclusion of variables for identification. This analysis is also better suited for policy simulations, allowing the researcher to clearly identify and quantify the impact of a shock over time. To tackle the identification problem, the task of identifying all lagged and contemporaneous coefficients in the model, SVAR imposes long-run and/or short-run restrictions, making possible recursive identification via a Cholesky decomposition (Gottschalk, 2001, pp.13-17).

An alternative methodology, local projections as in Jordà (2005), provide the added benefit of generating impulse response functions without having to specify the correct underlying dynamic model. By shifting the endogenous variable forward for several steps, the forecast is seen as multi-step process done at each point in time (p.162). This allows for simpler estimation methods such as ordinary least squares. The identification problem could be resolved by introducing exogenous variation in monetary policy shocks - for instance, by controlling for the central bank's forecasts of macroeconomic variables at the time of the policy meeting, as in Romer and Romer (2004).

Through a two-variable SVAR model identified by imposing short-run restriction, I find that contractionary monetary policy shocks have a lagged, but significant, impact on unemployment in Norway. Maximum response is obtained after 10 quarters and is associated with an increase in unemployment rates by 0.2 percentage points. A similar sized response is captured via impulse responses of local projections, though a more lagged reaction is noted. Slight variations in results are present when identification is achieved with exogenous monetary policy shocks - obtained via a regression of the interest rate on forecasts of macroeconomic series. I note the impact of the monetary policy shock to be amplified in states when the interest rates are low and unemployment is low. As a measure of robustness, I check the main result to be valid for polynomial local projections and various lags or variable orderings in the SVAR model.

The findings are closely connected to the existing literature quantifying the impact of normalized policy shocks. Stock and Watson (2001), using data from the US, finds the same 0.2 percentage points increase in unemployment 8 quarters following the policy shock. Jordà (2005), via local projections, estimates a 0.45 percentage points increase in unemployment 8 quarters post-shock. Using Norwegian data, Bjørnland (2008) observes peak effect on unemployment after 14 months. While aligned with existing studies, the contribution of this thesis lies in the comparison of impulse response functions from various methodologies. This comparison underlines how identification methods can affect forecast results.

The rest of the paper is organized as follows; section 2 outlines numerous studies with focus on the unemployment rate and monetary policy - theoretical models and empirical results are discussed. Sections 3 introduces the local projection and SVAR methodologies. The underlying model assumptions are also considered. Section 4 concerns the identification problem and includes a discussion of short-run restrictions, long-run restrictions, and external instruments. Section 5 provides a methodology comparison, while section 6 introduces the data. Statistical properties of the baseline model are presented in section 7 and empirical results are registered in section 8. Section 9 suggests model extensions that account for state-dependencies of monetary policy shocks. Section 10 focuses on robustness checks to validate main results, and section 11 concludes.

2 Unemployment Studies

The following provides a brief overview of the current literature regarding the connection between unemployment and monetary policy. Firstly, a model-based approach will be introduced, with focus on understanding how unemployment fluctuates over time in response to policy shocks. Secondly, empirical studies will be discussed to quantify the effects of these shocks. The presented papers concern data from the United States and Norway, and might offer a valuable basis for comparing the findings of this thesis.

2.1 Unemployment in the New Keynesian Model

In the textbook New Keynesian model, defined by the presence of nominal rigidities and monopolistic competition in the goods market, a contractionary policy action taken by the central bank affects various components of the economy, including unemployment. A more detailed explanation of the equations and transmission mechanisms of the New Keynesian model is provided in the appendix (12.1). I note here that in the short run, an increase in interest rate makes consumption today more expensive and causes a decline in aggregate demand. The model is demand driven and the reduction in demand lowers output and employment levels. Return to steady-state values depends mostly on the degree of price rigidities (Gàli, 2015, pp.68-69). A hump-shaped response of unemployment is noticed, so that the maximum impact of policy changes in not observed on impact.

Bernanke and Carey (1996) uses a New Keynesian model to explain the macro-conditions leading to, and following, the Great Depression. Due to the presence of nominal rigidites, wages adjust slowly to changes in monetary policy - showing patterns of inertia. The authors observe monetary contractions to be strongly associated with falling prices, output, and employment (pp.853-854). The research finds evidence that this delayed response of real wages depressed output, and consequently employment, for a prolonged period.

Galí (2011) provides an extension of the model, focused on labor market frictions, accounting for nominal rigidities and wage stickiness to better capture the dynamics of unemployment over time. The author provides evidence on the comovement between wage adjustments and unemployment in the New Keynesian model, detecting a relation similar to that of Phillips (1958) (p.442). The presence of this relation, providing some empirical evidence to support the theoretical discussion, leads the author to conclude that it might be beneficial for the central banks to respond to unemployment rate changes.

2.2 Unemployment in Empirical Studies

To shift the focus of this discussion to empirical studies, Christiano et al. (1998) considers impulse response functions of VAR models to trace the dynamic response to a monetary policy shock in the presence of nominal rigidities. The identification method is such that there are zero short-run restrictions on the response of other variables in the model to the policy rate. Following a surprise 1 pp. increase in the policy rate, maximum increase in the unemployment rate is observed with a delay of one to two quarters. The time of delay is longer for unemployment than it is for other macro aggregates (p.24). As a measure of robustness, and to depart from the need of implementing short-run restrictions, the authors also consider a narrative approach to estimate impulse responses. The narrative approach is based on Romer and Romer type shocks and the obtained results are similar to the initial SVAR analysis with recursive identification (p.60).

Stock and Watson (2001) looks at the forecast possibilities of VAR models, while providing an example that includes inflation rate, unemployment rate, and monetary policy. The identification method assumes that monetary policy follows a Taylor-rule approach, such that interest rates today are based on values of inflation and the unemployment rate. The equivalent of a recursive identification with interest rates ordered last, this method also indicates a contemporaneous response of monetary policy (pp.103-104). Monetary policy shocks are then described as deviations in the policy rate that are not endogenously determined by the variables in the system. Estimates suggest that a surprise increase of 1 pp. in the policy rate, leads to peak increase in unemployment of 0.2 pp., 8 quarters following the shock. To emphasize the hump-shaped response of macroeconomic variables, authors note that "most of the economic slowdown is in the third year after the rate hike" (p.108).

In a paper that extends the baseline VAR model to include securities, deposits, loans, and CPI as variables of interests, Bernanke and Blinder (1992) finds evidence of the federal funds rate affecting real economy. Allowing for six lags in their estimation, the authors note an interesting response of unemployment levels to monetary policy. On impact, the response of unemployment to policy shocks is not statistically different from zero, with peak impact on unemployment seen after 17 months (p.918). An observation of the paper is that the response of unemployment follows a similar pattern to that of loans, while noting that "bank loans are an important component of the monetary transmission mechanism, even though loans do not lead real variables and are therefore not useful in forecasting exercises with VARs" (p.919).

Similar studies have been conducted with Norwegian data. Notably, Bjørnland (2008) estimates the impact of monetary policy shocks in a small open economy, while paying particular attention to the inclusion of exchange rates in the model. The results suggest that the effect of unemployment reaches its peak after approximately 14 months. Additionally, variance decomposition tests suggest that almost 20 percent of the variation in unemployment can be explained by monetary policy shocks (pp.213-214).

As it concerns the relationship between the unemployment rate and monetary policy in other countries, the results are similar to the ones presented so far. In a case study from Canada, Rondina (2016) notes statistically significant impact of monetary policy changes on the unemployment rate. The peak effect of 0.1 percentage points is achieved after 20 months. The author tests whether the change into an inflation-targeting regime would lead to different responses of real economic activity, but the change in estimates is limited (p.10). Fisher and Huh (2022) uses short-run and sign restrictions to find that unemployment rises on impact given a contractionary monetary policy shock in Australia. The impact is of the small magnitude of less than 0.1 pp. (p.5).

This literature review section concludes that we expect an hump-shaped response of the unemployment rate to monetary policy changes. The response is significant, of a small magnitude, and delayed. This finding is valid across different methodologies and various countries.

3 Methodology Selection

3.1 The Local Projection Methodology

The first methodology employed to capture the impact of a monetary policy shock on the unemployment rate in Norway is that of local projections. Jordà first introduced the approach in his 2005 paper focused on improved estimation of impulse responses. In the paper, local projections are seen as an alternative to vector autoregressive models that provide the added benefit of not requiring the correct specification of the underlying multivariate dynamic system. Additionally, estimation of impulse response functions form local projections is seen as a multi-step forecast done at each point, rather than a forecast at an increasingly distant horizon (p.162). This property is believed to help avoid miscalculations of impulse responses in the long-run.

In its simplest form, a linear local projection of the unemployment rate on monetary policy would be given as follows - where y^{t+h} is the unemployment series at time $t{+}h$, and h is the forecast horizon. A normalized shock is imposed on the policy rate, x_t , and the β coefficients capture the response of the y series at the specified time. To estimate the impulse response function, the coefficients β_1^h to β_k^h are plotted against the forecast horizon. The plot is used to depict the dynamic effect of the shock on the outcome variable over time.

$$y^{t+h} = \mu^h + \beta_1^h x_t + \beta_2^h x_{t-1} + ... + \beta_k^h x_{t-k+1} + \epsilon^{t+h}$$

While presented as a linear model above, the local projection approach is flexible and does not impose any specific functional form on the relationship between the variables. It also does not require any assumptions about the identification of the shocks or the linearity of the model. By means of various Monte Carlo simulation, Jordà (2005) compares impulse responses derived from a two-lag VAR model with those obtained through linear and/or cubic local projections. The latter is noted as "considerably more accurate in capturing detailed patterns of the true impulse response over time" (p.169).

The same methodology is used by Holm et al. (2020) to quantify the influence of policy changes on household consumption. Although the paper's main focus lies on microeconomic influences, the authors also provide impulse responses for macro variables. The study uses a detailed Norwegian data set and a narrative sequence of monetary policy shocks. To overcome the endogeneity issue associated with monetary policy, the authors "orthogonalize policy changes against the central bank's forecasts of its macroeconomic targets" (p.5). By taking an approach similar to that of Romer and Romer (2004) the authors presume that the residuals from this regression estimate unsystematic, exogenous changes in monetary policy. The local projection is specified as in the equation that follows, where ϵ^{MP} is the Romer and Romer type shock. I note that the paper also includes a vector of controls and lagged values of monetary policy shocks in the estimation, not shown here.

$$y^{t+h} - y^{t-1} = \alpha^h + \beta^h \cdot \epsilon_t^{MP} + u_t^h$$

Importantly, this analysis interprets the estimated shocks "as direct observation of the structural monetary policy shocks, as opposed to instruments" (p.8). This assumptions removes the need to use instrumental variables (IV) regression, and allows for simple linear regression modeling methods. For each forecast horizon separate regressions between the outcome variable and lagged values of the shock variable are run. As related to this thesis, impulse responses from local projections show that a one percentage point increase in short-term interest rates leads to a peak increase in the unemployment rate of one percentage point, 42 months following the impact (p.9).

3.2 The SVAR Methodology

For a concise description of the use of the SVAR methodology for forecasting purposes in this thesis, the main literature will be Bjørnland and Thorsrud (2015). I will initially introduce autoregressive processes and their natural extension to VAR models. The importance of allowing for structural shocks and the need for specific identification methods will be further explained.

3.2.1 Autoregressive Models

Many economic time series are said to follow an autoregressive (AR) process, implying the presence of some 'memory' in the value of the series. The indication is that the value of the time series today is dependent on the value of the time series up to a certain lag, namely p. In many cases, one can think of stock prices or inflation rates following such processes. A representation of a two-lag ($p = 2$) AR process for a time series y is given as follows:

$$y_t = \beta_1 \cdot y_{t-1} + \beta_2 \cdot y_{t-2} + \epsilon_t$$

The β coefficients capture the degree of inertia from past values. At each point in time the series is also influenced by an error term (ϵ_t), which is assumed to be independently and identically distributed with a mean value $\phi = 0$, and variance $\sigma^2 = 1$. Deviations in the value of the series that are not explained by past values, are explained by the presence of this shock.

3.2.2 Stationarity of Autoregressive Models

A clarification of the concept of stationarity might be necessary at this point. A time series is *covariance stationary* if neither the mean nor the variance of the series is dependent on a time component. Moreover, the covariance between the series at time t and the series at time t-p, is only dependent on the distance p between the variables, and not on the time t (Wooldridge, 2019, p.367). The benefit of a stationary AR series is the opportunity to write it as a moving average process, so that the series can be presented as a sum of a constant (μ) and error terms (ϵ).

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ...$$

A moving average representation of the series also makes possible a visualisation of the dynamic impact of an initial shock on the series to the values of the time series in the future, via the impulse response functions. When moved forward in time, the impulse response functions suggest how long it takes for a shock to die in the series and contribute to the forecasting properties of the model (Bjørnland & Thorsrud, 2015, p.200). A stable series is necessary for forecasting reasons, as one expects the series to return to its stable value following a shock.

3.2.3 Vector Autoregressive Models

An extension of the AR processes, vector autoregressions allow for simultaneous modeling of several time series. In this case the matrix Y_t contains a vector of series rather than a single time series. In economics literature, the use of VAR models is generally made for the purpose of forecasting (Bjørnland and Thorsrud, 2015, p.190). For instance, one can express output in this quarter (y_1) as a function of output, inflation (y_2), and interest rates (y_3) in the last two quarters. Forecasting is possible by forwarding this equation several quarters ahead. The extended and compact matrix form of the model are presented below.

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \cdot \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \begin{bmatrix} \beta'_{11} & \beta'_{12} & \beta'_{13} \\ \beta'_{21} & \beta'_{22} & \beta'_{23} \\ \beta'_{31} & \beta'_{32} & \beta'_{33} \end{bmatrix} \cdot \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix}$$

$$Y_t = \mu + B \cdot Y_{t-1} + B' \cdot Y_{t-2} +_t$$

It is possible to write the VAR(2) model in a VAR(1) representation through an altering of the β coefficients into an C matrix, known as the companion form matrix.

$$\begin{bmatrix} Y_t \\ Y_{t-1} \end{bmatrix} = \begin{bmatrix} \mu \\ 0 \end{bmatrix} + \begin{bmatrix} C_1 & C_2 \\ I & 0 \end{bmatrix} \cdot \begin{bmatrix} Y_{t-1} \\ Y_{t-2} \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix}$$

Or more compactly,

$$Y_t = \mu + C \cdot Y_{t-1} + e_t$$

Such a representation is important since stability of a VAR model is proven in cases where the eigenvalues of the companion form matrix are less than 1 in absolute terms (Bjørnland and Thorsrud, 2015, pp.59-64). A stable VAR model indicates that the underlying autoregressive process is stationary. The result is valid for higher order AR processes as well.

3.2.4 Structural Vector Autoregressive Models

In cases when the researcher is interested in accounting for structural shocks, SVAR models might be better fitted for the purpose. Rather than for forecasting purposes, SVAR models are used for structural analysis such as the impact of monetary and fiscal policy on specified variables in the economy. While many of the properties of the VAR model carry on the SVAR methodology, the main difference occurs due to the presence of simultaneous relations in the latter. A matrix representation of the two lags SVAR model is given as follows, where the matrix A captures the "on impact" effect.

$$AY_t = \mu + B_1 Y_{t-1} + B_2 Y_{t-2} + \epsilon_t$$

This simultaneity, however, makes the OLS estimate inconsistent and does not allow for the same analysis used in the VAR model. It is therefore necessary to obtain the reduced formed VAR by multiplying both sides of the above system by the inverse of the A matrix, in cases when invertibility of A is possible. The reduced-form model equation is:

$$Y_t = A^{-1} \cdot \mu + A^{-1} \cdot B_1 Y_{t-1} + A^{-1} \cdot B_2 Y_{t-2} + A^{-1} \cdot \epsilon_t$$

The reduced-from error terms are now defined as:

$$e_t = A^{-1} \cdot \epsilon_t$$

One inital key assumption is that the structural shocks (ϵ_t) are not correlated. That is, the variance-covariance matrix is a diagonal matrix with each shock having an economic interpretation (Bjørnland, 2000, p.6). While the variance-covariance matrix for the structural model is diagonal, reduced form shocks (e_t) are generally correlated making it hard to recover the structural model.

From the above representation of the models, we can check that the structural form has more coefficients than the reduced form. In order to go back to the structural form and identify all the coefficients, additional restrictions need to be imposed. Without doing so, the SVAR parameters are not identifiable. Exact identification for a SVAR model with n variables, requires imposing n(n-1)/2 restrictions (Bjørnland & Thorsrud, 2015, pp.218-219). A possible solution, recursive identification allows "the orthogonalization of the reduced form innovations to be done through a Cholesky decomposition" (Bjørnland, 2000, p.7). This is the decomposition of a positive definite matrix, the variance-covariance matrix of e in this case, into a lower triangular matrix (say, P) and its conjugate transpose as follows:

$$cov(e_t) = P \cdot P'$$

where

$$P = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix}$$

Through this unique factorizarion, we are able to trace back the structural shocks (Bjørnland, 2000, p.7). Structural shocks are retrived as:

$$\epsilon_t = P^{-1} \cdot e_t$$

A more detailed description of solutions to the identification problem, including the main sources making use of short-run restrictions, long-run restrictions, and external instruments, follows in the next section.

4 The Identification Problem

4.1 Short-Run Restrictions

Sims (1980) is the first paper to address the identification problem in macroeconomic models using short-run restrictions. The study was motivated by an overall dissatisfaction with large-scale macroeconomic models achieving exact identification by excluding variables or defining exogeneity based on previous economic theory. The author argues against the use of "restrictions based on a priori knowledge," asserting that identification should be possible even when all variables are considered endogenous (p.15). While focusing on quarterly data from Germany and the US, the study generates impulse response functions for GNP, price level, wages, and unemployment.

The short-run identification approach places emphasis on the ordering of the variables, so that a contemporaneous shock on the variable placed first affects all other variables on impact. Contrarily, a contemporaneous shock on the variable placed at the bottom, affects the above-placed variables with a lag. Sims notes that "the contemporaneous values of other (lower) variables enter the right-hand-sides of the regressions with a triangular array of coefficients" (1980, p.21). The short-run restriction approach is also known as the zero contemporaneous restrictions approach, as the impact of the innovations impacting lower ranked variables is zero in the current period. After the first period, no restrictions are imposed on any of the shocks.

A second influential paper using short-run restrictions to trace the impact of monetary policy is Christiano et al. (2005). The main assumption is that macroeconomic variables such as GDP, investments, and labor productivity "do not react simultaneously to a monetary policy shock". The ordering is such that GDP is placed first in the Y_t matrix, and the federal funds rate is placed last. The analysis speaks in favor of long-term impacts, such that the neutrality of a contractionary monetary policy shock on output is observed after 17 quarters. Estimates from the historical variance decomposition demonstrate that monetary policy shocks account for a significant percentage of the variation in real variables- while also noting that confidence intervals are quite wide (pp.7-9).

4.2 Long-Run Restrictions

The long-run restrictions for the identification of a VAR model were first introduced by Blanchard and Quah (1989). The study makes use of a two variable VAR modeling the gross national income and unemployment levels, with data from the US. The authors introduce the concept of transitory and permanent shocks. The assumptions are that demand shocks have no long-run effect on either of the variables, while supply shocks have no long-run effect on unemployment but might have a long-run effect on output. The effect on unemployment in the long-run is zero for both disturbances. In comparison to the previous section, there are no restrictions on the contemporaneous effect of either shock. The authors also argue that the use of this restrictions in a simple two-variable model is made for its demonstrative properties and more complex mechanisms and price dynamics need to be taken into consideration so as to validate long-run neutrality (pp.657-658).

With these caveats in mind, the paper shows that transitory demand shocks do not display their largest effect on impact, but do so with a lag. The maximum response on variables of interest is shown after two to four quarters. On the other hand, permanent supply shocks have a long-run effect on output with a magnitude almost eight times the size of the initial shock (Blanchard and Quah, 1989, p.662).

A similar approach is taken by Galí (1999), focused on estimating the different impact of technology and monetary shocks on productivity and labor. The assumptions suggest that monetary shocks have only a temporary impact on employment and productivity. Galí notes that “only technology shocks can have a permanent effect on the level of labor productivity” (p.256). Therefore the long-run impact of monetary policy shocks on labor and output is set to zero.

4.3 The Narrative Approach and External Instruments

Although SVAR models were originally introduced to account for the simultaneous relationships among endogenous variables, it may be advantageous to make use of exogenous shocks that are related to some shocks of interest but are not related to shocks in the remaining part of the model. For instance, Romer and Romer (2004) proposes a new method to identify monetary policy shocks by addressing the issue of endogeneity and anticipation present in macroeconomic series. The authors utilize Greenbook forecasts by the Federal Reserve to control for already known information, such as inflation or output. Policy changes during given Federal Open Market Committee meetings are regressed on these forecasts, allowing for the residual of the regression to become the new, exogenous, measure of monetary policy shocks (p.1061). This is know as the narrative approach of identifying shocks. By employing a three variable VAR model, the study finds a larger impact of monetary policy using this new shock series compared to the model that uses the shocks from the actual federal funds rate (p.1080). Note that since the interest rate is generally used in levels in VAR models, the new shock series need to be accumulated for comparison purposes.

Mertens and Ravn (2013) estimates the effect of changes in personal and corporate income tax levels using a narrative series of tax changes. The narrative approach for obtaining shock series is based on the idea of ‘purifying’ the tax rate from the information that was already available to the fiscal policy authorities. The authors use this series of exogenous tax shocks as a proxy for the endogenous tax shocks since identifying tax changes has proven to be tricky given “the endogeneity and diversity of policy instruments” (2013, p.1212). The empirical results indicate a significant impact on output and consumption due to tax changes, with differences in results depending on the type of tax changes.

In a similar paper with focus on tax changes, Cloyne (2013) makes use of the narrative approach to identify "policy changes that are uncorrelated with other macroeconomic fluctuations" (p.1507). While differentiating between endogenous and exogeneous tax shocks, the paper notes that the latter explain over 20 percent of the output variance. Important to note might also be the fact that exogeneous tax changes appear to have a larger impact on macroeconomic variables, as compared to the results from endogeneous tax changes coming from a SVAR analysis with short-run restrictions (Cloyne, 2013, p.1525).

Shifting our focus once again to monetary policy changes, Gertler and Karadi (2015) makes use of high-frequency policy surprises as exogenous instruments in a VAR framework. High-frequency data is obtained by focusing on the impact on interest rates changes on a narrow window around the time of policy announcements (p.45). This instrument is believed to be exogenous to the economic and financial variables used in the VAR model. In contrast to the literature discussed previously, the authors use the one-year government bonds rate as a measure of monetary policy, instead of the federal funds rate. Reasons lie in the ability of the bond rate to account for forward-guidance shocks. The study presents a comparison of the results from a VAR model identified with Cholesky decomposition and a VAR model identified with external instruments. The authors argue that identifying policy shocks with Cholesky decomposition is doubtful, as there might appear puzzles in the impulse response functions for both CPI and industrial production (pp.61-62).

5 Methodology Comparison and Limitations

A comparison of the local projection and SVAR model is introduced to help explain how possible variation in the results of the baseline model can be attributed to the methodology selection. Identification possibilities and limitations of each model are also touched upon.

Plagborg-Møller and Wolf (2021) observes that local projections and VARs produce equivalent impulse response functions in the population, provided there are no restrictions on the lag structure. The authors emphasize that the advantage of local projections lies in their robustness to various underlying model specification (p.955). In cases where restrictions on the number of lags are imposed on the SVAR model, the paper concurs that "the two impulse response estimands still approximately agree out to horizon p", if p lags are included (p.956). To visually illustrate the similarity of impulse response functions, the authors make use of the response to output following a negative interest rate shock. The graphs suggest some slight differences in the response when the SVAR model is limited to a particular lag length (p.964).

An added benefit of local projections is that instead of doing recursive identification, as common in papers that define monetary policy shocks, one could estimate the local projection regression and collect the response coefficients at each forecasted horizon. In cases when restriction is necessary for identification purposes, long-run restrictions as in Blanchard and Quah (1989), short-run restrictions, or sign restrictions could also be implemented (pp.967-969).

Brugnolini (2018) uses Monte Carlo simulations to compare the impulse response functions of the vector autoregressive methodology outlined in Sims (1980) and local projections presented in Jordà (2005). Findings suggest that when the AIC test is used to determine the appropriate number of lags, any distortions and differences from the two impulse responses are likely to result from small sample bias (p.23). However, when the underlying model is intentionally misspecified by using the incorrect lag structure, results indicate that the impulse response functions of local projections are more precise compared to those of VAR models. Notably, the study shows that in cases of misspecified models, the VAR confidence intervals do not contain the true values more than 50 percent of the time (p.17).

Kilian and Kim (2011) examines the reliability of impulse responses derived from local projections under the assumption of a linear and stationary underlying process (p.1460). The research compares the accuracy of estimates from local projections to those of a VAR model with one lag, a VAR model with twelve lags, and ARIMA models. The authors find the precision of the local projection estimates to increase when the time horizon is extended, such as from T=100 to T=200, for both the VAR(1) and VAR(12) models. However, a drawback of the local projection method is that the asymptotic confidence interval is sometimes three times wider on average than other intervals (p.1463). As a result, the authors conclude that there are no apparent benefits to using the local projections method especially for limited time horizons (p.1466).

In regard to the limitation of implementing a SVAR methodology to trace the effect of a monetary policy shock, one major concern could be associated with the identification problem. Short-run restrictions must be based on prior reasoning of the contemporaneous or lagged impacts of shocks. To check that the dynamic ordering of the variables is right, the research should conduct additional test to prove invariance of results to model specifications (Bjørnland, 2000, p.10). Additionally, the need to implement short-run or long-run restrictions suggests that VAR models are better suited for small-scale modeling.

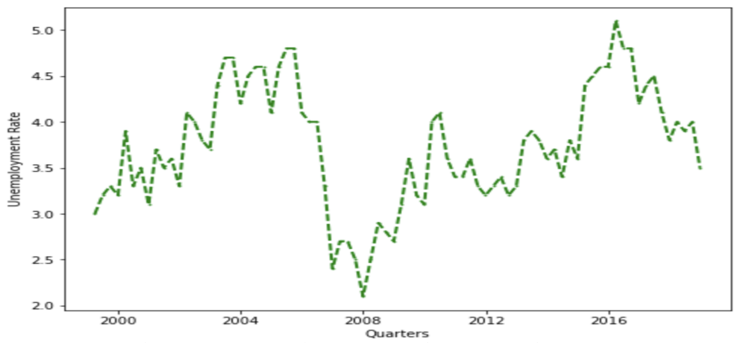
To conclude, the two methodologies proposed differ on the need to correctly specify the underlying dynamic model, identification methods, span of the forecast horizon, and lag structure. To help limit these differences, I use the same lag structure and the same forecast horizon in each model. Validity of the lag selection is supported by the use of AIC and BIC information criteria. However, the limited forecast horizon might favor more accurate impulse responses of the VAR methodology, as discussed by Kilian and Kim (2011). The same series of narrative policy shocks is used as an external instrument for both methodologies. I comment beforehand that issues concerning the exact identification of the underlying model could lead to different estimates from the models.

6 Data

The two macroeconomic series this paper focuses on are the unemployment rate and the monetary policy rate. The analysis is based on quarterly data from Norway covering the period from 1999 to 2019. Using quarterly data is a standard practice when aiming to assess the effects of monetary policy changes on macroeconomic variables, as for instance in Christiano et al. (1998), Stock and Watson (2001), or Bjørnland (2000). Additionally, our series of interest are easily available in quarterly frequency.

6.1 Unemployment Rate

Data on the unemployment rate is obtained from the yearly Labor Force Survey (LFS) conducted by Statistics Norway on individuals aged 15 to 74. An unemployed individual is defined as one who is not employed at the time of the survey, but has been actively seeking employment opportunities during the previous four weeks. The unemployment rate is expressed as a percentage of unemployed individuals over the labor force, where labor force is measured as the sum of employed and unemployed individuals (Statistics Norway, 2023). A visual depiction of the time series is presented below.

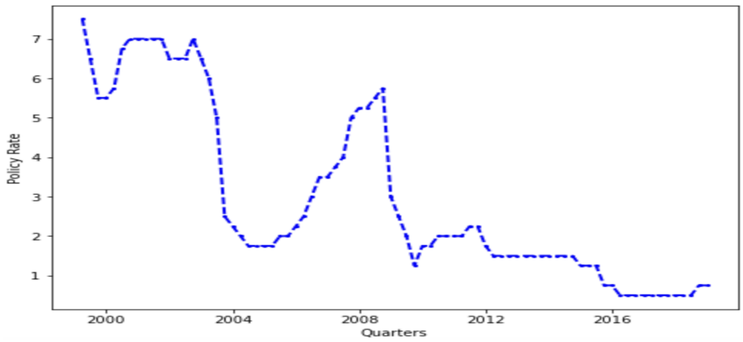


Note: The series is the quarterly unemployment rate in Norway from 1999 to 2019. The y-axis captures the percentage of unemployed individuals over the labor force, while the x-axis notes time. Data is obtained from Statistics Norway.

I note the average unemployment rate for the period considered to be 4.12 percent. Although the series appears to exhibit mean-reverting properties, an augmented Dickey-Fuller (ADF) test is conducted to test for the presence of a unit root. The test "regresses observed variables on its one period lagged values" and rejecting the null hypothesis favors stationarity of the series (Xiao and Phillips, 1998, p.27). Having received an ADF statistic of -2.78, I reject the null hypothesis of a unit root at the 10 percent statistical significance level. I note that numerous studies that employed VAR methodologies with Norwegian data model the unemployment rate as stationary, as is the case in Bjørnland (2000).

6.2 Monetary Policy

The sight rate, defined as the interest rates on banks' overnight deposits up to a certain quota in Norges Bank, is taken as the measure of monetary policy (Norges Bank, 2023). The Monetary Policy and Financial Stability Committee is responsible for setting the policy rate, and a decision on the rate is made public every six weeks. Data is acquired from the official website of Norges Bank and plotted below. It might be worth noting that the interest rate in Norway has never reached the zero lower bound during the period considered - a value that might hinder the transmission of policy changes in the economy. In recent years, however, the policy rate has been gradually approaching the zero bound.

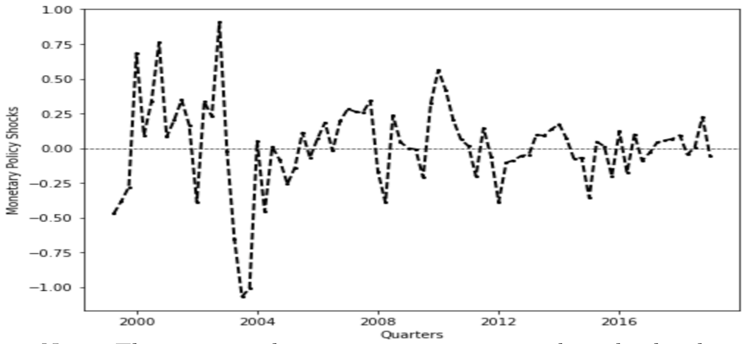


Note: The series is the quarterly policy rate in Norway from 1999 to 2019. The y-axis captures the policy rate in percentage, while the x-axis notes time. Data is obtained from Norges Bank.

Similarly to the unemployment rate analysis, a test of stationarity is performed. In this case, the results provide an ADF value of -2.52, and the null hypothesis of a unit root is only rejected at the 12 percent statistical level. Plotting the unemployment rate and the policy rate together does not lead to a clear conclusion regarding their relation over time.

6.3 Narrative Shocks

As previously discussed in this paper, I will employ a narrative series of monetary policy shocks to deal with the problem of endogeneity. The series is used in Holm et al. (2020), and the data was kindly provided by Professor Holm for use in this thesis. Similar to the approach taken in Romer and Romer (2004), authors regress changes in the policy rate to lagged values of itself and Norges Bank forecasts of inflation, GDP, and exchange rates. The residual of this regression is the narrative policy shock in the figure. Having accounted for already-known information, the series is said to capture exogenous variation in monetary policy.



Note: The series is the narrative monetary policy shocks obtained as the residual of the regression of policy rate changes on Norges Bank forecasts of inflation, GDP, and exchange rates. The y-axis captures the size of the shock in percentage points, while the x-axis notes time. Data is obtained from Holm et al. (2020).

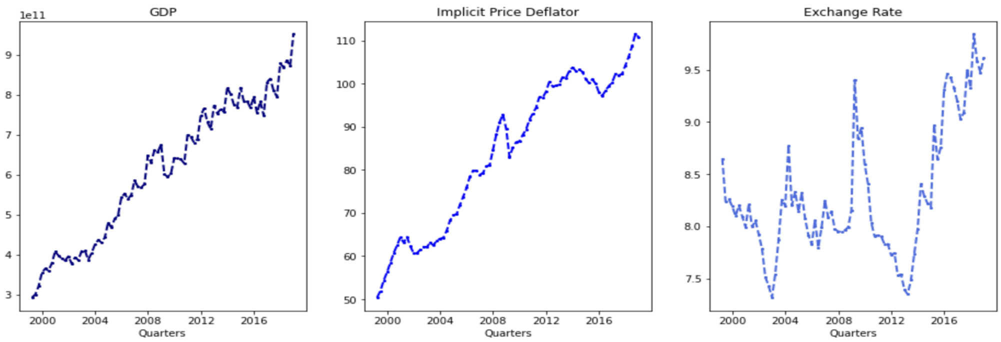
Holm et al. (2020) observes that significant shocks were prevalent during the 2002-2003 period, with the magnitude of the shocks declining towards the end of the sample (pp.6-7). Both the figure and an augmented Dickey-Fuller test indicate that the series is stationary at all levels of significance.

6.4 GDP, GDP Implicit Price Deflator, and Exchange Rates

In order to better capture the variation in the unemployment rate, I will expand the VAR model to include additional time series such as GDP, the GDP implicit price deflator, and the exchange rate of the Euro (EUR) to the Norwegian krone (NOK). The inclusion of exchange rates in VAR models is common in studies modeling small open economies such as Norway - see for instance Furlanetto and Robstad (2019). While a more detailed description of variable ordering follows in Chapter 8, I note here that ordering in this thesis will be similar to that of Robstad (2017) - examining the impact of monetary policy on housing prices and credit - and Furlanetto and Robstad (2019) - disentangling immigration shocks from demand shocks.

Data for GDP is obtained from the National Accounts of Statistics Norway, collected at current market prices and adjusted for seasonal variations. As a measure of inflation, data for the GDP price deflator is collected from FRED, where 2015 is used as the base year. The price deflator, a ratio of current price-value of GDP to its chain-volume value, closely mirrors the price index (BEA, 2018). A positive time trend is noticeable for both the GDP and the implicit price deflator.

Data for the exchange rate is obtained from Norges Bank at monthly frequencies, and turned into quarterly frequencies by taking an average of the monthly values. The provided exchange rate is the value in between the buying rate and the selling rate for the given month (Norges Bank, 2023). A visual representation of the data is provided for clarity.



Note: The time series are GDP - Current NOK (left), GDP Implicit Price Deflator - 2015 base year (center), and exchange Rate of EUR to NOK - middle price between buying and selling rate (right). Each series provides the quarterly values for Norway in the time span from 1990 to 2019. Data is obtained from Statistics Norway, FRED, and Norges Bank - respectively.

7 Statistical Properties of The Model

7.1 Stationarity

The SVAR methodology section outlined the importance of stationary series to correctly trace the impact of a shock over time. To determine stationarity of a VAR model, it is necessary to check that eigenvalues of the companion form matrix are less than one in absolute terms (Bjørnland and Thorsrud, 2015, pp.59-64). Given the graphical representation of the time series of interest, the model specification allows for both a constant and a time trend. For a VAR model with two variables - unemployment rate and monetary policy -

and a five-lag structure, the largest eigenvalue is shown to be approximately 0.94. This value indicates stability.

Companion Matrix Eigenvalues	
-0.8113	+0.0000i
0.1398	+0.7738i
0.1398	-0.77381i
-0.4197	+0.0000i
0.1788	+0.0000i
0.9367	+0.0000i
0.7236	+0.1471i
0.7236	-0.1471i

Note: Eigenvalues of the companion form matrix in a two variable SVAR model including quarterly values for unemployment rate and monetary policy. The model allows for five lags, a constant and a trend component. The maximal value is highlighted.

As a measure of robustness, I repeat the procedure for varying numbers of lags (4, 6, 7, and 8 lags are tested). The largest eigenvalue reached is 0.96. The eigenvalues do not exceed the value of one, even when the VAR model is extended to include five variables with the addition of GDP, GDP implicit price deflator, and exchange rates, as seen in the appendix (12.2). I conclude that the model is stationary for various lag selections and model specifications.

7.2 Cointegration

A common trend component is often observed in macroeconomic time series, a property known as cointegration. It is possible for a linear combination of nonstationary series, due to cointegration properties, to result in a stationary series (Bjørnland and Thorsrud, 2015, pp.249-254). In a SVAR setting, cointegrated series can be used in levels without the need of time-differencing or detrending procedures, which often cause a loss of information.

In the data section, I noted through ADF tests that the null hypothesis of a unit root can be rejected at the 10 percent level of statistical significance for the unemployment rate. For the policy rate, the null hypothesis of a unit root can only be rejected at the 12 percent level. I now make use of Engle-Granger cointegration test to "achieve a consistent estimate of the long-run relationship between $y_{1,t}$ and $y_{2,t}$, (allowing for) all dynamics and endogeneity issues to be ignored asymptotically" (Engle and Granger (1987) , as cited in Bjørnland and Thorsrud, 2015, p.255).

The test gives a p-value of 0.094. That is, we reject the null hypothesis of no cointegration between unemployment and monetary policy only at the 10 percent statistical level. A graph of the fluctuations of the two series over the time span considered is presented in the appendix, while noting that patterns of comovement are not clear from the graph (12.3).

From the reduced from variance-covariance matrix of the two-variable model, I find the contemporaneous relation between the unemployment rate and the monetary policy to be negative with a value of -0.006.

7.3 Lag Selection

To ensure that the model is correctly specified and avoid issues with serially correlated error terms, it is important to select the appropriate number of lags for the VAR model. Having too many lags could lead to overfitting and increased parameter uncertainty. Too few lags could lead to additional autocorrelation problems (Bjørnland and Thorsrud, 2015, pp.68-69).

I collect values from both the Akaike information criterion and Bayesian information criterion for model selection, considering a trade off between model fit and model size. Model fit is captured by the sum of squared residuals and model size is captured by the second parameter in the equations below, where p is number of lags. Note that BIC tests penalize an increase in the number of parameters more heavily. The model with the lowest information criterion provides the best fit and suggests the correct lag selection.

$$BIC(p) = ln(\frac{SSR(p)}{T}) + (p+1)\frac{ln(T)}{T}$$

$$AIC(p) = ln(\frac{SSR(p)}{T}) + (p+1)\frac{2}{T}$$

For the two variable SVAR model, I allow for a maximum of 10 lags and find the fifth lag to have the minimum value for both information criteria. To increase the robustness of the analysis, I extend the maximum lags to 16 and still find the fifth lag to have the lowest value.

Number of Lags	BIC	AIC
1	-2.6128	-2.7139
2	-2.6541	-2.8563
3	-2.5327	-2.836
4	-2.6632	-3.0677
5	**-3.0459**	**-3.5514**
6	-2.9209	-3.5275
7	-2.7579	-3.4657
8	-2.6504	-3.4592
9	-2.5555	-3.4655
10	-2.3835	-3.3945

Note: AIC and BIC information criteria values a for a two variable SVAR model including quarterly unemployment rate and monetary policy. Tests for model selection allow up to 10 lags, while minimal values are highlighted.

I conduct the same analysis for the five variable SVAR model, and find the fifth lag to provide the minimum value for the Akaike information criterion and the first lag for the Bayesian criterion. The table of values is provided in the appendix for completness(12.4). Results speak for the fact that BIC tests penalize an increase in the number of lags. However, including only one lag might be insufficient to capture all the variation present in macroeconomic series. Therefore, I use 5 lags in both baseline VAR models.

8 Model Specification and Results

In what follows I specify the baseline model for the local projections - estimated via OLS and IV regressions - and SVAR analyses -identified via short-run restrictions and external instruments. Impulse response functions and forecast error variance decompositions are provided to help the discussion of main results.

8.1 The Baseline Model for Linear Local Projections

The baseline model for this study is a local projection based on the methodology introduced by Jordà (2005). In order to compare outcomes generated by obtaining the policy shocks from the regression on the monetary policy rate with the outcomes generated by directly inputting Romer and Romer (2004) type shocks in the local projection, a two-step approach is adopted.

The initial approach involves estimating an ordinary least squares (OLS) regression in which the unemployment rate is regressed on the policy rate in Norway. To ensure robustness of the analysis, standard errors are obtained using the Newey-West procedure, a technique for addressing autocorrelation issues that arise due to the presence of lagged variables. If no lags are specified, the Newey-West procedure is equivalent to a standard OLS regression (Newey and West, 1987, pp.703-706). As suggested by AIC/BIC tests, the regression allows for five lags for both the unemployment rate and the policy rate. The policy rate is not instrumented in this approach.

To obtain the local projection impulse response functions, the forecast horizon (h) is set at 25 quarters, and an estimate of the equation that follows is captured at each horizon. The coefficients of interests, α_2 at h, are collected to obtain the time-path of the response of the unemployment rate to a monetary policy shock.

$$u_{t+h} = \mu_h + \sum_{s=1}^{s=5} \alpha_{1,h} \cdot u_{t-s} + \sum_{s=0}^{s=5} + \alpha_{2,h} \cdot i_{t-s} + \epsilon_{t+h}$$

The second local projection approach allows for the policy rate shocks to be instrumented with the Romer and Romer (2004) type shocks, obtained with Norwegian data from Holm et al. (2020). In this case, the use of a GMM IV regression allows the policy shocks to be directly substituted with shocks that remove already-know macroeconomic information in order to tackle the endogeneity problem.

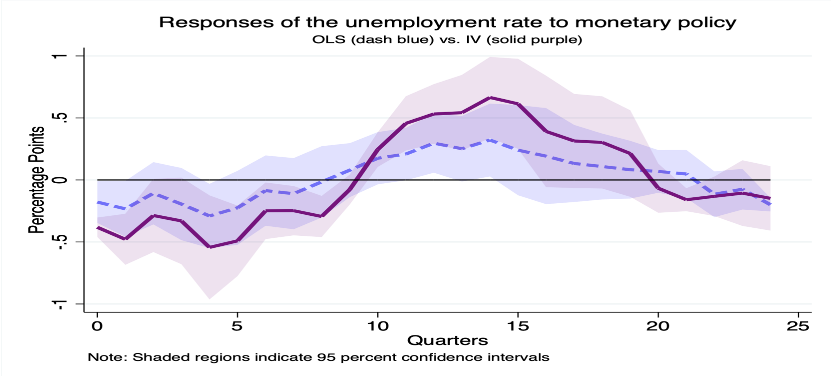
In the first stage of the regression, changes in monetary policy rate are regressed on the central bank's forecasted values of GDP, inflation, and exchange rates (Holm et al., 2020, p.5). Shocks are then obtained as the fluctuations of the policy rate not explained by the included variables. This is a step I do not run since the narrative shocks already come from this phase.

In the second stage, the unemployment rate is regressed on predicted values of the shock from the first stage, allowing for inclusion of lags. Standard errors of the local projections are obtained using a block-bootstrap procedure that accounts for the potential autocorrelation and heteroskedasticity of the errors. To maintain consistency in the analysis, I again allow for five lags for both the unemployment rate and the exogenous policy shock. Consistent with Jordà (2005) and Holm et al., (2020), no additional explanatory variables are included in the model.

8.1.1 Impulse Response Functions from Linear Local Projections

Impulse response functions capture the response to a shock ϵ at time t, of a time series y over time - where the size of the response is captured on the y-axis and the forecast horizon is shown on the x-axis (Bjørnland and Thorsrud, 2015, p.222). A graphical presentation of the impulse responses from the local projections is given as follows, where the blue line is the response coming from the OLS regression of the unemployment on the policy rate, and the purple line is the response coming from instrumenting the policy shocks. The bands allow for 95 percent confidence intervals.

The obtained results provides evidence of a relatively stronger response of the unemployment rate to a monetary policy shock when the policy shock is instrumented. The local projection derived from the first estimation yields statistically insignificant results for the first 10 quarters. The maximum response is observed after 14 quarters, where a normalized monetary policy shock leads to a 0.25 percentage points increase in the unemployment rate. After 20 quarters the response to the shock becomes slightly negative and insignificant.



Note: Impulse response functions from local projection analyses of a normalized monetary policy shock on the unemployment rate in Norway. The y-axis captures the percentage point change in the unemployment rate at the given horizon. The x-axis notes the forecasted horizon in quarters.

Similarly, the impulse responses coming from the instrumented-model local projection show a negative initial response of the unemployment rate given a contractionary monetary policy shock. The maximum response is reached after 14 quarters, but the increase in the unemployment rate is now above 0.5 pp.. Jordà (2005) obtains similar results with data from the US - peak impact on unemployment rate is achieved, through IV estimation, after 10 quarters with a value of 0.4 pp..

A possible explanation for the initial decline in the unemployment rate following a contractionary monetary policy shock could be attributed to anticipated and endogenous monetary policy movements. A similar explanation is given to the price puzzle - an empirical phenomenon where an increase in monetary policy rates leads to a slight decline in aggregate prices, contrary to the predictions of standard economic models (Christiano et al., 1999, pp.21-23). The result is valid for the first quarters, and an increase in prices is observed after a year and a half.

To interpret the puzzle in the response of prices, many papers consider the forward-looking behavior of economic agents - see for instance Tulip and Bishop (2017). Agents believe that an increase in policy rates today denotes an expected increase in inflation by the central bank. This in turn, leads to an increase in expectation of inflation in the future and today (p.3). Possibly, a similar mechanism causes the initial decline in unemployment following a contractionary policy shock. The increase in interest rates could be the endogeneous response to an expected decline in unemployment rates.

8.2 The Baseline Two-Variable SVAR Model

To compare the impulse response functions obtained from local projections with those obtained from SVAR models, I present the results of a two variable SVAR model including unemployment rate (u_t) and monetary policy (i_t). While the use of two variables might not allow for appropriate specification of the model, it might allow for a more accurate comparison between local projections and SVAR analyses. The reduced form model, shown below for one lag only, is set up as follows:

$$\begin{bmatrix} u_t \\ i_t \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \cdot \begin{bmatrix} u_{t-1} \\ i_{t-1} \end{bmatrix} + \begin{bmatrix} e_{u,t} \\ e_{i,t} \end{bmatrix}$$

Imposing short-run restrictions as in Sims (1980), the main assumption is that the unemployment rate responds with a one-period lag to the policy shock. On the other hand, policy responds contemporaneously to an unemployment shock. The moving average representation that allows for the Cholesky decomposition is:

$$\begin{bmatrix} u_t \\ i_t \end{bmatrix} = \begin{bmatrix} P_{11} & 0 \\ P_{21} & P_{22} \end{bmatrix} \cdot \begin{bmatrix} e_{u,t} \\ e_{i,t} \end{bmatrix} + \Gamma \cdot \begin{bmatrix} e_{u,t-1} \\ e_{i,t-1} \end{bmatrix} + ...$$

Such that:

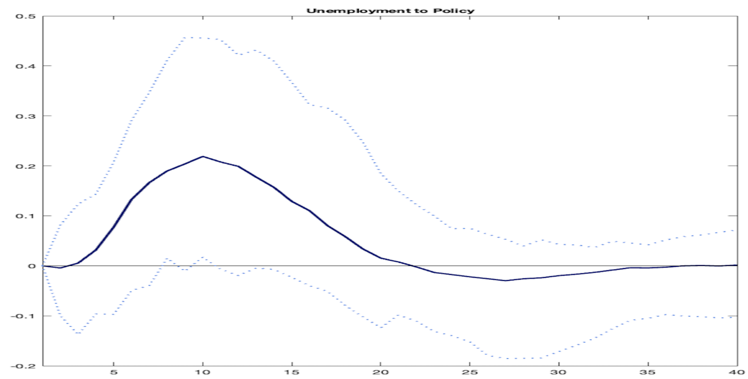
$$u_t = P_{11} \cdot e_{u,t} + 0 \cdot e_{i,t} + lags\ of\ all\ previous\ shocks$$

$$i_t = P_{21} \cdot e_{u,t} + P_{22} \cdot e_{i,t} + lags\ of\ all\ previous\ shocks$$

Note that the impact of $e_{i,t}$ on u_t is zero. The structural shocks are then retrieved through multiplication of reduced form shocks with the P' matrix.

8.2.1 Impulse Response Functions from a Two-Variable SVAR Model

The forecast horizon is set at 25 quarters and a constant and a trend component are accounted for in the analysis. Allowing for five lags in both variables we get the following results, where the bands allow for the 95 percent confidence intervals.



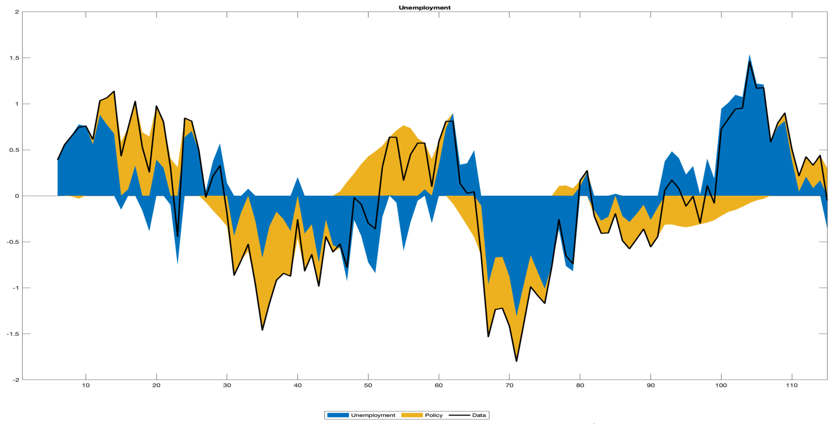
Note: Impulse response functions from a normalized monetary policy shock on unemployment rates, in a two variable SVAR model. Identification is achieved through zero short-run restrictions. The y-axis captures the percentage point change in unemployment at the given horizon, while the x-axis notes the forecasted horizon in quarters. Bands indicate 95 percent confidence intervals.

The impulse responses we get from this VAR model are aligned with the impulse responses of the local projection where the policy shocks are not instrumented. Response is borderline significant, while peak effect is reached after approximately 10 quarters, where the normalized monetary policy shock increases the unemployment rate by 0.2 percentage points. Results are similar to the previous analysis, even though local projections do not impose restrictions on the contemporaneous impact of any of the shocks in the system.

8.2.2 Forecast Error Variance Decomposition from a Two-Variable SVAR Model

The forecast error variance decomposition provides insights on the relative importance of each shock in explaining the variability of variables of interest over a forecast horizon (Bjørnland and Thorsrud, 2015, p.225). The provided graph decomposes the forecasted variance of the unemployment rate in variance due to unemployment shocks and variance due to monetary policy shocks.

The figure depicts how both shocks are of significant importance for understanding unemployment rate fluctuations. It seems however that unemployment is more strongly influenced by own shocks, than by monetary policy



Note: Forecast error variance decomposition for the unemployment rate in a two-variable SVAR model identified with short-run zero restrictions. The y-axis captures the size of the shock, while the x-axis notes the time horizon in quarters.

shocks.

8.3 The Baseline Proxy SVAR Model

As a complementary model, I provide the impulse response functions of a two-variable proxy SVAR, where monetary policy shocks are instrumented with the same narrative shocks used in the local projection, presented in Holm et al. (2020). The main assumptions require the narrative shocks to be correlated to the monetary policy shocks, but not to additional shocks that impact the system. In this case, not correlated to unemployment shocks. The assumptions are given as follows, where $\epsilon_{t,RR}$ are the narrative shocks of the Romer and Romer (2004) type:

$$(1)\ \textit{Relevance} \quad E[\epsilon_{i,t}, \epsilon_{t,RR}] \neq 0$$

$$(2)\ \textit{Exogeneity} \quad E[\epsilon_{u,t}, \epsilon_{t,RR}] = 0$$

If the instruments are not correlated with the variable they instrument for, they will not provide any information about the structural shocks. In this case the identification strategy will not be accurate (Cloyne, 2013, pp.1508-1510). The exogeneity assumption is also important because validity of the identification strategy relies on the instruments being uncorrelated with additional error terms in the SVAR model.

While noting that we are trying to estimate the two equations presented below, we can use external identification and reduced-form errors to estimate SVAR coefficients.

$$u_t = \sum_{s=1}^{s=5} \alpha_{1,s} u_{t-s} + \sum_{s=0}^{s=5} \alpha_{2,s} i_{t-s} + \epsilon_{u,t}$$

$$i_t = \sum_{s=0}^{s=5} \alpha_{2,s} u_{t-s} + \sum_{s=1}^{s=5} \alpha_{2,s} i_{t-s} + \epsilon_{i,t}$$

Reduced form residuals can be presented as a linear combination of structural shocks, as shown in (3) and (4) for unemployment and monetary policy. In addition, the first stage regression of policy shocks on external instruments helps identify (5). Through (4) and (5) we can identify γ_{21} up to a scaling factor (Mertens and Ravn, 2013, pp.1215-1217).

$$(3) : e_{u,t} = \gamma_{11}\epsilon_{i,t} + \gamma_{12}\epsilon_{u,t}$$

$$(4) : e_{i,t} = \gamma_{21}\epsilon_{i,t} + \gamma_{22}\epsilon_{u,t}$$

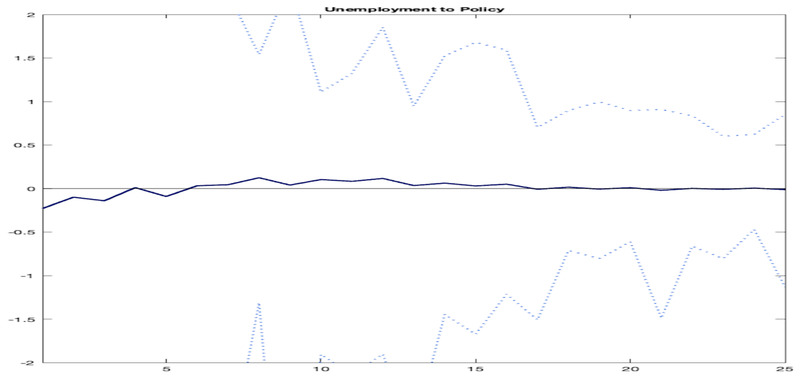
$$(5) : e_{i,t} = \sigma\epsilon_{t,RR} + \phi_t$$

Through the second stage regression, a regression of the reduced-form residual of the unemployment rate on the fitted value of $\epsilon_{i,t}$ from (5), we can identify the ratio of γ_{11} to γ_{21}. With the assumption of a normalized effect of γ_{21} on i_t, we can evaluate γ_{11} - capturing the response of the unemployment rate to the monetary policy shock in the reduced form equations. This methodology identifies structural shocks only up to a scalar.

8.3.1 Impulse Response Functions from a Proxy SVAR Model

In terms of the number of lags and variables included, no other changes are implemented in comparison to the SVAR model identified with short-term restrictions. The impulse response functions to a normalized monetary policy shock are graphed below. In the proxy SVAR model, no statistically significant impact of monetary policy on the unemployment rate is observed.

These results are conflicting with the response achieved through local projection impulse functions, even though the same narrative shocks are used for



Note: Impulse response functions from a normalized policy shock on unemployment rates, in a proxy two-variable SVAR model. Identification is achieved through external instruments, where policy shocks are instrumented with narrative shocks. The y-axis captures the percentage point change in unemployment at the given horizon, while the x-axis notes the forecasted horizon in quarters. Bands indicate 95 percent confidence intervals.

identification. It might be the case that the limited response of unemployment to monetary policy shocks - observed in local projections - is not fully captured in the proxy SVAR since identification is only possible up to a scaling factor. However, results can differ if the model is extended to include more variables.

8.4 The Baseline Five-Variable SVAR Model

As the impulse responses generated from a two-variable SVAR model may be insufficient to account for the variation observed in the unemployment rate, I expand the SVAR model by including GDP as a measure of real economic activity, GDP deflator as a measure of inflation, and the exchange rate of the Euro to the Norwegian krone -given Norway's status as a small open economy.

Many regression models assume a linear relationship between the predictors and the response variable. However, variables with a trend component may violate this assumption. To account for the positive time-trend, I use logged values for GDP, and log-differenced values for the implicit price deflator. Log-linearization can help decompose the series into a trend component and a cycle component. Controlling for the trend component, makes it easier to approximate output changes during the cycle. Additionally, difference logged series correspond to growth rates, which are often of interest for macroeconomic analysis (Bjørnland and Thorsrud, 2015, p.45; p.112). Graphs of the transformed series of GDP and GDP implicit price deflator are presented for completeness in the appendix (12.6). The rest of the variables are used in levels.

In the extended five-variable VAR model, the variables are ordered as follows: GDP, GDP implicit price deflator, unemployment, exchange rate, and monetary policy, all with a five-lag allowance. This ordering allows for the following zero short-run restrictions:

1. GDP responds contemporaneously only to own shocks.
2. The implicit price deflator responds to own shocks and shocks from GDP contemporaneously, but responds with a lag to all other shocks.
3. The unemployment rate responds to own shocks and shocks from GDP and the implicit price deflator contemporaneously, but responds to shocks from the exchange rate and monetary policy with a lag.
4. The exchange rate responds with a lag to monetary policy shocks only.
5. Monetary policy responds contemporaneously to all shocks in the system.
6. After the first lag, no restrictions are imposed on any of the shocks.

The moving average specification for this is:

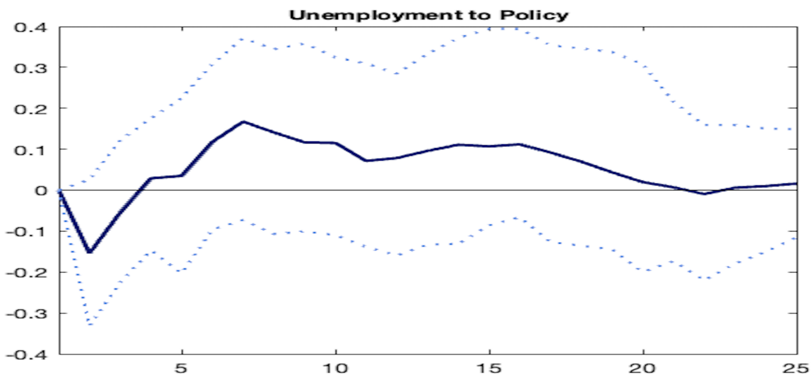
$$\begin{bmatrix} y_t \\ \pi_t \\ u_t \\ ex_t \\ i_t \end{bmatrix} = \begin{bmatrix} P_{11} & 0 & 0 & 0 & 0 \\ P_{21} & P_{22} & 0 & 0 & 0 \\ P_{31} & P_{32} & P_{33} & 0 & 0 \\ P_{41} & P_{42} & P_{43} & P_{44} & 0 \\ P_{51} & P_{42} & P_{53} & P_{54} & P_{55} \end{bmatrix} \cdot \begin{bmatrix} e_{y,t} \\ e_{\pi,t} \\ e_{u,t} \\ e_{ex,t} \\ e_{i,t} \end{bmatrix} + \Gamma \cdot \begin{bmatrix} e_{y,t-1} \\ e_{\pi,t-1} \\ e_{u,t-1} \\ e_{ex,t-1} \\ e_{i,t-1} \end{bmatrix} + ...$$

This variable ordering is based on various studies that consider the impact of monetary policy on macro aggregates and rank output first, inflation second, and monetary policy last. This is the case in Bernanke and Blinder (1992) and Christiano et al. (1999). The ordering of the unemployment rate and the exchange rate can be a matter of discussion. Furlanetto and Robstad (2019) order unemployment rate before the exchange rate in a SVAR model aimed at capturing the impact of an immigration-related labor shock. The assumption

I make is that the same ordering might still be relevant when analyzing a monetary policy shock.

8.4.1 Impulse Response Functions from a Five-Variable SVAR Model

The results obtained from this model are similar in size to those from the local projection, an approximate 0.2 pp. maximum impact reached after 7 quarters. However, in difference from the case with local projection, the responses are not statistically significant at any forecast horizon. Assuming the model is correctly specified, the results show negligible impacts of monetary policy on unemployment - especially in the short-run.

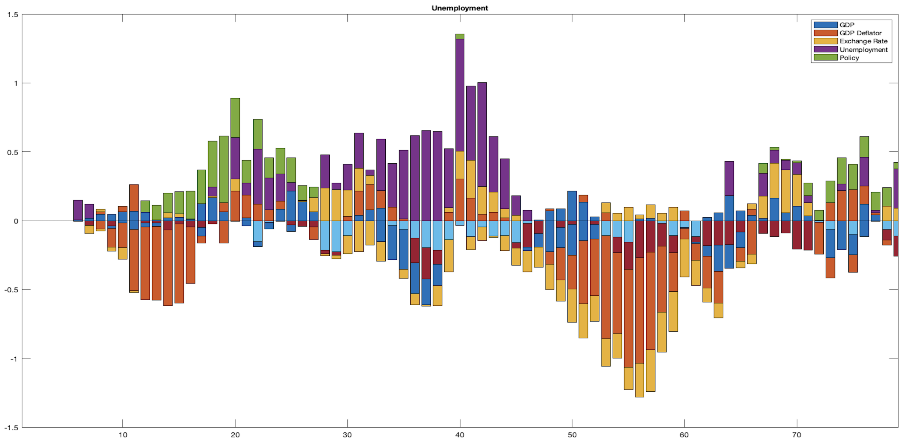


Note: Impulse response functions from a normalized monetary policy shock on unemployment rates. The underlying model is a five variable SVAR model including GDP, GDP price deflator, unemployment rate, exchange rate and monetary policy. Identification is achieved through zero short-run restrictions. The y-axis captures the percentage point change in unemployment, while the x-axis captures the forecasted horizon in quarters. Bands indicate 95 percent confidence intervals.

8.4.2 Forecast Error Variance Decomposition from the Five-Variable SVAR Model

The forecast error variance decomposition is included in the case of the five variable SVAR as well. We can see that policy shocks explain a small variation in the variance of unemployment rate. Unemployment responds strongly to own shocks and shocks to the value of GDP deflator. In a similar way, the forecast error variance decomposition for the policy rate shows that unemployment shocks explain little of the variation in policy, as seen in 12.7.

Quantitatively speaking, the forecast error variance decomposition plots illustrate that policy shocks do not explain any of the variation of the un-



Note: Forecast error variance decomposition for the unemployment rate in a five-variable SVAR model identified with short-run zero restrictions. Variables included are GDP, GDP implicit price deflator, unemployment rate, exchange rate, and monetary policy. The y-axis captures the size of the shock, while the x-axis notes the time horizon in quarters.

employment rate on impact, and explain almost 10 percent of the variation after 10 horizons. On impact, variance of the unemployment rate is explained almost 85 percent by own shocks. The rest of the variation is explained by the three remaining shocks in the system. Even after 25 forecast horizons, 50 percent of the variation in unemployment rates is explained by own shocks. Additional FEVD graphs are provided in the appendix (12.8).

9 Model Extensions

It might be interesting to check if the impact of a monetary policy shock on the unemployment rate is dependent on the current state of the economy. The use of local projections allows for the inclusion of interaction terms and non-linearities in the model, making this analysis possible (Jordà, 2005, p.167). In the following extensions I test whether the effect of a normalized monetary policy shocks on unemployment is more pronounced during periods of low interest rates compared to high interest rates, and whether the impact is reduced when unemployment levels are already high.

9.1 Monetary Policy Shocks in Low Interest Rate States

I recall once again that this thesis considers the time period from 1999 to 2019. A quick look at the interest rate graph in section 6.2 suggests that the period after 2009 is a low-interest-rate state. While there are some quarters of low interest rates at the beginning of the sample, it might be a good approximation to separate the high-interest-rate state and low-interest-rate state in the first quarter of 2009. I introduce a dummy variable, namely D_i, that takes the value of one in the low-interest-rate state and zero otherwise. The rest of the linear projection model remains unchanged.

$$u_{t+h} = \mu_h + \sum_{s=1}^{s=5} \alpha_{1,h} \cdot u_{t-s} + \sum_{s=1}^{s=5} +\alpha_{2,h} \cdot i_{t-s} + +\alpha_{3,h} \cdot D_i \cdot i_t + \epsilon_{t+h}$$

Initially, we were interested in capturing the α_2 coefficient, quantifying the impact of a normalized monetary policy shock on the unemployment rate. We are now also interested in the α_3 coefficient, capturing the additional impact of a monetary policy shock on the unemployment rate when interest rates are low. That is, we are considering a shock on the i_t value. Prior to 2009, the impact on the unemployment rate is given by α_2 at the forecast horizon h. After 2009, the impact is given by the sum of α_2 and α_3.

I find the α_3 coefficients to have a positive value that becomes statistically significant only after the 10 quarter. Quantitatively, the value of α_3 ranges from 0.18 pp. to 0.4 pp. That is, a normalized monetary policy shock has a significantly larger impact on the unemployment rate, if the interest rates are low. Knowing that values of the α_2 coefficient range from 0.12 to 0.3 pp., the interaction terms accounts for a considerable size of the impact.

9.2 Monetary Policy Shocks in High Unemployment States

In this model, I test whether the impact of a normalized monetary policy shock is dependent on the current level of unemployment. In the period considered, unemployment rate in Norway ranges from 2.1 to 5.1 percent. I generate a dummy variable, D_u, taking the value of one if unemployment is above the mean value of 3.75 percent, and zero otherwise. The estimated local projection is as follows:

$$u_{t+h} = \mu_h + \sum_{s=1}^{s=5} \alpha_{1,h} \cdot u_{t-s} + \sum_{s=1}^{s=5} + \alpha_{2,h} \cdot i_{t-s} + + \alpha_{4,h} \cdot D_u \cdot i_t + \epsilon_{t+h}$$

Similarly to the analysis presented above, the additional impact of a normalized monetary policy shock on the unemployment rate, when unemployment is already high, is captured by the α_4 coefficient. When the unemployment rate is low, the impact is captured by the α_2 coefficient.

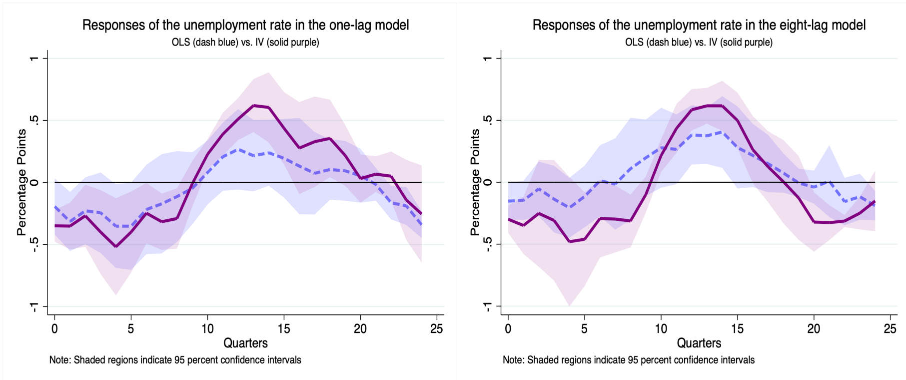
I find the α_4 coefficient to be of a negative sign, and statistically significant for only a few of the forecast horizons considered. The value of the coefficient ranges from -0.07 pp. to -0.2 pp. in the 16^{th} quarter following the shock. In the meantime, the value of the α_2 coefficient does not exceed 0.33 pp.. That is, the impact of a normalized monetary policy shock is of a smaller size when the unemployment rate is at a high level already. At such a state, the individuals employed are likely necessary in the market, and interest rate changes are not sufficient to further increase unemployment. The results speak for state-dependencies of policy shock outcomes.

10 Robustness Checks

In order to test robustness of the results for both the local projections and the five-variable SVAR models identified with short-run restrictions, I repeat the same IRF-generating procedure for a lag length of one and a lag length of eight. The use of one lag is suggested by the BIC test for the five-variable SVAR model. The choice of eight lags is made to allow for long-term influences of macroeconomic variables. Besides the lag choice, the rest of the models remain unchanged.

10.1 Testing Lag Lengths for Linear Local Projections

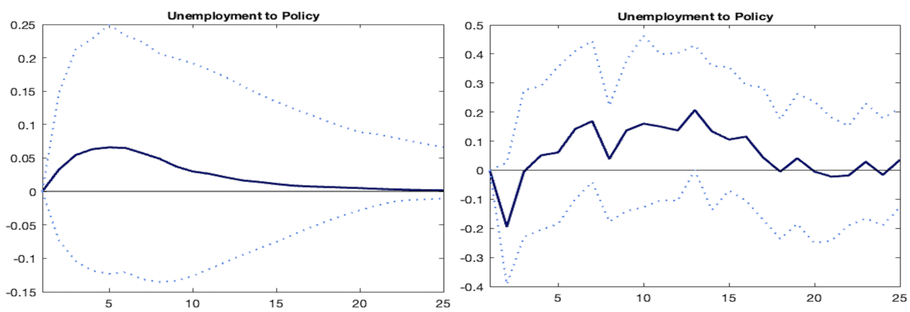
Allowing for one lag and eight lags in the local projection models leads to results that are almost identical to the five lag model. The response of the unemployment rate to monetary policy changes is similar in size and in the time horizon it materializes. The only difference lies in the smoothness of the impulse response functions and on the significance of the response from the local projection computed with OLS estimation in the eight lag model.



Note: Impulse response functions of the unemployment rate to a monetary policy shock in a local projection analyses. The model allows for one lag (left) and eight lags (right). The y-axis captures the percentage point change in the unemployment rate at the given horizon. The x-axis notes the forecasted horizon in quarters.

10.2 Testing Lag Lengths for SVAR Models

The impulse response functions from the five variable SVAR model differ slightly depending on the lag selection. Importantly, allowing for only one lag in all the variables seems to remove the initial decrease in unemployment following the contractionary monetary policy shock. Peak unemployment rate is achieved after five quarters, but in this case the size of the response is 0.05 percentage points. Responses from the eight-lag model are quite similar to the five-lag baseline model presented initially. In both models, the estimate does not appear to be statistically significant.



Note: Impulse response functions of the unemployment rate to a monetary policy shock in a SVAR model identified with short-run restrictions. The model allows for one lag (left) and eight lags (right). The y-axis captures the percentage point change in the unemployment rate at the given horizon. The x-axis notes the forecasted horizon in quarters.

10.3 Testing Polynomial Local Projections

An added benefit of local projections is that they allow for non-linearities in the underlying model. If uncertain about the underlying dynamics, diverging from linear models allows for potentially improved model fit and more accurate predictions. Following Jordà (2005) I extend the local projection model to allow for a polynomial of the third degree in the monetary policy rate. For reasons of parsimony, nonlinearities are restricted to the first lag (Jordà, 2005, p.167). Inclusion of only the first lag is also validated by the fact that impulses here are estimated after each forecast horizon. The model becomes:

$$u_{t+h} = \mu_h + \sum_{s=1}^{s=5} \alpha_{1,h} \cdot u_{t-s} + \sum_{s=0}^{s=5} + \alpha_{2,h} \cdot i_{t-s} + \alpha_{3,h} \cdot i_{t-1}^2 + \alpha_{4,h} \cdot i_{t-1}^3 + \epsilon_{t+h}$$

10.3.1 Impulse Response Functions from Polynomial Local Projections

I find the impulse response function of the polynomial local projection to be very similar to the result from the linear local projections. To avoid repetitive figures, the graph is provided in the appendix (12.5). One noticeable difference lies in the fact that peak impact on unemployment is observed after 11 quarters, as compared to 14 quarters in the linear local projection. The second difference is that estimates from the OLS model and estimates from the IV model are almost identical in the polynomial local projection. In the linear local projections, the two estimation methods lead to somewhat different results. Maximum impact on unemployment rate is 0.25 percentage points, confirming the value from the linear local projection estimated via OLS.

10.4 Testing Variable Ordering for SVAR Models

I conduct the same five-variable SVAR analysis with a slightly different ordering of the variables, so that the exchange rate is placed after the policy rate. In this scenario, the policy rate responds with a lag to the exchange rate but contemporaneously to all other shocks in the system. The unemployment rate responds with a lag to policy shocks and exchange rate shocks. Impulse response functions of the unemployment rate to a normalized monetary policy shock are traced in the appendix (12.9). Results are quite similar to those with the initial ordering. Peak unemployment rate is achieved after 10 quarters with a value of 0.5 percentage points. In this scenario as well, estimates are not statistically significant.

11 Conclusion

This thesis compares impulse response functions from local projections and from SVAR analyses to study the dynamic effect of a normalized shock to monetary policy on the unemployment rate. The main difference between the two approaches lies in their identification strategy. SVAR methodology uses economic theory or external information to identify the structural shocks that drive the system, whereas local projections rely on external shocks and offer flexibility for the underlying model specification.

The main result of the paper suggests a 0.2 percentage points increase in the unemployment rate following a normalized monetary policy shock, approximately 14 quarters after the shock. This results holds for a local projection specified as in Jordà (2005) and for a two-variable SVAR model identified as in Sims (1980). The local projection estimate is amplified when monetary policy shocks are replaced with Romer and Romer (2004) type shocks, leading to a peak 0.5 pp. increase in the unemployment rate. Surprisingly, I observe an initial negative response of the unemployment rate to a contractionary shock. An explanation similar to that of the price-puzzle is provided to account for possibly anticipated fluctuations of the policy rate. I find the impact of monetary policy to be dependent on the current state of the economy. The response to the shock increases when interest rates are low and unemployment levels are low. Results of the linear local projections are robust to various lag selections and polynomial specifications.

Extending the SVAR model to include additional series such as GDP, the GDP price deflator, and the exchange rate, amplifies the value of the response but the results do not appear to be statistically significant at any forecast horizon. The unemployment estimate is sensitive to the choice of one lag but not sensitive to the choice of eight lags. Forecast error variance decomposition tests suggests that monetary policy shocks explain only a small fraction of the variation in the unemployment rate - approximately 10% after 10 quarters.

As a conclusion of this thesis, and aligned with numerous previous studies, the unemployment rate shows a hump-shaped response to a monetary policy shock. The response is limited in size and materialized after a period of almost two years.

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12 Appendix

12.1 The New Keynesian Model

To trace the impact of a monetary policy shock on a standard New Keynesian model, I provide the set of equations that characterize the model as in Galì (2015). In what follows c denotes consumption levels, y output, i interest rates, π inflation levels, mc marginal costs, p price levels, w real wages, n hours worked, and a technology. Fluctuations are associated with two demand shocks, z - discount factor shock, and v- monetary policy shock. The only supply shock is on the level of technology, a. Shocks are assumed to follow a random walk.

$$(1) : c_t = E_t c_{t+1} - \frac{1}{\sigma}(i_t - E_t \pi_{t+1} - \rho) + \frac{1}{\sigma}(1 - \rho_z) z_t$$

$$(2) : \pi_t = \beta E_t \pi_{t+1} + \lambda(mc_t - mc)$$

$$(3) : i_t = \rho + \phi_\pi \pi_t + \phi_y \tilde{y}_t + v_t$$

$$(4) : w_t - p_t = \sigma c_t + \mu n_t$$

$$(5) : mc_t = w_t - p_t - a_t$$

$$(6) : y_t = a_t + n_t$$

$$(7) : y_t = c_t$$

The contractionary monetary policy shock this thesis considers enters as an increase in v_t in equation (3), leading to a direct increase in the interest rate. Due to higher interest rates, consumption today is more expensive - causing a decline in consumption through equation (1). In this simplified version of the model output equals consumption in every period as in (7). So output also declines following a contractionary monetary policy shock. Assuming there is no change in the technology level , a_t, hours worked decrease in equation (6). This is assumed to be the equivalent of a decline in employment rates.

12.2 Stationarity for the Five Variable SVAR Model

The following are the eigenvalues of the companion form matrix for the five-variable SVAR model including quarterly data from Norway on GDP, the GDP implicit price defalator, unemployment rates, exchange rates, and monetary policy. The model allows for five lags, a constant and a trend component. All eigenvalues obtained are less than one in absolute terms, indicating stability of the underlying model.

Companion Matrix Eigenvalues	
-0.0028	-0.9790i
-0.9809	+0.0000i
-0.8079	+0.0000i
-0.6526	+0.3691i
-0.6526	-0.3691i
-0.4112	-0.6108i
-0.4112	-0.6108i
-0.4705	+0.4519i

Note: Eigenvalues of the companion form matrix in a five variable SVAR model including GDP, GDP implicit price deflator, unemployment rates, exchange rates, and monetary policy. Maximal value (in absolute terms) is highlighted.

12.3 Time Series Cointegration

The figure is included to provide a visual representation of fluctuations of the unemployment rate and the monetary policy rate in Norway. The Engle-Granger cointegration test rejects the null hypothesis of no cointegration at the 10 percent statistical significance level.

Note: The series are quarterly unemployment rate and quarterly monetary policy rate in Norway from 1999 to 2019. The y-axis captures the values in percentages, while the x-axis notes time. Data is obtained from Statistics Norway and Norges Bank.

12.4 Lag Selection for the Five Variable SVAR Model

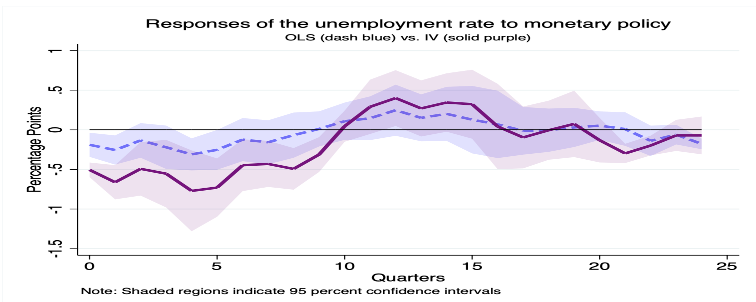
Akaike information criterion and Bayesian information criterion values for a five variable SVAR model including GDP, GDP implicit price deflator, unemployment rate, exchange rate, and monetary policy. Minimum value is achieved at the first lag for the BIC test and at the fifth lag for the AIC test.

Number of Lags	BIC	AIC
1	**42.8323**	42.0479
2	43.4128	41.8440
3	44.0763	41.7231
4	44.2965	41.1589
5	44.5029	**40.5808**
6	45.3517	40.6452
7	46.6365	41.1457

Note: AIC and BIC information criteria values for a five variable SVAR model including GDP, GDP implicit price deflator, unemployment rate, exchange rate, and monetary policy. Tests for model selection allow up to 7 lags, while minimal values are highlighted.

12.5 Impulse Response Functions from the Polynomial Local Projection

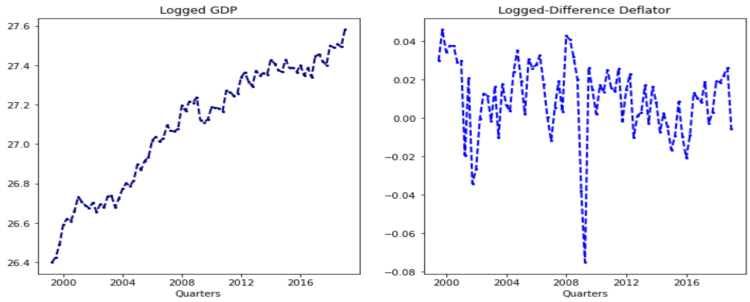
This model considers a regression of the unemployment rate on past values of unemployment and a cubic polynomial of monetary policy. For the unemployment rate and the linear values of monetary policy, five lags are allowed. For the quadratic and cubic monetary policy values, I allow for only one lag.



Note: Impulse response functions from a polynomial local projection analysis of a normalized monetary policy shock on the unemployment rate. The y-axis captures the percentage point change in the unemployment rate at the given horizon. The x-axis notes the forecasted horizon in quarters.

12.6 Logged Variables for the Five Variable SVAR Model

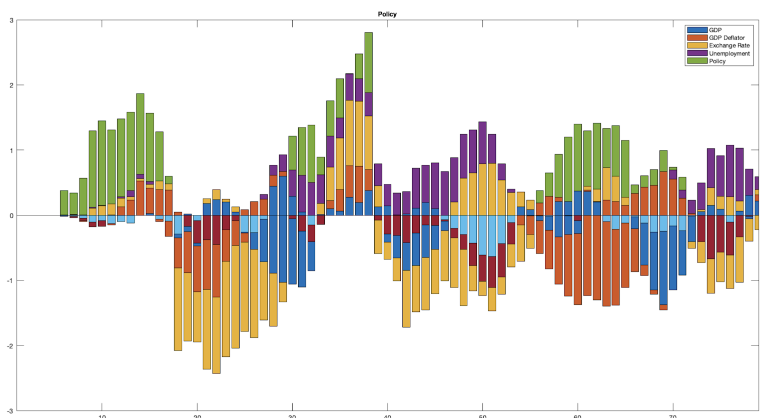
To account for the presence of a trend component in the time series, data on GDP is log-linearized and data on the implicit price deflator is logged-differenced. The quarterly change in the logged series is to be thought of as a growth rate.



Note: The series are quarterly logged GDP (left) and quarterly logged-difference GDP implicit price deflator (right) for Norway from 1999 to 2019. Data is obtained from Statistics Norway and FRED - respectively.

12.7 Forecast Error Variance Decomposition for the Policy Rate

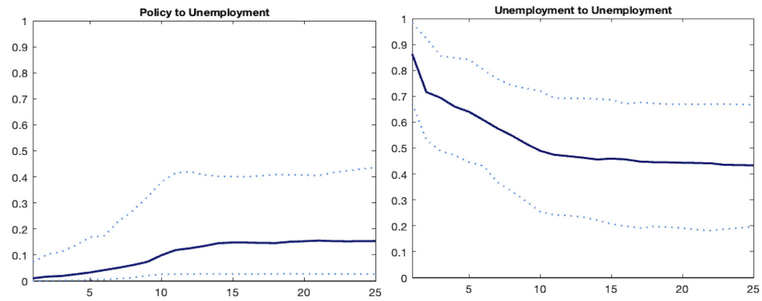
The forecast error variance decomposition of the policy rate in the five variable SVAR model shows that unemployment explains a significant amount of the variation, especially in the first quarters. Overall, it appears that, variation in the policy rate is explained more strongly by exchange rate variations.



Note: Forecast error variance decomposition for the policy rate in a five-variable SVAR model identified with short-run zero restrictions. Variables included are GDP, GDP implicit price deflator, unemployment rate, exchange rate, and monetary policy. The y-axis captures the size of the shock, while the x-axis notes the forecasted horizon in quarters.

12.8 Forecast Error Variance Decomposition for the Unemployment Rate

The graphs below provide insights on the percentage of the variation explained by each shock in the forecast error variance decomposition of the unemployment rate - for the five variable SVAR model. On impact, the policy shock explains almost none of the variation on unemployment, while approximately 85 percent of the variation is explained by unemployment shocks.



Note: Contribution of policy shocks (left) and unemployment shocks (right) to the forecast error variance decomposition for the unemployment rate. The y-axis captures the variation explained in percentage, while the x-axis notes the forecast horizon in quarters. The model is a five-variable SVAR model including GDP, GDP implicit price deflator, unemloyment rate, exchange rate, and monetary policy.

12.9 Robustness Checks for Variable Ordering

Impulse response function coming from a five variable SVAR model with the following order: GDP, GDP implicit price deflator, unemployment rate, monetary policy, and exchange rate. The model allows for five lags for each of the variables. Data for GDP is log-linearized and data for the price defaltor is log-differenced. The rest of the variables are used in levels. Assumption for identification are as follows:

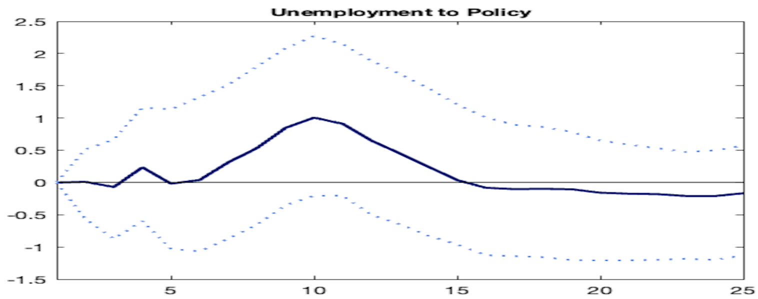
1. GDP responds contemporaneously only to own shocks.
2. The implicit price deflator responds to own shocks and shocks from GDP contemporaneously, but responds with a lag to all other shocks.
3. The unemployment rate responds to own shocks and shocks from GDP and the implicit price deflator contemporaneously, but responds to shocks

from the exchange rate and monetary policy with a lag.

4. Monetary policy responds with a lag to exchange rate shocks only.

5. Exchange rate responds contemporaneously to all shocks in the system.

6. After the first lag, no restrictions are imposed on any of the shocks.



Note: Impulse response functions of a normalized monetary policy shock on unemployment rate. Ordering of the variable is GDP, GDP implicit price deflator, unemployment rate, monetary policy, and exchange rate. Identification is achieved through zero short-run restrictions. The y-axis captures the percentage point change in unemployment at the given horizon, while the x-axis notes the forecast horizon in quarters. Bands indicate 95 percent confidence intervals.