

NHH



Evolving Monetary Policy Effects and Financial Turmoil In Norway

A Factor-augmented VAR Approach

by

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Abstract

In this paper we have analyzed how the effects of monetary policy in Norway might have been changing over time. In particular, we have paid special attention to how the impact of policy shocks on key economic variables (such as GDP, industrial production, consumption, CPI, stock price index and employment) have evolved around the time of the bankruptcy of Lehman Brothers.

By using a FAVAR framework based on a data set of 122 Norwegian variables and estimating the model recursively from 2000:M1 to 2014:M12, we show that the effects of monetary policy on our variables are indeed time-varying. The impulse responses of key economic variables to a monetary policy shock strengthen as we enter into a period of financial turmoil in late-2008. In general, we find that if a policy shock were to happen around late-2008 its cumulated impact on a variable after 50 months would be stronger than if the shock were to happen, say, before the crisis. It seems that the cumulated effect of a policy shock is the strongest precisely during the worst moment of the crisis - the period right after bankruptcy of Lehman Brothers.

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1 Introduction

The financial crisis that started in 2008 had severe impact on the world economy on several fronts. The crisis did not only lead to the worst worldwide economic contraction since the Great Depression, it also seemed to have impaired people's confidence in monetary authorities' ability to manage the economy [Mishkin, 2011]. Most notably, Nobel laureate Paul Krugman has long argued that the recent crisis had led the US. economy into a state in which the usual monetary policy tools, e.g. reducing short-term interest rate, "have lost all traction" [Krugman, 2008]. Other prominent economists such as John Cochrane¹ and Frederic Mishkin maintain, on the other hand, that aggressive cuts in policy rate by the US. Federal Reserve had not only been effective in limiting the repercussions of the crisis, but the policy actions had been even more potent than during normal times [Mishkin, 2009].

As the world economy starts to recover from the wounds of the recent crisis and policy makers around the world begin to end their "crisis regimes", we are presented with ample opportunities to evaluate the impact of monetary doctrines and policies. In this regard an accurate measurement of the effects of monetary policy tools is essential for the further discourse, and especially the question of monetary policy effectiveness during the crisis is becoming increasingly relevant.

The crisis in Norway is a particularly interesting case for several reasons. Firstly, in contrast to many developed countries, the impact of the recent crisis on the Norwegian economy has been limited, except for the stock mar-

¹For a spirited reply to Krugman's New York Times article "How Did Economists Get It So Wrong", see John Cochrane's blog post "How Did Paul Krugman get it so Wrong".

ket. Even during the height of the financial turmoil in 2008-2009, Norway suffered only a mild stagnation of one percent and had substantially lower unemployment than almost any comparable western economies [Grytten and Hunnes, 2010]. Secondly, in dealing with the crisis, Norges Bank (the Norwegian central bank) responded by only using conventional policy tools. During the initial stage of the crisis Norges Bank enacted significant cuts in its key policy rate. From 5.75 percent in October 2008 the key rate was reduced to record-low 1.25 percent a year later. Beside policy rate cuts Norges Bank also provided extraordinary liquidity measures to support the banking system, and did not see the need for unconventional measures of the type used by US. Federal Reserve. Thus, when analyzing policy actions in Norway the confounding factors presented by unconventional measures such as quantitative easing will not be present. Thirdly, compared to many other western countries the financial crisis in Norway was relatively short-lived. OECD declared, already in 2010, that Norwegian economy had avoided the immediate dangers of crisis and the authorities' main challenges were to withdraw the extraordinary monetary and fiscal measures in order to prevent overheating the economy [OECD, 2010]. The absence of a prolonged crisis means that the Norwegian economic time-series can be conveniently divided into "pre-crisis", "crisis" and "post-crisis" periods.

In this study we seek to provide an empirical analysis of how the effects of monetary policy in Norway might have been changing over time. More specifically, we seek to assess the effects of monetary policy shocks on key macroeconomic variables and evaluate whether these effects have varied over the pre-crisis, crisis and post-crisis periods.

With these goals in mind we adopt the factor-augmented vector autoregressive (FAVAR) approach of analyzing monetary policy effects. Since the pioneering work of Sims [1980], the vector autoregression (VAR) framework has been the workhorse in empirical analysis of monetary policy. This framework provides a systematic way to capture the rich dynamics in multiple time series and a coherent approach to policy analysis [Stock and Watson, 2001]. However, the low-dimension nature of these models ignores the usually large information set used by central banks. Therefore, measurement of policy innovation is likely to be contaminated [Bernanke et al., 2005]. The standard illustration of this problem is the "price puzzle", the common finding that a contractionary monetary policy shock induces a slight increase in the price level. Sims' explanation of the puzzle is that it is the result of imperfectly controlling for the extra information that the central bank has on future inflation. To remedy the shortcomings of low-dimensional VARs we choose the FAVAR framework, in which VARs are augmented with latent common factors extracted from a large data set of 122 economic variables.

The FAVAR model is estimated using a two-step principal component method developed by Bernanke et al. [2005]. In the first step, we estimate a small number of latent factors based on a version of the dynamic factor model outlined in Stock and Watson [1998, 2002]. In the second step, the estimated factors are used in a standard VAR in order to identify and measure the effects of monetary policy shocks. Finally, in order to allow for time-variation in policy effects we estimate the model recursively over the sample 2000:M1 - 2014:M12. That is, the FAVAR model is estimated repeatedly based on incrementally increased data sample length. Starting with a sample spanning

from 2000:M1 to 2007:M1, the FAVAR model is re-estimated repeatedly by adding one month of data at a time. In this way, we allow for heterogeneity in the estimated coefficients along the time dimension whilst keeping the computational cost manageable. In all, 96 estimations of FAVAR are done using sample length from 2000:M1 - 2007:M1 to 2000:M1 - 2014:M12. Subsequently, the changing effects of monetary policy is investigated by assessing the impulse responses of key economic variables to an one-standard-deviation shock in the policy variable. Since the recursive estimation provide a large number of impulse responses over time, we pool all responses to construct a contour/"heat" map so that both the time-variation and the magnitude of the responses can be assessed simultaneously. This procedure is done for six key economic variables: real GDP, industrial production, consumption expenditure, stock price index, consumer price index and employment.

Our results show that the effects of monetary policy on our variables of interest in Norway are indeed time-varying. Also, we find evidence that supports the notion that the impact of monetary policy is stronger at the height of the crisis. The impulse responses of all six variables to a monetary policy shock first remain rather homogeneous before the crisis and subsequently strengthen as we move into the crisis period. Further, for real GDP, industrial production, consumption expenditure and stock price index we find that the cumulated effect of a policy shock seems to be the strongest precisely during the worst moment of the crisis - the period right after bankruptcy of Lehman Brothers. That is, if a monetary policy shock were to happen around late-2008, its impact on the above-mentioned variables would be larger than otherwise. For instance, if an one-standard-deviation policy shock were to

happen on November 2008 its cumulated effect on real GDP after 50 months would be almost -0.60. If, instead, the shock were to happen on January 2007 the cumulated effect on real GDP would be only -0.15 after 50 months. For consumer price index and employment we find that even though the strongest responses do not coincide with the bankruptcy of Lehman Brothers there still seems to be a noticeable increase in the cumulated impact of monetary policy around that time.

This paper makes two contributions with respect to the related literature. First, as far as we are aware, this is the first attempt to combine a FAVAR model with time-varying recursive estimation to measure the changing impact of monetary policy in Norway. Second, our results are in line with and reinforce the existing studies done on the European level. For instance, Ciccarelli et al. [2013] show significant variation over time of the responses of GDP growth to a monetary policy shock, with peak impact on GDP during the height of the financial crisis being both significantly stronger and faster. Also, Bagzibagli [2012] shows that the global financial crisis leads to important variations in the responses of nominal variables such as price level and money supply.

The rest of this paper is organized as follows. In section 2 we provide a summary of the relevant background literature and theory. We present a number of existing empirical studies on monetary policy effects and a background for the FAVAR framework. Section 3 describes the theoretical foundations of our preferred econometrical framework. Section 4 first summarizes the choice and treatment of data used in the estimation, and subsequently describes some practical aspects of the implementation of FAVAR. In sec-

tion 5 we present the relevant output from the FAVAR estimation in the form of impulse responses. Moreover, we check the robustness of our results to changes in certain assumptions of the model. Finally, section 6 draws the main conclusions and presents possible extensions of our work for future research.

2 Summary of literature

2.1 Why look at shocks?

The central feature of our analysis is the assessment of monetary policy shocks. In this regard, the choice to focus on shocks when measuring policy effect should first be motivated. Why not simply analyze the actions of monetary policy makers?

Christiano et al. [1996] argued that monetary policy actions in the traditional sense reflect, in part, policy makers' responses to non-monetary development in the economy. These patterns of response are often summarized in feedback rules, which relate policy actions to the state of the economy represented by variables such as the inflation, real output and etc. To the extent that a policy action is the result of such feedback rule, the responses of economic variables following this action would represent the combined effect of the action itself and the variables that the policy reacts to. Therefore, to capture the effects of monetary policy *per se* one needs to isolate and identify the component of the policy that is not reactive to other economic variables.

An illustration of such feedback rules is a so-called "Taylor-type" rule [Taylor, 1993]. In its simplest form it relates the level of policy instrument (r_t) to important economic variables such as output gap and inflation gap,

$$r_t = \beta_y(y_t - y^*) + \beta_\pi(\pi_t - \pi^*) + \varepsilon_t, \quad (1)$$

where $(y_t - y^*)$ and $(\pi_t - \pi^*)$ denote output gap and inflation gap respectively. More generally, feedback rules that relate the policy instrument, e.g. key

interest rate, to the various elements in the economy can be expressed as

$$r_t = f(\Omega_t) + \varepsilon_t, \tag{2}$$

where the (unspecified) policy rule is given by $f(\Omega_t)$, and it characterizes the endogenous part of monetary policy. It gives the appropriate policy action based on policy makers' information set Ω_t , which potentially contains a large number of economic variables. The term ε_t then denotes changes in the policy instrument not based on the information set Ω_t . Consequently, ε_t is the part of monetary policy that fulfills requirement of not reacting to other economic variables. This component is often referred to as the exogenous part of policy action, or as an exogenous policy shock. Another common way of characterizing the different components of monetary policy is to denote policy makers' choice of reaction coefficients in $f(\Omega)$ (such as β_y and β_π from equation (1) when $f(\Omega_t)$ is specified) as systematic monetary policy, and ε_t as unsystematic policy. Hence, we follow Christiano et al. [1996] in interpreting the question "how does the economy react to a monetary policy action?" as "how does the economy react to an exogenous policy shock which represent the unsystematic part of monetary policy?".

On the note of the meaning of shocks, another clarification is needed. Hoover and Jorda [2001] pointed out that the usual method of analysing policy shocks and the way the results are interpreted (implicitly) assume policy actions to be unsystematic as well as *unanticipated*. More critically, there is often no clear distinction between the two terms. The implication is that the term ε_t is always a surprise. In a typical rational-expectation framework with surprise-only aggregate supply, it means unsystematic monetary policies

always have real effects.

Hoover and Jorda [2001] argued, however, that this equivalency between unsystematic and unanticipated policies is not necessarily always valid. If we consider the systematic elements of policies as what monetary authorities usually do, it is conceivable that certain policy actions might be both atypical (unsystematic) and predictable (anticipated). Hoover and Jorda [2001] pointed to the liquidity injection by the Federal Reserve in anticipation of the so-called "Y2K" demand as one such example. For our purposes it seems plausible that during a financial crisis the characterization of policies as both unsystematic and anticipated could again be applicable. During financial turmoils, especially one on the scale of what we recently witnessed, economic agents are likely to correctly expect monetary authorities to enact extraordinary, i.e. atypical, policies that match the severity of the crisis.

In a simple rational-expectation framework with surprise-only aggregate supply this would suggest we should expect unsystematic policies during crises to have negligible effects. However, the rational-expectation framework in its simplest form is a rather extreme case. Cochrane [1998] proposed a potentially more realistic intermediate version in which only a portion of economic agents form fully rational expectations while the rest do not. With such a model it can be shown that even unsystematic policies that are anticipated can be real effects². Thus, we base our expectation on this intermediate framework and anticipate unsystematic policies to have real effects, regardless of whether they are anticipated.

²See Hoover and Jorda [2001] for a simple algebraic illustration.

2.2 Strategies for isolating policy shocks

Having established the motivation for assessing monetary policy shocks the next step is to decide on a strategy to identify such shocks. Christiano et al. [1996] showed that there are, in general, two categories of strategy for isolating monetary policy shocks. The first is the so-called "narrative approach", pioneered by Friedman and Schwartz in their *Monetary History of the United States*. The central element of the narrative approach is the identification of monetary shocks through non-statistical procedures. It involves investigation of historical records, such as minutes of the monetary authorities' policy deliberations, to pinpoint decisions that might account for significant monetary disturbances. The goal is to identify episodes of large shifts in policy assumed not to be driven by development of the real economy.

Romer and Romer [1989] identified six shocks with this narrative approach in the post-World War 2 era. They showed that a shift to anti-inflationary policy led, on average, to a 12 percent reduction in industrial production and two percentage points increase in the unemployment rate. More recently, Romer and Romer [2003] combined narrative and quantitative records to produce a key interest rate "shock series" free of endogenous responses to economic developments. They found monetary policy shocks to have large and statistically significant effects on both output and inflation for the United States. Using the same narrative method Cloyne and Hurtgen [2014] demonstrated that a 100 basis point tightening of the Bank Rate in UK leads to a decline in output of 0.6 percent and one percentage point reduction in inflation after two to three years.

However, given the extensive use of policy makers' internal documents

the narrative approach to isolating policy shocks would not be suitable for our purposes. Thus, we will concentrate on the second category of strategy labelled the "vector autoregressive (VAR) approach".

2.3 The vector autoregressive (VAR) approach

Christopher Sims first introduced the VAR models in his influential 1980 article *Macroeconomics and Reality*. The new framework was intended as an alternative to the large-scale macroeconomic models in the tradition of the Cowles Commission. The new methodology grew out of a dissatisfaction with large scale models in which identification was achieved by excluding variables without theoretical justification [Bjornland, 2000]. The identification procedure of large-scale models contradicted the notion that often all of the macroeconomic variables in a complex system are endogenously and simultaneously determined.

A VAR, on the other hand, is a system of n -variables and n -equations in which each variable is determined by its own lagged values, and past values (and possibly current values) of the remaining $n - 1$ variables. Thus the VAR approach, in which all variables in question are endogenously determined, offers a more credible framework for empirical macroeconomic studies, without what Sims called "incredible" (non-justifiable) exclusion restrictions. VAR models also have the advantage of not requiring complete specification of the structure of the economy.

The VAR approach of isolating monetary policy shocks involves making enough identifying assumptions so that the monetary authorities' feedback functions can be estimated and thus isolating policy shocks [Christiano et al.,

1996]. Assumptions regarding a number of things must be made including the functional form of feedback rule, economic variables covered in the policy makers' information set and what primary policy instrument is. Most critically, assumptions must be made regarding the interaction between policy shocks and variables in the information set. One common identifying assumption is that policy shocks are orthogonal to these variables, the so-called recursiveness assumption. It implies that the correlation between policy shocks and other economic shocks is removed and, in practical terms, variables in the information set only respond to policy shocks with a lag.

Several other identification schemes exist such as long-run restrictions and sign restrictions. Long-run restrictions are based on theoretical long-run neutrality properties such as monetary policy shocks not having long-run impact on real economic activities. The idea is that if plausible long-run neutrality assumptions can be imposed, then reliable short-run inferences regarding the dynamics of the economy can also be drawn [Faust and Leeper, 1994]. In a similar fashion, sign restrictions entail assumptions on the dynamic reaction of certain variables, e.g. that prices do not increase after a contractionary policy shock.

Following the work of Bernanke and Blinder [1992] and Sims [1992], a substantial body of literature have used VAR methods to identify and measure effects of monetary policy shocks on macroeconomic variables. These VAR methods generally deliver empirically credible descriptions of the dynamic responses of the variables to monetary policy changes. Here, we only seek to provide a picture of the typical results from VAR analyses and give some illustrative examples due to the sheer size of VAR literature. Christiano et al.

[1999] and Auer [2014] showed that there is considerable agreement over the qualitative effect of a policy shock across a large number of identification schemes. A contractionary policy shock generally lead to fall in aggregate output, investment, employment, profits, monetary aggregates and various measure of wages. A range of empirical estimates have shown that one percentage point increase in policy instrument has effect on output and inflation at between 0.5 and 1.0 percent [Cloyne and Hurtgen, 2014]. For instance, using sign restriction Uhlig [2005] found that for the US economy a contractionary policy shock of one percent would lead to 0.8 percent decrease in GDP and decline in prices of 0.4 percent. With the same methodology, Mountford [2005] demonstrated a fall in GDP of 0.6 percent and a decline in GDP deflator of 0.15 percent for the UK economy. Koray and McMillin [1999] and Kim [2001], based on recursive identification scheme, found initial improvement and subsequent deterioration of the US trade balance following a contractionary policy shock.

2.4 Factor-augmented VAR approach

The VAR approach does not, however, lack for criticism. Bernanke et al. [2005] highlighted several shortcomings of the VAR methods. One major weakness of VAR models is the fact that they are small-scale models that incorporate relatively few variables. In order to conserve degrees of freedom in estimation a typical VAR rarely employ more than six to eight variables. This contradicts the fact that central banks monitor hundreds of data series when deciding on their policy stance.

There are mainly three problems with using sparse information sets in a

VAR model. First, if central banks and the private sector have information that is not reflected in the VAR, then the empirical results will most likely be polluted. The price puzzle mentioned in the introduction is often considered an example of such contamination. Secondly, using sparse information sets requires that we take a stand on which observable variables should represent more general economic concepts such as economic activity and inflation, which could often be a somewhat arbitrary exercise. For instance, the general concept of economic activity may not be perfectly covered by using real GDP or industrial production in a VAR. Finally, the impulse response functions can only be estimated for the small set of variables included in the VAR. This prevents the assessment of the dynamics of other variables that the central bank may care about, and thus limit our ability to have a more comprehensive evaluation of the economy.

Recent research on dynamic factor models suggests that a small number of factors can effectively summarize large amounts of information about economy. Therefore, a natural solution to the challenges faced by standard VARs would be to combine a VAR model with factor analysis. Bernanke et al. [2005] introduced the factor-augmented VAR framework in which a standard VAR is augmented with estimated factors that effectively summarize information from a large data set. The authors outlined two alternative estimation procedures; a two-step method based on principal components and a more computationally demanding Bayesian method based on Gibbs sampling. In general, both methods produced qualitatively similar results that are in line with economic theory. For example, a policy tightening would lead to decline in real activity, money aggregates and prices. The authors did find, however,

that the two-step method tends to produce more plausible responses. More interestingly, the price puzzle disappeared in the FAVAR framework, which provide some support for the view that the puzzle results from exclusion of conditioning information.

Stock and Watson [2005] found, using a two-step estimation method with principal components, results confirming the findings of Bernanke et al. [2005]. An increase in federal funds rate led to a decline in employment and industrial production of 0.5 percent and 1.0 percent, respectively. Also in line with the results of Bernanke et al. [2005], Bork [2009] used expectation-maximization algorithms to estimate the FAVAR and confirmed that using large information set solved the price puzzle. Moreover, Ahmadi and Uhlig [2007] estimated a FAVAR model using Bayesian estimation and identified via sign restrictions to show, compared to previous studies, qualitatively similar results. Blaes [2009] estimated a FAVAR model to find that in the short-run, portfolio shifts due to rise in the short-term interest rate may increase the money growth. However, in the long run the M3 is growing at a slower pattern due to a restrictive monetary policy.

3 Econometric framework

For the estimation of FAVAR we follow the two-step principal component approach used by Bernanke et al. [2005]. In the first step, we estimate a small number of latent factors based on a dynamic factor model using the principal component method. Subsequently, the estimated factors are used in a standard VAR model in order to identify and measure the effects of monetary policy shocks.

3.1 Dynamic factor models

Dynamic factor models were first proposed by Geweke [1977] as a time-series extension to the static factor models designed for cross-sectional data. Since the early influential work of Geweke [1977] and Sargent and Sims [1977] dynamic factor models has received considerable attention. Versions of the dynamic generalization of the classic factor analysis have been used by several researchers to study dynamic covariation among sets of economic variables³. The premise of a dynamic factor model is that a time-series variable can be seen as linear combination of a common component, driven by a small number of latent factors, and an idiosyncratic component. Moreover, it is the dynamic factors that drive the co-movements of a large number of variables.

Regarding the theoretical formulation of the model an important distinction must be made between an exact and an approximate formulation of a dynamic factor model. The exact formulation assumes the idiosyncratic component of the variables to be cross-sectionally and serially independent and

³See Stock and Watson [2010] for an excellent survey on dynamic factor models.

uncorrelated with the common factors. As Stock and Watson [1998] pointed out, these assumptions are rather implausible for most macroeconomic applications. Therefore, an approximate factor model which allows for moderate correlation between the common factors and the idiosyncratic components, and limited dependence among the latter may be more appropriate. Thus for our purposes we follow the approximate dynamic factor model as described in Stock and Watson [1998, 2002] and estimate the factors using the non-parametric principal component method⁴.

Let X_t be an N -dimensional multiple time series, observed for $t = 1, \dots, T$, where X_t is stationary and standardized to have zero mean and unit variance. We assume that X_t admits a dynamic factor model representation with \bar{r} common dynamic factors f_t ,

$$X_{it} = \lambda_i(L)f_t + e_{it}, \quad (3)$$

for $i = 1, \dots, N$, where $e = (e_{it}, \dots, e_{Nt})'$ is an $N \times 1$ vector of idiosyncratic disturbances and $\lambda_i(L)$ is a lag polynomial in non-negative powers of L . Importantly, $\lambda_i(L)$ is modeled to have finite orders of at most q , i.e. $\lambda_i(L) = \sum_{j=0}^q \lambda_{ij}L^j$, and equation (3) can be conveniently rewritten as

$$X_t = \Lambda F_t + e_t, \quad (4)$$

where $F_t = (f_t', \dots, f_{t-q}')'$ is a $r \times 1$ vector of static factors and Λ is an $N \times r$ matrix of loadings and the i th row of Λ is $(\lambda_{i0}, \dots, \lambda_{iq})$. Since the factors F_t appear to enter only contemporaneously, equation (4) is therefore referred to

⁴Stock and Watson refer to factors as "diffusion indexes".

as the static representation of the dynamic factor model.

The main advantage of this static representation is that the factors can be estimated using principal components. Moreover, this static form is not as restrictive as it seems in practice because F_t can be interpreted as including arbitrary lags of the dynamic factors f_t . Stock and Watson [1998] showed the theoretical results for the estimation of equation (4) by principal components. The principal component estimator of F_t is a weighted averaging estimator and is derived as the solution to the least squares problem⁵,

$$\min_{F_1, \dots, F_t, \Lambda} V_r(\Lambda, F) = \frac{1}{NT} \sum_{t=1}^T (X_t - \Lambda F_t)'(X_t - \Lambda F_t), \quad (5)$$

subject to the normalization $N^{-1}\Lambda'\Lambda = I_r$. Stock and Watson [1998] showed that the solution to this classical principal components problem is to set $\hat{\Lambda}$ equal to $N^{\frac{1}{2}}$ times the eigenvectors of sample covariance matrix corresponding to its r largest eigenvalues. Given the normalization, $\Lambda'\Lambda = NI_r$, the least square estimator of F_t is

$$\hat{F}_t = N^{-1}\Lambda'X_t, \quad (6)$$

which are the scaled first r principal components of X_t . Let \hat{Z} be the eigenvectors of the sample covariance matrix, the principal components estimator

⁵The actual formulation of the minimization problem here is slightly different than what is presented in Stock and Watson [1998]. In Stock and Watson [1998] the minimization is expressed in terms of the individual time-series variables X_{it} . Here, the minimization is expressed in terms of the vector of containing all variables X_t . Following Stock and Watson [2010] this formulation was chosen to give it a "cleaner" look.

of F_t is thus given by

$$\hat{F}_t = N^{-1}(N^{\frac{1}{2}}\hat{Z})'X_t \quad (7)$$

$$\hat{F}_t = \frac{1}{N^{\frac{1}{2}}}\hat{Z}'X_t \quad (8)$$

3.2 Determination of number of (static) factors

One important empirical question is how many factors should be extracted from the large set of economic data. Stock and Watson [2010] suggest to determine the number of factors by a combination of *a-priori* knowledge, visual inspection of the eigenvalues of the covariance matrix of the data set, and optimizing a particular information criterion. For instance, Stock and Watson [1998] showed with a simulation study that standard measures such as Akaike and Bayesian information criteria perform reasonably well.

More recently, Bai and Ng [2002] developed a class of estimators for r (the number of static factors) that are motivated by information criteria used in model selection. The authors propose information criteria that trade off the benefit of including additional factors against the cost of increased variability coming from estimating another parameter. Two classes of information criteria were introduced:

$$PC(k) = V(\hat{\Lambda}_k, \hat{F}_k) + kg(N, T) \quad (9)$$

$$IC(k) = \ln \left(V(\hat{\Lambda}_k, \hat{F}_k) \right) + kg(N, T) \quad (10)$$

where $V(\hat{\Lambda}_k, \hat{F}_k)$ is the sum of squared residuals from a k -factor⁶ model as

⁶Note that k denotes the assumed number of factors, while r denotes the true number.

defined in equation (5), $\hat{\Lambda}_k$ and \hat{F}_k are the estimated factors and loadings from the k -factor model, and $g(N, T)$ is a penalty function such that $g(N, T)$ goes to zero and $\min\{N, T\}g(N, T)$ goes to infinity as (N, T) goes to infinity. Several forms of the penalty function $g(N, T)$ were suggested:

$$g_1(N, T) = \left(\frac{N+T}{NT} \right) \ln \left(\frac{NT}{N+T} \right) \quad (11)$$

$$g_2(N, T) = \left(\frac{N+T}{NT} \right) \ln(\min\{N, T\}) \quad (12)$$

$$g_3(N, T) = \left(\frac{\ln(\min\{N, T\})}{\min\{N, T\}} \right) \quad (13)$$

A specific choice for $g(N, T)$ that performs well in simulation studies turns out to be $g_2(N, T)$ [Stock and Watson, 2010]. Following Stock and Watson [2010], the combination $IC_2(k) = IC(k) + g_2(N, T)$ will be used as the information criterion of choice:

$$IC_2(k) = \ln \left(V(\hat{\Lambda}_k, \hat{F}_k) \right) + k \left(\frac{N+T}{NT} \right) \ln(\min\{N, T\}), \quad (14)$$

and the combination $PC_2(k) = PC(k) + g_2(N, T)$ will be used as a check.

3.3 Factor-augmented VAR

Let Y_t be an $M \times 1$ vector of observable economic variables assumed to have pervasive effect on the economy. It is, however, plausible that there is additional economic information relevant to modelling of the dynamics of the economy that is not fully captured by Y_t . Suppose this additional information can be summarized by a $k \times 1$ vector of unobserved factors F_t , where k is small. Following Bernanke et al. [2005], we assume that the joint

dynamics of (F_t, Y_t) are given by:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t, \quad (15)$$

where $\Phi(L) = \Phi_1 + \Phi_2 L + \Phi_3 L^2 + \dots + \Phi_d L^{d-1}$ is a conformable lag polynomial of finite order d , Φ_j is the coefficient matrix and v_t is zero-mean errors with covariance matrix Q . Equation (15) is often referred to as the transition equation and Bernanke et al. [2005] denoted it *factor-augmented vector autoregression*.

Note that equation (15) cannot be estimated directly as the factors F_t are unobservable. Nevertheless, if we interpret F_t and Y_t as common forces that drive the dynamics of many economic variables, it is possible to infer something about the factors based on a large set of these variables. Let X_t be a $N \times 1$ vector of background or "informational" variables. The number of informational variables is large and will be assumed to much greater than the number of factors and observed variables. Following Bernanke et al. [2005], the relationship between informational variables X_t , unobserved factors F_t and observed variables Y_t can be expressed by an observation equation,

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \quad (16)$$

where Λ^f is an $N \times k$ matrix of factor loadings, Λ^y is an $N \times M$ matrix, and e_t is an $N \times 1$ vector of error terms that are mean zero and assumed to display a small amount of cross-correlation. Hence, conditional on Y_t , X_t can be viewed as noisy measures of the underlying unobserved factors

F_t . Note that equation (16) implies X_t only depend on current and not lagged values of factors. Just as the case for the static form of dynamic factor model in the previous section, this is not restrictive in practice since F_t can be interpreted as containing arbitrary lags of the fundamental factors. Equation (16), without the observable factors, can be seen as equivalent to the static form of dynamic factor model (4).

To estimate (15) and (16), we adopt the two-step principal components approach used by Bernanke et al. [2005]. This is a non-parametric way of uncovering the space spanned by the common components, $C_t = (F_t, Y_t)$, in (16). In the first step, C_t is estimated using the principal component estimator described in the previous section. Stock and Watson [2002] showed that when N is large and the number of principal components extracted is at least as large as the true number of factors, the principal components consistently recover the space spanned by F_t and Y_t . Next, F_t is obtained as the part of the space covered by C_t that is not covered by Y_t . In the second step, FAVAR (15) is estimated by standard procedures with F replaced by \hat{F}_t .

Furthermore, given that we are mainly interested in analyzing the impulse responses of various variables to monetary policy shocks we can rewrite equation (15),

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \iff \Phi^*(L) \begin{bmatrix} F_t \\ Y_t \end{bmatrix} = v_t, \quad (17)$$

where $\Phi^*(L) = I - \Phi(L)(L) = I - \Phi_1 L - \dots - \Phi_d L^d$. The advantage of

expressing equation (15) in this way is that the impulse response functions of F_t can be found as

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = v_t = \sum_{j=0}^{\infty} \Psi_j L^j v_t = \sum_{j=0}^{\infty} \Psi_j v_{t-j}, \quad (18)$$

where $\Phi^*(L)$ is assumed to be invertible and $[\Phi^*(L)]^{-1} = \sum_{j=0}^{\infty} \Psi_j L^j$. Next, the impulse response functions of each variable i in X_t can be calculated by the following transformation:

$$X_{it}^{IRF} = [\hat{\Lambda}_i^f \quad \hat{\Lambda}_i^y] \left(\sum_{j=0}^{\infty} \Psi_j v_{t-j} \right), \quad (19)$$

where $\hat{\Lambda}_i^f$ and $\hat{\Lambda}_i^y$ are factor loadings estimated for variable i according to equation (16).

4 Empirical analysis

4.1 Data

The data set consists of a balanced panel of 122 monthly macroeconomic time-series variables for Norway spanning from 2000:M1 to 2014:M12. The starting date of the sample was chosen for several reasons. Firstly, 2000:M1 was chosen to maximize both the length and the variety of Norwegian economic data in our sample. Secondly, it was chosen to approximately correspond with a regime change in Norwegian monetary policy. In 1999 Norges Bank abandoned its long-held fixed exchange rate regime and (unofficially) adopted flexible inflation-targeting⁷. Hence, the choice of 2000:M1 was made so to avoid having the data set straddle two different policy regimes and the potential effects of regime change on the underlying structure of the economy.

Further, we prefer to use monthly data instead of quarterly data because a balanced quarterly panel from 2000 to 2014 may not have enough observations to ensure precise estimation. Interestingly, Stock and Watson [2002] showed that factors can still be extracted from a data set with irregularities such as missing values, unbalanced panels and mixed sampling frequencies. In these cases standard principal component method described in previous section no longer applies. However, the expectation-maximization (EM) algorithm can be used to estimate the factors by solving a suitable minimization problem iteratively⁸. For our purposes we chose not to explore this option and work exclusively with monthly data due to the EM algorithm's computational complexity.

⁷The change was formalized in 2001 [Kleivset, 2012].

⁸See Stock and Watson [2002] Appendix A for details.

The data set is chosen to reflect a broad range of economic concepts such as economic activity, prices and other financial indicators. The individual series are chosen from the following categories: real output, employment and earnings, real consumption, housing starts, price indices, exchange rates, interest rates, stock price indices, money aggregates and credit conditions, and confidence indicators⁹. Most of the non-financial series are taken from Statistics Norway's (SSB) StatBank, while the financial series such as stock prices and interest rates were taken from Oslo Stock Exchange, Norges Bank's data bases and/or Bloomberg.

The data are processed in the following ways. First, as seasonal patterns for some variables could be large enough to muddle the variables' underlying dynamics, the series are seasonally adjusted. Note that financial variables such as stock prices, exchange rates and interest rates are not seasonally adjusted as we do not believe they have seasonal patterns. The adjustment is done by either choosing series that are already adjusted or by estimating the seasonal effects and removing them "manually". For the manual adjustment the X-13-ARIMA program published by US. Census Bureau is used¹⁰.

Second, given that a number of important economic variables are only available at a quarterly frequency (e.g. consumption and employment) these variable have to be temporally disaggregated into monthly figures to ensure a balanced panel. In the statistical literature, there are two broad categories of approaches to disaggregate low-frequency data into compatible higher frequency data: (1) mathematical algorithms which ensure a smooth

⁹See Appendix A for a list over all series and their transformation

¹⁰More specifically, we used X-13's R interface, downloadable at the US. Census Bureau's home page.

and continuous curve through the lower frequency benchmark points, and (2) statistical procedures which uses related higher frequency data to construct new time-series that is consistent with the low frequency data whilst preserve the short-term movements in the related higher frequency series [Chamberlin, 2010]. Given that we have a large data set with a number of variables that need to be disaggregated, identifying proper related higher frequency data for all quarterly series was considered be too time-consuming¹¹. Therefore, we choose to use the purely mathematical method to disaggregate the quarterly series. The disaggregation is done by using the ECOTRIM software published by Eurostat, and the Denton¹² method without related series was the algorithm of choice.

Third, since the theoretical models presented in the previous section assume X_t to be $I(0)$ the series were transformed to induce stationarity. The decision to take logarithm and/or differences is based on unit root tests, more specifically the augmented Dickey-Fuller test. Given that the augmented Dickey-Fuller test has been shown to be somewhat sensitive to the number of lags included in the test, the Ng and Perron's sequential-t algorithm is used to determine the optimal number of lags for each variable first. In general, first differences of logarithms are taken for all non-negative series that are not already expressed in rates or percentage units, and first differences are taken for series already in percentage units. Where first differences were not

¹¹Note, however, that there exist a compromise between identifying related higher frequency indicators for each quarterly variable and purely mathematical approaches. Angelini et al. [2006] use the estimated factors as related indicators in the disaggregation and demonstrated this factor approach has reasonably good performance.

¹²See Chamberlin [2010] for details on Denton method.

enough to induce stationarity second differences are taken¹³. Moreover, the same type of transformation is generally taken for all variables in the same category (e.g. first differences of logarithm were taken for all consumption series).

Lastly, following the standard procedure in principal component analysis all series was standardized to have zero mean and unit variance. This is done so that all series are on the same scale, and the same variance will make sure that the principal component analysis will not be biased towards variables with large variances.

In regard to data another interesting question is what the "optimal" composition of the data set should. As mentioned earlier, our data set is collected to reflect a number of economic concepts. In choosing the specific series we largely follow Bernanke et al. [2005] and other comparable empirical studies. But, a composition of series that is appropriate for factor analysis for the US. or Europe might not be optimal for the Norwegian economy. Hence, there is a risk that we have an unknown number of "noisy" variables that do not contribute to the common components, or that they are other important variables specifically for the Norwegian economy that we have not included. Also, Boivin and Ng [2006] suggests that little is known in the literature about how the size and the composition of data affect the factor estimates. They suggest a method to pre-screen the data set in order to remove "superfluous" variables, and found that factors estimated from as few as 40 pre-screened variables had better predictive performance than using the full set of 147 series. However, for our purposes, we do not find this

¹³If second differences still cannot induce stationarity the variable was dropped.

kind of pre-screening appropriate. This is because pre-screening reduces the benefit of time-varying estimation. Since it might well be that certain variables considered to be superfluous at one time can become very important at another time.

4.2 Empirical implementation

4.2.1 Choice of policy variable

An important question when estimating a FAVAR (or a standard VAR) model is what variable should be considered the most appropriate measure for monetary authority's policy stance, and thus be interpreted as *the* key policy instrument (since most central banks have several policy instruments at their disposal). In literature several instruments have been considered; reserve requirements for the banking sector, monetary aggregates such as M2, direct lending by the central bank, and even unconventional measures such as quantitative easing. Still, the most common choice of key policy instrument is some short-term interest rate controlled by the central bank.

Bernanke and Blinder [1992] were among the first to argue that the federal funds rate was a good indicator of US. monetary policy. Since then, the bulk of empirical research on US. monetary policy has modeled the un-forecasted innovations of the federal funds rate as monetary policy shocks. In the euro area, the ECB repo rate has often been considered the key policy variable. In the case of Norway, the obvious choice would be Norges Banks sight deposit rate¹⁴ because Norges Bank explicitly states the deposit rate as its key policy rate.

¹⁴Which is the interest rate on banks' deposits up to a quota.

Here, we follow the convention in empirical studies that an effective rate is used in the estimation rather than the actual target rate. For the US., the effective federal funds rate is often used instead of the target federal funds rate. In the euro zone, the Euro Overnight Index Average (EONIA) is often the preferred proxy for the ECO repo rate. In the case of Norway, a good candidate for the proxy would be the Norwegian Overnight Average rate (NOWA), which is an index rate calculated by Norges Bank based on interbank transaction records. Unfortunately, NOWA is only available from 2011 and therefore not suitable for our applications. Therefore, the 3-month Norwegian Interbank Offered Rate (NIBOR) was chosen as proxy for the key policy rate, because it tends to follow the sight deposit rate reasonably well. Further, other studies on the Norwegian economy using VAR models such as Bjornland and Jacobsen [2009] and Robstad [2014] have also used 3-month NIBOR as a proxy for monetary policy. Moreover, we assume the short-term policy rate to be the only observable factor in the economy, i.e. Y_t contains only the policy interest rate. This means we assume that the policy interest rate does not suffer from measurement error issues, and other variables commonly included in VARs such as industrial production and price indices do.

4.2.2 Identification of (FA)VAR

As in a standard VAR, some identifying restrictions must be imposed on the FAVAR in order to properly identify the monetary policy shocks. This is because using unrestricted VAR for structural analysis could be extremely risky as the un-forecasted innovations in the VAR system might be correlated

with each other and hence making the interpretation of the effects of these innovations very difficult. For our purposes we follow Bernanke et al. [2005] and assume the simple recursive structure in which the factors in equation (15) respond only with a lag (i.e. they do not respond contemporaneously) to shocks in the monetary policy variable. This identification scheme entails that the policy instrument is ordered after the factors in equation (15), and treats its innovations as policy shocks.

As we mentioned in literature summary, there are other identification schemes available to be imposed on a VAR such as sign restrictions, long-run restrictions, some combinations of long and short-run restrictions and etc. Bernanke et al. [2005] stress that there is in principal nothing, other than computational constraints, that prevents using other, non-recursive identification schemes in a FAVAR. Nevertheless, the recursive identification, with its non-requirement of a complete structural model of the economy, have been shown to deliver empirically believable results. Therefore, we consider it to be a valid point of departure. Also, an optimal lag length for the (FA)VAR equal to 1 is chosen with the Schwarz-Bayesian criterion and the Hannan-Quinn criterion.

4.2.3 Identification of factors

As previously described, in order to estimate the FAVAR model (equations (15) and (16)) we apply the two-step principal components approach developed by Bernanke et al. [2005]. The two-step approach is a non-parametric way to consistently recover the space spanned by both the unobserved factors F_t and the observed factor Y_t , $C_t = C(F_t, Y_t)$.

In the first step, the common components \hat{C}_t are estimated using the first $k+1$ principal components¹⁵ of X_t . However, it would be incorrect to estimate a VAR in \hat{C}_t and Y_t directly. This is because \hat{C}_t also contains the observed factor Y_t and our choice of the recursive identification scheme described in the previous subsection require factors not to be contemporaneously affected by the Y_t . Therefore, the two-step estimation requires first controlling the part \hat{C}_t that corresponds to the policy interest rate. Following Bernanke et al. [2005], this is achieved in the following way.

Firstly, the data set is divided into a group of "slow-moving" variables and a group of "fast-moving" variables. The slow-moving variables (e.g. industrial production) are those that are largely predetermined within the current period, while fast-moving variables (e.g. stock prices) are those that are more sensitive contemporaneous shocks. Secondly, "slow-moving" factors $\hat{C}^s(F_t) = \hat{F}_t^s$ are extracted as principal components of the slow-moving variables. Thirdly, the following regression,

$$\hat{C}_t = \beta_f \hat{F}_t^s + \beta_y Y_t + e_t, \tag{20}$$

is estimated. Finally, the factors \hat{F}_t are constructed as $\hat{C}_t - \beta_y Y_t$. With the factors \hat{F}_t we can now estimate the (FA)VAR in \hat{F}_t and Y_t , with recursive ordering, according to equation (16).

¹⁵Note that in the general formulation of the model \hat{C}_t is estimated by the first $k + M$ principal components. Remember that we assume policy interest rate to be the only observable factor in the economy, i.e. we set $M = 1$ and Y_t is the policy interest rate

4.2.4 Number of factors

Applying the Bai and Ng [2002] criteria to determine the optimal number of (static) factors yielded some rather peculiar results. Using the main specification of $IC_2(k)$ and calculating for $k = (1, 2, \dots, 15)$ showed that $IC_2(k)$ is minimized for $k = 1$, indicating that in our data set only one static factor exists. Calculating for $PC_2(k)$ for $k = (1, 2, \dots, 15)$ gave the conclusion. However, further testing using $k = 1$ showed that one factor only explains about 9.8 percent of the variation in our set of 122 variables. Moreover, individually regressing important variables such as GDP, industrial production and consumption with $k = 1$ according to equation (16) showed abysmal adjusted R^2 around 2 to 5 percent. One factor does not seem to explain enough of the variations in the data to yield empirically meaningful results.

In order to explore this further, we employed the other specifications suggested by Bai and Ng [2002]. The following results emerge: (1) $IC_1(k)$ gives $k = 3$, (2) $PC_1(k)$ gives $k = 1$, (3) $IC_3(k)$ does not stop decreasing as k increases, and (4) $PC_3(k)$ gives $k = 4$. The diversity in these results and the one factor's inability to explain the variables makes us feel less confidence in trusting optimal k really is 1.

There may be several reasons for these peculiar results. Firstly, the Bai and Ng [2002] criteria were developed for when $N, T \rightarrow \infty$, i.e. they work well only if the number of periods (sample length) and the number of variables go to infinity. Since our data set is far from having those dimensions it may explain the rather inconsistent results based on these information criteria. Secondly, as mentioned before the composition of our data set was based on other empirical studies for other countries and thus may not be "optimal"

for the Norwegian economy. That is, the data set might contain too many "noisy" variables that do not contribute to the average common component of the data set. As more "noisy" variables are added to the data set the average common component becomes smaller so that the precise estimation of the factors become more difficult. Therefore, we do not seem to be able to determine the optimal number of factors based on the Bai and Ng [2002] criteria.

Still, trusting the Bai and Ng [2002] criteria exclusively in deciding the optimal number of factors may not be unproblematic either. Bernanke et al. [2005] stress that these information criteria only seek to plausibly determine the number of factors present in the data. They do not, however, address the important question of how many factors should be included in the (FA)VAR in order to properly identify effects of monetary policy. Therefore, Bernanke et al. [2005] determined the number of factors included in the FAVAR in a more *ad hoc* fashion. Bernanke et al. [2005] used three factors as their base specification and found that increasing the number of factors beyond five did not change the qualitative nature of their results. Several other studies such as Shibamoto [2007] and McCallum and Smets [2007] employed the same strategy. Consequently, we also determine the number of factors in an *ad hoc* way. We identified $k = 6$ as a somewhat reasonable compromise between having too few factors and not being able to explain the data on the one hand, and choosing too many factors and overfitting the FAVAR on the other hand¹⁶. With $k = 6$ around 36 percent of the variation in the data set can be explained.

¹⁶Also, for simplicity, we assume the number of factors among the slow-moving variables is the same as for the entire set.

4.2.5 Time-varying estimation

The aim of this study is to assess how the effects of monetary policy have changed over time, especially compared with the situation at the peak of the crisis. However, the theories outlined in the previous sections are all based on the assumption of time-invariant coefficients. Both the Stock and Watson [1998] theories regarding dynamic factor model and the Bernanke et al. [2005] FAVAR model assume the estimated coefficients to be constant over time, which implies the effects of monetary policy are also constant. Nevertheless, the fact that studies such as Bagzibagli [2012] and Ciccarelli et al. [2013] demonstrated increased effects of monetary policy during the crisis for the euro area leads us to believe such effects may also exist in Norway. Hence, we need a strategy to capture potential heterogeneity along the time dimension.

Following Ciccarelli et al. [2013], we allow for time-variation in the coefficients by adopting the technique of estimating our model recursively over the sample 2000:M1 - 2014:M12. This technique allows us to study the nature of time-variation while keeping the computational costs manageable. It entails repeated estimation of the model outlined in the previous section, based on incrementally increased sample length. That is, the first estimation is run over a sample starting at 2000:M1 and ending at, say, 2007:M1. In all subsequent estimations we add one month of data at a time, until the last period of 2014:M12. In this way, we can identify the marginal effects of additional data and assess the evolution of some key economic relationships when moving from "normal" to "crisis" times.

The bankruptcy of Lehman Brother on September 2008 has often been considered to mark the start of the global financial crisis. Looking at some

Norwegian economic data it is worth noticing that variables such as the benchmark stock price index and industrial production for the manufacturing sector also peaked and started to decline rapidly during the mid-2008. As such mid-2008 seems to be a reasonable candidate for the start of the crisis.

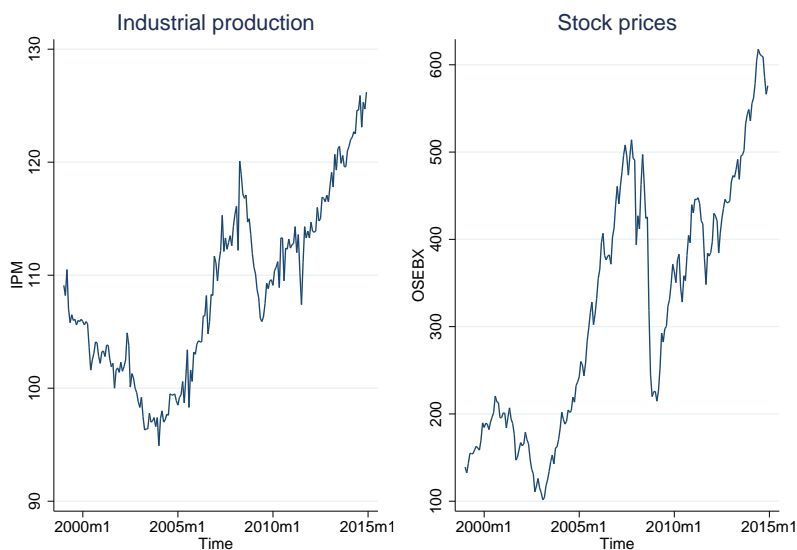


Figure 1: Development of industrial production and stock prices over time

Since an investigation of the crisis period necessarily requires a comparison with "non-crisis" periods, the sample of the first estimation must end before mid-2008. Therefore, we choose to set the sample for the first estimation to be 2000:M1 - 2007:M1 and the last estimation period to be 2000:M1 - 2014:M12. In this way the recursive estimation will loop through "pre-crisis", "crisis" and "post-crisis"¹⁷ periods, and a comparison between the crisis and the non-crisis periods can be made. Hence, our repeated estimation procedure will begin with 2000:M1 - 2007:M1, add one month of data at a time

¹⁷Remember that OECD declared already in 2010 that Norway was out of the crisis.

and loop through 96 different sample lengths until the last one 2000:M1 - 2014:M12¹⁸. The changing effects of monetary policy will be investigated by looking at the impulse response of a number of important economic variables to a monetary policy shock. Following Fernald et al. [2014], we choose to investigate the cumulative impulse responses because, as it turns out, the cumulated responses make visual examination of the changing monetary effects easier.

For each of the 96 estimations, the procedure will perform factor extraction, estimate a FAVAR using the estimated factors and calculate impulse response functions for a particular variable. Subsequently, we pool the 96 impulse responses over all sample periods for that variable together, and construct a contour map or a "heat map" which can be examined visually to assess how effects of monetary policy have changed over these years. This procedure is applied on the following collection of key economic variables: real GDP, industrial production, consumption, employment, consumer price index, and Oslo Stock Exchange benchmark index.

¹⁸An algorithm in Stata was designed so that the estimations and looping is done automatically. See the computational appendix for more details.

5 Results

5.1 Impulse responses

In this section we present the estimation results in the form of pooled cumulative impulse responses of our six variables to one-standard-deviation contractionary policy rate shocks. First, as a demonstration of the typical results from cumulative impulse response functions figure (2) shows the cumulated impulse responses of real GDP and consumption expenditure to a tightening in monetary policy rate.

Figure (2) shows the responses at one point in time and they come from an estimation over the first sample period, 2000:M1 - 2007:M1. The impulse responses seem to be in line with what we might expect from economic theories: both real GDP and consumption expenditure slow in response to a monetary tightening. The magnitude of the fall seems, however, to be much larger for consumption than for real GDP. Figure (2) shows that if a contractionary monetary policy shock were to happen on 2007:M1, cumulated effect on GDP after 50 months would be -0.15, while the cumulated effect on consumption after 50 months would -3.5.

The cumulated impulse responses for the rest of the variables under consideration follow the same patterns, i.e. they are in line with economic theory and other empirical studies. It is, however, worth noticing that not all 122 variables in the data set yield plausible results. Producer price index, for instance, gives the unintuitive result that monetary tightening seems to increase producer prices. This could be due to some misspecification in the model or be attributed to data set having too many "noisy" variables since

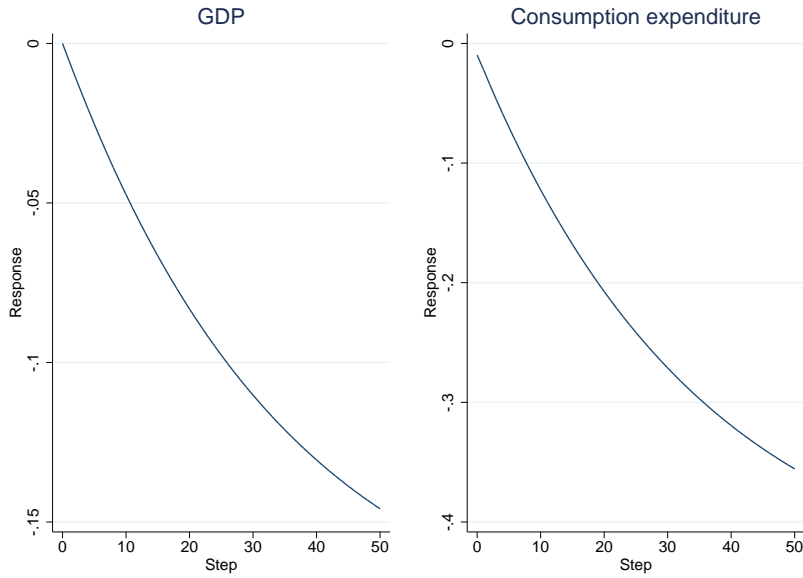


Figure 2: Cumulated impulse responses for GDP and consumption expenditure

six factors only explain around 36 percent of all variation in the data. Hence, for certain variables the model does not seem to be able to properly identify their responses to monetary policy shocks.

After having obtained the cumulative impulse responses (of the type shown in figure (2)) for a particular variable the next step is to investigate whether the responses have changed over the course of the financial crisis. Figure (3) to (8) show the contour or "heat" maps for each of the six variables. Each of these heat maps pool together the (cumulative) impulse responses for one variable from all of the repeated estimations and thus capture the potential time-variation in the impulse responses. The horizontal axis of the heat map shows the number of periods after a monetary policy shock has occurred and has the same meaning as in a standard impulse response graph.

The vertical axis indicates the different estimation periods outlined in the previous section. Since all estimation periods have the same starting date, 2000:M1, the vertical axis shows the end date of the sample. Previously, we defined the sample for the first estimation to be 2000:M1 - 2007:M1, so 1 on the vertical axis correspond with a sample length of 2000:M1 - 2007:M1 and 2 indicates 2000:M1 - 2007:M2 and so on. So that the result at each month show the response of the variables of interest based on the information until that month. The different colors indicate the magnitude of the responses, as the scale on the right-hand side defines the different levels of magnitude of response and their corresponding colors. As the colors go from dark blue to red, so "increases" the magnitudes of the response of a variable to a monetary policy shock. To assess potential time-variation in the responses one should pay particular attention to the part of the heat map to the right (near or at step = 50) where the map shows the cumulative responses of a variable around 50 months after a policy shock has occurred.

Figure (3) shows impulse responses of real GDP estimated at different moments during and around the financial crisis, and the cumulated impulse response for GDP displayed in figure (2) is expressed as the lowest horizontal stripe (end date = 1) in figure (3). Interestingly, for real GDP there are clear time-variation in impulse responses and some distinctive phases emerge. First of all, for estimations with end dates in 2007 (end date < 12) their strongest responses at step = 50 tend to be smaller and more muted than for end dates beyond 2007, as indicated by the blue colors in the beginning of the sample. Secondly, for a couple of months right after August 2008 (end date > 20) there seems to be a rather clear increase in cumulative effects of monetary policy

shock, as the cumulative effect at step=50 quickly changed from around -0.2 to ca. -0.6 and then back again at -0.2 (as indicated by the change of color from light blue to dark red). As an illustration, if an one-standard-deviation policy shock were to happen on November 2008 its cumulated effect on real GDP after 50 months would be almost -0.6, the strongest response for all sample. If, instead, the shock were to happen on January 2007 the cumulated effect on real GDP would be only -0.15 after 50 months. The most interesting point here is that the strongest responses for real GDP also roughly coincides with the bankruptcy of Lehman Brothers in late 2008. This period is considered dramatic even for Norway as Norwegian stock prices fell rapidly in the second half of 2008 and money markets periodically ceased to function. It seems the impact of monetary policy strengthens precisely at the worst moment of the crisis. Thirdly, the second half of the sample from around 2010 (end date > 40) seems much more homogeneous than the first half, as both the timing and the magnitude of the responses stay quite stable. This is interesting since we consider Norway to be out of the crisis period after 2010. In all, the responses of real GDP there seems to provide evidence for time-variation and that the impact of monetary policy are stronger at the height of the crisis.

For the responses of industrial production¹⁹ and consumption expenditure, figure (4) and (5) paint a similar picture as for real GDP. First, there is again evidence of time-variation in the responses, since the sample in 2007 give weaker responses than for the rest of the sample, indicated by the blue colors at the bottom of the heat maps. Second, the strongest responses at

¹⁹This is industrial production index for capital goods.

step=50 again roughly corresponds with the Lehman bankruptcy. For industrial production the strongest responses seem to happen quite close to September 2008, while for consumption the strongest responses come a couple of months after. Third, just as for real GDP the sample beyond 2010/2011 seem to yield rather stable responses for industrial production and consumption. Interestingly, the heat map for consumption shows that in the years after 2010 the responses are still quite strong compared to the mid to late-2008, while for industrial production the responses after 2010 are much more muted compared to its peak responses at mid to late-2008.

The evolution of the price indices, for both consumer and stock, further strengthen the results shown by the previous variables. The responses of benchmark index displayed in figure (6) look remarkably similar to those of real GDP. Responses based on 2007 samples are weaker and slower than for sample beyond 2007. The strongest responses of benchmark index are happen in mid till late-2008 and then quickly disappear, and the second half of the sample yield quite stable responses. The consumer price index shows once again the strongest responses to be around mid till late 2008, a time of instability and turmoil. However, the responses of CPI no longer indicate that the sample in 2007 consistently gives weaker impulse responses than the rest. Rather, as the estimation period move beyond 2010 the impulse responses become weaker, and 2013 and 2014 give increasingly slower impulse responses.

Among the six variables of interest the only one that shows more erratic impulse responses over time is employment (number of employed persons). For the first half of the sample (end date < 40) there are less clear evidence

of time-variation than for the other variables. Even though around August 2008 (end date = 20) there still seems to be visible increases in both the magnitude and pace of the responses, the strongest responses did not happen in late 2008. Rather, it was from around 2011 that the strongest responses took place, and the increased magnitude of the responses then suddenly disappeared around 2012. One reason for this delay could be connected to the common observation that employment lags after real variables such as GDP.

In all, the heat maps for the six variables seem to provide evidence for time-variation in the impulse responses around the time of the financial crisis. Moreover, times during which financial instability is high seem to coincide with larger impact of monetary policy. Although the pooled impulse responses of different variables can be quite diverse, the overall qualitative results are surprisingly consistent. They are also in line with both the prevalent expectations regarding the effects of monetary policy based on economic theories and previous empirical studies.

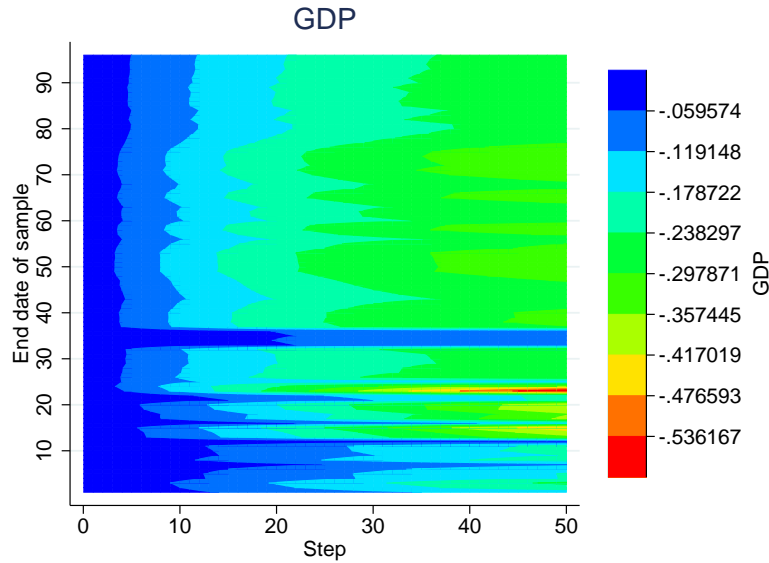


Figure 3: Pooled impulse responses of GDP to an one-standard-deviation contractionary shock^a

^aAll heat maps should be read in the following way. The horizontal axis shows the number of periods after a monetary policy shock has occurred and has the same meaning as in a standard impulse response graph. The vertical axis indicates the different estimation periods outlined in the previous section. Since all estimation periods have the same starting date, 2000:M1, the vertical axis shows the end date of the sample. For instance, since we defined the sample for the first estimation to be 2000:M1 - 2007:M1, 1 on the vertical axis indicates that the cumulated response was estimated based on a sample spanning from 2000:M1 - 2007:M1, and 2 indicates 2000:M1 - 2007:M2 and so on. The different colors indicate the magnitude of the responses at different steps (how "deep" the responses are at different steps). The scale on the right-hand side defines the different levels of magnitude of the cumulated response and their corresponding colors. As the color go from dark blue to red, so "increases" the magnitudes of the response of a variable to a monetary policy shock. To assess potential time-variation in the responses one should pay particular attention to the part of the heat map to the right (near or at step = 50) where the map shows the cumulative responses of a variable around 50 months after a policy shock has occurred.

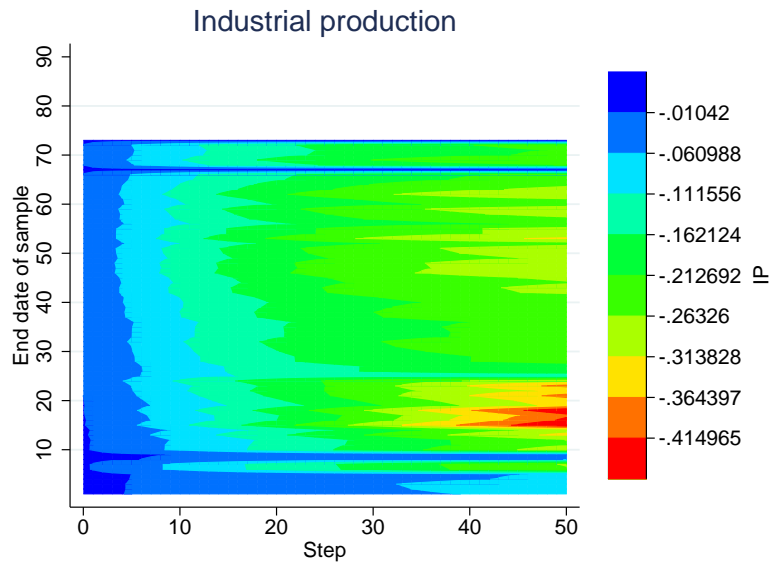


Figure 4: Pooled impulse responses of industrial production

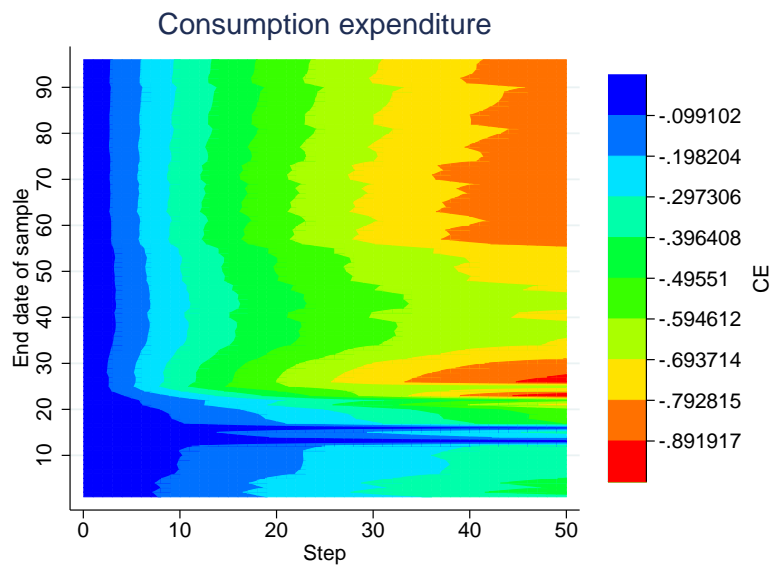


Figure 5: Pooled impulse responses of consumption expenditure

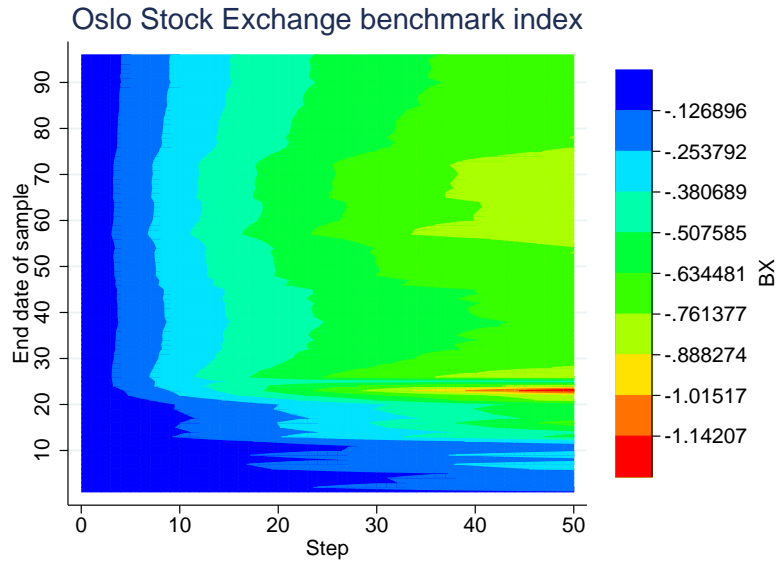


Figure 6: Pooled impulse responses of stock prices

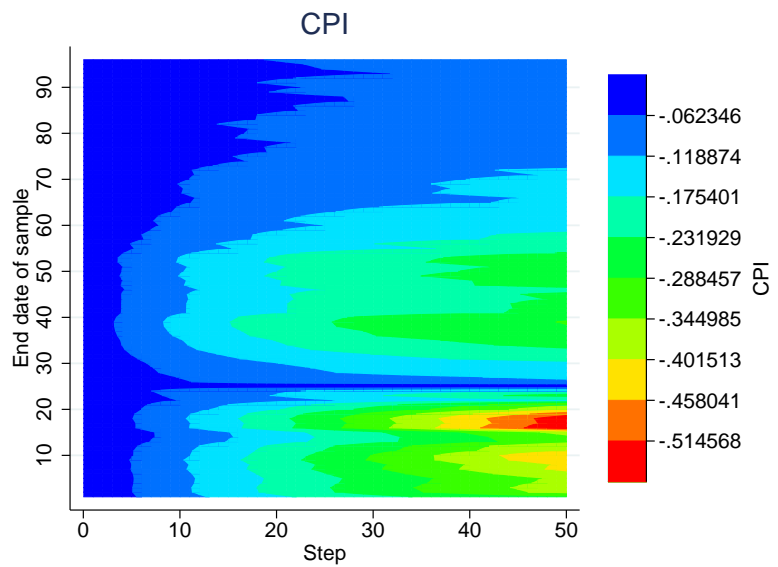


Figure 7: Pooled impulse responses of CPI

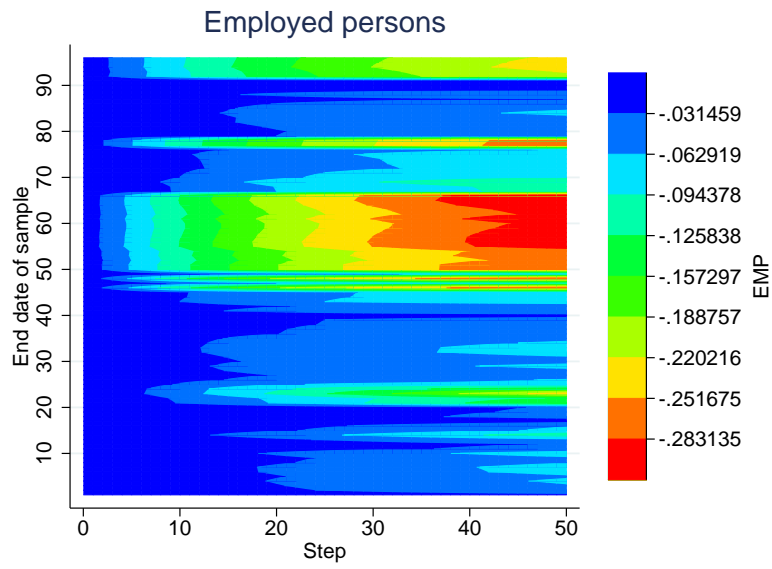


Figure 8: Pooled impulse responses of employment

5.2 Robustness check

Given the fact that one uncertainty in our model is the optimal number of factors, we re-run our entire procedure with different numbers of factors to check the sensitivity of our results²⁰. Heat maps (9) - (16) for the variables are constructed using 4 and 8 factors²¹.

For GDP, using 4 or 8 factors does not seem to change the main qualitative result, i.e. the impact of a monetary policy shock seems to be the strongest precisely at the worst moment of the crisis. However, the rather homogeneous responses after 2010 when using 6 factors seem to disappear with 4 or 8 factors. Although the responses after 2010 are still weaker than at the height of the crisis, there are more variation in the responses after 2010 when using 4 or 8 factors. Also, the magnitude of the strongest responses seem to decrease with the number factors, i.e. the strongest responses are -0.84, -0.60 and -0.37 for 4, 6 and 8 factors respectively.

For consumption and stock price index the heat maps with 4 and 8 factors look remarkably similar to those with 6 factors. For both, the strongest responses again seem to coincide with Lehman bankruptcy and the responses after 2010 are quite homogeneous. Again, the magnitude of the strongest response around the periods right after August 2008 seem to decrease with the number of factors.

For CPI, the heat map with 4 factors seem quite similar to the one with 6 factors. Both maps show a graduate increase in the impact of policy

²⁰In the interest of space, industrial production index is not included in the robustness checks because real GDP and industrial production cover somewhat similar concept. Employment is not included because its heat map did not show its strongest responses around the height of the crisis.

²¹Remember in the main specification: $k = 6$.

shock during the period right before August 2008, with the magnitude of the strongest impact with 4 factors larger than the one with 6 factors. With 8 factors the strongest responses still happen during the period right before August 2008, but the responses after 2010 become more homogeneous like for the other variables.

All things considered, it seems changing the number of factors do not change our main conclusion, i.e. the responses of key variables are time-varying and monetary policy is most potent around height of the financial crisis.

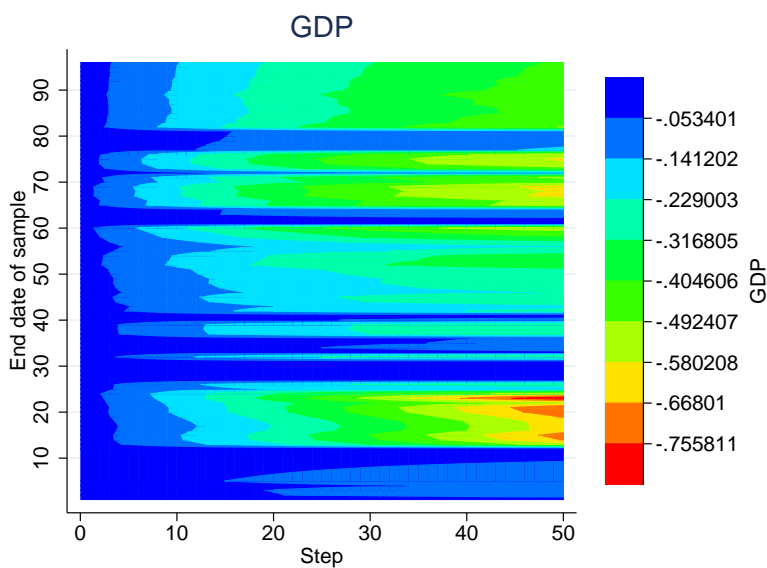


Figure 9: Pooled impulse responses of GDP using 4 factors

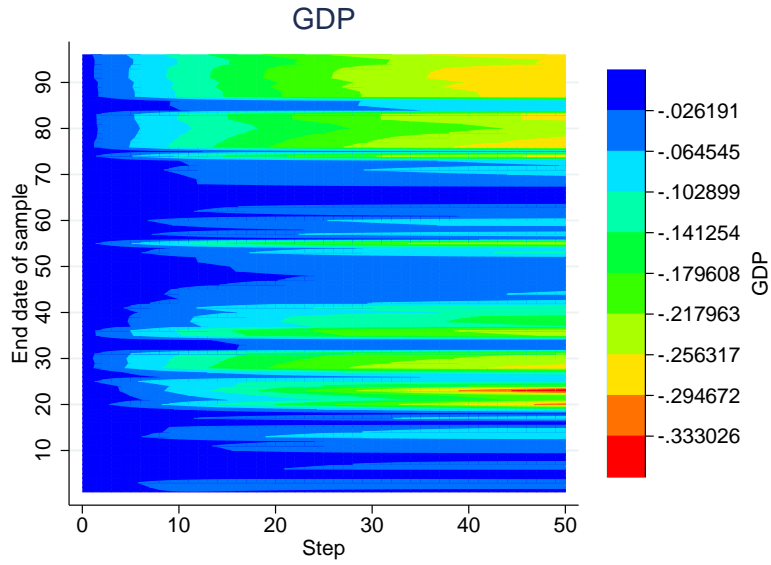


Figure 10: Pooled impulse responses of GDP using 8 factors

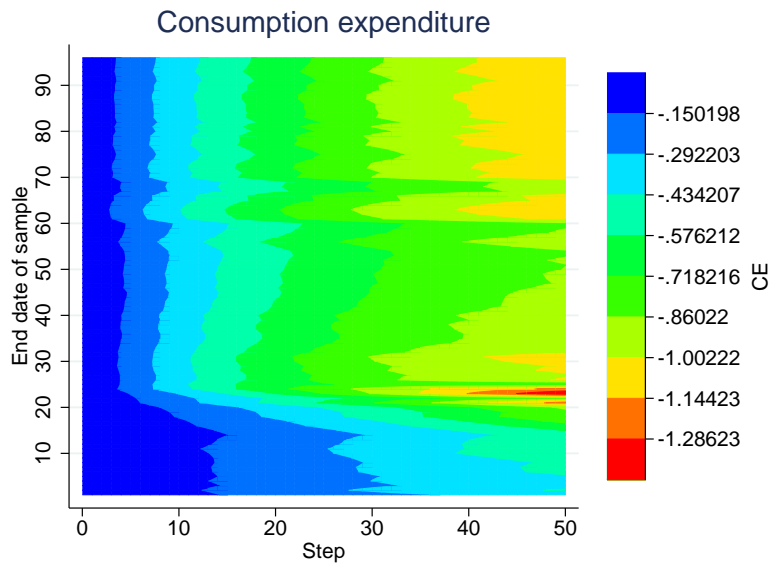


Figure 11: Pooled impulse responses of consumption using 4 factors

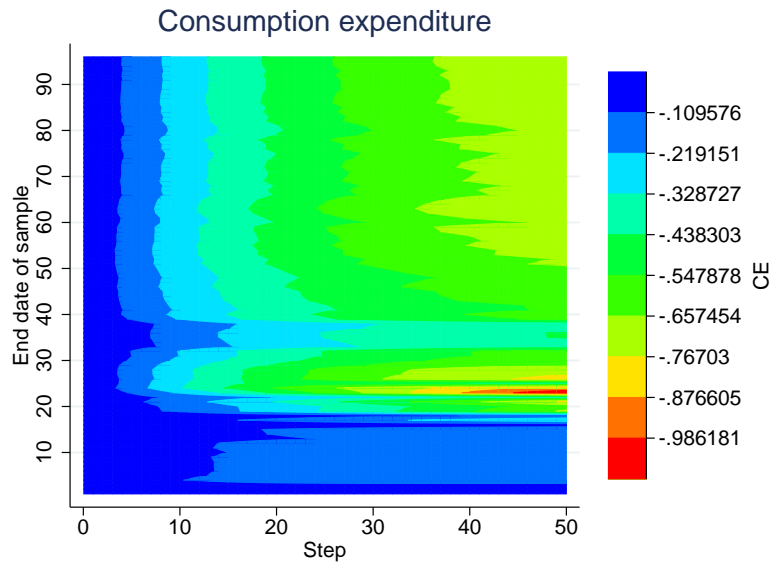


Figure 12: Pooled impulse responses of consumption using 8 factors

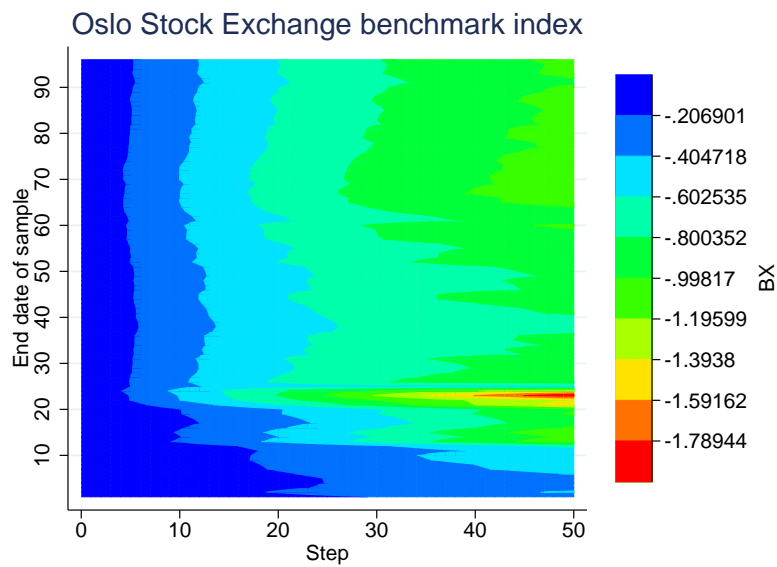


Figure 13: Pooled impulse responses of stock prices using 4 factors

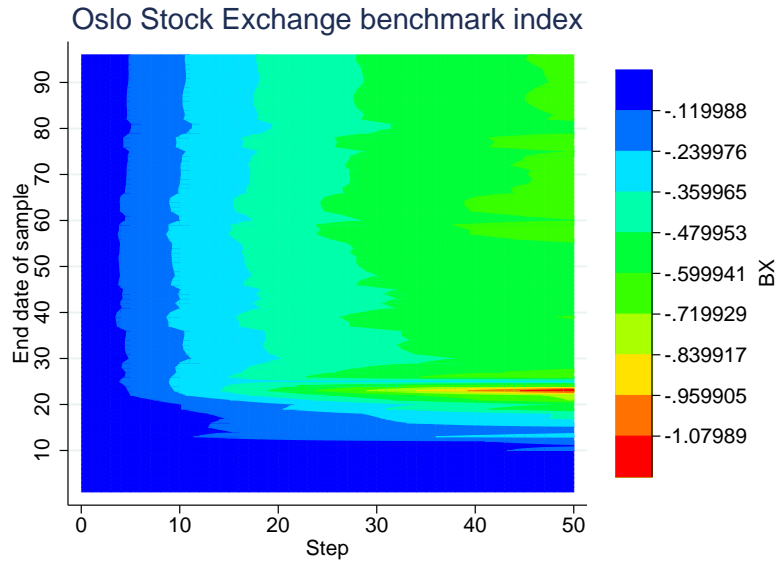


Figure 14: Pooled impulse responses of stock prices using 8 factors

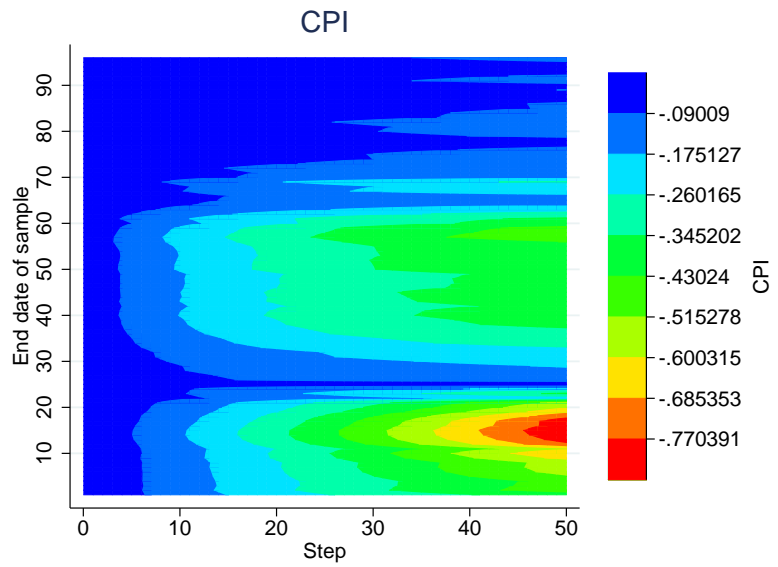


Figure 15: Pooled impulse responses of CPI using 4 factors

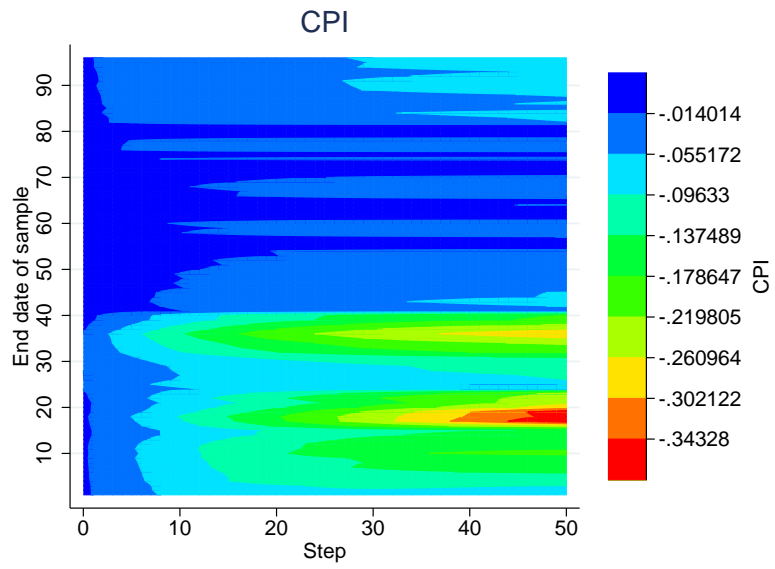


Figure 16: Pooled impulse responses of CPI using 8 factors

6 Conclusion

In this paper we have analyzed how the effects of monetary policy in Norway might have been changing over time. In particular, we have paid special attention to how the impact of policy shocks on key variables have evolved around the time of the bankruptcy of Lehman Brothers on September 2008, commonly considered to be one of the worst moments of the recent financial crisis.

By using a FAVAR model based on a large data set of 122 Norwegian variables and estimating the model recursively from 2000:M1 to 2014:M12, we have shown that the effects of monetary policy on our variables are indeed time-varying. The impulse responses of all six variables (GDP, industrial production, consumption, CPI, stock price index and employment) to a monetary policy shock first remain somewhat constant before the crisis, and subsequently strengthen as we move into the crisis period. Moreover, for all but one variable (employment) we find that the cumulated effect of a policy shock seems to be the strongest precisely during the worst moment of the crisis - the period right after bankruptcy of Lehman Brothers. That is, if a monetary policy shock were to happen around that time, its impact on the above-mentioned variables would have been more potent compared to other periods. The implication of our results is that the strong actions by the monetary authority in Norway during the financial crisis were warranted. Furthermore, people's impaired confidence in monetary authorities' ability to affect the economy during the crisis may have been built on false premises, as the impact of central banks in the crisis could have been underestimated.

An important caveat in our analysis is that we have not, in a systematic

way, tried determine why the impact of monetary policy seems to be amplified at the height of the crisis. One possible explanation is related to the credit channel theory of monetary policy transmission mechanism. When financial frictions in the credit market increases substantially due to the crisis, a higher external finance premium has to be paid by the borrowers. This should, via the credit channel, lead to higher effects of a monetary policy shock on variables such as GDP [Ciccarelli et al., 2013]. In this regard, a possible extension of our work could be to include more balance sheet variables and credit conditions for both financial and non-financial borrowers and investigate further the credit channel of monetary policy. Another interesting extension could be to see if we, instead of looking at this recent crisis, investigate some previous crises in Norway. A good candidate for a such crisis would be the banking crisis in Norway in the late 1980s. If similar results were to be found also for the banking crisis it could imply that the strengthened impact of monetary policy during a crisis is a more permanent, structural feature of the economy rather than an one-off outcome of the most recent crisis.

At the time of writing, Europe seems to be on the verge of another period of financial turmoil. The Greek government has yet to come to an agreement with its European counterparts on structural economic reforms necessary to receive more bailout funds, which the country desperately needs to avoid a default on its debt. However, as it stands right now the probability of a Greek default and an exit from the eurozone seems to increase by the day. If such events were to come to pass we have, at the very least, reason to believe that monetary policies would again rise to the occasion.

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Appendix A: Data description and transformation

The table below shows the list of data series used in the estimation and their transformations. The list contains only "informational" variables used in factor extraction. The transformation codes are as follows: 1 - first difference, 2 - second difference, 3 - logarithm, 4 - first difference of logarithm, 5 - second difference of logarithm. An asterisk next to the name denote a variable assumed to be fast-moving in the estimation

Name	Tr.
Industrial production - intermediate goods (2005=100)	4
Industrial production - capital goods (2005=100)	4
Industrial production - capital goods (2005=100)	4
Industrial production - total (2005=100)	4
Industrial production - extraction and related services (2005=100)	4
Industrial production - mining and quarrying (2005=100)	3
Industrial production - manufacturing (2005=100)	4
Industrial production - electricity, gas and steam (2005=100)	3
Industrial production - durable consumer goods (2005=100)	4
Industrial production - non-durable consumer goods (2005=100)	3
Industrial production - consumer goods (total) (2005=100)	3
GDP - final consumption of households (NOK million)	4
GDP - final consumption of general government (NOK million)	4
Gross fixed capital formation (GFCF) (NOK million)	5
Total exports (NOK million)	3
Total imports (NOK million)	4
GDP - total (market value) (NOK million)	4

Name	Tr.
Consumption expenditure - total (NOK million)	4
Consumption expenditure - durable goods (NOK million)	4
Consumption expenditure - non-durable goods (NOK million)	4
Consumption expenditure - semi-durable (NOK million)	5
Consumption expenditure - services (NOK million)	5
Employment - total (thousands of persons)	3
Employment - employed persons (thousands of persons)	5
Employment - self-employed (thousands of persons)	5
Employment - family workers (thousands of persons)	4
Employment - hours worked: total (thousands of persons)	3
Employment - hours worked: employed persons (thousands of persons)	4
Employment - hours worked: self-employed (thousands of persons)	3
Employment - hours worked: family workers (thousands of persons)	5
Employment - agriculture and forestry (thousands of persons)	4
Employment - mining and quarrying (thousands of persons)	5
Employment - oil and gas extraction (thousands of persons)	4
Employment - manufacturing (thousands of persons)	5
Employment - electricity, gas and steam (thousands of persons)	4
Employment - construction (thousands of persons)	5
Employment - wholesale and retail trade(thousands of persons)	5
Employment - transport activities (thousands of persons)	4
Employment - financial and insurance activities (thousands of persons)	5
Employment - general government (thousands of persons)	5

Name	Tr.
Unemployment - unemployed persons: total (thousands of persons)	5
Unemployment - duration 1-4 weeks (thousands of persons)	4
Unemployment - duration 5-13 weeks (thousands of persons)	5
Unemployment - duration 14-26 weeks (thousands of persons)	4
Average monthly earning - oil and gas extraction and mining (2005=100)	4
Average monthly earning - manufacturing (2005=100)	5
Average monthly earning - electricity, gas and steam (2005=100)	5
Average monthly earning - construction (2005=100)	5
Average monthly earning - wholesale and retail trade (2005=100)	4
Average monthly earning - transportation and storage (2005=100)	5
Consumer price index - all items (1998 = 100)	3
Consumer price index - food and non-alcoholic beverages (1998 = 100)	4
Consumer price index - alcoholic beverages and tobacco (1998 = 100)	4
Consumer price index - clothing and footwear (1998 = 100)	4
Consumer price index - housing, water, electricity, gas(1998 = 100)	4
Consumer price index - health (1998 = 100)	4
Consumer price index - transport (1998 = 100)	4
Consumer price index - miscellaneous goods and services (1998 = 100)	5
Producer price index - intermediate goods (2000 = 100)	5
Producer price index - investment goods (2000 = 100)	4
Producer price index - consumer goods (total) (2000 = 100)	4
Producer price index - durable consumer goods (2000 = 100)	4
Producer price index - non-durable consumer goods (2000 = 100)	4

Name	Tr.
Producer price index - energy goods (2000 = 100)	5
Producer price index - industry total (2000 = 100)	5
Producer price index - extraction and related services (2000 = 100)	5
Producer price index - manufacturing (2000 = 100)	5
Producer price index - mining and quarrying (2000 = 100)	4
Producer price index - electricity, gas and steam (2000 = 100)	3
Commodity price index (2000 = 100)	5
Stock prices* - Oslo Stock Exchange: all-share index	4
Stock prices* - Oslo Stock Exchange: benchmark index	4
Stock prices* - Oslo Stock Exchange: mutual fund index	4
Stock prices* - Oslo Stock Exchange: small cap index	4
Stock prices* - Oslo Stock Exchange: OBX index	5
Stock prices* - Oslo Stock Exchange: oil service index	4
Exchange rate* - USD per NOK	4
Exchange rate* - EUR per NOK	4
Exchange rate* - GBP per NOK	5
Exchange rate* - CHF per NOK	4
Exchange rate* - SEK per NOK	4
Exchange rate* - JPY per NOK	4
Exchange rate* - import-weighted	4
Exchange rate* -competition index	4
Monetary aggregates* - M0	4
Monetary aggregates* - M1	5

Name	Tr.
Monetary aggregates* - M2	5
Gross domestic debt* - general government (NOK million)	3
Gross domestic debt* - non-financial corporations (NOK million)	5
Gross domestic debt* - households etc. (NOK million)	5
Dwelling starts* - Oslo	3
Dwelling starts* - mid-Norway	4
Dwelling starts* - east	4
Dwelling starts* - south	4
Dwelling starts* - west	4
Dwelling starts* - north	4
Dwelling starts* - total	4
Capacity utilization rate - manufacturing, mining and quarrying	2
Capacity utilization rate - intermediate goods	2
Capacity utilization rate - capital goods	2
Capacity utilization rate - consumer goods (total)	2
Confidence indicator* - manufacturing, mining and quarrying	2
Confidence indicator* - intermediate goods	1
Confidence indicator* - capital goods	2
Confidence indicator* - consumer goods (total)	1
Confidence indicator* - consumer expectation	1
Interest rate* - treasury bill 3-month	1
Interest rate* - treasury bill 6-month	1

Name	Tr.
Interest rate* - treasury bill 9-month	1
Interest rate* - treasury bill 12-month	1
Interest rate* - government bond 3-year	1
Interest rate* - government bond 5-year	1
Interest rate* - government bond 10-year	1
Interest rate* - spread between 3-month and key policy rate	1
Interest rate* - spread between 6-month and key policy rate	1
Interest rate* - spread between 9-month and key policy rate	1
Interest rate* - spread between 12-month and key policy rate	1
Interest rate* - spread between 3-year and key policy rate	1
Interest rate* - spread between 5-year and key policy rate	1
Interest rate* - spread between 10-year and key policy rate	1
Inventory index* - manufacturing	3
New order index* : manufacturing (2005 = 100)	2

Appendix B: Computational issues

Here, we seek to explain how our estimation procedure is structured in Stata. The estimation program is done in 5 steps; (1) data processing, (2) Bai and Ng [2002] information criteria, (3) factor estimation, (4) (FA)VAR estimation, and (5) calculation of pooled impulse responses. The entire program is structured in the following way. Actual Stata-codes are available upon request from the authors.

- Define a program for data processing, called "cdata"
 - Set program parameters; (1) method²², (2) significance level, (3) sample length.
 - Design algorithm so that for each variable that are not already expressed in percentage points or rates: check if taking logarithm is enough to induce stationarity using augmented Dickey-Fuller test²³. If not, check if taking first-difference of log is enough. If not, check if second difference log is enough. If not, drop variable. And for each variable that are already expressed in percentage points or rates: check if taking first-difference is enough to induce stationarity. If not, check if taking second-difference is enough. If not, drop variable. Next, standardize all retained variables. The looping is done using the "foreach" and "if...else" environments.
 - Run "cdata" with the desired parameters.

²²Only the method described below was used in the actual estimation

²³Note that the number of lags to include is determined by Ng and Perron's sequential-t algorithm

- Calculate Bai and Ng [2002] information criteria according to the equations outlined in the previous section. Note that the residuals were found by taking the difference between the actual time-series and "reconstructed" series calculated with command "predict, fit" after using "pca".
- Define a program for factor estimation, called "fex"
 - Set program parameters; (1) policy instrument/variable, (2) number (k+1) of factors to be extracted and included in FAVAR, (3) sample length for recursive estimation.
 - Extract "initial factors", i.e. recover the space spanned by both F and Y , $C(F, Y) = k + 1$ first principal components. This is done with the "pca"-command, and scaled according to Stock and Watson [1998]
 - Remove space spanned by Y , i.e. remove dependency of $C(F, Y)$ on Y to obtain estimates of factors. This is done with the "pca"-command, and scaled according to Stock and Watson [1998]
- Define a program for running FAVAR, called "favar"
 - Set program parameters; (1) number of lags in the VAR, (2) number of steps for the cumulated impulse responses.
 - Set A and B matrices for Cholesky identification.
 - Run VAR in factors and policy variable using the "svar"-command, and create impulse responses of factors to policy shocks.
 - Merge impulse responses with existing data set.

- Run recursive estimation using the programs we have already defined
 - For one particular variable, loop through 96 different sample length starting with 2000:M1 - 2007:M1 and ending with 2001:M1 - 2014:M12. This is done by changing the parameter for end date in "fex"
 - Each of the 96 estimations will use "fex" and "favar" programs, and obtain factor loadings by regressing the variable on factors and policy variable
 - For example an estimation for 2000:M1 - 2007:M1 would look like:
 - * qui fex 1 7 1 2000 1 2007 1
 - * qui favar 1 50
 - * reg x f*(factors) i(policy instrument)
 - With the factor loadings and responses of factors, responses of variables can be calculated
 - The entire procedure can be done for the variables of choice
- Having all 96 impulses responses of a variable to a policy shock we can now use "tway contour" to make the heat map.