CENTRE FOR APPLIED MACROECONOMICS AND COMMODITY PRICES (CAMP)

CAMP Working Paper Series
No 2/2020

The Impact of Monetary Policy on Leading Variables for Financial Stability in Norway

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March 2020

Abstract

We search for leading determinants of financial instability in Norway using a signaling approach, and examine how these respond to a monetary policy shock with the use of structural VAR models. We find that the wholesale funding ratio and gap, credit-to-GDP gap, house price-to-income ratio and gap, and credit growth provide good signals of future financial instability. Following a contractionary monetary policy shock, the credit-to-GDP gap and house price-to-income ratio decrease significantly. The implication of our findings is that the central bank can respond to an increase in these indicators by increasing the interest rate, which in turn will decrease the indicators and thereby the probability of financial distress.

Keywords— Financial stability, Monetary policy, Structural VAR, Signaling Approach

*This paper was first submitted as our master thesis at BI Norwegian Business School in June 2019, supervised by Professor Hilde C. Bjørnland. The thesis was further developed after submission, and is now a part of the Centre for Applied Macroeconomics and Commodity Prices (CAMP) Working Paper Series. We are very grateful for the help provided by Hilde C. Bjørnland, Jamie L. Cross, Tommy Sveen, Steffen Grønneberg, and the entire economics department at BI Norwegian Business School. This work is part of the research activities at the Centre for Applied Macroeconomics and Commodity Prices (CAMP) at the BI Norwegian Business School.

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1 Introduction

On 2 March 2018, the Norwegian Government issued new regulation for the conduct of monetary policy. The new regulation specifies that the inflation targeting regime shall contribute to the standard goals of monetary policy, high and stable output and employment, and in addition, counteract the build-up of financial imbalances (Forskrift for pengepolitikken, 2018). The Governor of Norges Bank, Øystein Olsen, in a hearing before the Norwegian parliament, highlights that counteracting build-ups of financial imbalances may contribute to the two other targets of monetary policy as well. However, he points out that the primary responsibility for financial stability lays with financial regulation and supervision, not monetary policy (Norges Bank, 2018). In this paper, we investigate the relationship between financial stability and monetary policy in light of the new regulation.

In the aftermath of the global financial crisis, a large literature has developed on how to combat financial imbalances. The macroeconomic research has focused mainly on macroprudential policy (Borio, 2003; Arnold et al., 2012; Detken et al., 2014; Shin, 2016; Akinci and Olmstead-Rumsey, 2018), and to some extent monetary policy (Assenmacher-Wesche and Gerlach, 2008; Bjørnland and Jacobsen, 2010; Svensson, 2013, 2017; Robstad, 2018). Both macroprudential policy and monetary policy influence the financial cycle through the financial intermediation process. They both affect the demand for credit by reallocating spending over time, and the supply of credit by influencing funding costs (Shin, 2016). While macroprudential policy is seen as the first line of defense against financial imbalances (Mester, 2017), monetary policy can act as a second line of defense by leaning against the wind. The policy paradigm after the global financial crisis is one in which both monetary policy and macroprudential policy are used to stabilize the financial cycle (Smets, 2014).

This paper attempts to find determinants of financial stability in Norway and research whether these determinants respond to a monetary policy shock. Research on the interaction between financial imbalances and monetary policy has mainly focused on the second part of our research, namely whether asset prices and credit responds to monetary policy shocks, see for example Bjørnland and Jacobsen (2010); Robstad (2018); Assenmacher-Wesche and Gerlach (2008). We do not take the determinants of financial stability as given, but rather analyze the characteristics of variables associated with financial distress in Norway over the past 35 years. We include the variables that historically has proven to be good indicators of financial distress in a structural VAR model. Knowledge about the transmission from monetary policy to financial stability is important as it can aid policymakers achieve their goal of maintaining a stable financial cycle, and reduce the severe costs associated with financial crises (Jordà et al., 2013).

Our research consists of two steps. In step 1, we explore measures of financial (in)stability. The primary difficulty is that financial stability is a latent state. Borio and Drehmann (2009) defines financial instability as a situation in which normal-sized shocks to the financial system are sufficient to produce financial distress, while financial stability is its converse. We analyze how ten candidate indicator variables have acted over the past 35 years in Norway, using the signaling approach first suggested by Kaminsky and Reinhart (1999). We assess the candidate variables based on how they signal past crises, given a threshold value for which the indication switched from normal to signaling, and rank them according to a loss function specified in section 2. Borio and Drehmann (2009) build on the methodology of Kaminsky and Reinhart (1999), and find that the methodology is a step towards a better framework for financial stability. However, since all indicator variables will provide a false signal at some point, they highlight the role of judgment when interpreting the signals.

In step 2, we examine the transmission from the monetary policy instrument to the accepted indicator variables from step 1. The motivation is to establish whether monetary policy can affect the key determinants of financial stability. Previous studies on the effect of monetary policy on financial stability in Norway have mainly focused on asset prices and credit, for example Bjørnland and Jacobsen (2010), who investigates the role of house prices in the monetary policy transmission in Norway. They find that house prices react strongly to interest rate shocks, and therefore that the interest rate can be used to stabilize the housing market. Robstad (2018) builds on the research of Bjørnland and Jacobsen (2010) and includes household credit in his structural VAR model. In line with Bjørnland and Jacobsen (2010), he finds that house prices react to changes in the interest rate, while the response of credit is small. Assenmacher-Wesche and Gerlach (2008) finds that the interest rate has an impact on both property prices and equity prices in Norway. We notice that since financial stability is not directly observable, a broader set of variables might be useful. Therefore, we contribute to the literature by using a broader set of financial stability indicator variables.

The remainder of the paper is structured as follows. Section 2 explains the data, methodology and results from the quest for financial instability determinants. Section 3 explains the data, methodology and results from the Structural VAR models of the Norwegian economy. Our concluding remarks are presented in section 4.

2 Step 1 - The signaling approach

In step 1, we analyze indicators from the early warning indicators (EWI) and early warning systems (EWS) literature, along with key indicators used by Norges Bank in their assessment of financial stability. A good indicator needs to be a leading indicator of financial distress because policymakers need time to react to imbalances. In addition, if the economy has already entered financial distress, it will be evident in several economic variables and the indicator will not add new information. For each indicator, we assess the findings from the technical assessment using the signaling approach. To aid our assessment, we plot each indicator variable against the two recessions that have hit Norway during our sample period. For additional stylized facts of the candidate indicators, see appendix B.

2.1 Data

As candidate indicator variables in step 1, we use three of the four key variables Norges Bank use in their assessment of financial imbalances (Norges Bank, 2013). These are, private credit-to-GDP (ratio and gap), house price-to-disposable income (ratio and gap), and banks' wholesale funding (ratio and gap). Data for the last key indicator the central bank use, real commercial property prices, is not available. For these variables, we have data from 1983 to 2018. The gaps are provided by Norges Bank and are constructed using the one-sided HP-filter. In addition to these variables, we include two variables from the EWI literature. The EWI and EWS literature search for variables that provide an indication of the future state of the financial system, see for example Davis and Karim (2008); Borio and Drehmann (2009); Gramlich et al. (2010); Alessi and Detken (2011); Oet et al. (2013); Drehmann and Juselius (2014); Azis and Shin (2015); Aldasoro et al. (2018). From the literature, we include household credit and house prices, which we assess in both log-levels and growth rates. For these variables, we have data from 1983 to 2018, except for the growth rates, for which we lose one year at the beginning of the period due to the transformation from level to growth. The candidate indicator variables are presented in Table 2, and the justification for their inclusion is provided in the following.

Credit

Credit-to-GDP is a widely used and accepted indicator in the EWI literature (Drehmann, 2013). The Bank of International Settlement (BIS) regularly publish and monitor credit-to-GDP, which is in line with Norges Banks' stand, namely that it is one of the most important determinants of financial instability (Norges Bank, 2013). Papers from BIS include Drehmann et al. (2010, 2011) who find that the credit-to-GDP gap is an appropriate indicator for the accumulation of capital, because it captures system-wide vulnerabilities typically leading to banking crises. Researchers have found that not only is credit-to-GDP among the best indicators for financial instability (Detken et al., 2014), but also that the signals come at an early stage, making it appropriate in a monetary policy framework (Giese et al., 2014). Furthermore, Alessi and Detken (2011) find that using credit-to-GDP will reduce the crisis loss by 25 percentage points compared to when ignoring it.

For many countries, the credit-to-GDP gap is negatively correlated with GDP, this is also the case for Norway, as can be seen in appendix B.2. Repullo and Saurina (2011) and Sohn and Park (2016) propose that *credit growth* is a better indicator of banking crises. For the Norwegian economy, Anundsen et al. (2016) have found that an increase in household credit contributes positively to the probability of a crisis. Additional studies support the effectiveness of household credit, due to the fact that household credit growth raises debt levels without much effect on future income (Büyükkarabacak and Valev, 2010). Furthermore, credit growth can be a good leading indicator variable because a crisis can occur several years after the peak of the credit cycle (Davis and Karim, 2008).

We include the ratio of credit-to-GDP, the credit-to-GDP gap, credit in logartihms, and four-quarter growth in credit as candidate indicator variables in our signaling exercise.

House prices

House prices are important for the financial system because a large fraction of households' wealth is in housing, and a large fraction of banks' assets are in mortgages. Anundsen et al. (2016) finds that house prices exercise a positive and significant impact on the probability of a crisis in Norway, and Barrell et al. (2010)'s study finds that a one percentage point increase in real house price growth in Norway increases the probability of a crisis with 0.31 percentage points. Furthermore, during the Norwegian banking crisis in the 1990s, the burst of the house price bubble was a significant contributor to the instability in the economy (Stamsø, 2009). However, Ragnarsson et al. (2019) point out that housing cycles have almost twice the frequency of credit cycles, and that this high frequency can lead to a high level of noise if used as an indicator for financial distress. Another problem with using house prices as an indicator, is that the prices can increase due to changes in fundamental values, and at the time of the increase it is hard to know whether the increase is due to fundamental causes, or due to the build-up of financial imbalances.

The ratio of *house prices-to-disposable income* may be a more suitable indicator for financial stability because it captures changes in house prices, but takes an important potential fundamental cause for house price changes into account, namely disposable income. If disposable income increases, this provides an explanation for increased house prices, and an increase in house prices does not necessarily imply future distress. Hermansen and Röhn (2017) find that the ratio of house price-to-income is the best performing indicator among the 23 indicators they test. Norges Bank include house prices-to-disposable income as one of the key indicators for financial stability in Norway.

We include the ratio of house prices-to-disposable income, the house prices-to-disposable income gap, house prices in logarithms, and four-quarter house price growth as candidate indicator variables.

Banking sector

The third indicator used by Norges Bank is the *Banks' wholesale funding ratio.* This is the ratio of total liabilities net of customer deposits and equity, as a percentage of total liabilities. Deposits from households and firms finance a large share of banks' lending, however these deposits grow in line with the size of the economy and the wealth of households and firms. When credit is growing faster than the pool of available deposits, the bank will turn to other sources of funding to support credit growth (Hahm et al., 2012; Shin, 2016). Therefore, an increase in the wholesale funding ratio may indicate an increase in household spending, and may reinforce an increase in debt and asset prices. In turbulent times, banks' access to wholesale funding often dries up, or the costs increase substantially. This in turn may lead to a tightening in the banks' lending policies (Norges Bank, 2013). Hahm et al. (2012) use wholesale funding as an indicator and finds that it has significant predictive power for credit crises.

We include banks' wholesale funding ratio, and the gap, as candidate indicator variables for financial instability.

2.1.1 HP-filter

Following Borio and Lowe (2002), much of the EWI literature focuses on macroeconomic imbalances, see for example Alessi and Detken (2011); Csortos and Szalai (2014); Borio (2014) and Hermansen and Röhn (2017). To capture imbalances, a gap measure is often constructed, and the imbalances are defined as the gap between the original series and its trend. A time series y_t can be decomposed into four components, a trend component g_t, a cycle component c_t, a seasonal component s_t, and noise e_t. To filter out desired components we use Matlab code on one-sided HP-filters provided by Meyer-Gohde (2010). While the normal double-sided HP-filter is both backward and forward looking, the one-sided HP-filter is only backward looking and runs recursively while expanding the sample each period (Drehmann and Yetman, 2018). This is the recommended approach since at each point in time, the one-sided HP-filter only use information known at the time to construct g_t (Stock and Watson, 1999), which mimics the information available to the policymaker at any point in time, given that the data itself is not revised. Norges Bank use the one-sided HP-filter in their assessment of financial stability, and their main argument for using it is that it puts more weight on recent observations, which can effectively capture structural breaks (Norges Bank, 2013).

We use five gaps in step 1, all of which are constructed using the one-sided HP-filter with $\lambda = 400,000$ (Norges Bank, 2013). In step 2, we use the gaps from step 1, and construct the output gap using the one-sided HP-filter. We set $\lambda = 40,000$ following Hagelund et al. (2018), and discard the first 40 observations, so that we get filtered data from 1993 and onward, as with the rest of the data in step 2.

2.2 Methodology

When assessing the candidate indicator variables' ability to give good signals of financial distress, we use the signaling approach. The signaling approach was first proposed by Kaminsky et al. (1998) and Kaminsky and Reinhart (1999), and has since become a workhorse model in the EWI literature. The idea is to consider each potential indicator variable, and see whether they provide signals in times before financial distress.

First, we look at each indicator variable, V_i, throughout the sample, and see whether the variable provides a signal or not. The signal $S_{i,t}$ is a binary variable taking on the value 1 if the variable signals a crisis, and 0 otherwise. Hence, if the threshold value is θ and the signal goes off when the variable is above the threshold value, we have

$$S_{i,t} = \begin{cases} 1, & \text{if } V_{i,t} > \theta \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Second, we gather the signals, $\sum_{t=1}^{n} S_t$ for each indicator i, in a vector and categorize the signals as either true or false. A signal is true if it appears within a specified time period before a crisis, and false otherwise. Hence, we can categorize the signal at time t, S_t, in one of two possible categories, and the variable V_t in one of four possible categories:

	Crisis	No crisis
Signal	True signal	False signal
No signal	False negative	True negative

Table 1: Classification of indicator variables at time t.

Now, we can assess the properties of each indicator by looking at two ratios:

$$\text{Ratio of true signals} = \frac{\text{True signal}}{\text{True signal+False negative}}$$

$$\text{Ratio of false signals} = \frac{\text{False signal}}{\text{False signal+True negative}}$$

The ratio of true signals tells us how many of the periods before the crisis the indicator actually signals, as a fraction of all the defined pre-crisis periods. We want this ratio to be as large as possible, as a higher ratio implies more signals given before a crisis. The ratio of false signals tells us how many periods the indicator provides a false signal as a fraction of the total number of periods that are not followed by a crisis.

To use this approach, we need to make four sets of judgments (Kaminsky and Reinhart, 1999). First, we need a list of candidate indicator variables. Second, we need to define the beginning of the crisis periods during our sample period. Third, we need to define a threshold value to indicate when the signal will go off, and, lastly we need to determine when the signal is true or provides a false alarm.

The candidate indicator variables are listed in Table 2, and the justification for including them are in Section 2.1.

Indicator	Used by Norges Bank
Private credit-to-GDP ratio	Yes
Private credit-to-GDP gap	Yes
House price-to-income ratio	Yes
House price-to-income gap	Yes
Banks' wholesale funding ratio	Yes
Banks' wholesale funding gap	Yes
Household credit growth	No
Household credit (log)	No
House price growth	No
House prices (log)	No

Table 2: Candidate indicator variables, and whether they are among the main indicators Norges Bank use in their assessment of financial imbalances.

Our sample size goes from the first quarter of 1983 until the fourth quarter of 2018. This sample contains two crises for the Norwegian economy. The Norwegian recession started in 1988Q2, while the global recession started in 2008Q3. The starting periods are chosen following (Anundsen et al., 2016).

	Start
Norwegian recession	1988Q2
Global recession	2008Q3

Table 3: Classification of crises in our sample.

To conduct our analysis, we need to define time periods for which the signal should be accepted as true or false. The signals from house prices (log-levels and growth rate), house price-to-income (ratio and gap) and wholesale funding (ratio and gap) provides a true signal when it appears within four quarters prior to the crisis. The signals from credit-to-GDP (ratio and gap), credit (log-levels) and credit growth are accepted as true signals when they appear within eight quarters prior to the crisis. Credit variables have proven to provide timely signals before previous crises (Giese et al., 2014), and the crisis can occur several years after the peak of the credit cycle (Davis and Karim, 2008). Therefore, we allow the credit variables to provide signals at a longer horizon than the other variables. The four-quarter period for the remaining indicators is following Kaminsky and Reinhart (1999)'s horizon for indicators for banking crises. Furthermore, we omit all signals given by the variables during the crises and the six quarters succeeding the crises to avoid the post-crisis bias as discussed by Bussiere and Fratzscher (2006).

	Signal horizon
Credit-to-GDP gap	Within eight quarters prior to recession
Credit-to-GDP ratio	
Credit growth	
Credit (log)	
House price growth	Within four quarters prior to recession
House prices (log)	
House price to income gap	
House price to income ratio	
Banks' wholesale funding gap	
Banks' wholesale funding ratio	

Table 4: How many quarters prior to a crisis we accept the signal as true.

The most important part of the set-up is to define threshold values for the indicators. That is, the threshold value for when the indicator variable switches from normal to signaling. To evaluate the optimal threshold value, we follow Borio and Drehmann (2009) and minimize a loss function consisting of type 1 errors and type 2 errors in the following way:

$$\min L = \beta \text{ Type } 1 + (1 - \beta) \text{ Type } 2 \tag{2}$$

Type 1 errors are the fraction of missed signals during the pre-crisis periods over all pre-crisis periods, while type 2 errors are the fraction of false signals over all normal periods. This approach allows us to determine the optimal threshold value based on how much weight the central bank puts on avoiding false signals versus missing a true signal. One disadvantage with this approach is that it is hard to assess the relative costs of missing a crisis against overreacting in normal times, and therefore it is hard to determine the optimal value of β. In our analysis, we assume that $\beta \geq 0.5$, that is, the central bank care more about detecting a crisis than receiving a false signal when there is no crisis, or that the weights are equal. Furthermore, we assume that the central bank put some value on avoiding false signals, namely $\beta \leq 0.8$, because if not, the signal would go off in almost every period, and thereby devalue the information provided by the indicator. We minimize the loss function for values of $\beta = [0.5, 0.6, 0.7, 0.8]$, and find the optimal threshold for each indicator given the values of β.

The candidate threshold values are the percentiles $X \in [1, 100]$. Hence, the signal, $S_{i,t}$, goes off when the following condition is fulfilled:

$$\mathrm{V}_{i,t} > X(\mathrm{V}_i)$$

and we determine the optimal threshold by minimizing the loss function corresponding to each candidate threshold value, and choose the value giving the lowest loss.

We will use the percentile method for all variables, except the level variables, as these are not stationary, but drifting upwards and it would not be sensible to find a threshold value based on percentiles. Instead, our candidate thresholds are that the variables are less than they were h quarters ago while still above trend, with h ranging from one to four quarters back in time. That is, the signal goes off when the following condition is fulfilled:

$$\mathrm{V}_{i,t} < \mathrm{V}_{i,t-h} \;\text{ AND }\; \mathrm{V}_{i,t} > \mathrm{trend}(\mathrm{V}_{i,t}), \text{ for } h = 1, \ldots, 4$$

and we determine the optimal threshold as we do under the percentile method. The rationale for having opposite inequality signs for the level variables and the other variables is that the level variables are non-stationary. Using the condition that the signal goes off when the level variable is larger than h quarters ago would result in a positive signal in almost every quarter because the variables are drifting upwards. By including the condition that the variable also needs to be above trend for the signal to go off, we make sure that the variable is at alleviated levels, and we aim to capture the peak of the cycle.

In the following, we present the indicators together with the corresponding false signal ratio, true signal ratio, loss and threshold value, using $\beta = 0.6$, while the results for $\beta = [0.5, 0.7, 0.8]$ are in appendix B.4.

2.3 Results

The results from the signaling approach using $\beta = 0.6$, meaning that the central bank puts 60 percent weight on not missing a crisis, and 40 percent weight on avoiding false signals, is presented in Table 5. The results are similar when using $\beta = [0.5, 0.7, 0.8]$, as can be seen from appendix B.4.

	True signals	False signals	Loss	Threshold
Wholesale funding gap	1.00	0.22	0.09	71
House price to income ratio	1.00	0.32	0.13	70
Credit-to-GDP gap	1.00	0.34	0.14	55
House price to income gap	1.00	0.39	0.15	66
Wholesale funding ratio	1.00	0.40	0.16	59
Credit growth	1.00	0.41	0.16	62
House price growth *	0.75	0.21	0.23	39
Credit-to-GDP ratio	1.00	0.61	0.25	29
House prices (log)	0.63	0.09	0.26	2**
House price growth	1.00	0.99	0.40	1-16
Credit (log)	0.06	0.01	0.57	1**

Table 5: True signals is the periods a true signal is provided, divided by the number of periods we want a signal. False signals is the periods of false signals made divided by the number of periods we do not want a signal. Loss is the loss stemming from the loss function in section 2.2. Threshold shows the percentile value for which the signal goes off. * The result for house price growth when using an alternative threshold method, the signal goes off when the growth rate is below the threshold percentile. **The threshold of the logarithms is by how many quarters back we compare the logarithms with when determining the signal value. The loss function is minimized using $\beta = 0.6$.

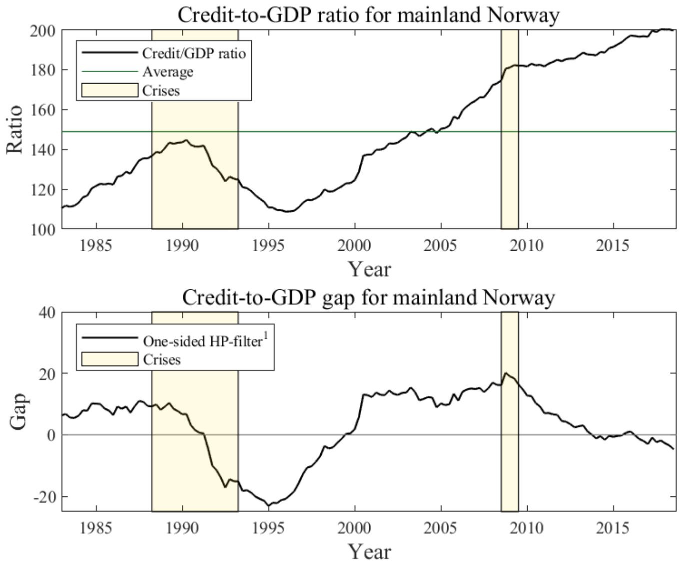

Figure 1: Credit-to-GDP mainland Norway. The ratio is plotted against its average value. The yellow shaded areas are the two recessions that have hit Norway in our sample period. The Norwegian recession lasted from 1988Q2 to 1993Q2. The Global recession lasted from 2008Q3 to 2009Q3. [1]One-sided Hodrick-Prescott filter. Lambda=400,000.

The *credit-to-GDP ratio* increased prior to both recessions. Before the Norwegian recession, the ratio had grown at the same pace of approximately five percent per year for at least five years preceding the peak. From 1996 up until the peak of the Global recession in 2009, the ratio again increased steadily. Following the Global recession, the ratio stagnated for 1.5 years before it picked up yet again. The ratio provides good lagging indications, that is, a crisis implies a stagnation or decline in the ratio. However, an increase in the ratio does not necessarily imply a crisis, and in real-time it is hard to assess whether the indicator is responding to changes in fundamentals or imbalances. The assessment of the plot is in line with the technical assessment. We find that the ratio could have provided true signals in all sixteen quarters preceding the two recessions in

Norway. However, it would also have provided a false signal in three-fifths of the quarters not followed by a crisis. Due to the high variation of the ratio, the signaling approach finds a low threshold value, namely that the signal goes off whenever the ratio is in its 29th percentile or above. This is also reflected in a high standard deviation and the largest coefficient of variation in our sample, as can be seen in appendix B.1. The *credit-to-GDP gap* provides a more clear signal of past recessions compared to the ratio. Both recessions follow years where the gap has been above zero. Before the Norwegian recession, the gap rose from 5.59 percent in 1983 to 11.02 percent in 1987, and before the Global recession, the gap rose from 8.91 percent in 2004 to 20.20 percent in 2008. This is in line with the results of the technical assessment. We find that the credit-to-GDP gap provides a true signal in all quarters preceding a crisis, and a false signal in 34 percent of the normal quarters. The gap thereby provides less false signals than the ratio. Using the gap measure is also supported by the lower coefficient of variation of the credit-to-GDP gap, and the higher lagged correlation between the credit-to-GDP gap and GDP growth, see appendix B.

Despite serving as a good indicator before the Norwegian banking crisis, the credit-to-GDP ratio has increased steadily since 1996 and did not provide a good warning signal before the Global recession. In line with the literature (Drehmann et al., 2011; Aldasoro et al., 2018), we find the credit-to-GDP gap to act as a good indicator for financial distress. We proceed with the credit-to-GDP gap in step 2.

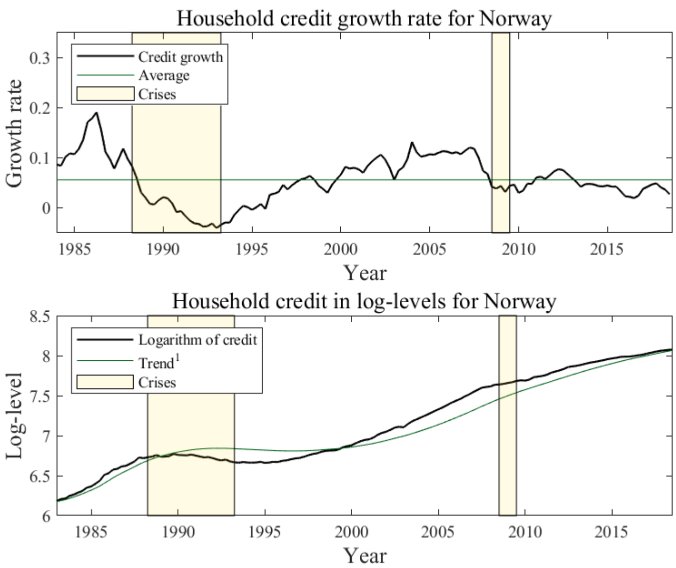

Figure 2: Household credit measures Norway. The growth rate is plotted against its average value. The logarithm is plotted against the logarithm of its trend. The yellow shaded areas are the two recessions that have hit Norway in our sample period. The Norwegian recession lasted from 1988Q2 to 1993Q2. The Global recession lasted from 2008Q3 to 2009Q3.[1] Trend constructed using one-sided Hodrick-Prescott filter, discarded first 12 observations. Lambda=400,000.

The financial liberalization preceding the Norwegian recession started in 1984-1985 when credit regulations were abolished. This combined with increased economic activity, low real interest rates, and favorable tax deductions, resulted in a credit-fueled boom (Stamsø, 2009). We see this credit boom during the build-up to the Norwegian recession in Figure 2. The *household credit growth* *rate* was at its highest, at 19.11 percent, in April 1986, one year prior to the Norwegian recession. Credit growth was also at alleviated levels one year before the Global recession, with a high of 12.05 percent in the third quarter of 2007. In the technical assessment, we find that credit growth provides a true signal in all quarters prior to both recessions, while it provides a false signal in 41 percent of the quarters not preceded by a crisis. Repullo and Saurina (2011) and Sohn and Park (2016) find credit growth to provide more reliable signals than the credit-to-GDP gap, but in our assessment, the gap performs better than credit growth due to the lower share of false signals. However, we still find credit growth to be a good indicator for financial distress. Figure 2 shows that following a period of decreasing after the Norwegian recession, *household credit in logarithms* increases steadily from 1996 and up until the Global recession, and stays above trend from 1999 up until 2016. Household credit slowly flattens at the breach of the Global recession. We find household credit to be among the poorest of the indicators we test. It provides a true signal in only six percent of the quarters before the recessions and a false signal in one percent of the non-crisis quarters. However, as discussed in section 2.2, the threshold for this indicator is not optimal. Yet, given our specification, credit in log-levels does not act as a good indicator for financial imbalances.

Our assessment is that the household credit growth rate is a good indicator of financial imbalances. We proceed with household credit growth in step 2.

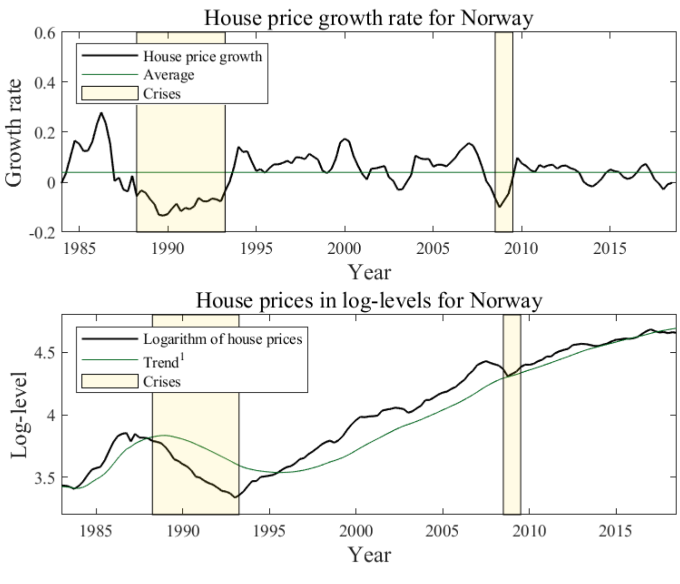

Figure 3: House prices Norway. The growth rate is plotted against its average value. The logarithm is plotted against the logarithm of its trend. The yellow shaded areas are the two recessions that have hit Norway in our sample period. The Norwegian recession lasted from 1988Q2 to 1993Q2. The Global recession lasted from 2008Q3 to 2009Q3. [1] Trend constructed using one-sided Hodrick-Prescott filter, discarded first 12 observations. Lambda=400,000.

From Figure 3, it is evident that the *house price growth* reached a peak one year prior to both recessions, and then stayed below its average growth rate throughout them. Prior to both recessions, the growth rate was above 15 percent, which is far above the average rate of 3.46 percent. However, in non-crises periods such as 1994 and 2000, growth rates were above 14 percent. In real-time, it is hard to know whether these high growth rates are due to changes in fundamentals or due to imbalances, and with large and frequent deviations from average this indicator has the potential to produce false warning signals. In fact, the house price growth proves to be the indicator with the highest false signal ratio of 99 percent. This reflects the fact that the optimal threshold value is the first percentile. In the search for the optimal threshold, we found that all percentiles between the first and the sixteenth provide the same loss. Another potential problem is that the variable only signals distress when it is above the optimal percentile, since the plot shows that house price growth has decreased substantially one year prior to both recessions. A more reliable signal might be that house price growth is below some percentile, not above. Therefore, we test the performance of the indicator when changing the signs of the condition, namely that the signal goes off when house price growth is below the threshold value. The results of this alternative approach are also in Table 5. It yields a lower ratio of false signals, and a lower loss. However, the variable still provides poor indications compared to the other variables in our sample. *House prices in log-levels* peak approximately one year before both recessions. After the Norwegian recession, the house price index was above its trend up until the Global recession. Moreover, it is difficult to find an appropriate threshold value. The plot of house prices shows that house prices decrease prior to both recessions. Therefore, the signal goes off when the house prices are lower than they were 2 quarters ago while still above trend. We find that house prices provide a true signal in 63 percent of the quarters before crises, while it gives a false signal in 9 percent of the quarters not followed by a crisis. The false signal ratio is among the best in our sample, but the true signal ratio is lower than for most other variables, resulting in a relatively high loss.

We find house price growth to give the second-largest loss among our indicator variables, and the house prices in log-levels, despite the low ratio of false signals, provide a too low ratio of true signals. Based on our discussion, we will not proceed with either of the two indicators.

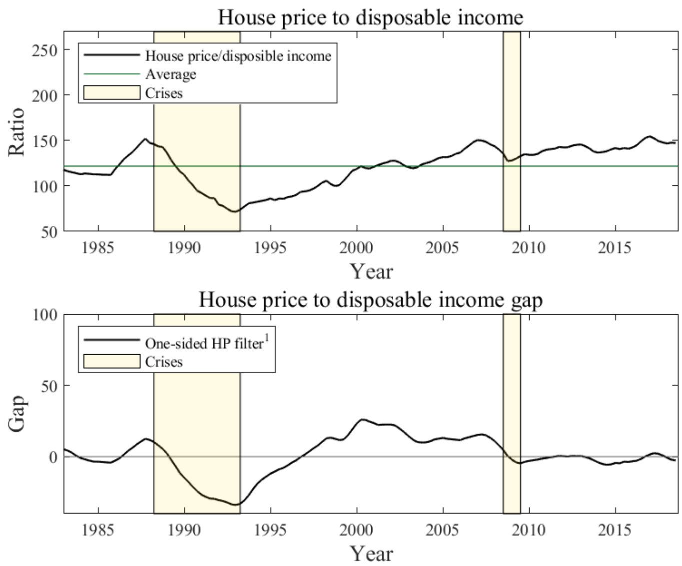

Figure 4: House prices to disposable income Norway. The ratio is plotted against its average value. The yellow shaded areas are the two recessions that have hit Norway in our sample period. The Norwegian recession lasted from 1988Q2 to 1993Q2. The Global recession lasted from 2008Q3 to 2009Q3. [1]One-sided Hodrick-Prescott filter. Lambda=400,000.

Figure 4 indicates that the *ratio of house prices-to-disposable income* is a leading indicator of crises.

In the time preceding both recessions, the ratio increased extensively above its average level. This is also evident in the technical assessment, where we see that the house price-to-income ratio provides true signals in all the pre-crisis quarters. Furthermore, the ratio provides a false signal in less than one-third of the quarters not succeeded by a crisis. The *house price-to-income gap* also peaked prior to the two recessions. However, this gap was high during the period of 1997-2004, and could therefore provide false warnings. In our analysis, the house price-to-income gap provides false signals in 39 percent of the normal quarters, while it gives a true signal in all pre-crisis quarters.

Both the house price-to-income gap and ratio proves to be good indicators for the previous recessions in Norway. For our further assessment, we will only include the house price-to-income ratio. This is because the ratio has a lower rate of false signals compared to the gap, and monetary policy will work through the same channels for both indicators.

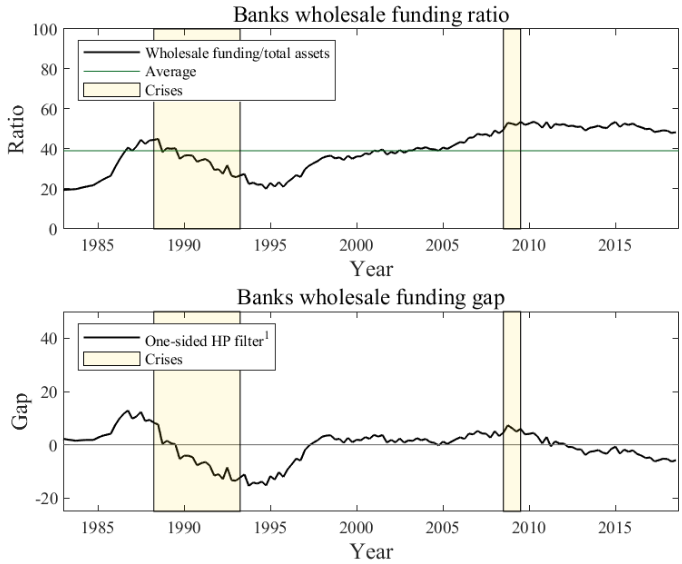

Figure 5: Banks' wholesale funding ratio. The ratio is plotted against its average value. The yellow shaded areas are the two recessions that has hit Norway in our sample period. The Norwegian recession lasted from 1988Q2 to 1993Q2. The Global recession lasted from 2008Q3 to 2009Q3. [1]One-sided Hodrick-Prescott filter. Lambda=400,000.

The *wholesale funding ratio* increased from 20 percent in 1983 to over 40 percent when the Norwegian recession started in 1987. The ratio increased before the Global recession as well, although it did not reach a peak as it did during the Norwegian recession. The high rate of false signals in the technical analysis reflects the fact that the ratio has yet not decreased after the Global recession. To find a threshold that gives a high rate of true signals, we need to accept a high rate of false signals. The wholesale funding ratio provides false signals in 40 percent of the periods. The *wholesale funding gap* was well above zero in the time preceding the Norwegian recession, before it declined during the 1990s. Prior to the Global recession, the gap was at its highest level since before the Norwegian banking crisis. The alleviated level of the gap prior to the Norwegian recession is reflected in the high (negative) correlation coefficient between the wholesale funding gap and GDP growth one year ahead, as can be seen in appendix B.3. As opposed to the ratio, the gap has a downward sloping curve after the global recession. The distinction of the gap in periods followed by distress and other periods makes it an excellent indicator of financial distress. This is evident in the technical analysis, where the funding gap is the highest performing indicator variable among all variables tested. With a true signal ratio of 100 percent, and giving false signals in less than one-fourth of the normal quarters, the loss associated with this indicator is the least of all indicator variables we test. The high threshold value of the 71st percentile also reflects the distinction of the properties of the gap in normal periods and distress periods.

Both the wholesale funding gap and ratio has provided good indications for the previous recessions in Norway. For our further assessment, we will only include the wholesale funding gap. This is because the gap performs the best of the two variables, and monetary policy will work through the same channels for both indicators.

2.4 List of indicators

Indicator	Proceed to step 2
Private credit-to-GDP gap	Yes
Household credit growth	Yes
House price-to-income ratio	Yes
Banks' wholesale funding gap	Yes
Private credit-to-GDP ratio	No
Household credit (log)	No
House price-to-income gap	No
House price growth	No
House prices (log)	No
Banks' wholesale funding ratio	No

Table 6: Assessment of indicator variables.

3 Step 2 - SVAR

In step 2 we assess whether monetary policy can affect the indicators from step 1. The rationale for this assessment is that the central bank wants to minimize a loss function consisting of the output gap, inflation and financial stability (Woodford, 2012). To do so, the central bank needs to consider future financial distress to minimize the loss function. In step 1, we found four financial stability indicators and following our reasoning above the central bank needs to know how their tool influences these variables. Therefore, we will look into whether, and to which extent, the central bank can influence these variables using the monetary policy instrument.

3.1 Data

In the structural VAR models, we include four non-indicator variables that feature in standard New Keynesian models for small open economies with an inflation-targeting central bank (Clarida et al., 2002; Galí and Monacelli, 2005). These are, the *short-term nominal interest rate, inflation, the output gap*, and the *foreign exchange rate*. In accordance with the literature, we use the 3-month Nibor for the short-term interest rate, since it should capture expectations about monetary policy within the quarter (Lund et al., 2016). For inflation, we use the annual growth rate of CPI, since this gives a more direct measure of the central banks' inflation target, and in addition, we avoid the seasonal component of inflation (Bjørnland and Jacobsen, 2010). The use of the output gap is motivated by it being a better measure of the target of the central bank, and that it might be helpful in addressing the price puzzle (Giordani, 2004). Woodford (2012) shows that structural VAR models can be augmented taking financial stability into consideration, by adding indicators for financial imbalances. Therefore, in addition to the non-indicator variables, we add indicator variables from step 1 to the models. This specification is similar to Bjørnland and Jacobsen (2010) and Robstad (2018). The inclusion of multiple indicators in some of our models is motivated by the information content these variables can generate together.

We use data from 1993 to 2018, and the starting period is chosen, first because of the deregulation of the housing and credit markets, and second because of the completion of the disinflationary process, both spanning into the early 1990s. Thus after 1993, Norway has had a stable housing and credit regulation, and a relatively stable monetary policy regime, even though inflation targeting was not formally introduced before 2001 (Steigum, 2011). Following policy regime shifts, we might get structural breaks in the data, and these supposed breaks can cause misleading parameter estimation results since the OLS estimates reflect the average over the sample (Bjørnland and Thorsrud, 2015). The sample only contains one recession, but this is not a problem because we are assessing the effect of a monetary policy shock in normal times. It is in normal times, during the build-up of financial imbalances, the central bank should use contractionary monetary policy to address these imbalances.

The four non-indicator variables are included in all models, and table 7 provides an overview of which indicator variables are included.

Model	Indicator 1	Indicator 2
Model 1	Credit-to-GDP gap	
Model 2	Credit-to-GDP gap	Credit growth
Model 3	Credit-to-GDP gap	House price-to-income
Model 4	Credit-to-GDP gap	Wholesale funding gap
Model 5	Credit growth	
Model 6	Credit growth	House price-to-income
Model 7	Credit growth	Wholesale funding gap
Model 8	House price-to-income	
Model 9	House price-to-income	Wholesale funding gap
Model 10	Wholesale funding gap	

Table 7: Overview of structural VAR models. All ten models include the non-indicator variables, output gap, inflation, foreign exchange rate, and interest rate.

3.2 Methodology

The structural VAR methodology is mainly based on Bjørnland and Thorsrud (2015); Lütkepohl (2005) and Kilian and Lütkepohl (2017), while the Matlab code is based on code from Cesa-Bianchi (2015) and algorithms from Kilian and Lütkepohl (2017). For estimation of the reduced form VAR, we use the unmodified code of Cesa-Bianchi (2015), while for identification of the structural VAR, we have written our own code. We use two identification approaches, the agnostic sign restriction approach of Uhlig (2005), and the recursive restriction approach of Sims (1980).

The premise of the structural VAR approach is that the data generating process can be approximated by the K-dimensional structural VAR(p) process:

$$B_0 y_t = \mu + B_1 y_{t-1} + \cdots + B_p y_{t-p} + w_t \tag{3}$$

Where K is the number of variables within the system, μ is a constant, p is the number of lags, y_t is a $(K \times 1)$ vector of variables and B_i for $i = 1, \ldots, p$ are $(K \times K)$ parameter matrices, w_t is a $(K \times 1)$ vector of structural shocks, with $\mathbb{E}[w_t] = 0$ and $\mathbb{E}[w_t w_t'] \equiv \Sigma_w = I_k$. This means that the number of structural shocks equals the number of variables, that the structural shocks by definition are uncorrelated, that Σ_w is diagonal, and that the variance of all structural shocks are normalized to one.

We follow the general modelling strategy of first estimating the reduced form VAR from equation (4) and then recover the structural VAR from equation (3) (Lütkepohl, 2005). By premultiplying both sides of equation (3) by B_0^{-1}, we obtain the corresponding reduced form VAR:

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{4}$$

Where $A_i = B_0^{-1} B_i$ for $i = 1, \ldots, p$, $u_t = B_0^{-1} w_t$ and $\nu = B_0^{-1}\mu$. In the reduced form VAR, u_t is a vector of error terms, with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[e_t e_s'] \equiv \Sigma_e$ if $t = s$ and 0 if $t \neq s$. For derivation of the companion form and moving average representation, see appendix D. For each of the K variables we have a sample size of T, in other words, $\{y_t\}_{t=1}^{T}$. We can estimate the reduced form VAR equation-by-equation for all K equations in (4) by OLS. After estimating the reduced form VAR, we want to recover the structural parameters of the structural VAR in equation (3), to use them for impulse response analysis. Knowledge of B_0 or B_0^{-1} enable us to identify w_t and B_i for $i = 1, \ldots, p$ through:

$$w_t = B_0 u_t \tag{5}$$

We call B_0^{-1} the structural impact multiplier matrix. We know that $u_t = B_0^{-1} w_t$ and hence, the variance of u_t is:

$$\Sigma_u = \mathbb{E}[u_t u_t^{'}] = B_0^{-1}\,\mathbb{E}[w_t w_t'] B_0^{-1\prime} = B_0^{-1} \Sigma_w B_0^{-1\prime} = B_0^{-1} B_0^{-1\prime} \tag{6}$$

Where we have used the fact that $\Sigma_w = I_K$, and consider Σ_u as known from the estimation. In order to solve the *structural identification problem*, we need to disentangle the structural shocks,

w_t, from the reduced form errors, u_t, by putting restrictions on B_0^{-1}. The structural identification problem refers to identifying the structural relationship untangling the simultaneity. We use two different approaches to solve this problem. First, we will use recursive approach of Sims (1980), and secondly the agnostic sign restriction approach of Uhlig (2005).

3.2.1 Recursive restrictions

First, we disentangle the structural shocks by orthogonalizing the reduced form errors, in other words, we make the shocks uncorrelated (Sims, 1980). When applying the Cholesky decomposition, we impose a particular causal chain (recursive structure), rather than learning about the causal relationship from the data. By doing so, we solve the structural identification problem, namely which structural shock causes the variation in the error term, by imposing a particular solution. The recursive structure poses a problem when there are multiple asset prices in the model, since asset prices and the interest rate may respond simultaneously to news (Bjørnland and Jacobsen, 2010). The normal procedure is either to assume that asset prices are restricted from responding contemporaneously to monetary policy shocks, or the opposite, that the central bank does not respond contemporaneously to asset price shocks. We identify the monetary policy shock by ordering the short-term nominal interest rate last in a recursive structure, so that all variables above it is part of the monetary policy function, and the residual variation is treated as a monetary policy shock. As we are only interested in identifying the monetary policy shock, the ordering of the variables above the interest rate does not matter. We report the point estimate of the uniquely identified model. The bands are 84 percentage confidence intervals constructed around the point estimate using bootstrapping.

3.2.2 Sign restrictions

In our second identification scheme, we allow for both the interest rate and asset prices to simultaneously respond to each other. Following Faust (1998), Canova and Nicoló (2002) and Uhlig (2005), we disentangle the structural shocks from the reduced form errors by imposing a sign structure on the impact multiplier matrix. We generate a large number of candidate matrices from the set of all orthogonal matrices by using the Householder transformation approach. This approach is taken from Kilian and Lütkepohl (2017), but was first proposed by Rubio-Ramírez et al. (2010).

We identify the monetary policy shock by restricting the signs of all non-indicator variables, and leave the signs of the indicators unrestricted. The impulse response functions are constructed using ten thousand accepted draws of the impact multiplier matrix. Following a contractionary monetary policy shock, captured by a one percentage point increase in the interest rate, we assume a decline in output, a decline in inflation, and an appreciation of the foreign exchange rate. The restrictions derives from economic theory and empirical evidence.

	Restriction
Interest rate	+
Output gap	-
Inflation	-
Foreign exchange rate	-
Indicator variables	Unrestricted

Table 8: Sign restrictions.

According to Walsh (2017), empirical evidence from VAR models suggest that following a contractionary monetary policy shock, *output* will fall and follow a hump-shaped pattern, he refers to both Sims (1992) and Christiano et al. (1999). This response is also suggested in theoretical models, for example Christiano et al. (2005). The restriction on *inflation* is not as clear cut, even though this assumption is often made in sign restriction models, see for example (Uhlig, 2005; Vargas-Silva, 2008; Rafiq and Mallick, 2008; Carstensen et al., 2009). Many empirical studies find that inflation initially increases following a contractionary monetary policy shock. An explanation for this *price puzzle* is that monetary policy acts in anticipation of inflation (Walsh, 2017). From this, it follows that the solution is to add forward-looking variables to the VAR model, which are supposed to proxy for expected inflation and capture more of the central banks information set (Sims, 1992). An alternative explanation for the price puzzle, is that the increased interest rate increase firms' costs, and when the costs increase, prices increase as well (Barth and Ramey, 2001). Furthermore, another alternative explanation is that that using output, as opposed to the output gap, spuriously produce a price puzzle (Giordani, 2004). The overshooting model of Dornbusch (1976) is consistent with the fact that the *foreign exchange rate* should appreciate following a contractionary monetary policy shock. Empirical evidence is provided by Bjørnland (2009) who finds that a contractionary monetary policy shock has a strong effect on the foreign exchange rate which appreciates on impact. Other puzzles related to the foreign exchange rate, like the forward discount puzzle, and the delayed overshooting puzzle, has more to do with the shape of the response, than the sign of the response (Scholl and Uhlig, 2008).

We report two impulse responses, the median impulse response for each variable, and the mean target of Fry and Pagan (2011), that uniquely identifies the model with the impulse response function closest to the mean impulse responses over all variables. The bands represent impulse responses within the 16-84 percentiles of responses.

3.3 Results

In the following, we will see how the accepted variables from step 1 react to a monetary policy shock. An overview of the structural VAR models is presented in Table 7. Appendix C shows all models with impulse responses and bands.

In all models, there seems to be signs of money neutrality with a negative output gap turning positive before the effect dies out. In the sign models, the *output gap* decreases instantly between -1.5 and -2 percentage points and in the recursive models after one quarter with approximately

-0.5 percentage points. In all sign restriction models, the *foreign exchange rate* appreciates on impact, where the initial appreciation of the exchange rate is followed by a gradual depreciation back to baseline. These results are in line with Bjørnland (2009) who find evidence in support of Dornbusch's overshooting hypothesis. In the recursive model, there is a delayed response, followed by either a small appreciation or a non-significant response. *Inflation* decrease around 2 percentage points on impact. This effect dies out rather quickly without a reversal in the price level, which is consistent with the effect in standard New Keynesian models with inflation-targeting central banks. In the recursive models that usually produce the price puzzle, we find no evidence of it. The initial increase in inflation is non-significant in all recursive models. Overall, the effect on the non-indicators is consistent over all model specifications, and in line with previous literature.

Continuing with the indicator variables, we look at the responses of household credit growth, house price-to-income ratio, private credit-to-GDP gap, and the wholesale funding gap, to a contractionary monetary policy shock, in the models where they are included.

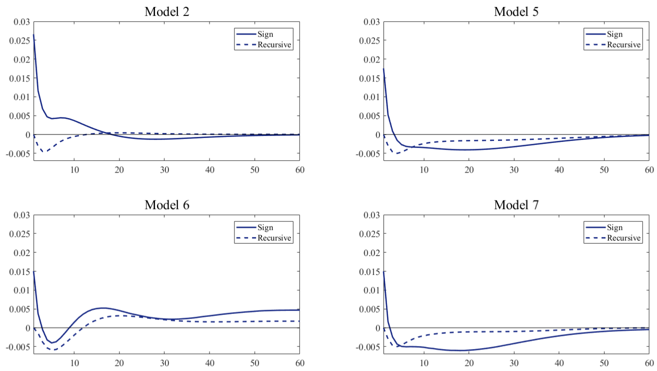

Figure 6: Response of credit growth to a one percentage point contractionary monetary policy shock. Solid lines show the impulse response function using sign restrictions. Dashed lines show the impulse response function using recursive restrictions. All models include credit growth and the core variables, output gap, inflation, foreign exchange rate, and nominal interest rate. Model 2 includes credit-to-GDP gap. Model 6 includes house price-to-income. Model 7 includes wholesale funding gap.

The main results for *credit growth* are presented in Figure 6. Both restriction schemes show that the change in credit growth is small. The small effect is in line with the previous VAR study of credit and monetary policy in Norway (Robstad, 2018). All recursive models show small but significant declines following a hump-shaped pattern. The response of the sign models show an initial increase before decreasing below baseline, however, the spread of responses differs substantially, see appendix C. Hence, if credit growth increases to the extent that it will be followed by financial instability, the central bank can not interrupt this credit growth effectively by increasing the interest rate.

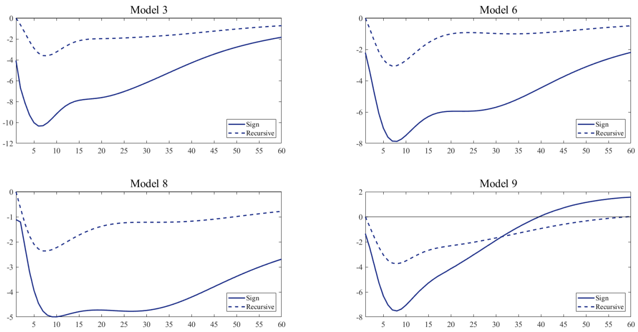

Figure 7: Response of house price-to-income to a one percentage point contractionary monetary policy shock. Solid lines show the impulse response function using sign restrictions. Dashed lines show the impulse response function using recursive restrictions. All models include house price-to-income and the core variables, output gap, inflation, foreign exchange rate and nominal interest rate. Model 3 includes credit-to-GDP gap. Model 6 includes credit growth. Model 9 includes wholesale funding gap.

The main results for the *house price-to-income ratio* are presented in Figure 7. In line with Robstad (2018) and Bjørnland and Jacobsen (2010)'s results that house prices react strongly to a monetary policy shock, we find that the house price-to-income ratio decrease significantly. In all recursive specifications, the ratio declines significantly during the first 3-4 years. For the sign models, the response decreases on impact and stays below baseline in all models, except model 9 where the wholesale funding gap is included. In model 9, the ratio instead returns to baseline after 10 years. Remarkably, all responses of the sign models show declines in the ratio, see appendix C. These findings imply that an interest rate increase will effectively decrease the house price-to-income ratio. Given the results from step 1, namely that when the ratio is high it is often followed by financial instability, the central bank can use the interest rate to impact the future stability of the financial system.

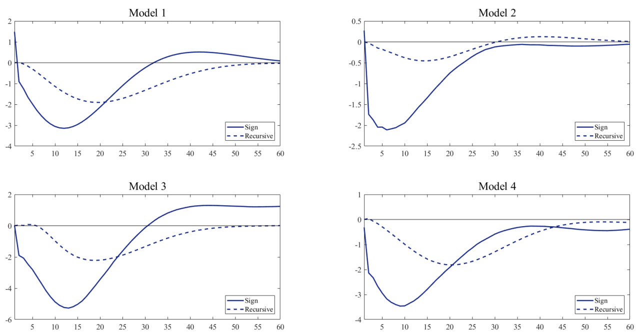

Figure 8: Response of credit-to-GDP gap to a one percentage point contractionary monetary policy shock. Solid lines show the impulse response function using sign restrictions. Dashed lines show the impulse response function using recursive restrictions. All models include credit-to-GDP gap and the core variables, output gap, inflation, foreign exchange rate, and nominal interest rate. Model 2 includes credit growth. Model 3 includes house price-to-income. Model 4 includes wholesale funding gap.

The main results for the *credit-to-GDP gap* are presented in Figure 8. Our results are contrary to the findings of Robstad (2018), who find that the credit-to-GDP ratio increase slightly but insignificant following a monetary tightening. We also debunk the argument of Svensson (2013), who claims that following a contractionary monetary policy shock, this ratio increase. Our results give support to the argument of Borio and Lowe (2004), that one can lean by targeting the credit-to-GDP ratio. In all models, the indicator first decreases before returning to baseline at the end of the horizon. The results are significant under recursive restrictions in model 1 and 3, while under the sign restriction, all responses falls below baseline in model 1, 3 and 4, see appendix C.

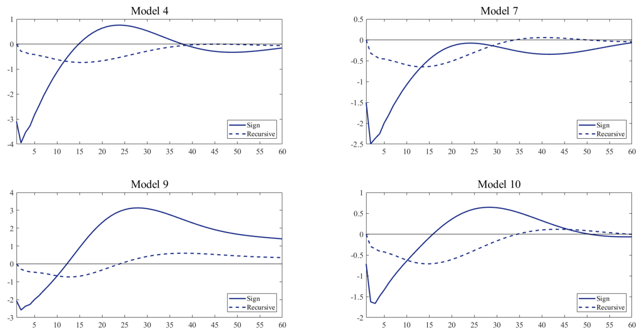

Figure 9: Response of wholesale funding gap to a one percentage point contractionary monetary policy shock. Solid lines show the impulse response function using sign restrictions. Dashed lines show the impulse response function using recursive restrictions. All models include wholesale funding gap and the core variables, output gap, inflation, foreign exchange rate, and nominal interest rate. Model 4 includes credit-to-GDP gap. Model 7 includes credit growth. Model 9 includes house price-to-income.

The main results for the *wholesale funding gap* are presented in Figure 9. Previous results from Halvorsen and Jacobsen (2016) find that following an expansionary monetary policy shock, the wholesale funding ratio increases. Given symmetry, their result implies that a contractionary monetary policy shock should lead to a decrease in the ratio. We find non-significant effects in all recursive models while we get mixed results from the sign models. In model 7 all sign responses decrease below baseline briefly after 3 quarters. In model 9 all sign responses increase above baseline after 6 years, similar for model 10 where all sign responses increase above baseline after 8 years, see appendix C. Given the non significant results from the recursive models and the mixed results from the sign models, the central bank can not efficiently target the wholesale funding gap with an interest rate increase.

Overall, we find that following a contractionary monetary policy shock, both the credit-to-GDP gap and the house price-to-income ratio decreases, while there are small or insignificant effects on credit growth and the wholesale funding gap. The identification method seems to be important for the magnitude of the responses, where the effect seems to be stronger with sign restrictions in all models. Furthermore, the combination of indicators seems to matter in some cases. The house price-to-income ratio responds differently when combined with the wholesale funding gap compared to when alone or combined with the other indicators. The credit-to-GDP gap is significant when alone and when combined with the house price-to-income ratio, but not significant when combined with credit growth or the wholesale funding gap.

4 Conclusion

In 2018, the Norwegian Government issued a new regulation for the conduct of monetary policy. It explicitly states that the central bank shall counteract the build-up of financial imbalances. For monetary policy to do so, it is important to know how monetary policy affects financial imbalances. This paper attempts to build a bridge between financial stability and monetary policy by answering the descriptive question of whether and how monetary policy affects financial stability. In order to do so, we first find good indicators for financial stability, and second, assess the impact of a contractionary monetary policy shock on these indicators.

We have investigated the predicative ability of five indicators of financial stability for the past two Norwegian recessions, using a signaling approach. Our results show that the private credit-to-GDP gap, household credit growth, house price-to-income ratio and gap, and banks' wholesale funding ratio and gap have provided good indications of financial distress in Norway in the past. Particularly, the wholesale funding gap performs best of all indicator variables in our sample. Furthermore of interest, Norges Bank use credit-to-GDP as a main indicator for financial stability, while we found credit growth to be a better indicator for financial stability than the credit-to-GDP ratio, providing a false signal in two-thirds of the quarters the ratio does. However, among our credit indicators, the credit-to-GDP gap is the best performing indicator, which is in line with Norges Banks view on the gap as an important indicator variable. House prices-to-income, both in gap and ratio, showed good predicative abilities over the past 35 years in Norway, and provided the smallest loss after the wholesale funding gap. Since these indicators are determinants of financial stability, we further ask the descriptive question of whether and how the central bank can affect these variables using the monetary policy instrument.

We examined the effect of monetary policy on financial stability using ten structural VAR models, with a fixed set of non-indicator variables, and different combinations of indicator variables. Compared to previous studies on financial stability and monetary policy in Norway, we use a broader set of indicators. Our findings suggest that monetary policy is not neutral when it comes to financial stability. We show that monetary policy can affect some of the important determinants of financial stability, by using the short-term nominal interest rate. In particular, we find that monetary policy influences the credit-to-GDP gap, which falls as a response to a contractionary monetary policy shock. In addition, the house price-to-income ratio falls in all our models. Nevertheless, the effects on household credit growth and the wholesale funding gap are either small or insignificant.

We found variables that provide good signals for periods of financial instability and showed that the central bank can use monetary policy to influence some of these variables. The central bank can include the four variables above when assessing the probability of financial distress. Since a high house price-to-income ratio signals financial instability, the central bank should react to an increase in the ratio by increasing the interest rate, which in turn decrease the ratio and thereby lower the probability of future financial distress. The same rationale goes for the private credit-to-GDP gap. However, our results show that a contractionary monetary policy shock will not affect credit growth or the wholesale funding gap. In a framework where the determinants of financial stability are included in the loss function, we advise the central bank to put particular importance on the credit-to-GDP gap and the house price-to-income ratio.

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A Data

We use quarterly data for Norway. The data and its sources are reported in Table 9.

Data	*Source*	Transformation
Real GDP	*FRED*	Output gap constructed using one-sided HP-filter.
3-month Nibor	OSE	
CPI	SSB	Inflation as annual growth rate of CPI.
Nominal foreign exchange rate I-44	Norges Bank	
Nominal house price index	OECD	Deflated by CPI. In log and growth.
House price index over disposable income ratio	Norges Bank	
House price index over disposable income gap	Norges Bank	
Household credit (C2)	BIS	Deflated by CPI. In log and growth.
Private credit (C2 and C3) to real GDP	Norges Bank	
Banks' wholesale funding ratio	Norges Bank	
Banks' wholesale funding gap	Norges Bank	

Table 9: Quarterly data. Mainland Norway when applicable.

B Indicators

B.1 Summary statistics

	Mean	Median	Std	CoV	Min	Max
Credit-to-GDP	151.84	143.53	28.88	5.26	108.76	200.23
Credit-to-GDP gap	2.43	4.51	11.34	0.21	-23.18	20.20
Household credit	1547.89	1178.43	817.79	1.89	684.27	3193.84
Household credit growth	0.05	0.05	0.05	1.15	-0.04	0.19
House prices	62.56	56.78	25.27	2.48	28.06	107.81
House price growth	0.03	0.05	0.08	0.45	-0.13	0.28
House price-to-income ratio	122.66	128.53	23.41	5.24	71.67	154.75
House price-to-income gap	0.73	0.40	14.40	0.05	-33.85	25.89
Wholesale funding ratio	40.66	40.09	9.39	4.33	20	53.64
Wholesale funding gap	-0.88	0.57	6.31	-0.14	-15.43	12.91

Table 10: Summary statistics of all indicator variables. Mean is the mean of each series. Median is the median of each series. Std is standard deviation of each series. CoV is the standard deviation divided by the the mean of each series, commonly referred to as the coefficient of variation. Min is the smallest number in each series. Max is the largest number in each series.

B.2 Lagged correlations (1986-2018)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GDP growth * (1)	1	-0.3588	-0.3341	-0.3142	-0.2733	0.2556	-0.2267	-0.1462	-0.1192	-0.0899	-0.0104
Wholesale funding ratio (2)	-0.3588	1	0.8369	0.447	0.5571	-0.1185	0.9104	0.8838	0.8469	0.3254	0.1866
House price-to-income ratio (3)	-0.3341	0.8369	1	0.6417	0.7137	0.1251	0.7539	0.7985	0.6864	0.5756	0.5502
Wholesale funding gap (4)	-0.3142	0.4470	0.6417	1	0.8019	0.2649	0.1576	0.2230	0.0511	0.6999	0.7719
Credit-to-GDP gap (5)	-0.2733	0.5571	0.7137	0.8019	1	0.0100	0.4181	0.3681	0.2288	0.5937	0.6536
House price growth (6)	0.2556	-0.1185	0.1251	0.2649	0.0100	1	-0.1520	0.1017	-0.0190	0.4167	0.6071
Credit-to-GDP ratio (7)	-0.2267	0.9104	0.7539	0.1576	0.4181	-0.1520	1	0.9448	0.9590	0.0939	0.0455
House prices (8)	-0.1462	0.8838	0.7985	0.2230	0.3681	0.1017	0.9448	1	0.9772	0.2948	0.1987
Household credit (9)	-0.1192	0.8469	0.6864	0.0511	0.2288	-0.0190	0.9590	0.9772	1	0.1086	0.0134
House price-to-income gap (10)	-0.0899	0.3254	0.5756	0.6999	0.5937	0.4167	0.0939	0.2948	0.1086	1	0.7060
Household credit growth (11)	-0.0104	0.1866	0.5502	0.7719	0.6536	0.6071	0.0455	0.1987	0.0134	0.7060	1

Table 11: Correlation coefficients. * GDP growth is one year ahead

B.3 Lagged correlations (1987-1989 and 2006-2008)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GDP growth 1 (1)	1	0.5684	0.5531	0.5334	0.5082	-0.4409	0.2740	-0.2292	0.2197	-0.1095	0.0320
Credit-to-GDP gap (2)	0.5684	1	0.9458	0.9625	0.9743	-0.8770	-0.1067	0.3809	0.8483	0.5159	-0.3955
House prices (3)	0.5531	0.9458	1	0.9908	0.9704	-0.9211	0.0588	0.3437	0.7811	0.5327	-0.2828
Household credit (4)	0.5334	0.9625	0.9908	1	0.9927	-0.9394	-0.0547	0.3543	0.8283	0.5231	-0.3774
Credit-to-GDP ratio (5)	0.5082	0.9743	0.9704	0.9927	1	-0.9335	-0.1527	0.3966	0.8773	0.5402	-0.4553
Wholesale funding gap (6)	-0.4409	-0.8770	-0.9211	-0.9394	-0.9335	1	0.0744	-0.4008	-0.7385	-0.5670	0.3080
House price growth (7)	0.2740	-0.1067	0.0588	-0.0547	-0.1527	0.0744	1	-0.4148	-0.4678	-0.2290	0.8409
House price-to-income ratio (8)	-0.2292	0.3809	0.3437	0.3543	0.3966	-0.4008	-0.4148	1	0.6455	0.9547	-0.3545
Wholesale funding ratio (9)	0.2197	0.8483	0.7811	0.8283	0.8773	-0.7385	-0.4678	0.6455	1	0.6869	-0.6961
House price-to-income gap (10)	-0.1095	0.5159	0.5327	0.5231	0.5402	-0.5670	-0.2290	0.9547	0.6869	1	-0.2769
Household credit growth (11)	0.0320	-0.3955	-0.2828	-0.3774	-0.4553	0.3080	0.8409	-0.3545	-0.6961	-0.2769	1

Table 12: Correlation coefficients. * GDP growth is one year ahead.

B.4 Crisis predictability

B.4.1 $\beta = 0.5$

	True signals	False signals	Loss	Threshold
Wholesale funding gap	1.00	0.22	0.11	71
House price to income ratio	1.00	0.32	0.16	70
Credit-to-GDP gap	1.00	0.34	0.17	55
House price to income gap	1.00	0.39	0.19	66
Wholesale funding ratio	1.00	0.40	0.20	59
Credit growth	1.00	0.41	0.20	62
House prices (log)	0.63	0.08	0.23	2*
Credit-to-GDP ratio	1.00	0.61	0.31	29
Credit (log)	0.06	0.01	0.48	1*
House price growth	1.00	0.99	0.50	1

Table 13: True signals is the periods a true signal is provided, divided by the number of periods we want a signal. False signals is the periods of false signals made divided by the number of periods we do not want a signal. Loss is the loss stemming from the loss function in section 2.2. Threshold shows the percentile value for which the signal goes off. *The threshold of the logarithms is by how many quarters back we compare the logarithms with when determining the signal value. The loss function is minimized using $\beta = 0.5$.

B.4.2 $\beta = 0.6$

	True signals	False signals	Loss	Threshold
Wholesale funding gap	1.00	0.22	0.09	71
House price to income ratio	1.00	0.32	0.13	70
Credit-to-GDP gap	1.00	0.34	0.14	55
House price to income gap	1.00	0.39	0.15	66
Wholesale funding ratio	1.00	0.40	0.16	59
Credit growth	1.00	0.41	0.16	62
House price growth *	0.75	0.21	0.23	39
Credit-to-GDP ratio	1.00	0.61	0.25	29
House prices (log)	0.63	0.09	0.26	2**
House price growth	1.00	0.99	0.40	1-16
Credit (log)	0.06	0.01	0.57	1**

Table 14: True signals is the periods a true signal is provided, divided by the number of periods we want a signal. False signals is the periods of false signals made divided by the number of periods we do not want a signal. Loss is the loss stemming from the loss function in section 2.2. Threshold shows the percentile value for which the signal goes off. *The threshold of the logarithms is by how many quarters back we compare the logarithms with when determining the signal value. The loss function is minimized using $\beta = 0.6$.

B.4.3 $\beta = 0.7$

	True signals	False signals	Loss	Threshold
Wholesale funding gap	1.00	0.22	0.07	71
House price to income ratio	1.00	0.32	0.10	70
Credit-to-GDP gap	1.00	0.34	0.10	55
House price to income gap	1.00	0.39	0.12	66
Wholesale funding ratio	1.00	0.40	0.12	59
Credit growth	1.00	0.41	0.12	62
Credit-to-GDP ratio	1.00	0.61	0.18	29
House prices (log)	0.63	0.09	0.29	2*
House price growth	1.00	0.99	0.30	1-16
Credit (log)	0.06	0.01	0.66	1*

Table 15: True signals is the periods a true signal is provided, divided by the number of periods we want a signal. False signals is the periods of false signals made divided by the number of periods we do not want a signal. Loss is the loss stemming from the loss function in section 2.2. Threshold shows the percentile value for which the signal goes off. *The threshold of the logarithms is by how many quarters back we compare the logarithms with when determining the signal value. The loss function is minimized using $\beta = 0.7$.

B.4.4 $\beta = 0.8$

	True signals	False signals	Loss	Threshold
Wholesale funding gap	1.00	0.22	0.04	71
House price to income ratio	1.00	0.32	0.06	70
Credit-to-GDP gap	1.00	0.34	0.07	55
House price to income gap	1.00	0.39	0.08	66
Wholesale funding ratio	1.00	0.40	0.08	59
Credit growth	1.00	0.41	0.08	62
Credit-to-GDP ratio	1.00	0.61	0.12	29
House price growth	1.00	0.99	0.20	1-16
House prices (log)	0.63	0.09	0.32	2*
Credit (log)	0.06	0.01	0.75	1*

Table 16: True signals is the periods a true signal is provided, divided by the number of periods we want a signal. False signals is the periods of false signals made divided by the number of periods we do not want a signal. Loss is the loss stemming from the loss function in section 2.2. Threshold shows the percentile value for which the signal goes off. *The threshold of the logarithms is by how many quarters back we compare the logarithms with when determining the signal value. The loss function is minimized using $\beta = 0.8$.

C SVAR models

In the sign restriction models, the solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles. The sign restrictions are applied to the last column of the B_0^{-1} matrix, and follow from the signs of the right hand side vector. In the recursive models, the solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals. The recursive restrictions on the B_0^{-1} matrix follow from the ordering of the left hand side vector.

C.1 Model 1

A five variable model, including the indicator credit-to-GDP gap. We use two lags since that is the overall best performer in the information criterion tests, see Table 17 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9382.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit-to-GDP gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

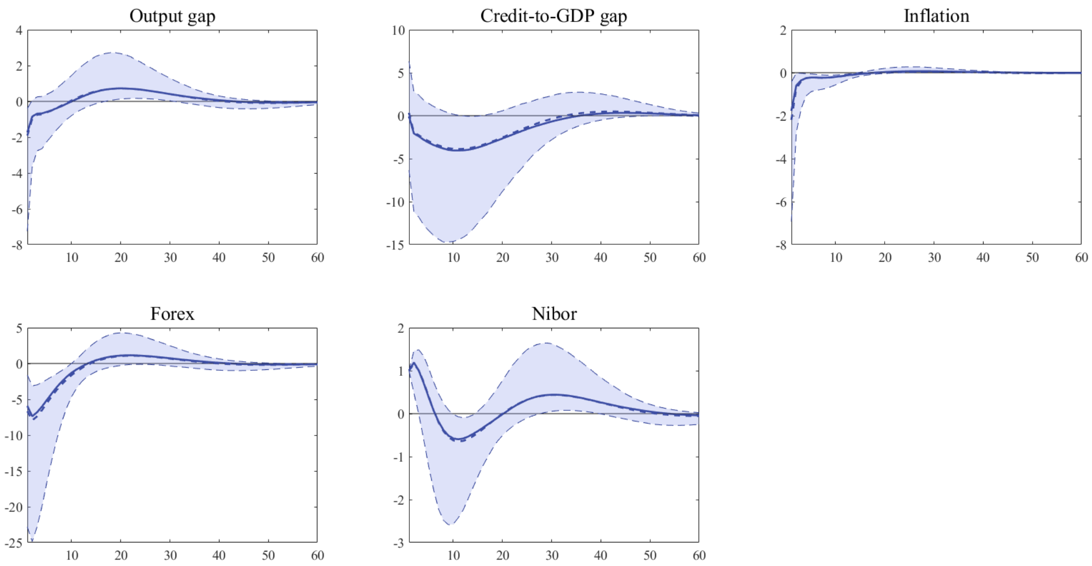

Figure 10: Model 1: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

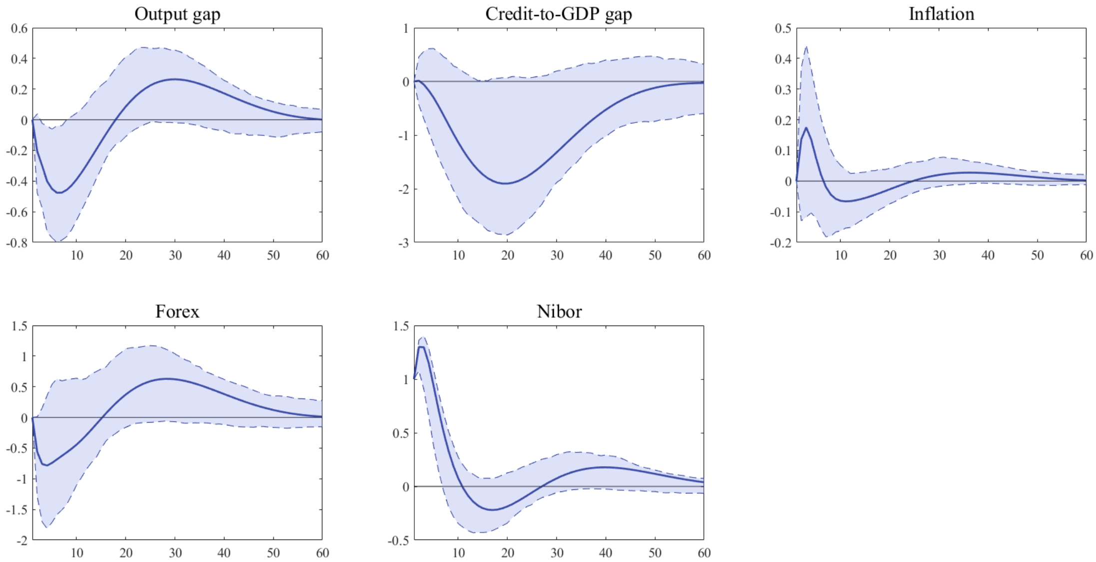

Figure 11: Model 1: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.2 Model 2

A six variable model, which includes the indicators credit-to-GDP gap and credit growth rate. We use two lags since that is the overall best performer in the information criterion tests, see Table 18 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9229.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit-to-GDP gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Credit growth rate} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

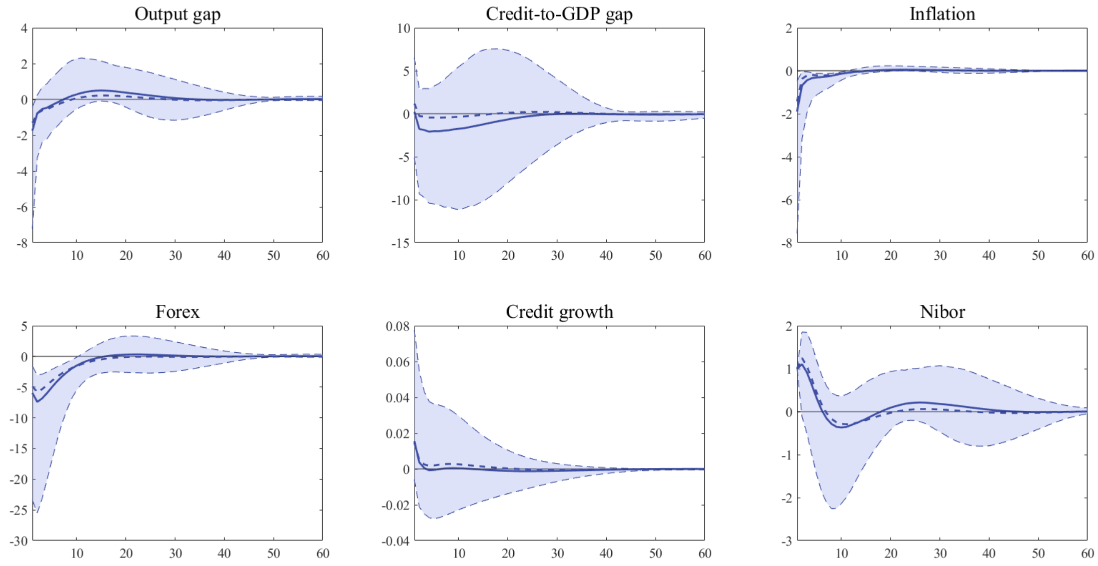

Figure 12: Model 2: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

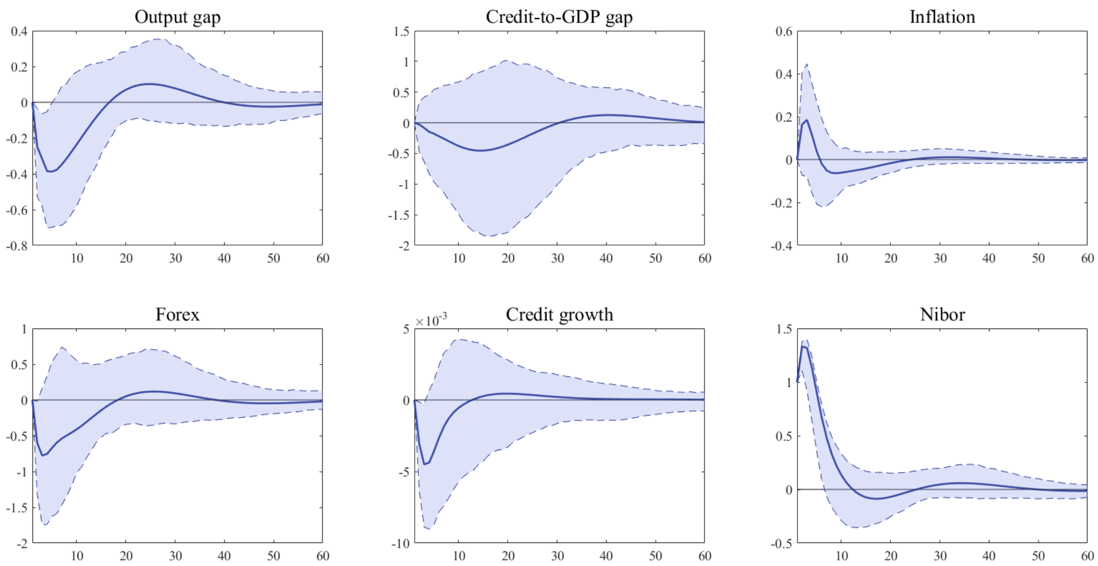

Figure 13: Model 2: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.3 Model 3

A six variable model, which includes the indicators credit-to-GDP gap and house price-to-income. We use two lags since that is the overall best performer in the information criterion tests, see Table 19 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9808.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit-to-GDP gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{House price-to-income} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

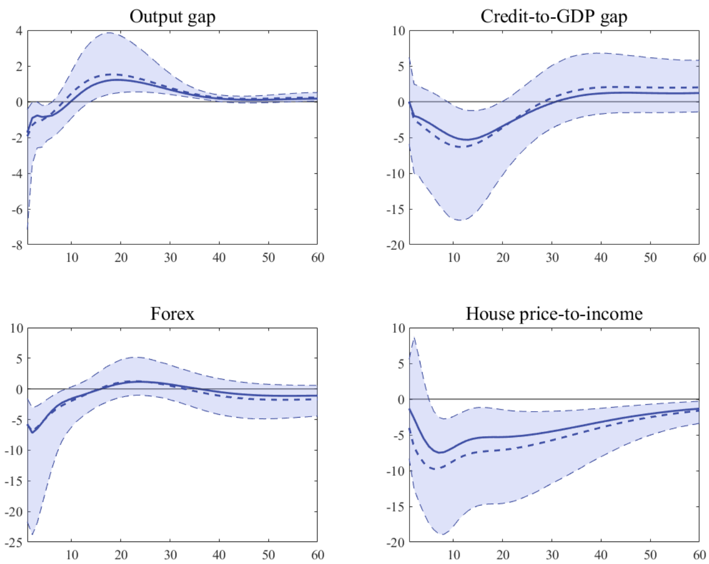

Figure 14: Model 3: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

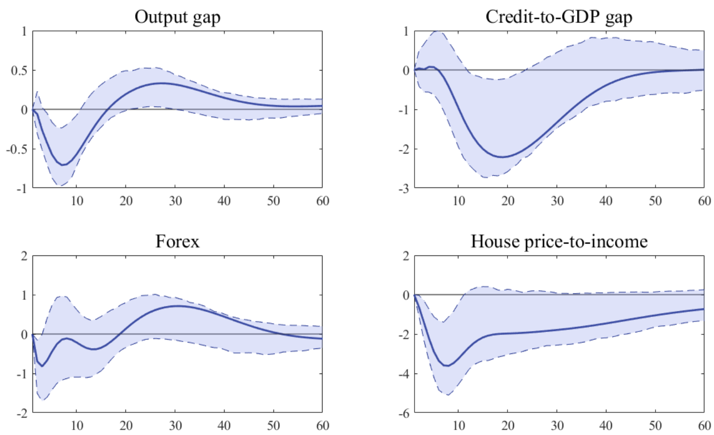

Figure 15: Model 3: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.4 Model 4

A six variable model, which includes the indicators private sector credit-to-GDP gap and house price-to-income. We use two lags since that is the overall best performer in the information criterion tests, see Table 20 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9523.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit-to-GDP gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Banks' wholesale funding gap} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

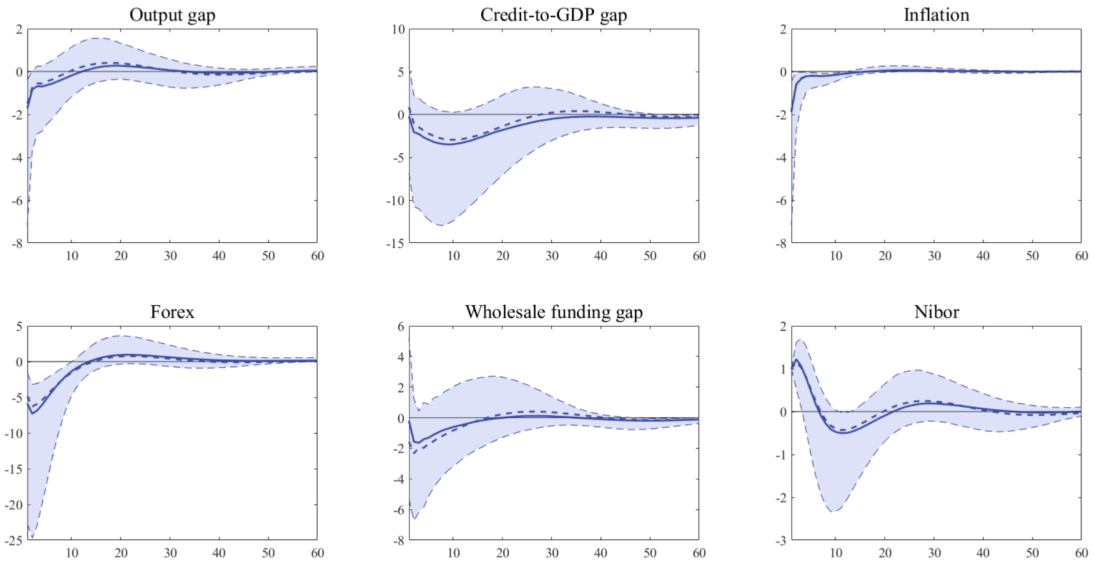

Figure 16: Model 4: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

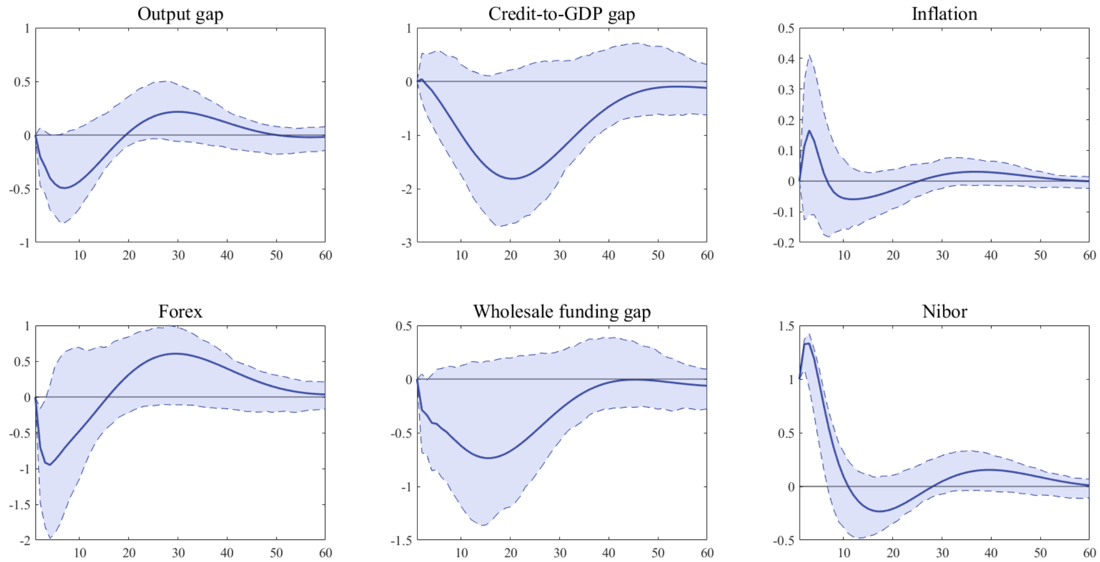

Figure 17: Model 4: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.5 Model 5

A five variable model, which includes the indicator household credit growth rate. We use two lags since that is the overall best performer in the information criterion tests, see Table 21 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9331.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit growth rate} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

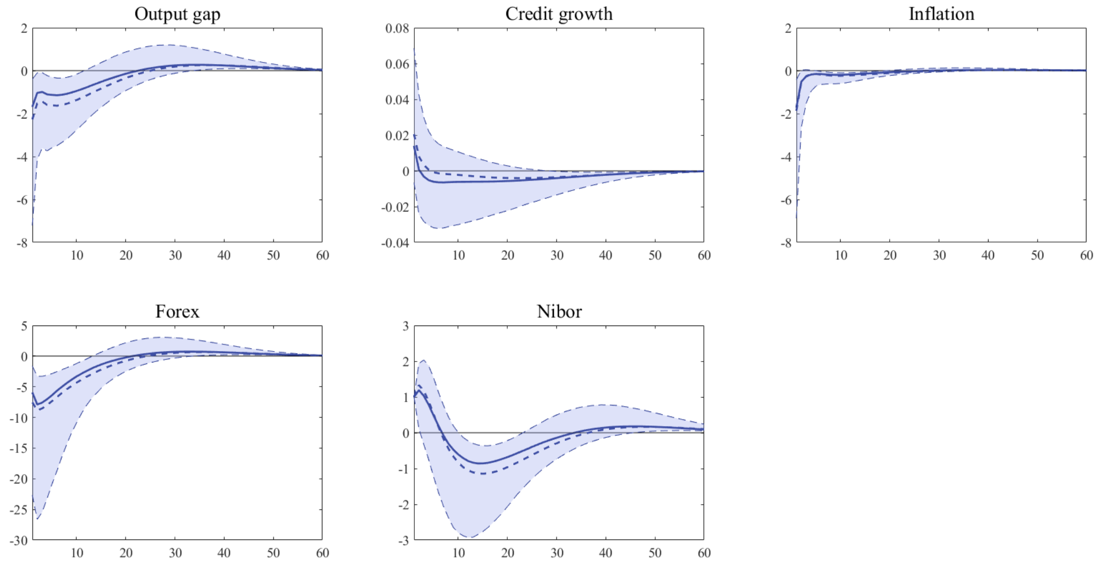

Figure 18: Model 5: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

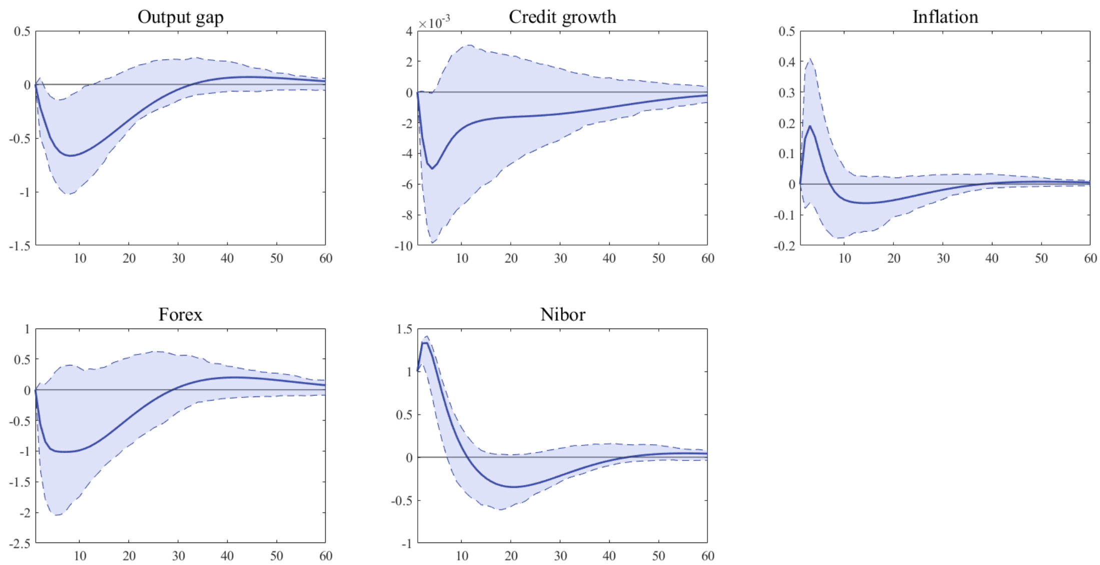

Figure 19: Model 5: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.6 Model 6

A six variable model, which includes the indicators household credit growth rate and house price-to-income. We use two lags since that is the overall best performer in the information criterion tests, see Table 22 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9749.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit growth rate} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{House price-to-income} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

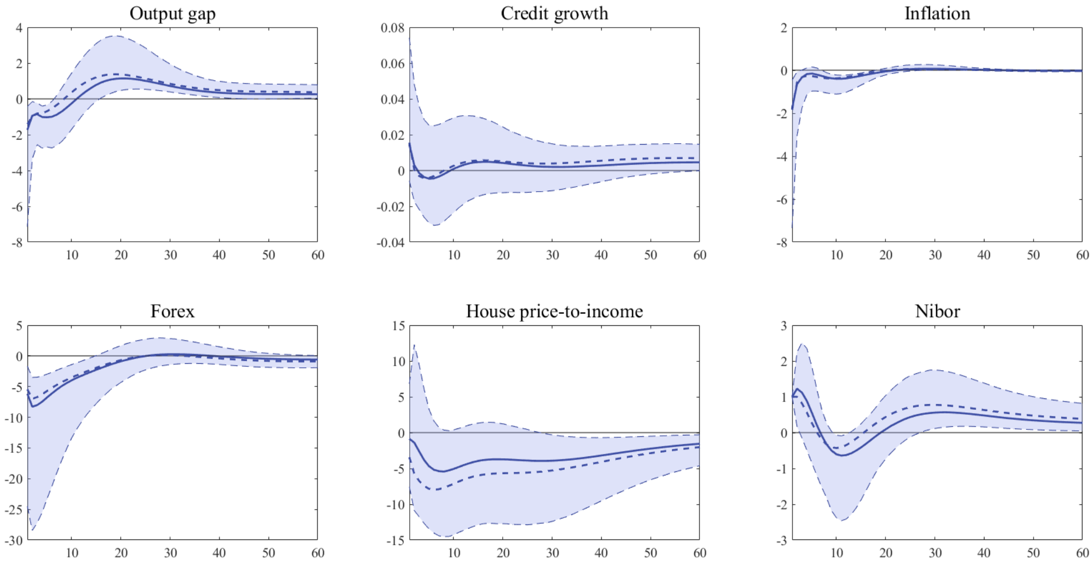

Figure 20: Model 6: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

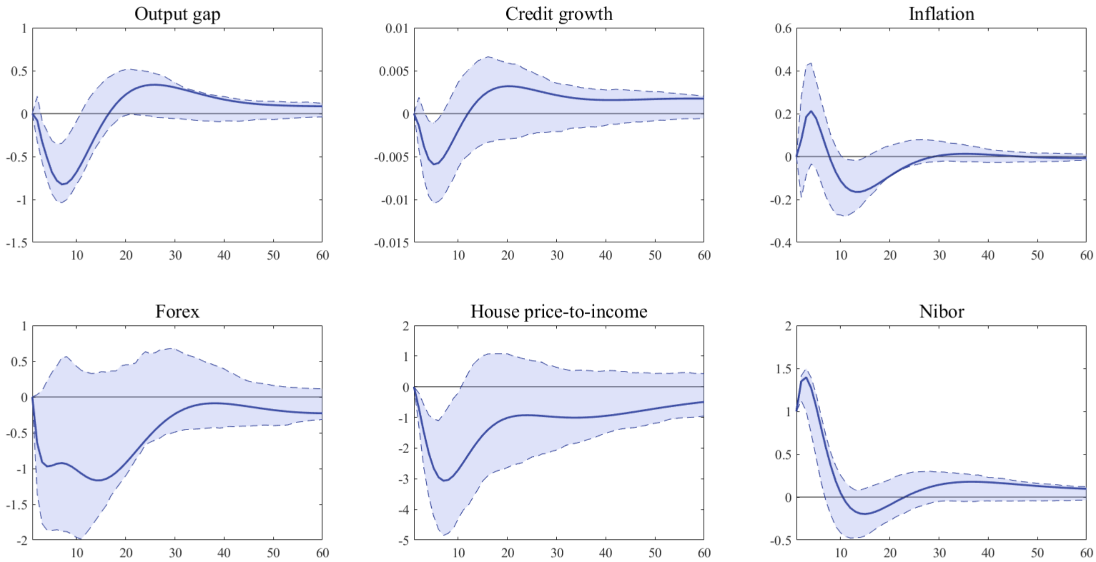

Figure 21: Model 6: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.7 Model 7

A six variable model, which includes the indicators credit growth rate and banks' wholesale funding gap. We use two lags since that is the overall best performer in the information criterion tests, see Table 23 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9482.

$$\begin{bmatrix} \text{Output gap} \\ \text{Credit growth rate} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Wholesale funding gap} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

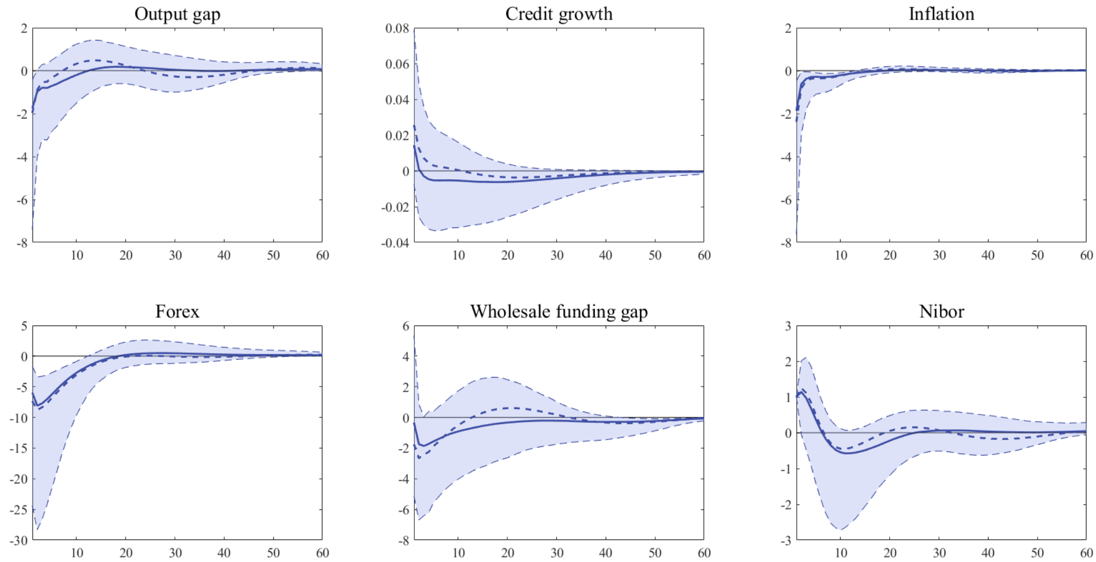

Figure 22: Model 7: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

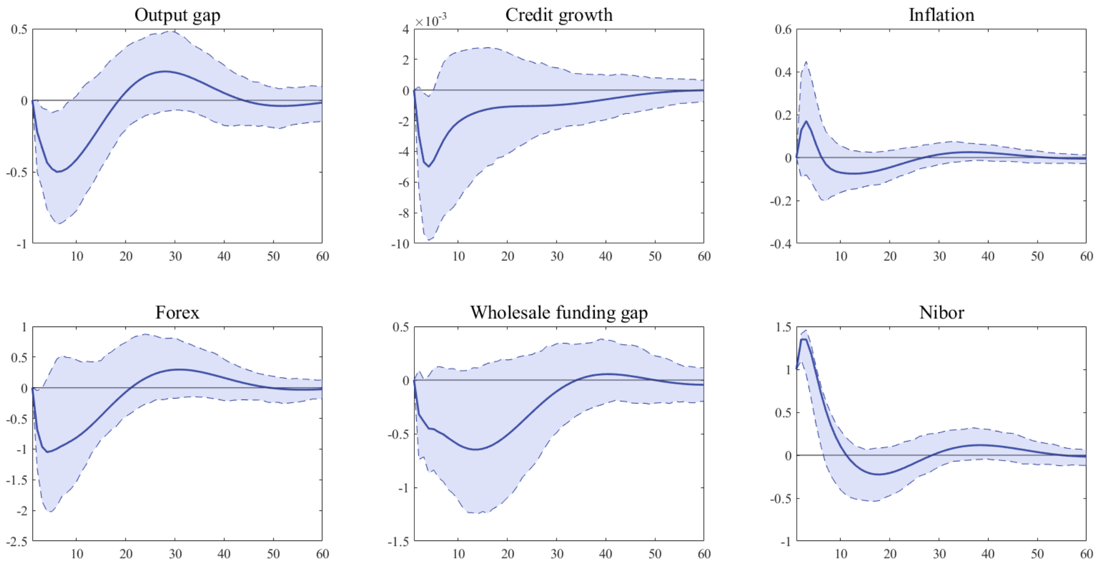

Figure 23: Model 7: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.8 Model 8

A five variable model, which includes the indicator house price to disposable income. We use two lags since that is the overall best performer in the information criterion tests, see Table 24 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9797.

$$\begin{bmatrix} \text{Output gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{House price-to-income} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ - \\ - \\ * \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

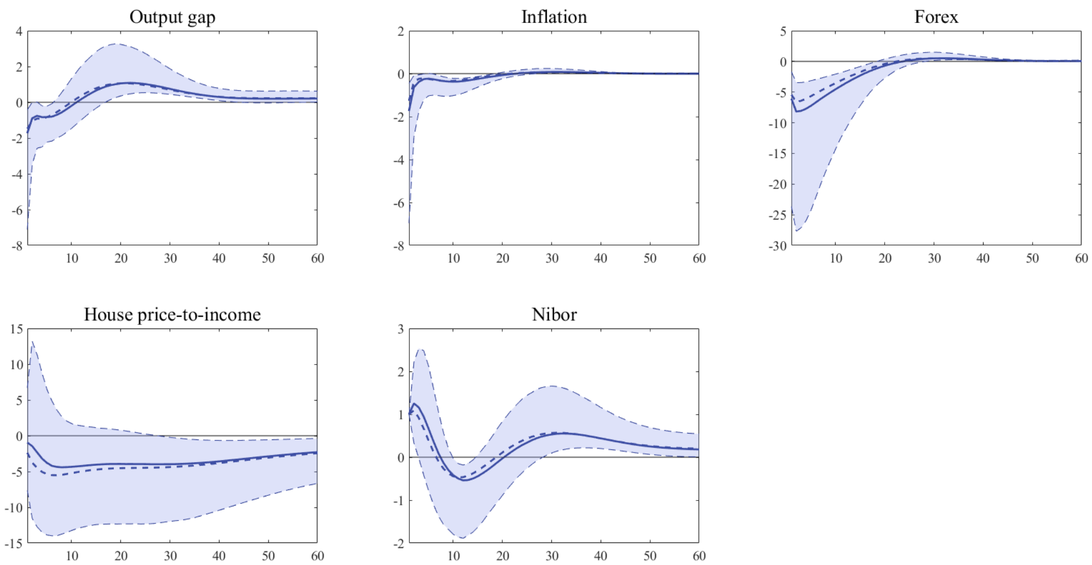

Figure 24: Model 8: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

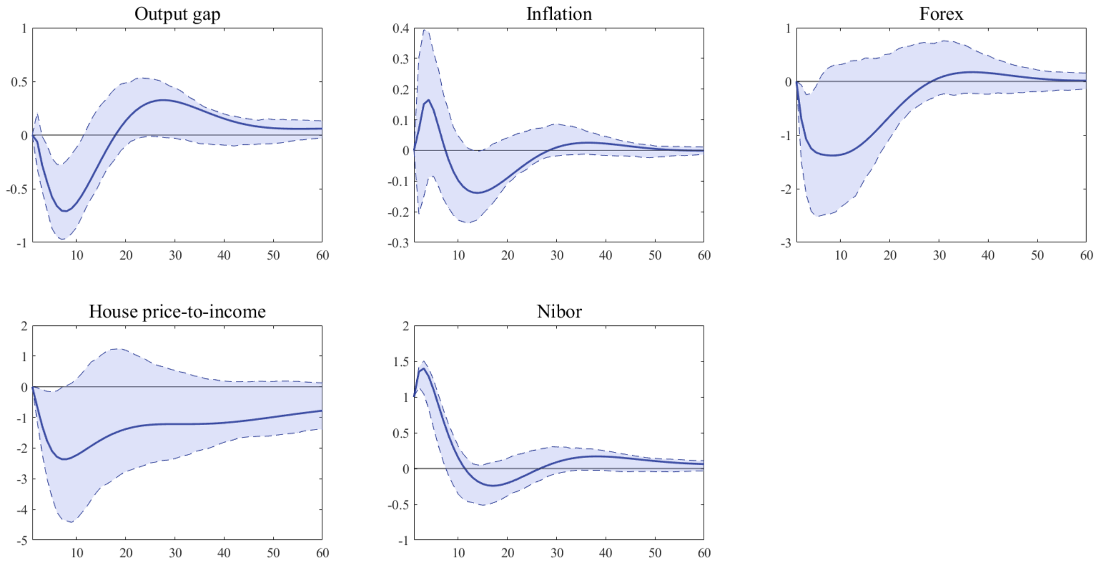

Figure 25: Model 8: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.9 Model 9

A six variable model, which includes the indicators house price-to-income gap and banks' wholesale funding gap. We use two lags since that is the overall best performer in the information criterion tests, see Table 25 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9752.

$$\begin{bmatrix} \text{Output gap} \\ \text{House price-to-income gap} \\ \text{Wholesale funding gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ * \\ - \\ - \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

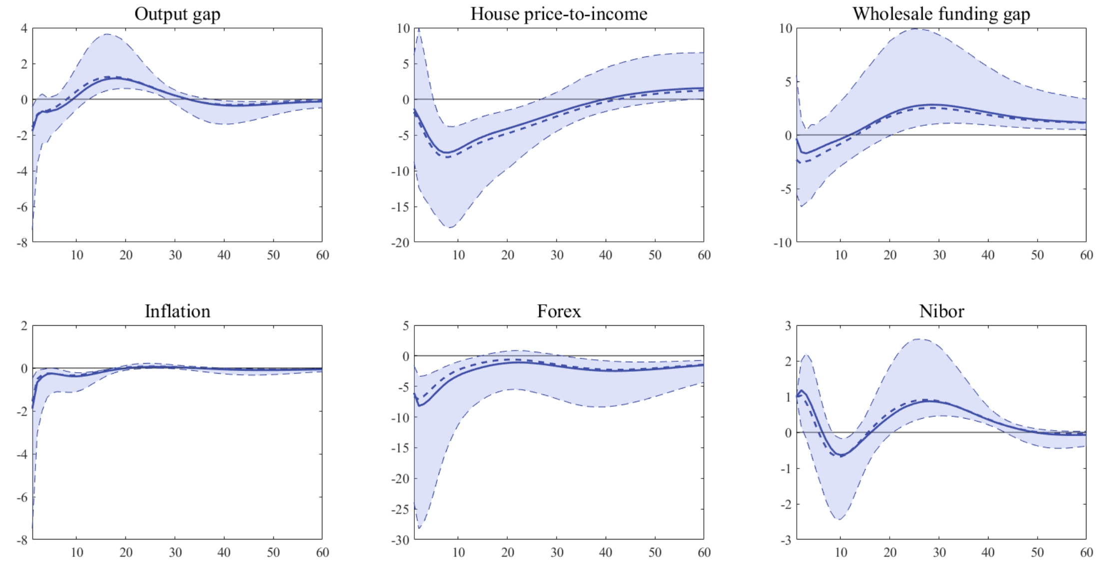

Figure 26: Model 9: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

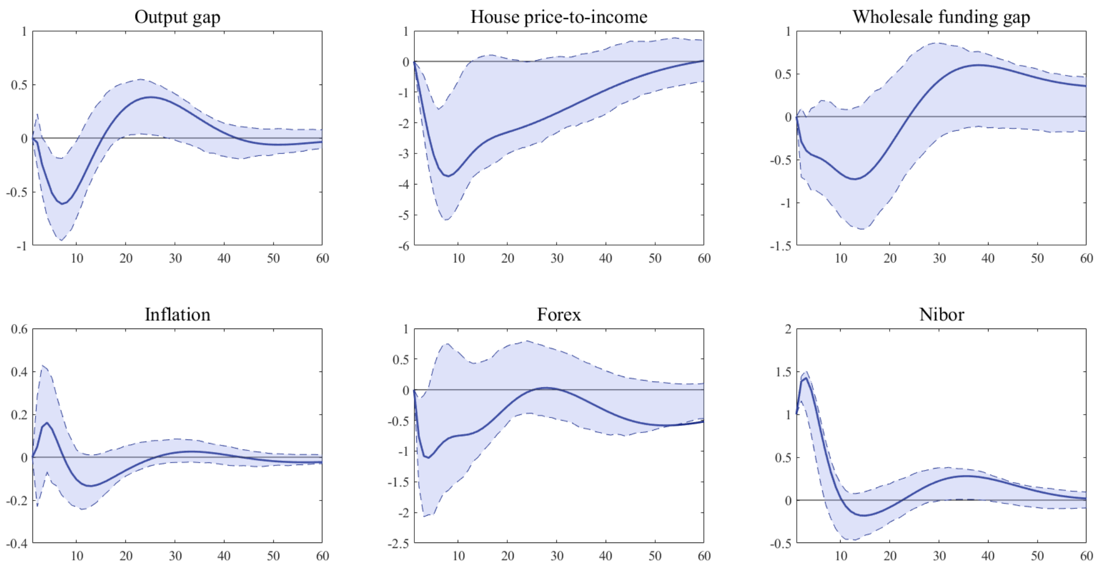

Figure 27: Model 9: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.10 Model 10

A five variable model, which includes the indicator banks' wholesale funding gap. We use two lags since that is the overall best performer in the information criterion tests, see Table 26 in appendix C.11. The model is stable with a maximum eigenvalue of 0.9470.

$$\begin{bmatrix} \text{Output gap} \\ \text{Wholesale funding gap} \\ \text{Inflation} \\ \text{Foreign exchange rate} \\ \text{Interest rate} \end{bmatrix}_t = \begin{bmatrix} - \\ * \\ - \\ - \\ + \end{bmatrix}_t \text{Monetary policy shock}_t$$

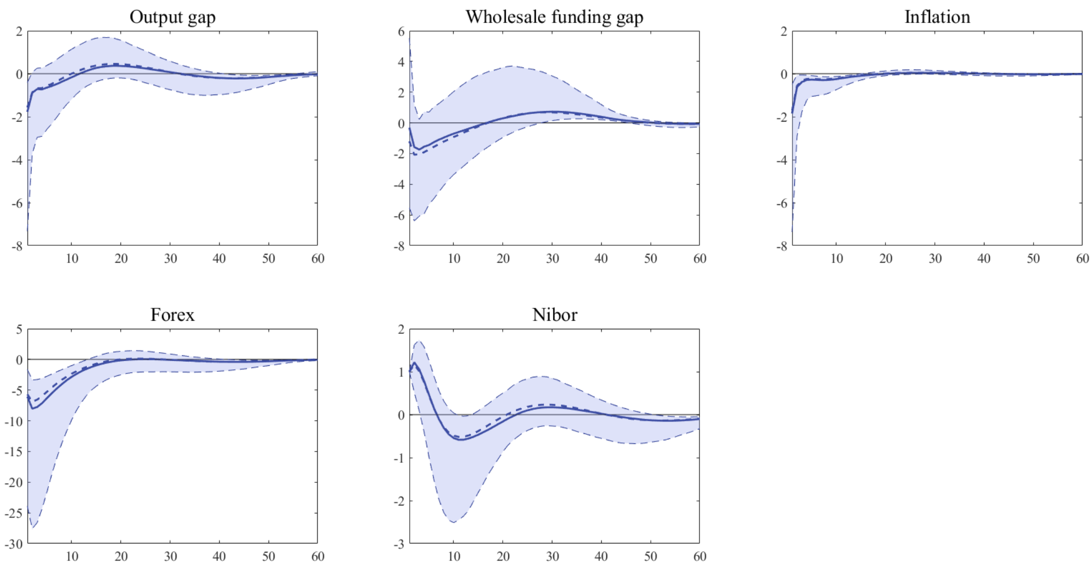

Figure 28: Model 10: Sign restrictions. The solid line represents the median over impulse responses for each variable, while the thick dashed line represents the mean target model. The thin dashed lines and the shaded area between them, represents all impulse responses within the 16-84 percentiles.

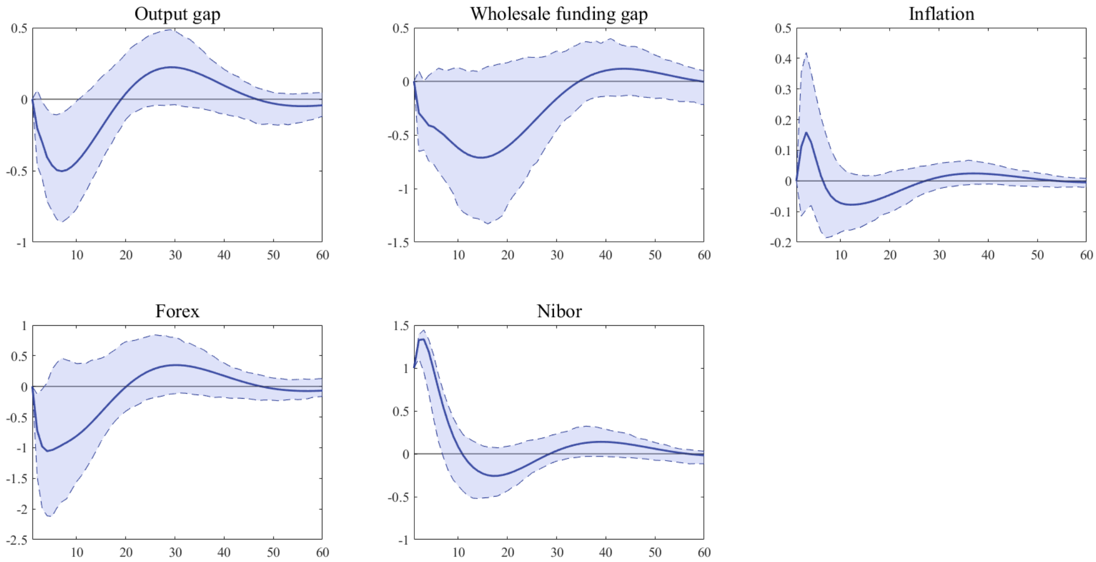

Figure 29: Model 10: Recursive restrictions. The solid line represents the point estimate, and the thin dashed lines and the shaded area between them, are 84 percentage confidence intervals.

C.11 Lag length

We have found the optimal lag lengths according to AIC, BIC and HQC. The figures below are the ranking of the lag lengths in descending order from best fit to worst fit. For methodology, see appendix D.1.

Rank	AIC	BIC	HQC
1	8	1	1
2	2	2	2
3	3	3	3
4	5	4	4
5	4	5	5
6	1	6	6
7	7	7	7
8	6	8	8

Table 17: Model 1. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	8	1	1
2	5	2	2
3	7	3	3
4	4	4	4
5	6	5	5
6	2	6	6
7	3	7	8
8	1	8	7

Table 18: Model 2. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	8	1	2
2	4	2	1
3	2	3	3
4	5	4	4
5	6	5	5
6	7	6	6
7	3	7	8
8	1	8	7

Table 19: Model 3. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	8	1	2
2	7	2	1
3	5	3	3
4	4	4	4
5	6	5	5
6	3	6	6
7	2	7	7
8	1	8	8

Table 20: Model 4. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	5	1	1
2	7	2	2
3	8	3	3
4	4	4	4
5	6	5	5
6	3	6	6
7	2	7	7
8	1	8	8

Table 21: Model 5. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	8	1	2
2	6	2	1
3	7	3	3
4	5	4	4
5	4	5	5
6	2	6	6
7	3	7	7
8	1	8	8

Table 22: Model 6. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	5	1	2
2	8	2	1
3	7	3	3
4	4	4	4
5	6	5	5
6	3	6	6
7	2	7	7
8	1	8	8

Table 23: Model 7. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	4	1	2
2	5	2	1
3	2	3	3
4	8	4	4
5	3	5	5
6	6	6	6
7	7	7	7
8	1	8	8

Table 24: Model 8. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	8	1	2
2	4	2	3
3	5	3	1
4	2	4	4
5	6	5	5
6	3	6	6
7	7	7	7
8	1	8	8

Table 25: Model 9. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

Rank	AIC	BIC	HQC
1	4	1	2
2	5	2	3
3	3	3	1
4	6	4	4
5	8	5	5
6	2	6	6
7	7	7	7
8	1	8	8

Table 26: Model 10. Optimal lag length using the Akaike information criterion, Bayesian information criterion and Hannan-Quinn information criterion.

D VAR and SVAR theory

D.1 Lag length

We do not know the true data generating process, hence we do not know the correct lag length. For example, if a standard New Keynesian model is the true data-generating process we should use infinitely many lags (Clarida et al., 2002; Galí and Monacelli, 2005). There are pitfalls when including both too few and too many lags in the analysis. First, a too short lag length will imply that the model is misspecified and the OLS estimates will be biased. Including too few lags omit valuable information. Since everything not included as an independent regressor ends up in the residual, this might lead to autocorrelated residuals and biased estimators. Second, a large lag length relative to the number of observations will typically lead to poor and inefficient estimates of the parameters. Including too many lags and hence estimate more coefficients than needed might lead to estimation errors and less precise estimates (Bjørnland and Thorsrud, 2015).

Information criteria used for VAR lag-order selection have the general form:

$$C(m) = log\left(det\left(\sum_{i=u}(m)\right)\right) + c_T\,\phi(m) \tag{7}$$

where $\sum_{i=u} = T^{-1}\sum_{i=u} u_t u_t^{'}$ is the residual covariance matrix estimator for a reduced form VAR model of order m based on least square residuals, u_t, and m is the candidate lag order at which the criterion function is evaluated. $\phi(m)$ is a function of order m that penalizes larger lag orders, and c_T is a sequence of weights that may depend on the sample size. The function $\phi(m)$ corresponds to the total number of regressors in the system of VAR equations. Since there are mK lagged regressors in each equation, and there are K equations in the VAR model in absence of any deterministic regressors, $\phi(m) = mK^2$, and when including an intercept $\phi(m) = mK^2 + K$. Information criteria are based on the premise that there is a trade-off between the improved fit of the VAR model as m increases, and the parsimonity of the model. Given T, the effective sample size, the fit of the model by construction improves with larger m, which is indicated by a reduction in the first term. The second term however, increases unambiguously with m. Hence, we are looking for the value m, which is the lag order that balances the objectives of model fit and parsimony (Kilian and Lütkepohl (2017)). The VAR order is chosen such that the respective criterion is minimized over the possible orders $m = p_{min}, ..., p_{max}$. A key issue in implementing information criteria is the choice of the upper and lower bound, p_{min} and p_{max}. In the context of a model of unknown finite lag order, the default is to set $p_{min} = 0$ or sometimes $p_{min} = 1$, reducing the problem to one of choosing a suitable upper bound. The value of p_{max} must be chosen large enough to allow for delays in the response of the variables to the shocks. In practice, common choices would be 4-8 lags for quarterly data (Kilian and Lütkepohl, 2017).

We have employed three methods in the search for the optimal lag length for the VAR models, the Akaike information criterion (AIC), Bayesian information criterion (BIC) and the Hannan-Quinn information criterion (HQC). We use equations (8), (9) and (10) for implementation in Matlab.

D.1.1 Akaike information criterion (AIC)

The Akaike information criterion was proposed by Akaike (1973, 1974).

$$AIC(m) = log\left(det\left(\sum_{i=u}(m)\right)\right) + \frac{2}{T}(mK^2 + K) \tag{8}$$

where $c_T = 2/T$.

D.1.2 Bayesian information criterion (BIC)

$$BIC(m) = log\left(det\left(\sum_{i=u}(m)\right)\right) + \frac{log(T)}{T}\,(mK^2 + K) \tag{9}$$

where $c_T = log(T)/T$.

D.1.3 Hannan-Quinn information criterion (HQC)

$$HQC(m) = log\left(det\left(\sum_{i=u}(m)\right)\right) + \frac{2log(log(T))}{T}\,(mK^2 + K) \tag{10}$$

where $c_T = 2log(log(T))/T$.

D.2 Model diagnostics

D.2.1 Stability

A stochastic process, y_t, is stationary (covariance-stationary) if its first and second moments are time invariant. In other words, y_t is stationary if y_t have a finite mean vector and the autocovariances of the process do not depend on time t but only on the time period h for which the two vectors y_t and y_{t-h} are apart. The stationarity condition from Lütkepohl (2005) states that: A stable VAR process y_t is for all t stationary. In other words, if the VAR is stable it is also stationary. To assess the stability of a VAR system we check that the eigenvalue of the A matrix is less than one in the complex plane. From equation (12) we see that this is equivalent to checking that the elements of $A^i \to 0$ as $i \to \infty$.

Stationarity requires time-invariant first and second unconditional moments. That assumption may be violated if the parameters change over time. This is a question of whether or not there are structural breaks in the data, for discussion, see section 3.2. Going forward we assume stationarity.

In accordance with the literature we use logarithms as opposed to the levels when applicable. Log-transformation reduces the impact of outliers, as large but few outliers will be of less significance when the numbers are in logarithms. In addition, it reduces the increasing variance of trending time series (Ariño and Franses, 2000). There are some conflicting views on whether one should take the first difference of the logarithms or not. The main argument for taking first differences in a VAR model is to make the variables stationary. The eigenvalues of the companion form matrix in our case is less than one in absolute value for all models, see appendix C. This means that the VAR models are stable, and we do not need to use first differences of the variables.

D.2.2 Residuals

Given our assumption that the reduced form residuals u_t are white noise, we need to make sure that they are normally distributed and that they are neither autocorrelated nor heteroskedastic (Kilian and Lütkepohl, 2017).

Normally distributed residuals are not required for the *validity* of most asymptotic procedures related to VAR modelling. However, if residuals do not have normal distribution this may signal model defects. To make sure that the condition for no autocorrelation is at least approximately satisfied, we use information criterion to choose the lag order of the model, see appendix D.1. Unmodeled conditional heteroskedasticity in u_t does not invalidate the *consistency* of standard estimators of the parameters, they will still converge to their true value given that the unconditional error variance remains finite. However, unmodeled conditional heteroskedasticity undermines the *efficiency* of the estimator and affects how to conduct inference about the parameters (Kilian and Lütkepohl, 2017).

D.3 Companion form

Any K-dimensional VAR(p) process can be written in companion form as a pK-dimensional VAR(1) model. By stacking p consecutive y_t variables in a pK-dimensional vector, $Y_t = (y_t^{'}, \ldots, y_{t-p+1}^{'})$ we get:

$$Y_t = N + AY_{t-1} + U_t \tag{11}$$

Where A is the companion matrix.

D.4 Moving average representation

If y_t is covariance stationary, then starting from a VAR(p) process we can derive the process infinite moving average representation MA(∞):

$$\begin{aligned}
y_t &= \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \\
y_t &= A(L)^{-1}\nu + A(L)^{-1}u_t \\
y_t &= \mu + \sum_{i=0}^{\infty} JA^i J^{'} JU_{t-i}
\end{aligned}$$

Where $J \equiv [I_K, 0_{K\times K(p-1)}]$ is a $(K \times Kp)$ matrix, $\mu = A(L)^{-1}\nu$ and $A(L)^{-1} = \sum_{i=0}^{\infty} \Phi_i L^i$ where $\Phi_i = JA^iJ^{'}$ for $i = 1, \ldots,$ where A, as before, is the companion matrix. And the reduced form MA(∞) is:

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{12}$$

y_t is here expressed as a weighted average of current and past shocks, with weights Φ_i. The structural MA(∞) representation can be found by using $w_t = B_0 u_t$ and define Θ as $\Theta_i \equiv \Phi_i B_0^{-1}$.

$$\begin{aligned} y_t &= \mu + \sum_{i=0}^{\infty} \Phi_i B_0^{-1} B_0 u_{t-i} \\ y_t &= \mu + \sum_{i=0}^{\infty} \Theta_i w_{t-i} \end{aligned} \tag{13}$$

D.5 Impulse response

Given B_0 and u_t we obtain the structural shocks $w_t = B_0 u_t$, see section 3.2. After identifying the structural shocks we can perform impulse response analysis on each element of y_t to a one time impulse in w_t. Starting from the structural MA representation in equation (13) we see that the impulse response of y_{t+i}, for propagation horizon $i = 0, 1, \ldots, H$, to a w_t impulse in time period t, are given by Θ_i:

$$\frac{\delta y_{t+i}}{\delta w_t'} = \Theta_i, \;\; i = 0, 1, \ldots, H$$

The elements of the Θ_i for any given time period i are:

$$\theta_{jk,i} = \frac{\delta y_{j,t+i}}{\delta w_{k,t}'}$$

Such that $\Theta_i = [\theta_{jk,i}]$.

Kilian and Lütkepohl (2017) mentions two implications of the linearity of our VAR model for the impulse response functions. First, responses to positive and negative shocks are the same but with opposite sign. Second, the magnitude of the structural shock does not matter for constructing impulse response functions, rescaling of the shock only rescale the entire response function. Since the magnitude does not matter, one can choose B_0^{-1} such that the structural shocks represent one standard deviation of the time series of the structural shocks. Or, as we do, choose B_0^{-1} such that the structural shock represents a one percentage point change in the interest rate.

Since there are K variables and K structural shocks, there are K^2 impulse response functions each of length $H + 1$. To find the impulse responses we need to find Θ_i. We start by finding the responses of y_{t+i} to the reduced form errors u_t captured in Φ_i and then use the relationship $w_t = B_0 u_t$ to get the responses of y_{t+i} to the structural shocks w_t captured in Θ_i.

We start by re-writing the companion form (11) using recursive substitution for Y_{t-i}:

$$Y_{t+i} = A^{i+1}Y_{t-1} + \sum_{s=0}^{i} A^s U_{t+i-s} \tag{14}$$

Then left-multiply with $J \equiv [I_K, 0_{K\times K(p-1)}]$ to unstack the variables $JY_{t-i} = y_{t-i}$ and $JU_{t+i-j} = u_{t+i-j}$, and multiply in $J'J$:

$$y_{t+i} = JA^{i+1}Y_{t-1} + \sum_{j=0}^{i} JA^j U_{t+i-j}$$
$$y_{t+i} = JA^{i+1}Y_{t-1} + \sum_{j=0}^{i} JA^j J'JU_{t+i-j}$$
$$y_{t+i} = JA^{i+1}Y_{t-1} + \sum_{j=0}^{i} JA^j J'u_{t+i-j}$$
$$y_{t+i} = JA^{i+1}Y_{t-1} + \sum_{j=0}^{i} \Phi_i u_{t+i-j}$$

We see that the response of $y_{k,t+i}$ for $k = 1,\dots,K$ to a unit shock in $u_{k,t}$ for $k = 1,\dots,K$, i periods ago is given by $\Phi_i = [\phi_{jk,i}] \equiv JA^iJ'$. Using the the reduced form MA representation (12) and re-writing it as the structural MA representation (13) we get:

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

And we see that Θ_i is:

$$\Theta_i = \Phi_i B_0^{-1} = JA^iJ'B_0^{-1} \tag{15}$$

Where the jkth element of Θ_i, $\theta_{jk,i}$ represents the response of variable j to a structural shock k at horizon $i = 0, 1, \dots, H$. We use (15) to calculate the impulse response functions in Matlab.

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CAMP Working Paper Series
ISSN: 1892-2198