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Financial imbalances, crisis probability and monetary policy in Norway

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RAGNA ALSTADHEIM,
ØRJAN ROBSTAD
AND
NIKKA HUSOM VONEN



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FINANCIAL IMBALANCES, CRISIS PROBABILITY AND MONETARY POLICY IN NORWAY*

RAGNA ALSTADHEIM[†] ØRJAN ROBSTAD[‡]

NIKKA HUSOM VONEN[§]

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Abstract

We assess the strength of the impact of a monetary policy shock on financial crisis probability in Norway. Policy effects go via the interest rate impact on credit, house prices and banks' wholesale funding. We find that the impact of a monetary policy shock on crisis probability is about 10 times larger than what previous studies suggest. The large impact is mostly due to a fall in property prices and banks' wholesale funding in response to a contractionary monetary policy shock. In contrast, and in line with existing literature, there is a more limited contribution to reduced crisis probability from the impact of monetary policy on credit.

Keywords: *Monetary Policy, Financial Imbalances, Financial Crisis, Structural VAR.*

JEL Classification: *E32, E37, E44, E52.*

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[†]*Corresponding author:* Norges Bank. Email: ragna.alstadheim@norges-bank.no.

[‡]Norges Bank. Email: orjan.robstad@norges-bank.no.

[§]The Ministry of Labour and Social Affairs. Email: nikka-husom.vonen@asd.dep.no.

1 INTRODUCTION AND SUMMARY

The question of how strongly monetary policy affects the probability of a financial crisis is of interest to policymakers. It is for example necessary to gauge the size of this effect when assessing the costs and benefits of “leaning against the wind” (LAW), see e.g. Svensson (2017) and Gerdrup, Hansen, Krogh, and Maih (2017).¹

Early warning models for financial crises are used when calibrating the size of the effect of monetary policy on crisis probability. In the early warning models typically applied in the LAW literature, credit predicts the probability of a financial crisis, following e.g. Borio and Lowe (2004), Gourinchas and Obstfeld (2012) and Schularick and Taylor (2012). The impact of monetary policy on credit to GDP or real credit growth is therefore the (only) relevant link between monetary policy and financial stability in the LAW-literature, and the size of the impact of monetary policy on crisis probability is always found to be very small. The reason is that the impact of monetary policy on credit is mostly found to be very limited.²

But in some of the early warning literature, see e.g. Anundsen, Hansen, Gerdrup, and Kragh-Sørensen (2016) and Drehmann and Juselius (2014), variables such as house prices and the share of wholesale (non-deposit and non-equity) funding of banks are also found to have significant and independent effects on financial crisis probability.³ Adrian and Liang (2016) call for a broader approach than just looking at credit when conducting cost-benefit analysis of LAW policy. Svensson (2017) also notes that an analysis of the benefits of LAW based on the impact of monetary policy on credit has limitations, including limitations due to a moderate effect of monetary policy on real credit and credit to GDP.

Models excluding any impact of monetary policy on crisis probability through property prices and banks’ wholesale funding ratio are therefore arguably incomplete. In this paper, we assess the combined impact of monetary policy, via both credit, property prices and banks’ wholesale funding ratio, on crisis probability. We estimate the total impact of monetary policy on crisis probability through the various channels using a version of the model of Anundsen et al. (2016). Since we do not conduct a cost-benefit analysis of LAW, we abstract from a full general equilibrium model of the economy. We can thereby easily take into account more channels than e.g. Svensson (2017) and Gerdrup et al. (2017), who work with quite small and stylized macroeconomic models.

¹Svensson (2017) defines LAW as “a monetary policy that is somewhat tighter (that is, a somewhat higher interest rate) than what is consistent with flexible inflation targeting without taking any effect on financial stability into account”.

²See e.g. Bauer and Granziera (2016), Laséen and Pescatori (2016), Alpanda and Ueberfeldt (2016), Ajello, Laubach, Lopez-Salido, and Nakata (2016) as well as Svensson (2017) and Gerdrup et al. (2017).

³See Kauko (2014) for a recent survey of the early warning literature. Barrell, Davis, Karim, and Liadze (2010) note that the focus on credit as a crisis predictor may have been driven by access to data for emerging markets. Using a long data sample, Jordà, Schularick, and Taylor (2015b) find that credit growth is a significant predictor of crises only when it is preceded by house price growth. Lee, Posenau, and Stebunovs (2017) note that a wide range of indicators are useful in crisis prediction. In practice, a set of variables is typically used as early warning indicators, see for example Norges Bank (2013) and Giordani, Spector, and Zhang (2017).

This paper is, to our knowledge, the first to provide a broader based assessment of the size of the impact of monetary policy on crisis probability. We investigate the case of Norway, which might be of wider interest, since the country operates an independent monetary policy regime with flexible inflation targeting, and the Norwegian central bank implements a monetary policy with explicit LAW.⁴ We find that the effect of a monetary policy shock on crisis probability is about 10 times larger than previous studies suggest, and this is mainly due to the new channels that we include.

With the exception that we include a broader set of channels for monetary policy, the approach in this paper follows convention, and the quantitative econometric results are in line with comparable studies. We use structural VAR models estimated on quarterly data from 1994 to 2014 to assess the transmission of monetary policy to the various financial indicators.⁵

Confirming previous studies, we find that a surprise monetary policy tightening leads to an initial *increase* in credit as a share of GDP, both for households and non-financial enterprises.⁶ The long-run impact on credit-to-GDP tends to be negative. Higher credit to GDP ratios contribute to a higher - not lower - crisis probability, and if the crisis prediction function only includes credit, the conclusion is necessarily reached that the impact on crisis probability of monetary policy is small and possibly even counterproductive in the short run.

Contractionary monetary policy is well known to reduce *house prices*, see e.g. Jordà, Schularick, and Taylor (2015a) and Williams (2015) for international evidence, and Anundsen and Jansen (2013) and Bjørnland and Jacobsen (2010) for estimates using Norwegian data. The quantitative estimates in this paper are well in line with these earlier studies. Including a channel from monetary policy to crisis probability via house prices therefore contributes to a larger impact on crisis probability.

Halvorsen and Jacobsen (2016) study the bank lending channel of monetary policy and document a negative effect of contractionary monetary policy on *the wholesale funding ratio of banks* in Norway. Our estimates confirm their result, and this channel contributes to further strengthen the impact of monetary policy on crisis probability.⁷

Taken together, the estimated impact of monetary policy through these channels indicate that the effect of monetary policy on crisis probability may be much larger than earlier

⁴See Olsen (2015).

⁵Empirical estimates of the effects of monetary policy are usually obtained using structural VAR-models (SVAR-models), see among (many) others Christiano, Eichenbaum, and Evans (1999), Uhlig (2005) and Jarociński and Smets (2008).

⁶The effect of a monetary policy shock on credit is usually estimated to be relatively modest, see e.g. Robstad (2014), and for estimates with a DSGE-model, see Gelain, Lansing, and Natvik (2017). Credit to *households* as a share of GDP and credit to *non-financial enterprises* have been found to respond somewhat differently to monetary policy shocks in the existing literature; den Haan, Sumner, and Yamashiro (2007) find that credit to non-financial enterprises increases when interest rates are raised in the US.

⁷The link between monetary policy and banks' funding structure is also discussed in Borio and Zhu (2012).

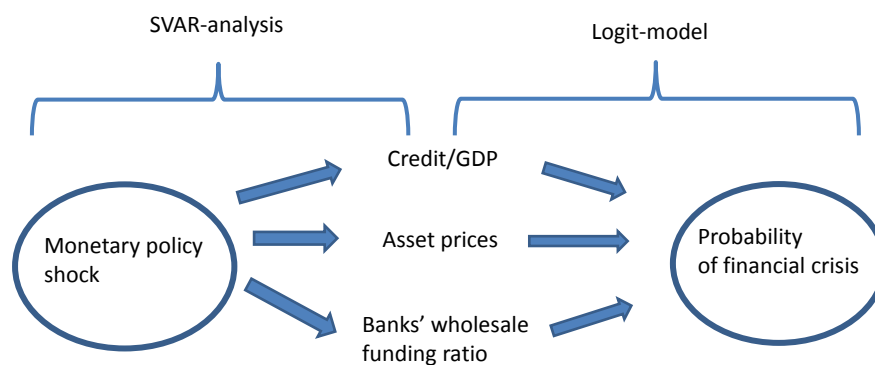
studies have suggested. Since we have not conducted a complete cost-benefit analysis, we cannot conclude that it is a good idea to use monetary policy to stabilize e.g house prices, nor can we conclude that LAW is good or bad. This paper does however show that it is premature to conclude that monetary policy has a negligible effect on crisis probability.

The rest of this paper proceeds as follows: The modeling framework and data are described in Section 2. Section 3 presents the estimated impact of monetary policy on financial variables, Section 4 shows how this translates into crisis probability. Robustness and sensitivity are discussed in section 5 and Section 6 concludes.

2 A MODELING FRAMEWORK THAT CAPTURES SEVERAL CHANNELS OF TRANSMISSION

Our approach is illustrated in figure 1. For the SVAR-step, we choose variables of interest based on our review of the early warning literature and empirical work on Norwegian data, see Gerdrup, Kvinlog, and Schaanning (2013). In the second step, we apply a reestimated version of the logit model in Anundsen et al. (2016), in order to capture the impact of monetary policy shocks on crisis probability through real housing prices, credit to households and non-financial firms and the wholesale funding ratio of banks. Due to data limitations commercial property prices is not included in the logit model, but we nonetheless analyze their response to monetary policy, given commercial property prices potential importance for financial stability, as discussed in Gerdrup et al. (2013).

Figure 1: *Links between monetary policy and the probability of a financial crisis.*



2.1 SVAR MODELS

2.1.1 DATA FOR VAR ESTIMATIONS

We let the dataset for the VAR-estimations start after the fixed exchange rate regime in Norway had been abandoned and after disinflation had allowed nominal interest rates to

come down in the early 1990s.⁸ We therefore use data for the period Q1 1994 to Q4 2014. A sample period with low and stable inflation and a relatively stable monetary policy regime is crucial when trying to identify monetary policy shocks in a structural VAR model.

We estimate our benchmark models with data in levels, which Bayesian estimation allows for (see Sims, Stock, and Watson, 1990), in order to retain as much information as possible. Variables all enter in logarithmic form, except for the interest rate, which enters without any transformation. As a robustness exercise we also estimate models with HP filtered data, since this is the technique used to detrend data in the logit model. HP filtering is also widely adopted among practitioners and academic researchers alike to separate cyclical fluctuations from underlying trends (see e.g. Kydland and Prescott (1990), Backus and Kehoe (1992) and Ravn and Uhlig (2002)). A description of the data is provided in appendix C on page 36.

2.1.2 VARIABLE SELECTION

We estimate a separate baseline SVAR for each financial indicator. Ideally, we would like to estimate one large VAR that includes all the financial variables. But in order to get precise estimates of the parameters and avoid the curse of dimensionality, we need some parsimony. Our maintained hypothesis is that we identify the same structural monetary policy shock across the models. The historical monetary policy shock series that we identify does indeed seem to be highly correlated across the different SVAR models (see figure A.1 on page 24).

Each benchmark model includes the core consumer price index and an activity variable, in addition to the three-month money market interest rate, which is our measure of monetary policy. Since we want to identify the unsystematic part of monetary policy, it is essential to control for the systematic response of monetary policy to inflation and economic activity.

The starting point for further variable selection in each benchmark model is an out-of-sample forecasting race between a large number of reduced form VARs, containing a number of variables that might be of relevance for each financial indicator. The forecasts are evaluated by the root mean squared out-of-sample forecast error (RMSFE) of the median forecast up to 8 quarters ahead. We evaluate all the reduced form VAR models' ability to jointly forecast the interest rate and the financial indicator of interest. Inspired by the forecast evaluation, we choose one benchmark model specification for each financial stability indicator. For details on this procedure, see appendix A.2.

⁸The fixed exchange rate regime was abandoned in December 1992, and inflation targeting was formally adopted in 2001, see Alstadheim (2016). Monetary stability with a lower inflation rate was gradually established in the early 1990s, after the Norwegian financial crisis around 1990.

2.1.3 ESTIMATION AND IDENTIFICATION OF THE SVAR MODELS

The reduced form VARs are estimated using Bayesian techniques with an uninformative prior and are of the following form:⁹

$$\mathbf{y}_t = A_1 \mathbf{y}_{t-1} + \dots + A_l \mathbf{y}_{t-l} + u_t \quad (1)$$

where \mathbf{y}_t is a vector of endogenous variables, $A_1 \dots A_l$ are the coefficient matrices on the lags and u_t is a vector of reduced form error terms.

In order to identify the structural shocks from the reduced form estimation, we use a Cholesky decomposition, see appendix A.3. We allow the interest rate to respond contemporaneously to all variables in the VARs, except for real house prices, which is ordered last.¹⁰ Each SVAR-model is discussed in more detail section 3.

Alternative and frequently used identification schemes are probably unsuitable for our purpose. First, since our benchmark models are estimated in levels, imposing zero *long run restrictions* would e.g. imply that an initial increase in one variable would need to be followed by a subsequent fall in order to result in a net level effect of zero, which is a response we do not want to impose. Second, our aim is to investigate, rather than impose, the *sign* of the impact of a monetary policy shock on our chosen indicators of interest. This would require leaving some of the variables in the VARs unrestricted when using sign restrictions. That feature might hamper the identification of a monetary policy shock, resulting in highly uncertain impulse responses, as pointed out by Fry and Pagan (2011).

Table A.2 on page 23 summarizes the details of the SVAR models.

2.2 A LOGIT MODEL

The link between financial indicators and crisis probability that we consider is a re-estimated version of the panel logit model in Anundsen et al. (2016).¹¹ The dating of financial crises is based on the classification in (among others) Laeven and Valencia (2008, 2010, 2012), Reinhart and Rogoff (2009) and Babecký, Havránek, Matějů, Rusnák, Šmídková, and Vašíček (2014). The data set is quarterly and includes 33 financial crises episodes in a panel of 20 advanced (OECD) countries, in the period Q1 1975 to Q2 2014.

The probability of being in a financial crisis, as a function of financial indicators \mathbf{x}_t , is estimated with a logistic regression:¹²

$$p_t(\text{crisis}) = \frac{\exp(\alpha + \beta' \mathbf{x}_t)}{1 + \exp(\alpha + \beta' \mathbf{x}_t)}, \mathbf{y}_t \supset \mathbf{x}_t. \quad (2)$$

⁹For more on the estimation procedure, see appendix A.

¹⁰This ordering is consistent with the work in Bjørnland and Jacobsen (2010). They examine the role of house prices in the monetary policy transmission mechanism in small open economies and find a strong immediate effect on house prices in response to a monetary policy shock. Our recursive ordering is also in line with the preferred Cholesky ordering in Robstad (2014).

¹¹We are grateful to Frank Hansen for reestimating the crisis probability model in Anundsen et al. (2016).

¹²The model is a gap model and is estimated on detrended data using a one-sided HP filter with $\lambda = 400000$.

The dependent variable takes a value of one whenever a financial crisis is dated to have started in one of the quarters that lie 1-3 years ahead in time. The estimated model thus describes the probability of being in a pre-crisis period. Since monetary policy impacts the economy with a lag, it seems relevant to predict the probability of being in a state where a crisis erupts one to three years into the future. Because the pre-crisis period lasts for two years, dividing the estimated crisis probability by 2 gives the approximate annualized probability of being in a pre-crisis state. The estimated coefficients are given in table A.3, and the estimation procedure is described in Anundsen et al. (2016).

We let a contractionary monetary policy shock that raises the short term interest rates by one percentage point, as identified in our SVAR models, represent a policy of *leaning against the wind* (LAW), that is, an extraordinary increase in the interest rate in order to counteract a build-up of financial imbalances. The probability of being in a pre-crisis state after a contractionary monetary policy shock (Δmp) is:

$$p_t(\text{crisis} \mid \text{leaning}) = \frac{\exp(\alpha + \beta'(\mathbf{x}_t + \text{response to } \Delta mp))}{1 + \exp(\alpha + \beta'(\mathbf{x}_t + \text{response to } \Delta mp))} \quad (3)$$

The net (annualized) effect of LAW policy on the probability of a future crisis is calculated as:

$$\frac{\Delta p_t(\text{crisis})}{\Delta mp} = 0.5[p_t(\text{crisis} \mid \text{leaning}) - p_t(\text{crisis})]. \quad (4)$$

3 CREDIT-TO-GDP INCREASES, PROPERTY PRICES AND WHOLESALE FUNDING FALL AFTER MONETARY POLICY TIGHTENING

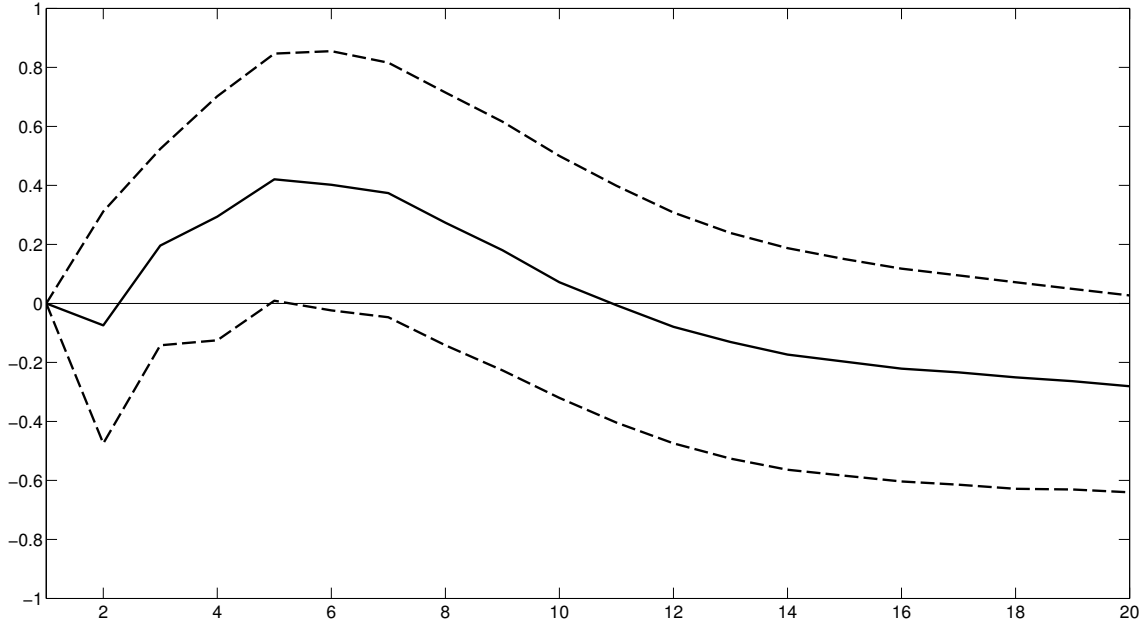
3.1 MONETARY POLICY AND CREDIT TO HOUSEHOLDS

Figure 2 shows the estimated impact of a contractionary monetary policy shock on household credit as a share of GDP in the benchmark model. The stock of credit is a slow moving variable with new loans typically constituting only a small share of the total stock of debt. Hence, in response to a monetary policy shock, credit (the numerator) is likely to react more slowly or less than GDP (the denominator), resulting in an initial increase in the ratio. The response turns negative further out in time, after around three years. The decline is however highly uncertain. This pattern is confirmed when we allow credit and GDP to enter separately in the model, see appendix A.6.

The variables included in the model (in addition to the interest rate and prices, which are included in all models) are private consumption, real house prices and the wholesale funding ratio of banks.¹³

¹³Impulse responses for all variables are shown in figure A.2

Figure 2: *Household credit/GDP. Response to a 1 pp. interest rate increase. Percent. Solid line is median estimate, dotted lines 16th and 84th percentile probability bands. Quarters.*



A similar pattern is found in Gelain et al. (2017), where simulations based on a small scale DSGE model point to an increase in the household debt-to-GDP ratio in the short run. Empirically, this paper also confirms the results in Robstad (2014). In contrast, examining the household debt-to-GDP ratio using data for Sweden, Laséen and Strid (2013) find that an contractionary monetary policy shock leads to a fall in the household credit-to-GDP ratio.¹⁴

3.2 MONETARY POLICY AND CREDIT TO NON-FINANCIAL ENTERPRISES (FIRMS)

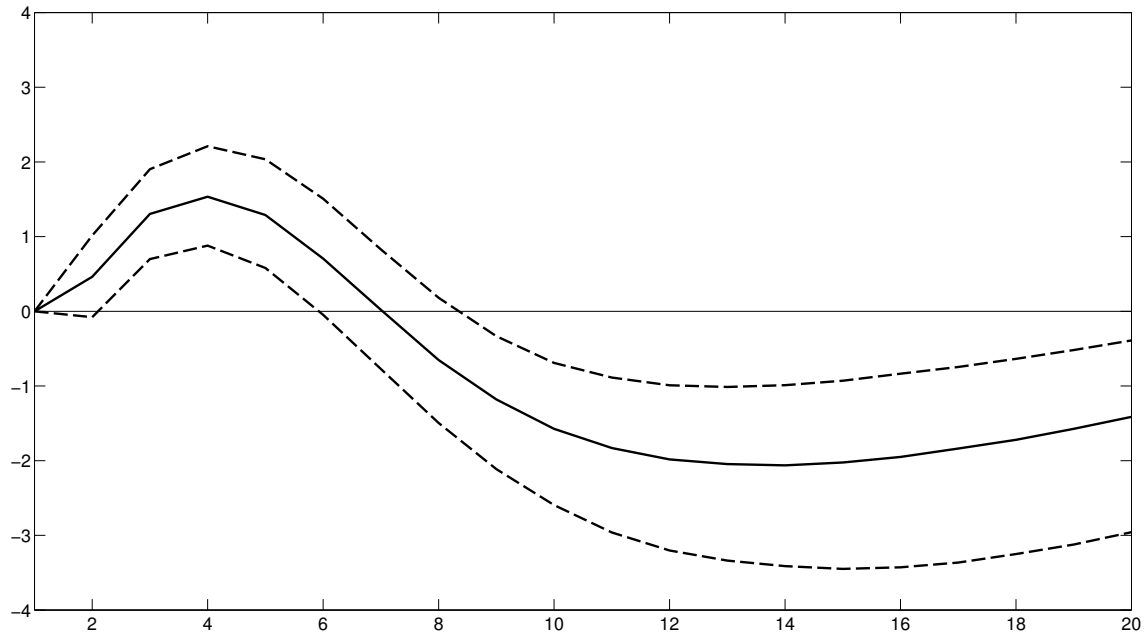
Figure 3 shows an immediate and significant increase in firms' credit-to-GDP ratio in response to a contractionary monetary policy shock. After around two years, the impact turns negative. The increase is larger than the corresponding upswing in household credit-to-GDP, and the same is true for the subsequent decline.

More fluctuation in the credit series for firms may in part stem from recurrent refinancing of business loans or downpayment of loans over the course of the economic cycle. Households are probably more inclined to stick to their original debt contracts. The model for firms includes corporate investment, the wholesale funding ratio and real house prices.¹⁵

¹⁴The model specification in Laséen and Strid (2013) and Robstad (2014) differ, possibly accounting for some of the discrepancy between the two studies. See also Sveriges Riksbank (2014) for a summary of Laséen and Strid's results.

¹⁵Impulse responses for all variables in the benchmark level model are shown in figure A.6

Figure 3: *Non-financial enterprises credit/GDP. Response to a 1 pp. interest rate increase. Percent. Solid line is median estimate, dotted lines 16th and 84th percentile probability bands. Quarters.*



Examining credit to firms and GDP separately (see figure A.9), real credit (not divided by income) is actually found to exhibit an initial increase, albeit not large. This may in part explain the substantial increase in the ratio observed in our benchmark model, which is also affected by the negative impulse from the interest rate to GDP.

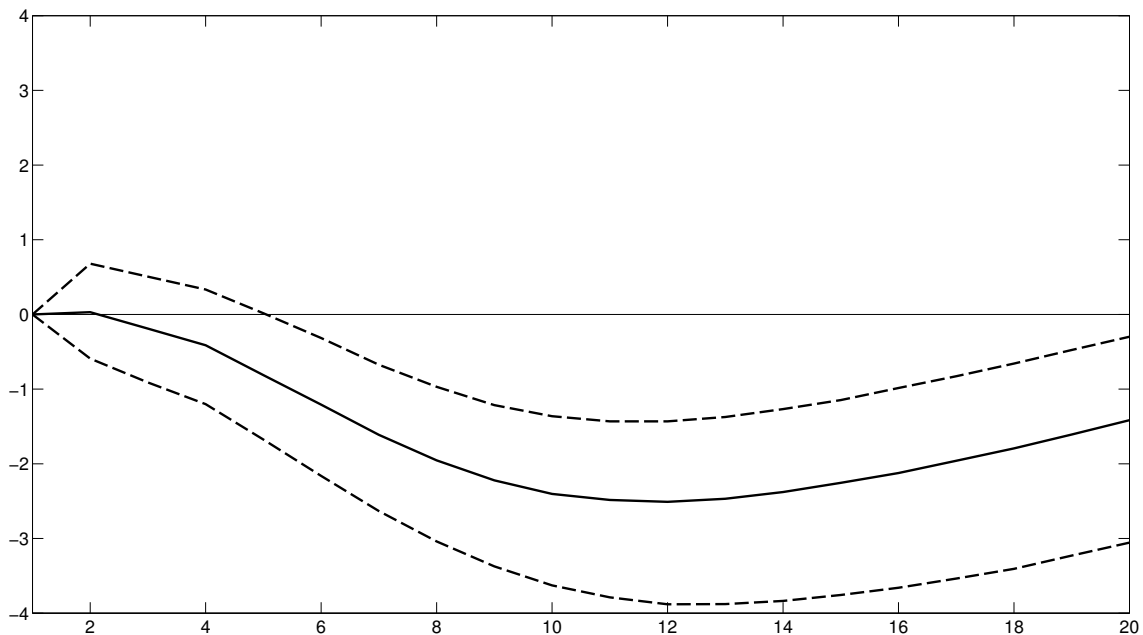
One might assume that a monetary policy tightening would reduce rather than increase the amount of firm credit. However, firms may need to increase their short-term funding in order to pay a higher interest rate on existing debt, representing a *cost channel*. Also, firms' short-term borrowing may increase in order to finance inventory buildup following reduced demand, thus increasing interest expenses further, as pointed out by Bernanke and Gertler (1995).

Our finding is well in line with results from the BVAR analysis reported in Giannone, Lenza, and Reichlin (2012). In that study, short- and longer- term debt is examined separately, and both variables are found to increase in response to a monetary policy tightening. The impact is by far most prominent for short term loans, which may fit well with the above-mentioned explanations. The authors also note that loans might increase in response to a monetary tightening as firms draw on credit lines during the time span between policy rate hikes and increases in lending rates (so-called front-loading). It is also well in line with the findings of den Haan et al. (2007). They suggest that in the US, the reason for increased lending to non-financial enterprises when monetary policy is tightened might be due to a reallocation of banks' lending portfolio in the direction of variable interest rate exposure.

3.3 MONETARY POLICY AND BANKS' WHOLESALE FUNDING SHARE

Credit institutions' wholesale funding share clearly falls in response to a monetary policy shock, see figure 4, confirming evidence established by Halvorsen and Jacobsen (2016). This decline may reflect the role of market funding as a marginal source of funding for banks. Domestic demand for credit might fall following a monetary policy tightening, while households' and firms' appetite for holding deposits relative to other assets might stay high or even increase. This may reduce banks' wholesale funding share in equilibrium, and this interpretation may also be consistent with a gradual decline in total credit to the non-financial sector.¹⁶ Banks' preferred wholesale funding share will also be related to relative costs of deposit- and market funding conditions. If deposit rates are slower to adjust to tighter monetary policy than the banks' market funding rates, it might be relatively attractive for banks to have a lower market funding share when interest rates are increased.¹⁷

Figure 4: *Wholesale funding share. Response to a 1 pp. interest rate increase. Percent. Solid line is median estimate, dotted lines 16th and 84th percentile probability bands. Quarters.*



A large fraction of Norwegian banks' market funding (about 60 percent) consists of foreign currency funding (see Molland (2014)). International conditions might be important for the development of the wholesale funding share. See appendix A.8 for a discussion of

¹⁶The initial effect of issuing a loan by a bank is always an immediate creation of a corresponding deposit, see e.g. Werner (2014) and references therein. But when issuing e.g. bank certificates to increase market funding, banks "destroy" deposits. Each bank chooses its own funding structure. The degree to which banks in aggregate use deposits to fund credit to the non-financial sector is an equilibrium outcome, which depends both on banks' funding preferences and also on other sectors' portfolio preferences.

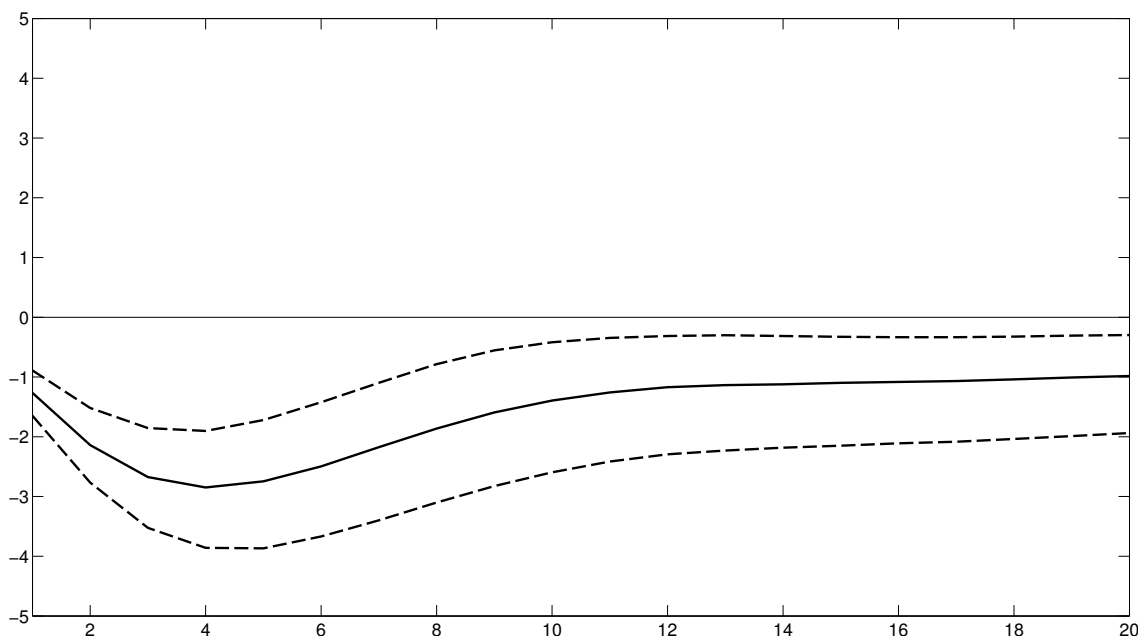
¹⁷Impulse responses for all variables in the benchmark level model are shown in figure A.11

robustness with respect to inclusion of other variables in the VAR-estimation.

3.4 MONETARY POLICY, HOUSE PRICES AND COMMERCIAL PROPERTY PRICES

Real house prices are included in all benchmark SVAR model specifications, and the impulse responses to a monetary policy shock are quite similar across models. Figure 5 shows the response in house prices taken from the benchmark SVAR model with credit to households. House prices are allowed to react to a monetary policy shock on impact, and a significant fall is observed. The estimated impact is well in line with Bjørnland and Jacobsen (2010) and Robstad (2014).

Figure 5: *Real house prices. Response to a 1 pp. interest rate increase. Percent. Solid line is median estimate, dotted lines 16th and 84th percentile probability bands. Quarters.*



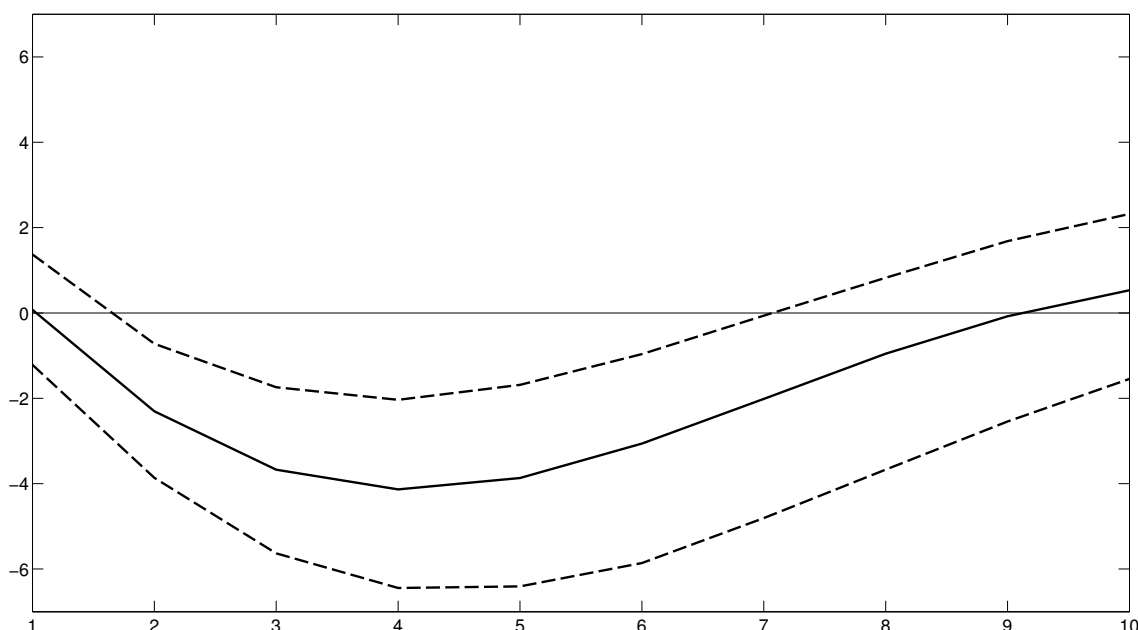
Commercial property represents the largest industry in terms of bank’s credit exposure in Norway (see e.g. Norges Bank (2013) and Hagen (2016)). It is also among the industries that historically has exposed banks to the largest loan losses. Commercial property prices are thus important for financial stability and included here for completeness, although for data reasons they are not included in our logit model.

The impact of a monetary policy shock on real commercial property prices is presented in figure 6. We apply a more parsimonious specification given the semiannual data available for commercial property prices and include five endogenous variables. Also, the zero restrictions implied by the Cholesky factorization are more restrictive when semiannual data is used. The identified impulse responses should therefore be interpreted with more caution than for the other financial variables.¹⁸

¹⁸Impulse responses for all variables in the benchmark level model are shown in figure A.15

Commercial property prices fall in response to a monetary policy tightening, but there is no significant effect on impact, in contrast to what we and others have previously found for real house prices. One reason may be that the use of semiannual data makes it harder to identify the short-run impacts of monetary policy. This is evident in the cross-check model with semiannual real house prices data, where the short-run effect of monetary policy on real house prices is modest and insignificant, see figure A.16 in appendix A.9.

Figure 6: *Real commercial property prices. Response to a 1 pp. interest rate increase. Percent. Solid line is median estimate, dotted lines 16th and 84th percentile probability bands. Semiannual.*



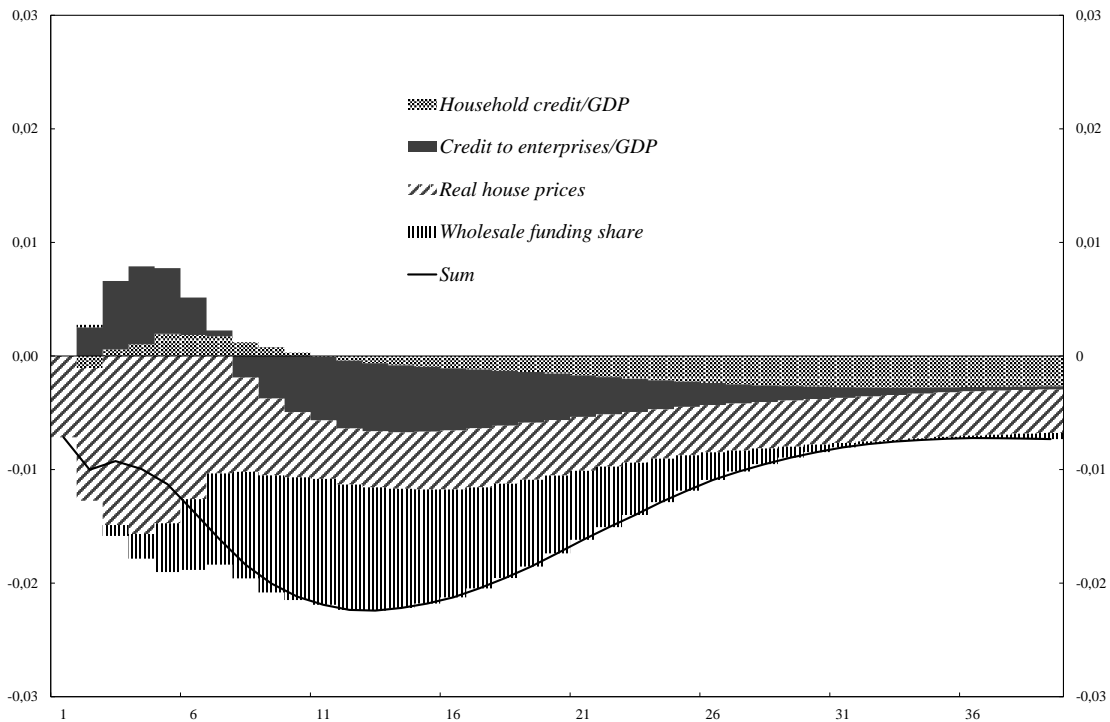
4 CRISIS PROBABILITY DECLINES MARKEDLY AFTER MONETARY POLICY TIGHTENING

Figure 7 presents our main finding. It shows the unconditional response of crisis probability to a monetary policy shock (solid line), and decomposes the impact of monetary policy via the different financial indicators. The response is calculated according to equation (4), assuming that the vector \mathbf{x}_t is zero in the absence of leaning. Since the crisis probability is a nonlinear function of the input vector \mathbf{x}_t , the initial state of the financial indicators \mathbf{x}_t and its' (expected) development going forward (without LAW) are important for the estimated net effect of policy on crisis probability. When the probability of a crisis goes to zero or one, the derivative of the probability of crisis with respect to the arguments of the logistic function goes to zero, which makes sense since you cannot reduce the crisis probability below zero or increase it above one no matter how much the financial indicator gaps are reduced or increased.¹⁹ The unconditional response of the crisis probability to

¹⁹The marginal effect on the crisis probability of the arguments in \mathbf{x}_t peaks when p_t is near 50 percent.

LAW can therefore not surpass the steady state probability, which is approximately 410 basis points (annualized) in this model.

Figure 7: Median unconditional response in annualized probability of a crisis 1-3 years ahead (solid line). One percentage point contractionary monetary policy shock. Contributions from different financial indicators as indicated. Quarters.

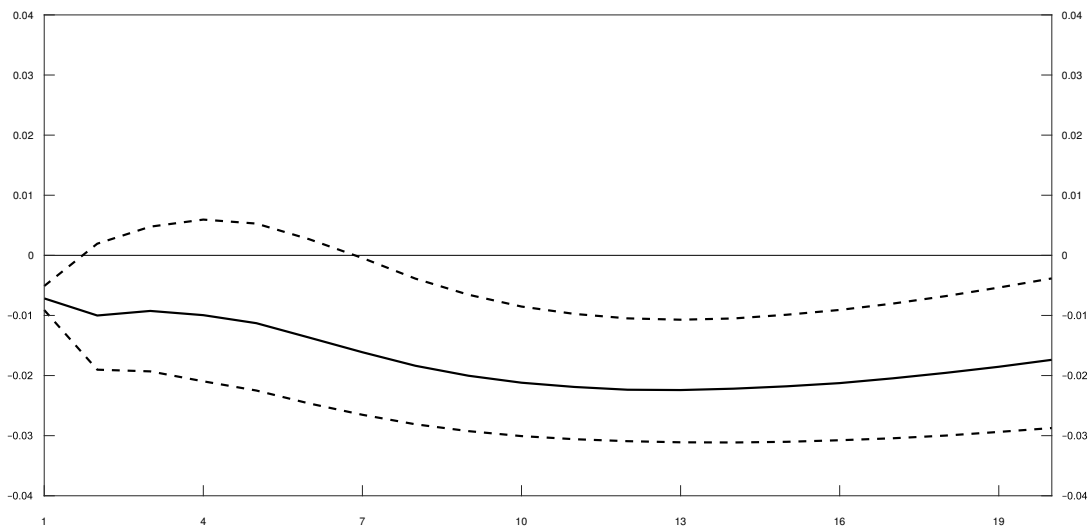


The reduction in annualized (pre-crisis state) probability peaks at around 220 basis points after 2-3 years, which implies that the reduction in the probability of *being* in a crisis is strongest 3-6 years after the monetary policy tightening. On average the annual pre crisis state probability is reduced by approximately 130 basis points the 10 years following the monetary policy shock. The fall in real house prices and the wholesale funding share account for most of this reduction (80 percent), while the two credit indicators are less important, as illustrated in figure 7. It is therefore not surprising that our quantitative estimate is much larger than what is typically reported in the literature. Svensson (2017) and Laséen and Pescatori (2016) find that the maximum impact of a one percentage point increase in interest rate reduces the unconditional crisis probability by around 20 basis points, when only including credit in the logit model. When we exclude the effect from monetary policy shocks on crisis probability via house prices and wholesale funding and only consider the credit channel, we get similar quantitative estimates.

Uncertainty regarding the estimated SVARs contribute to uncertainty about the estimated effect of monetary policy on crisis probability. The dotted lines in figure 8 are calculated

by inserting the 68 percent Bayesian credible bands from the estimated impulse-response functions in the crisis probability function. As we see from figure 8 the uncertainty regarding the effects of monetary policy on crisis probability is relatively large, although all three lines indicate a larger peak reduction in crisis probability than what is commonly found in the literature.

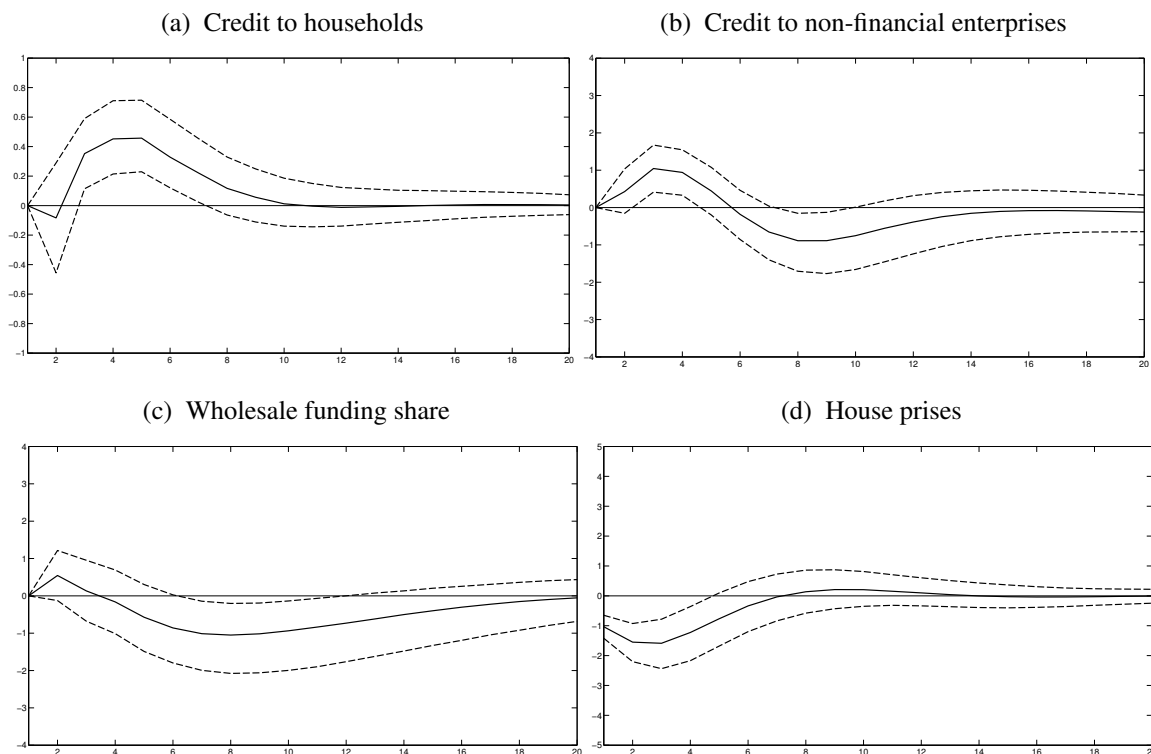
Figure 8: *Unconditional impulse to annualized probability of a crisis 1-3 years ahead. One pp. contractionary monetary policy shock. Solid line is the median, dotted lines are calculated using the 16th and 84th percentile IRFs. Quarters.*



All quantitative estimates of the effect of LAW on crisis probability is so far conditioned on a steady state level of crisis probability in the absence of leaning. In appendix B the counterfactual net effect of LAW at two different historical periods is presented. This counterfactual exercise illustrates that the net effect of LAW in terms of reduced crisis probability is largest in periods with relatively high crisis probability.

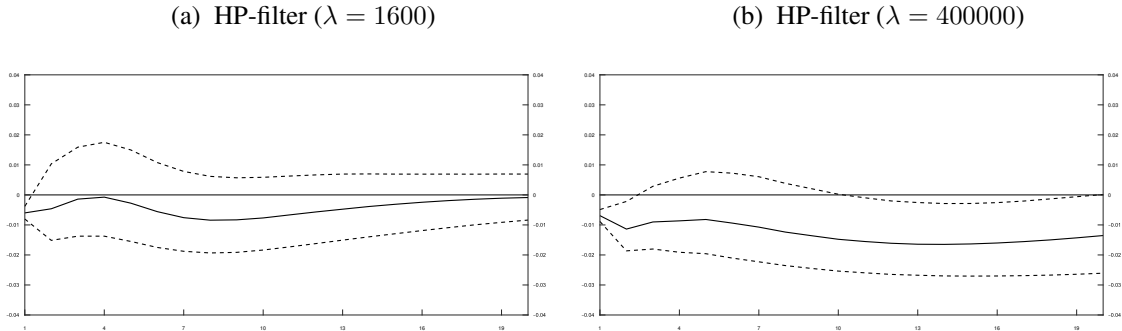
5 ROBUSTNESS AND SENSITIVITY

Figure 9: *HP-filtered data ($\lambda = 1600$): Response to a one pp. interest rate increase. Percent. Solid lines are median estimates, dotted lines are 16th and 84th percentile probability bands. Quarters.*



Using HP filtered data with a smoothing-parameter $\lambda = 1600$ hardly alters the qualitative impulse responses to a contractionary monetary policy shocks in the short and medium run, see figure 9. However the quantitative responses, especially to house prices and wholesale funding, is more muted and the subsequent tentative fall in credit to households as a share of GDP is no longer present. When using these impulse responses in the logit model the response of crisis probability is much smaller. This indicates that important information can be lost when data is filtered before the SVAR model is estimated, at least when the trend is relatively flexible. Using a smoother HP-trend ($\lambda = 400\,000$) when filtering the data, the overall impact of monetary policy on crisis probability increases (compared to the more flexible trend) and gives similar quantitative estimates as the level models, see figure 10.

Figure 10: *Crisis probability with HP-filtering in the SVAR models: Response to a one pp. interest rate increase. Percent. Solid lines are the median estimates, dotted lines are calculated using the 16th and 84th percentile IRFs. Quarters.*



The estimated peak effect of monetary policy on crisis probability in the benchmark specification is also sensitive to the parameters in the logit model. If we reduce all the coefficients (including the constant term) by one standard deviation and recalculate the impact of a monetary policy shock, the peak effect from the median IRF of an interest rate increase on the unconditional crisis probability is still minus 123 basis points, and if we reduce them by two standard deviations, the effect peaks at minus 57 basis points. More robustness exercises are presented in the appendix, including inclusion of other variables in the VAR. Overall, the qualitative results are relatively robust to different model specifications.

6 CONCLUDING REMARKS

We follow the methodology of the papers that study potential benefits of “leaning against the wind” (LAW). Our results show that the impact of monetary policy on the likelihood of a financial crisis might be much stronger than earlier work suggests. This is the case when considering that bank balance sheets and house prices impact the probability of a financial crisis over and above the effect through credit. This is not in itself evidence that LAW policy is associated with net benefits, but it highlights that monetary policy might play a larger role in financial stability than what is sometimes assumed. There are still significant challenges remaining in modeling structural links between monetary policy and financial stability.

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APPENDIX

A MODEL SPECIFICATION

A.1 BAYESIAN ESTIMATION OF THE SVAR MODEL

We use an uninformative version of the natural conjugate priors described in Koop and Korobilis (2010). For simplicity, assume equation (1) is rewritten in the following form:

$$Y = XA + E \quad (\text{A.1})$$

where X now includes all regressors in equation 1, i.e. lagged endogenous, the constant and the time trend and E has a variance-covariance matrix Σ .

Since $A = (A_1 \ A_2 \ \dots \ A_l)'$ equation A.1 can be written in the following form:

$$y = (I_n \otimes X)\alpha + \epsilon \quad (\text{A.2})$$

where n is the number of endogenous time series variables in the VAR and $\alpha = \text{vec}(A)$. The natural conjugate prior has the following form:

$$\alpha | \Sigma \sim \mathcal{N}(\underline{\alpha}, \Sigma \otimes \underline{V}) \quad (\text{A.3})$$

and

$$\Sigma^{-1} \sim \mathcal{W}(\underline{S}^{-1}, \underline{\nu}) \quad (\text{A.4})$$

where $\underline{\alpha}$, \underline{V} , $\underline{\nu}$ and \underline{S} are prior hyperparameters. Noninformativeness is then achieved by setting $\underline{\nu} = \underline{S} = \underline{V}^{-1} = cI$ and letting $c \rightarrow 0$. With this prior, the posterior becomes:

$$\alpha | \Sigma, y \sim \mathcal{N}(\bar{\alpha}, \Sigma \otimes \bar{V}) \quad (\text{A.5})$$

and

$$\Sigma^{-1} | y \sim \mathcal{W}(\bar{S}^{-1}, \bar{\nu}) \quad (\text{A.6})$$

where

$$\bar{V} = (\underline{V}^{-1} + X'X)^{-1}, \quad (\text{A.7})$$

$$\bar{A} = \bar{V}(\underline{V}^{-1}\underline{A} + X'X\hat{A}), \quad (\text{A.8})$$

$$\bar{\alpha} = \text{vec}(\bar{A}), \quad (\text{A.9})$$

$$\bar{S} = S + \underline{S} + \hat{A}'X'X\hat{A} + \underline{A}'\underline{V}^{-1}\underline{A} - \bar{A}'(\underline{V}^{-1} + X'X)\bar{A} \quad (\text{A.10})$$

and

$$\bar{\nu} = T + \underline{\nu} \quad (\text{A.11})$$

where T is the number of observations and $\hat{A} = (X'X)^{-1}X'Y$ is the OLS estimate of A .

A.2 VARIABLE SELECTION EXERCISE

We estimate a large number of reduced form VAR models and compare their out-of-sample forecasting performance. The number of variables in each VAR is 4, 5 or 6 and we allow for a lag order of 2 or 3, in order to contain the number of parameters to estimate. Each VAR includes the interest rate and the main financial variable of interest. The candidate reduced form VARs are generated by adding all possible two, three or four-variable subsets from a larger set of potentially relevant variables. The possible variables are listed in table A.1 below. For each financial stability indicator, we include a slightly different selection of these potential variables.

Table A.1: Potential variables in the reduced form VARs

Three-month interest rate
Real house prices
Real credit to households
Real credit to non-financial enterprises (C2)
Real credit to non-financial enterprises (C3)
Total real credit to the private sector
Household credit as a share of GDP
Credit to enterprises (C2) as a share of GDP
Credit to enterprises (C3) as a share of GDP
Total credit to the private sector as a share of GDP
Banks and credit institutions' wholesale funding share
Banks' and credit institutions' equity share
Bank's lending premiums
Vix
Real exchange rate
GDP mainland Norway
Private consumption
Housing investment
Corporate investment
Oil investment
Consumer prices adjusted for tax changes and excluding energy products (CPI-ATE)
Consumer prices for domestically produced goods and services (in the CPI-ATE)

All the reduced form models are estimated from 1994 Q1 to 2003 Q4 and then recursively estimated from 2004 Q1 to 2014 Q4. In the recursive estimation period the out-of-sample point-forecast error is computed. RMSFE for the interest rate and the financial variable of interest 1 to 8 quarters ahead is then calculated. The RMSFE is adjusted for the standard deviation of the variables when the RMSFE for the interest rate and the financial variable of interest are weighted together. For each financial indicator, the ten models with the lowest RMSFE are reviewed with respect to variables included, lag length and whether they include a time trend or not. Inspired by this exercise variables included in the benchmark SVAR model for each of the four financial indicators are selected.

A.3 IDENTIFICATION: CHOLESKY DECOMPOSITION

Equation (1) can be rewritten compactly with the lag operator:

$$\hat{A}(L)y_t = u_t, \quad (\text{A.12})$$

and the MA representation can be written as:

$$y_t = \hat{B}(L)u_t, \quad (\text{A.13})$$

where $\hat{B}(L) = \hat{A}(L)^{-1}$, or

$$y_t = u_t + B_1u_{t-1} + B_2u_{t-2} + \dots. \quad (\text{A.14})$$

The Cholesky decomposition involves decomposing the variance-covariance matrix of the reduced form error terms with a P -matrix that is such that $E[u_t u_t'] = PP'$. Defining $C_j \equiv B_j P$, and $\varepsilon_t \equiv P^{-1}u_t$ so that $E[\varepsilon_t \varepsilon_t'] = P^{-1}E[u_t u_t'](P^{-1})' = I$, equation (A.14) can be rewritten:

$$y_t = P\varepsilon_t + B_1P\varepsilon_{t-1} + B_2P\varepsilon_{t-2} + \dots, \quad (\text{A.15})$$

where P is a matrix describing contemporaneous zero-restrictions above the diagonal:

$$P = \begin{bmatrix} P_{11} & 0 & 0 & \dots & 0 \\ P_{21} & P_{22} & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ P_{N1} & P_{N2} & \dots & \dots & P_{NN} \end{bmatrix},$$

and ε_t is the vector of identified structural shocks. The variable ordered first in the y_t -vector will be affected contemporaneously by the first structural shock only. After the first period, all shocks may impact the first variable, depending on the B_1 -matrix.

A.4 THE SVAR MODELS

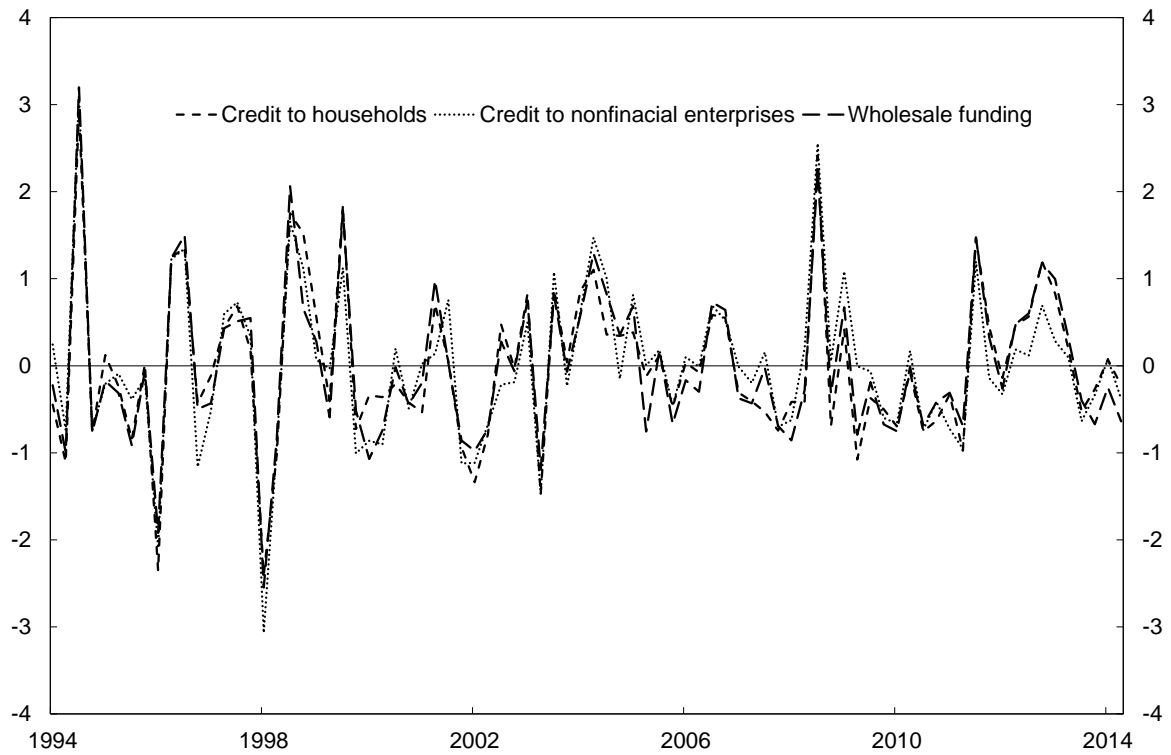
Table A.2: Summary of the SVAR models

Indicator	Credit to household (ch)	Credit to enterprises (ce)	House Prices (hp)	Wholesale funding (wf)	Commercial property prices (cp)
Other variables	Interest rate (r) CPI (p) Consumption(c) Wholesale funding (wf) House prices (hp)	Interest rate (r) CPI (p) Investment (i) Wholesale funding (wf) House prices (hp)	Interest rate(r) CPI (p) Consumption (c) Wholesale funding (wf) Credit to household (ch)	Interest rate (r) CPI (p) GDP (y) house prices (hp) Total credit (ctot)	Interest rate (r) CPI (p) GDP (y) Credit to enterprises (ce)
Lag length	2	2	2	2	1
Number of obs.	84	84	84	84	42
Chol. ordering	ch, p, c, wf, r, hp,	ce, p, i, wf, r, hp	p, c, ch, wf, r, hp	ctot, p, y, wf, r, hp	p, y, ce, r, cp

A.5 MONETARY POLICY SHOCKS

The identified monetary policy shocks from the three main VAR models used in the logit model (the model for credit to households, which also delivers the impulse-response function for real house prices, the model for credit to non-financial firms and the model for the wholesale funding ratio of banks) are shown below.

Figure A.1: *The identified monetary policy shocks from the three quarterly level models.*



A.6 HOUSEHOLD CREDIT AS A SHARE OF GDP

Figure A.2: *Monetary policy shock. Response of all variables in benchmark model for credit to households as a share of GDP. Quarters.*

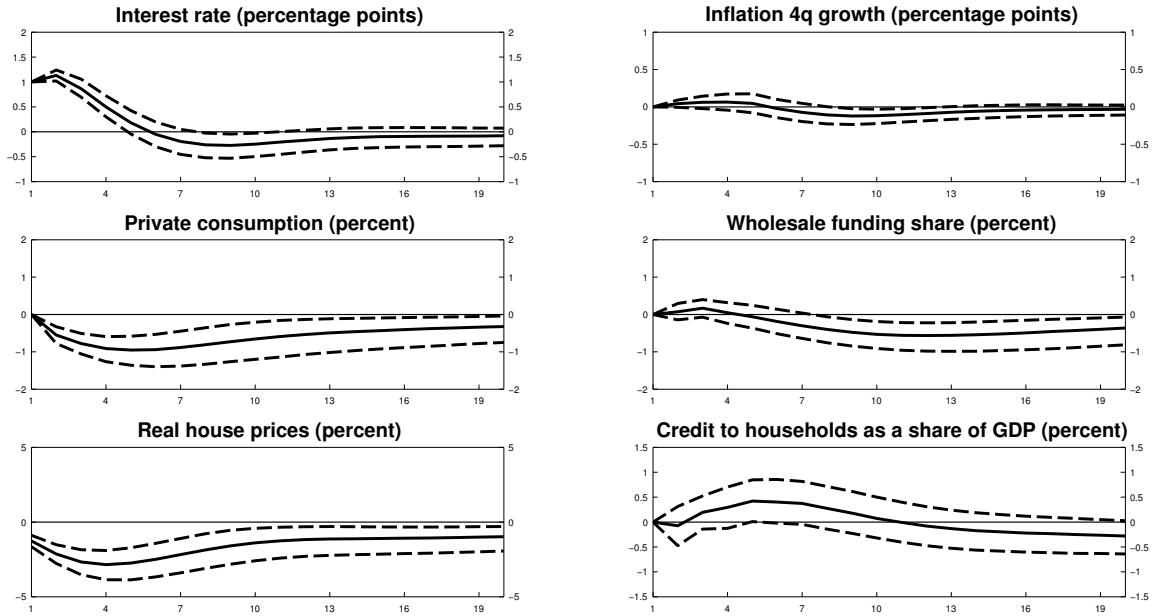


Figure A.3: *Responses of all variables in model for credit to households as a share of GDP using HP filtered data with $\lambda = 1600$. Quarters.*

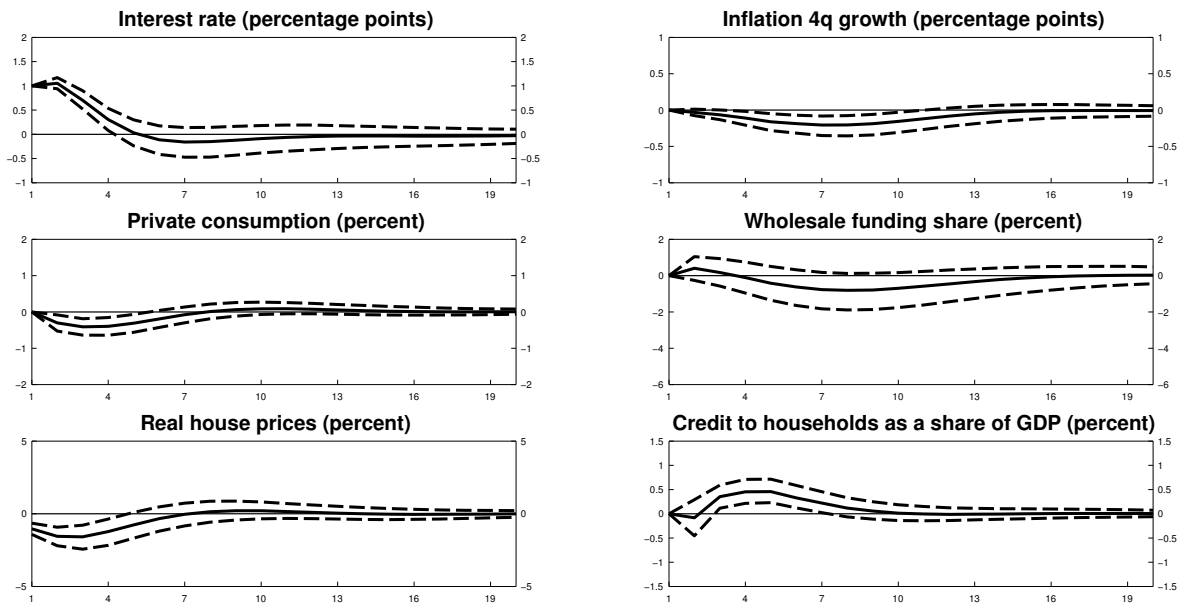
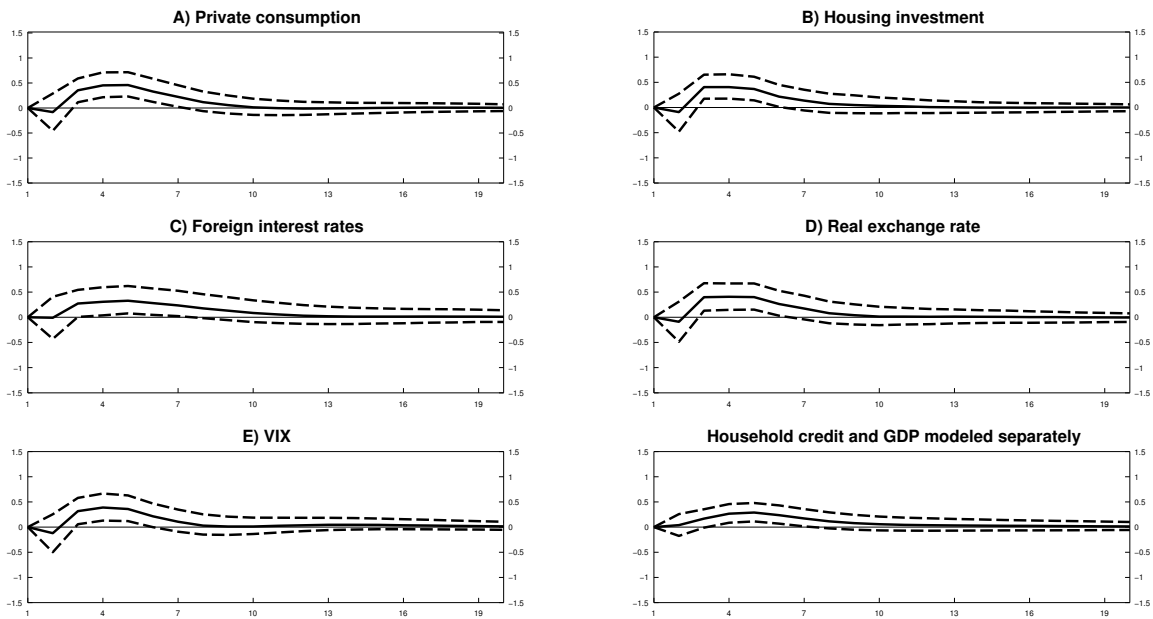


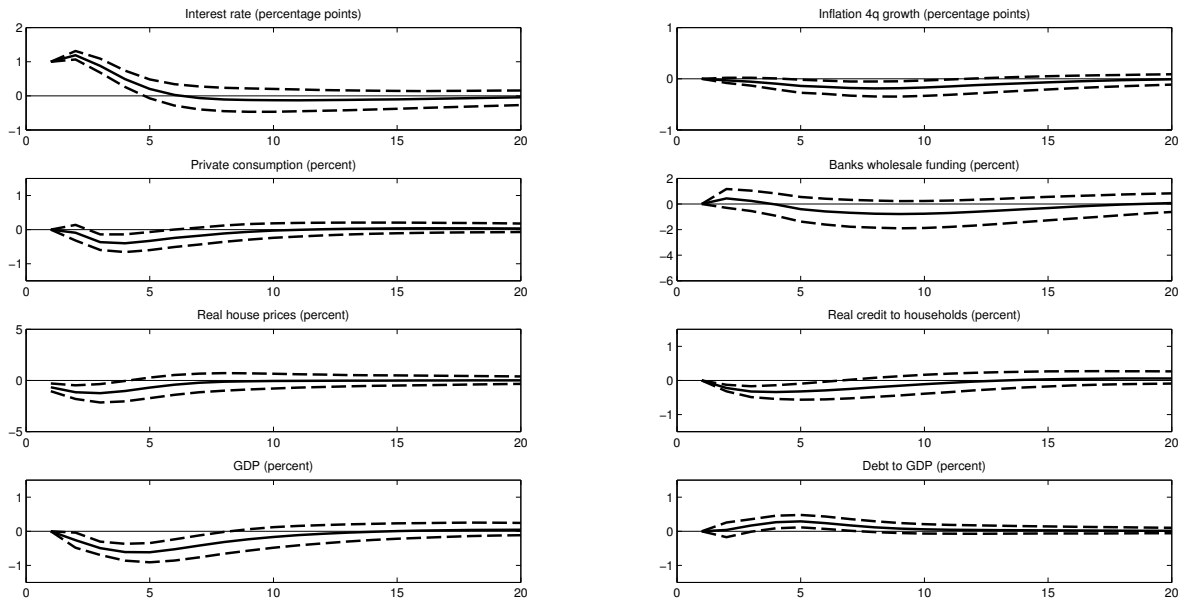
Figure A.4: *Credit to households as a share of GDP. Alternative explanatory variables. HP-filtered data. Quarters.*



Using HP filtered data with $\lambda = 1600$, we cross-check our results by including alternative explanatory variables, either added to or substituted into the model, see figure A.4. Ideally we would like to estimate all crosscheck models in levels. Unfortunately this was not possible for all the different model specifications we want to test, due to explosive roots in some of the models. We therefore use HP-filtered data in crosschecks with alternative variables. To examine whether the initial increase in the credit-to-GDP ratio is caused by GDP declining more or faster than credit itself, we perform one cross-check where real credit and GDP enter separately in the estimation. Impulse responses for each of these two variables, as seen in figure A.5 below, show that this is indeed the case.

Other real economic variables could be included in stead of private consumption. However, replacing this variable with e.g. housing investment hardly affects the responses other than for the demand side variable in question. With Norway being a small open economy, it is conceivable that foreign factors could influence domestic credit developments. Introducing exogenous foreign variables such as foreign interest rates or the VIX may thus potentially aid in the identification of a monetary policy shock. Similarly, the real exchange rate could also be of importance, and hence we also run a cross-check with these variables added to the main model. Taken together, all these robustness checks lead to results similar to the benchmark HP-filter model. For all specifications however, the effect is found to fade out after a few years. Yet another robustness check adding oil price as an exogenous variable does not change the results.

Figure A.5: *Monetary policy shock: Responses of all variables when real household credit and GDP enter separately in the model. Quarters. HP-filtered data.*



A.7 CREDIT TO NON-FINANCIAL ENTERPRISES AS A SHARE OF GDP

Figure A.6: *Monetary policy shock. Response of all variables in benchmark model for credit to non-financial enterprises as a share of GDP. Quarters.*

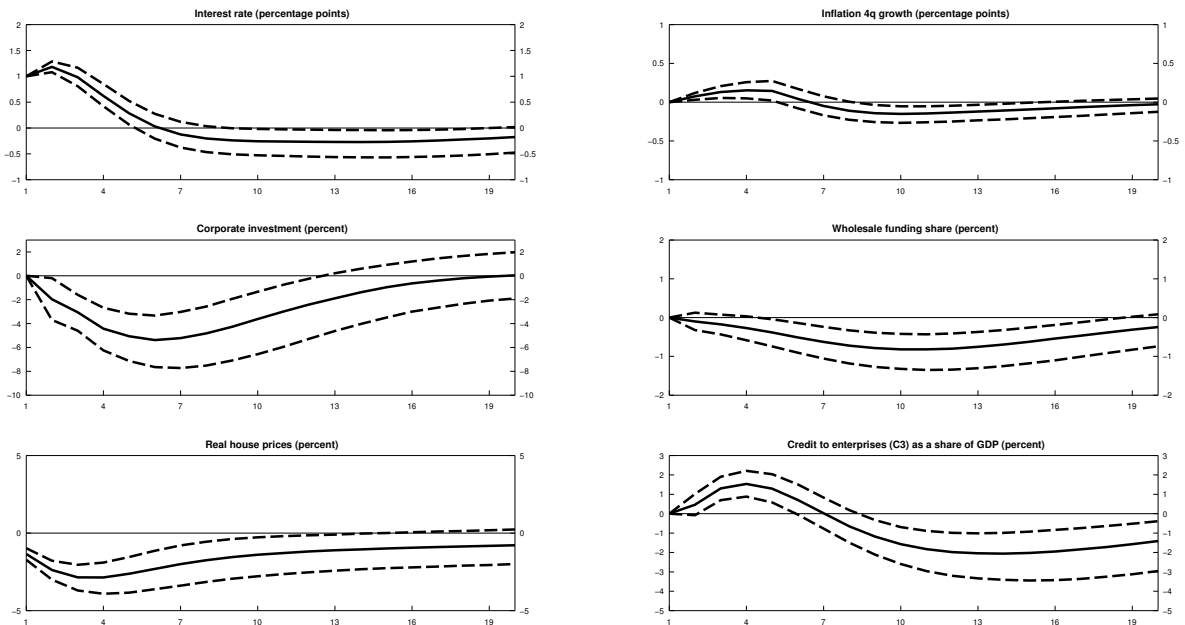


Figure A.7: Responses of all variables in model for credit to non-financial enterprises as a share of GDP using HP filtered data with $\lambda = 1600$. Quarters.

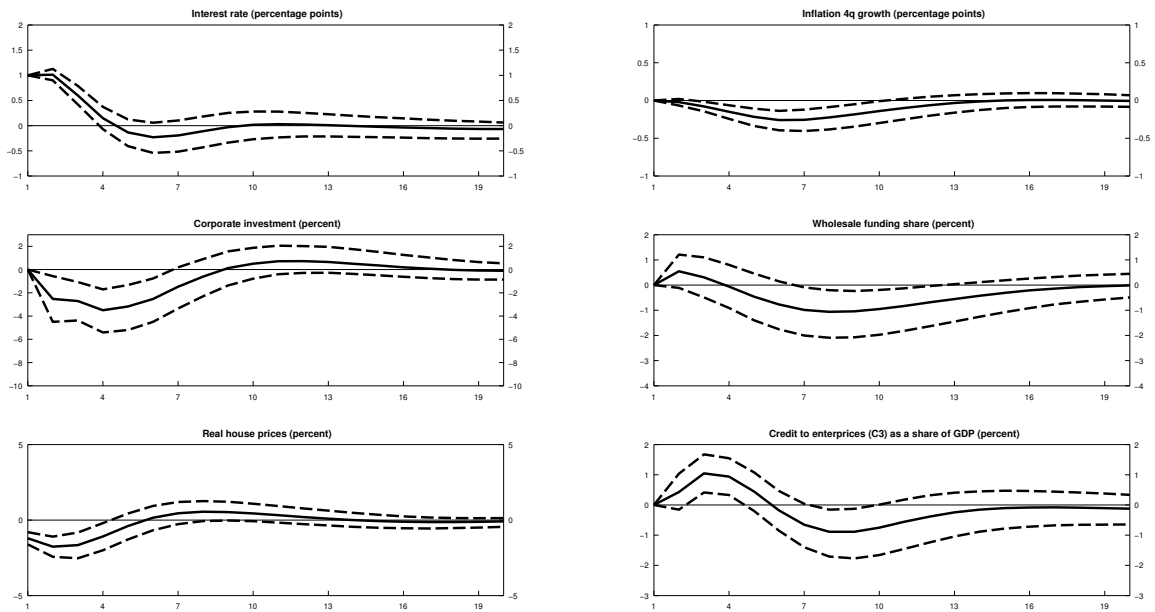
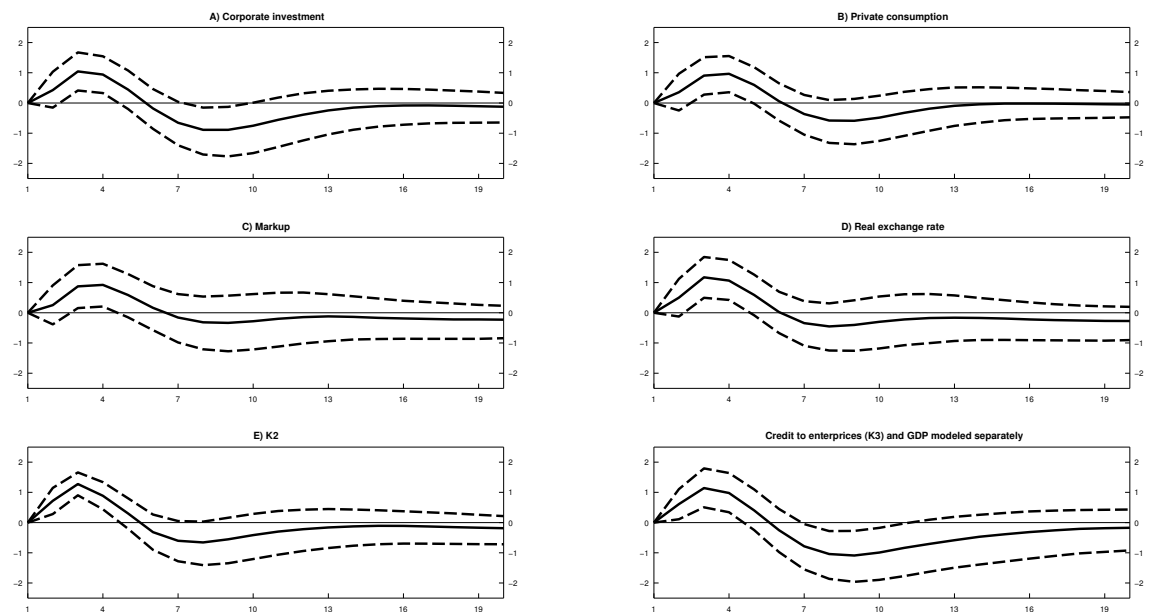


Figure A.8: Monetary policy shock: Responses for credit to non-financial enterprises as a share of GDP. HP-filtered data. Quarters.



Alternative explanatory variables leave our results for credit to enterprises as a share of GDP largely unchanged, see figure A.8. The credit aggregate used in the benchmark

model, C3, contains both foreign and domestic debt. We cross-check our results restricting our credit measure to domestic debt (C2) only, excluding the rather volatile series for foreign debt. A slightly stronger positive response during the first few quarters is observed, with somewhat narrower confidence bands across the entire horizon.

When we let real credit and GDP enter separately into the model, we see that GDP declines faster than real credit (real credit actually shows an initial increase), resulting in an increase in the ratio, as seen in figure A.9.

Results from cross-checks using exogenous foreign variables such as foreign interest rates or the VIX are shown in figure A.10. The response in enterprise credit-to-GDP is now more muted and less significant.

Figure A.9: *Monetary policy shock: Responses of all variables when real credit to non-financial enterprises and GDP enter separately in the model. HP-filtered data. Quarters.*

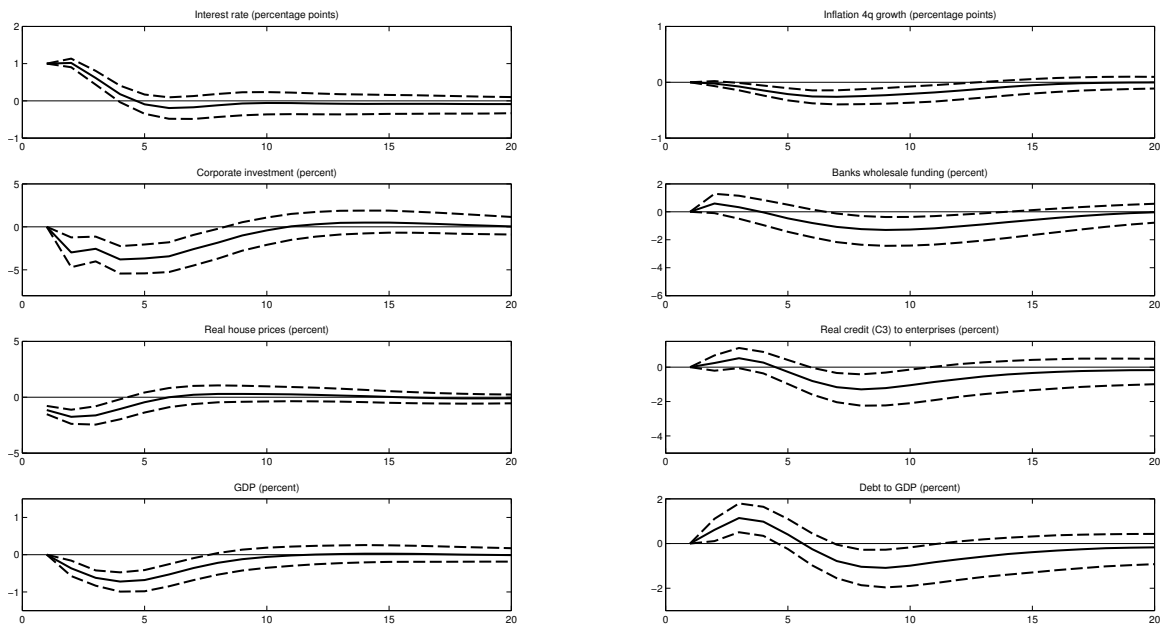
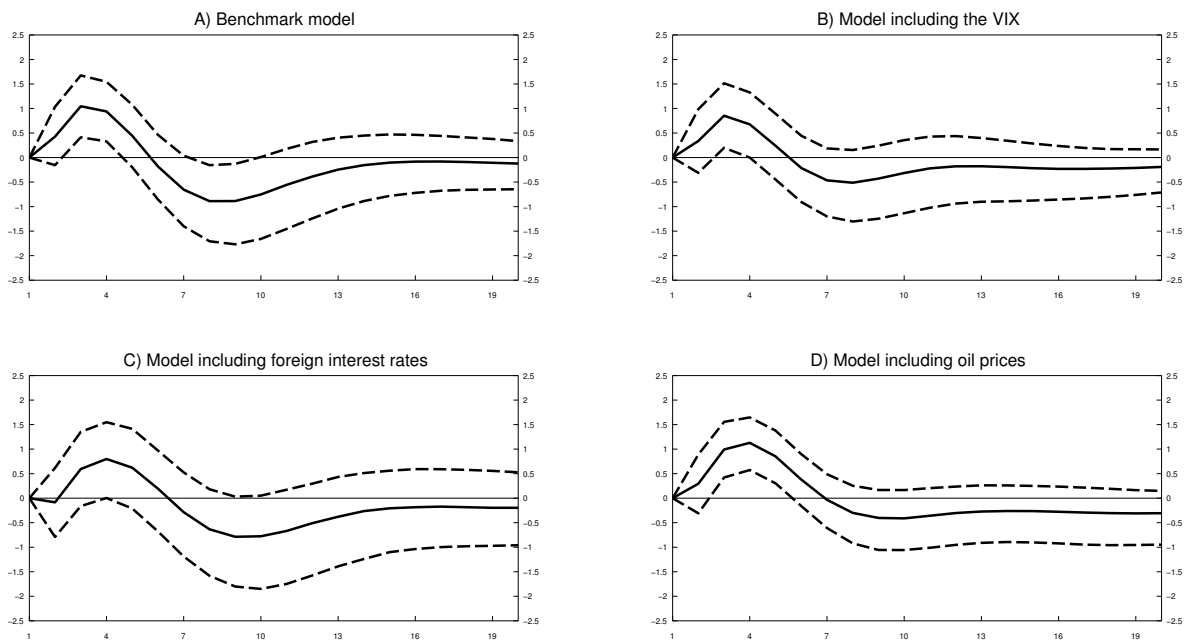


Figure A.10: *Monetary policy shock: Responses of credit to non-financial enterprises as a share of GDP in different models with various exogenous variables. HP-filtered data. Quarters.*



A.8 CREDIT INSTITUTIONS' WHOLESALE FUNDING SHARE

Figure A.11: *Monetary policy shock. Response of all variables in benchmark model for credit institutions' wholesale funding share. Quarters.*

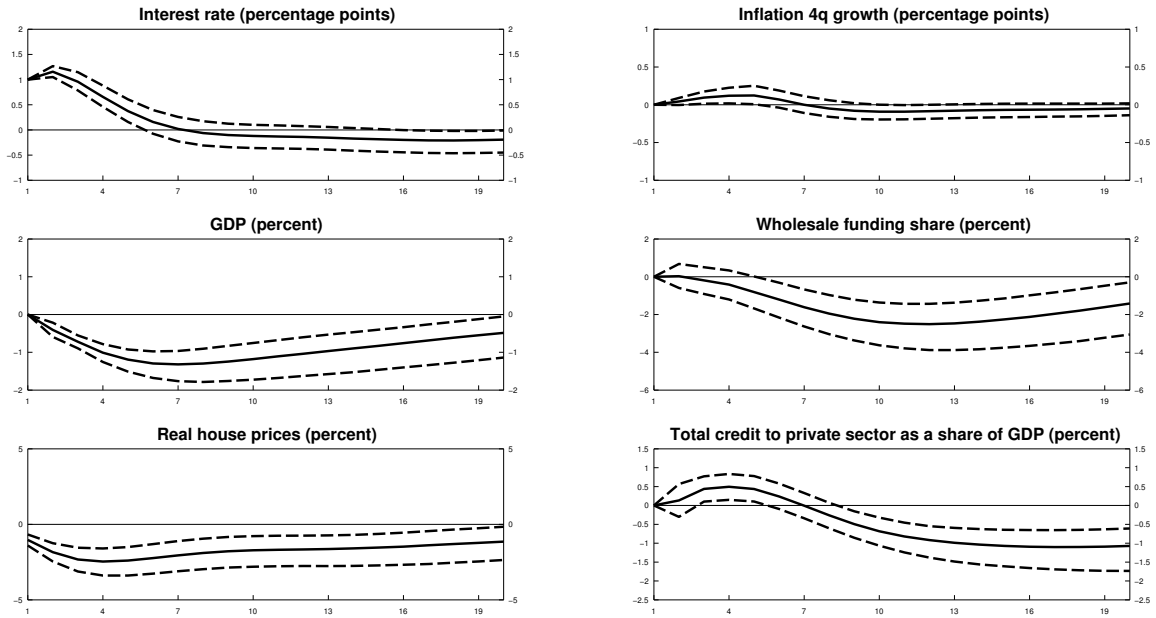
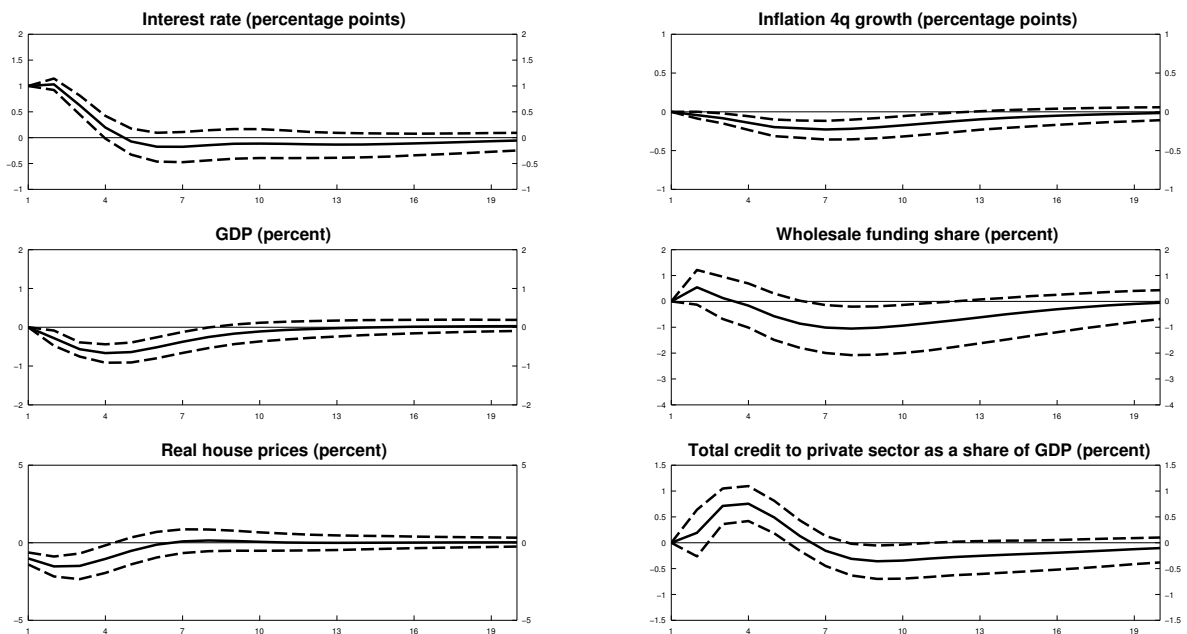
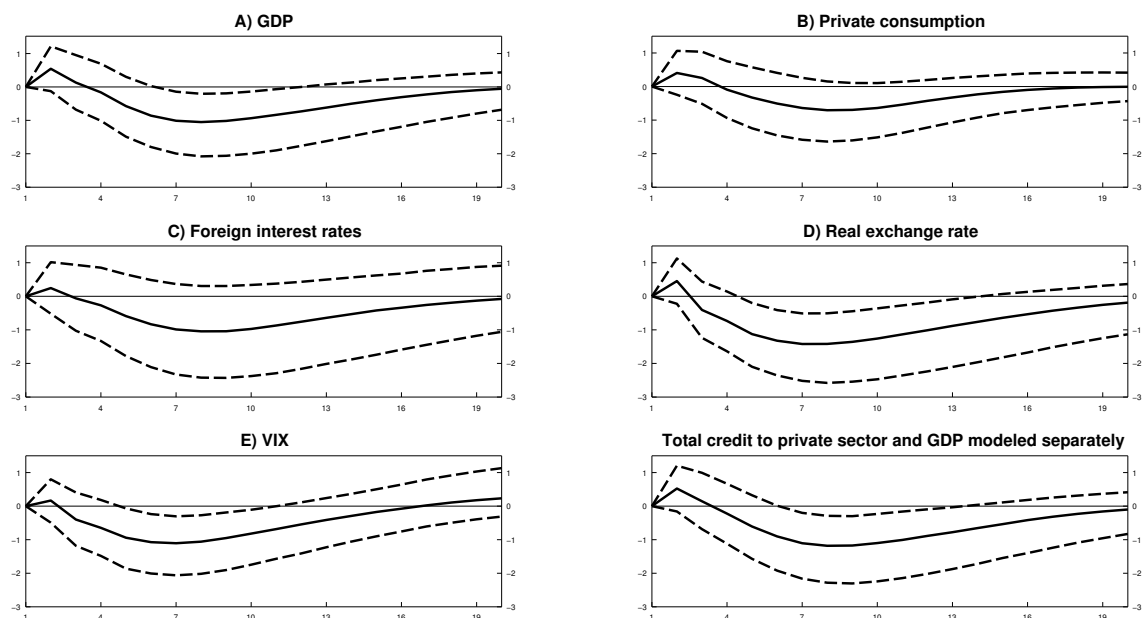


Figure A.12: *Monetary policy shock: Responses of all variables in model for wholesale funding as a share of total assets using HP-filtered data with $\lambda = 1600$. Quarters.*



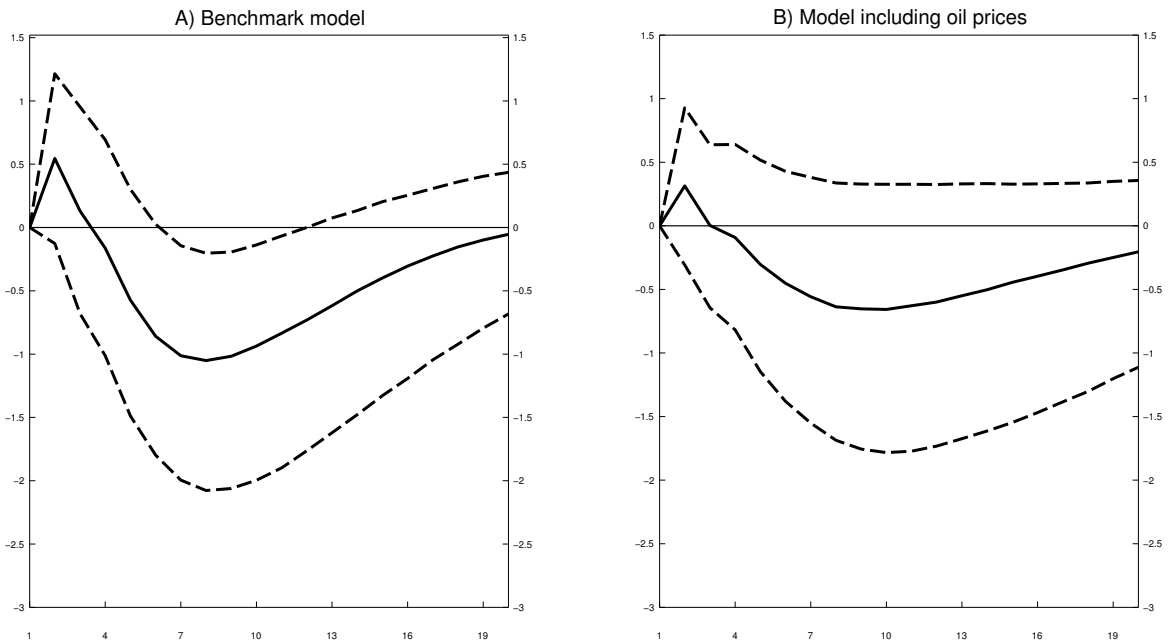
We also examine the impact on the wholesale funding share when alternative explanatory variables are included in the model, see figure A.13.

Figure A.13: *Monetary policy shock: Wholesale funding as a share of total assets. Alternative explanatory variables. HP-filtered data. Quarters.*



As a substantial share of credit institutions' wholesale funding is funding from abroad, we cross-check our results with variables that may be of relevance in an open economy setting. Adding either foreign interest rates, the VIX or the real exchange rate leaves the overall impact on the wholesale funding share largely unchanged. However, adding oil prices leaves the impulse response of the wholesale funding share more muted, as seen in figure A.14.

Figure A.14: *Monetary policy shock: Responses to wholesale funding share in the HP-filter model and in the HP-filter model with oil prices as exogenous variables. Quarters.*



A.9 REAL COMMERCIAL PROPERTY PRICES

Figure A.15: *Monetary policy shock. Response of all variables in model for real commercial property prices. Benchmark model. Semiannual.*

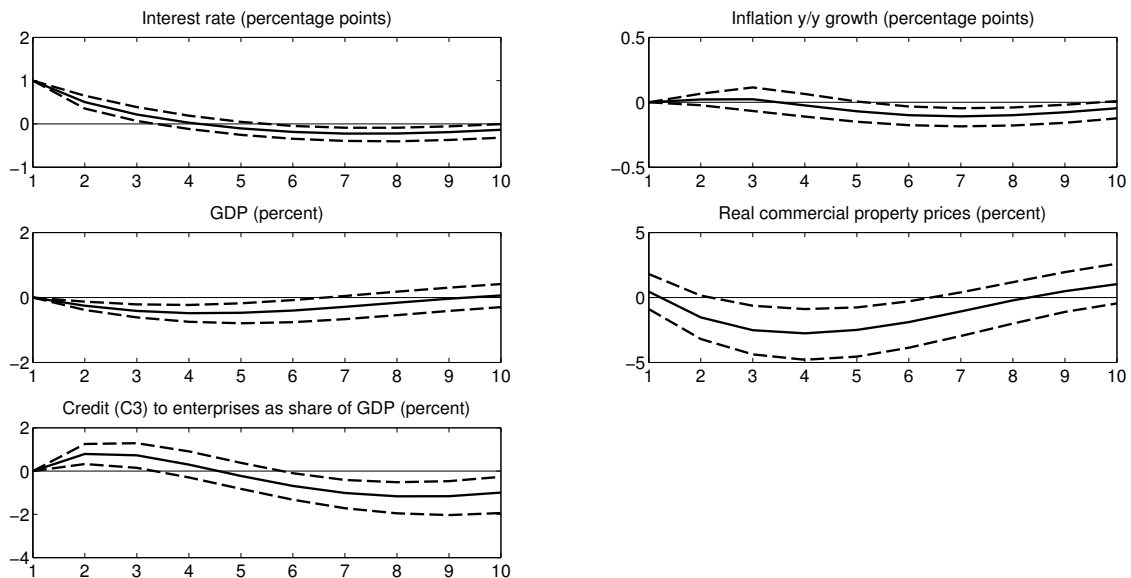


Figure A.16: *Monetary policy shock: Responses for real commercial property prices. Alternative explanatory variables. Semiannual.*

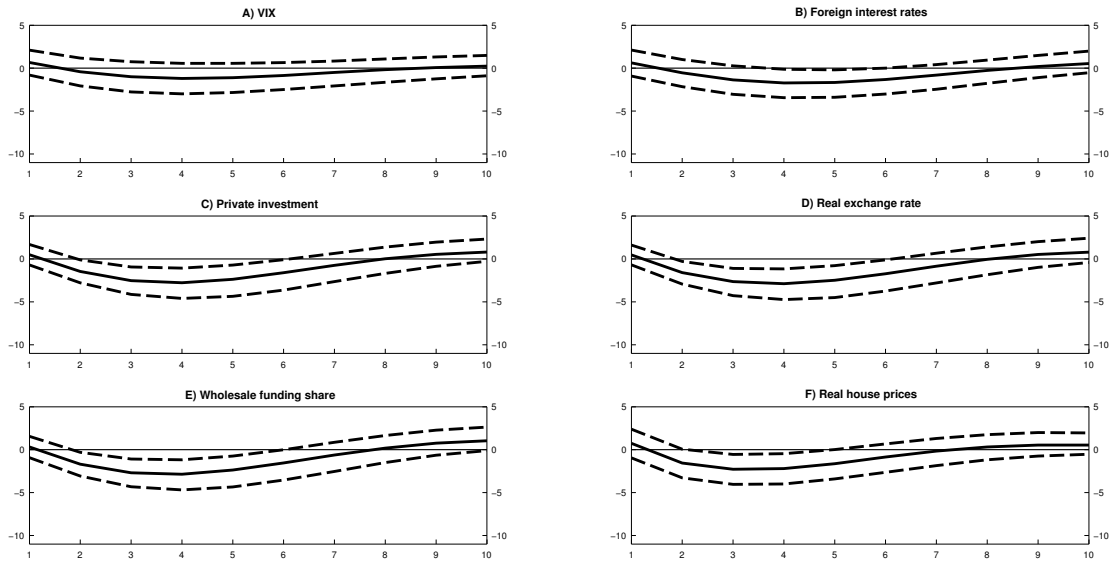


Figure A.16 shows the impact on real commercial property prices when alternative variables are substituted into the model.

A.10 THE LOGIT MODEL

Table A.3: *The financial crisis probability model^a*

Household credit/GDP gap	19.31*** (6.197)
NFE credit/GDP gap	13.46*** (3.495)
Real house price gap	16.55*** (1.691)
Wholesale funding gap	16.55*** (5.782)
Constant	-2.418*** (0.420)
Country fixed effects	Yes
Pseudo R ²	0.425
Observations	1075

^aAll coefficients are significant at the 1 percent level.

B COUNTERFACTUAL LAW POLICY IN 1999 AND IN 2006

The importance of initial financial imbalances for the impact of LAW can be seen by comparing figures B.1 and B.2. In the first quarter of 1999, financial gaps were close to zero and crisis probability was therefore low (see solid line in figure B.1). In 2006, financial gaps were rising and crisis probability was increasing (see figure B.2). This makes the estimated effect of counterfactual LAW on crisis probability somewhat stronger in the latter case.

Figure B.1: *Historical crisis probability estimates (solid line). Counterfactual probability (dashed line), after 1 pp. interest rate shock in first quarter of 1999. Probability of crisis in 1-3 years, approximately equal to annualized probability multiplied by two.*

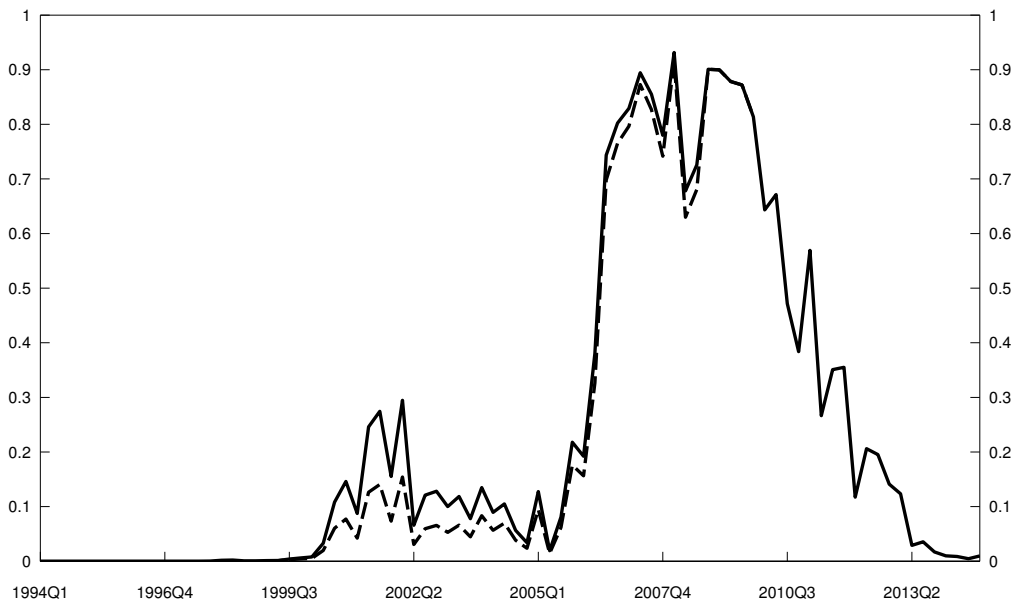
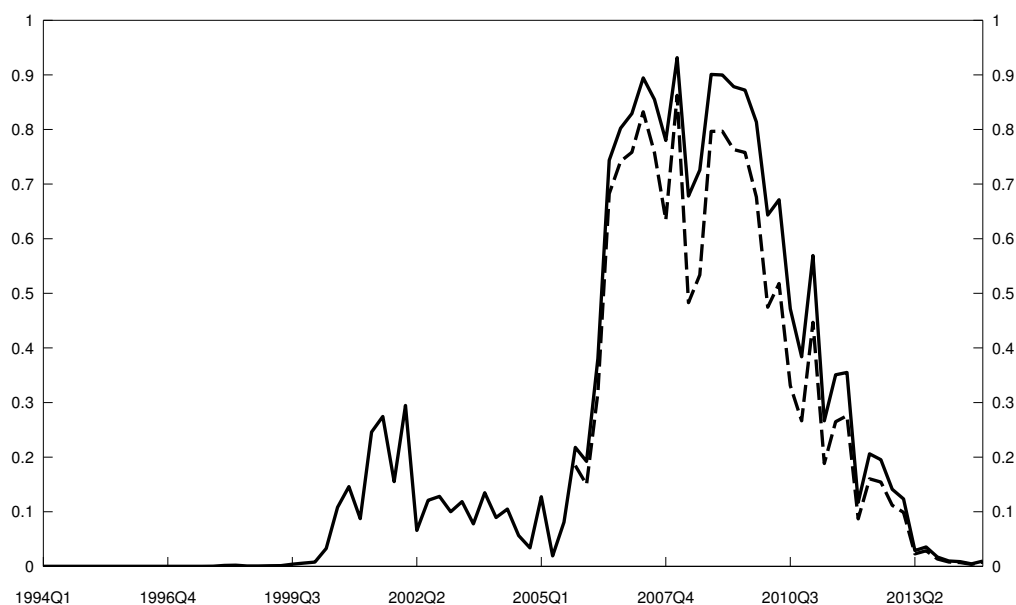


Figure B.2: *Historical crisis probability estimates (solid line). Counterfactual probability (dashed line), after 1 pp. interest rate shock in first quarter of 2006. Probability of crisis in 1-3 years, approximately equal to annualized probability multiplied by two.*



C DATA

- Nominal interest rate: Three-month money market rate (NIBOR). *Source: Norges Bank*
- Consumer prices: Seasonally adjusted consumer price index adjusted for tax changes and excluding energy products (CPI-ATE). *Sources: Statistics Norway and Norges Bank*
- GDP deflator mainland Norway: Seasonally adjusted GDP deflator for mainland Norway. *Source: Statistics Norway*
- Population: Population from 16 to 74 years. *Source: Statistics Norway*
- Real house prices: Seasonally adjusted nominal house prices deflated by the CPI-ATE. *Sources: Statistics Norway, Eiendom Norge, Finn.no, Eiendomsverdi and Norges Bank*
- Real commercial property prices: Estimated selling prices for centrally located high-standard office space in Oslo deflated by the GDP deflator for mainland Norway. *Sources: Dagens Næringsliv, OPAK, Statistics Norway and Norges Bank*
- Household credit: Nominal credit (C2) to households, chained and break-adjusted. *Sources: Statistics Norway and Norges Bank*
- Credit to non-financial enterprises (C2): Nominal credit to non-financial enterprises (C2, domestic sources), chained and break-adjusted. *Sources: Statistics Norway and Norges Bank*
- Credit to non-financial enterprises (C3): Nominal credit to non-financial enterprises (C3, total including foreign debt), chained and break-adjusted. *Sources: Statistics Norway and Norges Bank*
- Total credit: Total nominal credit to the private sector (C3, domestic and foreign sources), chained and break-adjusted. *Sources: Statistics Norway and Norges Bank*
- GDP for mainland Norway: Seasonally adjusted GDP for mainland Norway (volume) adjusted for population growth. *Source: Statistics Norway*
- GDP for mainland Norway (value): GDP for mainland Norway (value) adjusted for population growth. *Source: Statistics Norway*

- Household consumption: Seasonally adjusted final consumption expenditure of households and non-profit institutions serving households (volume) adjusted for population growth. *Source: Statistics Norway*
- Housing investment: Seasonally adjusted gross investment in housing (volume) adjusted for population growth. *Source: Statistics Norway*
- Corporate investment. Seasonally adjusted gross corporate investment (volume) adjusted for population growth. *Source: Statistics Norway*
- Real exchange rate: Trade-weighted nominal exchange rate index (I-44) for 44 trading partners adjusted for relative prices in Norway (CPI-ATE) and abroad (CPI for 25 trading partners, import-weighted). *Sources: Thomson Reuters, Statistics Norway and Norges Bank*
- Wholesale funding share: Bank's and covered-bonds mortgage companies' wholesale funding as a share of total liabilities. Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Bank's lending premiums (markup): Bank's lending rates to non-financial enterprises less three-month money market rate (NIBOR). Prior to 2002, calculations are based on lending rates on all loans. *Sources: Statistics Norway and Norges Bank*
- VIX: CBOE (Chicago Board Options Exchange) Volatility Index, end of period. *Source: Federal Reserve Bank of St. Louis*
- Oil prices: Brent blend spot. *Source: Thomson Reuters*
- Foreign interest rates: Trade-weighted three-month nominal money market interest rate for four trading partners (SWE, USA, EUR and GBR). *Sources: Thomson Reuters and Norges Bank*
- Real household credit: Nominal credit (C2) to households (chained and break-adjusted) deflated by the CPI-ATE and adjusted for population growth. Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Real credit (C3) to non-financial enterprises: Nominal credit (C3) to non-financial enterprises (chained and break-adjusted) deflated by the CPI-ATE and adjusted for population growth. Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Total real credit to the private sector: Total nominal credit to the private sector (C3, domestic and foreign sources), (chained and break-adjusted), deflated by the CPI-ATE and adjusted for population growth. Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Credit to households as a share of GDP: Nominal credit (C2) to households (chained and break-adjusted) as a share of GDP for mainland Norway (value). Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Credit to non-financial enterprises (C2) as a share of GDP: Nominal credit (C2) to non-financial enterprises (chained and break-adjusted) as a share of GDP for mainland Norway (value). Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Credit to non-financial enterprises (C3) as a share of GDP: C3 for non-financial enterprises (chained and break-adjusted) as a share of GDP for mainland Norway (value). Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*
- Total credit as a share of GDP: Total credit to the private sector, C3 (domestic and foreign sources), (chained and break-adjusted) as a share of GDP for mainland Norway (value). Seasonally adjusted. *Sources: Statistics Norway and Norges Bank*