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Macro financial linkages in a SVAR model with application to Denmark

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Abstract
We analyse macro financial linkages in the Danish economy by estimating a structural VAR model using Bayesian techniques and construct a new financial condition index for the Danish economy. We measure financial conditions as the aggregate impact of financial variables on real activity from the historical shock decomposition of GDP. We find that financial conditions have been an important driver of GDP in the Danish economy in recent years. Financial conditions stimulated GDP before the financial crisis and deepened the subsequent recession. Financial conditions have also contributed to the current expansion in the Danish economy. We compare the model properties with the properties of Danmarks Nationalbank's two other macroeconometric models and find striking similarities between the estimated VAR model and other models. The financial conditions index resembles the overall narrative of the Danish economy.

Resume
Vi analyserer makro finansielle links i dansk økonomi ved at estimere en strukturel VAR model ved hjælp af bayesiske teknikker og konstruerer et nyt indeks for finansielle forhold for dansk økonomi. Vi måler finansielle forhold som den samlede effekt af finansielle variable på den reale aktivitet fra en historisk dekomposition af BNP. Vi finder, at de finansielle forhold i de senere år har været en vigtig drivkraft for BNP i dansk økonomi. Finansielle forhold stimulerede BNP før finanskrisen og gjorde den efterfølgende recession dybere. Finansielle forhold har også bidraget til det nuværende opsving i dansk økonomi. Vi sammenligner modelegenskaberne med egenskaberne i Nationalbankens to andre makroøkonometriske modeller og finder slående ligheder mellem den estimerede VAR-model og andre modeller. Indekset for finansielle forhold genfinder den overordnede fortælling om dansk økonomi.

Key words
Economic activity; Financial markets; Models.

JEL classification
C32; C54; E32; E44; E47; G17.

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Macro financial linkages in a SVAR model with application to Denmark*

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Danmarks Nationalbank

January 31, 2019

Abstract

We analyse macro financial linkages in the Danish economy by estimating a structural VAR model using Bayesian techniques and construct a new financial condition index for the Danish economy. We measure financial conditions as the aggregate impact of financial variables on real activity from the historical shock decomposition of GDP. We find that financial conditions have been an important driver of GDP in the Danish economy in recent years. Financial conditions stimulated GDP before the financial crisis and deepened the subsequent recession. Financial conditions have also contributed to the current expansion in the Danish economy. We compare the model properties with the properties of Danmarks Nationalbank's two other macroeconometric models and find striking similarities between the estimated VAR model and other models. The financial conditions index resembles the overall narrative of the Danish economy.

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1 Introduction

The financial crisis reminded the economic profession that shocks to financial markets can have profound consequences for the real economy. These lessons highlighted the importance of developments in financial markets for projection exercises and for scenario analysis. Subsequently, policymakers have introduced macroprudential regulation, and academics and policymakers studying the financial cycle have found evidence for slower output growth after turning points in credit and house prices which has further heightened the importance of understanding macro financial linkages.[1] One way of analysing this issue is to construct measures of the aggregate conditions in financial markets and estimate their effect on the real economy.

In this paper, we investigate macro financial linkages in the Danish economy. We define financial conditions as the *aggregated impact of financial shocks in financial markets on activity in the real economy* and summarise these conditions in an index called a financial condition index (FCI). The aim is to quantify the overall contribution to GDP growth from exogenous changes in financial variables. The main challenge with financial condition indices is that financial variables are endogenous to the economic cycle and to developments in other segments of financial markets. In itself, an economic upswing is likely to drive up prices of financial assets. Usually, an upswing will also entail rising interest rates, in step with the central banks' wish to combat rising inflation. The task, when studying FCI and its impact on GDP, is to take these relationships into account and separate the endogenous and exogenous parts of the developments in the financial variables. The measure of financial conditions applied in this paper is a measure of the contribution to GDP growth *beyond* the effects of the cyclical developments. This is accomplished by estimating a structural VAR (SVAR). Our financial condition index follows immediately from the historical decomposition from our estimated model.

Our main results can be summarised as follows. The financial condition index estimated here is consistent with the overall narrative of developments in the Danish economy since 2000. We find that financial conditions — calculated as the sum of the shock to house prices, credit growth, stock prices and interest rates in a historical shock decomposition from a SVAR — stimulated the Danish economy during the period leading up to the financial crisis, and that financial conditions were an important factor behind the contraction during the crisis. In the 3rd and 4th quarter of 2006, financial conditions contributed with 1.9 percentage point to y-on-y GDP growth. The most important financial variables during this period were credit and house prices. During the current economic expansion since 2013, financial conditions have stimulated the economy positively. Compared to earlier, credit growth plays a minor role in the current upswing. Currently, GDP growth is supported by financial conditions with a magnitude of 0.5 percentage points p.a. The estimated model for Denmark yields intuitive impulse responses that are consistent with Danmarks Nationalbank's other models. We confirm the strong relationship between house prices and credit growth in the Danish economy and find large spillovers from these variables to the real economy. The strong relationship between credit and the real house price reflects the well-developed

[1] See Borio (2014) or Grinderslev et al. (2017) for a study using Danish data.

Danish mortgage bond market.

To our knowledge, we are the first to construct a financial condition index using the part of the historical decomposition of GDP driven by financial shocks using a SVAR. This approach has several advantages. Firstly, we do not have to make any choices regarding the weighting of the financial variables in the FCI. Secondly, it has a clear and structural interpretation: at any point in time, we can evaluate the contribution from the financial block on GDP growth, as the model in a clear and transparent manner controls for the endogeneity between the real economy and the financial economy. Thirdly, we can explain how much of the development in GDP is attributable to individual financial shocks.

We are neither the first to analyse financial conditions in general nor the first to analyse financial conditions for the Danish economy. A widely used approach is to use a large data set comprising many different financial variables and extract one factor from these variables using principal component analysis to determine the weights of the variables. The factor can then be regarded as being financial conditions, see e.g. Brave and Kelly (2017). The advantage of this approach is that the information set included in the model can be arbitrarily large. However, if data is not adjusted for movements in the business cycle, it is not clear what financial conditions are capturing, which reflects that financial conditions are expected to vary closely with the business cycle, as explained above. One common approach which addresses this critique is to control for lagged GDP growth and inflation, see e.g. Hatzius et al. (2010), Darracq Paries et al. (2014) and Davis et al. (2016). By adjusting for business cycle developments the financial condition index will capture the part of movements in financial variables which cannot be explained by the current position in the business cycle.

Another widely used approach is a regression-based approach where the weights are determined by regressions of the financial variables impact on the real activity. Weights are usually based on either the maximum effect on GDP growth of a shock to a financial variable or the average effect over a number of periods. Therefore, the regression-based approach usually involves some choices regarding the weights. Our approach is closely related to the regression-based approach but we do not make any choices regarding weights.

On Danish data, at least two studies exist on constructing financial condition indices, and one paper studying macro financial linkages in a VAR. Hansen (1997) defines the weighted sum of the short-term interest rate, the long-term interest rate, and the exchange rate as the financial condition index. The weights are determined by the peak impact on GDP of shocks to these three variables in Danmarks Nationalbank's macroeconometric model, MONA. Compared to that study, we apply a broader range of financial variables and include them in a structural model. Another study on Danish data applies both the principal component approach and a VAR approach, see Skaarup et al. (2010). The scope of that paper is to forecast output gap using FCI's. Abildgren (2012) was among the first to estimate a VAR with financial variables using data for Denmark from 1948-2010. The results indicate that periods of financial crisis have been characterised by an extraordinarily large increase in the banking sector's write-down ratio and a related persistent decline in real GDP. The study also finds that the contribution from financial shocks to volatility in output and unemployment have been non-trivial even during periods characterised by tight regulation of the financial sector and widespread stability.

While intuitively appealing, financial condition indices can be criticised for lack of theoretical foundation. The critique goes in two directions. Firstly, it is not clear-cut that shocks to financial markets should affect the real economy, as shocks to financial markets reflect shocks to fundamental factors in the real economy. Most macroeconomic models used before the financial crisis assumed perfect capital markets.[2] Financial markets allocated savings unhindered to households and firms, and shocks to financial markets, thereby, did not affect the real economy. Banks and financial markets were simply an accounting identity playing no role for equilibrium output and inflation. This was partly due to the apparent empirical observation that financial shocks were not important for the business cycle.[3] Importantly for the estimation of FCIs, financial markets can be expected to vary closely with the business cycle; both stock prices and house prices can be expected to increase during expansions as income is rising, profits and confidence are high and credit constraints tend to be looser. Monetary policy is on the other hand expected to be tightened during booms. Rapidly increasing house prices are for instance, according to this view, just a result of the strong underlying economy. A structural VAR model solves the endogeneity of financial variables to the business cycle.

The second issue is centered around which variables to include in an empirical model and how to make the distinction between financial and real shocks. This is not the place for a complete literature review of theoretical links between financial markets and the macroeconomy. Instead, we will point to some theoretical arguments for the inclusion of house price, credit, and stock prices in our model. The role of credit constraints for firms and households was pointed out early in theoretical macroeconomics, see Iacoviello (2005) and later Iacoviello and Neri (2010) for the housing market and the household side, and Bernanke et al. (1999) and Kiyotaki and Moore (1997) for the stock market, or net worth, on the firm side.[4] According to this theory, stock prices and house prices can be key determinants for the development in the real economy, as these prices are crucial factors for the collateral the firms and households can post. This introduces an explicit role for the stock price and the house price for the determination of prices and output *over and above* what can be expected from the business cycle.

The relationship between credit and GDP has been investigated in a long list of papers. For instance, Mian et al. (2017) finds that periods with expanding credit to households are followed by a subsequent decline in GDP growth on a cross-section data set. This empirical finding is consistent with the predominance of credit supply shocks. Mian and Sufi (2018) argue for a credit-driven demand channel. What happens first is an (exogenous) expansion in the supply of credit. Next, the expansionary phase of the credit cycle affects GDP through higher consumption and investments boosted by access to cheap credit. Third, the

[2]Economists did though pay attention to macro financial linkages before the financial crisis. For instance, there is an explicit role of house prices in Danmarks Nationalbank's model MONA as it enters into household wealth. In the theoretical academic models, some of the prominent models are Bernanke et al. (1999) and Kiyotaki and Moore (1997).

[3]See Gadea Rivas and Perez-Quiros (2015).

[4]While the models are silent about the existence of such a credit constraint it can be motivated by e.g. asymmetric information – defaults are costly for lenders, and lenders cannot perfectly observe the type of borrowers. Hence, lenders demand collateral when they lend to either firms or households.

subsequent contraction is driven by a fall in aggregate demand. The resulting recession is amplified by nominal rigidities, constraints on monetary policy, and problems in the banking sector due to excess leverage and loss of capital.

The remainder of this paper is organised as follows. In section 2, we present the data used, set up our model, describe the estimation method and the identification strategy. We also present the properties of our baseline model as well as our preferred financial condition index by analysing the effects from changes of the financial variables on the real economy emphasising the current expansion in the Danish economy. In section 3, we use the model to conduct scenario analysis around the financial crisis. In section 4, we conclude. Our approach is, like all other structural VARs, dependent on the identifying assumptions which we carefully check in the paper in Appendix A. The robustness checks are with a focus on the identification strategy, expanding the model, and comparing the FCI to non-parametric methods.

2 A model for macro financial linkages

The main purpose of financial condition indices is to quantify the impetus to growth from financial markets. In that regard, a VAR-model is a suitable tool. Our approach is to use the structural shocks and derive the corresponding historical decomposition. Hence we use the structural shocks and the structural moving average (MA) representation to evaluate the effect of financial variables on GDP.[5] Our FCI is the sum of the shocks to the stock price, the real house price, credit and the interest rate in a historical shock decomposition to the growth rate in GDP.

A standard requirement for a VAR model for a small open economy and thereby the Danish economy is the inclusion of GDP, inflation, and some variables describing the foreign economy. As we are interested in financial linkages we include financial variables as well. We choose to include the real house price, acceleration in credit growth, interest rates, and stock prices. Our approach investigating how conditions on financial markets affect the real economy or vice versa necessitates a structural econometric model. The rather large number of data series points to the advantages of using Bayesian techniques: The priors on the parameters mitigates the curse of parameter dimensionality and hence parameter instability.

We include credit and interest rates as changes in these reflect changes in the availability and price of external financing for households and firms. On the other hand, changes in house prices and stock prices reflect changes in household wealth and for credit-constrained households changes in their collateral. Investments by companies are also likely to increase when stock prices go up according to the Tobins-q theory.

Our model is based on the work of Hubrich et al. (2013). In this section, we will explain in detail the model, the identification strategy, and our financial condition index.

[5] See Kilian and Lütkepohl (2017) for a discussion of structural MA representations.

2.1 Estimation

The unrestricted reduced form VAR can be written as

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t, \tag{2.1}$$

where Y_t is a $n \times 1$ vector of the endogenous variables, and A_i for $i = 1 \ldots p$ is an $n \times n$ matrix of coefficients. ε_t is a $n \times 1$ vector of serial uncorrelated error terms with mean zero and variance-covariance matrix, Σ.

As Denmark is a small open economy, we also need to condition on developments in the global economy. We estimate the model such that export market growth, foreign prices, and oil prices enters as block exogenous. The assumption implies that these three variables are unaffected by economic and financial developments in Denmark but affect the Danish economy. The model is thus estimated with zero-restrictions on the contemporaneous matrix and the lagged matrices.

In order to asses the effect of shocks to the VAR system, we derive the structural VAR. The elements in ε_t from equation (2.1) are residuals. We are interested in the effect of the structural shocks in the model and the effect from these on the variables in the model. The structural VAR is derived by rewriting equation (2.1) as

$$D_0 Y_t = D_1 Y_{t-1} + \cdots + D_p Y_{t-p} + \eta_t, \tag{2.2}$$

where $\eta \sim N(0, \Gamma)$. In order to derive the structural form from the reduced form we therefore need to find D_0^{-1}, such that $A_i = D_0^{-1} D_i$, $C = D_0^{-1} F$, and $\varepsilon = D_0^{-1} \eta_t$. The matrix D_0^{-1} is a structural matrix that rotates the reduced form system into the structural form. The structural form is identified by triangular factorisation of D_0^{-1}.This implies that D_0^{-1} is lower triangular. We order the variables according to a standard identification scheme from slow moving to fast moving: GDP, inflation, credit impulse, house prices, interest rates, and stock prices. The ordering implies that GDP reacts with a lag to shocks to all other variables, and inflation reacts with a lag to shocks to all variables except GDP and so forth.

We estimate the system with 6 endogenous variables and 3 block-exogenous variables. A lag length of 1 is chosen as we work with growth rates. We estimate the model using Bayesian methods due to the size of the model and the relatively short estimation period. We estimate the model using normal-inverse Wishart prior, following e.g. Hubrich et al. (2013) and Comunale and Kunovac (2017).[6]

[6] A widely used prior for the estimation of SVARs is the Minnesota or Litterman prior, where it is assumed that the VAR residual matrix, Γ, is known. Hence, only the matrix of parameters in A_1 needs to be estimated. The advantage of the Minnesota prior derives from the mathematical simplicity, but it comes with a cost: The variance-covariance matrix is assumed to be known, which clearly can be very restrictive. This assumption is relaxed when using the normal-inverse Wishart prior. However, even though this prior is more flexible than the Minnesota prior, it has drawbacks. Specifically, it constrains the variance-covariance matrix, which for each equation in the model creates a dependence between the variance of the residuals and the variance of the VAR coefficients. This assumption is, in turn, relaxed when using the normal-inverse Wishart prior. The drawback is mathematical complexity and the need to simulate the model to get the posterior distributions.

2.2 Data

We estimate the model using data from 1994Q1-2018Q3. Most of the data is obtained from Danmarks Nationalbank's model database, MONA. Credit data is compiled by Danmarks Nationalbank. For the baseline specifications, the variables are real activity (GDP, private consumption and gross fixed-capital formation), inflation, real house prices (using the private consumption deflator), a variable we denote credit impulse (to be defined below), real stock prices (using the private consumption deflator), and the 30-year mortgage bond interest rate. Variables are defined as year-on-year growth rates in per cent with the exception of the credit impulse, the quarterly differenced 30-year mortgage bond rate, and the quarterly change in the stock price in per cent. We use the difference in interest rates due to the downward trend observed during the estimation period. Inflation is calculated as the year-on-year growth rate in the private consumption deflator in Denmark. We furthermore include a de-trended weighted export market growth, foreign price growth and oil prices as block-exogenous variables. This is standard in the VAR literature for small open economy models.[7].

The credit impulse is defined as follows

$$Credit\ impulse = \frac{Credit_{i,t} - Credit_{i,t-1}}{Y_{t-1}} - \frac{Credit_{i,t-4} - Credit_{i,t-5}}{Y_{t-5}}$$
$$\text{for } i = \text{total, households, non-financial corporations,} \tag{2.3}$$

where $Credit_i$ denotes nominal credit for sector i and Y is annualised nominal GDP. The credit impulse variable is thereby a measure of the *acceleration* in total credit as a per cent of GDP. The credit impulse has been used in a number of papers, see for instance Hubrich et al. (2013).

2.3 Identification

As already stated, we identify the structural model using a triangular factorisation which implies that shocks are identified through the ordering of the variables. The ordering is relatively standard with respect to the real block of the model, GDP, inflation, and interest rates, see e.g. Christiano et al. (1999). We order the financial block after the real block – asset pricing variables react quickly to shocks and are forward-looking variables. The ordering within the financial block is less straightforward. House prices, interest rates, and stock prices have a forward-looking component and should thereby react faster than the credit variable. Furthermore, Grinderslev et al. (2017) find that the real house price is a leading indicator of credit. Based on these observations, we order credit before house prices. Changes in house prices require actual sales of houses which means that a change in the interest rate will be transmitted to house prices with a lag. House prices are thereby ordered before interest rates. Stock prices are assumed to be the most forward-looking variable and are thus ordered last.

One drawback of our identification strategy is the forward-looking nature of financial variables, interest rates and stock prices, and the apparent fact that financial markets are fast moving. Prices on bonds and

[7] For an example of Danish data see e.g. Ravn and Spange (2014)

stocks react simultaneously to shocks. By using the chosen identification scheme we ignore this fact. An alternative scheme for identification of financial shocks could be through sign restrictions, where shocks are identified via the theoretical effect on the system of variables. However, our identification scheme is less restrictive in terms of the structure we impose on the system of variables. Thereby, we can compare our estimated structural model with economic theory and compare the models' description of the Danish economy with the *narrative* and prior knowledge of the Danish economy. Specifically, we check the dynamics of our estimated model with a DSGE and a large-scale macroeconometric model and compare the historical decomposition of GDP with our expert knowledge. If these are aligned, we believe that our identification is valid.

In appendix A we conduct various robustness checks of the model with an emphasis on the identification strategy. We find comparable effects on the real economy from shocks to the financial variables in Danmarks Nationalbank's two other macroeconometric models – a medium-scale DSGE model and a traditional macroeconometric model. This points to the appropriateness of the identifying strategy as well as the robustness of the results.

We also re-estimate the model with both real consumption and real investments to investigate whether financial conditions in the benchmark model explains the same part of the variance as these two variables. Thereby, we can investigate whether house prices are just a stand-in for consumption. We find that financial conditions are robust to the inclusion of these two variables.

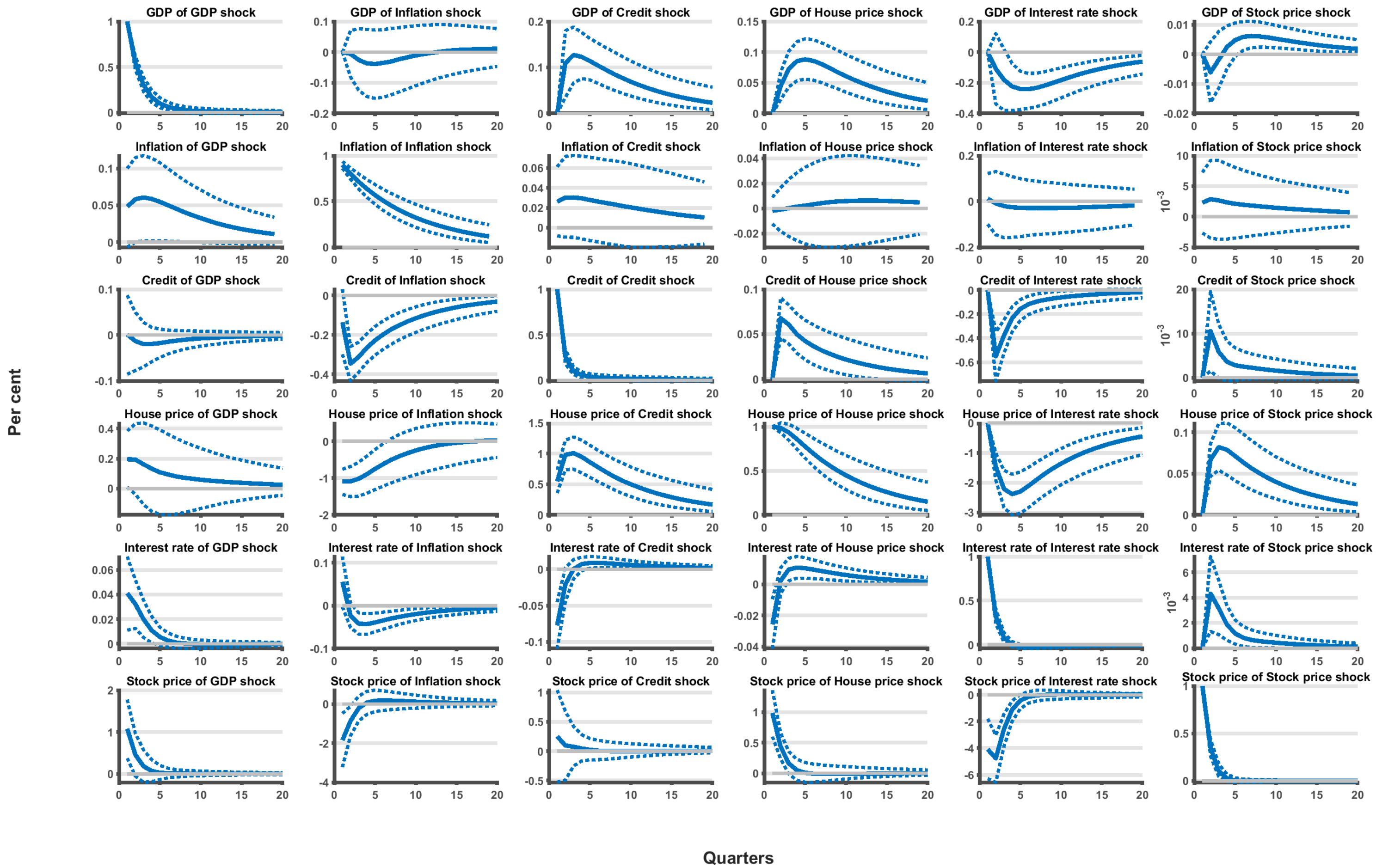
We also estimate two separate models, one for the household sector and one for the firm sector, by substituting GDP with private consumption and investments of non-financial firms and include credit to households and non-financial firms respectively, which yields intuitive results with comparable effects on the economy. As a further robustness check, we construct two additional financial condition indices based on a non-parametric principal component analysis inspired by Brave and Kelly (2017). Finally, we analyse the model's ability to forecast GDP out of sample. While this is not the main aim of the model, the model's ability to forecast enhances the credibility of the model.

2.4 Model validation – Impulse response function

The impulse responses, IRFs, from the baseline model are shown in figure 1 together with 67 per cent confidence sets.[8] The IRFs from the model and the identifying assumptions give rise to intuitive dynamics that are in line with economic theory. We focus on the linkages between the financial block and GDP. A shock to the financial variables are followed by reaction of GDP and inflation with the expected sign in all four cases. A house price shock, credit shock and a stock price shock is followed by an increase in GDP and inflation whereas an increase in the interest rate is followed by a decline in GDP and inflation.

[8] While it is standard to use 95 per cent in econometrics using classical techniques, a 67 per cent cut-off is standard in econometrics using Bayesian techniques, see also Canova (2011). One reason behind the differences is that in classical method, the models are usually pre-tested. That is, the models have already undergone test for their appropriateness. That is usually not done in Bayesian econometrics, and thus the cut-offs are less strict.

Figure 1: Impulse responses from 1 unit shock – baseline model



The figures depict median impulse responses from the baseline model and 67 per cent confidence sets (dotted lines). Source: Own calculation.

Within the financial block of the model, the interrelationships are in line with economic theory. An increase in the real house price is followed by an increase in credit and vice versa emphasising the close relationship between credit and house prices in the Danish economy, see also Grinderslev et al. (2017). There is almost a one-to-one relationship between a shock to the credit impulse and the real house price. A positive shock to the interest rate is followed by a sharp decline in the credit impulse, a long-lasting fall in the real house price and stock price. A positive shock to stock prices is followed by an increase in the credit impulse, the real house price and a small increase in the interest rate.

One drawback of our model is that we do not separately identify demand and supply shocks. This is a potential bias for our results. This is probably most obvious for a credit shock. A supply shock to credit is characterised by an exogenous shift in the supply of credit. This can, for instance, reflect increased competition between lenders, increased foreign demand for domestic bonds or looser regulation of financial intermediaries. In all three cases, the shock implies that the supply of credit would increase and interest rates on credit would decline. A credit demand shock would, on the contrary, for a fixed-supply of credit lead to increasing interest rates. In the case that both shocks are prevalent in the economy, our results will be biased, as we cannot distinguish between demand and supply credit shocks. Specifically since the effect of a credit shock on the real economy is dependent on whether it is a supply or demand shock, the impulse responses would be biased. The IRFs, however, show that credit supply shocks seem to have been dominant since the credit shocks have been associated with a fall in the interest rate.

For the Danish economy, it seems reasonable that supply shocks have been dominant in the period under consideration. In 1996, flexible interest rates mortgage loans were introduced but the demand for these types of loans only started to rise in the 2000s. In 2003, interest-only mortgage loans were introduced constituting a significant relaxation of credit condition for households.

Since 2012, the ECB has actively suppressed longer-term yields in the Euro Area, which have led to a similar decline in interest rates in Denmark. Furthermore, Denmark has in a number of periods experienced safe-haven flows that have increased foreign demand for Danish bonds including mortgage bonds, see for instance Jørgensen et al. (2013). These episodes can all be seen as exogenous shifts in the price of credit, and hence supply shocks.

2.5 Financial condition index for Denmark

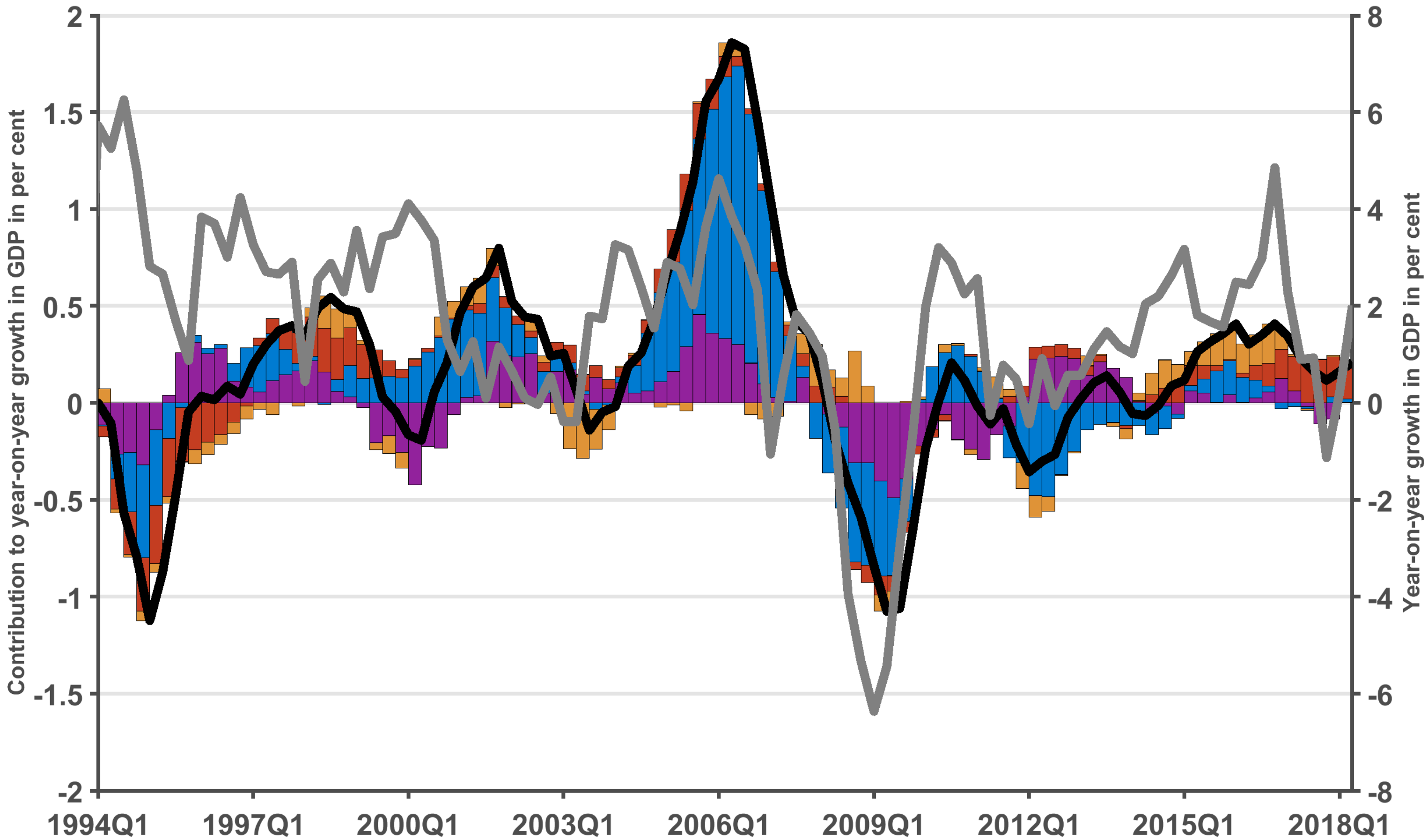
Using the above model, we use the historical decomposition to derive our preferred financial condition index, FCI, for Denmark. Our FCI and the underlying historical decomposition are depicted in figure 2. Our FCI resembles the overall narrative of developments in the Danish economy in the past. According to the model, financial conditions have contributed to year-on-year GDP growth by a magnitude of 0.2-0.4 percentage points in the past few years. The contribution has been positive since the beginning of 2015, which is coinciding with very accommodative monetary policy in the Euro Area aimed at easing financial conditions and spurring real activity. The accommodative monetary policy also caused fall in interest rates in Denmark, see Jensen et al. (2017), and is thereby likely to have affected broader financial conditions in

Denmark as well. It can also be seen from figure 2 that financial conditions have been driven by interest rates, house prices, and stock prices in the past years. The stock market has also contributed positively to GDP growth especially during the period from 2013 to 2016. The model confirms the strong relationship between developments in the housing market and GDP in Denmark.

The estimated financial condition index shows that in the period prior to the financial crisis, financial conditions were very loose. This mainly reflects that house prices grew at an unsustainable pace, see also Hviid (2017). At its peak, the contribution from financial conditions to GDP growth was 1.9 percentage points. From figure 2, it follows that the boom/bust period in the 2000s also was driven by an acceleration in credit. As discussed above, this probably reflects credit supply shocks. At the beginning of the 2000s, new mortgage loans such as interest-only loans were introduced, and variable rate loans rose in popularity. During the mid-2000s, increased competition between banks eased the access to credit for households and companies. Based on this, we interpret the credit shocks during the early 2000s as supply shocks.

We observe a break down of the correlation between growth in GDP and the FCI since the middle of the 2000s. Before the financial crisis, FCI was typically loose when growth in GDP was low or negative, and vice versa. What was unusual with regards to financial conditions during the build-up to the financial crisis was the procyclicality: The FCI was very accommodative during the period leading up to the financial crisis and very contractionary during the recession. During the recovery phase, financial conditions continued to be contractionary right up until the end of the European debt crisis. As noted previously, only lately has the contribution from financial conditions to GDP been positive, which, of course, has been the intention of the imported monetary policy stance of the ECB.

Figure 2: Estimated FCI and historical shock decomposition



Financial condition index together with the decompositions into structural shocks to house prices, credit impulse, interest rate and stock prices based on the structural MA representation from the baseline VAR model (left axis). In the figure is also shown the year-on-year growth rate in GDP (right axis). The figure only shows the contribution from financial shocks.

Interest rate *House price* *Stock price* *Credit* *Financial condition index* *Growth rate in GDP (right-hand axis)*

3 Which factors were most important for the depth and duration of the financial crisis?

In this section, we conduct a simple scenario analysis to show how the model can be used in policy context. Denmark is a small and open economy and is therefore highly exposed to developments in the global economy. Domestic shocks, being real shocks or financial shocks, affect the Danish economy, as we have shown in this paper. We have, however, not investigated whether foreign or global shocks are more important than domestic shocks, and whether that is the reason why the model fails to predict the depth of the financial crisis.[9]

The model is a useful tool to address questions of this type. An answer can be provided through *conditional* forecasts. These types of exercises are conducted by using the model estimated on the full sample. The model is then used to forecast GDP growth during the period 2008Q1-2010Q4 *conditioning on actual developments in subgroups of variables*. The conditional forecast thereby answers the question of how real activity would have been expected to behave if we had known the exact development in a subgroup of variables.

We use the above method to conduct two conditional forecast exercises. First, we condition on developments in the global economy, defined as the variables in the block exogenous part of the model: Export market growth, foreign price growth, and oil price growth. Second, we condition on financial variables: Stock prices, house prices, credit, and interest rates.[10]

Figure 3 shows the development in the growth rate of GDP together with the conditional forecast and 67 per cent credible sets. We point to the following observations. Financial factors did play a role for the developments in the real economy during the period. The growth rate of GDP should have fallen by more initially than it did, given the developments in financial factors. The development in financial variables does, however, not account for the depth and duration of the financial crisis. The model predicts that the growth rate of GDP should have returned to around zero already around 2009.

Global factors, in turn, can explain the duration of the financial crisis though not all of the large contraction in activity during the period under study. Specifically, the large downturn in the Danish economy starting end-2008 until 2010 can largely be explained by foreign shocks.

Hence, and not too surprisingly, for Denmark, a small and open economy, the foreign economy is of great importance for activity and was more important than developments in financial variables during the financial crisis. According to the conditional forecasting exercise, the financial crisis was for Denmark to a large extent imported from the global economy.[11] That is not to say that developments in financial markets were unimportant for activity as well, but the model finds that foreign variables were more important.

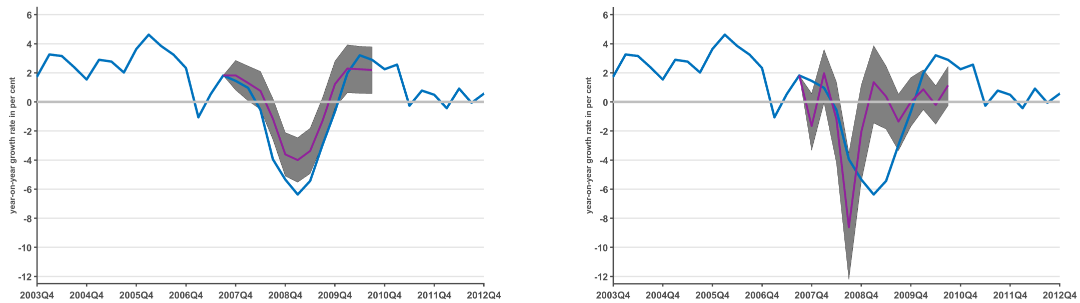
[9] See appendix A.6

[10] We notice that this distinction between global and financial shocks is not straightforward. As an example, the interest rate in Denmark is highly correlated with interest rates in the Euro Area, especially Germany, which in turn are highly correlated with interest rates in the US.

[11] This confirms previous studies on the causes of the financial crisis in Denmark, see Spange (2010).

Figure 3: Conditional forecast of real year-on-year growth rate in GDP

(a) Conditional on foreign variables **(b)** Conditional on financial variables



In the figure is shown the actual year-on-year growth rate in real GDP together with conditional forecasts from the SVAR from 2008Q1 to 2010Q4 together with credible sets (gray shaded area). In the figure to the left, the model is provided with the actual development in foreign variables while all other shocks from 2008Q1 are set to zero. In the figure to the right, the model is provided with the actual development in financial variables while all other shocks are set to zero.

4 Concluding remarks

Since the financial crisis, the relationship between financial markets and the real economy has received more attention, as central banks have been active stimulating the economy and as new regulation and macro prudential policies are changing the financial landscape. In this paper, we investigated the role of financial conditions for the Danish economy. We have done so by estimating a model with macro financial linkages and used it to derive an index summarising financial conditions in Denmark. We have argued that we need a structural quantitative model approach in order to decompose movements in GDP into economic interpretable shocks. In addition, the model needs to be quantitative such that we can provide quantitative answers to questions related to macro financial linkages. To satisfy these requirements, we have used a Bayesian structural vector autoregressive regression model.

Our approach has some advantages over traditional methods for constructing financial condition indices, such as factor analysis or regression-based approaches. The SVAR explicitly and in a transparent way controls for the business cycle and thus handles the main problem with the financial condition index; that financial variables are endogenous to the economic cycle and to developments in the financial markets. Furthermore, regression-based approaches often involve arbitrary choices regarding weighting of the different variables in the index. This is not needed in a historical shock decomposition using the SVAR.

Instead, our model is dependent on the identification of the underlying structural model. We identified the shocks through timing restrictions and ordered the variables in the following way from slow-moving to fast-moving credit, house prices, interest rate, and stock prices. In appendix, we carefully check the robustness of the identifying assumptions. Firstly, we have compared the impulse response functions from the SVAR to Danmarks Nationalbank's DSGE model and to Danmarks Nationalbank's traditional macroeconometric model and have shown that these three models provide similar dynamics. Secondly, we have shown that the dynamics of the model is robust to the ordering of the financial variables. Thirdly, we have shown that the financial variables are not a reflection of developments in other parts of the economy and are then regarded as financial shocks. Lastly, we have shown that the results are robust to incorporating different measures of economic activity combined with different measures of credit.

We can summarise our findings as follows. The estimated SVAR model gives robust, intuitive and plausible results both in terms of impulse responses and in terms of the derived financial condition index. We find that financial conditions, especially real house price growth and credit growth, were pro-cyclical before and after the financial crisis. House price growth and credit growth were high in the period before the financial crisis and fell rapidly during the crisis period, contributing further to the fall in output. Financial conditions have stimulated the economy during the current expansion since 2013, but the stimulus has this time around been driven by low interest rates together with a booming housing and stock market. The contribution from credit growth has been muted.

Lastly, we point to further research areas within the macro financial sphere. We did not, a priori, expect to be able to forecast the depth of the financial crisis. We did, however, expect that the inclusion of macro-financial linkages would improve the model's ability to capture turning points. While the model does forecast a much slower recovery after the financial crisis, future work could focus on how the forecasting performance of the model can be enhanced. One possible route could be to take account of time variation in the parameters, especially in the house price relation, as the housing market underwent structural changes during the period under study.[12]

[12] Among these are the introduction of new types of mortgage contracts with interest-only features and flexible interest rate together with a tax-freeze on taxation on housing wealth. For an analysis of the impact on both the house price and the real economy for Denmark, see Pedersen (2019).

A Appendix: Identification and robustness

In this appendix, we analyse the robustness of our results with an emphasis on the identification of the model. We begin by comparing the IRFs in the SVAR with IRFs from a traditional macroeconometric model and a DSGE model, both estimated on data for Denmark. Next, we change the ordering of the variables in the SVAR and proceed by analysing the effect of our results from including other measures of real activity, private consumption, and real private investments, as well as other measures of credit, credit to households and non-financial firms, respectively. We proceed by comparing a purely data-driven financial conditions index using statistical techniques to our index and by conducting a forecasting exercise, before we finally address parameter stability.

A.1 Validation of identification – Comparing impulse response function

In order to validate the identifying assumptions in the SVAR, we compare the IRFs from the SVAR with other models used at Danmarks Nationalbank. We compare the effect of a shock to the real house price, credit, and the interest rate in the SVAR with similar or comparable shocks in Danmarks Nationalbank's traditional macroeconometric model, MONA, and Danmarks Nationalbank's DSGE model with financial frictions, housing, and banking.[13] If the responses to shocks to the financial variables in the DSGE model and MONA approximately reside within the credible sets in the SVAR, it is supporting evidence in favour of the identifying assumptions in the model.

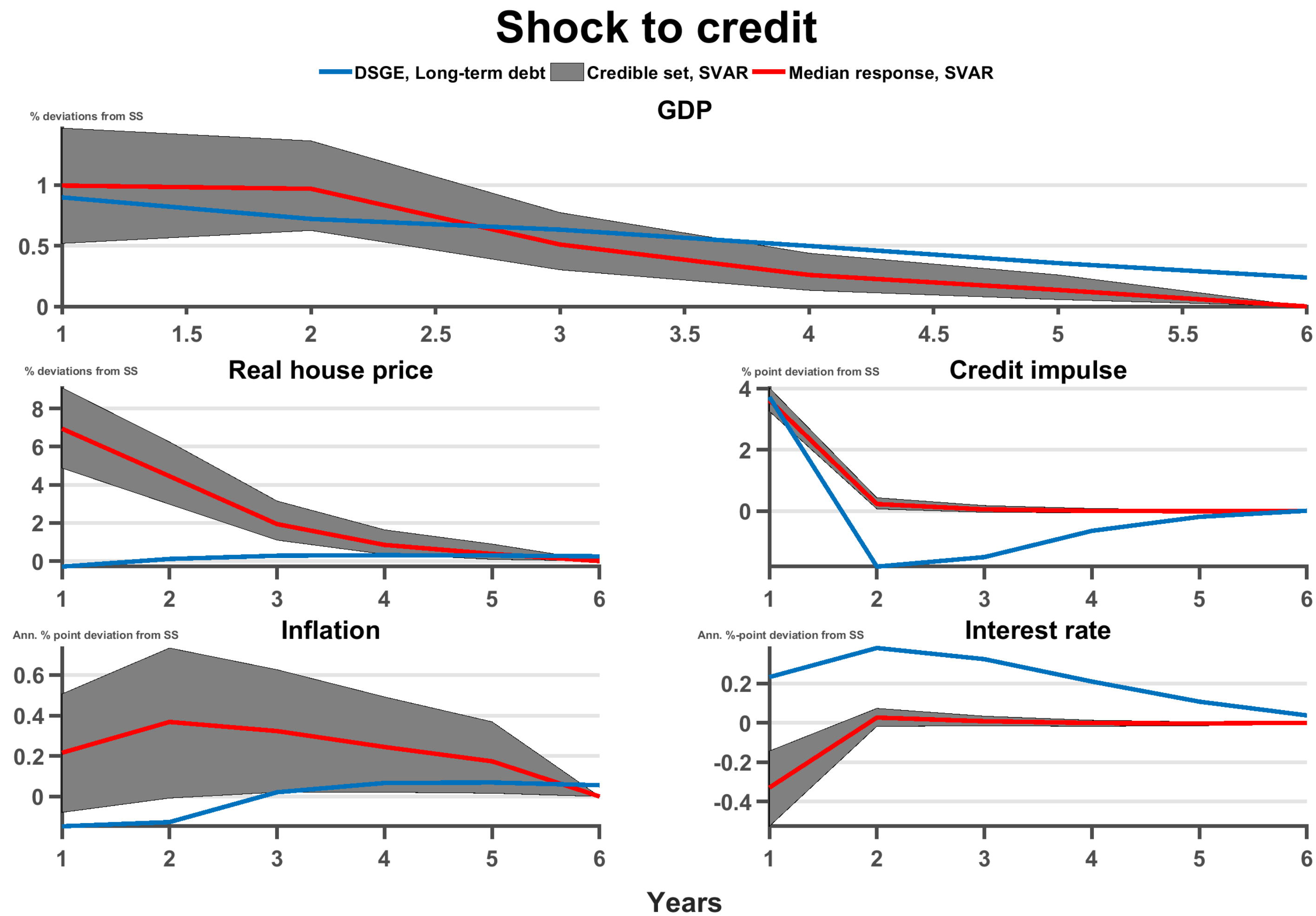
An interest rate shock and a house price shock can be given similar interpretations within the three models. This is less clear for the credit shock. In MONA there is no role for credit in the determination of GDP, so the response in MONA is not analysed here. In the SVAR, it is not possible to distinguish between credit supply shocks and credit demand shocks. In the DSGE model, the credit shock is modelled through a shock to the LTV ratio and is interpreted as a credit supply shock.

A.1.1 Effect of a credit shock

In figure A.1, we compare the impulses from a 4 percentage points shock to the credit impulse in the SVAR with a similarly sized shock in the DSGE model. An increase in credit – a positive credit impulse – stimulates GDP and inflation both in the SVAR and the DSGE model. The response of GDP in the DSGE model resides within the credible set of the SVAR. In the DSGE model, the transmission of the credit shock to real activity goes through consumption and investments. The increased activity leads to upward pressure on wages and employment leading to further increases in consumption.

[13] MONA is documented in Nationalbanken (2003), while the DSGE model is documented in Pedersen (2016) and we refer to these publications for further detail.

Figure A.1: Impulse responses from a 4 percentage point shock to the credit impulse – Comparison between SVAR and DSGE



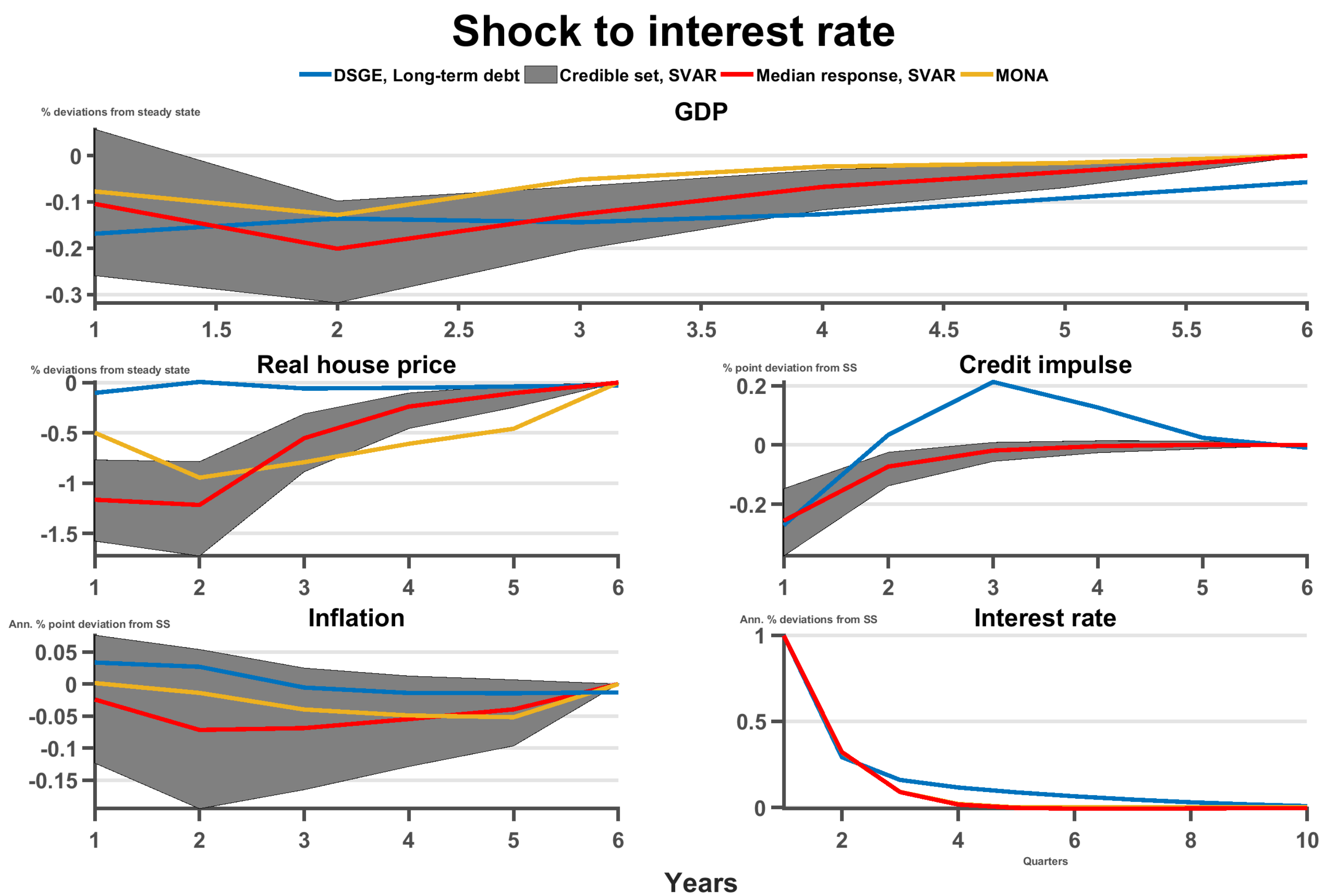
The figure depicts the effects from a shock to the credit impulse on a subset of variables in the models. Blue lines correspond to the responses in a DSGE model featuring long-term debt contracts, see also Pedersen (2016). Red lines correspond to the impulse responses with 68% credible intervals estimated in this paper, see also figure 1. The figures depict the average value of the respective variables over four quarters. Source: Own calculation.

Following a credit shock, the interest rate increases in the DSGE model, contrary to the SVAR. This is, however, due to a technical assumption needed to ensure a stable net foreign asset position. Specifically, an increase in credit leads to a deterioration of the net foreign asset position, which slightly increases the risk premium on investing in the Danish economy. The increase in the interest rate does not change the quantitative impact on GDP and the real house price by much. Of greater concern is that the real house price hardly reacts in the DSGE model following a credit shock, whereas there is a strong relationship between house prices and credit in the SVAR model. We will have more to say about this effect in the DSGE model at the end of this section in this appendix, as it also affects the IRFs from a shock to the interest rate.

A.1.2 Effect of an interest rate shock

In figure A.2 we compare the responses to a 100 basis point shock to the interest rate in MONA, in the DSGE model and in the SVAR. As expected, a positive shock to the interest rate is contractionary for output in all three models and with similar magnitude. On impact, the response of credit is of similar magnitude in the DSGE model and the SVAR. While credit overshoots in the DSGE model, it converges slowly towards zero in the SVAR. That partly reflects the fall in GDP in the DSGE model. The effect on the real house price is similar in MONA and the SVAR and yields the expected sign. Like a credit shock, house prices react too little in the DSGE model relative to the other two models. In overall terms, the three models provide quite similar responses to a shock to the interest rate.

Figure A.2: Impulse responses from 1 percentage point shock to the interest rate – Comparison between SVAR, DSGE and MONA



The figure depicts the effects from a shock to the interest rate on a subset of the variables in the models. Blue lines correspond to the responses in a DSGE model featuring long-term debt contracts, see also Pedersen (2016). Red lines correspond to the impulse responses with 68% credible intervals estimated in this paper, see also figure 1. Yellow lines correspond to the responses in MONA, see also Nationalbanken (2003). The figures depict the average value of the respective variables over four quarters. Source: Own calculation.

A.1.3 Effect of a house price shock

In figure A.3 we compare the responses to a shock to the real house price in the three models. The house price shock in the two larger macroeconomic models is implemented as a "taste"-shock: The households suddenly get more utility from their housing stock.[14] The effect of the house price shock on GDP is similar in magnitude across the three models, though more protracted in the DSGE model. In MONA, the effect on GDP is slightly lower and less persistent. The credit impulse increases in the SVAR and is positive throughout the 1^{st} to 3^{rd} year, meaning that the growth rate in credit to GDP is increasing. It increases slightly in the DSGE model during the first year and then falls back during the subsequent years.

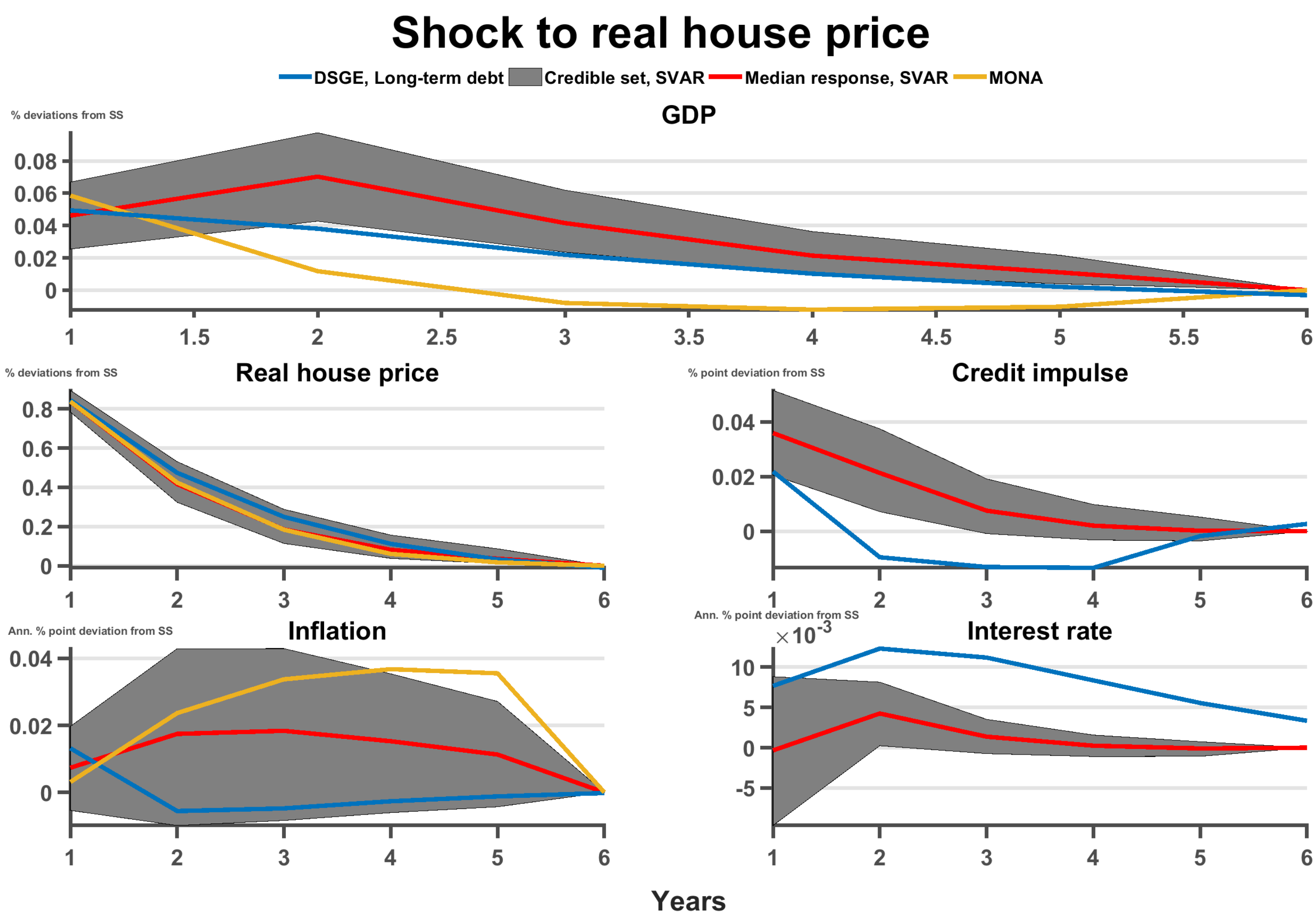
Overall, we find by the three comparison exercises above evidence in favour of the identifying assumption in the SVAR. By this, we mean that the SVAR qualitatively, and partly quantitatively, provides the same responses to the shocks we have analysed. The interest rate shock and the house price shock seem to be identified when compared against the DSGE model and MONA. However, there is a tension between the DSGE model and the SVAR in terms of credit shocks. When credit increases in the DSGE model, the house price does not react by much, while the SVAR finds a strong positive house price response and a fall in the interest rate.

The issue is to a larger degree the theoretical constraints put upon movements in the real house price in the DSGE model, and not so much the identifying assumptions in the SVAR.[15] We, therefore, believe that the effect of a credit shock in the SVAR provides intuitive responses to increases in credit, and the misalignment between the two models works in favor of the SVAR model.

[14] In MONA, we restrict the house price relation such that we allow for spill-overs between the rest of the economy and the house price relation, but we restrict the relation such that there are no spill-overs between house prices today and yesterday.

[15] The issue in the DSGE model is a widely acknowledged theoretical issue, see also Barsky et al. (2007), Sterk (2010) etc. In the model, savers sell part of their housing stock to borrowers, who demand more housing, and thus shocks to a lesser extent give rise to house price changes than in the other models. It can, in fact, be shown that in a model with fixed housing stock, the real house price reacts strongly following a credit shock; its reaction is close to the reaction in the SVAR. Further, the model provides a too tight relationship between movements in marginal utility of consumption for savers and the real house price.

Figure A.3: Impulse responses from 1 percentage point shock to the real house price – Comparison between SVAR, DSGE and MONA



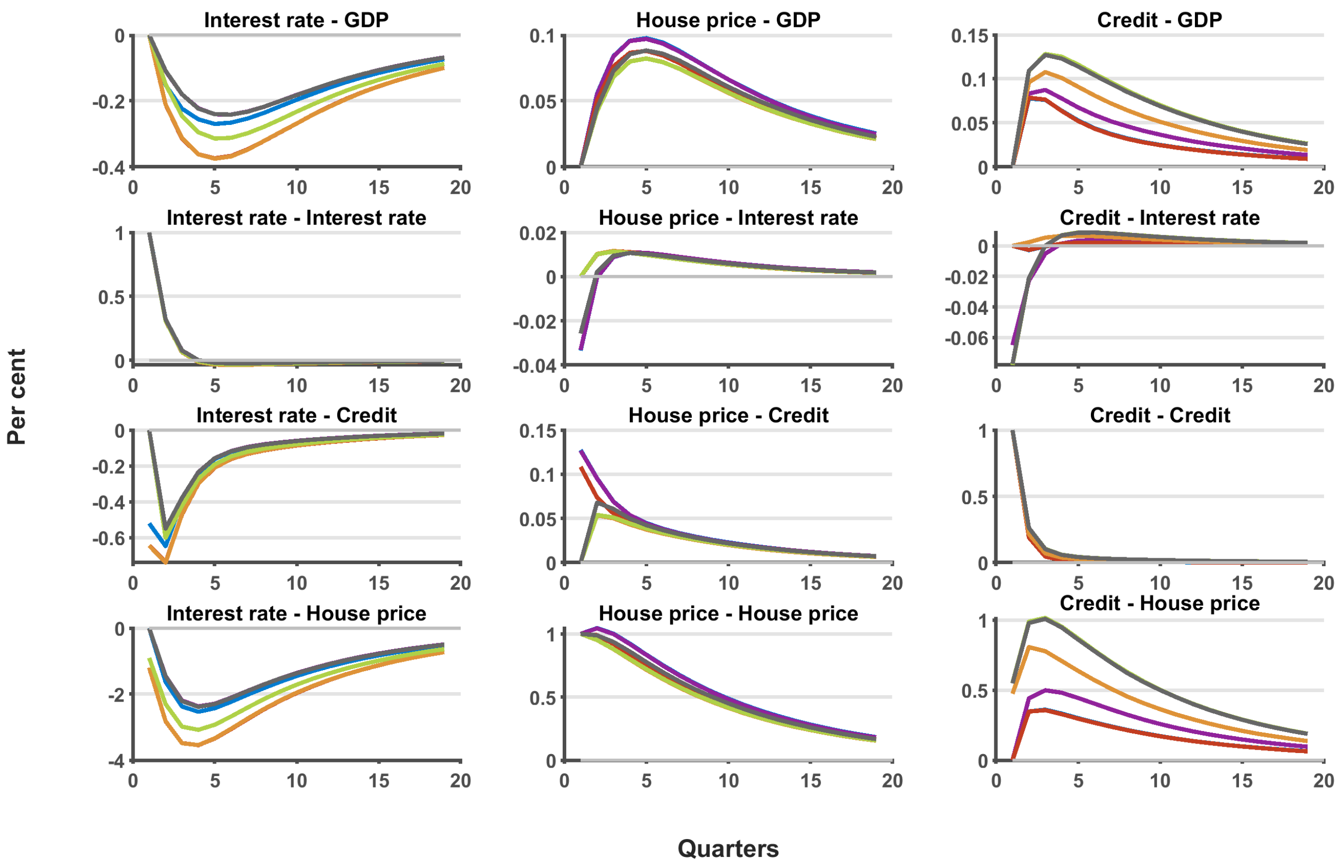
In the figure is shown the effects from a shock to the interest rate on a subset of the variables in the models. Blue lines correspond to the responses in a DSGE model featuring long-term debt contracts, see also Pedersen (2016). Red lines correspond to the impulse responses with 68% credible intervals estimated in this paper, see also figure 1. Yellow lines correspond to the responses in MONA, see also Nationalbanken (2003). The figures depict the average value of the respective variables over four quarters. Source: Own calculation.

A.2 Robustness of FCI: The effect of ordering

We next investigate the impact for the IRFs of the timing restrictions in the baseline model by rearranging the financial variables in the identification scheme. We assume that stock prices always are ordered last, but then change the ordering of the other financial variables. The resulting impulse responses from the different identification schemes are shown in figure A.4.

Overall, the IRFs do not depend greatly on the ordering of the variables. This points to the robustness of our results with regard to the financial condition index. There are, however, exceptions. Take as an example the responses of GDP. Shocks to the interest rate, the house price, and to the credit impulse all have qualitatively similar effects on GDP, but quantitatively there are differences. In the case of a house price shock, it appears that the effect of the shock on GDP is larger when the house price is ordered first in the financial block, while on the other hand, the effect of the shock on the credit impulse is lower. Also, when the response of GDP to a house price shock is relatively strong, the response of GDP to a shock to the credit impulse is relatively weak, and vice versa.

Figure A.4: Financial index – Effect of ordering of financial variables



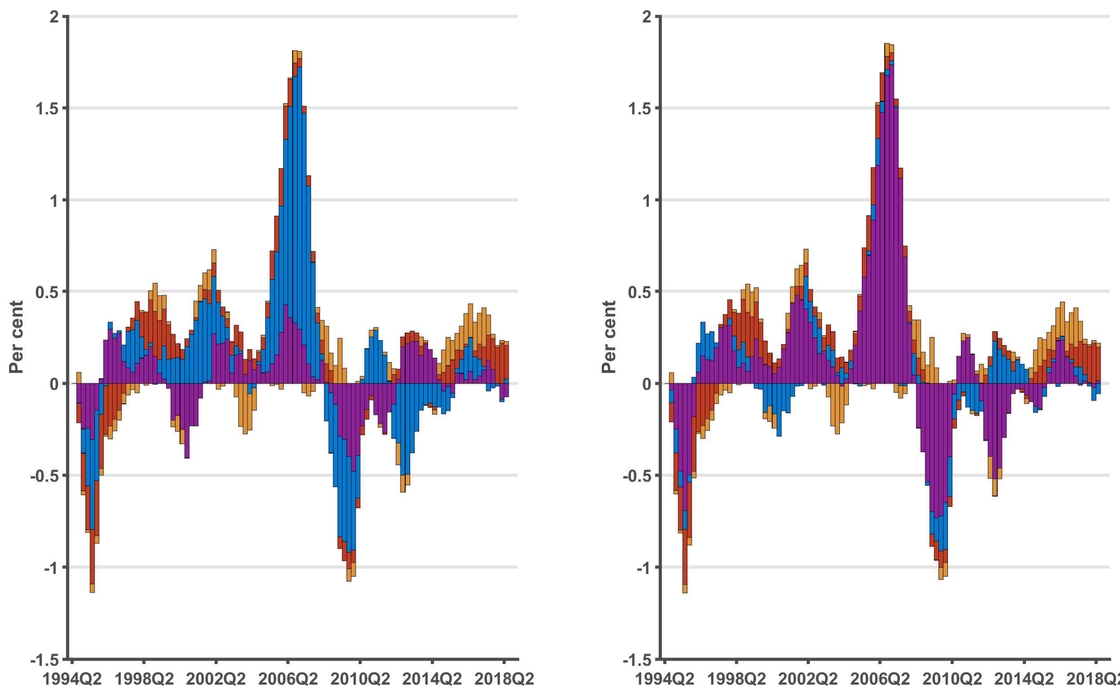
The figures depict selected impulse responses based on different ordering of financial variables. Stock prices are always ordered as the last variable.

House price - Interest rate - Credit | *House price - Credit - Interest rate* | *Interest rate - House price - Credit* | *Interest rate - Credit - House price* | *Credit - Interest rate - House price* | *Baseline*

Source: Own calculation.

The ordering can, based on the IRFs, be expected to affect the historical decomposition of financial condition index while leaving the size of the overall index unchanged. This is verified in figure A.5. The figure to the left shows the financial condition index in the baseline model, repeated here for convenience. The figure to the right shows the financial condition index in the model where the ordering is house prices, credit, interest rate, and the stock price. The effect of the ordering of the variables do not change the financial condition indices – the financial block still accounts for the same fraction of the variation in GDP – but the relative contribution to movements in the financial condition index from house price shocks and credit shocks is changed. Like for the IRFs, it seems that the model has difficulties in distinguishing between house price shocks and credit shocks. However, one variable does not completely drive out the other.[16]

Figure A.5: Estimated FCI and historical shock decomposition – Effect of ordering of financial variables



Left: FCI and the decomposition into structural shocks based on the structural MA representation from the baseline SVAR model in the baseline model. Right: FCI and the decomposition into structural shocks based on the structural MA representation from the model with the ordering house prices, credit, interest rate, and the stock price. The figures only show the contribution from financial shocks.

Interest rate *House price* *Stock price* *Credit*

[16] This is verified in models where one variable at a time, the real house price or credit, is left out of the model, not shown for brevity. If as an example the real house price is left out of the model, the FCI is markedly lower. And if credit is left out of the model, then the FCI changes sign in some periods from 2010 to 2018, thus confirming that both variables are important in the model.

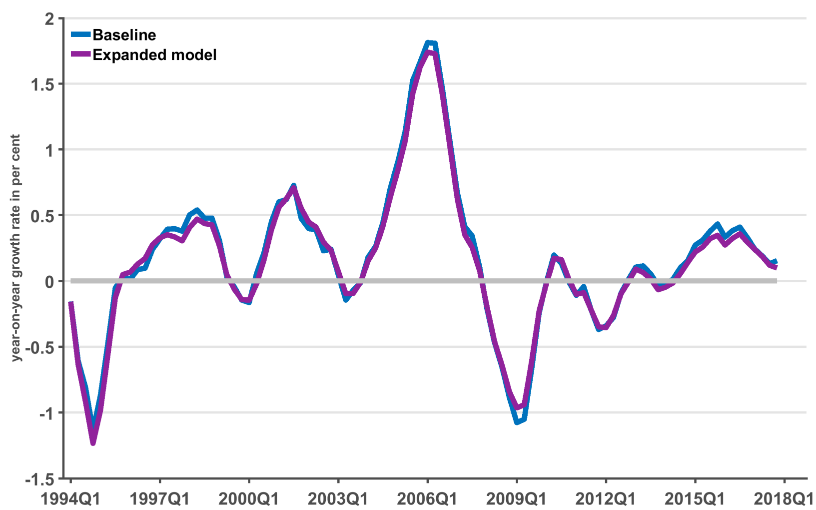
Thus, we point to two findings. Firstly, depending on the ordering of the variables, the model attaches different importance to house price and credit impulse shocks in the financial condition index. Secondly, the size and movements in the financial conditions index do not to a great extent depend on the ordering of the variables, and the combined contribution of the credit and house prices. Our conjecture is that these findings partly can be explained by the strong relationship between credit, GDP, and the real house price.[17]

A.3 Are we capturing financial shocks?

One possibility is that the structural shocks we derive are not truly financial shocks. If one of the shocks simply reflects a development in the economy that we do not control for, we would overestimate the impact of financial conditions on the economy. An example can be revealing. If the impact of stock prices on the real economy does not reflect a financial shock, but instead reflects improved prospects for real investments in the economy, the estimated financial conditions would be upward biased.

To investigate this hypothesis, we expand the baseline model to include private consumption and private investments together with GDP. Figure A.6 shows the financial index. It appears that there is no difference between the baseline financial index and the extended financial index.

Figure A.6: Extended financial index – Including private consumption and investments in the baseline model



The figure shows in blue the contribution to GDP growth from structural shocks to house prices, credit impulse, interest rate, and stock prices based on the structural MA representation from the baseline SVAR model. In purple is shown the equivalent series but from a model extended with private consumption and private investments. The figure only shows the contribution from financial shocks. Source: Own calculation.

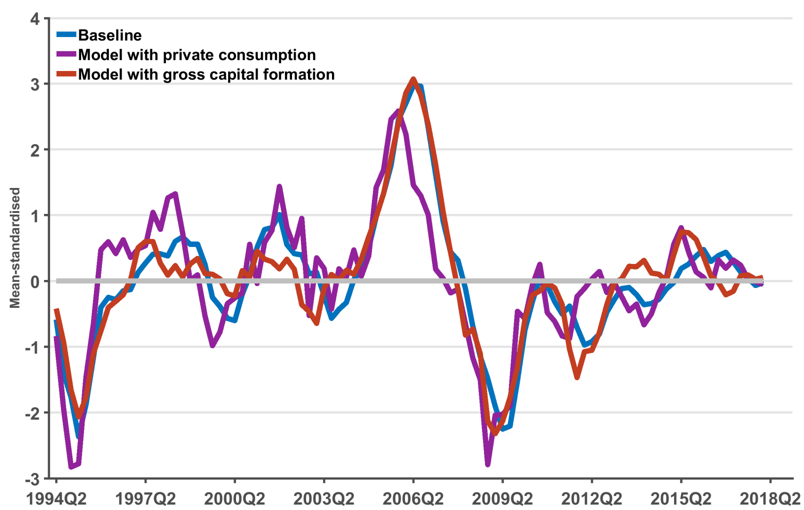
[17] See also the analysis in Pedersen (2019).

A.4 FCI based on private consumption and investments

We next estimate two additional models. In the first model, we substitute GDP and total credit with private consumption and credit to households, respectively. In the second model, we substitute GDP and total credit with private investments and credit to non-financial firms, respectively. Our motivation for doing so is twofold. Firstly, we want to analyse whether the measure of real activity and credit matters for the FCI. Secondly, we want to study in greater detail the interrelationship between credit to non-financial firms and credit to households on one side and investments and private consumption on the other side. This provides us with the benefit that we get an additional instrument for analysing macro financial linkages.

Figure A.7 depicts three FCIs: The baseline FCI, the FCI derived from the SVAR with investments and credit to non-financial firms, and the FCI derived from the SVAR with private consumption and credit to households.

Figure A.7: FCIs based on investments and consumption SVAR model



Notes: All three FCIs have been mean-standardised for ease of comparison. Gross capital formation excluding inventory.

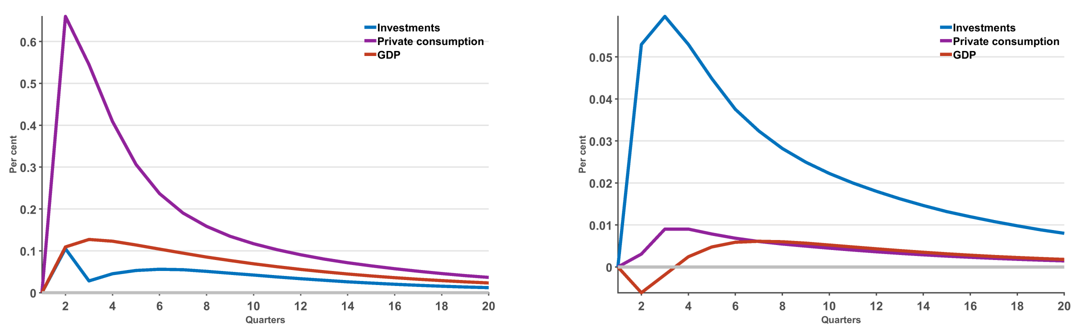
The FCIs (standardised) are in overall terms quite similar: They were high before the crisis, they fell rapidly during the crisis, and they have stimulated activity during the current expansion. The turning points are not completely aligned. As an example, the FCI based on private consumption peaks before the FCIs based on GDP and private investments around the outset of the financial crisis.

Figure A.8 shows the effect of a credit shock and a stock price shock on the activity in the three SVARs. A shock to credit affects consumption by much more than a shock to credit affects investments. This can possibly be explained by the structure of the Danish mortgage system which makes it relatively easy to take on additional debt in response to increases in the house price. This additional debt can then be used to finance extra consumption. Higher house prices can also be thought of as a positive wealth effect for the consumers even without credit constrained households. The strong relationship between housing, credit, and consumption can perhaps explain why the FCI based in the model with consumption peaks before the other two indices; house prices in Denmark peak well before activity and investments around the financial crisis.

In turn, a shock to stock prices affects investments by much more than a similar shock to consumption. This makes intuitive sense: The Tobin's-Q theory supports a strong relationship between the stock market and investments, see also the discussion in section A.3. On the contrary, theory points to a weaker relationship between private consumption and the stock market. A stock market shock can be thought of as a positive wealth effect that should induce households to consume more. Whether the positive shock to stock prices leads to increased consumption depends, among other things, on whether consumers perceive the increase to be temporary or permanent, and to what extend the consumers are liquidity constrained etc.

Figure A.8: Estimated IRFs from three models

(a) Credit shock on activity **(b)** Stock price shock on activity



Left: The effect on the three measures of activity from a shock to three credit variables.
Right: The effect on the three measures of activity from a shock to the stock price.

A.5 Comparison of FCIs

In this section, we compare the FCIs based on a non-parametric approach with the FCI derived from the SVAR. We stress at the outset that the comparison is imperfect. The FCI based on the estimated SVAR measures the effect from financial variables on growth, while the FCIs based on statistical analysis are only a qualitative index showing how stimulative or contractive financial conditions are. As statistical based FCIs are the norm, we however find it useful to make the comparison.[18]

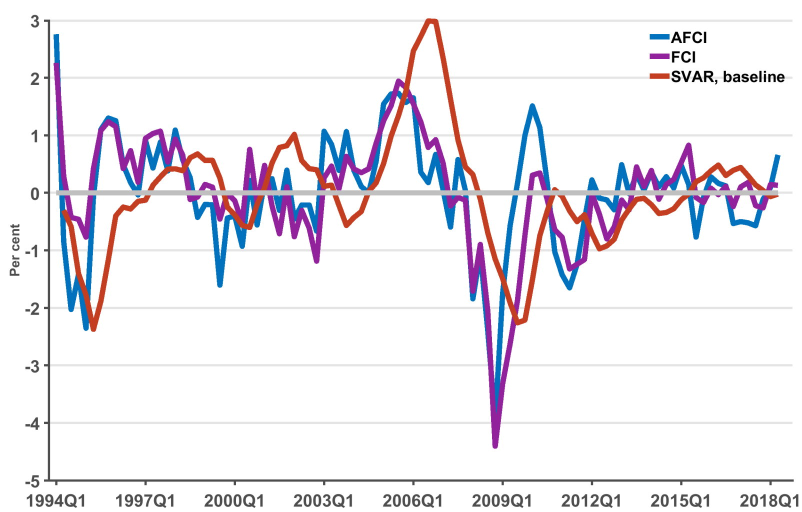
In the non-parametric approach, principal component analysis is used to extract a common factor, or component, which is then given the interpretation as being an FCI. We construct two different FCIs based on this method. The first FCI is the first principal component extracted from the standardised four data

[18] See the literature review in the introduction.

series: house prices, stock prices, change in 30-year mortgage rate, and the credit impulse. The second FCI is adjusted for the business cycle. Here, we regress the four financial variables on lagged inflation and the growth in GDP in order to account for the possible endogeneity of financial condition to the business cycle. The residuals from these four regressions are then standardised and the principal component is extracted. We denote this FCI as the adjusted FCI, AFCI. Figure A.9 shows the two FCIs. To facilitate a comparison, the figure also shows the baseline FCI from the VAR approach.

It appears that there is no significant difference between the first principal component on the adjusted FCI and the unadjusted FCI. However, there are differences between the principal component approach and the VAR approach. The FCIs based on principal components appear to be leading the SVAR-FCI. This probably reflects the differences in the construction of the FCIs. The SVAR approach generates persistence in shocks. That is, persistence in the SVAR model implies that a shock affects the real economy in the following quarters as well as the current quarter. However, the principal component analysis does not account for this persistence.

Figure A.9: FCIs based on principal component and VAR model



Notes: All of the three FCIs have been mean-standardised.

A.6 Forecasting

Financial variables are forward-looking and thereby entail information about investors' expectations about future macroeconomic developments. This should in principle enhance forecast performance of models. We, therefore, investigate our model's forecasting abilities by conducting two different forecasting exercises. We do as follows:

1. Exercise 1: For every quarter starting in the first quarter of 2005, we re-estimate the model and let the model forecast GDP growth for the proceeding 8 quarters. We repeat this moving the data

sample one quarter at a time thereby using 40 quarters of data. The model is thereby re-estimated (parameters and shocks) using a rolling window with a fixed sample size.[19]

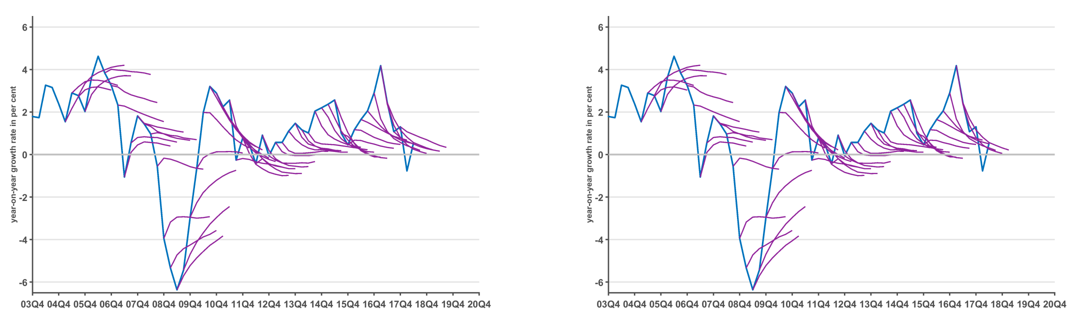
2. Exercise 2: We estimate the model using an expanding window. In the first iteration, the estimation is conducted using data ranging from 1994Q1-2005Q1 and we then let the model forecast 8 quarters. We then add one quarter at a time, reestimate the model, let the model forecast for 8 quarters, and repeat this until the end of the sample. The sample size is thereby increased by one quarter for each iteration.

Figure A.10 shows the results of these two forecasting exercises. Forecasts in VARs usually have fast mean reversion to its steady state. If the VAR is estimated in growth rates, the model tends to forecast a return to a steady state (long run) *growth rate*, but typically not a return to a *level* of GDP. That is, a forecast of GDP in a VAR estimated in growth rates usually does not return to a long run steady state level of GDP.

The issue of too fast reversion to a mean is also an issue for the model estimated in this paper. There are periods with exceptions. Firstly, the mean reversion of the forecast to the structural growth rate is much slower during the downturn around the financial crisis in 2008-09 compared with the periods after. Secondly, both forecast methods predict further increases in the growth rate just prior to the outbreak, around 2005-06 of the financial crisis, and thereby no mean reversion. From 2010 and onwards the mean reversion is much faster. Notice, that the unconditional forecast in 2008Q1 pointed towards a slow return to a steady-state growth rate, but the model did not predict a large fall in GDP.

Figure A.10: Forecast of real year-on-year growth rate in GDP

(a) Rolling window **(b)** Expanded window



In the figure is shown the actual year-on-year growth rate in real GDP (blue line) together with forecasts from the baseline model 8 quarters ahead (purple line) and 67 per cent credible sets (grey-shaded area). Left: Rolling window: The model is estimated in a rolling window. Right: The model is estimated using an expanding window. Source: Own calculation.

The forecasting exercises indicate that the model captures some features of the events surrounding the business cycle under study, but not the large swings in the Danish economy during this period. In fact, the root mean-squared errors, RMSE, increase from 1.30 on the one-quarter horizon, which is comparable to other studies forecasting GDP with SVAR-models, to 3.30 on the eight-quarter horizon. Leaving out

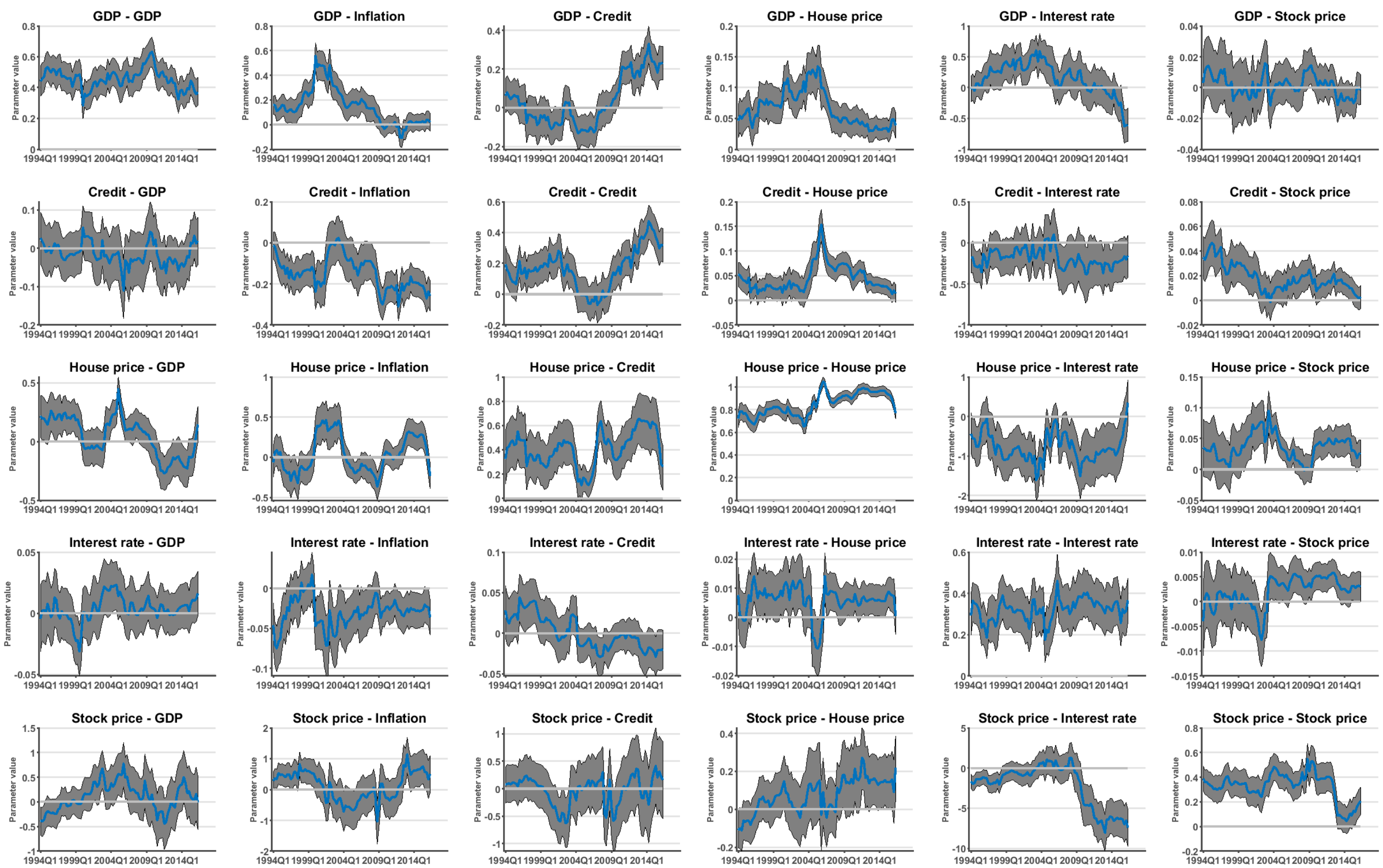
[19] We do not use real-time data, which means that we do not take data revisions into account.

the period from 2005 to 2010, the RMSEs fall to 0.9 and 1.50 respectively, which implies that in "normal" times, the performance of the model is comparable to other studies, see e.g. Christoffel et al. (2010). The reduction in the RMSE, leaving out the financial crisis, indicates that financial factors are not sufficient to capture all of the large fall in Danish GDP during the financial crisis. As shown in the main text, a likely driver behind the events surrounding the financial crisis is large negative shocks to the Danish economy imported from the global economy.

A.7 Time-varying parameters and impulse response functions

As a further robustness check, we investigate the parameter stability of our baseline model through the sample. To this end, we estimate the model using a 10-year balanced rolling window beginning in 1984Q1. Figure A.11 shows the reduced-form parameter estimates throughout the sample. We stress on the outset the uncertainty surrounding the estimates especially compared with the parameter estimates from the baseline model, as the sample size is smaller.

Figure A.11: Parameter stability



The figures show the reduced-form parameter estimates using a rolling window of length 40 quarters or 10 years. Grey-shaded areas denote 67 per cent credible sets. Blue lines indicate median value of the parameters.
Source: Own calculation.

We point to the following observations. For the GDP equation (row 1 of figure A.11), we see that GDP reacted more to house prices during the build-up to the financial crisis and became more sensitive to changes in the interest rate. More recently, there is evidence that GDP has become more sensitive to interest rate changes during the current expansion, while GDP has become less responsive to changes in credit. This might reflect that during the current expansion, credit growth has been moderate.

For the credit impulse equation (row 2 of figure A.11), we find that the parameter of house prices was growing through the 2000s. In the remainder of the period, the parameter of house prices has been nearly constant. The effect of interest rates on credit is negative in the entire period reflecting the close relationship between the price of credit and changes in the stock of credit.

In the house price equation (row 3 of figure A.11), we find evidence in favour of growing persistence in house prices during the 2000s surpassing a value of 1 in 2006. This implies that house prices had explosive behaviour during this part of the sample. During the same period, we see that the real house price became less dependent on credit and interest rates, i.e. on fundamentals. This reflects bubble-like behaviour of real house prices during the period.

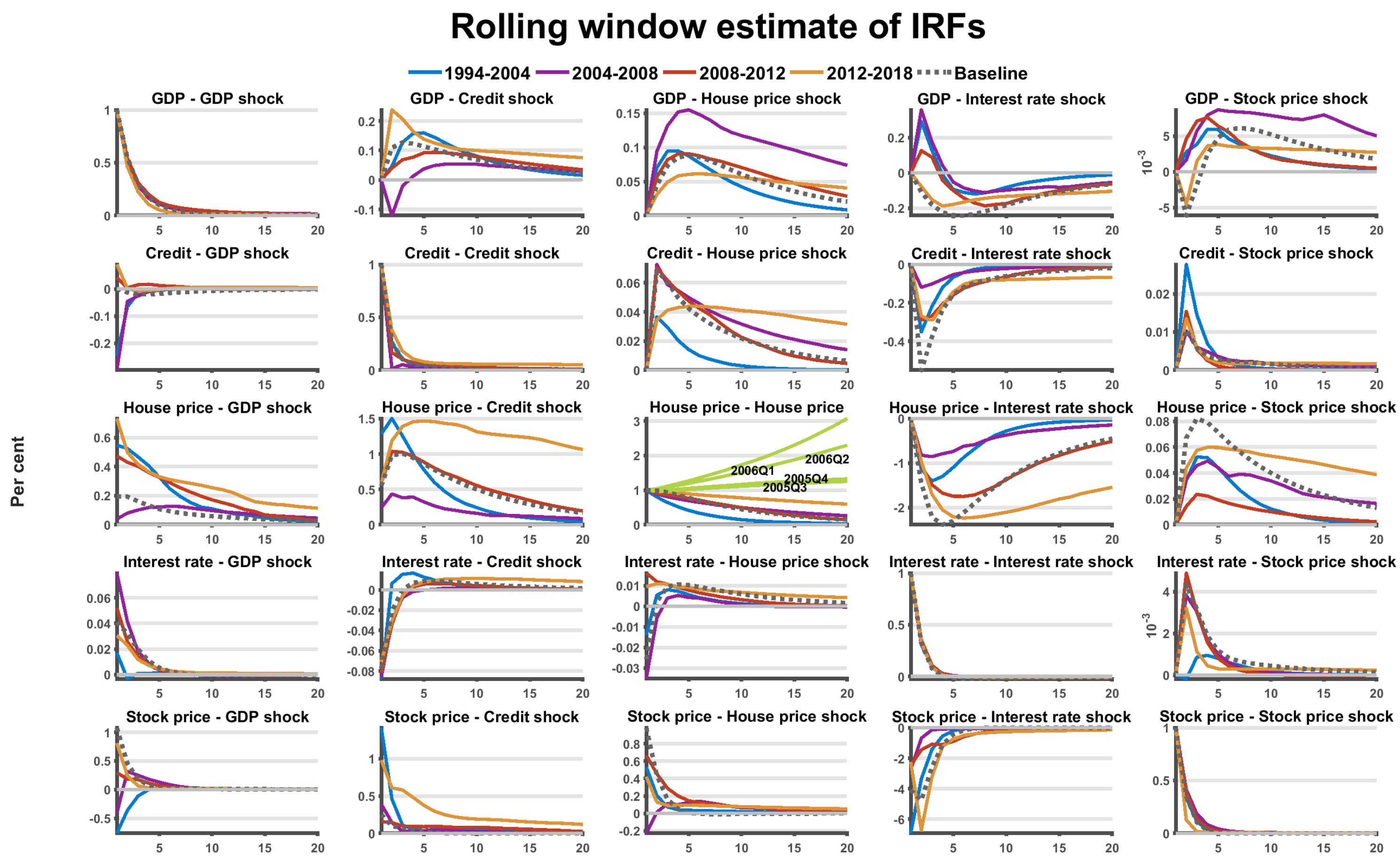
The above exercise indicates time-varying reduced-form parameters but it does not necessarily imply that the structural form of the model has changed significantly over the sample. To analyse this, we show the IRFs for a subgroup of the variables in figure A.12. For ease of exposition, we have divided the IRFs into 4 subsamples reflecting a relatively quiet period before the build-up to the financial crisis, 1994-2004, the "bubble-years", 2004-2008, the recession period including the European sovereign debt-crisis, 2008-2012, and lastly the recovery, 2012-2018. Figure A.12 shows the median of the median IRFs estimated within these subsamples.

The structural responses to shocks appear to reflect the variation in the reduced-form median estimates. We observe that house prices have become more interest rate sensitive since the 1990s. This can partly reflect the introduction of flexible-rate and interest-only mortgage contracts. It can, however, not be the whole story as Danish households recently to an increasing extent have switched to fixed-rate mortgage contracts with principal payments.[20] Likewise, the effect of the real house price from shocks to credit seems to be more persistent now relative to the 1994-2004 and 2008-2012 periods. The relationship between GDP and house prices seems to be very stable outside the bubble period. That includes the relationship between credit and real activity, and credit and the interest rate. The bubble period 2004-2008 stands out. This period was characterised by rapidly rising house prices and high credit growth. We find in this period explosive IRFs for house price shocks as shown by the green lines in figure A.12.

We observe that the time variation in the IRFs can mainly be found in the financial block of the model, and mainly in the house price relation. This might be less of a concern, as it reveals the bubble-like behaviour of the real house price.

[20]For a theoretical analysis of the Danish economy of the effects on house prices and the real economy from the introduction of new type of mortgage contracts during the 2000s, see Pedersen (2019).

Figure A.12: Time variation in estimated impulse response functions



The figures show the median IRFs from four different sub-periods of the total sample. The IRFs are estimated using a balanced rolling window. The IRFs must be interpreted as follows, taking the first row, first column IRFs as an example; here is shown the effect on GDP from a shock to credit.
Source: Own calculation.

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