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FINANCIAL CYCLES: WHAT ARE THEY AND WHAT DO THEY LOOK LIKE IN DENMARK?

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RESUME

Efter den finansielle krise er der kommet øget fokus på finansielle cykler. I dette arbejdspapir undersøger vi, hvad finansielle cykler er, hvordan de ser ud i Danmark, og hvad sammenhængen er mellem dem og realøkonomien. Vi viser, at mellemlange udsving i huspriser og kredit kan anvendes til at illustrere den finansielle cykel i Danmark. Der er dog udfordringer med at bestemme finansielle cykler i realtid. På tværs af lande og i Danmark er der stærk samvariation mellem huspriser, kredit og BNP både på konjunktur og mellemlange (11-30 år) frekvenser. Det betyder, at finansielle cykler er stærkt forbundne med realøkonomien. Toppunkter i den finansielle cykel har ofte været sammenfaldende med finansielle kriser. Finansielle cykler kan derfor bruges som en indikator i forbindelse med overvågning af risici, som kan føre til finansiel stress.

ABSTRACT

Financial cycles have received a lot of attentions since the financial crises. In this paper we study what financial cycles are, what they look like in Denmark, and what their relationship is with the real economy. We show that medium term swings in house prices and credit should be used as an illustration of the financial cycle in Denmark. There are, however, difficulties in detecting financial cycles in real time. Across countries and in Denmark, there are strong co-movements in house prices, credit and GDP at both business and medium term frequencies (11-30 years), i.e. financial cycles are strongly connected with the real economy. Peaks in the financial cycle have in fact historically been predictors of financial crises. The financial cycle can therefore be used an indicator when monitoring risks that can materialize into financial stress.

INTRODUCTION

A central concept in the literature following the crisis has been the existence of a financial cycle, see e.g. BIS (2014). While there is no consensus on the exact definition of such cycles, they can in the most general sense be thought of as common fluctuations in a set of variables important for financial stability. Financial cycles are generally found to be longer than traditional business cycles and their peaks tend to coincide with episodes of financial stress.

Given this, financial cycles are often interpreted as indicators of financial imbalances that can be used for guiding macro-prudential policy, see Schüler et al. (2016). Based on this, the aim in this paper is to answer the following questions: What is the financial cycle? How does it look for Denmark? Across countries, are fluctuations in financial variables different from the regular business cycle, and what is the relationship between the financial cycle and the real economy? Is there a global financial cycle? Which role do banks and other credit institutions play?

Our main findings can be summarized as follows: Across countries there are strong co-movements in house prices, credit and GDP at both business cycle (2-11 years) and medium-term (11 to 30 years) frequencies. Hence, there are also longer (i.e. medium-term) cycles in GDP and not only in financial variables. During expansions of the medium-term cycle – i.e. 11 to 30 years – growth is stronger, there are fewer technical recessions (two consecutive quarters with a fall in real GDP), and the recessions that do occur are milder compared with recessions during contraction periods of the medium term cycle. Such long periods of robust growth with only few and weak contractions can lead to over-optimism among borrowers, lenders, regulators and policy makers alike which in turn can lead to the build-up of financial imbalances that can turn into financial stress. On the other hand, during medium-term contractions recessions are more frequent and more severe which can lead to "under-optimism", e.g. through a lack of risk appetite. At medium-term frequencies, GDP and house prices lead credit, but clearly causality can go in both directions.

Moreover, medium-term cycles contain an important global component. In general, the US medium-term cycles – both real and financial – lead the medium-term cycles in other countries and can therefore be viewed as the global cycle. Even though the medium-term cycles are correlated with the US, there are also clear country specific elements, especially for the financial variables.

For Denmark we find that compared to GDP a larger part of the movements in credit and real house price are driven by a medium-term cycle. This is not the case for other financial variables as e.g. equity indices. Furthermore, a principle component analysis shows that house prices and credit have a common component. Based on this we define the Danish financial cycle as low frequency movements in the real house price and credit. The GDP cycle is in phase with the cycle in the real house price, while the credit cycle is lagging around 8 quarters. This means that the real house price is a leading indicator for credit. Denmark is among the advanced economies where the correlation between GDP, credit and real estate prices is the highest. This likely reflects the advanced and deep Danish financial markets. We analyze the robustness of our estimates in real time and find that the size of the credit and house price gaps change as new information becomes available.

When investigating the role of the financial sector in explaining financial cycles, it appears that – particularly in the years preceding the financial crisis – banks contributed to an unsustainable build-up of credit and the expansion of the financial cycle by having lenient credit standards and by levering up and relying more on unstable funding sources. In turn this decreases their ability to withstand negative shocks.

Filtering techniques focuses on trend removal. This implies that the focus is on the growth rates – such as that in credit – relative to the trend growth. To complement this approach, we estimate a vector error-correction model for the household sector based on historical correlations between income, debt, house prices and interest rates following the approach in Juselius et al. (2016). The residuals in the long-run relationships in the model have been characterized by persistent deviations and these deviations are similar to the financial cycles based on the filtering approach. There is a tendency for GDP and house prices to lead these disequilibria whereas credit build-up or deleveraging happens only slowly. The speed of adjustment indicates that excessive credit levels suppress output for an extended period of time as households deleverage. This accentuates the importance of avoiding balance-sheet recessions.

FINANCIAL CYCLES: WHAT, HOW AND WHY?

There is no widely agreed definition of a financial cycle. It is often thought of as a common deviation from trend of variables important for financial stability. The general idea is to try to capture a build-up of financial imbalances which in turn can be used for guiding macro-prudential policy. Furthermore, financial imbalances captured by the financial cycles affect the real economy. Hence, identifying financial cycles can potentially help to improve real growth forecasts. As episodes of financial stress are events that occur at a lower frequency than business cycles, financial variables with an important medium-term component (cyclical swings that are longer than business cycles) are especially relevant as input into the financial cycle.

In the literature, focus has been on credit and real estate prices. Clearly, credit has to take the center stage when looking at financial stability. Credit creates a strong and direct inter-connectedness between different economic agents, as a shock to borrowers can propagate directly on to lenders. Furthermore, the stock of credit is slow moving and has fewer turning points than e.g. GDP. This in turn implies that it has an important medium-term component. Real estate prices are closely related to debt, as real estate is used as collateral for credit and therefore often heavily leveraged. Variables with a less important medium-term component such as equity prices, interest rates, credit spreads, risk premiums or non-performing loans are also sometimes included or used as additional information on stress, risk perception and risk appetite.

Apart from which variables to include in the financial cycle, it has to be decided how to separate trend and cycles in the financial variables. It is important that the de-trending method used allows for cycles that are much longer than traditional business cycles in order to capture infrequent episodes of financial stress. This can be done in a number of ways where the simplest is through a filter, e.g. a band-pass filter, but in the literature more advanced filtering methods have been used, e.g. multivariate spectral measure of power cohesion (see Schüler et al. (2015)) or unobserved component models (see Rünstler and Vlekke (2016)). Trends can also be based on predicted equilibrium levels in estimated models. In this paper we use a band-pass filter as a benchmark and an unobserved component model for our final estimate of the Danish financial cycle. We then compare these cycles with deviations from estimated equilibrium levels from a model based on co-integration (see Juselius et al. (2016)).

It should be highlighted that the interpretation of the financial cycle is difficult. However, in general peaks of the identified financial cycles tend to coincide with episodes of financial stress, cf. Box 1, and such episodes should obviously be avoided if possible.

Are peaks of the financial cycle closely associated with financial crises?

Box 1

Borio (2014), Drehmann et al. (2012) and BIS (2014) are all among the papers that argue how one of the defining features of financial cycles is that their peaks tend to coincide with episodes of financial stress. BIS (2014) for instance illustrate how peaks in the financial cycle from 1985 to 2014 tend to overlap with financial crises in both advanced and developing economies. For most countries their sample only contains one financial crisis. Using a much longer sample, Aikman et al. (2015) investigate the relationship between cycles in credit and banking crises using data from 14 countries (including Denmark) from 1880 to 2008. Aikman et al. (2015) find that booms in the credit-to-GDP ratio (a very basic financial cycle calculated as credit divided by GDP de-trended using a HP-filter) are a systematic indicator of banking crises, also when including other explanatory variables.

In addition to this they find tentative evidence that recessions tend to be more severe when they were preceded by a boom in credit. However, they also pointed to multiple periods of rapid credit growth in the UK that were not followed by a banking crisis. Along the same lines, Taylor (2015) uses a dataset containing bank lending to the non-financial sector for 17 advanced economies from 1870 to 2013 to investigate whether this measure of credit can be used to predict financial crises. Taylor's results confirm those of Aikman et al. (2015), namely that credit contains information on the likelihood of future financial crises but that some periods of credit expansions were not followed by a financial crisis.

Drehmann (2013) estimate the share of true predictions and false signals when using the credit-to-GDP gap as a predictor for future crises covering 39 countries from 1970 to 2013 encompassing 33 crises. In general the credit-to-GDP gap was able to predict many of the banking crises in the sample, however, the high share of true predictions came at the expense of a relatively high share of false signals, particularly for low thresholds of the credit-to-GDP gap, cf. the table below.

Although periods with high credit growth are not always followed by a crisis, the literature in general points to credit growth as a good predictor of future financial crises. This has led the Basel Committee on Banking Supervision to recommend using the credit-to-GDP gap as one of the measures for deciding on the level for the countercyclical capital buffer, cf. BCBS (2010).

The performance of the credit-to-GDP gap as an early warning indicator

Threshold (per cent)	True predictions (per cent)	False signals (per cent)
2	91	44
6	82	27
10	70	15

Note: Threshold is measured as the deviation from trend for the credit-to-GDP ratio. 'True predictions' is the fraction of correctly predicted crises. A crisis is correctly predicted if it occurs within three years after receiving the signal. 'False predictions' is the fraction of false signals, i.e. the number of type II errors relative to the number of periods with no crises.
Source: Drehmann (2013).

FINANCIAL CYCLES AND THE REAL ECONOMY: AN INTERNATIONAL OVERVIEW

This section studies the cyclical movements of both the real economy and financial variables across two frequency bands; namely business cycles frequencies and medium term frequencies. This is done in order to get a better understanding of connection between the real economy and financial cycles. Specifically, for a set of 17 advanced economies, we analyze the cyclical movement of real GDP and compare this with the cyclical movement of the level of total private debt and real estate prices both in real terms.[1] Debt and real estate prices are among the most commonly used variables when constructing financial cycles, see e.g. Drehmann et al. (2012) and Rünstler and Vlekke (2016). Fluctuations around trends are found using a band-pass filter, cf. Box 2.[2]

1 Data on credit is from BIS, credit to non-financial sectors, from all sectors to private sector. Data on real estate prices are from OECD, house prices, OECD Economic Outlook, calendar adjusted. Both series are in real terms using the private consumption price index from the national accounts.
2 This approach is computational easy and often used in the literature, see BIS (2014).

Properties of the band-pass filter Box 2

The spectral representation theorem states that any stationary time-series can also be represented in the frequency-domain, see Hamilton (1994). In broad terms, a filter intends to separate different frequencies of a given time-series by removing any component which is not in that particular frequency, e.g. removing the long-run trend. The so-called ideal filter eliminates all unwanted frequencies while the complement is kept unchanged. Formally, we want to decompose the process $x_t = \tilde{x}_t + residual_t$ where $\tilde{x}_t$ has cycles with periods in the interval $[p_l, p_u]$. The so-called ideal filter (which passes $\tilde{x}_t$ unchanged while completely discarding $residual_t$) is not feasible as it requires the time-series to have infinite length. Hence, in practice some approximation, $\hat{x}_t$, is needed.

A widely used approximation is the band-pass filter by Christiano & Fitzgerald (1999). The band-pass filter is a linear approximation that allows for fluctuations with length between some chosen cut-offs but attenuates short-term noise (high frequencies) and long-term variations in the trend (low frequencies). The band pass-filter minimizes the mean squared error between $\hat{x}_{1,t}$ and $x_{1,t}$ under the assumption that x_t follows a random walk. It is computed as

$$\hat{x}_{1,t} = B_0 x_t + \sum_{j=1}^{T-t-1} B_j x_{t+j} + \tilde{B}_{T-t} x_T + \sum_{j=1}^{t-2} B_j x_{t-j} + \tilde{B}_{t-1} x_1,$$

$$B_j = \frac{\sin(jb) - \sin(ja)}{\pi j}, B_0 = \frac{b-a}{\pi}, a = \frac{2\pi}{p_u}, b = \frac{2\pi}{p_l}$$

and where $\tilde{B}_{T-t}$ and $\tilde{B}_{t-1}$ are functions of B_0 and B_j. p_u and p_l are the frequency domain. Setting $p_u = 44$ quarters and $p_l = 8$ quarters imply that all frequencies outside this range are removed. If a series e.g. has a fixed cycle of 24 quarters, this cycle would be picked up. Note that increasing $p_u = 50$ will not change the filtered series – the time-domain is still 24 quarters. However, if the series also had a cycle of 40 quarters changing p_u from 32 to 50 would yield a difference in the filtered series.

The filter is asymmetric which allows for real-time estimates of $\tilde{x}_T$. Unlike symmetric filters this also introduces some (unknown) degree of phase shift relative to the underlying series. Christiano & Fitzgerald (1999) find that this is a minor issue for macroeconomic series at business cycle frequencies.

However, this implies that lead-lag comparisons of band pass-filtered series should be done with some caution. The band pass-filter is obviously time-varying which means that estimated cycles will vary as the sample is expanded. This is especially true near the endpoints of the data where the accuracy of filters is generally relatively poor.

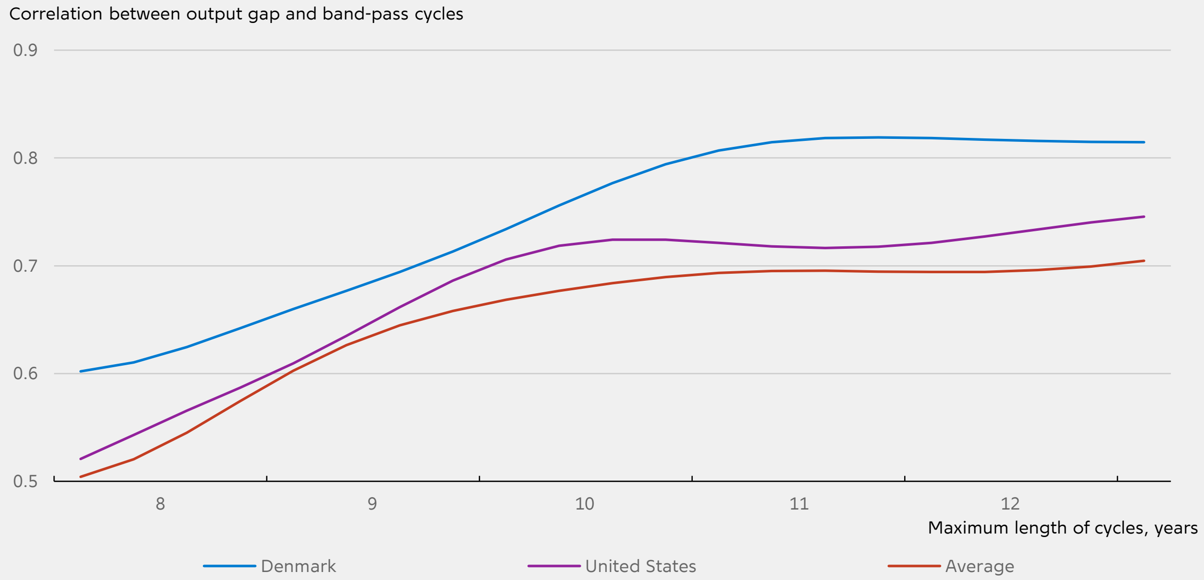
All series are in log levels and de-trended using a linear trend.[3] Cycles are decomposed into business cycles frequencies, defined as cycles between 2 and 11 years, and medium-term cycles with frequencies between 11 and 30 years. Our definition of business cycle frequencies differ a bit from what is standard in the literature as we allow cycles up to 11 years instead of the typical 8 years. Our reason is that by allowing the band-pass filter to include longer cycles the correlation between business cycles based on the filter and the output gab estimated by the IMF is increased substantially, cf. Box 3. The motivation is that business cycles at times are longer than 8 years. These longer business cycles are not captured by the band-pass filter if the frequency domain is restricted to a maximum of 8 years.

[3] Others de-trend by applying the band-pass filter in the log-differences which yields a trend growth rate. This can be used to find a trend level, see e.g. Comin and Gertler (2006). The method yield almost identical results.

The frequency domain of business cycles Box 3

Business cycles are typically thought of as between 2 and 8 years but are on some occasions longer. According to the NBER, the longest business cycle in the US was 128 month, i.e. just shy of 11 years. When using a band-pass filter to identify business cycles it is important to allow the filter to include the longer cycles. Looking across 17 advanced economies the correlation between the output gap identified by the IMF and cycles identified by the band-pass filter is relatively low if the frequency domain of the band-pass filer does not allow for cycles above 8 years. Raising the frequency domain increases the correlation considerably, cf. the chart below. Increasing the frequency domain allows the band-pass filter to capture e.g. the long US expansion through the 1990's. We therefore refer to business cycle frequencies as between 2 and 11 years.[1] Note, increasing the frequency domain does not necessarily increase the time domain so the medium length of a business cycle is not changed.

The frequency domain of business cycles should be allowed to be up to 11 years



Note: When calculating the band-pass cycle the minimum cycle length is kept fixed at 2 years.
Source: Own calculations using data from Macrobond.

[1] When applying the band-pass filter, we set the lower bound at 8 and the upper bound at 44 quarters.

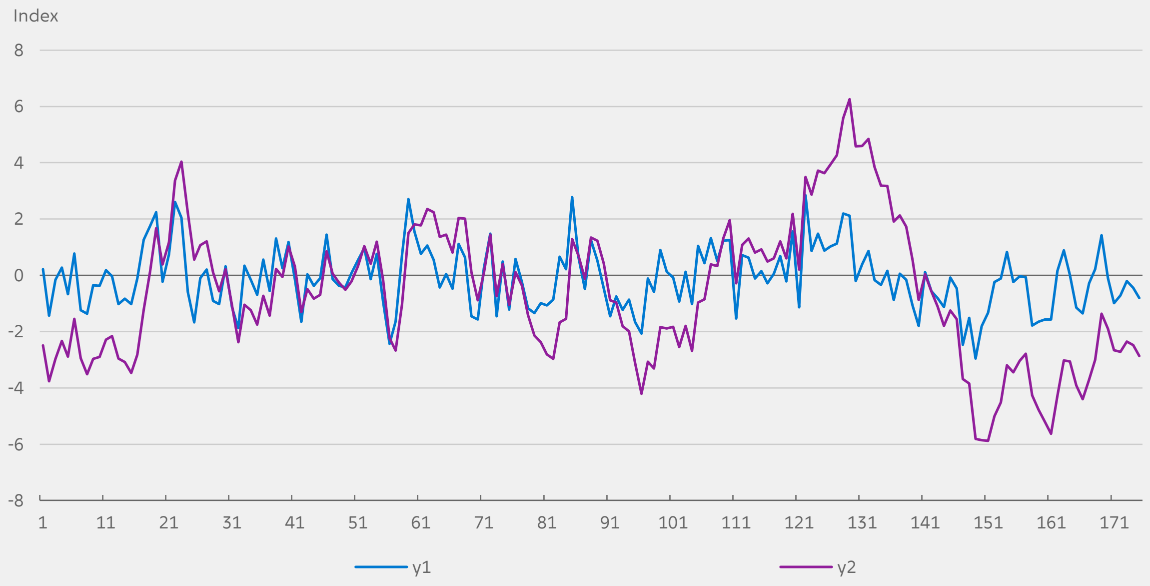
At the business cycle frequencies, the financial variables are highly correlated with GDP, cf. Chart 1. The median correlation between GDP and real estate is 0.7 and between GDP and credit it is only a bit lower at 0.6. Credit lags GDP and real estate prices while the two latter are typically almost in sync. As such these lags indicate that causality mainly runs from GDP and house prices to credit, but as noted in Box 4 the lag in the credit cycle can also partly be due to credit being slower moving than GDP as credit is a stock variable. Apart from the lags, the cycles also differ as the standard deviation is higher for credit and especially real estate prices than for GDP. As for credit the large standard deviation can partly reflect the sluggish nature of credit, cf. Box 4.

Persistent time series and cycles

Box 4

To see how the Band Pass filter works and to underline the importance of persistence in the underlying series, consider the following simulation exercise: Let two AR(1)-processes $y_{i,t+1} = \rho_i y_{i,t} + \varepsilon_{t+1}$ be driven by the same series of shocks, $\{\varepsilon_t\}_{t=1}^{250}$. Hence, they differ only with respect to the parameter $\rho_i = \{0.4, 0.9\}$. This can be considered a very stylized example of two economic time series affected by the same structural shock (e.g. productivity) but where the propagation of these shocks differs due to different persistence. For simplicity, we do not include a trend so the series could be thought as having a common deterministic trend which has been removed.

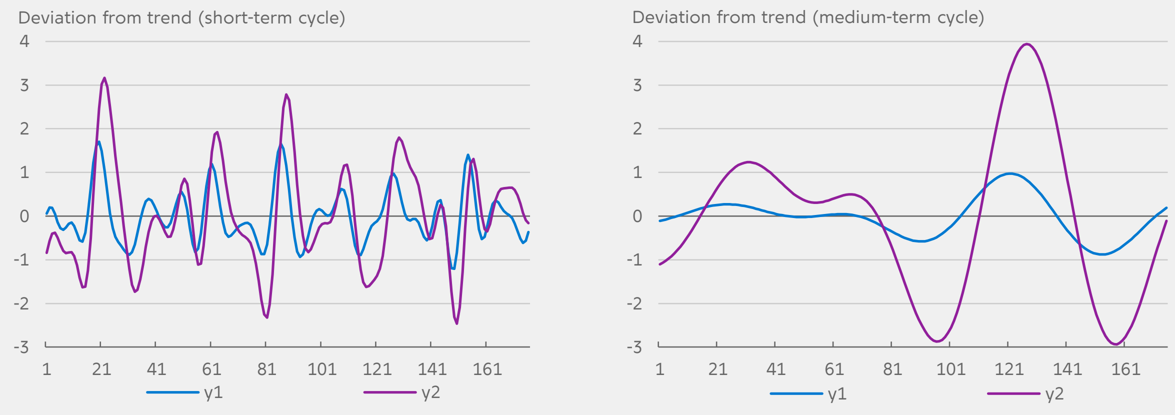
Simulated AR(1)-processes



Source: Own calculation.

Now, consider the same processes but where they have been filtered by a Band Pass filter at business and medium term cycles (setting $\{p_l^{bc}, p_u^{bc}\} = \{8,44\}$ and $\{p_l^{mtc}, p_u^{mtc}\} = \{44,120\}$, respectively). First, we note that the two series are quite similar and with a high correlation at business cycle frequencies where the common shock is driving most of the variation. The larger unconditional variance of y_2, due to a higher persistency parameter, is much more pronounced for the medium term cycle where this effect dominates. Finally, note that the filtered series seem to indicate that y_1 is leading y_2 even though they are driven by the same shock.

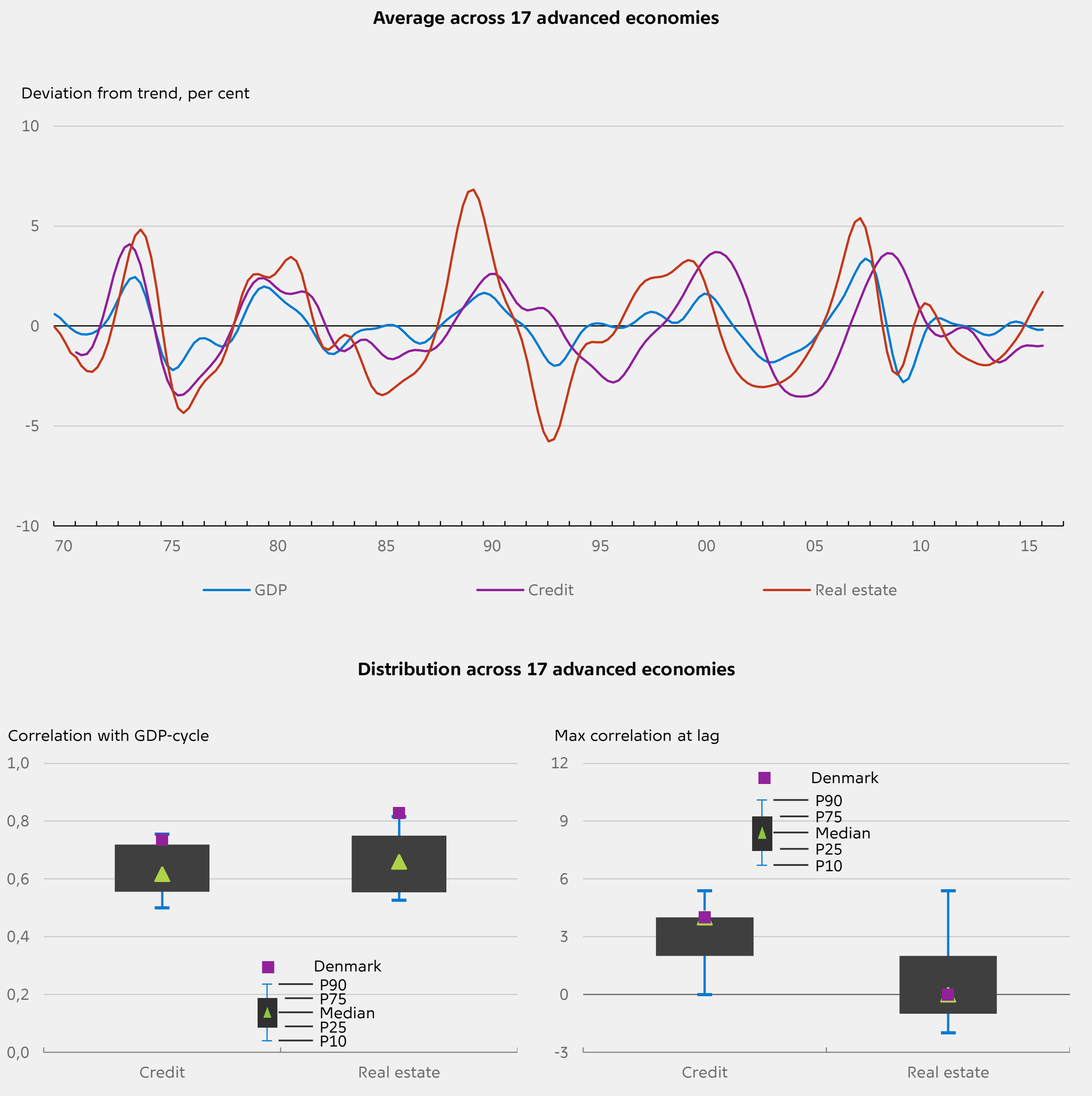
Band Pass filtered series



Source: Own calculations.

Denmark is among the advanced economies where the correlation between GDP, credit and real estate prices is highest, cf. Chart 1 (bottom left). This might reflect that Denmark has advanced and deep financial markets where, among others, mortgage credit is easily available.

At business cycle frequencies GDP is highly correlated with real estate prices and credit Chart 1

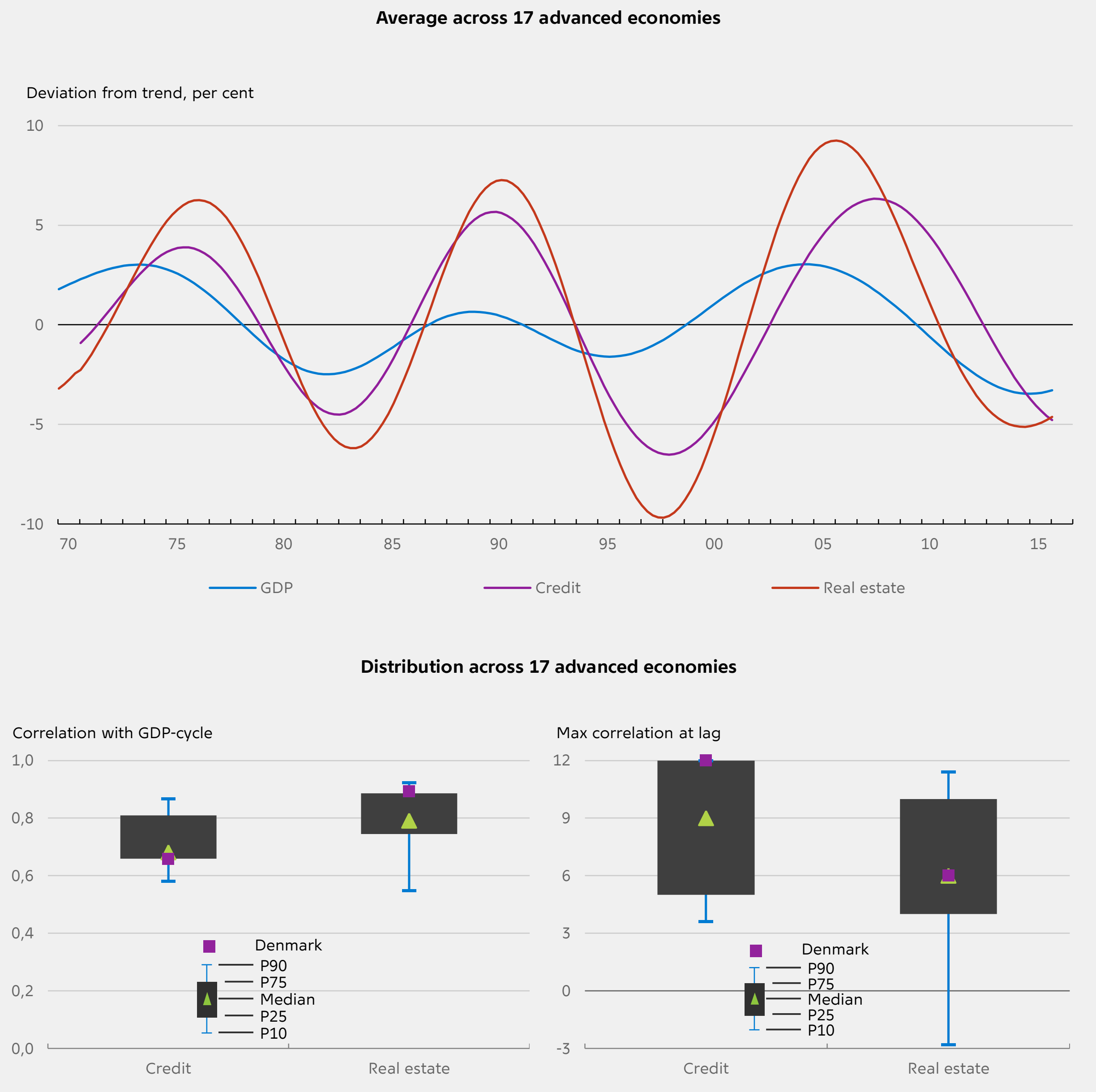


Note: Business cycles are between 2 and 11 years and calculated using a band-pass filter. Top graph: Simple average for Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK and USA.

Source: Own calculations on data from Macrobond.

Clearly, business cycle swings occur at a much higher frequency than episodes of financial stress. Thus, it is also relevant to study longer cycles. Using the band-pass filter on real GDP to identify oscillations in the frequency domain of 11 to 30 years we find longer cycles, which are on average around 16 years, i.e. around twice that of business cycles. The cross-correlations for these longer cycles between GDP, real estate prices and credit are even higher than at the business cycle frequencies, cf. Chart 2 (top). GDP generally leads both real estate prices and credit but with a large variation across countries. The standard deviation of both real estate prices and credit is much larger than that of GDP. As already mentioned both of these stylized facts could in part be a result of house prices and especially credit being slower moving than GDP.

The medium term GDP cycle leads real estate and credit cycles Chart 2



Note: Medium-term cycles are between 8 and 30 years and calculated using a band-pass filter. The total cycle is between 2 and 30 years. Top graph: Simple average for Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK and USA.
Source: Own calculations on data from Macrobond.

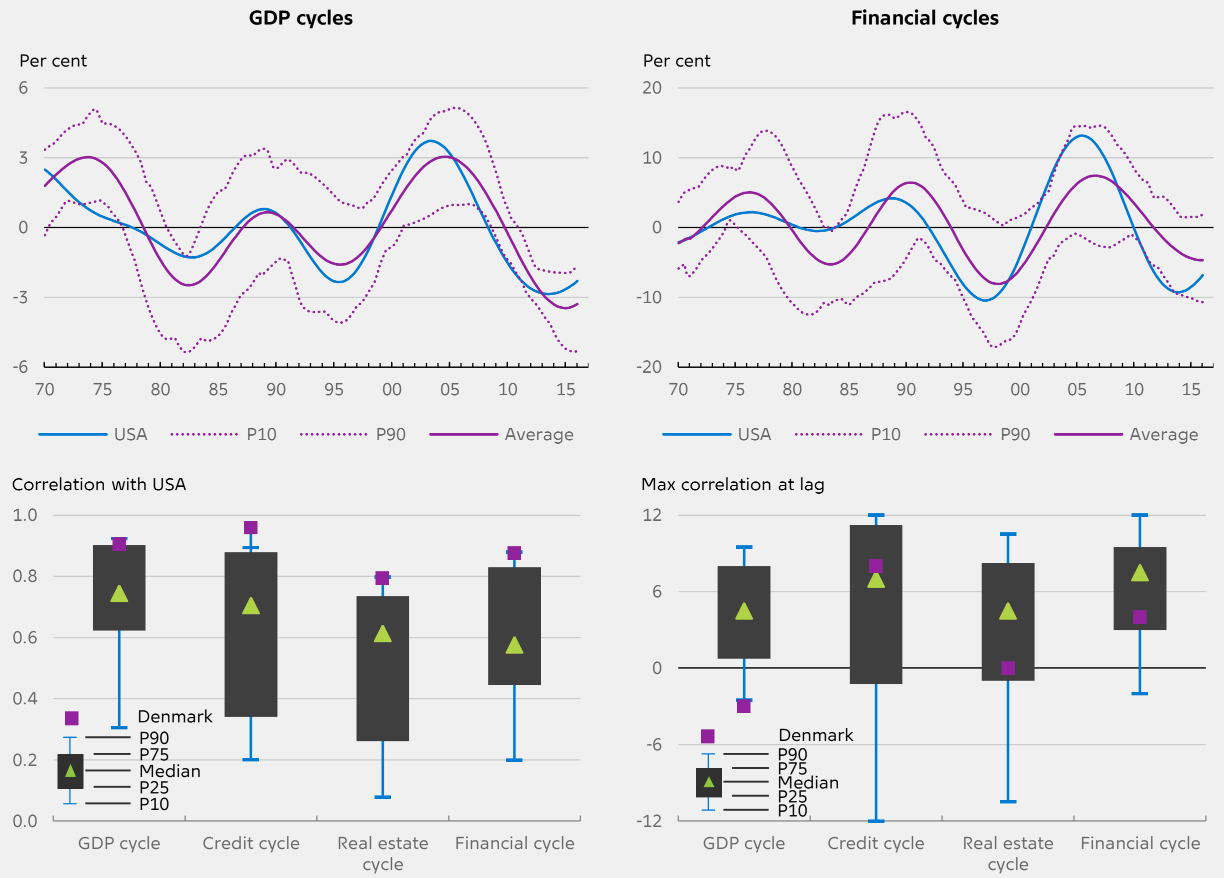
A stylized fact often highlighted in the literature is a tendency that the volatility of the medium term cycles of real estate prices and credit increases over time, see e.g. Drehmann et al. (2012). However, this is mainly due to the latest financial crisis and the time-varying property of the band-pass filter. Cycles based on a recursive real time band-pass filter do not indicate increasing volatility over time, cf. Appendix A1.

The above stylized facts show that financial variables and the real economy are highly correlated both at business cycle and medium term frequencies. GDP and real estate prices typically lead credit, but it is not possible to make any clear claims about causality.[4] We will come back to this below, but first we look at the international spill-overs.

THE US IS LEADING MEDIUM-TERM REAL AND FINANCIAL CYCLES

Both the real and the financial medium-term cycles are being led by the US, i.e. the US cycle typically reaches peaks and troughs before other countries, cf. Chart 3. Real estate prices and debt rose earlier and more in the US than in most other countries. Since the 1970s, the US has lead the average medium-term real cycle by around 4 quarters and the average medium-term financial cycle by around 6 quarters. We therefore use the US medium term cycles as the global cycle. The importance of the US for the global financial cycle has been shown by others, see e.g. Miranda-Agrippino and Rey (2015). Even though there is a strong global component in the medium term cycles, there are however clear country differences where e.g. Germany and to some extent Japan at times have had cycles that differs from the US. On the other hand, Denmark has a very strong correlation with the US.

The US leads the medium term cycles across advanced economies Chart 3



Note: Financial cycles are simple average of the cycle in real estate prices and credit. Medium term cycles are between 11 and 30 years and calculated using the band-pass filter. P10 and P90 are respectively the 10th and 90th percentile. Simple averages across Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK and USA.

Source: Own calculations on data from Macrobond.

4 A Granger causality test between the 3 medium term cycles indicates that they all Granger-cause each other.

WHAT ARE THE DRIVERS OF THE MEDIUM-TERM CYCLE?

As shown above, the real and financial parts of the economy are closely integrated both at business cycle and medium-term frequencies. The stylized facts indicate that the medium-term real cycle tends to lead real estate prices and especially credit. Since 1970 the medium-term cycle in GDP has on average peaked and bottomed out by around 3 quarters before real estate prices and by around 4 quarters before credit. But clearly the real and financial cycles are part of an endogenous system where causality goes in both directions. This is supported by e.g. Granger causality test which shows that medium term financial and real granger-cause each other.

But what are medium term cycles in GDP? During expansions of the medium term cycle growth is stronger (as also noted by Comin and Gertler (2006)), there are fewer technical recessions (two consecutive quarters with a fall in real GDP) and the recessions that do occur are milder compared recessions during contraction periods of the medium-term cycle. From 1970 to 2016 advanced countries had on average 7 technical recessions each and only 2 of these where during medium term expansions, cf. Table 1. Furthermore, when an economy experienced a quarter with negative growth, GDP fell on average 1.3 per cent during periods where medium-term cycles was contracting but only 0.7 per cent if the medium-term cycle was expanding, cf. Table below. The 2001-recession is an example of a recession during a medium-term expansion. It was for most countries short and the output loss was limited.

Some characteristics of medium-term cycles Table 1

	Medium-term contractions	Medium-term expansion
Average growth, quarter-quarter	0.3	0.8
Number of recessions	5	2
Number of quarters with negative growth	26	15
Average growth in quarter with negative growth	-1.3	-0.7

Note: Technical recessions are defined as two consecutive quarters with a fall in real GDP. Growth rates are quarter-quarter, not annualized. Data for 1970q1 to 2016q3 (186 quarters). Simple average across 17 advanced economies.
Source: Own calculations based on data from Macrobond.

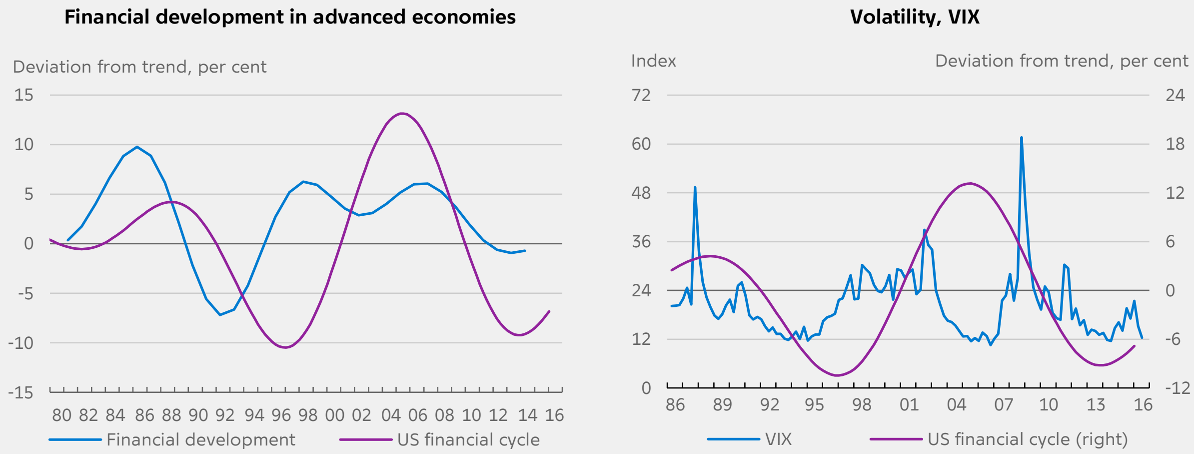
So real medium-term cycles are longer oscillations between periods of relative stable and strong growth and periods with a more volatile and feeble economic development. These swings are not captured by business cycles but are typically viewed as changes in the structural/potential growth rate.

The driving force behind medium-term real cycles is not clear but they may be a result of slow moving productivity cycles. Comin and Gertler (2006) develops a model where high frequency shocks affect the pace of both R&D and adoption and thereby productivity. These endogenous changes in productivity propagate the high frequency shocks into persistent medium term real cycles. The resulting cycles in income and investments will then be the source of cycles in real estate prices and credit demand.

If medium-term financial cycles indeed are a result of real economic developments, then medium-term financial cycles cannot be interpreted as an imbalance. However, long and stable real expansions might lead to over-optimism among borrowers, lenders, regulators and policy makers alike which in turn can give rise to the build-up of financial imbalances that can materialize into financial stress. This can help to explain why medium-term cycles in financial variables, i.e. the financial cycle, tends to peak around the time of episodes of financial stress. During medium-term contractions, recessions are more frequent and more severe which in turn can lead to "under-optimism", e.g. through a lack of risk appetite.

However, causality also runs from the financial side to the real economy, i.e. shocks to financial variables affect the real economy. Financial liberalization can increase firms' and households' access to credit and thereby allowing them to better optimize consumption and investments. Nonetheless, financial deregulation has also been associated with financial stress, e.g. through an easing of lending standards. Dell'Ariccia et al. (2016) among others point to financial liberalization as preceding credit booms. Other authors have found that financial liberalization reduces the risk of a financial crisis; see e.g. Shehzad and de Haan (2009). How to measure liberalization and financial globalization is far from straightforward. However, some measures of financial development do seem to lead the global financial cycle, i.e. the US cycle, cf. Chart 4 (left).

Financial cycles, financial development and volatility Chart 4



Note: Left chart: Financial development index is from Svirydzenka (2016), Introducing a New Broad-based Index of Financial Development. Average index for advanced economies. Only the following sub-indexes are used: Access and Efficiency. The sub-index "depth" is not used as it is among others based on measures of debt. Including this sub-index will therefore by construction yield a high correlation with the financial cycle.

Source: Left chart: own calculation on data from Svirydzenka (2016) and Macrobond. Right chart: Own calculations on data from Macrobond.

Risk perception is also a factor behind growth in real estate prices and credit. Both high and low risk premiums, as measured by VIX, are found to be a predictor of financial stress, cf. Danielsson et al. (2016), "*High volatility can be seen by forward-looking economic agents as a signal of the increased risk of adverse future outcomes and a pending crisis… Low risk induces economic agents to take more risk, which then endogenously affects the likelihood of future shocks*". Since 1986 the correlation between VIX and the financial cycle has in general been positive, but with a notable exception; the years leading up to the great recession, cf. Chart 4 (right). This illustrates the over-optimism and mispricing of risk that prevailed during the years leading up to the financial crisis of 2008-09.

THE FINANCIAL CYCLE AND THE FINANCIAL SECTOR

In this section we briefly describe some of the theoretical mechanisms between the real economy and the financial sector. A large literature describes the financial sector as an amplifier of shocks leading to pro-cyclical credit provisioning. This idea is not new; see e.g. Kindleberger (1976) and

Minsky (1986, 1992). Both argue that changes in the supply of credit tend to be pro-cyclical and in particular that credit supply tends to increase during longer expansions – which might result in an unstable economy that is prone to a financial crisis.

One strand of the literature focuses on the interplay between credit constraints and the value of collateral; see e.g. Kiyotaki & Moore (1997) and Bernanke & Gertler (1999). In both their models lending increases in asset prices which can amplify real cycles (so-called "financial accelerator" effects). Other models introduces features such as moral hazard (bailing out banks with public funds) and fluctuations in uncertainty and show that they can create rather long and persistent cycles in credit and leverage, see e.g. Aikman et al. (2015) and Geanakoplos (2010). Shin (2013) argues that financial intermediaries tend to increase the supply of credit during good times when asset prices are increasing and risks appear low and vice versa. In turn this can give rise to a feedback loop that will contribute to fluctuations in the credit cycle, as the credit provisioning from financial intermediaries can fuel further increases in asset prices and a lowering of measured risks during the expansionary phase of the credit cycle and the opposite during the contractionary phase. Gorton & Ordoñez (2014) present a model in which credit can build up when lenders pay little (or no) attention to the quality of collateral of the borrowers as even borrowers with poor collateral can borrow. Consumption and output will increase as the credit expansion continues and the economy can be in a state of "blissful ignorance" such that financial fragility can build up endogenously. After a long expansion of credit, a crisis can occur if a shock hits the economy after which lenders have an incentive to learn the true quality of collateral and they decide to reduce lending to more "questionable" borrowers.

Hence, there is an ample theoretical literature where risks to the financial stability can arise in or be amplified by the financial sector. In the next section we will look closer at how the Danish financial sector acts over financial cycles.

HAVE DANISH FINANCIAL INTERMEDIARIES ACTIVELY BEEN CONTRIBUTING TO FLUCTUATIONS IN THE CREDIT CYCLE?

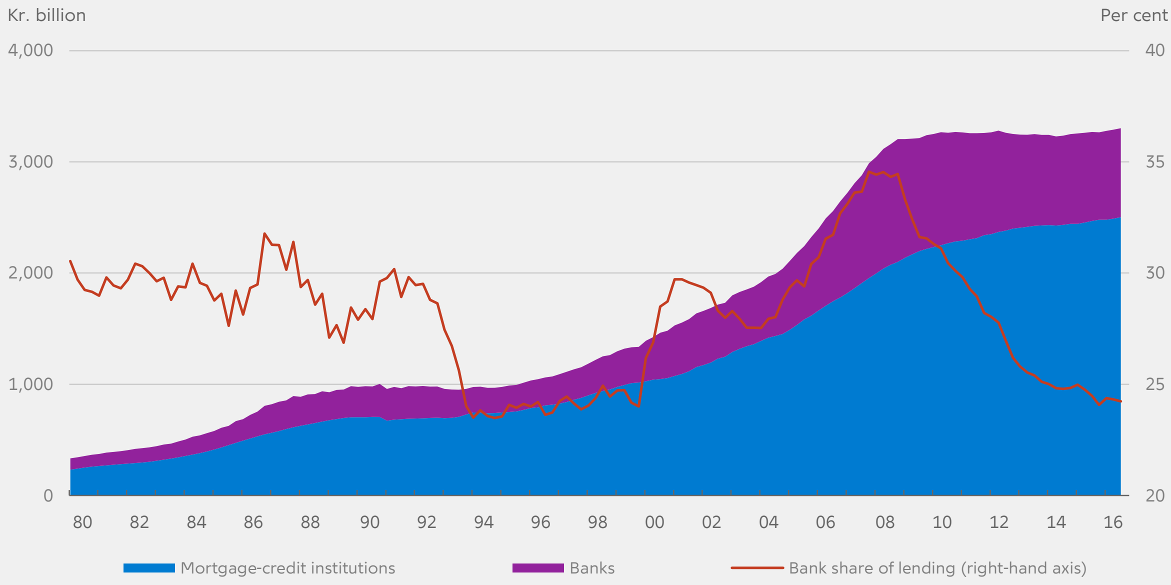
In Denmark there are two major domestic providers of credit: banks and mortgage-credit institutions. Mortgage-credit institutions only provide loans collateralized against the value of real estate and cannot grant loans with a loan-to-value that exceeds 80 per cent at origination. In addition to this, they are subject to a balance principle (match between cash-flow from the issued loans and funding). Lending by mortgage credit institutions therefore primarily depends on the evolution in housing prices and the willingness of households and firms to borrow against the value of their possessions of real estate.[5]

Banks on the other hand can provide the residual part of the mortgage financing[6] as well as other types of loans, such as corporate and consumer loans. That is, banks will typically be the marginal provider of credit. So if there are cycles in the credit standards of financial intermediaries that are contributing to fluctuations in the credit (and financial) cycle, this will most likely originate in the banking sector – consistent with this is the fact that the share of bank lending is more cyclical than lending by mortgage credit institutions, cf. Chart 5. For these reasons, below we will only consider the credit provisioning by banks.

5 These features imply that one would expect a close link between credit and house prices in Denmark, which is also what we find in the data, cf. Chart 1 and 2.

6 However, currently only up to 95 per cent of the value of the real estate.

Lending by domestic lenders Chart 5

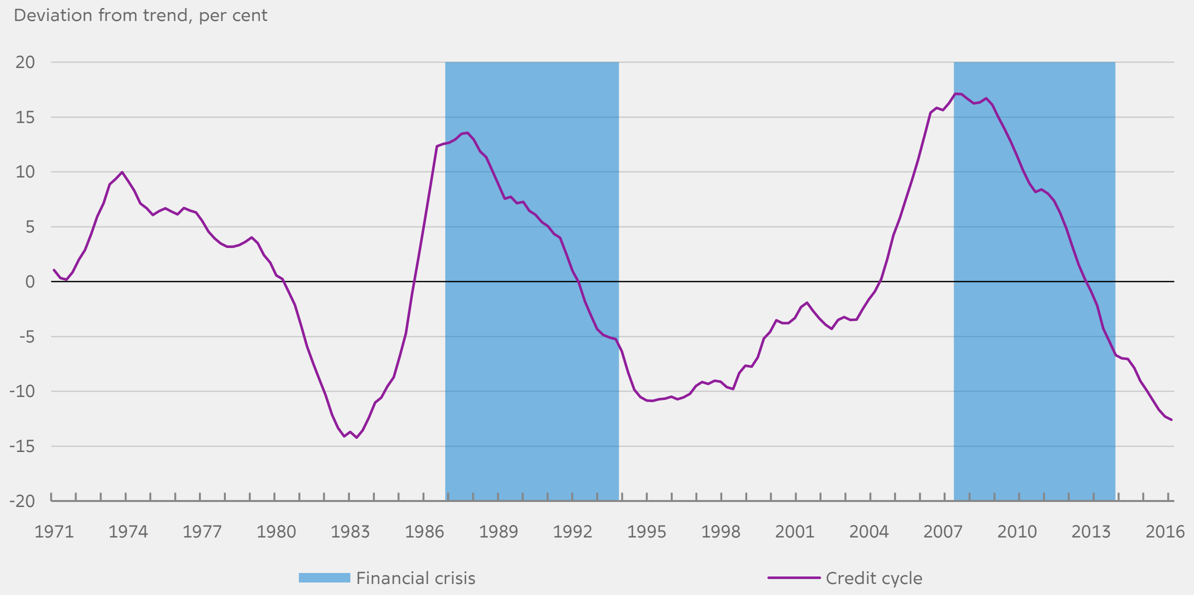


Note: Lending to households and firms by domestic banks and mortgage-credit institutions.
Source: Danmarks Nationalbank.

Since 1970 there have been two major peaks in the credit cycle, both of which occurred during the early phases of a financial crisis, cf. Chart 6. During both crises several Danish banks became insolvent and closed or merged, many due to difficulties that originated from lending to sectors that subsequently faced severe problems.[7] In isolation this could indicate that banks actively contributed to fluctuations in the credit cycle by having credit standards that were too lenient in the expansionary phase of the cycle and by reducing the supply of credit during the contractionary phase of the cycle.

[7] The crisis from 1987-93 had character of a banking crisis where a total of 102 (mainly small or middle-sized) banks went out of business, 52 of them due to difficulties that primarily were solvency-related (Abildgren et al. (2010)). During the financial crisis that started in 2007/08 4 out the 15 largest banks went out of business and the government provided a safety net for the banks through e.g. depositor guarantees, capital injections, cf. Abildgren et al. (2011). See Abildgren and Thomsen (2011) for a more thorough comparison of the two crises.

Credit cycle and financial crises in Denmark Chart 6



Note: Financial crises are dated using Table 2.1 in Abildgren et al. (2011). The banking crisis in 1984-85 where one bank, Kronebanken, was in trouble is ignored. The credit cycle is estimated using an unobserved component model, cf. section on The Danish Financial Cycle(s) later.
Source: Danmarks Nationalbank.

To investigate this further, one can consider the loan-to-income (LTI) ratio as an indicator of banks' credit standards. All-else-equal a higher ratio implies a larger risk of default of the debtor such that a higher LTI is indicative of a loosening of credit standards. In the run-up to the financial crisis, the share of homebuyers with a high LTI ratio rose rapidly suggesting that credit standards were loosened during this period, cf. Chart 7 (left).[8] However, the increase in LTI occurred during a period with rapid price increases on residential real estate, implying that homeowners in general experienced a strengthening of their balance sheets, cf. Chart 7 (right). If the increases in housing prices were believed to be based on fundamentals (e.g. expectations towards higher future income), this could potentially rationalize why banks increased their lending, as the households would have more collateral to post even if they had less current income to cover the debt payments.

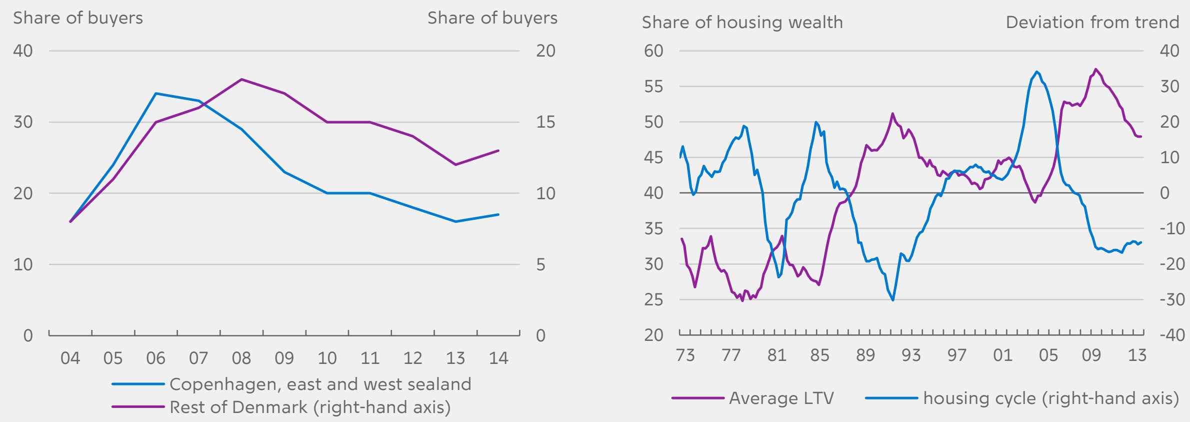
However, the analysis in Abildgren et al. (2016) suggest that over-optimism (sentiments decoupled from economic fundamentals) among households contributed to the upwards pressure on housing prices during this period. It therefore appears that the easing of credit standards (in terms of higher LTIs) accommodated – and perhaps even accelerated – the over-optimism among households, which in turn contributed to the increase in housing prices and credit.[9]

8 Note that the denominator is income the year *after* the house was bought. Hence the measure is somewhat forward looking. Data is only available from 2004 and onwards.

9 A general tendency for optimism and underestimation of risks was also emphasized as one of the factors behind the financial crisis in Denmark in a report by an expert committee on the causes for the financial crisis, cf. Ministry of Business and Growth (2013).

Share of homebuyers with a loan-to-income ratio > 400 per cent (left) and average loan-to-value for all homeowners (right)

Chart 7



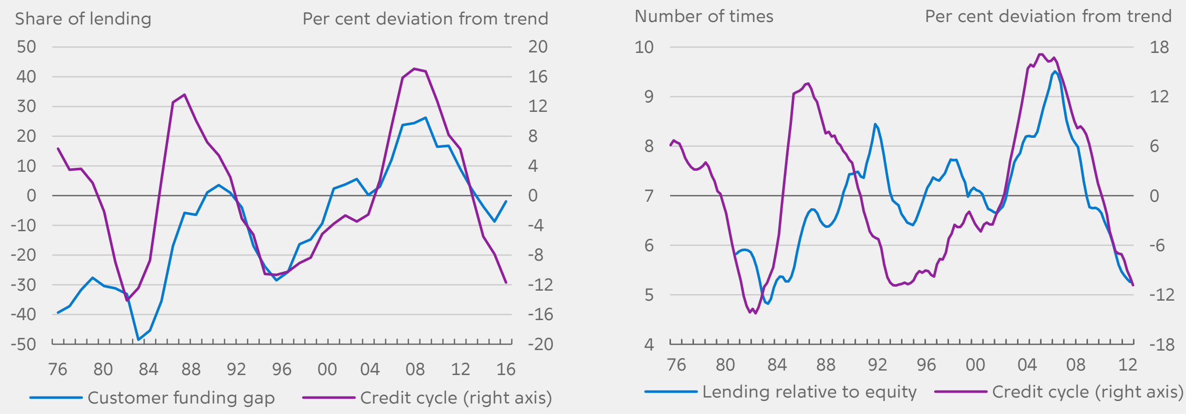
Note: Left chart: Homebuyers are defined as all families that in a given year have moved and still has mortgage debt. The loan-to-income is calculated as a family's total debt divided with its income the following year. The observation in 2014 is based on a projection. Right chart: The average loan-to-value is calculated as households' total debt to banks and mortgage credit institutions with collateral in the house relative to the total value of housing. The housing cycle is estimated using an unobserved component model, cf. section on The Danish Financial Cycle(s) later.
Source: Danmarks Nationalbank.

Regarding bank lending to corporates, Abildgren and Kuchler (2013) have analyzed whether key financial ratios for a firm, such as solvency and profit ratios, had an effect on the probability of obtaining a bank loan in 2007 (pre-crisis) and in 2009-10 (during the crisis). They found that while firm characteristics did *not* appear to matter in 2007 for whether or not a bank would grant a loan – reflecting that almost all firms got their loan applications accepted in 2007 – they *did* matter in 2009-10. This could indicate that the high lending growth in the years prior to the financial crisis was partially a result of an easing of credit standards by banks and they thereby actively contributed to the expansionary phase of the credit cycle.

Banks' credit standards affect the risk on their assets and can have an impact on the level of credit, e.g. by allowing credit-constrained households to borrow more. But in order to finance changes in their supply of credit banks will also have to change the composition of their liabilities over the financial cycle. Shin (2013) therefore considers the composition of bank liabilities "*as a signal of the degree of risk-taking by the bank and hence of the stage of the financial cycle*" (Shin (2013, p. 8)). One simple metric in this regard is the customer funding gap – the gap between customer loans and deposits.

When bank lending is increasing more rapidly than deposits this is suggestive of increased risk-taking by banks which in turn can contribute to an expansion of the financial cycle. Consistent with this there is a clear tendency for the customer funding gap and the credit cycle to co-move, cf. Chart 8 (left). A high customer funding gap, i.e. a high reliance on other funding sources than deposits – such as wholesale market funding – also exposes banks to sudden shifts in market sentiment and the potential for "liquidity crunches". In turn this might force banks to reduce lending and thereby contribute to a "credit crunch" (i.e. a sharper reduction in the supply of credit by banks than what the underlying economic development could justify) that can amplify the contractionary phase of the credit cycle. In addition to this, banks also appear to lever up during the expansionary phase of the credit cycle and de-lever during the contractionary phase, cf. Chart 8 (right). A poorly capitalized bank is vulnerable and therefore could choose to reduce its supply of credit to reduce the size of its balance-sheet (i.e. de-lever) in the face of a negative shock. Hence, the tendency for leverage to follow the credit cycle could be another indication that banks contribute to the contractionary phase of the credit cycle by reducing their supply of credit more than what real developments can justify.

Customer funding gap (left) and leverage (right) together with the credit cycle Chart 8



Note: The customer funding gap is calculated as the difference between lending and deposits and is illustrated as a share of lending. The credit cycle is estimated using an unobserved component model.
Source: Finanstilsynet and Danmarks Nationalbank.

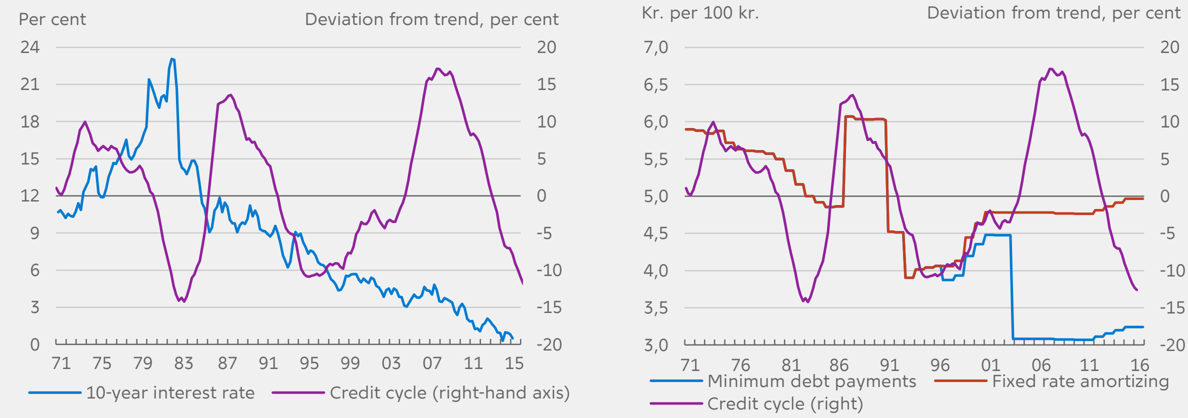
Although both the capital situation and liquidity situation of banks in 2008 in particular would suggest that a credit crunch could have taken place, Abildgren et al. (2011) and Abildgren and Kuchler (2013) did not find any indications of banks' lending capacity being an impediment to the general development in lending, suggesting that a credit crunch did not take place during the financial crisis. Their analyses did, however, indicate that banks' credit standards were tightened from a lenient pre-crisis level, but despite of this the overall level of credit-to-GDP did not decrease substantially following the financial crisis. Something that Abildgren and Kuchler (2013) relate to the ability of mortgage credit institutions to meet the credit demand of households and firms and the considerable government interventions in the form of bank rescue packages that provided capital and liquidity relief for the Danish banking sector.[10]

Other factors, such as changed financial regulation, also appear to have had an effect on the evolution in credit. Interestingly, changes in financial regulation differed substantially in the periods leading up to the crisis in 1987-93 relative to the financial crisis of 2008-09. The credit boom of the early 1980's – that was partially driven by a sharp decrease in interest rates, cf. Chart 9 (left) – led policymakers to tighten the financial regulation making it more costly to borrow, cf. Chart 9 (right). Leading up to latest financial crisis, there was instead a substantial financial liberalization by allowing interest-only loans. These loan-types contributed to the increase in housing prices and credit at the time by decreasing the minimum first-year payments necessary to service a mortgage, cf. Dam et al. (2011). Overall, the financial regulation was largely counter-cyclical during the boom of the late 1980'ies (perhaps the tightening came a bit late) but it was somewhat pro-cyclical during the last boom.

[10] See e.g. Ministry of Business and Growth (2013) for a description of the bank rescue packages that were implemented during the financial crisis.

Interest rates (left) and the payments for servicing mortgage debt (right) together with the credit cycle

Chart 9



Note: The credit cycle is estimated using an unobserved component model, cf. below. Right chart: The red line shows the yearly payment of a fixed-rate mortgage loan after tax. Swings reflects changes in interest rate, tax deductibility, maturity and amortization profile (during part of the 1980'ies it was mandatory to take part of the loan as a serial loan). The blue line is the minimum payments required to service mortgage debt. From 1996 to 2002 it represents payments on a variable rate loan with amortization and from 2003 and onwards it represents payments on a variable rate loan without amortization.

Source: Danish FSA and Danmarks Nationalbank.

In sum, particularly for the period leading up to the financial crisis there is evidence suggesting that banks' lenient credit standards contributed to increases in credit growth above and beyond what real developments could justify. This coincided with a loosening of the financial regulation that also contributed to the increase in housing prices and credit. At the same time banks have tended to increase the risk on their liabilities during the expansionary phase of the credit cycle by reducing their loss absorbing capacity and relying more on unstable funding sources. In turn this made them more vulnerable towards negative shocks and increased the likelihood of a credit crunch. Although a credit crunch did not appear to take place during the financial crisis, the state of the Danish banking sector during the crisis necessitated considerable government interventions and coincided with a reduction in banks' share of lending relative to mortgage credit institutions.

THE DANISH FINANCIAL CYCLE(S)

The properties of the financial cycle are likely to depend on the financial regime, the monetary policy regime and the fiscal policy regime, as argued by Borio (2014). Both the mortgage-credit institutions and the fixed exchange rate regime in Denmark are to some extend special features of the Danish economy. We therefore seek answers to the following questions:

- Which variables should we include in a financial cycle for Denmark?
- How does the financial cycle look for Denmark?
- What is the relationship between real and financial variables?
- Are our findings robust in real-time?

WHICH VARIABLES SHOULD WE INCLUDE IN A FINANCIAL CYCLE FOR DENMARK?

In this section we study which variables should be included in a financial cycle for Denmark. We look for financial variables with a strong degree of co-movement and where the medium term cycle is predominant. Our search is limited to variables typically studied in the literature. These include house prices, credit, stock prices, interest rates, exchange rates, trade data and oil price, cf. Box 5.

DATA Box 5

We use data for the following variables with source in parentheses:

- GDP, (MONA[1] database)
- Loans to households and NPISH, All sectors, market value, adjusted for break (BIS database)
- Private non-financial sector, total credit volumes, all sectors, market value and real (BIS database and DN)
- Loans to non-financial corporations, all sectors, market value, adjusted for breaks, (BIS database and DN)
- House prices, index for single family houses in Denmark (MONA database)
- Stock index, OMXC20 index, (MONA database)
- Long interest rate, 10-year government bond, (MONA database)
- Interest rate spread, Long interest rate minus money market rate, (MONA database)
  Spread between bank deposit and lending rate, (MONA database)
  German 10-year bund rate, (MONA database)
- Effective exchange rate, (MONA database)
- Dollar exchange rate (MONA database)
- Oil price, (MONA database)
- Trade balance to GDP ratio, (MONA database)

Real variables are constructed deflating the series with the GDP deflator. We consider the longest possible sample, 1971-Q1-2016-Q3 on a quarterly frequency.

1. MONA is Danmarks Nationalbank's macro-economic model. The data in MONA is mainly from Statistics Denmark and Danmarks Nationalbank.

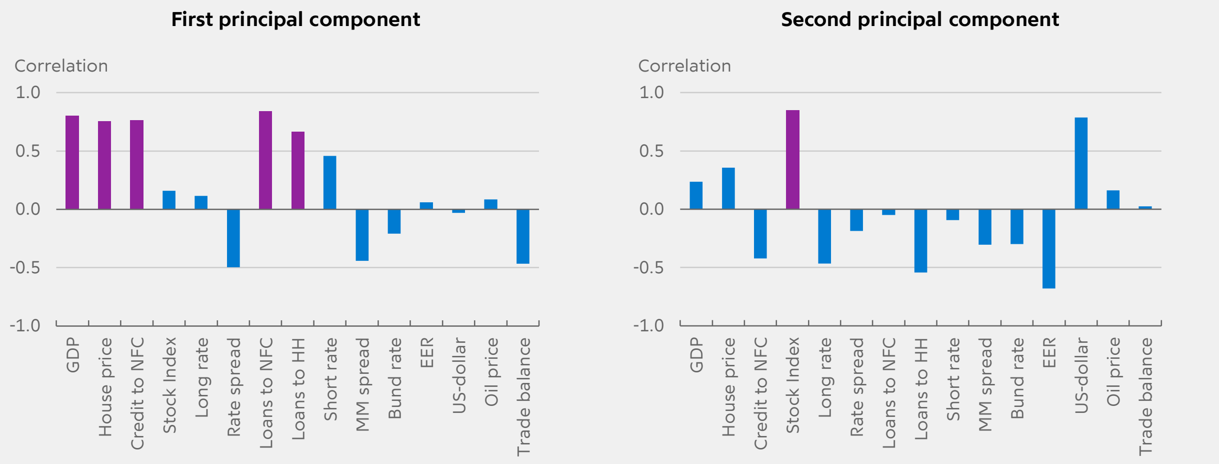
For studying the co-movement, we first extract the cyclical movement of each variable using a Band-pass filter identifying cycles between 2 and 30 years. In this way co-movements in both business and medium-term cycles are captured. We apply the filter individually on each time-series.

For evaluating the degree of co-movement, we do a principal component analysis of the data set. A principal component analysis converts series of data into a linearly uncorrelated variables or principal components. The transformation ensures that the first component accounts for as much of the variability as possible. The individual data series load with a factor on this first component, and this loading helps to determine, firstly, the importance of this variable in explaining the movements in the component, and, secondly, whether it co-moves strongly with other variables.

A high loading indicates that a certain variable follows the respective common factor to a large degree. GDP, the real house price, and the credit variables have a relatively high loading on the first principal component, cf. Chart 10 (left). The stock price has a relative low loading on the first principal component, while its loading on the second component is relatively high.

Principal component analysis of cycles 2-30 years

Chart 10



Note: Factor Loadings on Principal Components, first and second factor. The two charts show the factor loadings for each variable in the data set for the first (left chart) and second factor (right chart).
Source: Own calculations.

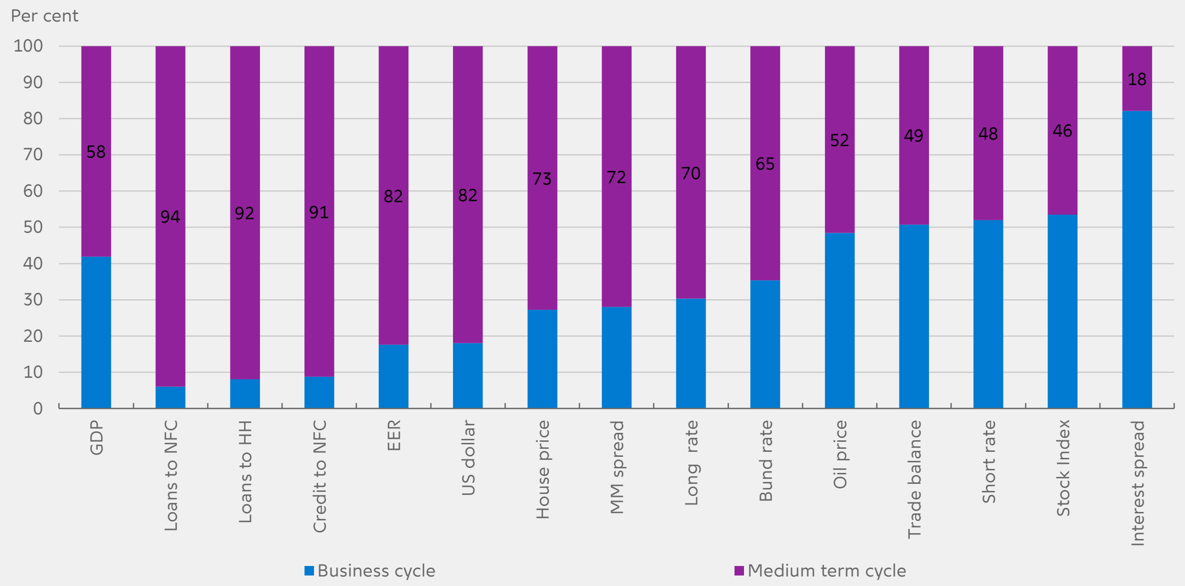
As GDP, the real house price, and the credit variable have relatively low loadings on the second component, we conclude that the stock price follows a different component than these variables, and the stock price should therefore not be included in a financial cycle.

Next, we analyze how important the medium-term cycles are compared to the business cycle frequencies. To this end, again we apply the band-pass filter to identify business cycle (8-44 quarters), and medium-term cycles (44-120 quarters). The results are shown in Appendix A3.

A visual inspection indicates that cycles for especially loans to households and credit to non-financial institutions are dominated by the medium term cycle in the sense that the medium-term cycle in these variables explains a relatively large part of the total cycle. The real house price falls in between. That is, for the real house price, the business and medium-term cycle explain an equal part of the total cycle.

This is confirmed by a formal variance-decomposition. The relative importance of the business and medium-term cycles respectively can be determined by decomposing the variance of the total cycle into a part coming from each sub-cycle. A property of the band-pass filter is that the business cycle and the medium-term cycle are orthogonal. The variance of the total cycle is therefore simply the sum of the variance of each of the two sub-cycles. In Appendix A6 we show that the variance-decomposition is stable over time, and therefore not just a result of the severe financial crises of 2008-10.

Variance-decomposition Chart 11



Note: Variance-decomposition of the total cycle for the period 1971Q1-2016Q3. The total cycle is defined as the sum of the business and medium term cycle. The business cycle is cycles of frequencies of 8-44 quarters, and the medium term cycle is cycles of frequencies of 44-120 quarters.
Source: Own calculations.

Credit variables are the ones with most of the total variance explained by the medium-term cycle (up to around 90 per cent), cf. chart 11. The medium-term cycle is also very dominant (explains more than 70 per cent of the total variance) for real house price and long-term interest rate. For GDP around 50 per cent of the variance is explained by the medium-term cycle.

The combined results from the principal component analysis and the variance decomposition allow us to decide on which variable to use in the financial cycle. Real house prices and credit are both highly correlated with the first common component of the analyzed financial variables. Furthermore, the variance in the total cycles of both these variables is dominated by the medium term. We therefore base a financial cycle for Denmark on these two variables. Intuitively, credit captures financing constraints, while the real house price captures expectations of the future state of the economy and risk. Only total credit to non-financial sector is included, as having credit to households and firms separately does not change the results qualitatively. Although GDP in fact contains a significant medium term cycle and is strongly correlated with credit and house prices we do not include GDP into a financial cycle, as we are looking for co-movements on medium-term frequencies in financial variables.

UNOBSERVED COMPONENT MODEL

A clear drawback of using a band-pass filter to identify cycles is that the cycle length to a large extent is defined by the user and not estimated from data. To overcome this weakness we estimate cycles in house prices, credit and GDP in an unobserved component model (UOC). The aim is to answer the questions: How does the financial cycle look for Denmark? And what are the relationship between the different variables at different cycle lengths? To this end, we follow Rünstler and Vlekke (2016) closely. They setup a multivariate time series model that allows for correlation between the cycles. Importantly, we do not a priori define the length of the cycles; that is determined by the estimates of the parameters. The model is presented in Box 5.

Unobserved Component Model Box 6

Following Rünstler and Vlekke (2016), we model a vector of *n* time series, X'_t. In the model we use data from 1971-Q1 to 2016-Q for real GDP, real house price, and real credit; X'_t is consequently of size (183, 3). We decompose X'_t into a trend, μ_t, cyclical, X^C_t, and irregular components, ε_t, assumed to be normally and independently distributed with mean zero and a covariance matrix,

$$X'_t = \mu_t + X^C_t + \varepsilon_t$$

The stochastic trend, μ_t, is assumed to follow the process

$$\mu_t = \beta_{t-1} + \eta_t$$
$$\Delta\beta_{t-1} = \zeta_t$$

, where the level, η_t, and slope innovations, ζ_t, also are assumed to be normally and independently distributed.

The cyclical components for each variable are modelled from stochastic cycles defined as a bivariate stationary process:

$$\phi_{1t} = \rho_1 \cos(\lambda_1)\,\phi_{1t-1} + \rho_1 \sin(\lambda_1)\phi_{2t-1} + \kappa_{t1}$$
$$\phi_{2t} = -\rho_1 \sin(\lambda_1)\,\phi_{1t-1} + \rho_1 \cos(\lambda_1)\phi_{2t-1} + \kappa_{t2},$$

with decay ρ_i and frequency λ_i. κ_i are cyclical innovations which are assumed to be normally and independently distributed. We allow for different dynamics of cycles for each variable; hence we estimate potentially three different ρ_i's and λ_i's. Intuitively, the λ_i's help to determine the length of the cycles while the ρ_i's determines the peaks. We allow for cross-correlations between the cycles in the estimation such that, as an example, the cycle for GDP can affect the cycle for the real house price. Specifically, we allow for cross-correlated slope and level innovations, and thus let the cross-correlation matrices to η_t, ζ_t be lower triangular.

To provide more insight into how the model works it can be instructive to consider a univariate model for, say, GDP, y_t:

$$y_t = \mu_{t-1} + \alpha^1 C^1_{t-1} + \alpha^2 C^2_{t-1} + \varepsilon^{irr}_t$$
$$\mu_t = \mu_{t-1} + \beta_{t-1} + \varepsilon^{level}_t$$
$$\beta_t = \beta_{t-1} + \varepsilon^{slope}_t$$
$$C^1_t = c^1_{t-1} + \rho^C C^1_{t-1}$$
$$C^2_t = c^2_{t-1} + \rho^C C^2_{t-1}$$
$$c^1_t = \rho\cos(\lambda)\,c^1_{t-1} + \rho\sin(\lambda)\,c^2_{t-1}$$
$$c^2_t = -\rho\sin(\lambda)c^1_{t-1} + \rho\cos(\lambda)c^2_{t-1}$$

Hence, GDP is assumed to depend on a time-varying trend, β_t, μ_t, and a cyclical component, which is a function of sine and cosine terms. In the multivariate model, the cyclical components for, say, GDP is allowed to be dependent on past cyclical components of the other variables and vice versa.

The model is cast in state-space form, and estimated using the Kalman filter. Although Rünstler and Vlekke (2016) use classical maximum likelihood estimation, we use Bayesian techniques. This is motivated by the large parameter space, which makes the classical approach challenging. We estimate the model in Dynare 4.3.3.

We estimate the model on data for the period 1971-Q1 to 2016-Q3. We apply the model on data for real GDP, the real house price and total credit to private non-financial sector. We provide details and further results – identification (comparison of posteriors and priors), and parameter estimates – in Appendix A4. Here we will only show the main findings.

FINDINGS FROM THE MODEL

The estimated cycles for the Danish economy confirm what was found using a band-pass filter. GDP, credit and house prices are clearly highly correlated, cf. Chart 12. GDP does, however, have more turning-points, which can be interpreted as having shorter cycles. Credit and house prices have larger amplitude and the real house price and GDP are both leading the credit cycle. Apparently, GDP and house prices increase first and then credit picks up with an average lag of 8 quarters.

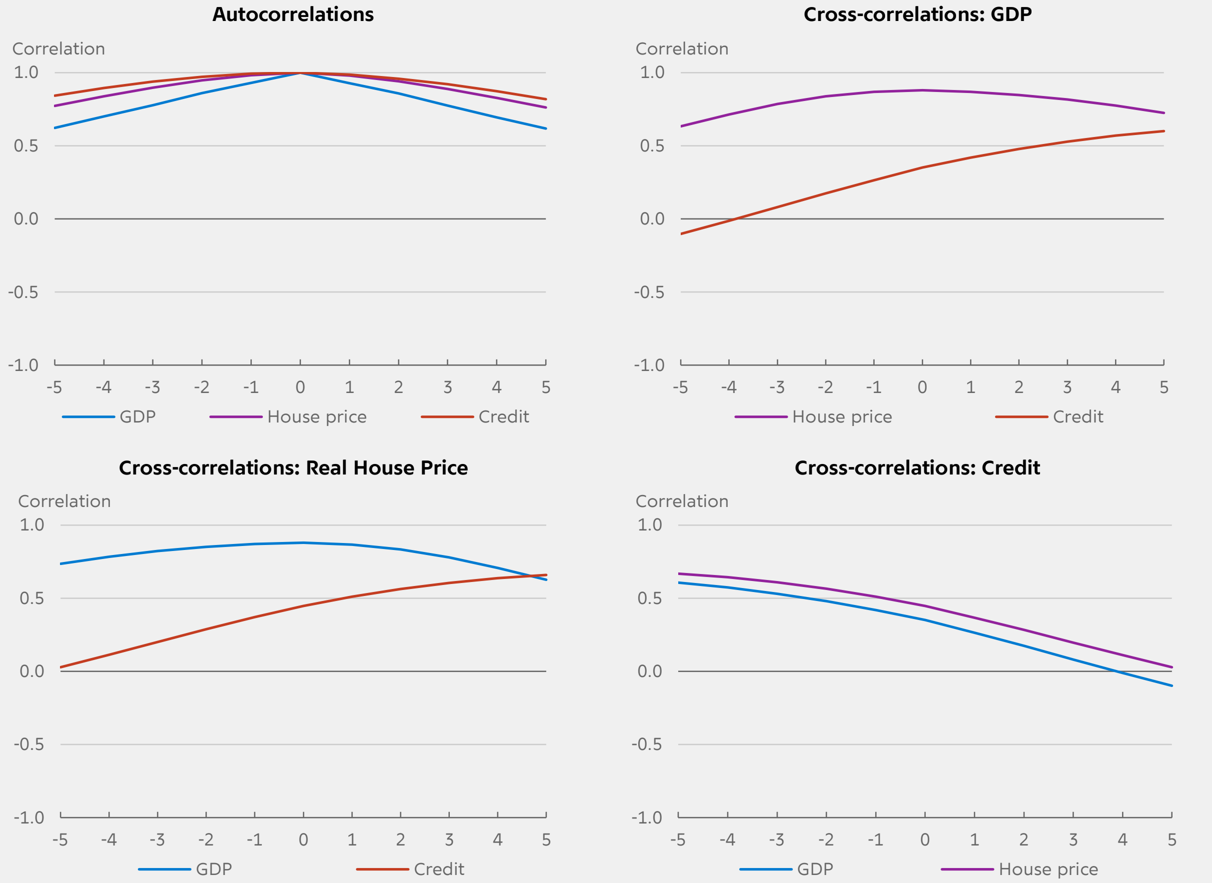
Estimated cycles

Chart 12

Note: Estimated cycles from unobserved component model.
Source: Own calculations.

The latter finding is confirmed when analyzing correlation. We observe much higher autocorrelations for credit and the real house price confirming GDP has more turning points, cf. Chart 13 (top-left). Moreover, credit clearly lags both the real house price and GDP, while the real house price and GDP are in the same phase, cf. Chart 13 (top-right). The estimate -0.16 for credit is consequently the cross-correlation between GDP at time t and credit at time -5.

Correlation for cycles Chart 13



Note: The charts show correlations and autocorrelations for the three variables in the UOC model. Top-left chart: The autocorrelations in the three cycles for 5 leads and 5 lags. By construction at lag 0 autocorrelation is 1. Top-right, bottom-left and bottom-right: Cross-correlations with respect to the variables for various leads and lags.
Source: Own calculations.

We observe that the real house price cycle is stronger correlated with the cycle in GDP than credit (the blue line is above the red line), and that the credit-cycle at long leads is negatively correlated with the GDP cycle. Cycles in GDP and real house price are highly positively correlated at time t, but both are higher correlated with credit leads 3-5. This shows that the credit cycle is lagging the other two cycles.

Based on this finding we choose not to aggregate the house and credit cycles, as an example Drehmann et al. (2012). The house-price cycle seems to lead the credit cycle, which is a property of the cycles that potentially can be exploited in policy – the house-price cycle is an indicator of future credit growth.

We provide summary statistics for the estimated cycles, cf. Table 2. It can be seen, that on average the standard deviation of the GDP cycle is 2.75 per cent. This is only half of the credit cycle while on average the real house price gap is almost 5 times larger. However, while GDP and the real house price are highly correlated and in the same phase, the credit price and real house price cycle are longer than the GDP cycle. Furthermore, the total variance of the cycles is dominated by the medium term cycle for credit and the real house price, while this is less so for GDP.

Some characteristics of estimated cycles

Table 2

	GDP	House price	Credit
Standard deviation, cyclical component	2.73	12.75	6.03
Cycle length (quarters)	36	48	48

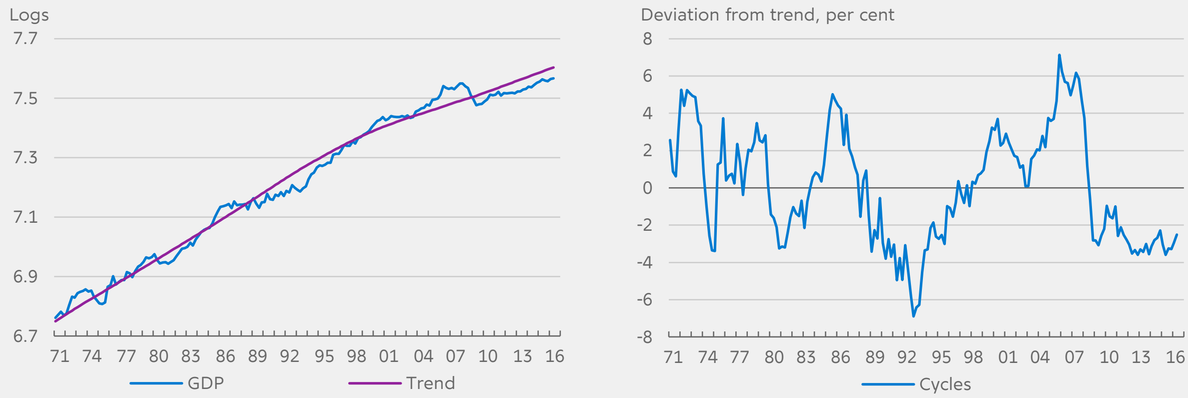
Note: The results are based on spectral theory, see Hamilton (1994) and Vlekke and Runstler (2016).
Source: Own calculations.

Trend and cycles

For GDP we find constant trend growth up until the outbreak of the financial crisis, cf. Chart 14. At this point, the trend growth rate falls markedly. The model consequently captures some of the large fall in real GDP after the outbreak of the financial crisis with a break in the trend. This can be interpreted as a fall in the economy's long-run growth rate or potential growth. The estimated cycle reflects quite closely a priori information about the Danish economic history. As an example, the crisis in the 1980s and the financial crisis are clearly detectable.

Real GDP

Chart 14

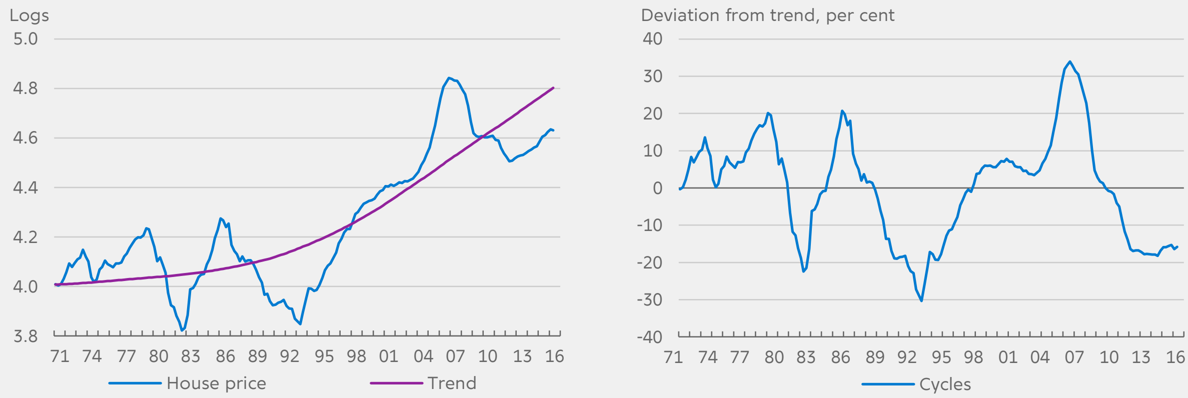


Note: Estimated cycle, trend and slope from unobserved component model. Left chart: Data and estimated trend. Right chart: The estimated cycle.
Source: Own calculations.

Turning to the real house price, the model finds an up-swing in the trend around the beginning of the 1990s, cf. Chart 15. Comparing the cycle for the real house price with the cycle for GDP it has decidedly higher amplitude. The very rapid increases in real house prices during the 2000s pushed up the trend in the real house price. This leaves a quite large negative house price gap at the end of the sample.

Real house prices

Chart 15

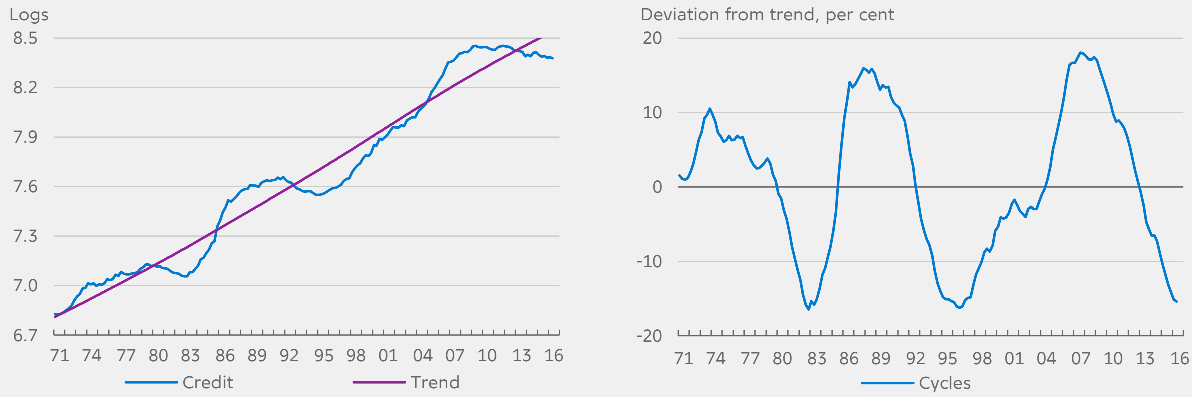


Note: Estimated cycle, trend and slope from unobserved component model. Left chart: Data and estimated trend. Right chart: The estimated cycle.
Source: Own calculations.

For credit, we observe an almost linear trend, or, equivalently, a constant slope, cf. Chart 16. Also, the cycle is smoother with fewer turning points compared to the cycle for GDP and the real house price. As an example, according to the model, the credit cycle has been contracting throughout 2008 to the end of the sample.

Credit

Chart 16



Note: Estimated cycle, trend and slope from unobserved component model. Left chart: Data and estimated trend. Right chart: The estimated cycle.
Source: Own calculations.

Summarizing the findings from the unobserved component model, we confirm the findings from the filtering analysis: Cycles in especially credit are smoother and have fewer turning points than cycles in the real house price and GDP. We also stress differences in amplitude: The cycles in credit and the real house price have much larger amplitude. There also seems to be a clear lag structure between the cycles with the real house price and GDP being highly correlated and leading the credit cycle.

REAL-TIME ANALYSIS AND ROBUSTNESS

In this section, we analyze the robustness of our estimates in real-time, as reliable policy recommendations depend on whether the cycles can be estimated in real-time. In Appendix A5 we look at the ability of the model to forecast.

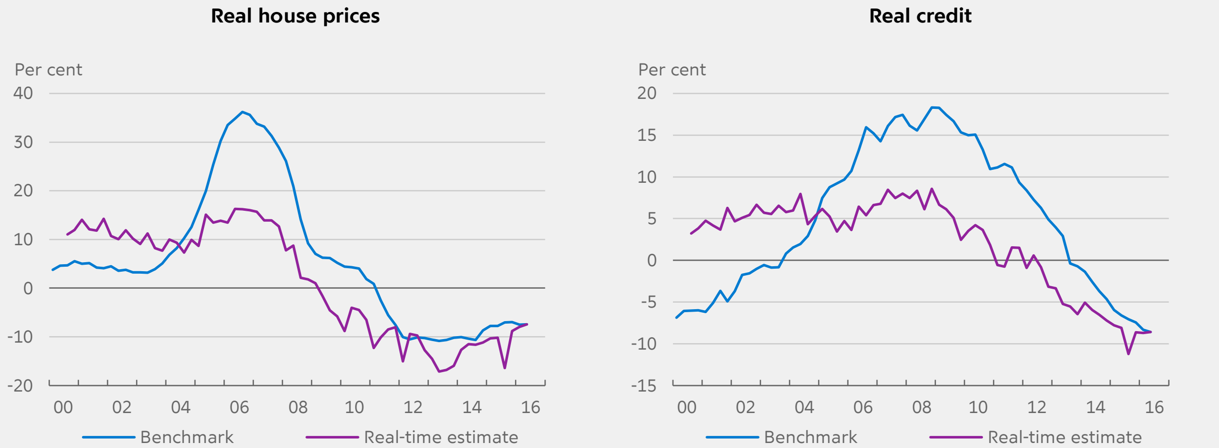
In general, possible lack of robustness in real-time can be attributed to data revisions, filter uncertainty and parameter uncertainty. Here, we will only consider parameter uncertainty and filter uncertainty; although data revisions can play a role, the source to unreliability of econometric models in real time can largely be attributed to the first two sources.

The challenge for the model is to separate cycle from trend in real time. It can be relatively easy for the model to distinguish this ex post when more information has been received. But when an increase in a variable happens, it can be hard to distinguish between movements in trend and movements in cycles.

To evaluate how the model performs in real time, we re-estimate it each quarter starting from 2000Q1 until the end of the sample. In doing so, we started out with the relatively uninformative priors also used in the benchmark model when estimating the model on the 1999-Q4 subsample. We then use the posteriors as priors in the next estimation for 2000-Q4 and so forth. We use the estimation based on the full data set presented in the previous section as our benchmark to which we compare our real-time estimates.

For the real house price there are some level effects at the beginning of the sample due to the acceleration in the growth rate of house prices around the beginning of the 1990s. So, in real time the model indicated a house price boom all through the 2000s. During the boom period 2005-07, the model does capture a real house price gap in the real time, but the size of the gap is only about half the gap based on the full sample, cf. Chart 17 (left). The downturn is captured with some precision. The same observations concern the credit gap, cf. Chart 17 (right).

Recursive estimates of real house price and credit cycles Chart 17

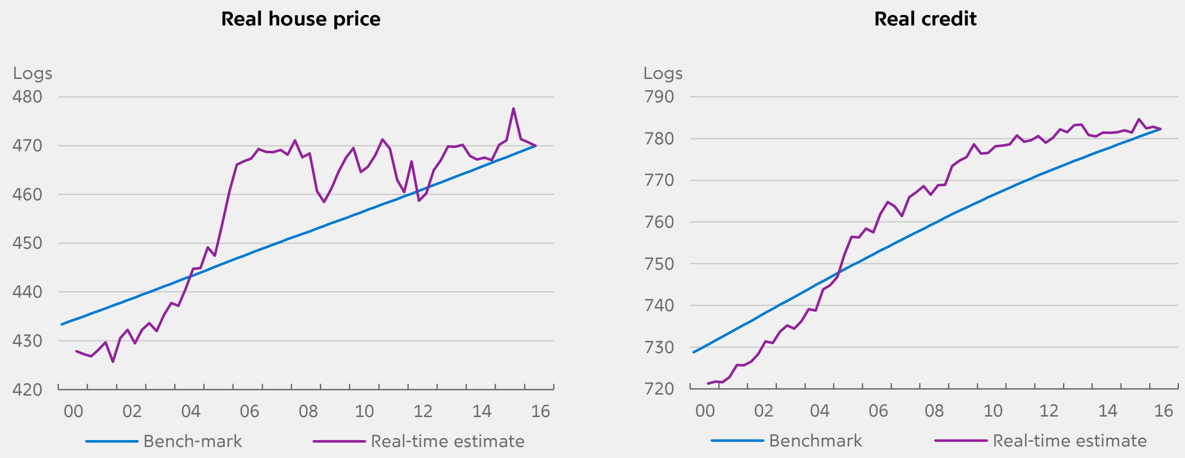


Note: Starting from 1971Q1 to 2000Q1 we add one data point at time reestimating the parameters and run the Kalman-filter. The thick red line corresponds to the last estimate of the various samples. The thick black line is the full-sample estimate of the cycle.
Source: Own calculations.

One reason for why the model has difficulties in detecting the size of the gaps in real time, is that the model attributes a sequence of positive shocks to the variables as shocks to the trend. So the recursively estimated trends are consistently above the full-sample-trend during the boom years for house prices and credit, cf. Chart 18. That is, the boom pushes the trend up and therefore the size of the gap down. Another reason for why the model has difficulties in detecting the gap is parameter uncertainty. That is, the parameter estimates change over time as new data is used in the estimation, and this implies different estimates of the gap relative to the bench-mark estimate, which uses the whole sample to estimate the parameters of the model.

Recursive estimates of house price and credit trend

Chart 18

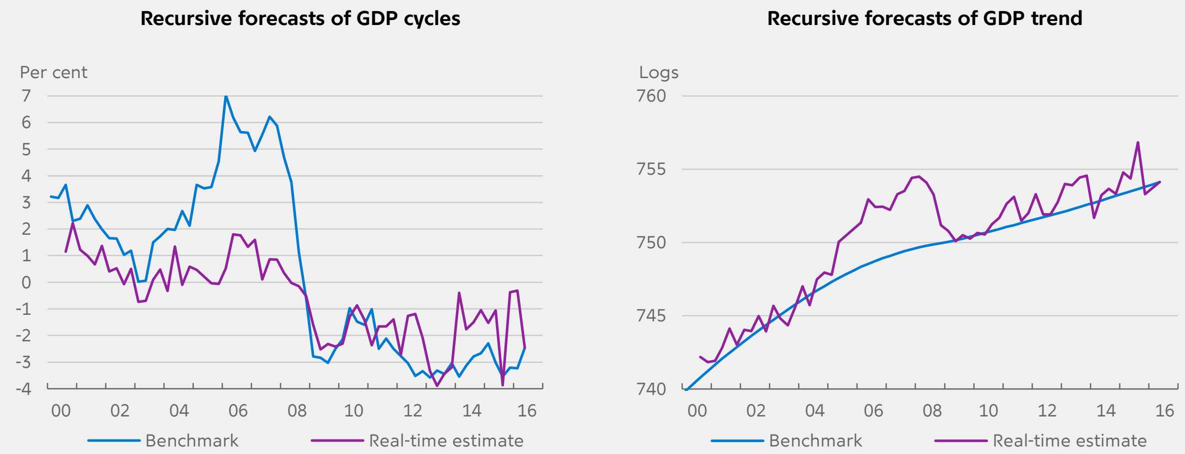


Note: Starting from 1971Q1 to 2000Q1, we add one data point at time re-estimating the parameters and run the Kalman filter. The real-time estimate corresponds to the last estimate of the various samples. The benchmark line is the full-sample estimate of the cycle.
Source: Own calculations.

Regarding GDP we find that the model has trouble detecting the boom in the Danish economy from 2003 to the outset of the financial crisis in 2008-Q3, cf. Chart 19. Only in 2006 did the model point to a positive gap but only of around 1/3 of the "true" gap. However, once again the downturn is captured closely in real time.[11]

Recursive estimates of the GDP cycle and trend

Chart 19



Note: Starting from 1971Q1 to 2000Q1, we add one data point at time re-estimating the parameters and run the Kalman filter. The real-time estimate corresponds to the last estimate of the various samples. The benchmark line is the full-sample estimate of the cycle.
Source: Own calculations.

[11] The output gap estimated by Danmarks Nationalbank did also under-estimate the true size of the gap in real time.

Finally, one advantage of using an estimated model and not a filter is that an estimated model can provide an estimate of the uncertainty surrounding the cycles, cf. Chart 20.

Uncertainty bounds

Chart 20

Note: Estimated cycles and uncertainty bounds from unobserved-component model. The uncertainty bounds are the upper and lower bound of a 90 per cent highest probability distribution interval. It can be thought of a being analogous to confidence intervals in frequentist statistics.
Source: Own calculations.

We have chosen only to show the end of the sample to highlight the uncertainty bounds. For the GDP cycle the uncertainty surrounding the mean estimate is of an order of magnitude of +/- 0.5 percentage points on average, but higher at the end of the estimation sample. For the real house price and credit the uncertainty is somewhat higher; of an order of around +/- 5 percentage points. This again underscores the uncertainty of relying too much on the point estimate. But it also highlights the advantage of using a model, as it provides an estimate of the uncertainty.

A VAR-MODEL OF THE CREDIT-TO-GDP RATIO

Filtering techniques – such as the ones applied in the above – basically focuses on trend removal. This implies that the focus is on the growth rates such as that in credit relative to the trend growth. To complement this approach, the purpose of this section is two-fold: First, we will specify two long-run credit-to-GDP relationships, following the approach in Juselius et al. (2016).

Second, these long-run relations are embedded in a VAR-model including total credit to Danish households, GDP, housing prices and interest rates. By estimating the resulting vector error-correction form, the interaction between these long-run relationships and short-run dynamics can be assessed. The model is described in Box 7.

The approach makes use of the common stochastic trends shared by GDP, the aggregate level of credit, house prices, and the long-term interest rates. This is a simple (albeit a bit crude) way to determine the interaction between real and financial variables at the aggregate level and to separate short-term movements from those around a long-run equilibrium by using their historical correlations.[12] It should be noted, that this approach cannot be interpreted as a structural equilibrium of the debt level, e.g. based on utility optimizing households. Instead it is a statistical equilibrium in the co-integrating sense, based on historical correlations

At the core of the model are two co-integrating relationships that define the long-run relationships: The first assumes that leverage – defined as the aggregate credit to Danish households as a fraction of their total housing wealth – is assumed to be constant in the long run. Under certain assumptions, this leverage constraint is consistent with a co-integrating relationship between the credit-to-GDP ratio and a house price index.[13] A similar leverage constraint is often found in the theoretical macroeconomic literature. This is typically motivated by some sort of asymmetric information problem combined with limited liability of the borrower. However, a constant long-run equilibrium level of leverage also seems like a natural consequence of financial regulation such as the LTV-limit of 80 per cent on Danish mortgage loans obtained from MCI's. There might be short-term deviations as house prices go up, e.g. when leverage decreases for existing home owners and only new owners enter the housing market with mortgage loans close to the LTV-limit.

The second relationship assumes that the aggregate debt burden is constant in the long run. If debt is structured as an instalment loan at the aggregate level, this relationship is the (log-) linear approximation of the aggregate debt-service ratio, which we will denote the debt-service burden (see Juselius & Drehmann (2015) for a discussion hereof). It is given as a (log-) linear relationship between aggregate household credit, GDP, and the average interest rate after taxes. In the simplest sense, the assumption of a constant long-run debt burden implies that the credit-to-GDP is inversely related to the average interest rate. At the household level, lower interest rates means that more debt can be taken on for a given income. Conversely, a limit to the debt burden rules out a continuing roll-over of debt by taking on new debt. For borrowers, a higher debt burden would reduce their consumption/investments provided that no new debt is taken on. However, at the aggregate level the relationships between the debt burden and household expenditure is less clear as the interest rate payments serves as income for lenders. Ultimately, this is an empirical question and depends for example on the relative marginal propensity to consume for lenders and borrowers, respectively.

12 One simplifying assumption is that pension's savings are ignored.

13 Specifically, it is assumed that a fixed proportion of real output is invested in real, pledgeable assets, and that these assets have a constant depreciation rate. These assumptions will be discussed below.

The vector error correction model Box 7

Formally, the two long-run relationships are defined as

$$cr_t - y_t - \beta_{1,1} - p_t^h = 0$$
$$cr_t - y_t - \beta_{2,1} - \beta_{2,2}\tilde{r}_t = 0$$

where cr_t is credit, y_t is GDP, p_t^h is a house price index, and $\tilde{r}_t$ is the average interest rate after tax deductions on the existing stock of credit.[14] Small letters denote the natural logarithm has been taken. All variables except for the interest rate have been deflated by the implicit GDP deflator.

These two co-integrating relationships are embedded in the following, otherwise standard VAR model

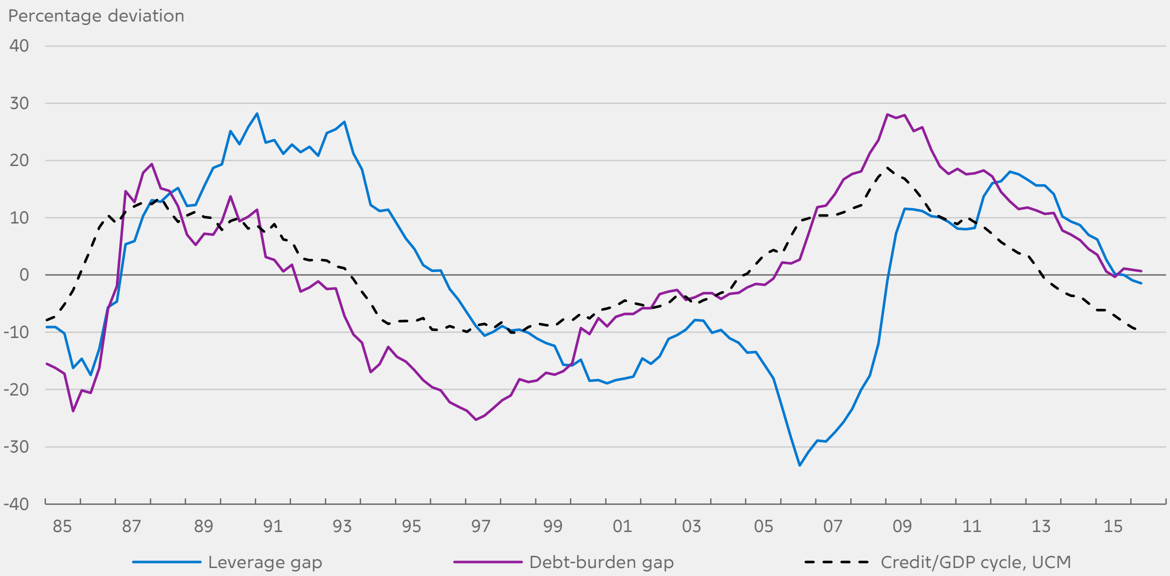
$$\Delta X_t = C + \sum_{j=1}^{p} \Phi\, \Delta X_{t-j} + \Gamma D_t + \alpha\beta' X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\Omega)$$

where $X_t = (cr_t, y_t, p_t^h, \tilde{r}_t)'$. A number of impulse dummies, D_t, are included for periods with very large residual outliers that otherwise affect the estimated dynamics of the model and violates the normality assumption. α and β are both $4 \times r-$ matrices, where r is the number of co-integrating relationships that characterizes the long-run properties of the model. $\beta' x_{t-1}$ is an $r \times 1$ vector of stationary linear relations, whereas α can be interpreted as the force with which the system is pulled back towards its long-run equilibrium – defined as the credit-to-GDP ratio consistent with asset prices and the interest rate. The rank r of $\alpha\beta'$ is tested by Johansen's trace test and is found to be two at the 10 percent significance level.[15] The model is estimated on quarterly data from 1985Q1-2016Q2. All data comes from the MONA database.

The assumption of co-integration is formally tested and confirmed at the 10 per cent significance level in the fully specified VAR model with short-term dynamics, cf. Box 7. We find that there are persistent residuals from our statistical long-run relationships over the sample considered, cf. Chart 21. The estimated residuals, especially in the debt-burden gap exhibits a cyclical pattern similar to the financial cycle, defined as the cyclical component of the aggregate credit in Denmark found in the above. The residuals are stationary which implies that a high credit-to-GDP ratio precedes periods of below-trend credit growth, relative to GDP. The cycles are persistent and the length of these cycles tends to be longer than the average business cycle, consistent with the filtered cycle found previously. Currently, both the leverage and debt-burden gaps are close to zero. Both gaps have been declining steadily but slowly since the crisis.

[14] See Juselius et al (2016).
[15] This and other test statistics can be found in the appendix.

Residuals in the long-run relationships of credit-to-GDP ratio of households Chart 21



Note: The deviations from the long-run equilibria for the leverage and debt-burden relationships, respectively.
Source: Own calculations.

Leverage in Denmark was low before the crisis as house prices increased faster than credit expanded. However, when house prices began to decline in the second quarter of 2007, leverage increased rapidly as household assets depreciated. As a result, the estimated leverage gap increased by more than 40 percentage points in the period from 2007 to 2009. Generally, we find that the leverage is a strong predictor of the subsequent development in aggregate credit growth. As we will discuss below, this implies that house prices are an important catalyst for the Danish medium-term debt cycle, consistent with the earlier findings that the housing cycle tends to lead the credit cycle.

The debt-burden gap exhibits two different patterns: First, changes in the average interest rate after tax due to political reform or changes in financial regulation have induced somewhat sudden shifts in the debt-burden gap at times. Examples include the introduction of mixed-loans 1987 or the introduction of adjustable-rate loans in 1996. Several tax reforms have reduced the deductibility of interest rate expenses since 1985. Second, there is a persistent component consistent with the fact that credit adjusts only slowly over time. The debt-burden gap tends to have turning points later than the (inverse of the) leverage gap. For example, the leverage gap troughed in the 2006Q3 whereas the debt-burden gap peaked in 2009Q1.

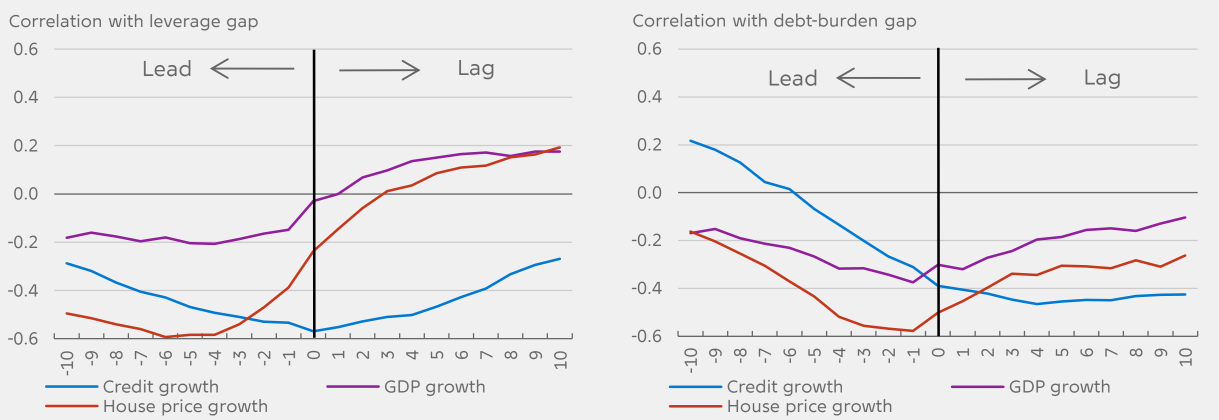
The estimated leverage and debt-burden gap of course says nothing about the causality. However, before looking at the full model with short-term dynamics it is illustrative to consider how the long-run disequilibria are correlated with the variables in the system.

Let us consider first the leverage gap: Credit growth is negatively correlated with the leverage ratio for both leads and lags; cf. Chart 22 (left). This is not surprising as a high aggregate leverage ratio implied that more borrowers will be credit constrained, since the value of their collateral is relatively low compared to the stock of debt. Subsequently, we would expect that households are unwilling or unable to continually increase their credit at a fast pace. This effect is highly persistent with the correlation only slowly tailing off, which underlines the slow-moving characteristics of credit accumulation and deleveraging. Higher house price growth on the other hand clearly seems to be associated with a lower leverage gap. This is consistent for example with the recent crisis where house prices decreased the leverage for home owners as credit followed only partly and at a slower pace. It is worth noting that the pattern of correlations between the leverage gap and GDP and house prices are qualitatively very similar, underlining the close relationship between the housing market and the real economy in Denmark as discussed earlier.

Now consider the debt-burden gap: Credit growth is negatively correlated, especially as the lag length increases, cf. Chart 22 (right). The correlation between credit growth and the debt-burden gap increases steadily for leads and turns positive at leads of more than 6 quarters, which is a reflection of the slow moving characteristics of credit. A positive debt-burden gap is also associated with subsequent lower GDP and house price growth but this effect is less persistent.

Variable correlations with long-run disequilibria

Chart 22



Note: The correlations are shown for growth rates in credit, GDP, and asset prices as well as changes in the interest rate.
Source: Own calculations.

Overall, the correlations suggest that the long-run adjustments to disequilibria happen to a large extend via changes in the credit growth but that this happens with a substantial lag.

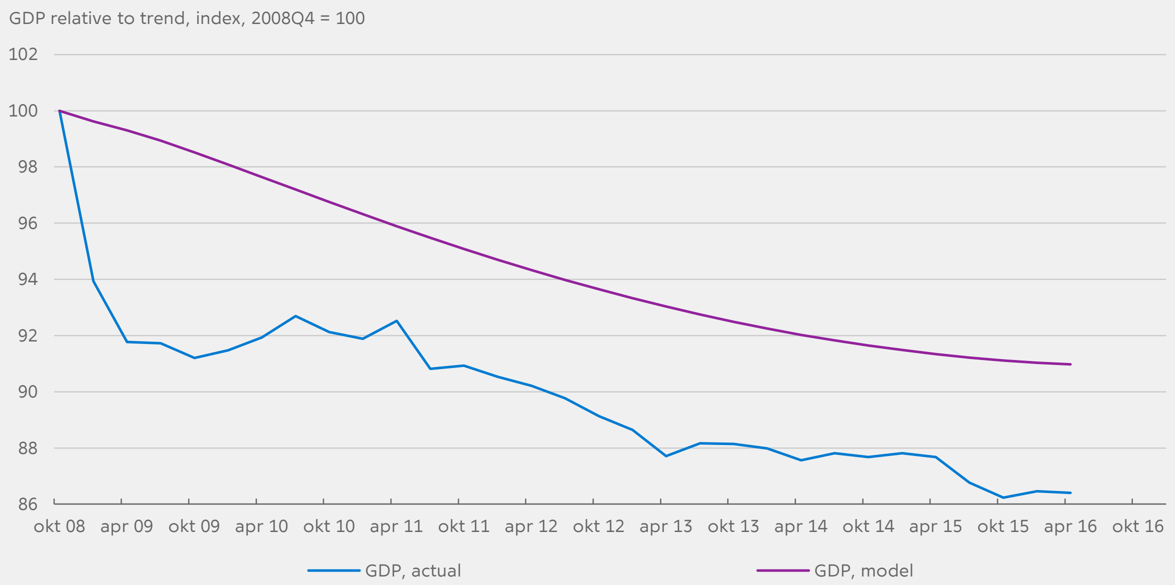
SHORT-TERM ADJUSTMENT TO A POSITIVE DEBT-BURDEN GAP

Next, we will examine the effects of the financial cycle specified in the above on the real economy. This allows us to study e.g. the drag on the real economy coming from debt overhang. In order to do so, we look at the full estimated model with short-term dynamics and the long-run relationships combined. We find that a higher debt-burden gap is associated with subsequent lower economic growth. Danish households have increased their gross debt by a lot, and at the same time they have built up large amounts of wealth in pension. This means that interest rate income will only increase the disposable income with a large lag while interest-rate expenditures affect the household budget more quickly.

Next, as an experiment, we will see how the model reacts when the credit-to-GDP ratio is "unsustainably high". Similar to Juselius et al. (2016), we do this by specifying the initial leverage and debt-burden gaps and letting the model adjust to a new long-run equilibrium. It should be noted that this is not a classical impulse response exercise as such and we take no stance as to which underlying shocks resulted in the initial gaps. But it serves as an indication of the "drag" on macroeconomic growth in a situation when the initial credit level is high. Specifically, we will consider a scenario where the leverage gap is closed and the debt-burden gap is 25 per cent, respectively. This corresponds roughly to the situation in the beginning of 2009, cf. Chart 23. The debt-burden gap would increase rapidly if interest rates were to increase from the current very low levels without a simultaneously increase in income.

Adjustment to a 25 percent debt-burden gap, compared to 2009Q1

Chart 23



Note: The model's adjustment to the initial debt-burden gaps. The trend growth rate of 2000-05 used is approximately 0.4 per cent, close to the full sample average.
Source: Own calculations.

Credit growth drops a lot as households start deleveraging to bring the credit level back to sustainable levels; cf. Chart 23. Private expenditure is suppressed due to the high debt burden. As credit falls faster than income, the credit-to-GDP ratio decreases. The drop in both economic activity and credit implies that house prices drop substantially exerting further downward pressure on expenditure.

It takes more than 7 years before the deleveraging is no longer a drag on GDP growth after which the economy recovers with growth slightly faster than the steady state. The average quarterly GDP-growth is 0.30 percentage points lower during the first 25 quarters with an accumulated GDP loss of approximately 8 per cent, compared to trend. This is a significant drop in economic activity but still only half of what was observed during the period from 2008Q1-2014Q1, when average quarterly GDP-growth slowed by more than 0.6 percentage point, compared to the pre-crisis period from 2000. The model clearly indicates that there are important feedbacks from the financial cycle to economic activity. Further, these effects might be highly persistent which suggests that balance sheet recessions are longer than normal recessions.

CONCLUSION

Across countries there are strong co-movements in house prices, credit, and GDP at both business and medium-term frequencies. Medium-term cycles in real economic variables lead credit and to a less extent house prices but clearly causality can go in both directions. Long periods of robust growth with only few and weak contractions can lead to over-optimism among borrowers, lenders, regulators and policy makers alike which in turn can lead to the build-up of financial imbalances that can turn into financial stress. Peaks in the financial cycle have in fact historically been good predictors of financial crises both in Denmark and for other countries. The financial cycle can therefore be a useful indicator for monitoring risks that can materialize into financial stress.

In Denmark the correlation between house prices and GDP is very high and the cycles are in phase. On the other hand the credit cycle is lagging around 8 quarters. This means that the real house price is a leading indicator for credit.

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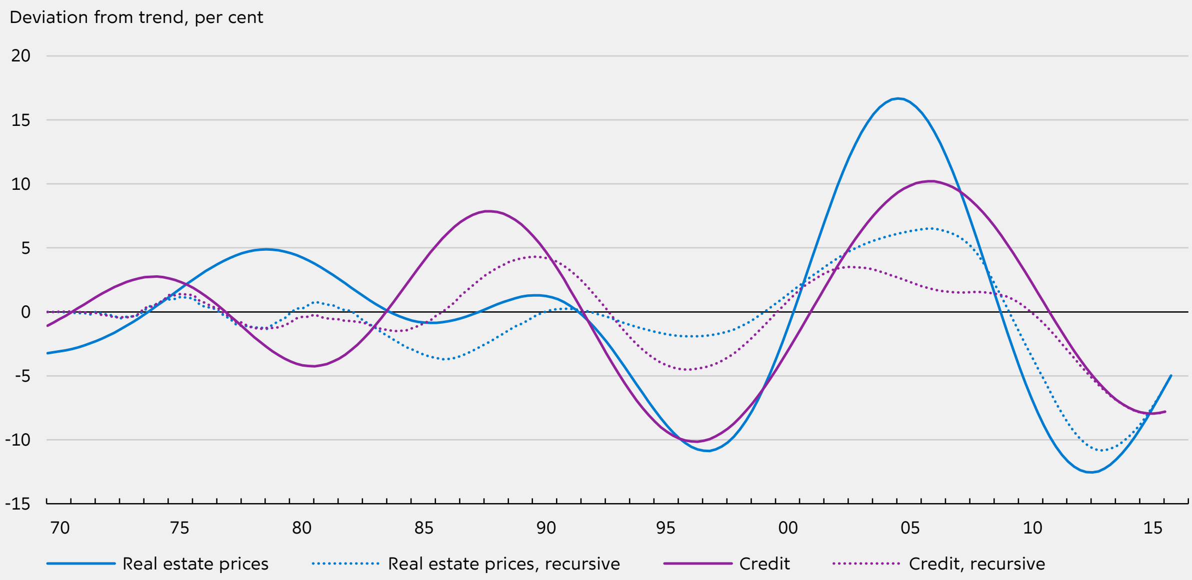
APPENDIX A1: RECURSIVE REAL TIME BAND-PASS FILTER

As noted in Box 2, the band-pass filter is time-varying so estimated cycles might change as the sample is expanded. This is very clear when looking at the financial crisis of 2008-10. The drop in house prices and credit was so large that the estimated of previous peaks went up, cf. Chart A1. Recursive estimated where the cycles is recalculated for each new observation shows that the tendency to higher volatility over time is mainly due to the financial crises. Furthermore, the recursive estimated shows that the time of peaks and troughs also can change as new data is added. This highlights the challenges of identifying unsustainable developments or bubbles in real time using the band-pass filter. Other filters have similar problem.

Difficulties with real time estimates using band-pass filter

Chart A1



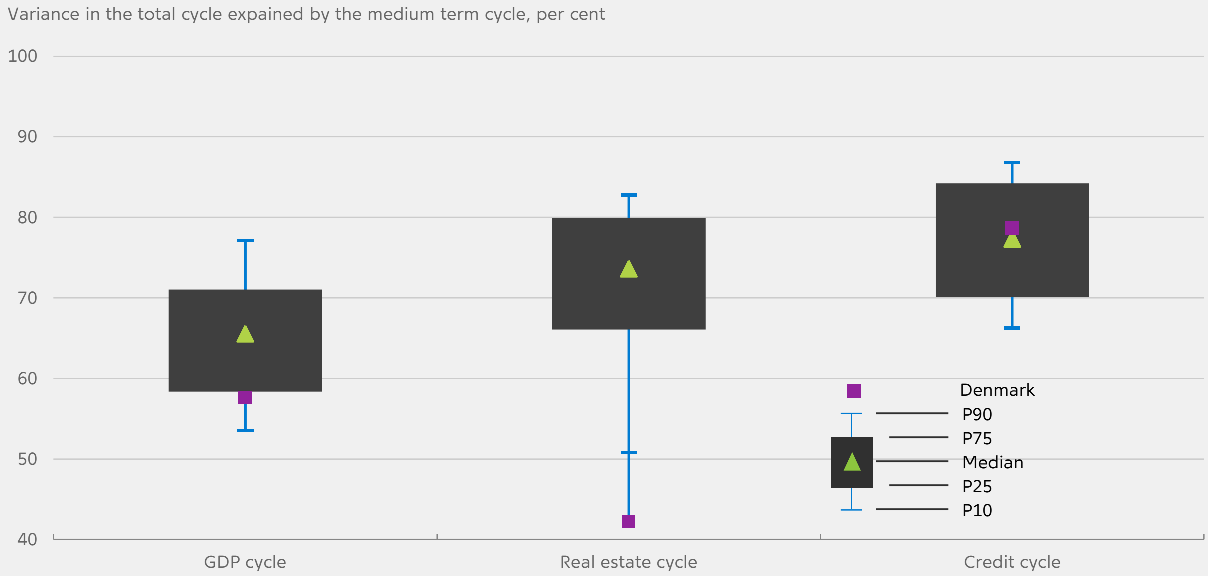
Note: For each new data point the cycles are re-calculated. Only the last observation of each cycle is shown.
Source: Own calculations on data from Macrobond.

APPENDIX A2: VARIANCE DECOMPOSITION ACROSS CROUNTRIES

Across 17 advanced economies calculations shows that the medium-term cycle is in general more important for house prices and credit than for GDP cf. Chart A2. The cyclical movements in credit are especially sluggish, i.e. the medium term cycle explains most of the volatility. This probably reflects that credit is a stock-variable and changes therefore take longer than for prices and GDP (a flow-variable). Denmark differs somewhat from other advanced countries as the short-term cycle explains a larger part of the volatility in GDP and real estate prices compared to other countries. This could be a result of Denmark being a small open economy. So both internal and external shocks affect income and production.

Variance decomposition: The medium-term cycle is more important for house prices and credit than for GDP

Chart A2



Note: Medium-term cycles are between 11 and 30 years and calculated using a band-pass filter. The total cycle is between 2 and 30 years. Data for Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK and USA.

Source: Macrobond and own calculations.

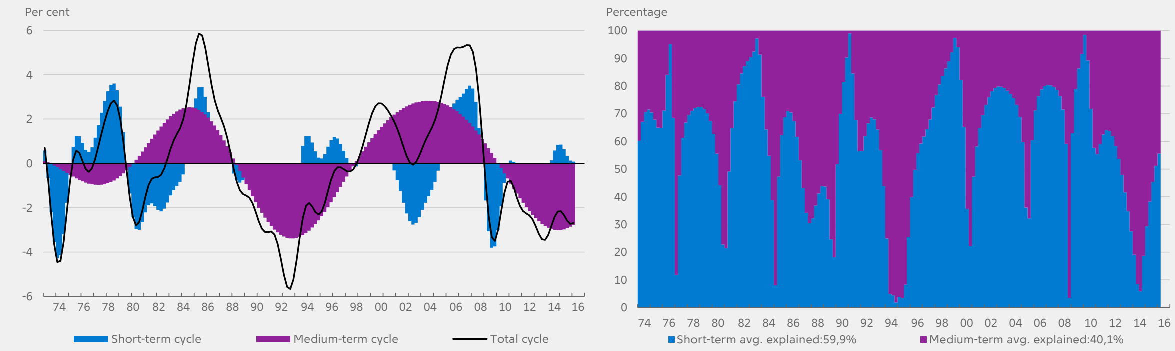
APPENDIX A3: BAND-PASS FILTER

In this appendix we show how important the medium term cycles are for Denmark compared to the short-term cycle. To this end, again we apply the band-pass filter to identify business-cycle (8-44 quarters), and medium term cycles (44-120 quarters). The results are shown in the following figures.

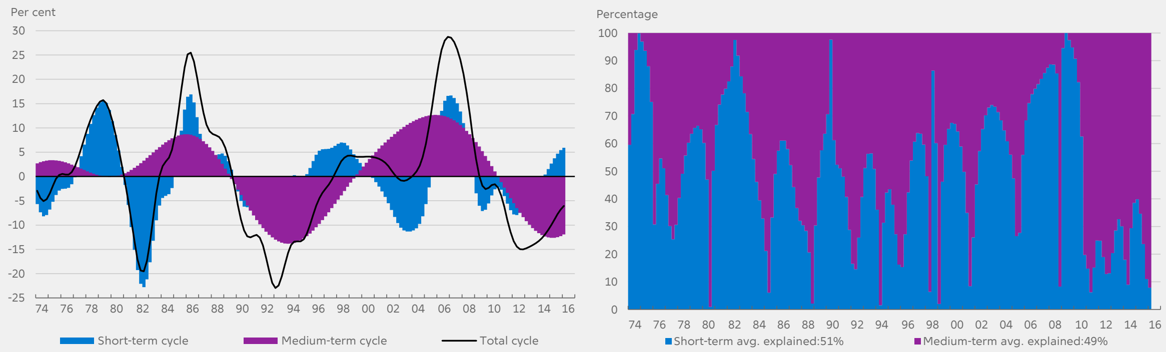
Short- and medium-term cycles and their relative contribution to the total cycle

Chart A3

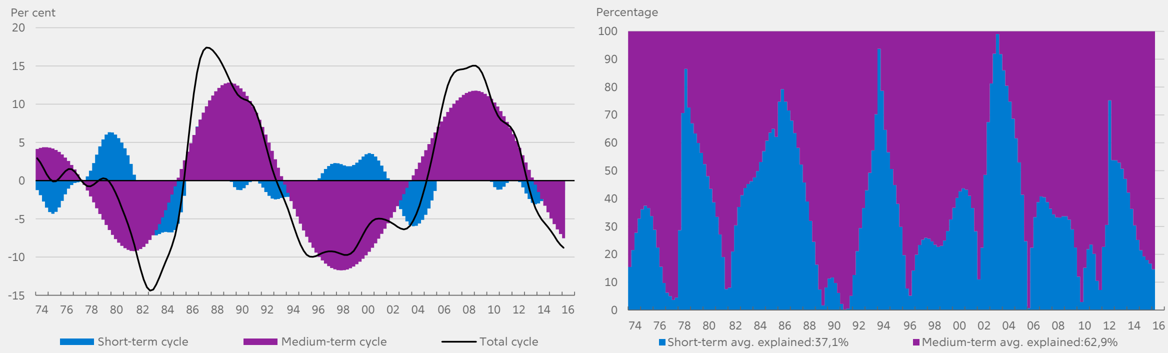
GDP



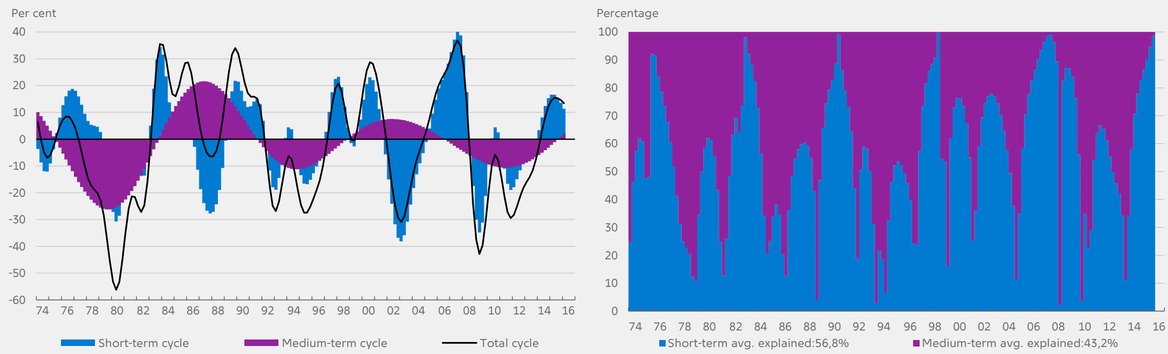
Real house price



Credit to non-financial institutions



Equity price



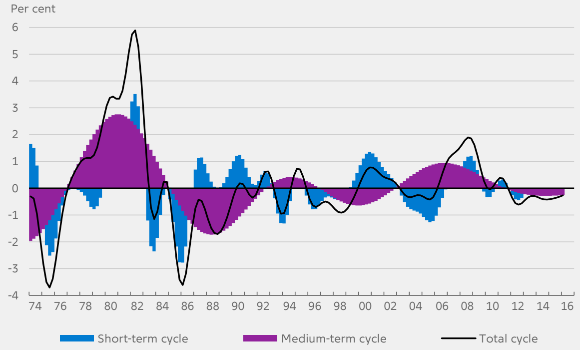
Note: In the figures are shown the short-term, medium-term and total cycles using filtering techniques, as explained in the text. In the figures in the right column are shown the relative contribution of the short-term and medium-term cycles to the total cycle.

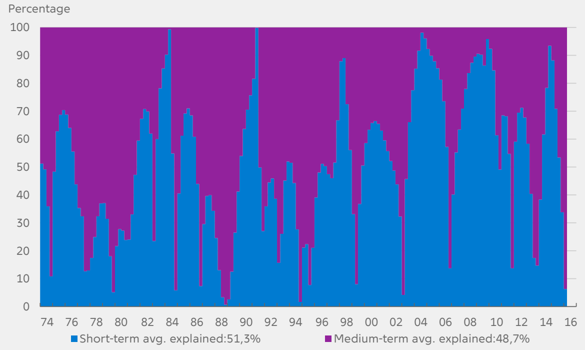
Source: Own calculations.

Short- and medium-term cycles and their relative contribution to the total cycle

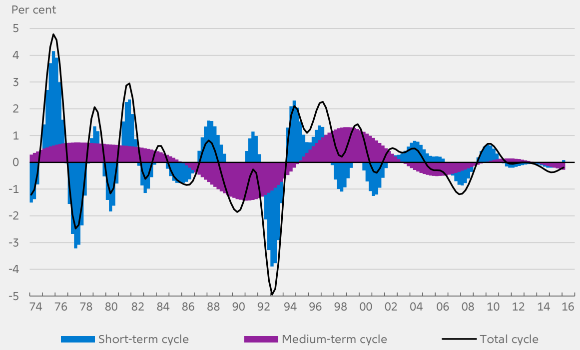
Chart A3

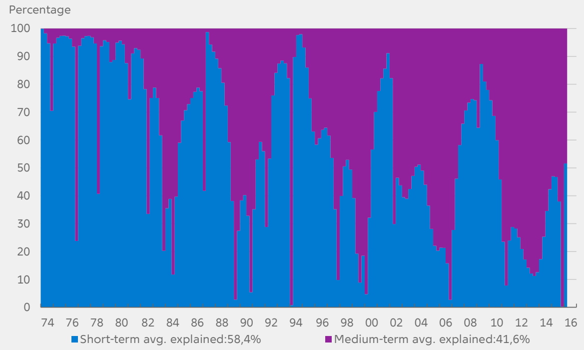
Long interest rate



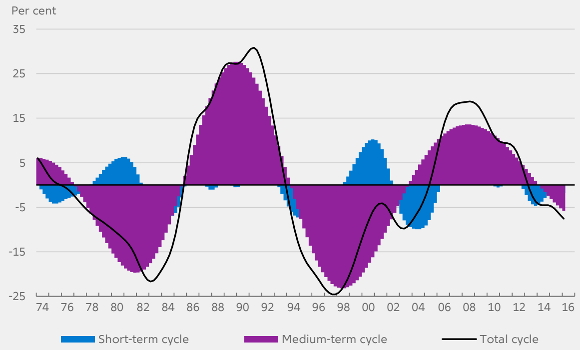


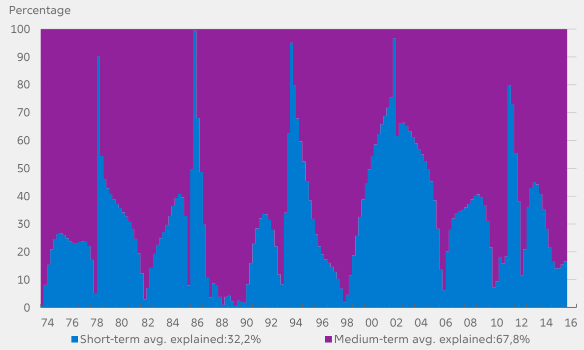
Interest-rate spread



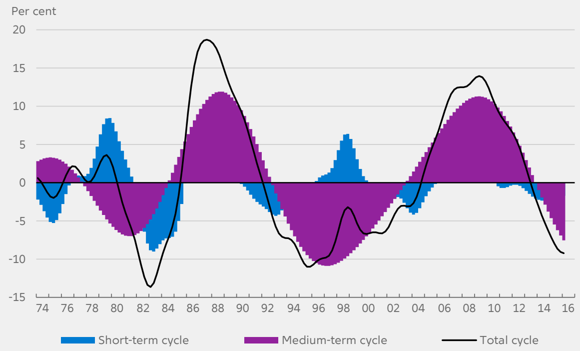


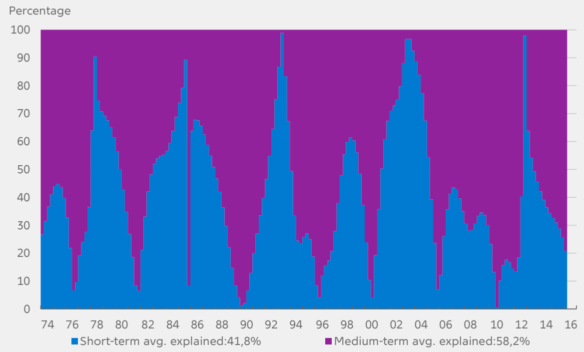
Loans to non-financial corporations





Loans to households





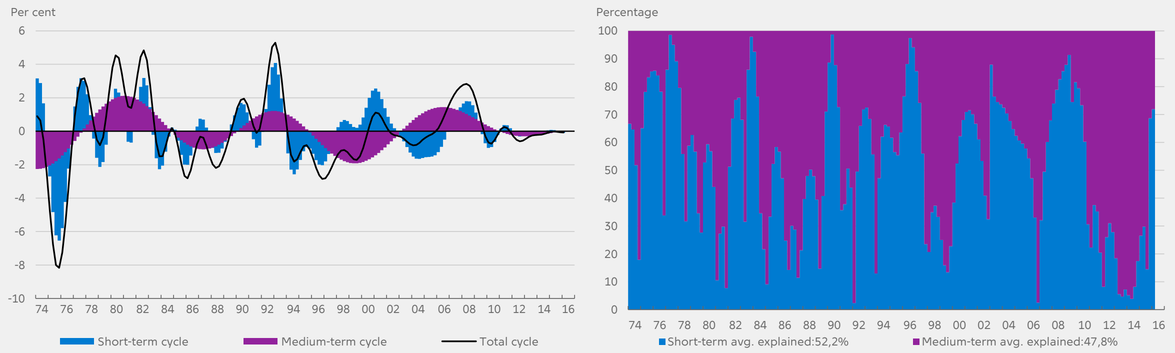
Note: In the figures are shown the short-term, medium term and total cycles using filtering techniques, as explained in the text. In the figures in the right column are shown the relative contribution of the short-term and medium term cycles to the total cycle.

Source: Own calculations.

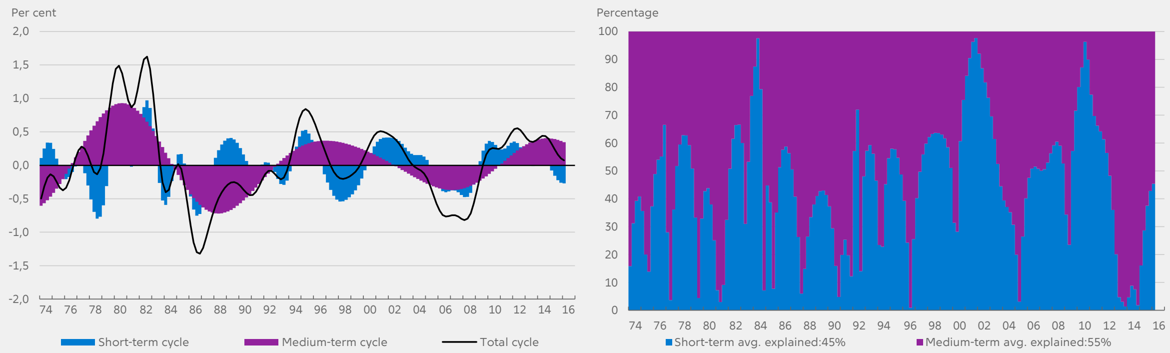
Short- and Medium term cycles and their relative contribution to the total-cycle

Chart A3

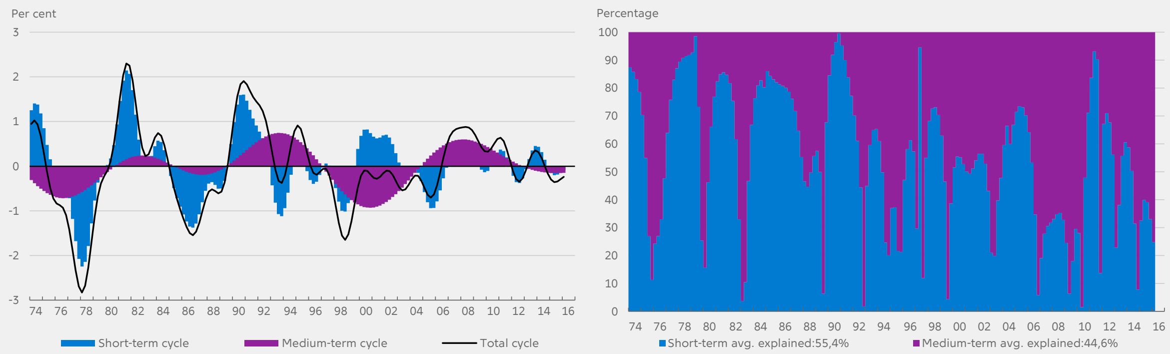
Short interest rate



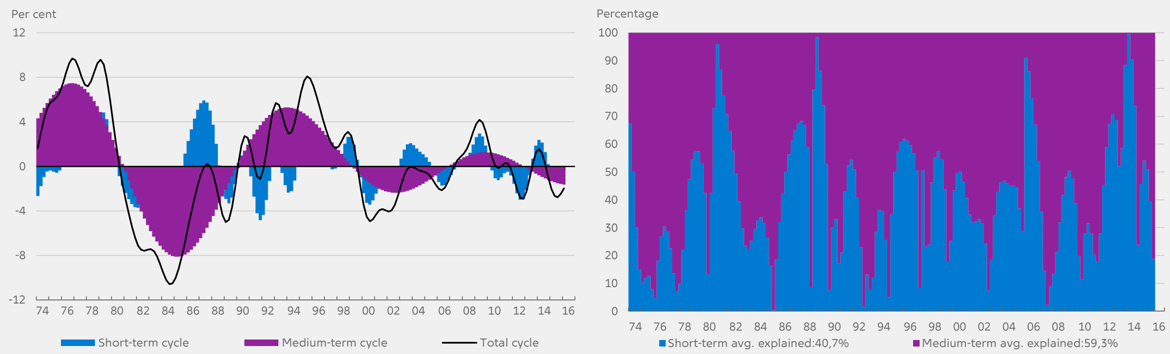
Money-market spread



German bund rate



Effective exchange rate



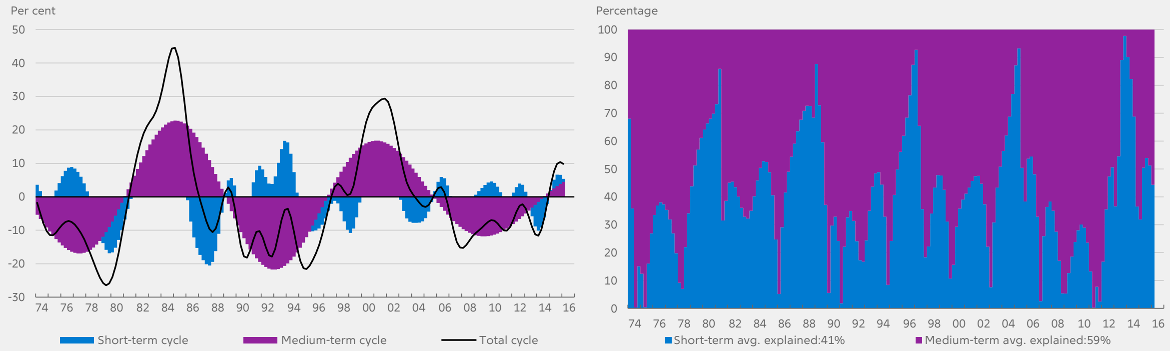
Note: In the figures are shown the short-term, medium-term and total cycles using filtering techniques, as explained in the text. In the figures in the right column are shown the relative contribution of the short-term and medium-term cycles to the total cycle.

Source: Own calculations.

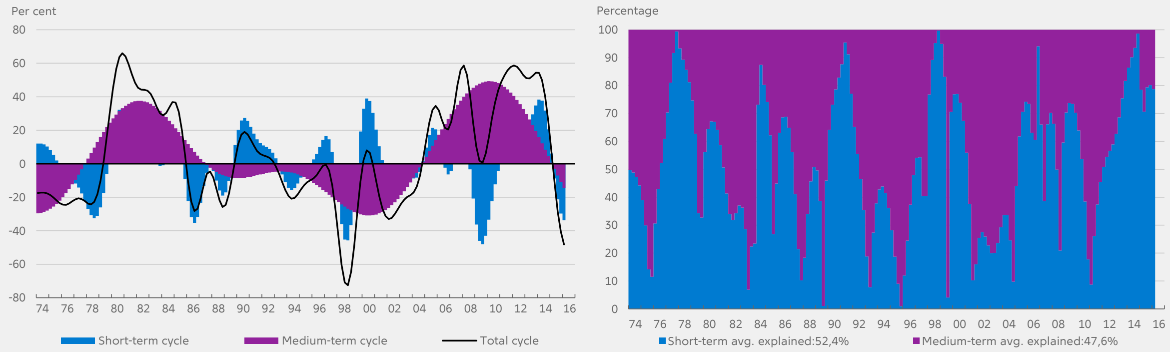
Short- and medium-term cycles and their relative contribution to the total cycle

Chart A3

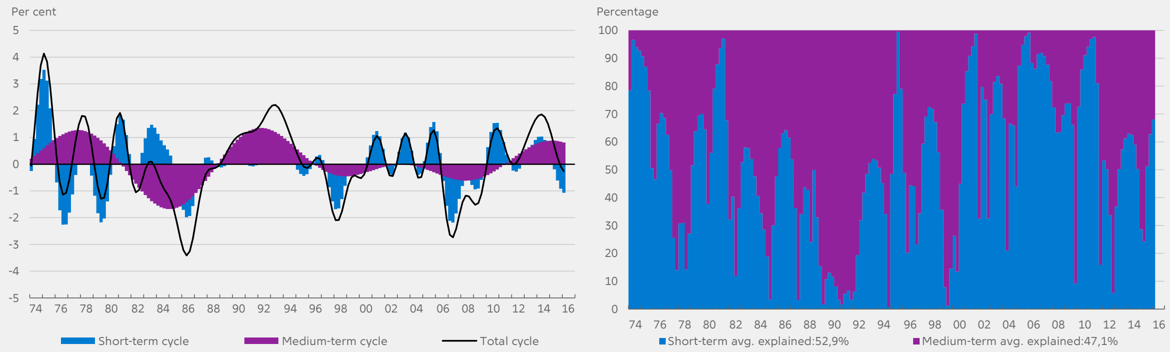
Euro-dollar exchange rate



Real oil price



Trade balance



Note: In the figures are shown the short-term, medium-term and total cycles using filtering techniques, as explained in the text. In the figures in the right column are shown the relative contribution of the short-term and medium-term cycles to the total cycle.

Source: Own calculations.

APPENDIX A4: PARAMETERS FROM THE ESTIMATED UNOBSERVED COMPONENT MODEL

Estimated parameters

Table A1

Parameters		Prior distribution				Posterior distribution					
		Type	Source	Mean	s.d.	Mean	Mode	s.d.	Median	5 per cent	95 per cent
Cycle length, FY	$\lambda 1$	Normal	RV2016	0.2	0.2	0.095	0.097	0.013	0.095	0.078	0.11
Cycle length, QHt	$\lambda 2$	Normal	RV2016	0.2	0.2	0.19	0.23	0.16	0.21	-0.0042	0.32
Cycle length, C	$\lambda 3$	Normal	RV2016	0.2	0.2	0.085	0.093	0.0065	0.093	0.047	0.11
Cycle decay, FY	$\rho 1$	Normal	RV2016	0.5	0.2	0.97	0.98	0.012	0.97	0.96	0.99
Cycle decay, QHt	$\rho 2$	Normal	RV2016	0.5	0.2	0.47	0.52	0.29	0.5	0.23	0.63
Cycle decay, C	$\rho 3$	Beta	RV2016	0.75	0.2	0.99	1	0.0037	1	0.96	1
Cycle AR(1), FY	$\phi 1$	Normal	RV2016	0.5	0.2	0.48	0.44	0.068	0.43	0.39	0.71
Cycle AR(1), QHt	$\phi 2$	Normal	RV2016	0.5	0.2	0.33	0.24	0.31	0.31	0.13	0.61
Cycle AR(1), C	$\phi 3$	Beta	RV2016	0.75	0.2	0.56	0.6	0.22	0.53	0.31	0.8
Loading, cycle, FY	$a11$	Inv. gamma	RV2016	0.005	Inf	0.0032	0.0034	0.00049	0.0033	0.0022	0.0036
Loading, cycle, FY,QHt	$a12$	Normal	RV2016	0	0.05	-0.0054	-0.0066	0.0074	-0.0064	-0.01	0.002
Loading, cycle, QHt,FY	$a21$	Normal	RV2016	0	0.05	0.018	0.019	0.0012	0.019	0.011	0.02
Loading, cycle, QHt	$a22$	Inv. gamma	RV2016	0.005	Inf	0.0029	0.0028	0.0018	0.0026	0.0014	0.0043
Loading, cycle, QHt,Ct	$a23$	Normal	RV2016	0	0.05	0.00061	-0.00032	0.0011	-0.00024	-0.0036	0.012
Loading, cycle, Ct,FY	$a31$	Normal	RV2016	0	0.05	0.003	0.0031	0.0012	0.003	0.0013	0.0037
Loading, cycle, Ct,QHt	$a32$	Normal	RV2016	0	0.05	-0.00069	-0.0021	0.0021	-0.00098	-0.0026	0.0032
Loading, cycle, Ct	$a33$	Inv. gamma	RV2016	0.005	Inf	0.0022	0.0019	0.00056	0.0021	0.0015	0.0034
Loading, cycle, FY,QHt	$ast12$	Normal	RV2016	0	0.05	-0.0035	-0.0071	0.007	-0.006	-0.0092	0.008
Loading, cycle, QHt,FY	$ast21$	Normal	RV2016	0	0.05	-0.0015	-0.002	0.003	-0.00093	-0.005	0.00067
Loading, cycle, QHt,Ct	$ast23$	Normal	RV2016	0	0.05	7.4e-05	-0.0011	0.0012	-0.0011	-0.0039	0.01
Loading, cycle, Ct,FY	$ast31$	Normal	RV2016	0	0.05	-0.0072	-0.0075	0.0011	-0.0073	-0.008	-0.0056
Loading, cycle, Ct,QHt	ast32	Normal	RV2016	0	0.05	0.0006	0.00077	0.0033	0.00098	-0.002	0.0029
Innovations											
Irregular, FY	ϵ_{1t}	Inv. gamma	RV2016	0.001	Inf	0.0012	0.00047	0.00014	0.00053	0.00036	0.0041
Irregular, QHt	ϵ_{2t}	Inv. gamma	RV2016	0.001	Inf	0.00059	0.00046	0.00013	0.00049	0.0003	0.00083
Irregular, C	ϵ_{3t}	Inv. gamma	RV2016	0.001	Inf	0.0056	0.0057	0.00074	0.0059	0.005	0.0067
Level, FY	η_{1t}	Inv. gamma	RV2016	0.001	Inf	0.00055	0.00046	0.00013	0.00046	0.00034	0.00085
Level, QHt	η_{2t}	Inv. gamma	RV2016	0.001	Inf	0.00074	0.00046	0.00013	0.0005	0.00024	0.0011
Level, C	η_{3t}	Inv. gamma	RV2016	0.001	Inf	0.00059	0.00046	0.00013	0.00048	0.00027	0.00095
Slope, FY	ζ_{1t}	Inv. gamma	RV2016	0.001	Inf	0.00031	0.00031	2.5e-08	0.00031	0.00031	0.00031
Slope, QHt	ζ_{2t}	Inv. gamma	RV2016	0.001	Inf	0.00055	0.00049	0.00013	0.00051	0.00037	0.00081
Slope, C	ζ_{3t}	Inv. gamma	RV2016	0.001	Inf	0.00045	0.00038	7.1e-05	0.00038	0.00035	0.00078

Note: RV2016 refers to Rünstler and Vlekke (2016). s.d. is standard deviation.
Source: Own calculations.

APPENDIX A5: FORECASTING THE CYCLES USING THE UNOBSERVED COMPONENT MODEL

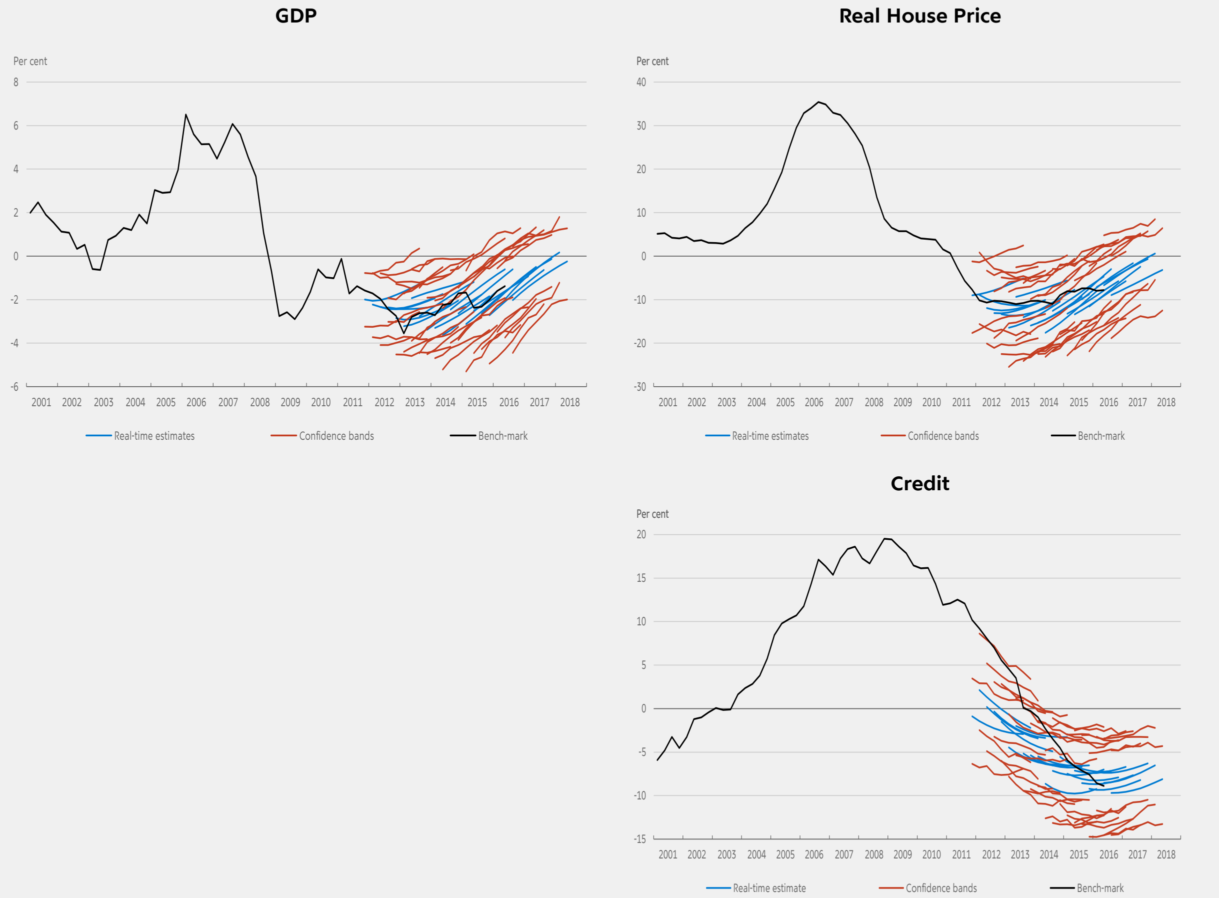
Another advantage of estimating the cycles in a multivariate model is that it allows us to forecast the cycles. That is clearly an advantage for the conduct of policy. Filters can only partly be used to forecast the cycles; by adding forecasts of the variables to the non-filtered series, the filter can provide a forecast of the cycle based upon the forecast in the model

We conduct a semi-real time analysis of the models ability to forecast. We recursively estimate the model from 2011-Q2 up until the end of the sample. From each end-point we forecast 8 quarters ahead and we compare these forecasts with the actual estimate of the respective cycle using the full sample. We also include posterior confidence bounds around these forecasts. These bounds are produced by the model, and reflect both parameter- and filtering uncertainty. We stress that this is only a pseudo-analysis of the models ability to forecast.

The results are shown in chart (A4).

In-sample forecast using the unobserved-component model

Chart A4



Note: In the figures are shown the estimated cycles using the unobserved-component model (black line) together recursive forecasts, (blue lines), and uncertainty bounds on the forecasts (red lines). The forecasts are calculated using the full-sample parameter estimates and start from 2011. The model forecast 8 quarters ahead.
Source: Own calculations.

Intuitively, when forecasting cycles using the models, the forecasts are often a mean reversion to 0. This is also the case for GDP, as can be seen from the figure above. However, that is also what partly happens in data. For the real house price the same observations assert themselves though the model does forecast a slower mean-reversion.

The forecast of credit is more interesting. The model forecasts a worsening of the credit cycle, and only later a very slow recovery back to equilibrium. All in all, we conclude that the model has a tendency to forecast mean-reversion, but it does give a quantitative answer to speed of the mean reversion.

APPENDIX A6: IS THE VARIANCE DECOMPOSITION DRIVEN BY THE FINANCIAL CRISES OF 2008-10?

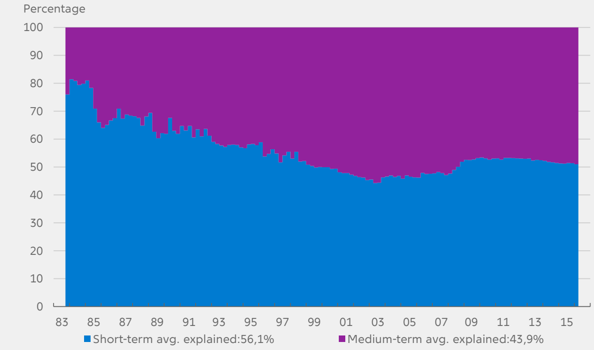
In this section, we analyze to what extent the variance decomposition is affected by the financial crisis in the 2000s. To this end, we calculate the variance decomposition of the total cycle starting from 1981 adding one observation at time. This is shown in Chart A5.

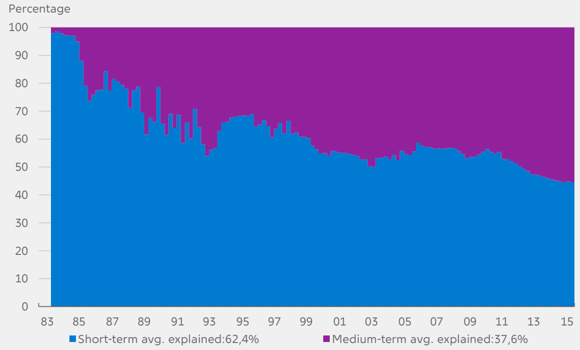
We observe is that the part explained by the medium term cycle stabilizes, i.e. the parameter estimate is stable over the financial crisis. Hence, our findings are not only driven by the 2000-10 cycle. For Denmark this finding can perhaps be explained by the rather large cycle in GDP, real house price and credit during the 1980s.

Variance decomposition of total cycle and real-time analysis

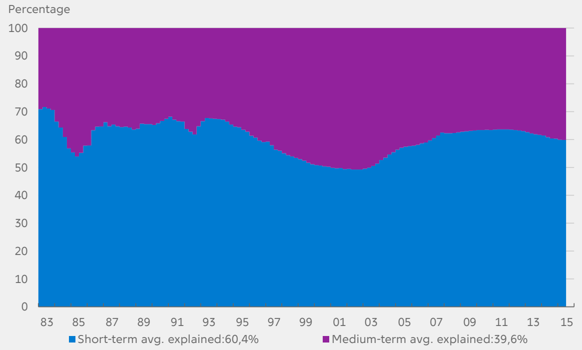
Chart A5

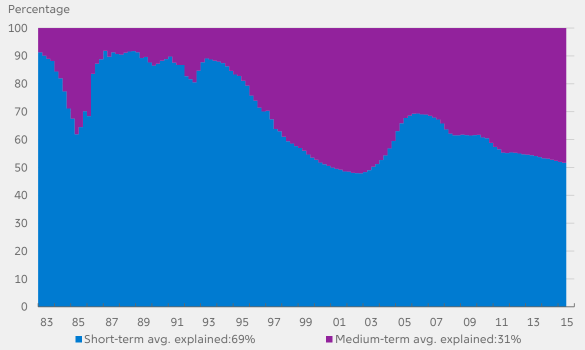
GDP



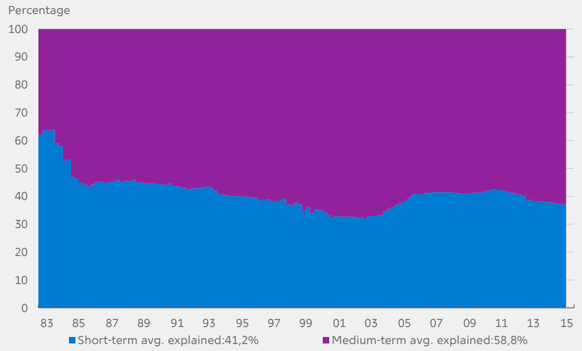


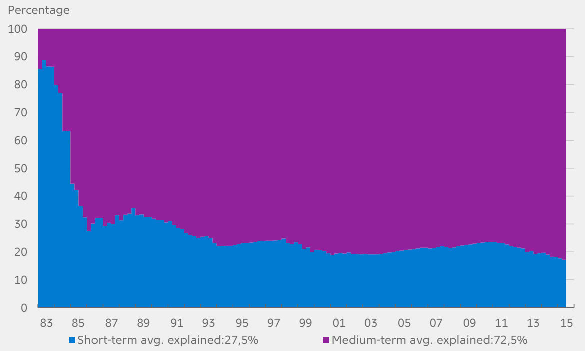
Real house price



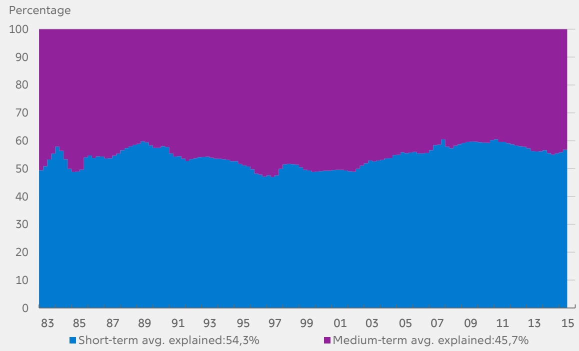


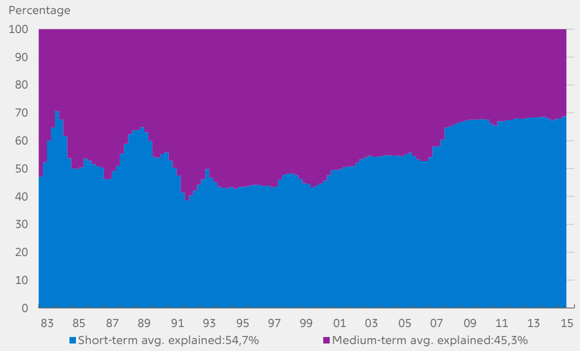
Credit to non-financial institutions





Equity price





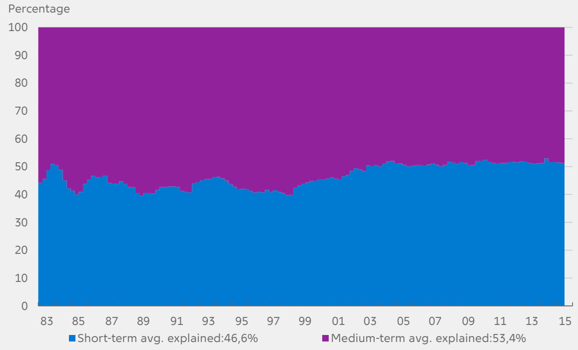
Note: In the figures are shown the variance decomposition of the total cycle into the variance of the short-term and medium-term cycles. In the right column are shown the variance decomposition estimated recursively.

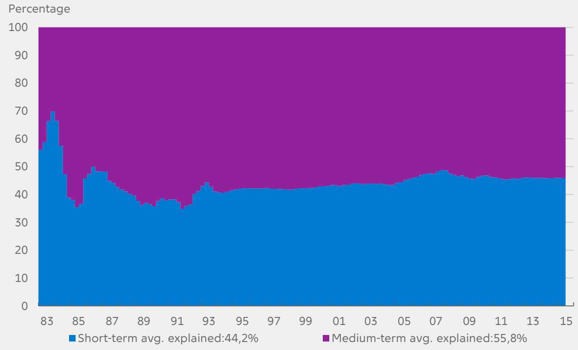
Source: Own calculations.

Variance decomposition of total cycle and real-time analysis

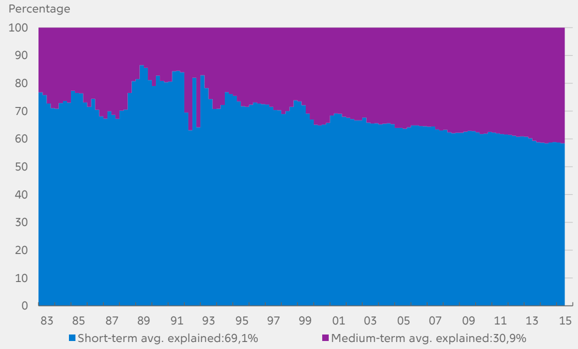
Chart A5

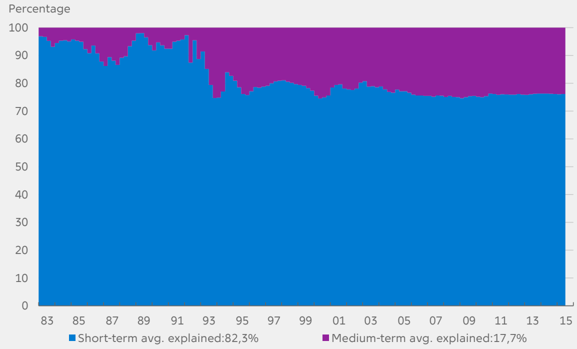
Long interest rate



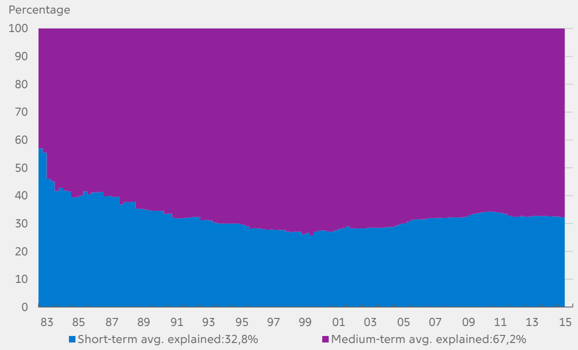


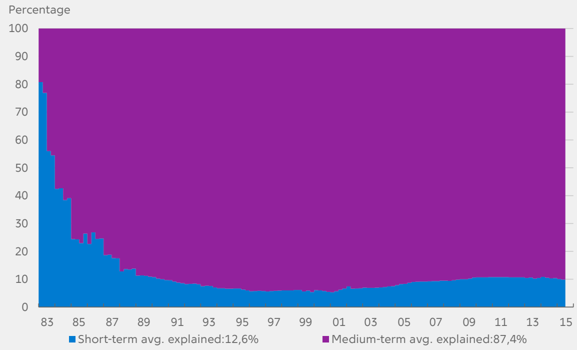
Interest-rate spread



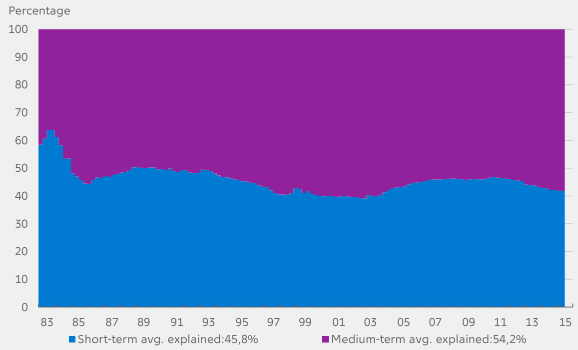


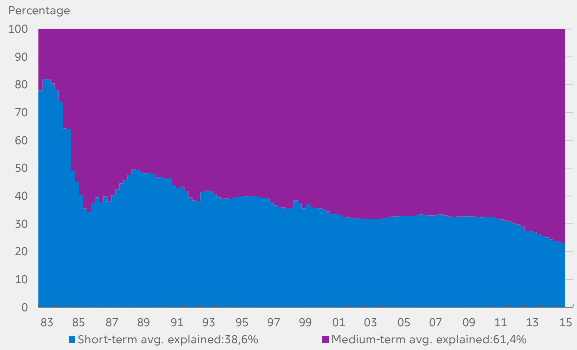
Loans to non-financial corporations





Loans to households





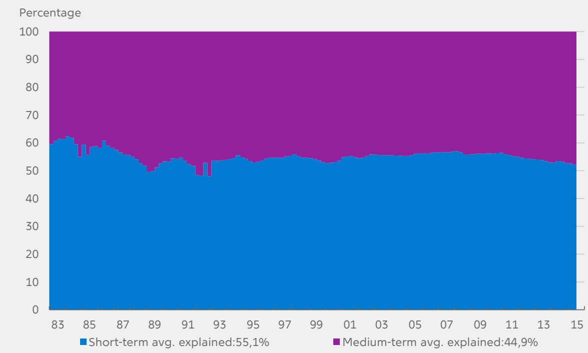
Note: In the figures are shown the variance decomposition of the total cycle into the variance of the short-term and medium-term cycles. In the right column are shown the variance decomposition estimated recursively.

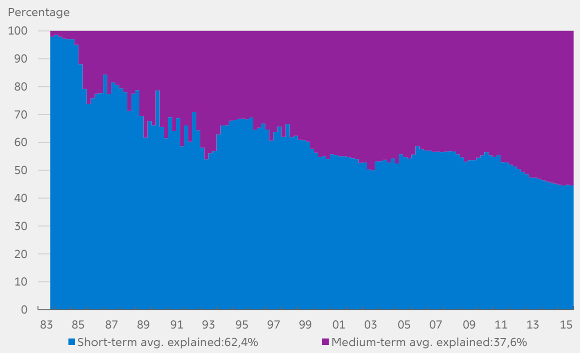
Source: Own calculations.

Variance decomposition of total cycle and real-time analysis

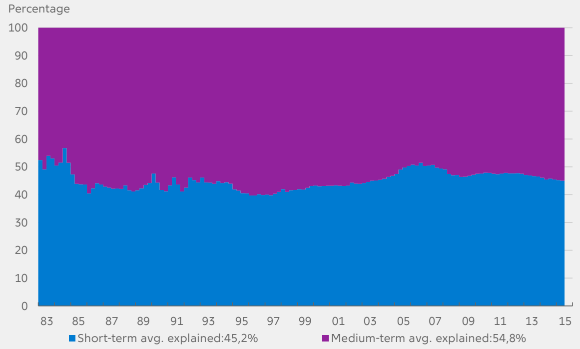
Chart A5

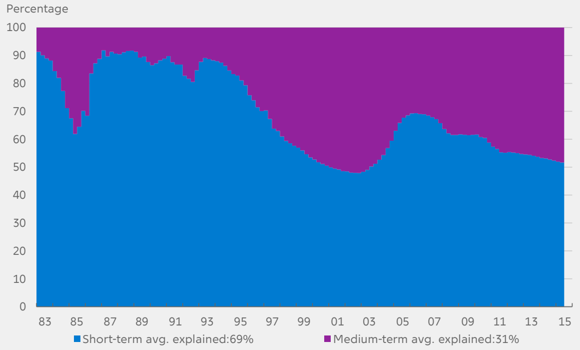
Short interest-rate



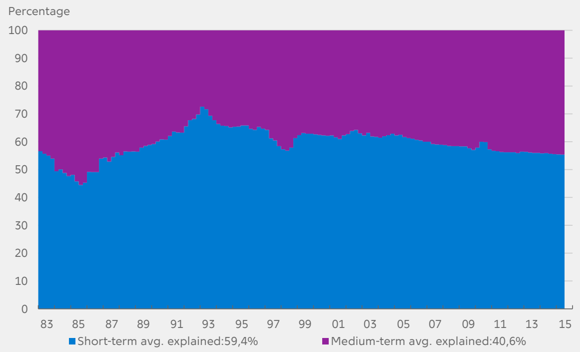


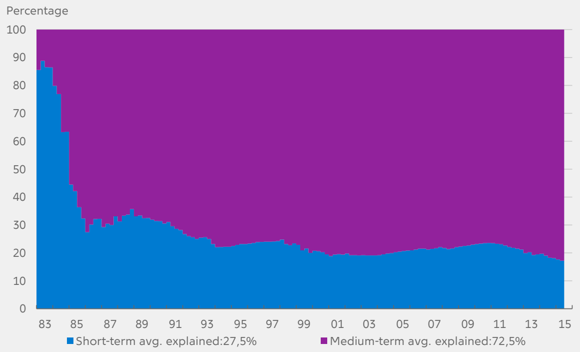
Money-market spread



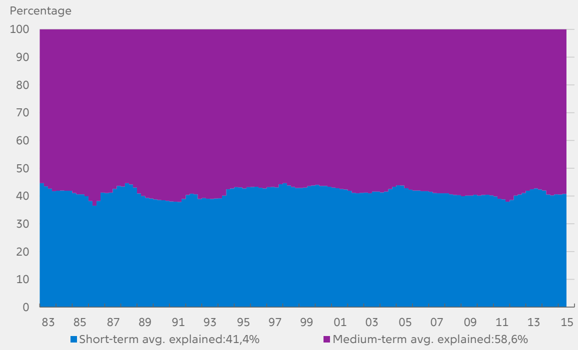


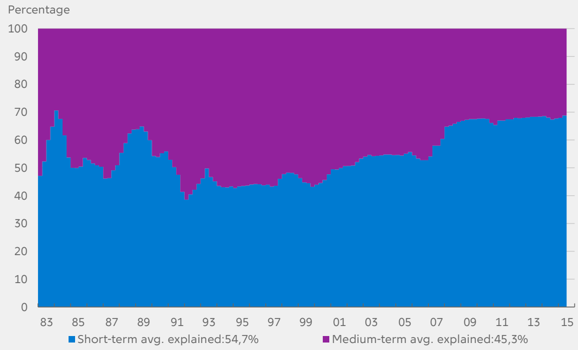
German bund rate





Effective exchange rate



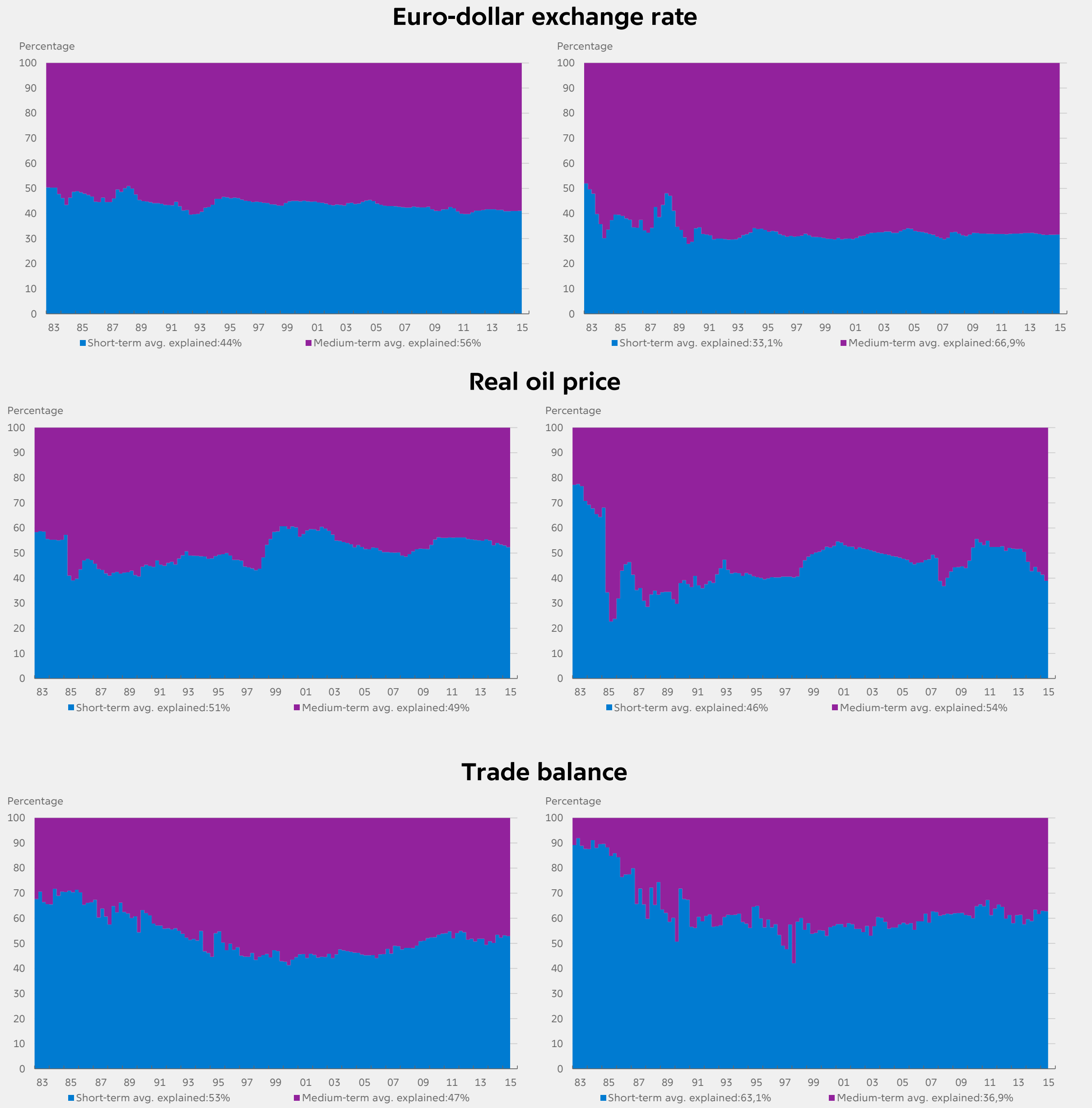


Note: In the figures are shown the variance decomposition of the total cycle into the variance of the short-term and medium-term cycles. In the right column are shown the variance decomposition estimated recursively.

Source: Own calculations.

Variance decomposition of total cycle and real-time analysis

Chart A5



Note: In the figures are shown the variance decomposition of the total cycle into the variance of the short-term and medium-term cycles. In the right column are shown the variance decomposition estimated recursively.

Source: Own calculations.

ADDENDUM: MITIGATING THE END POINT PROBLEM?

The UOC-model presented in the main text has been in use since the publication of the working paper. One point that was only partly addressed in the paper was end-point problems. This is the aim of this addendum.

In this addendum, the following is done. Firstly, the model is estimated in (quasi) real-time using an expanding-window adding one observation at the time beginning 2003Q1 ending 2018Q1. We derive both trends and cycles, and we compare these with the cycles and trends estimated using the full-sample; 2018Q2. In what follows, these full-sample estimates are denoted actual estimates.

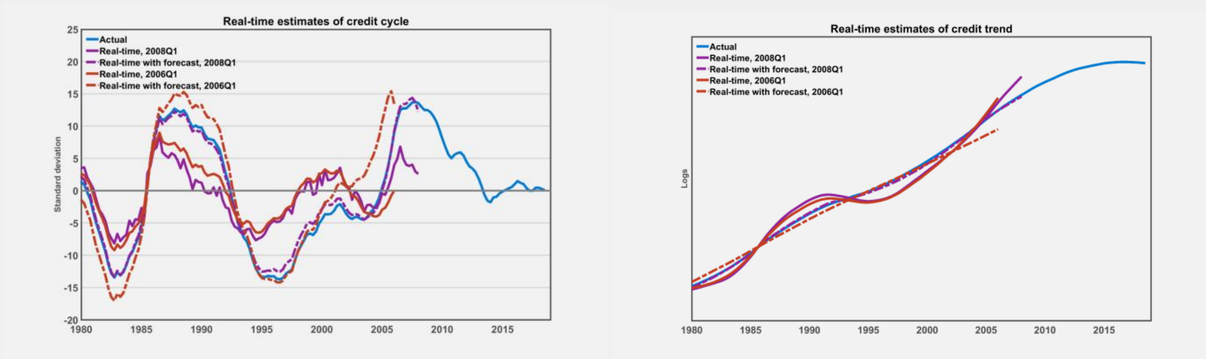
Secondly, we use official Nationalbankens forecast for the deflator, GDP, and real house prices 20 quarters ahead and do the same exercise the difference being that the forecasts are added to the sample and are treated as data. We only keep the cycles and trends up until the end of the historical data set. For credit, we rely on the results from Gerdrup et. al. (2013), who finds that a simple average of the preceding 5 years of credit data to forecast credit gives the best stabilising properties of the cycles and best real time properties. As the forecasts for the remainder of the variables are usually only done 12 quarters ahead, these are extended based upon the growth rate in the last quarter in the forecast. This is a quasi-real-time exercise, as data revisions are not taken into account. However, inflation, house prices and credit data to a large degree usually are not revised markedly. Only GDP is revised, but the impact on the cycles in credit and house prices from these revisions can be expected to be of second order, see Edge and Meisenzahl (2011).

The estimates from these two expanding-windows estimations are compared to the cycles and trends estimated using the full sample. The comparison is done through charts and two statistical measures: The standard deviation of the difference between the cycles and trends on one side and the full sample cycles and trends on the other side, and, the mean of absolute differences between these variables in percentage points.

USING FORECASTS FOR REAL HOUSE PRICE AND CREDIT DATA MITIGATE END-POINT PROBLEMS

Before proceeding to the results, in chart A.6 is presented two examples which can clarify how the real-time analysis is conducted; the real-time estimates up until 2006Q1 and 2008Q1 respectively. In the examples there are end-point problems meaning that in real-time there is a discrepancy between the actual cycle and trend and the end of the samples estimates. For the 2006Q1 estimates, the actual cycle was around 15 percentage points, while the model estimated in the real-time without forecasts added to the sample finds an estimate of the gab of 0. This is quite an extreme case, as in 2006Q1 the credit cycle was at its peak. In 2008Q1, the difference is close to 10 percentage pionts. However, the model provides the correct signals: While the cycles are smaller in real-time, the direction of the developments in the cycles are correct.

Real-time estimation of credit cycle with and without forecast Chart A.6



Note: In the figure is shown the credit cycle and the credit trend estimated using the unobserved component model described in the text.
Source: Own calculations.

The trends can provide an understanding of why the cycles are estimated imprecisely in real-time. The model has less information about the long-term developments of the economy and thus less information about the trends. This implies that in the two examples, the model wrongly assigns some of the large movements in credit to a change in the trend, which subsequently turned out to be wrong as credit fell. The trends are smooth, as expected, but vary considerably more in the real-time estimates compared to the full sample estimates.

Chart A.6 also reveals the potential benefits of using forecasts added to the sample when estimating the cycles and trends. Specifically, for 2006Q1-example the end-point estimate from the model estimated with forecasts is quite close to the actual cycle the main difference being, that in real-time the cycle begins to increase one year before. For the 2008Q1-example the difference and timing is close to being spot on. The trends reveal the explanation: they are more stable when estimated using the forecast and changes in credit is by the model attributed to changes in the cycle and less so to changes in the trends.

USING FORECASTS FOR REAL HOUSE PRICE AND CREDIT DATA MITIGATE END-POINT PROBLEMS

The overall results are shown in Chart A.7 and in Table A.2. We highlight the following points. Both the credit cycle and the real house price cycle are estimated with greater precision in the model estimated using forecasts relative to the case without. Specifically, the mean of absolute difference fall by respectively 2.75 and 2 points. Also, the standard deviations of the revisions are lower.

Some characteristics of the real-time estimates

Table A.2

	Without forecast	With forecast
Mean of absolute difference		
Credit cycle	6.50	3.75
Real house price cycle	8.25	5.00
Standard deviation of revision		
Credit cycle	5.75	3.75
Real house price cycle	7.50	6.75

Note: In the table is shown the mean of the absolute difference between the real time estimates of the cycles and the cycle estimated using the full sample. Next is shown the standard deviation of the revisions.

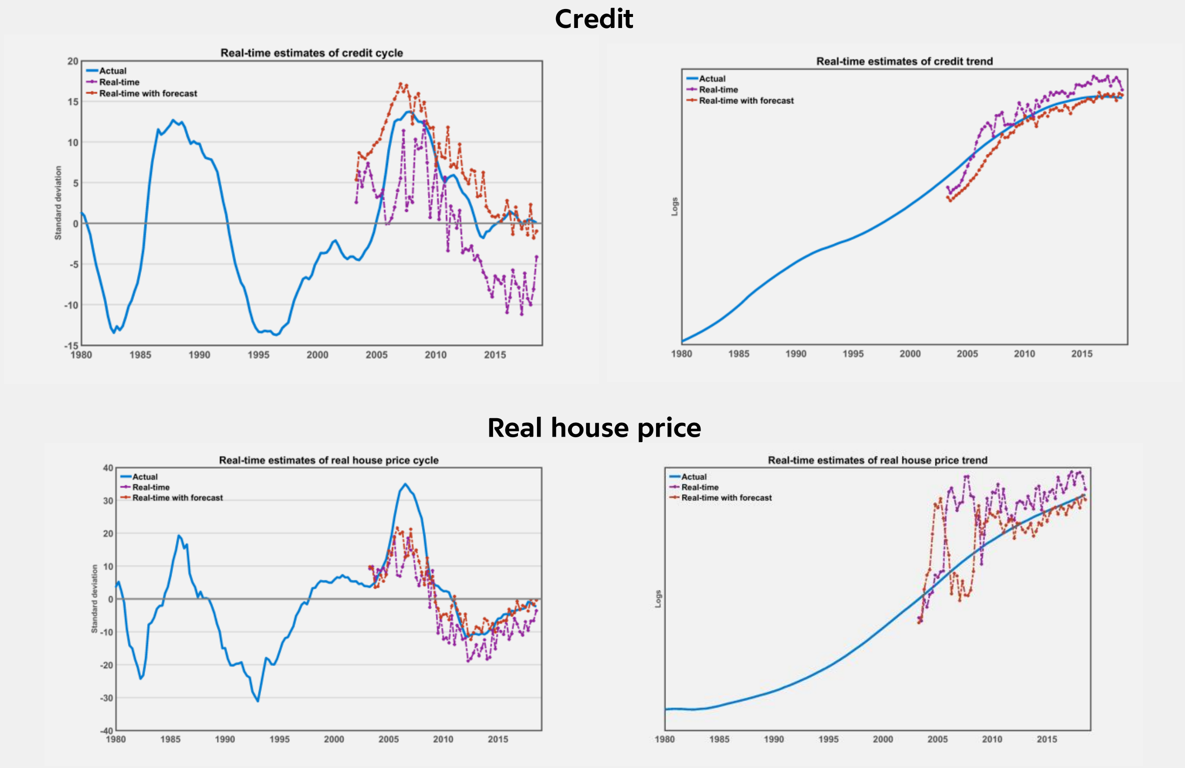
Source: Own calculations.

Analysing the charts, it can be seen that for the credit cycle, the model without forecasts used in the estimation tends to find the cycle to be too small during the build-up to the financial crisis, and the subsequent downturn is estimated to be too large.[16] The model with the forecast in turn finds credit cycles of almost equal size to the cycle estimated using the full sample. In total, the model estimated with forecasts provides clearer signal about the credit cycle in real time relative to the model estimated without the forecasts. These conclusions to a lesser extend hold when looking at the real house price. The pattern is still present, but it is less profound.

[16] The apparent spikes in the end-point of the real-time trends, it must be stressed, do not imply that the trends are volatile. This can be seen from Chart A.6.

Real-time estimation of credit and real house price cycles and trends with and without forecast

Chart A.7



Note: In the figures are shown the cycles and trends estimated using the unobserved component model described in the text.
Source: Own calculations.

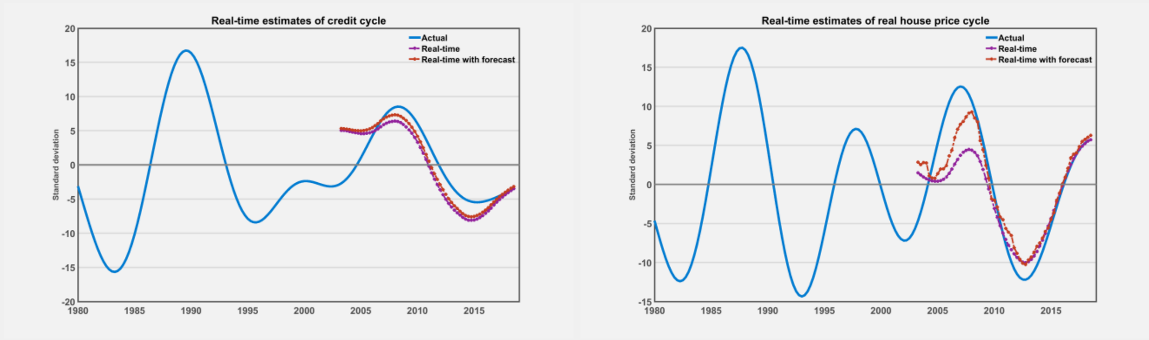
REAL-TIME ANALYSIS OF CYCLES ESTIMATED USING THE BAND-PASS FILTER

A common approach is to use both the UOC-model and the band-pass filter for estimating financial cycles. Both approaches are in use to guard against modelling uncertainty. Therefore, the real-time analysis presented above is also conducted for the band-pass filtered data. The results are shown in Chart A.8.

In the case of the band-pass filter, the conclusions are not clear cut. In the case of the real house price, the advantage of using forecasts in the estimation of the cycles is clear when the cycle is far from 0. For credit, it seem like the forecasts does not improve the precision of the cycles by a lot.

Real-time estimation of credit and real house price cycles and trends with and without forecast – the case of the band-pass filter.

Chart A.8



Note: In the figures are shown the cycles and trends estimated using the band-pass filter.
Source: Own calculations.

LITTERATURE

Edge, Rochelle M. and Ralf R. Meisenzahl (2011), *The unreliability of credit-to-GDP ratio gaps in real-time: Implications for countercyclical capital buffers,* International Journal of Central Banking 7.4 (2011), 261-298.

Gerdrup, Karsten, Aslak Bakke Kvinlog and Eric Schaanning (2013), *Key indicators for a countercyclical capital buffer in Norway – Trends and uncertainty*, Norges Bank Staff Memo, Paper 13.