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Financial cycles as early warning indicators: Lessons from the Nordic region

By

*Önundur Páll Ragnarsson, Jón Magnús Hannesson
and Loftur Hreinsson*

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Financial cycles as early warning indicators: Lessons from the Nordic region*

Önundur Páll Ragnarsson,[†] Jón Magnús Hannesson,[†] Loftur Hreinsson[‡]

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Abstract

Frameworks to handle cyclical systemic risk usually contain a wide selection of early warning indicators. Different indicators sometimes send diverging signals which can be hard to interpret. However, measures of aggregate financial cycles can serve as a way to synthesize information from many indicators. There are however many ways to construct a measure of such cycles. Many methods exist for cycle extraction, variable choice represents another dimension, and cycle aggregation the third. We tackle each step of the way by selecting the best out of six cycle extraction methods, then comparing variables from three groups: credit, house prices and bank funding, and lastly arguing for a simple method of cycle aggregation based on cycle correlation and frequency domain analysis. We then construct a trivariate financial cycle measure which outperforms the 'Basel gap', all univariate cycles and all other multivariate combinations for the Nordic countries in terms of a noise-to-signal ratio. In addition, it peaks much closer to crisis onset and does relatively well at real-time turning point identification. The trivariate band-pass filtered measure contains the best variable from each group, and outperforms them all. This indicates that aggregate cycles can be more than the sum of their parts, as early warning indicators. Furthermore, we examine potential weaknesses of our analysis in terms of small-sample problems, spurious cycles and the timing of crisis onset. We conclude with 15 lessons from the Nordic countries.

Keywords: Financial cycles, early warning indicators, turning-points, spectral analysis.
JEL classification: G01, G32, G38.

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[†]Central Bank of Iceland - Macprudential Policy - opr@cb.is (Corresponding author) jonm@cb.is

[‡]Financial Supervisory Authority of Iceland - lofturh@fme.is

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1 Introduction

Frameworks for macroprudential policy making usually include a wide selection of early warning indicators of cyclical systemic risk. Policy-makers make an overall appraisal of those indicators, and other available information, to form an expert opinion. Also they must take into account any operational lag associated with the tools at their disposal. Such an appraisal is not always straightforward, as indicators can produce diverging signals over extended periods of time. A recent example can be found in Iceland in the years 2011-2016, when indicators for credit and housing diverged in their signals. Perhaps, therefore, an objective quantitative measure which synthesizes a large part of the cyclical indicators can be useful. Although such a measure cannot replace expert opinion, it may help to ground it, as a point of reference.

A composite financial cycle indicator is a powerful means of justifying and communicating policy action. Its graphic representation of the financial system's gradual movement from a low to high-risk status is easily understood. Based on objective criteria, policy makers can derive early warning signals from it. But it also raises more general considerations, which can feed into an overall appraisal. What is the cyclical position now? Is the cycle in an upward or downward phase? Has the cycle just turned?

There is no general consensus on how aggregate financial cycles should be derived. In practice there are myriad ways to go about it. Choices present themselves along at least three dimensions: The choice of variables, the trend-cycle decomposition method and the method for cycle aggregation. We aim to shed light on what choice is likely to yield a financial cycle indicator with preferable real-time properties.¹ That entails providing a useful estimate of the current cyclical position, the current phase, recent turning points and, most importantly, looming financial crises. We tackle each step of the way by comparing performance, and mining the data a little bit.

For a measure of financial cycles applicable to macroprudential policy making, quarterly frequency is required. Time series need to reach back decades for tractable estimates of medium term cycles. Our dataset covers seven to nine variables for Denmark, Finland, Iceland, Norway and Sweden each. The variables fall into three groups. First, credit aggregates and ratios to gauge cyclical credit risk. Second, real house prices and house price ratios to gauge cyclical collateral quality. Third, measures of banks' foreign liabilities and total non-core funding, to gauge cyclical liquidity risk and wholesale funding market reliance.

¹The concept of real-time analysis here simply refers to using available information at each time, although the newest observation may be a few months old.

Five economies is a small panel, but they have in common their small size, openness, bank-dominated financial systems, geographical location and their cultural and political ties. Our findings may not be applicable outside the panel, and may fail to hold in the future.

Large panel studies on financial cycles and crises often quantify results in terms of noise to signal ratios and the 'area under the curve'. We follow that tradition by calculating noise to signal ratios. With a small panel, however, those are only partly informative. The 90's crises in the Nordics were all of similar roots (for background see e.g. Hansen (2003) or Honkapohja (2009)). The crisis episodes of 2008 were all in connection with the global financial crisis. Thus, one might say we only have two crises in our sample! In light of this, we aim for a more detailed analysis in addition to calculating ratios.

The paper is organized as follows: Section 2 reviews the relevant literature and briefly outlines the theory underpinning the analysis. Section 3 reports the results. Section 4 provides a discussion of the results, weaknesses of the analysis and topics for further research. Section 5 concludes with some lessons.

2 Theoretical insights

2.1 The Hodrick-Prescott filter and its cousin

Out of an array of econometric filters and estimators we compare six methods for trend-cycle decomposition. First, the Hodrick-Prescott (1997), or HP-filter because of its widespread use in econometrics. The Basel Committee on Banking Supervision (2010) recommends the use of a one-sided (backward looking) version of the HP-filter for the purpose of calculating a credit-to-GDP gap and calibrating the countercyclical capital buffer (CCyB) requirement. The Committee recommends setting the filter's smoothing parameter, λ , to 400,000. Calculated this way, the credit gap is known as the 'Basel-gap'. The European Systemic Risk Board (2014) takes the same approach. These recommendations are based on e.g. Borio and Lowe (2002) and Borio and Drehmann (2009). The Nordic countries have only partially followed the guidance of the Basel-gap in their recent implementation of countercyclical capital buffer requirements. Icelandic and Danish authorities have activated the buffer requirements despite having large negative gaps, while Sweden and Norway have built up theirs in times of a positive but diminishing gap. Finland has a negative gap and has not activated its requirement.

The trend and cycle from a one-sided filter are the same as a collection of end-points from the two sided version, calculated recursively throughout the sample. We include both

versions in our analysis, as we look at more factors than the latest deviation from trend, at each point in time. For example, we study real-time turning point identification, which is not the same for both versions. The two-sided filter retroactively revises the whole trend component series upon receiving new data, whereas the one-sided filter does not.² For both versions, we set the smoothing parameter, λ , at 400,000.

In filter theory, the HP-filter falls within the category of Wiener-Kolmogorov filters (see Pollock (2014)). A whole class of such filters, known as Butterworth-filters are less used in economics, but Gomez (2001) shows the HP-filter to be a special case Butterworth-filter. We include a generic 1st order Butterworth-filter with a cut-off frequency of 120 quarters, simply to try something different. As data series non-stationarity can cause problems for the Butterworth filter, we filter first differences and then cumulate the cyclical component, before standardizing it.

2.2 The Hamilton regression filter

Hamilton (2017) outlines three drawbacks to the HP-filter. First, potentially producing series with spurious dynamic relations. Second, its end-point problem.³ Third, common practice smoothing parameter values such as $\lambda=400,000$ are at odds with a statistical formalization. As an alternative, free of these problems, he proposes an autoregression:

$$y_{t+h} = \theta_0 + \theta_1 y_t + \theta_2 y_{t-1} + \theta_3 y_{t-2} + \theta_4 y_{t-3} + \epsilon_{t+h} \quad (1)$$

The part which cannot be forecasted by lagged values of the series itself, namely the error term, is the cycle. The fitted values are the trend. The choice of initial lag length, h , is then comparable to that of the HP-filters' λ , in that it can affect the frequency of the estimated cyclical component. For macroeconomic variables, Hamilton recommends a lag of three years, but for financial variables he proposes a five year lag. We follow this prescription and set $h=20$, for our quarterly dataset.

Schüler (2018) finds that the Hamilton-filter shares some of the HP-filters' drawbacks at business cycle frequencies for Germany, but may be better suited for data with lower

²The one-sided filter offers an easy way to graphically display series of real-time estimates, which may help to explain its popularity in application. But series of real-time estimates are easily displayed for other filters as well, as we do in section 3.

³The problem is as follows: The filter is based on a minimization problem with a trade-off between closing the gap, and smoothing the trend. Curving the trend to close the gap at one point results in a larger gap at another point in the series. Except if that point is outside the sample. Therefore, it is less costly to curve the trend and close the gap at the sample's end, than in the middle. See e.g. Ehlgen (1998).

frequency content. Drehmann and Yetman (2018) test it for calculating credit gaps as leading indicators for a panel of 42 countries. They find that gaps based on linear projections, such as the Hamilton filter, perform poorly and that the Basel-gap outperforms them.

2.3 A band-pass filter

Drehmann et al. (2012) employ the Christiano-Fitzgerald (2003) asymmetric band-pass filter (CF-filter) to study financial cycles for seven economies. Einarsson et al. (2016) also do so, in a thorough study of Icelandic financial cycles since the 19th century. The filter seeks out the most prominent cyclical component within a frequency band. For the study of financial cycles, this band is commonly set at 8-30 years. We follow that tradition, but provide a backstop by examining the data's unrestricted frequency content, by spectral analysis. (see sections 2.5, 3.1 and 3.8). Furthermore, the filter accommodates different cyclical frequencies at different time periods in the same series, which seems beneficial. There is no evidence to suggest that financial cycle's frequency should be deterministic.

As data series non-stationarity can cause problems for the CF-filter, we follow Einarsson et al. (2016) in filtering first differences and then cumulating the cyclical component, before standardizing it.

All aforementioned filters place restrictions on the cycle estimates to some extent. With a large λ or h , the HP and Hamilton-filters are low-pass filters of sorts. The difference in design between the HP and CF-filters actually underlines an issue regarding what we aim to measure, as a proxy for systemic risk build-up. At a given point in a series, a cyclical component from any of the other filters is the sum of cyclical movements around trend at different frequencies, and various shocks contained in the data. A CF-filtered cycle is more akin to a subset of those movements. On one hand, when proxying systemic risk build-up, the main issue is perhaps not the frequency at which financial variables are above trend, but whether they are above trend or not. On the other hand, if financial crises continue occurring with the same interval as they have in the past, medium term CF-cycles free of shorter term movements may turn out to have better signaling properties in the future.

2.4 A structural time series model

Lastly we include a structural time series model, representing the strain of literature initiated by Harvey (1989) with large contributions from Durbin and Koopman (2001). It explicitly specifies the data generating process but estimates parameters, such as the cycle frequency

from the data. It disaggregates observable data into unobserved components which can each be specified according to the theorized process. In this analysis we specify the model to include a trend, a cycle and an observation error as follows:

$$y_{i,t} = \mu_{i,t} + \psi_{i,t} + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \sigma_{\varepsilon,i}^2) \quad (2)$$

The trend, $\mu_{i,t}$, has fixed coefficients for its slope and curvature (deterministic first and second differences) but the third difference is stochastic. This specification fits financial data well and is consistent with the existing literature, e.g. Galati et al. (2016), Grinderslev et al. (2017) and Rünstler & Vlekke (2016).

$$\begin{aligned} \mu_{i,t+1} &= \mu_{i,t} + \beta_{i,t} \\ \beta_{i,t+1} &= \beta_{i,t} + \eta_{i,t} \\ \eta_{i,t+1} &= \eta_{i,t} + \zeta_{i,t}, \zeta_{i,t} \sim N(0, \sigma_{\zeta,i}^2) \end{aligned}$$

The cycle, $\psi_{i,t}$, is specified as a combination of sinusoidal waves, where the frequency of the cycle is given by λ and the damping factor, ϕ , describes the oscillation of the waves.

$$\begin{pmatrix} \psi_{i,t+1} \\ \psi_{i,t+1}^* \end{pmatrix} = \phi_i \begin{bmatrix} \cos \lambda_i & \sin \lambda_i \\ -\sin \lambda_i & \cos \lambda_i \end{bmatrix} \begin{pmatrix} \psi_{i,t} \\ \psi_{i,t}^* \end{pmatrix} + \begin{pmatrix} \omega_{i,t} \\ \omega_{i,t}^* \end{pmatrix}, \quad \begin{pmatrix} \omega_{i,t} \\ \omega_{i,t}^* \end{pmatrix} \stackrel{i.i.d.}{\sim} N(0, \sigma_{\omega,i}^2) \quad (3)$$

As well as allowing different specifications of the trend and cycle, state space models can accommodate more components, such as seasonality or additional explanatory variables.

The trend-cycle decomposition with a state space model consists of two steps. First the model is defined, as was done above, and the coefficients of the model estimated by maximum likelihood. The coefficients which define the model are the variances of the residual ($\sigma_{\varepsilon,i}^2$), trend ($\sigma_{\zeta,i}^2$) and cycle ($\sigma_{\omega,i}^2$), the frequency parameter, λ , and the damping factor, ϕ . They are called hyperparameters in this context. The next step is to apply the Kalman filter and smoother to obtain the state vectors, μ_i (the trend) and ψ_i (the cycle).

2.5 Frequency content

If the detrending methods described here are restricted to obtaining cyclical components of a certain frequency or frequency-band, they can generate spurious cycles that have little to do with the data generating processes involved. Therefore, unrestricted frequency domain analysis can help establish the frequency content of our dataset, to see whether the methods

are compatible with it. This provides a backstop and the associated significance tests can help with interpretation. Following Pollock (2014), who argues that econometric signal extraction should be guided by a careful appraisal of periodograms, we perform spectral analysis on the data after annual differencing.

Drehmann et al. (2012) find that housing and credit variables tend to co-vary strongly, especially at low frequencies. Based on this, Borio (2012) infers that the financial cycle is most parsimoniously described by credit and housing variables, referring to it as ‘the’ cycle. Strohsal et al. (2015) find that financial cycles tend to be longer in duration and larger in amplification than business cycles in the US and UK, but find little evidence of that for Germany. Our results for the Nordic region are discussed in section 3.1.

2.6 Cycle Aggregation

Einarsson et al. (2016), employ principal component analysis (PCA) to aggregate cycles. PCA is appealing, as it jointly captures many cycles’ variance to create a single cycle. In effect, it is a weighted mean with weights depending on each cycle’s degree of co-movement with that of all other cycles from the dataset. For the purpose of constructing a leading risk indicator, such an agnostic view to the relative importance of different cycles is not necessary, although it may suit historical analysis well. The credit cycle is at least as important as any asset price cycle, as it represents developments in financial system exposure to the private sector, which may turn out to be unsustainable. Credit risk is the risk type which historically has caused most major bank problems (see e.g. BCBS (2000)). Other things equal, and in the absence of credit growth, growing real estate prices usually signify stronger balance sheets in the non-financial private sector.

If credit cycles aren’t highly correlated with asset price cycles and bank funding cycles, that is little reason to lessen their weight in the final outcome. This notion is inspired by the Icelandic case, where CPI-indexation of residential housing credit is widespread. Also, a sizeable portion of credit to non-financial firms is foreign exchange denominated. Historically, foreign exchange credit to households was also prevalent for a short-lived period. As Einarsson et al. (2015) point out, financial and business cycle downturns in Iceland are often accompanied by currency depreciation and increased inflation in the short term. Furthermore, in the run-up to a crisis, foreign debt accumulation can be partly hidden away by a currency appreciation. Currency exchange rate movements can thus contribute to setting the credit cycle out of phase with other cycles, particularly housing. Furthermore, Iceland has seen a massive house price increase in recent years, coinciding with the remains

of a great deleveraging for households and firms. This sets the credit and housing cycles even further out of phase.

Applying PCA to this kind of dataset can produce an aggregate financial cycle where credit has a very small weight (see section 3.2). Although this is most prominent in Iceland, it also applies to the other countries to some extent. In addition, weights could change rapidly over time, complicating both interpretation and communication.

State-space models, such as the one described in section 2.4 allow for different specifications of dependencies between variables. One way is to test the hypothesis that either all or a subset of the variables can be described by a common frequency parameter and damping factor. The variables are said to have a 'similar cycle' when this hypothesis holds. Another way is to allow correlations between the error terms. For the purpose of this analysis we apply the model to each variable individually for consistency in performance evaluation across all trend-cycle decomposition methods.

2.7 Definitions and a turning point algorithm

To quantify performance, our out-of-sample exercise views financial cycles as any 'eyeball econometrician' would. We want to extract early warning signals, identify peaks and troughs as they occur and see how their timing holds up as observations are added. To this end, we make the following definitions, which add up to a turning point algorithm. In a financial cycle context, Hiebert et al. (2018) employ the algorithm suggested by Harding & Pagan (2006). Although similar, ours is more geared toward our real-time exercise:

A cycle is a cyclical component of a series, obtained from any given method of detrending or trend-cycle decomposition, demeaned and standardized. This is to ensure equal weights to all cycles, in the case of multivariate cycles.

A peak (trough) is a local maximum (minimum) value, in the middle of a 25 quarter window, if it lies above (below) trend. A local maximum below trend is not seen as a peak. A local minimum above trend is not seen as a trough. At points less than 12 quarters from an end point, the window reaches the end point. Series end points are not taken into consideration as potential turning points.

To study phase-shifts, we define correctly and falsely identified turning points. Real-time indications, using a limited sample are compared to those identified ex-post, using the full sample. A peak identified among the four latest observations, timed within a year from a 'true' (ex-post) peak, is deemed correctly identified. I.e. a peak signal. Conversely, if it is timed more than a year removed from a 'true' peak, it is deemed signal noise. Both are

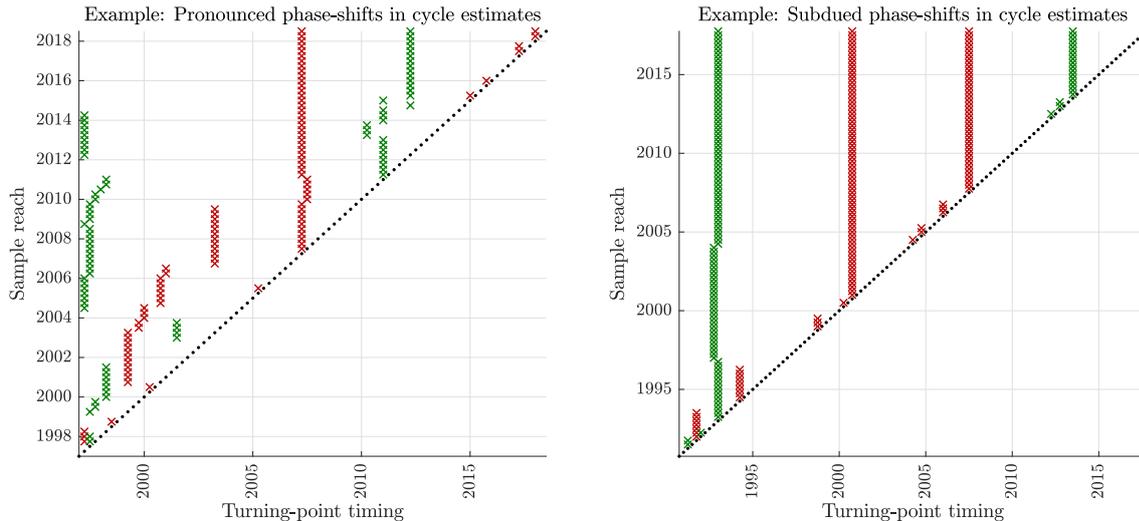


Figure 1: Examples of phase-shifting in financial cycle measures, as sample size varies. A peak is indicated by a red x, and a trough by a green x.

summed up and a noise-to-signal ratio is calculated. The same goes for troughs. Figure 1 shows stylized examples of phase-shifting behaviour in financial cycle measures, as the sample size varies. The upper-most turning points in the figures represent the 'true' or ex-post points. Those closest to the 45 degree line represent turning-points identified in real-time. Pronounced phase-shifting can complicate interpretation and communication for policy makers.

The cycle is in upward (downward) phase when the first difference between the two most recent observations is positive (negative). To evaluate real-time 'phase detection', we compare real-time phase indications to the ex-post cycle obtained using the full sample. The idea is to study whether an inverse relationship exists between retroactive revision of the cycle and the corresponding measure's early warning signal quality. The one-sided HP-filter does not retroactively revise its cycle estimates upon receiving new data, whereas other methods do. The hypothesis is that retroactive revision improves the signaling quality.

An early-warning signal is extracted if the cycle is in upward phase, and above trend. Such an indication, extracted within a given time window before crisis onset, is registered as a 'true' signal. If extracted outside the window, it is registered as noise. A noise-to-signal ratio along the lines of Reinhart & Kaminsky (1999) is then calculated.

The signal window lies between 4.5 and 1.5 years prior to crisis onset. Credit data available to policy makers is usually lagged by one to two quarters. Also, according to law in all countries in the sample, banks have 12 months to comply with an announced CCyB requirement. We use a rather long window, based on the experience from implementation

of countercyclical capital buffers in the Nordic region so far. Extrapolating the countries' build-up profile for the CCyB so far indicates roughly 4.5 years on average, to reach a binding requirement of 2.5%. Warning signals obtained after the signal window until two years after crisis onset are not taken into account, as they are moot.⁴

Timing of crisis onset in part follows Drehmann and Juselius (2014), but also other sources. For Denmark we follow the Danish Systemic Risk Council (2018). For Norway we follow Norges Bank (2018), and mark crises in Q2 1988 and Q3 2008. Although Norway experienced no systemic banking crisis in 2008 in terms of bank failures, the conditions for which the CCyB is designed were at hand. We take the same approach for Finland, and mark a crisis in Q3 2008. There were no systemic bank failures in Finland at that time. Bank of Finland (2008) however describes a situation fitting the release of a CCyB, with banks strengthening their capital base, tightening lending standards and the looming risk of large actors drifting into bankruptcy in a negative feedback loop between the financial and real sectors. Gulan et al. (2014) also find that although the Finnish recession of 2008 was an imported one, the feedback from the domestic financial sector to the real economy amplified it substantially. We only mark one systemic financial crisis for Iceland, in Q3 2008. Although the crisis reached its height in Q4 that year, the state announced a large capital injection into one of the three Icelandic systemically important banks at the end of Q3. The bank then went into administration, along with the other two systemically important banks, at the beginning of Q4.

Series expressed as amounts we transform by taking their natural logarithm. Those expressed as percentages, we leave unchanged.

Lastly, data revisions bear some mention. Revisions to the data underlying our cycle estimates lie outside the scope of this paper. In this respect, our analysis is not 'real-time' analysis. We use series which in many cases have been revised, because we do not have access to vintage time series. Edge and Meisenzahl (2011) study data revisions in the United States w.r.t. credit-to-GDP ratios, and their implications for countercyclical capital buffers. They find that revisions can be large, but that their main source stems not from data revision, but from filter end-point problems.

⁴Authorities are required to announce a period during which the CCyB requirement will not be raised, after they have lowered it. See the EU's Capital Requirements Directive 2013/36/EU, Article 137, paragraph 7 (g).

		Real credit	Credit to GDP	Household credit to income	Real house prices	House prices to rent	House prices to income	House prices to building cost	Real foreign liabilities	Real non-core funding	Non-core funding ratio	Avg.
Denmark	Strongest cycle	19.0	16.8	21.3	9.4	9.4	10.8	10.1	5.6	N/A	N/A	12.8
	Significant cycles (Wei, 1994)	4.8-57.0 2.8-3.6	4.6-50.3 3.6-3.9	21.3-41.5 7.1-10.6	3.9-47.0 2.4-3.4	3.1-47.0 1.8-2.8	5.4-43.3 2.1-4.3	3.4-30.3 2,0-2,8	3.6-39.3 2.2;3.0	N/A	N/A	
Finland	Strongest cycle	23.1	23.1	23.1	7.8	7.8	7.0	7.8	11.1	N/A	N/A	13.9
	Significant cycles (Wei, 1994)	4.6-46.3 1.6-3.9	30.8-92.5 1.7-5.8	2.4-46.3 1.9-2.1	4.3-47.0 1.8-3.6	4.3-47.0 1.8-3.6	4.2-21.0 1.9-3.5	2.6-47.0	2.8-33.3 1.5;1.9-2.2	N/A	N/A	
Iceland	Strongest cycle	21.0	21.0	14.6	6.2	N/A	6.0	6.1	19.9	7.8	N/A	12.8
	Significant cycles (Wei, 1994)	6.0-42.0 2.2-4.2	5.3-42.0 2.1-4.2	9.8-29.3 2.1-5.9	6.2-37.0 2.0-4.6	N/A	6.0-15.0 1.7-4.3	5.1-15.3 1.9-3.8	1.7-39.8	1.6-31.3	N/A	
Norway	Strongest cycle	31.6	28.1	19.1	11.8	N/A	9.8	9.8	11.1	30.0	10.0	18.9
	Significant cycles (Wei, 1994)	6.3-63.0 2.5-5.3	4.3-56.3 2.7-3.8	4.8-38.3 2.0;3.5	5.2-47.0 2.5-3.4;4.3	N/A	4.3-39.0 2.0-3.6	4.3-39.0 1.7-3.6	5.6-33.3 1.8-4.2	3.8-30.0 2.5-3.0	3.8-30.0 1.6-3.0	
Sweden	Strongest cycle	18.7	18.7	36.3	9.4	N/A	9.4	14.0	9.8	N/A	N/A	16.6
	Significant cycles (Wei, 1994)	3.3-56.0 2.1-2.7	18.7-56.0 5.1-11.2	4.5-36.3 1.8-3.6	47.0 5.2-15.7	N/A	47.0 9.4-15.7	7.0-42.0 1.7-5.3	2.5-39.3 1.6-2.2	N/A	N/A	
Avg.		22.7	21.5	22.9	8.9	8.6	8.6	9.6	11.5	18.9	10.0	14.8

Table 1: Frequency content. Maximum power cycles and statistically significant cycles. Numbers are cycle duration in years.

3 Analysis

3.1 Spectral analysis

Spectral analysis results are reported in table 1. Summarized, they are as follows: On average, periodograms indicate the power spectrum maximum at a cycle duration of 14.8 years.⁵ The duration of peak-power cycles is quite widely dispersed, ranging from 5.6 years for Danish banks' real foreign liabilities, up to 36.3 years for the household credit to disposable income ratio in Sweden. At the maximum-power frequency, the Wei (1994) test finds a cyclical component to be present at the 5% significance level in all 40 cases. Using Whittle (1952), a stricter test, a cyclical component at the maximum-power frequency is found present in 23 cases, at the 5% significance level.⁶

Referring to business cycle frequencies as 1.5-8.0 years and financial cycle frequencies as 8.0-30.0 years (as in e.g. Drehmann et. al (2012) and Aikman et al. (2012)), the maximum power frequency of our dataset lies in the latter in 30 out of 40 cases. In all cases where it lies in the business cycle domain, the Wei-test also finds a significant cycle somewhere among the lower financial cycle-frequencies. By country, the average maximum-power cycle ranges from 12.8 years in Iceland and Denmark, to 18.9 years in Norway. Grouping the variables by type, the credit variables seem to have the longest maximum-power cycles (22.4 years), then the bank funding variables (14.7 years) and lastly the housing variables (8.9 years).

A notable feature of maximum-power housing cycles is their relatively high frequency. In particular, housing cycles in Finland and Iceland seem to lie at a frequency within the so-called business cycle band of 1.5-8.0 years. Specifically, roughly 6 years in Iceland and almost 8 years in Finland, but closer to 11 years in Denmark, Norway and Sweden. This is in stark contrast with Drehmann et al. (2012), who find that credit and housing tend to co-vary strongly, especially at low frequencies. This raises two concerns.

First, whether housing and business cycles can easily be told apart in real-time? Spectral analysis of real GDP for the same time period in each country reveals an average 6.6 years

⁵Pollock (2014) argues for the removal of a linear time trend before analysing. For our dataset, that method seems to emphasize longer cycles. E.g. for Swedish credit data, this method yields the most prominent cycle at a duration of 228 observations for real credit, a series with 228 observations. Analysing a related but shorter series, household credit to disposable income, with 149 observations, finds the most prominent cycle at 149 quarters. Cycle duration depending heavily on the sample size, which is arbitrary, seems implausible. We therefore opt for analysing differenced series, although that can have its own drawbacks, such as overemphasizing measurement errors.

⁶Canova (1996) criticizes the Whittle-test for failing to acknowledge meaningful economic cycles when periodograms are not characterized by sharp peaks, but humps of mass within certain frequency bands, as is common with economic data. Although we do not employ the test Canova develops, his coverage shifts our emphasis to the Wei-test, away from the Whittle-test.

duration of maximum power cycles, but often another slightly less powerful cycle is found significant, averaging around 12.0 years in duration.

Second, whether it is more useful for signal extraction to focus on the maximum-power housing cycle, or some other statistically significant cycle at a lower frequency. Focusing on the higher frequency cycle may increase the indicators' noisiness. On the other hand, focusing on the lower frequency cycle may capture only a small part of the series variance. It may also be out of phase with a stronger, higher frequency cycle. Should such a low frequency cycle be given equal weight to, say, the credit cycle? The answer is not obvious.

All in all, applying low-pass filters to this dataset seems tractable, but it also seems that tailoring filters to each series may be necessary. If credit cycles indeed last more than twice as long as housing cycles, applying filters with the same smoothing parameter or initial lag for both seems dubious. We nonetheless proceed by using the same smoothing parameters for all variables, when using the HP and Hamilton filters. If this creates the danger of spurious cycles emerging, it should be reflected in worse early warning signaling performance, compared to methods more flexible with regard to the data's frequency content.

3.2 How (not) to aggregate cycles?

Across the whole panel, there is a high degree of correlation between different cycles within the same variable group (i.e. credit, housing and funding) within each country. Across all filtering techniques, the average correlation coefficient between pairs of credit cycles is 0.78, for housing cycle pairs it's 0.91 and 0.84 for bank funding. This is to be expected, as variables from the same group often overlap. I.e. real credit and the credit-to-GDP ratio are partly made up of the same data. In addition, bank funding cycles most often have a moderate to high correlation with credit and housing cycles, as table 2 shows.

	Denmark	Finland	Iceland	Norway	Sweden	Average
Credit-credit	0.86	0.70	0.81	0.77	0.75	0.78
Credit-housing	0.45	0.37	0.09	0.50	0.33	0.35
Credit-funding	0.80	0.68	0.36	0.53	0.63	0.60
Housing-housing	0.96	0.92	0.78	0.94	0.93	0.91
Housing-funding	0.46	0.59	0.79	0.70	0.79	0.67
Funding-funding	0.78	N/A	0.89	0.85	N/A	0.84

Table 2: Average pair-wise cycle correlation.

What stands out is the rather low correlation between pairs of credit and housing cycles. The average coefficient for these pairs is 0.35. It is pulled down heavily by Iceland, where

this correlation is very low. Excluding Iceland, the average coefficient is still much lower than for pairs of other types. In particular, credit-to-GDP gaps correlate very little with housing cycles. This would suggest that for each Nordic country, credit and housing cycles aren't in step, for most of the time. This fits well with the spectral analysis results, which suggest that these groups of variables have rather different frequency content. Moreover, the correlation is highly dependent on the time period chosen for analysis. Although Einarsson et al. (2016) find a rather low correlation between housing and credit cycles in Iceland from 1875-1980, they do find a high level of correlation in 1980-2013. In recent years however, Iceland saw a massive deleveraging by the non-financial private sector, which coincided with a pronounced increase of real estate prices. This has broken down the correlation.

Therefore we reiterate that by aggregating cycles we are not trying to identify 'the' financial cycle as a single cyclical movement common to many variables. With regard to multivariate structural time series models, such a restrictive definition proves difficult to estimate for a wide selection of variables. With regard to PCA, as pairwise cycle correlation is everchanging, so will be weights assigned to each variable in such an aggregation. Thus, credit cycles, which intuition deems central to cyclical systemic risk, could end up with a minimal weight in the outcome. The meaning and interpretation of such a measure would furthermore be too complicated for communication to the general public.

We proceed by aggregating univariate cycles with a simple mean. The multivariate cycle measures we construct are therefore not to be seen as representations of a single well-defined cyclical phenomenon which uniformly governs movements in the whole dataset for each country. Rather, they are a simple combination, or summary, of the main cyclical financial indicators.

3.3 How to decompose cycle and trend?

To evaluate the various detrending methods, we analyze their performance at extracting the same set of univariate cycles for each country. For this evaluation we use roughly the same time period for each variable across methods. Assuming that financial cycles are a good proxy for cyclical systemic risk and thus closely tied to the occurrence of financial crises, we evaluate the detrending methods based on the early warning signal quality of their cyclical outcomes. We add up noise and signals from each method, across variables and countries, to get a total ratio of noise-to-signals. This serves as our main measure of performance. In addition, we study how real-time properties compare with an ex-post estimate. Results are reported in table 3.

In this respect we choose the subset of data so that it includes the earliest crisis for all countries, the signal window before it and some time period prior to the window. We don't discard any observations, contrary to common practice. We do this to avoid making our limited sample even smaller. To compensate for this, we have inspected the outputs from each filter to establish whether small sample problems skew the outcome. They don't seem to. Rather, discarding initial observations seems likely to reinforce our results.

The Hamilton-filter bears special notice here, as it needs at least 23 observations to make an estimate. We allow it that advantage, so its early estimates are based on more information than other methods', and the period under review is shorter. In most cases a shorter period is an advantage, as the first signal window is more than five years removed from the sample beginning. In short, despite these advantages the Hamilton-filter performs rather poorly.

With regard to the noise-to-signal ratio for early warning, the CF- and two-sided HP-filters take first place with a ratio of 1.78. They are followed by the one-sided HP-filter, Hamilton-filter, Butterworth-filter and structural time series model, in that order.

	One-sided HP	Two-sided HP	Hamilton	CF	Butter- worth	STSM
T	5,067	5,034	4,242	5,100	5,100	5,082
Phase detection	91.9%	91.6%	75.6	72.3%	83.5%	82.9%
Noise	983	1,030	856	952	1,335	886
Signals	476	579	439	535	581	244
Noise to signal ratio	1.88	1.78	1.95	1.78	2.30	3.63
Lag, peak to crisis	16.3	15.0	15.9	11.1	16.9	17.0
Peak noise	404	470	559	272	474	439
Peak signals	528	391	347	104	377	410
Peak noise to signal	0.77	1.20	1.61	2.62	1.26	1.07
Trough noise	346	352	387	165	193	551
Trough signals	429	310	224	108	265	371
Trough noise to signal	0.81	1.14	1.73	1.53	0.73	1.49

Table 3: Performance of trend-cycle decomposition methods.

Ex-post, the CF-filter finds peaks closest to crisis onset, on average roughly 11 quarters removed in time. This is in part caused by the choice of frequency band. When most of the frequency content lies outside the band, the filter converges on some other frequency cycle within the band. This seems to be the case of housing variables in Finland and Iceland. This raises the question whether the frequency band should always be set around the most powerful cycle, regardless of its frequency. On the one hand, the high frequency of housing cycles increases the noisiness of their signalling. On the other hand, this other low-frequency component may have relatively little amplitude. Assigning it the same weight as other

variables, e.g. the credit-to-GDP gap, when aggregating cycles, may not be justified.

Our concept of noise-to-signal ratios for real-time peak and trough detection are dependent on each method's own ex-post cycle estimate. If the method doesn't retroactively revise the cycle upon receiving new data, such ratios will be low but potentially at the cost of worse results on other metrics. Namely the noise-to-signal ratio and the mean lag between peak and crisis. This trade-off is shown in table 3, where the one sided HP-filter has substantially lower noise-to-signal ratios for peaks and troughs than the two sided one. At the same time, the two-sided filter has a lower noise-to-signal ratio for early warning, and finds peaks closer to crisis onset.

3.4 Panel: Which univariate cycles perform best?

We proceed by applying the CF-filter to our dataset, and evaluating individual cycle's performance. Performance is evaluated on four metrics. First early warning signal quality, i.e. the noise-to-signal ratio. Second, the average time lag between peaks identified ex-post, and crisis onset. Third and fourth, the indicators' ability to correctly identify turning points in real-time is evaluated with noise-to-signal ratios for peaks and troughs separately. Results are reported in table 4.

Looking first at the variables in groups, funding variables have the lowest over all noise-to-signal ratio (1.25), then credit variables (1.70) and lastly housing (1.82). The good outcome for funding variables is driven mainly by banks' real foreign liabilities, which is also the only one available for all countries. Without it, credit variables do best.

Ex-post, credit cycles peak on average much closer to crisis onset (roughly 5 quarters removed) than both housing (14 quarters) and funding (13.5 quarters). This is not to say that housing and funding cycles don't peak close to crises. Rather, their relatively high frequency means that peaks also occur far removed from crisis. This is the main cause for higher noise-to-signal ratios for housing variables. In the wake of a crisis, housing cycles tend to shoot above trend much earlier than credit cycles. On average, around 4-5 years earlier.

In addition, credit cycles tend to peak after crisis onset. This does not translate into a lack of early warning signals. Rather, credit cycle's early warning signals are both timely and continuous, with the notable exception of the household credit to income ratio in Iceland.

Real-time identification of turning points seems affected by the variable's nature as either slow-moving stock variables or more volatile prices. Overall, correctly identifying credit and funding cycle peaks as they happen seems easier than identifying cyclical house price peaks. The likelihood of a real-time indication of a credit or funding cycle peak being false is

	T	Noise to signal ratio	Lag, peak to crisis (quarters)	Peaks noise to signal ratio	Troughs noise to signal ratio
Real credit	762	1.76	3.60	1.05	1.00
Credit to GDP	762	1.68	8.20	1.84	2.08
Household credit to income	750	1.65	3.70	1.15	9.50
Credit variables avg.	758	1.70	5.17	1.33	2.21
Real house prices	762	1.71	11.88	4.92	0.95
House prices to rent	329	1.78	11.00	8.33	0.89
House prices to income	762	1.66	17.60	3.14	0.95
House prices to building cost	726	2.08	15.55	4.40	0.90
Housing variables avg.	645	1.82	14.01	4.43	0.93
Banks' real foreign liabilities	707	0.86	7.87	1.22	1.89
Banks' real non-core funding	364	2.08	19.83	2.13	1.00
Banks' non-core funding ratio	122	2.29	12.67	0.57	2.00
Funding variables avg.	398	1.25	13.46	1.29	1.63

Table 4: Variables' panel-wide performance.

around 57%. Such an indication for housing, however, is more than three times more likely to be false than true. Visual inspection of turning points identified in real-time shows that a single indication of a cycle having turned is highly unreliable. Upon receiving three or four consecutive indications of a turning point, however, it is quite reliable. This supports the notion that aggregate financial cycle measure's are not well suited to guide sudden and complete release of countercyclical capital buffers. Other indicators are needed for that. They may however be well suited to guide gradual and partial release.

Looking at individual variables, banks' real foreign liabilities cycle takes first place, capturing all crises in a timely fashion, except Denmark in 1986. It comes out as the only univariate indicator with a noise to signal ratio below unity. Other variables in the bank funding group tend to do worse. This is perhaps due to our limited sample, as it doesn't include them for all five countries. Also, more intricately defined measures of non-core funding may be needed to give good results. Ex-post, the real foreign liabilities cycle peaks on average within two years from crisis onset. The real credit cycle comes out as a well rounded indicator, doing relatively well on all fronts. Out of the credit variables, however, household credit to disposable income comes out with the best noise-to-signal ratio, in spite of completely missing the 2008 crisis in Iceland. Outside Iceland's historical issues with CPI-indexed and foreign currency denominated household credit discussed in section 2.6, along with highly cyclical disposable income, this may be the best credit indicator for the Nordics. Among housing cycles, the ratio of house prices to disposable income comes out on top, both

in terms of the early warning noise-to-signal ratio, and real-time peak identification. This good performance of the two disposable income ratios perhaps underlines the importance of the household sector for financial stability in the Nordics. Although many countries have higher home-ownership rates, the rate of mortgaged home-owning households in the Nordics is the highest in Europe, along with that of the Netherlands, Belgium and Luxembourg, according to Eurostat data for 2016.

3.5 Panel: Do multivariate cycles outperform univariate ones?

Housing cycles tend to peak before crisis onset, whereas credit and funding cycles tend to peak after. Perhaps, combining them in some way hits a 'sweet spot', peaking close to crisis onset, and giving off less noise than univariate cycles? To investigate this we mine the data for all possible variable combinations, with anything from two to six variables included, across the panel. We include only the six variables available for all five countries, which cover at least all crises in the sample and the signal window before them.⁷ We then compare performance with the 'Basel-gap'. Table 5 shows results.

With respect to early warning signals, the single best combination comes out as a trivariate cycle with household debt to disposable income, house prices to disposable income and banks real foreign liabilities. Those are the best performing cycles from each group (see table 4). Figure 2 displays this trivariate cycle for each Nordic country. It has a noise-to-signal ratio of 0.87 across the panel, and outperforms all of its own components in that regard, including banks real foreign liabilities.

	Rank on early warning	Noise to signal ratio	Lag, peak to crisis (quarters)	Peaks noise to signal ratio	Troughs noise to signal ratio
Best performance	#1	0.87	1.6	1.53	1.67
Real foreign liabilities	#4	0.95	2.5	1.80	1.78
Bivariate housing cycle	#37	1.27	5.6	3.83	1.44
Trivariate credit cycle	#43	1.31	2.2	0.75	1.06
All 6 variables included	#44	1.32	5.6	3.83	1.44
Basel-gap (10yr advantage)	#50	1.36	9.1	0.88	0.94
Basel-gap	#64	1.87	5.9	1.03	1.25

Table 5: A few results for multivariate cycles. Univariate cycles for comparison.

⁷They are: Real credit, credit-to-GDP, household credit to disposable income, real house prices, house prices to disposable income and banks real foreign liabilities. Within each country we use the same sampling period for all combinations. This allows for 57 different bi- or multivariate combinations for each country, in addition to six univariate ones.

The result of the best multivariate cycle outperforming bank’s real foreign liabilities seems fragile with respect to the sample size. Table 4, which is based on a slightly different sample size, shows the univariate cycle with a ratio of 0.86, whereas it has a ratio of 0.95 in table 5. However, the top 20 multivariate combinations predominantly contain variables from different groups, which outperform their individual parts. In contrast, subcycles, i.e. multivariate cycles with components only from the same variable group, don’t do particularly well. A trivariate credit cycle ranks 43rd and a bivariate housing cycle ranks 37th. Ex-post, the winning cycle peaks on average 1.6 quarters before crisis onset, thereby vastly outperforming any univariate cycle. Also, ex-post, its upward phase goes hand-in-hand with the signal window in 8 cases out of nine. The only exception is Denmark in 1986. Lastly, this measure performs relatively well on real-time turning point identification. It ranks around the middle of the 63 different variable combinations w.r.t. peak identification and does better than the average of its components, with a ratio of 1.53.

All this suggests that aggregate financial cycle measures are potentially much more than the sum (in this case the mean) of their parts.

The Basel-gap performs poorly in comparison. A striking result is that on early warning signals, it ranks 64th out of 64, when compared to all uni- and multivariate cycles from the CF-filter. To check whether this is caused by small-sample problems, table 5 also shows its performance when given a 10 year advantage with data (still only taking the same period into account when counting noise and signals). Despite this advantage it only ranks 50th. Furthermore, it peaks much further away from crisis onset. The only metrics where it performs well are the noise-to-signal ratios for peaks and troughs, where its own ex-post cycle is the benchmark.

3.6 Country: Denmark

The Danish dataset has eight variables, covering two crises. Crisis onset is dated at 1987 Q1 and 2008 Q3. Figure 4 shows trivariate credit and housing cycles, and a univariate bank funding cycle all obtained with the CF-filter with a frequency band of 8.0-30.0 years.

In terms of early warning signals, banks’ real foreign liabilities performs best, with a noise-to-signal ratio of 0.50, the only one smaller than 1. Real credit, banks’ real non-core funding and the credit-to-GDP ratio come in 2nd-4th, respectively. The worst performers are the housing variables, especially the price ratios. Peaking close to crisis onset is also a desirable feature. Ex-post, banks’ real foreign liabilities also performed the best on that metric, peaking on average 5 quarters after crisis onset. Furthermore, in real-time, it issued

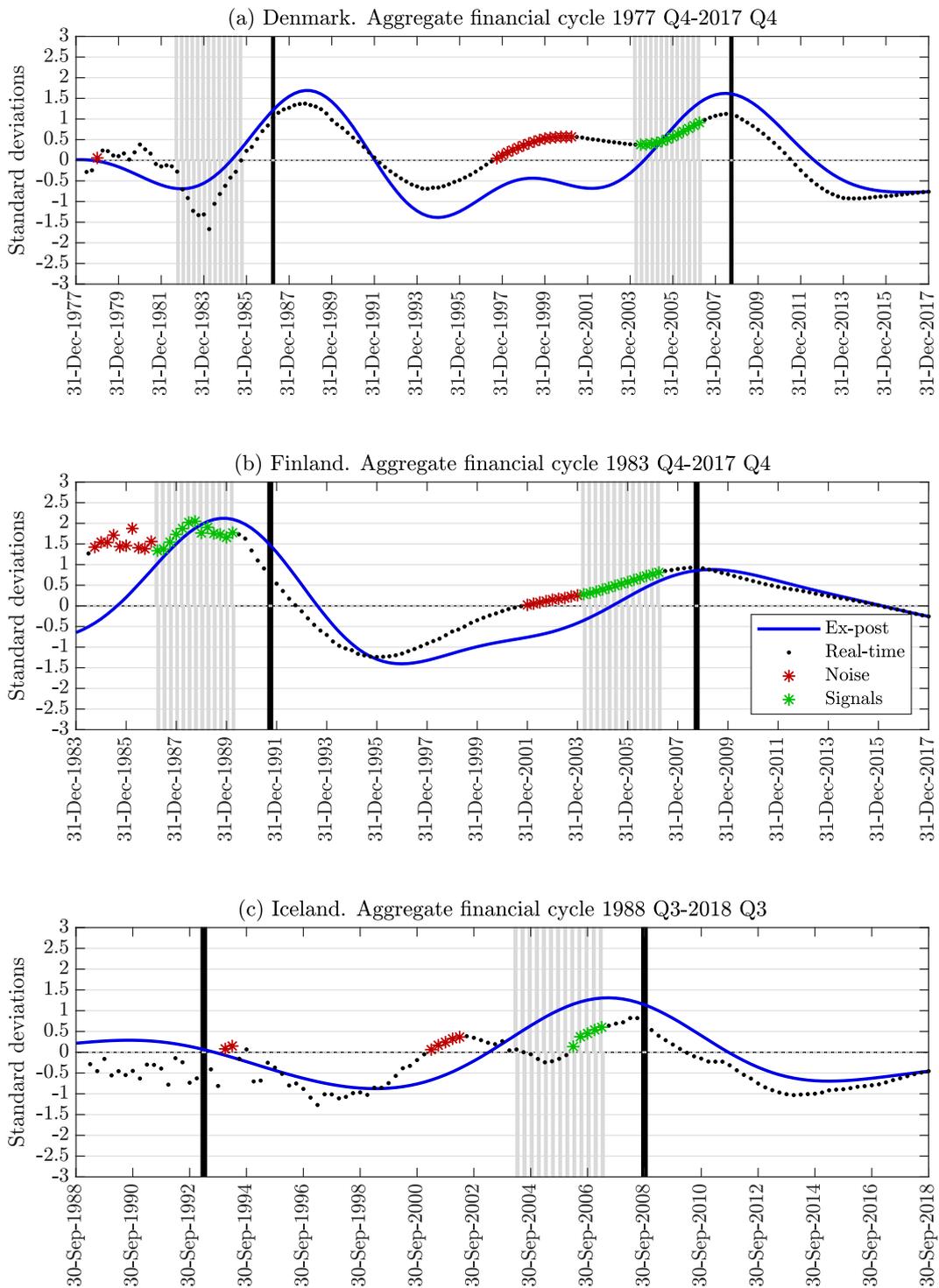


Figure 2: (a)-(c) The best aggregate financial cycle for the Nordics. Shaded grey areas show the signal window. Vertical black lines mark crisis onset.

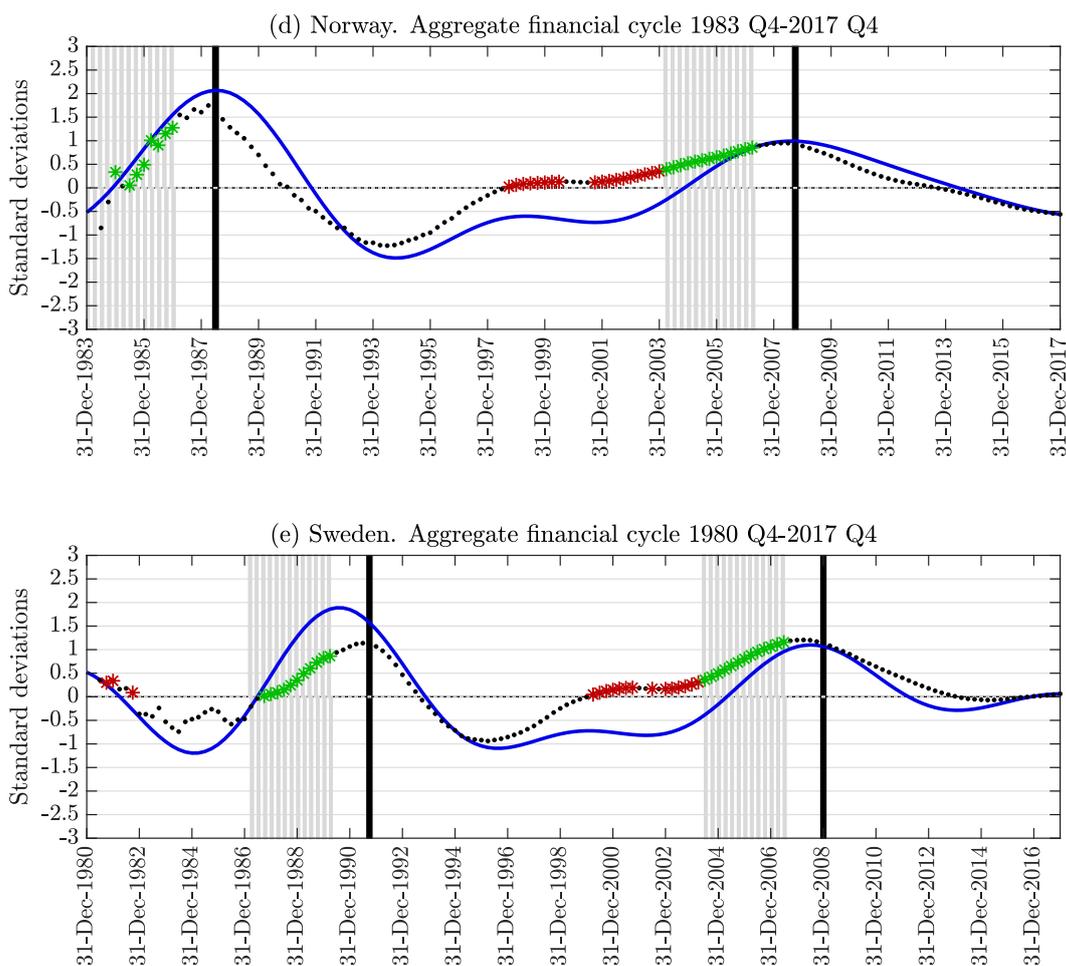


Figure 2: (d)-(e) The best aggregate financial cycle for the Nordics. Shaded grey areas show the signal window. Vertical black lines mark crisis onset.

few false signals of having peaked, reflected in a low noise-to-signal ratio for peaks. The only other variable coming close on this metric, is household debt to disposable income, peaking on average 6 quarters after crisis onset.

The good performance of banks' real foreign liabilities should be seen in light of the spectral analysis. Section 3.1 suggests that for Denmark, the most prominent cyclical component in this variable has duration of 5.6 years. It therefore lies outside the frequency band. Widening the band to 5.0-30.0 years yields more frequent cycles, which peak four times instead of two, over the sample period. Instead of peaking only in 1989 and 2008, implying a very low frequency, additional peaks appear in 1980 and 2014. The noisiness increases, reflected in the noise-to-signal ratio being raised to 0.77, which is still quite low. The Wei-test finds significant cycles at both the shorter and longer durations, so this cycle

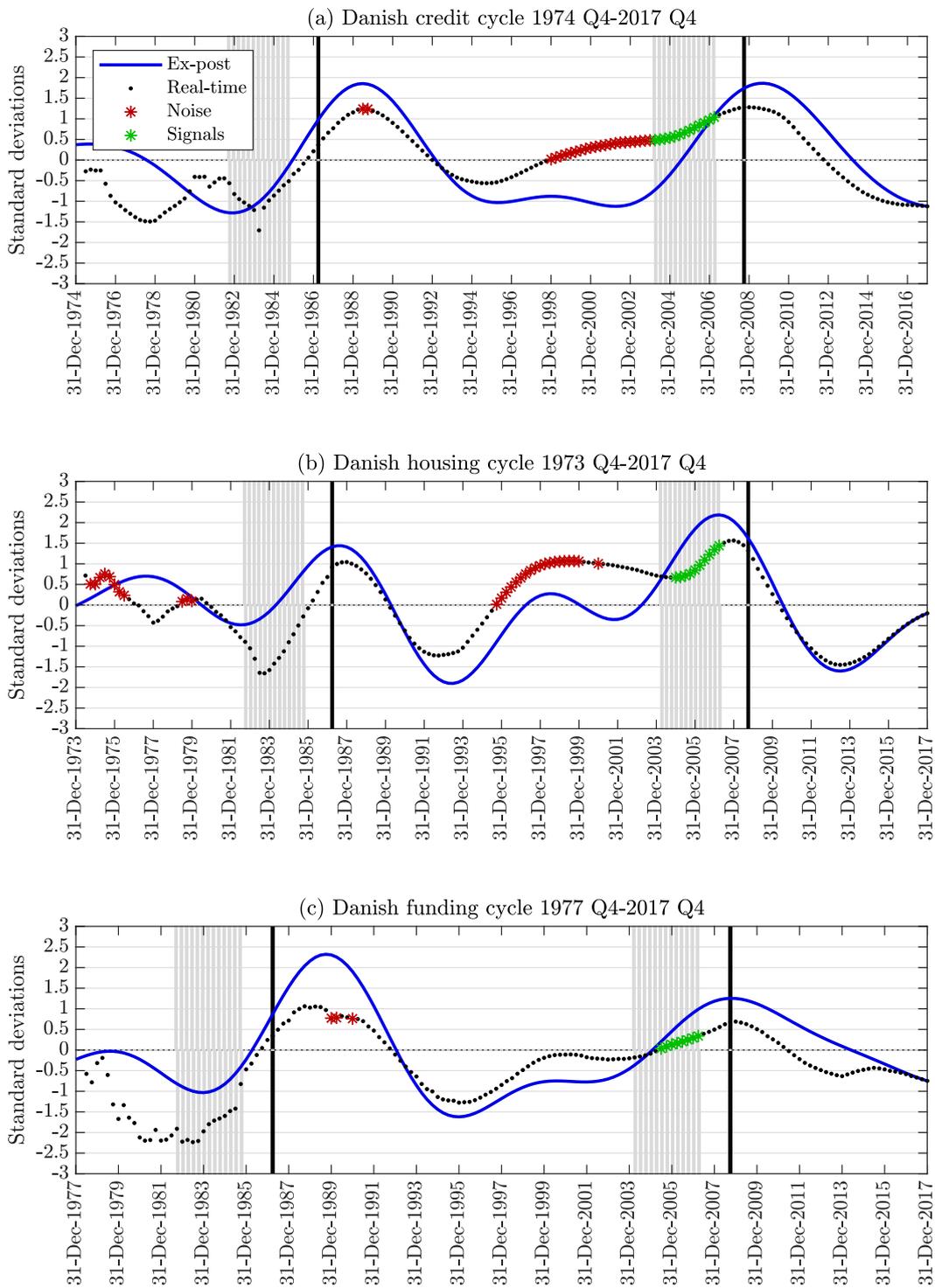


Figure 3: Danish financial subcycles and their real-time performance. Shaded grey areas are signal windows. Vertical black lines mark crisis onset.

need not be spurious.

For Denmark, ex-post analysis indicates different behavior among variable groups, or subcycles, shown in figure 3. Housing cycles peak more often than credit and funding cycles. A trivariate housing cycle peaked in 1977, 1987, 1998 and 2007, while a comparable credit cycle peaked only in 1989 and 2009. A univariate funding cycle peaked in 1989 and 2008. The housing cycle shows low peaks ($0 < X < 1$ std.) far removed from any financial crisis, but pronounced peaks (> 1 std.) close to or leading crisis onset. This contrasts the credit and funding cycles, which only have pronounced peaks close to or lagging behind crisis onset.

Results underpinning Table 3. show the one-sided HP-filter to have the lowest noise-to-signal ratio for Denmark, followed by the two-sided HP-filter. Results underpinning Table 5 show that for Denmark, no multivariate combination outperforms banks' real foreign liabilities with regard to the noise-to-signal ratio, and that the winning combination from Table 5 ranks 9th.

The crisis starting in 1987 is largely missed, perhaps due to small sample problems. Also, the timing of crisis onset may be odd, as there was a prolonged period of bank ailments in Denmark 1984-1995, although their height was in 1987-1993.⁸ In addition, cyclical systemic risk may not always build up quickly. Danish credit and housing cycles give off noise around 1980, but stop during the signal window, which largely coincides with an economic boom phase in 1982-1986. GDP and disposable income, the denominators in many of our variables, are themselves cyclical, which may hide risk build-up. Yet another explanation may be that not all systemic banking crises are caused by cyclical systemic risk. The causes may have been structural.⁹

3.7 Country: Finland

The Finnish dataset has eight variables, covering two crises. Crisis onset is dated at 1991 Q3 and 2008 Q3. Figure 4 shows a trivariate credit cycle in panel (a), a four-variable housing cycle in (b) and a univariate bank funding cycle in (c), all obtained with a CF-filter with a frequency band of 8-30 years. Both crisis episodes are captured by early warning signals from all subcycles, albeit with a great amount of noise for the credit cycle before 1991. This is not unique to the CF-filter, as all six detrending methods make the same error. In fact, the credit series for Finland don't show any obvious signs of cyclicity before that time.

⁸See e.g. Abildgren, K. & Thomsen, J. (2011) p. 127. In our timing of the crisis onset we follow Danish Systemic Risk Council (2018).

⁹Abildgren & Thomsen (2011) describe structural changes in the Danish economy, over a number of years in the run-up to the crisis.

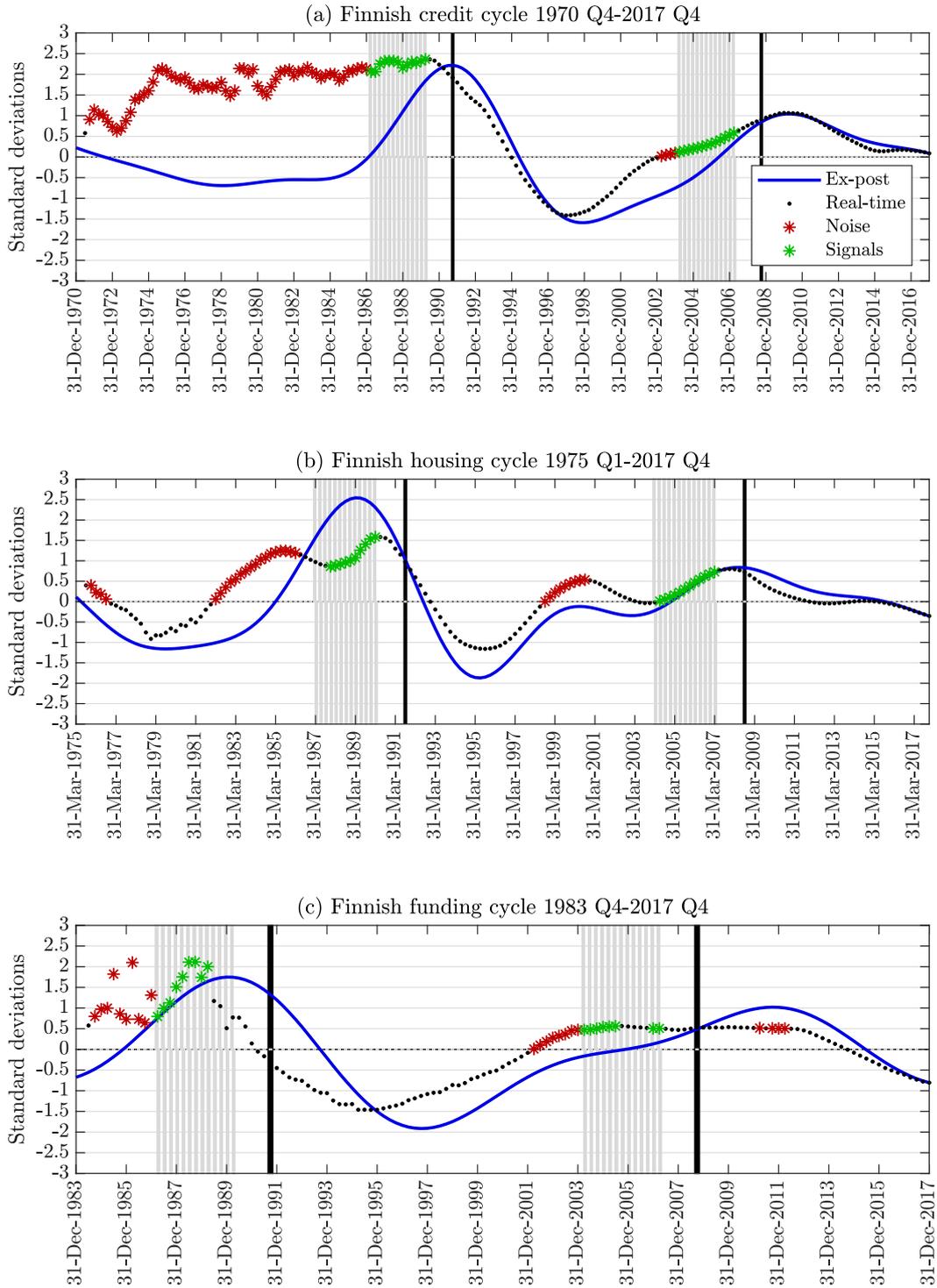


Figure 4: Finnish financial subcycles and their real-time performance. Shaded grey areas are signal windows. Vertical black lines mark crisis onset.

The best performing univariate cycle is real house prices, with a noise-to-signal ratio of 0.39. The housing cycle in figure 4 (b) peaked in 1989 and 2009, implying duration as long as 20 years. According to spectral analysis, however, the most prominent cycle contained in the data lies just outside the frequency band, at 7.8 years duration, but the Wei-test still finds a significant cycle at this frequency. This one need not be spurious. Widening the frequency band to 5-30 years gives a somewhat different picture, with the cycle peaking four times instead of two. With this wider band, real-time signaling is quite similar, but a little noisier.

Results underpinning Table 3. show the Hamilton-filter to have the lowest noise-to-signal ratio for Finland, followed by the CF-filter. Results underpinning Table 5 show that for Finland, 17 multivariate combinations outperform the real house price cycle with regard to the noise-to-signal ratio, and that the winning combination from Table 5 ranks 25th.

All the Finnish subcycles show a clear relationship between the amplitude at peaks, and the severity of crises. The peaks associated with the 1991 crisis are pronounced and sharp, whereas the ones associated with the global financial crises are low and flat. The same goes for early-warning signals.

3.8 Country: Iceland

The Icelandic dataset has eight variables, covering one crisis. Crisis onset is dated at 2008 Q3. Figure 5 shows a trivariate credit cycle in panel (a), a trivariate housing cycle in panel (b) and a bivariate funding cycle in panel (c), all obtained with the CF-filter with a frequency band of 8.0-30.0 years. Iceland had some non-systemic banking ailments between 1985 and 1993, although on a much smaller scale than the other Nordics (see Einarsson et al. (2015), p. 22 for details). Therefore a black line is marked in fig. 5, in addition to the systemic crisis of 2008, to show signals and noise in historical context.

Overall, Figure 5 illustrates our motivation for trying to improve signaling by combining different cycles. Ex-post, the credit cycle peak lags crisis onset by one and half year, and in real-time the cycle sent only four warning signals at the end of the signal window. The housing and funding cycles, on the other hand, peaked in 2006 Q2 and Q4 respectively, and sent many signals accompanied with long stretches of noise. No subcycle seems to have been able to tell apart business and financial cycle movements in real-time, as they all showed marked signs of upswing around the turn of the century, only to revise them downwards afterwards.

Out of univariate cycles, house prices to disposable income and the two bank funding

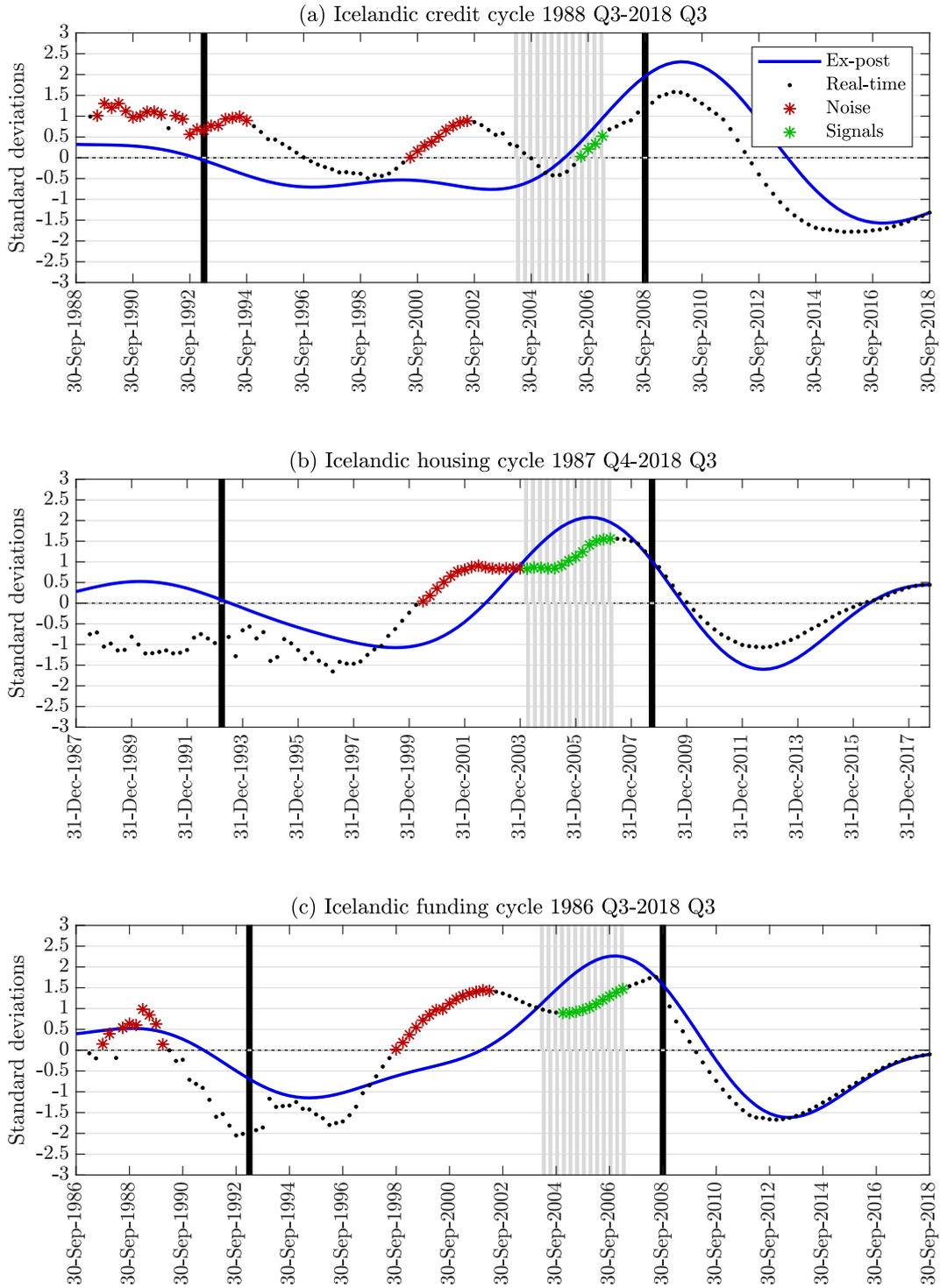


Figure 5: Icelandic financial subcycles and their real-time performance. Shaded grey areas are signal windows. Vertical black lines mark crisis onset.

variables have the best early warning signaling from 1988 onwards. Credit cycles do rather poorly, because of large quantities of noise in 1989-1994. That noise seems largely in line with the ex-post estimate however, and came in a period of occasional non-systemic banking ailments.

Results underpinning Table 3. show the Hamilton-filter to have the lowest noise-to-signal ratio for Iceland, followed by the Butterworth-filter. Results underpinning Table 5 show that for Iceland, no multivariate combination outperforms the house price to income cycle with regard to the noise-to-signal ratio, and that the winning combination from Table 5 ranks 18th.

The housing cycle in figure 5 (b) peaked in 1990, 2006 and is perhaps headed for a 2019 peak, implying duration as long as 16 years. According to spectral analysis, however, the most prominent cycle contained in the data lies outside the frequency band, at roughly 6 years duration. The Wei-test doesn't find a statistically significant cycle longer than 15.3 years in two variables out of three, so this cycle is possibly spurious. Widening the frequency band to 5-30 years gives a somewhat different picture, with much shorter cycles from 1986-2002, and long ones from 2002-2018. Real-time signaling is quite similar, but a little noisier. On the one hand, focusing exclusively on certain frequencies creates the danger of spurious cycles, whereas seeking out the most prominent cycle may increase noisiness, given that systemic crises will continue to be few and far apart.

3.9 Country: Norway

The Norwegian dataset has nine variables, covering two crises. Crisis onset is timed in 1988 Q2 and 2008 Q3. Figure 6 shows trivariate credit and housing cycles and a univariate bank funding cycle, all obtained with the CF-filter with a frequency band of 8.0-30.0 years.

In terms of early-warning signals, the single best indicator is the household debt to disposable income ratio, peaking only 2.5 quarters from crisis onset with a noise to signal ratio of 0.5. In fact, all three credit variables perform well, in addition to banks' real foreign liabilities. The dataset includes two additional variables related to bank funding. They are banks real non-core funding and non-core funding ratio. They perform rather poorly in terms of early-warning signals. Due to lack of data before 1987 they only cover one crisis, which is insufficient to draw any conclusions.

Results underpinning Table 3. show the two sided HP-filter to have the lowest noise-to-signal ratio for Norway, followed by the CF-filter. Results underpinning Table 5 show that for Norway, no multivariate combination outperforms the household debt to income cycle

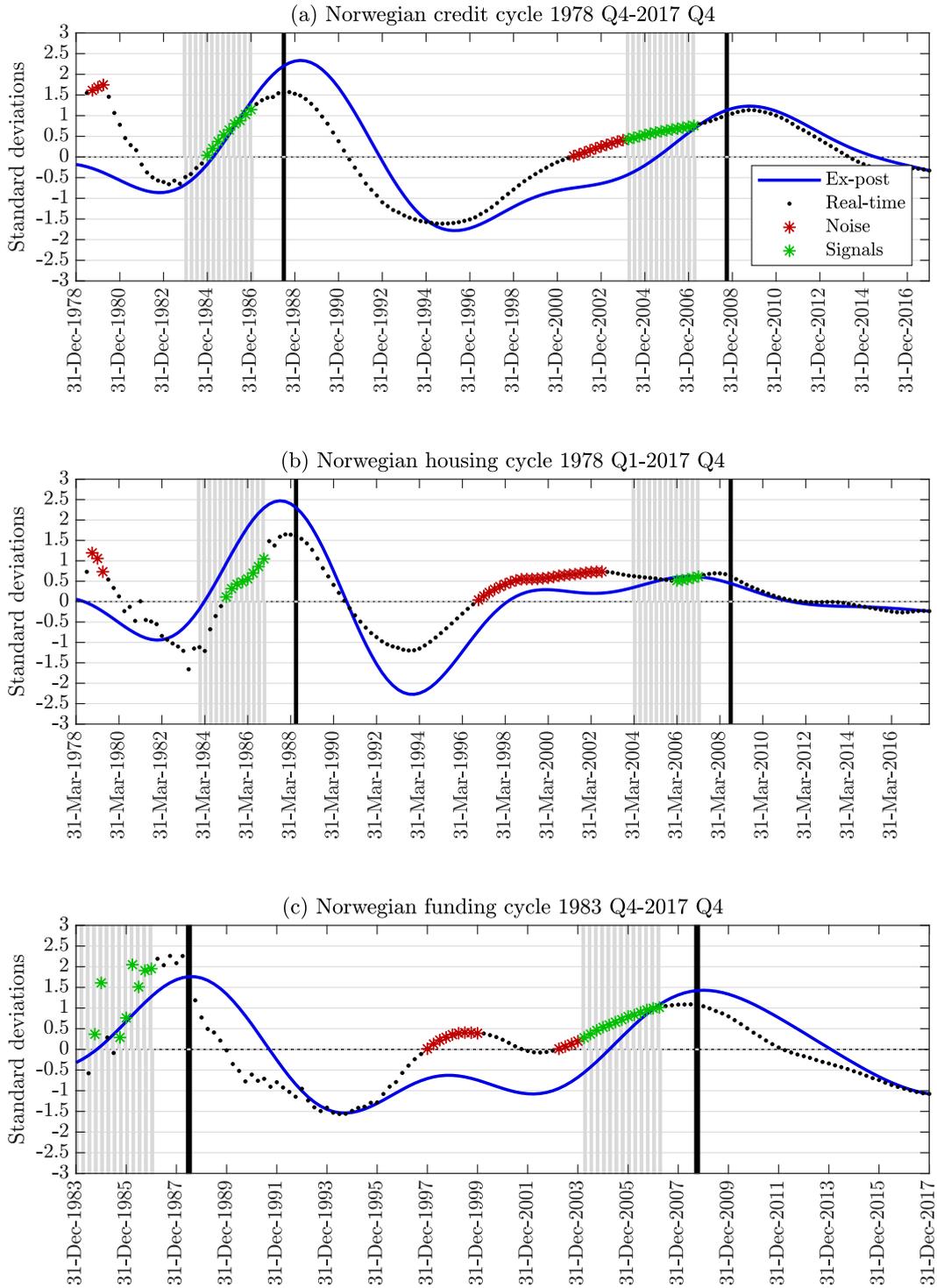


Figure 6: Norwegian financial subcycles and their real-time performance. Shaded grey areas are signal windows. Vertical black lines mark crisis onset.

with regard to the noise-to-signal ratio, and that the winning combination from Table 5 ranks 15th.

Ex-post, all subcycle's amplitude around the two crises is in line with the severity, as the peaks around 1988 are both taller and sharper than those around 2008. In terms of early-warning signals, however, there is not much difference. All subcycle's upward phase coincides with the signal windows for both crises. In terms of early-warning signals however, housing and funding cycles' relatively high frequency causes much noise in 1997-2003.

The good performance before the crisis of 1988 seems robust to the timing of crisis onset. Vale (2004) describes the crisis as reaching systemic proportions only in 1991 Q4, but also describes a period of widespread banking problems, where 13 small banks failed, between 1988 and 1990. In most cases the failures were dealt with by mergers, implying that 1988-1990 was a period where banks, and not only troubled banks, needed to utilize their capital buffers, rather than build them up. Prior to this, a process of mid-1980's deregulation was followed by a bank lending boom from 1984 to 1986, accompanied with bubbles in both residential and commercial real estate. Switching crisis onset to 1991 would not dramatically affect our results, as all subcycles sent early-warning signals until 1988.

Having a macroprudential framework could have benefited the Norwegian authorities at this time, as instead of tightening capital requirements in the run-up to the crisis, they loosened them in 1987 (Vale, 2004). Vale also notes that shortly after the crisis, in 1993, Norwegian banks became profitable again. As the first warning signals after that crisis, from any subcycle, came in 1997 and a year later from the aggregate cycle in figure 2 (d), the banks would have had five to six years of profitable operations to retain earnings and strengthen their capital position before our financial cycle measures indicated the need to raise capital requirements.

3.10 Country: Sweden

The Swedish dataset has seven variables, covering two crises. Crisis onset is dated at 1991 Q3 and 2008 Q4. In terms of early warning signals, banks' real foreign liabilities performs best. The crisis of 1991 had elements which all the subcycles should capture. Englund (1999) describes the nature and roots of the crisis in terms of a credit expansion in the years 1986-1990 along with a sharp increase in foreign currency lending, a commercial real estate bubble formed over roughly a decade prior to the crisis, and a residential housing bubble formed in 1985-1991.

Ex-post, all subcycles' upward phase coincides almost perfectly with the signal window

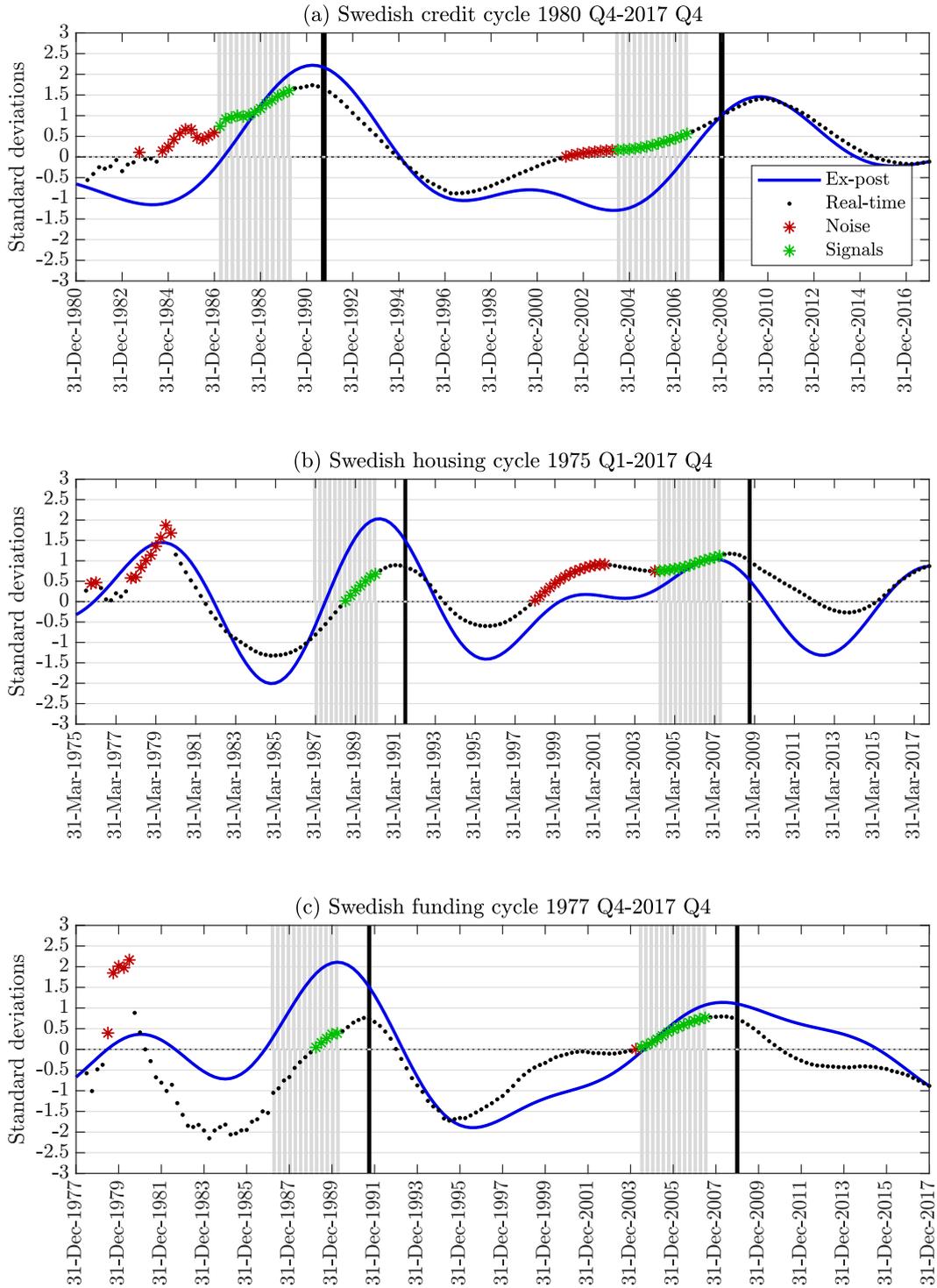


Figure 7: Swedish financial subcycles and their real-time performance. Shaded grey areas are signal windows. Vertical black lines mark crisis onset.

before the crisis of 1991. The real-time signals also capture the imminent crisis on all fronts. The trivariate credit cycle in figure 7.a captures the imminent crisis with timely and continuous signals, preceded by three years of noise. In light of Englund (1999), perhaps the signal window is simply too short in this case, rather than the signals being false. The other two subcycles catch the crisis in a cleaner manner, although their relatively high frequency causes some noise roughly a decade before the crisis.

Results underpinning Table 3. show the two sided CF-filter to have the lowest noise-to-signal ratio for Sweden, followed by the two sided HP-filter. Results underpinning Table 5 show that for Sweden, no multivariate combination outperforms the house price to income or banks real foreign liabilities cycles with regard to the noise-to-signal ratio. Also the winning combination from Table 5 ranks 18th for Sweden.

Spectral analysis suggests that Swedish credit cycles last more than twice as long as housing and funding cycles. The different frequencies are reflected in a bimodal credit cycle in fig. 7 (a), whereas the funding cycle has three peaks and the housing cycle has four. The higher frequency seems to add noisiness, particularly to the housing cycle.

All subcycles amplitude at the peaks closest to crisis onset seems in order with the severity of the crises. All peaks before the crisis of 1991 are more pronounced than those around 2008.

4 Discussion

Spectral analysis of our dataset indicates that in addition to medium term cyclical movements, credit, housing and funding variables for the Nordics exhibit higher frequency cyclical movements that have more to do with the business cycle. This means, for example, that financial variables can show marked signs of an upswing (i.e. rising real house prices and real credit growth) which have more to do with a business cycle pick-up, than a medium-term, financial one. This suggests that aggregate measures of financial cycles can help guide the implementation of macroprudential tools, such as countercyclical capital buffer activation. Activating the buffer requirement as soon as price increases or credit growth resume, in the wake of a crisis, can be premature. Waiting for signs of an upturn in the lower frequency cycle can mean a delay of buffer activation of a few years.

Likewise, a slight credit contraction and drop in real estate prices do not necessarily mean that the financial cycle has turned. It can be some transitory shock, or the result of a minor economic slow-down or contraction of non-financial origins. In this sense, medium-

term financial cycle measures can help avoid mistaken relaxation of macro-prudential policies. Nonetheless, the real-time signaling properties of such measures make it hard to immediately discern between high and low frequency movements.

Another important result of the frequency domain analysis is the high variability in cycle duration. On average, credit cycles seem roughly twice as long as housing cycles, with bank funding cycle duration somewhere in between. This rhymes well with the cross correlations presented in section 4, where there is sometimes modest or little correlation between credit and housing variables' cycles. These results do not support a notion of 'the' financial cycle as a single, well defined phenomenon which uniformly governs movements of the entire dataset for each country. More theorizing would be required to conceptualize the financial cycle in that way. It is in no way evident from the data alone. This is why we opt for a simple mean for cycle aggregation.

Although we do pick 'winners and losers' based on quantitative yardsticks such as noise-to-signal ratios, there is no denying that in many cases the difference in such ratios is not large and the results may well depend on our sample period and criteria definitions to some extent, although we have attempted to check their robustness to such issues. After competing the six cycle extraction methods we proceed by using the CF-filter, although the two sided HP-filter has an identical noise-to-signal ratio. The first reason for doing so is that the CF-filter found fewer peaks and closer to crisis onset. Furthermore, it gradually revises the series upon receiving new data, easing interpretation and communication. Large shifts in the level of a CF-cycle endpoint are uncommon.

The CF-filter has the greatest tendency to get things either consistently right or consistently wrong, since it seldom changes the end-point slope estimate. This means that it gives off less noise than other methods in times of a dwindling but positive cycle, in the wake of a crisis. On the other hand, preceding the 2008 crisis the CF-filter tends to send long stretches of noise before the signal window.

The weak historical performance of the structural time series model is partly due to the model's complexity. It has five parameters, whose confidence intervals are wide when observations are few. It seems that upwards of 75 observations are required for the estimates to stabilize and confidence intervals to narrow. By the time that happens many of the earlier crises have passed. We nevertheless believe this strain of the literature has promise in the future as more data amasses. Some positive aspect of this methodology are the diagnostic tests that are available and the possibility to test hypotheses of different model specifications.

In cases where filters may be affected by non-stationarity, small sample problems may

be greater, as taking first differences may not always insure stationarity for short series. In our real-time exercise, we do not recursively test for stationarity in every iteration of the filtering process.

Although outside the scope of this paper, the CF-filter's gradual and consistent signaling can also ease the calibration of our signaling threshold criteria. Setting it at some positive level instead of zero could help minimize noise-to-signal ratios. Fig. 2 shows that for our preferred multivariate CF-filtered cycle measure, setting it at .5 standard deviations would significantly reduce the noise-to-signal ratio, although running the risk of missing the Icelandic crisis of 2008. This can serve as a reminder that the amplitude of signals can matter.

5 Conclusion

To conclude, we summarize some lessons about financial cycles in the Nordic region for the last decades. We make no judgement whether they will hold in the future, or have done so for other regions in the past.

1. For a sample covering the Nordics in the last 35 years, aggregate financial cycle measures outperform a Basel-style credit gap in terms of early warning signaling and peak proximity to crisis onset.
2. An optimal measure for the Nordics may be a trivariate cycle combining banks' real foreign liabilities, household debt to income and house prices to income. It outperforms all of its component cycles, suggesting that there may be synergies between good indicators from different indicator groups.
3. Country specific issues can have a large effect and should be taken into account. The single best credit indicator for the Nordics, the household debt-to-disposable income ratio, performs very poorly for Iceland and completely misses the Icelandic crisis of 2008, despite its credit bubble precursor. This reminds us that some risk indicators have denominators which are cyclical themselves, such as GDP or disposable income. They should be seen in the light of cyclical movements in both denominator and numerator, which can cancel each other out to some extent.
4. Nordic housing cycles have a higher frequency than credit cycles, according to spectral analysis. Close to twice as high. Their correlation is only medium to low. Equating them as components of a single cycle is a simplification and may be misleading.

5. Nordic housing cycle's relatively high frequency serves to increase the noisiness of their early warning signals, given our definition of a signal window. Their frequency is closer to that of business cycles, taken to mean the cyclical component of real GDP, than credit cycles.
6. When trying to minimize noise-to-signal ratios there is always the chance of missing some crises. Our best financial cycle measure completely misses the Danish crisis beginning in 1987.
7. Revisions can be large. Real-time estimates sometimes get the sign of the cyclical position wrong, compared to ex-post full sample estimates. They also have trouble distinguishing short- and medium-term movements in real-time. Even our 'winning' method the CF-filter is capable, upon revising its prior estimates, of timing a trough at a point in time where it previously had timed a peak.
8. Bubbles can be hard to detect from within. In real-time, the two-sided HP, Butterworth and Hamilton-filters all fail to recognize the difference in amplitude between short term cyclical movements in Iceland ca. 1999-2002, and those directly preceding the crisis of 2008, ca. 2004-2007. It is not until after crisis onset that the cycle is revised to show a subdued peak in 2001, and a much more pronounced one in 2008. Before the crisis, they are shown as roughly equal in amplitude. The CF-filter only partially makes the same mistake, starting the revision as early as 2006.
9. A single indication of a cycle having turned is highly unreliable. Upon receiving three or four consecutive indications of a turning point, however, it is quite reliable. Thus, aggregate financial cycle measures are perhaps not well suited to guide sudden and complete release of countercyclical capital buffers. They may however be well suited to guide gradual and partial release.
10. According to spectral analysis, Nordic housing variables' most pronounced cyclical component sometimes lies outside the traditional 8.0-30.0 year frequency band applied to the CF-filter. In that case, the filter finds some other cycle within the band, which may not be statistically significant or have limited informational value. Inspection of the data's unrestricted frequency content is a necessary precursor to the filter's application, and helps with interpretation.
11. Ex-post analysis indicates that credit cycles tend to peak late, with a considerable lag from crisis onset. Often this lag is between one and three years. Ex-post analysis

also often shows credit cycles rising above zero only one to three years before a crisis. Contrary to what one might infer, that doesn't translate into a lack of warning signals. Usually the warning signals from an upward credit cycle are both timely and continuous. In fact they are so timely, according to our definition of a signal window, that they become noisy.

12. Real-time warning signals come with lots of noise, regardless of detrending method or variable choice. Noise-to-signal ratios are usually higher than one, although our chosen aggregate measure for the Nordics scores a ratio of 0.87. Receiving a signal provides no proof that a crisis looms within a window of four and a half years.
13. Ex-post, different detrending methods produce cyclical components which are qualitatively quite similar, although their early-warning signaling may have been somewhat different. This applies most strongly to the two-sided HP, Butterworth and Hamilton-filters.
14. After crisis onset, there is typically a prolonged period with very few or no warning signals. With respect to financial subcycles this period lasted between 8 and 12 years after the crises of the 80's and 90's. With respect to our best aggregate cycle, it lasted 9-11 years.
15. Ex-post, there is a visible relationship between the amplitude of our best multivariate financial cycles and the severity of the crisis that follows. In connection to systemic stress periods, such as the ones in Norway and Finland in 2008, cycles tend to peak around one standard deviation above zero. In contrast, they tend to peak close to two standard deviations from zero in connection to the more harmful kind of systemic crisis witnessed in Finland, Norway and Sweden in the 80's and 90's. Iceland in 2008 is the exception, due to highly cyclical disposable income. This reminds us that ratios sometimes have cyclical denominators, which can mask risk buildups. In this context it matters that fast growth in disposable income prior to the Icelandic crisis of 2008 was unevenly distributed, with capital income increasing much faster than wage income.

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Appendix A: Data

	Denmark	Finland	Iceland	Norway	Sweden
Real credit to NFPS	1960 Q1 - 2017 Q4	1970 Q4 - 2017 Q4	1975 Q4 - 2018 Q3	1953 Q4 - 2017 Q4	1961 Q1 - 2017 Q4
Credit to GDP ratio	1967 Q4 - 2017 Q4	1970 Q4 - 2017 Q4	1975 Q4 - 2018 Q3	1960 Q4 - 2017 Q4	1961 Q1 - 2017 Q4
Household credit to income	1974 Q4 - 2017 Q4	1970 Q4 - 2017 Q4	1988 Q3 - 2018 Q3	1978 Q4 - 2017 Q4	1980 Q4 - 2017 Q4
Real house prices	1970 Q1 - 2017 Q4	1970 Q1 - 2017 Q4	1980 Q4 - 2018 Q3	1970 Q3 - 2017 Q4	1970 Q1 - 2017 Q4
House prices to rent	1970 Q1 - 2017 Q4	1970 Q1 - 2017 Q4	N/A	N/A	N/A
House prices to income	1973 Q4 - 2017 Q4	1975 Q1 - 2017 Q4	1987 Q4 - 2018 Q3	1978 Q1 - 2017 Q4	1970 Q1 - 2017 Q4
House prices to building cost	1986 Q4 - 2017 Q4	1970 Q1 - 2017 Q4	1987 Q2 - 2018 Q3	1978 Q1 - 2017 Q4	1975 Q1 - 2017 Q4
Banks' foreign liabilities	1977 Q4 - 2017 Q4	1983 Q4 - 2017 Q4	1978 Q1 - 2018 Q3	1983 Q4 - 2017 Q4	1977 Q4 - 2017 Q4
Banks' real non-core funding	N/A	N/A	1986 Q4 - 2018 Q3	1987 Q1 - 2017 Q4	N/A
Banks' real non-core funding ratio	N/A	N/A	N/A	1987 Q1 - 2017 Q4	N/A

Table 6: Data availability for each country.

5.1 Data sources for Denmark

Credit to private non-financial sector. Source: Bank for International Settlements.

<http://www.bis.org/statistics/totcredit.htm>

Credit to households and NPISHs. Source: Bank for International Settlements from 1994 to 2016 and elongated with data from the Danmarks Nationalbank.

<http://www.bis.org/statistics/totcredit.htm>

Nominal disposable income of households. Source: Danmarks Nationalbank, Systemisk Risikoråd.

<http://www.risikoraad.dk/kontracyklisk-buffer/danmark/>

Nominal house price index. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Real house price index. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES
House price to rent ratio. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES
House price to disposable income per capita ratio. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES
Construction cost index, all costs, one-family houses. Source: Statistics Denmark from 2003-2017 elongated with a discontinued series from same source from 1986-2003.

<https://www.statbank.dk/BYG42>
Cross-border positions by location of reporting bank (total liabilities). Source: Bank for International Settlements, Locational banking statistics. Adjusted for breaks in series.

<http://www.bis.org/statistics/bankstats.htm>
Consumer price index. Source: Statistics Denmark for 1980-2016. The series was elongated to 1978 using a yearly CPI time series, interpolated and scaled to fit.

<http://www.statbank.dk/PRIS113>, <http://www.statistikbanken.dk/PRIS8>
Gross domestic production. Source: OECD Main Economic Indicators – Composite Leading Indicators.

http://stats.oecd.org/Index.aspx?DatasetCode=MEI_CLI#
Banks non-core funding, i.e. total liabilities less deposits. Source: Central Bank of Denmark, provided by staff. Quarterly data from 2004-2017. Series elongated to 1986 using interpolated annual and biannual data.

5.2 Data sources for Finland

Credit to private non-financial sector. Source: Bank for International Settlements.
<http://www.bis.org/statistics/totcredit.htm>

Credit to households and NPISHs. Source: Bank for International Settlements.
<http://www.bis.org/statistics/totcredit.htm>

Index of wage and salary earnings. Source: Statistics Finland.
http://www.stat.fi/til/ati/index_en.html

Nominal house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Real house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to rent ratio Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to disposable income per capita ratio. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Building cost index, total index. Source: Statistics Finland.

https://www.stat.fi/til/rki/2018/09/rki_2018_09_2018-10-15_tie_001_en.html

Cross-border positions by location of reporting bank (total liabilities) Source: Bank for International Settlements, Locational banking statistics. Adjusted for breaks in series.

<http://www.bis.org/statistics/bankstats.htm>

Consumer Price Index, All Sectors. Source: Statistics Finland via Macrobond.

Gross Domestic Production. Source: OECD Statistics, Quarterly National Accounts, Historical GDP. <http://stats.oecd.org/#>

5.3 Data sources for Iceland

Credit to private non-financial sector. Source: Central Bank of Iceland.

Credit to households. Source: Central Bank of Iceland.

Disposable income of households. Source: Statistics Iceland, Central Bank of Iceland. Retrieved from the Central Bank's QMM database.

www.cb.is/publications/publications/publication/2018/11/07/Monetary-Bulletin-2018-4/

House prices, nominal. Source: Registers Iceland.

<http://www.skra.is/markadurinn/visitala-ibudaverds/>

House price to rent ratio. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Building cost index. Source: Statistics Iceland. Hyperlink to data

Total foreign liabilities. Source: Bank for International Settlements - Locational banking statistics, Central Bank of Iceland. The series is constructed using bank data from the Central Bank of Iceland from 2003-2017, elongated with data on cross-border liabilities of banks from the BIS. Central Bank of Iceland.

<https://www.cb.is/statistics/statistics/2018/11/22/Monetary%20Statistics/?stdID=9>

<https://www.bis.org/statistics/bankstats.htm>

Banks' non-core liabilities. Source: Central Bank of Iceland. Constructed using bank data from the Central Bank of Iceland. Non-core liabilities are total liabilities less deposits in ISK.

<https://www.cb.is/statistics/statistics/2018/11/22/Monetary%20Statistics/?stdID=9>

Gross Domestic Production. Source: Statistics Iceland. [Hyperlink to data](#)
Consumer Price Index. Source: Statistics Iceland. [Hyperlink to data](#)

5.4 Data sources for Norway

Credit to private non-financial sector. Source: Bank for International Settlements.
<http://www.bis.org/statistics/totcredit.htm>

Credit to households and NPISHs. Source: Bank for International Settlements.
<http://www.bis.org/statistics/totcredit.htm>

Disposable income of households. Source: Norges Bank, provided by staff.

Nominal house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Real house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to rent ratio Source: OECD Analytical house price database .
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to disposable income per capita ratio. Source: OECD Analytical house price database.

https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Construction cost for residential buildings. Source: Statistics Norway
<https://www.ssb.no/en/statbank/table/08655/>

Cross-border positions by location of reporting bank (total liabilities) Source: Bank for International Settlements, Locational banking statistics.

<http://www.bis.org/statistics/bankstats.htm>

Banks' non-core liabilities. Source: Norges Bank, provided by staff. Calculated using bank data.

Gross Domestic Production. Source: OECD Statistics, Quarterly National Accounts, Historical GDP. <http://stats.oecd.org/#>

Consumer Price Index. Source: Statistics Norway. <http://www.ssb.no/en/kpi/>

5.5 Data sources for Sweden

Credit to private non-financial sector. Source: Bank for International Settlements.
<http://www.bis.org/statistics/totcredit.htm>

Credit to households and NPISHs. Source: Bank for International Settlements.

<http://www.bis.org/statistics/totcredit.htm>

Net disposable personal income. Source: Trading Economics
<http://www.tradingeconomics.com/sweden/disposable-personal-income>

Nominal house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Real house price index. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to rent ratio Source: OECD Analytical house price database .
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

House price to disposable income per capita ratio. Source: OECD Analytical house price database.
https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES

Construction Cost Index, Multi-dwelling Buildings. Source: Statistics Sweden via Macrobond

Cross-border positions by location of reporting bank (total liabilities). Source: Bank for International Settlements, Locational banking statistics.
<http://www.bis.org/statistics/bankstats.htm>

Gross Domestic Production. Source: OECD Statistics, Quarterly National Accounts, Historical GDP. <http://stats.oecd.org/#>

Consumer Price Index. Source: Statistics Sweden. Hyperlink to data