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Economic Commentaries

A new early warning indicator of financial fragility in Sweden

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Following global financial crisis of 2008, economists have been actively searching for numerical indicators that provide reliable warnings of financial risks in the economy. Building on the historical evidence, we propose a new early warning indicator of financial fragility and apply it to the Swedish financial sector. The early warning indicator is designed to give a numerical assessment of the build-up of systemic fragility in the credit sector of the economy. Pseudo real-time evaluations show that the EWI would have performed well prior to the 1990 and 2008 crises. Currently, the indicator predicts an increased probability of persistent reductions in new loans and aggregate credit volumes, which historically have coincided with persistently lower GDP growth.

1 Introduction

> We live in a world that is more financialized than ever before...with a banking system that is larger, relative to GDP, than anything we have ever seen in the past. ... But in taking a look at the same questions over the very long run, I will argue that, in many important respects, the causes and consequences of today's crisis are by no means unusual relative to prior experience, although they represent a very extreme version of phenomena we have seen many times before. - Alan M. Taylor, 2012.

The global financial crisis of 2008 and the consequent persistent sluggishness in GDP growth rates in most advanced economies have rekindled interest in the role of the credit sector in the macroeconomy. Researchers have assembled large datasets and re-discovered that financial crises are typically followed by large and persistent drops in real activity, and are often precursors to currency and sovereign debt crises (Reinhart and Rogoff 2009, Schularick and Taylor 2012).

Economy theory and policy both had a long tradition of focusing on the credit sector as a crucial driver behind the most severe recessions and the most dramatic spikes in economic uncertainty. This tradition was gradually abandoned after WW2, and by the time the crisis of 2008 hit, financial and credit aggregates had all but disappeared from mainstream macroeconomic analysis, or, if they were modeled at all, had only marginal impact (Schularick and Taylor 2012). Following the crisis, policy and academic economists found that the macroeconomic models they were relying on could not meaningfully address questions related to financial crises. Likewise, the models employed by regulators to stress test individual credit institutions had not provided reliable warnings of risks that, in retrospect, were clearly systemic in nature. Pressed for time, economists have since hurried to construct financial stress indicators and early warning indicators to bridge this gap, and give an economy-wide assessment of financial aggregates, without attempting to fully integrate macroeconomic and financial aggregates. So far, the attempts at providing numerical indicators still feel provisional, and there is certainly much room for improved modeling. Our own effort in this commentary is one such attempt, and we also hope that it will be superseded by better models in the not too distant future. Fortunately, the analysis of the historical evidence is well a head of the modeling efforts, and, in our view, provides a number of solid, useful regularities on the periods preceding and following financial crises.

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Building on the historical evidence, we propose a new early warning indicator of financial fragility and apply it to the Swedish financial sector. An early warning indicator (EWI) is designed to give a numerical assessment of the buildup of systemic fragility in the credit sector of the economy. In the policy and academic debate, “financial instability” and “financial vulnerability” are perhaps more common expressions, but we prefer to use “fragility” because the term has been given a more precise definition in the context of stress testing and financial risk in the work of Taleb and co-authors (Taleb et al. 2012). Following

their work, we think of the financial system as becoming more fragile if it is more harmed by a given stressor (deviation from the status quo), and if the harm increases more than linearly with the size of the stressor.

The outline of this commentary is as follows. We proceed with a discussion of “fragility”, and then outline desirable features in an early warning indicator. A very selective literature overview on the build-up to financial crises follows. This literature then informs our choices of which variables to monitor and include in our EWI, and we motivate these choices in some detail. A crucial but under-appreciated aspect of building a EWI is the choice of sample period and of the method used to filter trending variables. We will spend considerable time explaining how seemingly unimportant and arbitrary choices greatly affect the final result, and shed some light on these choices so that they can become part of the policy debate rather than remain hidden. The HP filter is used extensively in the EWI literature. We will argue that this is a poor choice and propose a simple filter that should outperform the HP filter under almost all reasonable assumptions. Pseudo real-time evaluations show that the EWI would have performed well prior to the 1990 and 2008 crises, giving stronger and less ambiguous signals than the measure of credit gap suggested by the BIS and incorporated in Basel III. The choice of filter has an ever larger effect in the current circumstances (2016q2). The EWI, calibrated using our favorite default parameters, is roughly as high today as in 1990 and 2008, indicating a high level of systemic financial fragility, while the standard credit gap is below mean and hence signals no risk. As explained in the next section, the expressions “financial fragility” and “financial crises” are used broadly (in line with the literature), so that a crisis implies sharp drops in the amount of new loans and in GDP, but not necessarily large losses in the banking sector.

2 Financial crises

2.1 Fragility

While a “recession” is associated with measures of GDP growth and can be defined fairly precisely algorithmically, the definition of “financial crisis” is broader, more vague, not tightly connected to any specific aggregates, and defined by experts’ judgment. Schularick and Taylor (2012), for example, define financial crises as “events during which a country’s banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions.” In particular, they point out that, after WW2, widespread public intervention by governments and central banks has resulted in “financial crises” (as classified by experts) with much less dramatic bankruptcies in credit institutions or drops in credit aggregates, but at least equally strong effects on GDP growth. The broad definition of financial crises used in the literature is also adopted here and extended to our understanding of financial fragility.

We prefer to speak of “fragility” rather than “instability” or “vulnerability” because it has been defined more precisely in the literature. Following the work of Taleb and co-authors (Taleb et al. 2012), we think of the financial system as becoming more fragile if it is more harmed by a given stressor and the harm increases more than linearly with the size of the stressor. This heuristic is useful in a formal stress test, but perhaps even more so in helping us identify likely sources of fragility prior to looking at the historical data. That historical data corroborates our a-priori reasoning then gives us more confidence in our indicator than purely data-driven statistics could provide, particularly given the relative in frequency of financial crises.

For example, a-priori we think a household or business with a larger debt in relation to income is more fragile to an increase in the interest rate, particularly if the debt has a short maturity. A highly leveraged credit institution is more fragile because its capital can be wiped out by a smaller drop in the value of underlying assets. A bank financed by short term debt is more fragile than one relying on relatively sticky deposits and long term debt. An environment of very low real interest rates and/or low price of risk is more fragile because asset valuations are more sensitive to movements in either factor (via standard valuation formulas). A large share of loans denominated in foreign currencies (and left unhedged) also increases risk. While our EWI is not a formal stress test, informally we wish for a high (low) value to indicate a high (low) sensitivity of the credit sector to movements in interest rates, credit spreads, and property and asset prices.

2.2 Desirable features of an early warning indicator

In agreement with Drehman and Juselius (2013), our ideal EWI would have a high degree of timing, stability and interpretability. We discuss each feature in turn, as well as our preferred position when trade-offs arise.

Timing refers to the ability of an EWI to reach a high value well in advance of a major financial crisis. In contrast to financial stress indexes, an EWI is meant to be a leading rather than a coincident indicator, and preferably with a long lead. Much of the literature has investigated the timing ability of different indicators using a binary classification of financial crises (via logistic regressions). Our view of financial fragility suggests a somewhat more limited role for timing: financial crises are non linear and non-Gaussian phenomena, making precise timing difficult. Besides, financial crises can vary from mild to devastating, a distinction that is lost by a binary classification. For example, it may be that a very high value of our EWI predicts not a very high probability of a crisis, but, should a crisis occur, a very severe one. We would be satisfied with this performance, while a logistic regression would deem it poor. We more modestly wish our EWI to have a high value at the point at which a major financial crisis starts, and ideally at least a few quarters before.

Stability implies that the indicator should not move quickly from low to high and from high to low. This reflects an assumption, corroborated by historical evidence, that financial fragility builds up gradually over the course of years.

A high degree of *interpretability* is a priority in the construction of our indicator. In practice, this will translate into few components and simple statistical procedures. Heat maps comprising dozens of variables have a place as a stepping stone for deeper analysis, but they are often difficult to interpret. We wish to focus on a handful of variables with the most predictive power and on a simple aggregation rule, so that the behavior of the indicator should be easy to understand given the movements in the component variables. This is important if the indicator is to be a useful tool for policy. More variables and more complex econometrics would decrease interpretability without, we conjecture, a corresponding increase in performance. As a rule, complexity and data-rich analyses in statistics are more fruitful when the process is ergodic (stable), the signal-to-noise ratio is high, and the number of observation is large. The long duration of financial cycles means that these conditions are not met, and therefore that sophisticatedly simple procedures are likely to perform well.

2.3 An introduction to the literature on the build-up leading to financial crises

Banking crises and boom-bust patterns in asset prices fascinated early economists since at least John Stuart Mill, who was writing after the financial crisis of 1826. Mill already understood how crises typically went hand in hand with credit expansions. Economic historians remind us that financial crises have been the rule in capitalist economists, in both advanced and emerging markets, for as long as we have reliable data (see for example Taylor, 2012). Credit expands and contracts over the business cycle, but also in larger and longer waves, which Borio et al. (2012) call the financial cycle. Financial cycles can last decades from peak to peak.

Ludwig von Mises built a comprehensive theory of credit expansions and contractions, which he believed were at the core of the business cycle, focusing on the role of central banks and of the banking sector. He is, to our knowledge, the only economist who publicly anticipated the events of 1929 and, before the bust had even materialized, attributed its quarely to the great world wide expansion in credit of the preceding decade. His work initially attracted much attention but was then largely forgotten. The American economist Hyman Minsky, in turn, attracted little attention in life but became posthumously famous when his work (Minsky 1977, 1986) was rediscovered by analysts and economists scrambling to make sense of the financial crisis of 2008. Minsky and von Mises accounts both stress the role of the banking sector and of leverage (for banks, in the form of fractional banking) in driving the fast credit expansions that typically proceed financial crises. Minsky believed that fractional banking and collateral valued at market prices made capitalist's financial systems inevitably prone to financial instability. von Mises attributed greater importance to the role of the interest rate in driving intertemporal choice, and in particular capital investment, and blamed excessively expansionary monetary policy and excessive bank leverage for distorting the signal contained in the interest rate and leading to credit booms and busts. The role of excessive debt and credit in leading to the Great Depression was also studied by Fisher (1933). Recently, Schularick and Taylor (2012) have repeated the interpretation of financial cycles as "credit booms gone bust".

The classic Kindlebergher, more recently updated by Alibert (2015), also reported credit booms as a frequent precedent to financial crises, with emphasis on inflows of foreign capital. Economists at the Bank of International Settlements have long been active in stressing the dangers related to excessive credit expansion. Brunnermeir and Schnabel (2016) study a long history of financial crises and find that the most severe were associated with credit expansion, expansionary monetary policy, and financial innovation or deregulation.

3 The early warning indicator

3.1 Choice of key component variables

The literature has explored a large number of potential predictors for financial crises. We have chosen to zoom in on a few that are reasonable a priori and show up most consistently in econometric exercises. They are the credit-to-GDP gap, house prices, and the ratio of unstable over stable sources of funding of the banking sector. We also suggest monitoring credit quality and commercial property prices, but exclude them from the index, at least for now, because available data for Sweden are not of the same quality as for the included variables. Finally, we briefly discuss some variables that did not make the index.

3.1.1 Credit-to-GDP

The aggregate volume of credit appears as a key indicator in virtually all the literature on financial cycles and crises from John Stuart Mill onwards. Credit-to-GDP is also the single best performing indicator according to Drehmann and Juselius (2013), and has a formal role in Basel III. The preferred measure includes all private credit by nonfinancial institutions. The main components are therefore household debt (mostly mortgages) and corporate debt, whether obtained from banks (the main channel in Sweden) or from the shadow banking sector, or by issuing corporate bonds.

3.1.2 House prices

Housing and commercial properties are the biggest class of financial assets by volume. They are also typically bought at considerable leverage. It is therefore not surprising that severe financial crises often follow rapid increases in house and commercial property prices (Taylor 2014). Besides the world wide experience of 2008, a well-known case is the crisis of 1990 in Japan, which also hit Sweden quite hard. The roaring twenties also witnessed rapid increases in property prices in several countries.

House prices are typically normalized by disposable income or GDP per capita in econometric studies and in building EWI. We normalized them by the CPI index instead. Drehmann et al. (2012) deflate house prices by the CPI in studying the financial cycle, but otherwise the standard approach is to use disposable income or GDP per capita. Our choice may seem surprising, but since 1875 house prices in central Stockholm and Göteborg have grown roughly at the same pace as inflation (Edvinsson et al. 2014). Case and Shiller reach the same conclusion studying long house price series for Manhattan (100 years) and Amsterdam (400 years), as does Ilmanen (2011) with a larger but shorter sample. As a result, the ratio of house prices to GDP per capita has a strong downward trend over sufficiently long periods (see Figure 1).

Many economists and commentators believe that house and property prices should grow at the same pace as income and GDP in the long run, but in free markets, as shown by Ilmanen (2011), yields on property implied by rents have been higher than stock dividend yields. Since stock market prices have historically grown at the rate of GDP, if house and property prices were also to grow at the same rate as GDP, their total return would be higher than stock market returns. This has not happened in the past and seems unlikely to hold in the future. We wish to emphasize that by deflating house prices by the CPI index, we do not rule out the possibility of an upward shift in this ratio to account for the price increases of the last decades. What we do implicitly rule out is for the future long run trend in prices to match that of nominal GDP or disposable income.

Our data on house prices do not include apartments because of a lack of a suitably long series. Apartment prices have been growing faster than house prices in Sweden in the last decade.

3.1.3 Unstable to stable funding ratio

The third variable in our EWI is the ratio of stable to unstable sources of funding of the Swedish banking sector. This and similar ratios are widely monitored by regulators and have been found to add some predictive ability to credit and property prices (Hahm et al. 2013). Stable funding is defined as deposits and market funding other than certificates and unstable bonds. Bonds are considered unstable if they are held by other MFIs (excluding the Riksbank) or investment funds (excluding money market funds). Because of data availability issues, the total bonds held by foreign investors, are assumed to have the same fraction of unstable bonds as the ones held domestically. Unstable funding is defined as the difference between the total lending to Swedish firms and households and our definition of stable funding. The general trend in our sample is for Swedish banks to rely increasingly on unstable funding (see Figure 7). This trend has been partially reversed since 2009, which has a downward effect on our EWI. What the indicator cannot take into account is that this reversal coincides with a massive increase in deposits in the same period (see Figure 2). Deposits currently account for over 65% of stable funds. The increase in deposits makes sense in a zero or negative interest rate environment in which most bank accounts match or better the returns offered by short-term debt, but leaves the stable funding ratio vulnerable to an increase in interest rates.

Figure 1. Ratio of Swedish house prices to GDP per capita
(in logs, built from data from central Stockholm and Göteborg, Edvinsson et al. 2014 updated by the authors) 1875-2015.

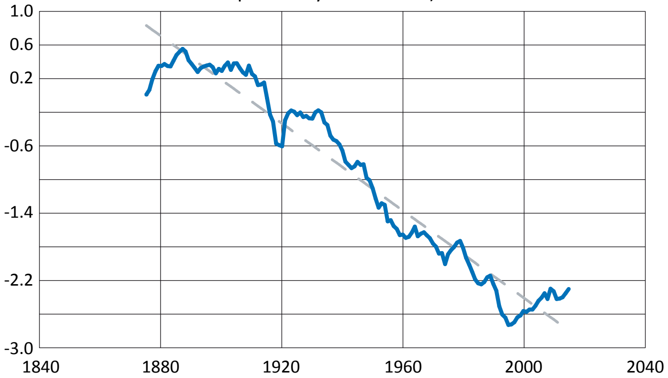
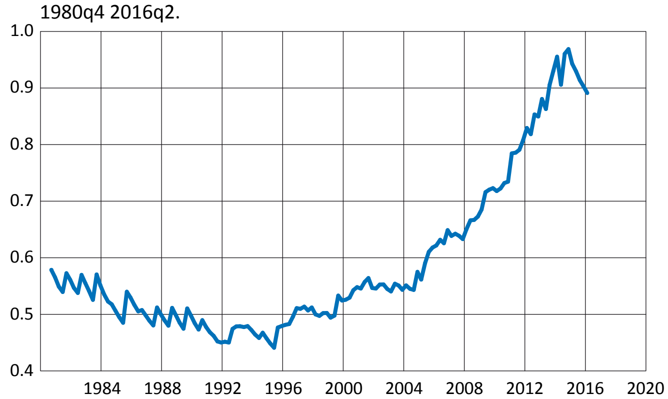


Figure 2. Deposits in Swedish banks over GDP,
1980q4 2016q2.



3.2 Some variables not included in the index

3.2.1 Variables worth monitoring, and perhaps being included in a future extension

Commercial property prices. We would have liked to include commercial property prices in the index. We believe that few Swedish households would default even in the event of severe drops in house prices. Businesses, however, can and do default in the same circumstances. The Swedish (and Norwegian, and Japanese) experience of the 1990 financial crisis was precisely that households reduced consumption but did not default on their mortgages, while businesses did so in large numbers. Monitoring commercial properties is therefore desirable. Unfortunately, we have much more accurate data for house prices and household mortgages than for property prices and contracts. While we wish for this mismatch to be addressed in the future, we have decided not to include property prices in the current version of the index, and instead implicitly assume them to behave broadly as house prices, as they should in the long run.

Volatility. Hyman Minsky believed that a persistently low level of volatility in financial and property markets sets the stage for excessive build-ups of risk and credit. His intuition has found some confirmation (e.g. Guimaraes et al. 2013). However, the increase in predictive power is not large after conditioning on broad credit aggregates.

Credit quality. Periods of rapidly expanding credit are often associated with low credit spreads and a decrease in the average credit quality. In a long historical analysis of US data, Greenwood and Hanson (2011) find that a high share of issuance of low-quality, high-yield corporate bonds predicts future spikes in defaults and financial instability. More generally, students of financial crises have long observed a deterioration in credit quality during the boom years that precede them. Sub-prime borrowers are an obvious example from the 2008 crisis. While the qualitative observation is difficult to dispute, quantifying it in real time can be tricky for the purpose of building an EWI, as credit ratings can also be affected by the general optimism of the boom years (for instance, Triple A rated securitized mortgages before the 2008 crisis). An additional difficulty for Sweden is that the corporate bonds market is small, and mostly investment grade, making data on high-yield bonds very noisy. We have already mentioned the limited availability of data on commercial property contracts.

Having motivated why credit quality does not currently figure in our EWI, we do wish to note that the share of high-yield bonds issued in the period 2011-2015 in Sweden was high (see Giordani et al. 2015). Internationally, the data are richer and give much clearer indications of decreased credit quality incorporate bonds in the last few years, with record emissions of junk bonds in the US.

Foreign business of Swedish banks. Swedish banks currently issue roughly half their loans outside Sweden. This does not show up in our measures of credit and house prices, which are domestic. Loans to foreign businesses and households do not necessarily increase fragility: geographical diversification could in principle increase resilience. In specific instances, though, it may work the other way. Since it is not obvious how to incorporate data on foreign activities by Swedish banks, and we know of no reliable empirical literature on the topic, they are left out of foreign indicators. However, we note that in 2008 the largest losses for Swedish banks (and, in a different form, for German banks) came from foreign activities, suggesting that further thinking on this topic would be useful.

3.2.2 Some excluded variables

Non-performing loans are a very informative contemporary or slightly leading indicator for a financial stress index, but only spike when a crisis (or at least a recession) is on its way, and are therefore not suited for our purpose, which is to give *early* warnings. We would expect a high *leverage ratio* in the banking sector to cause increased fragility, and there is little doubt, theoretically and empirically, that high levels of leverage in important sectors of the economy were features of the worst financial crises (e.g. Brunnermeir and Schnabel, 2016). It is also clear that the financial sector was highly leveraged prior to the last financial crises. Unfortunately, the measurement problems are severe for our purposes: bank leverage is a slippery variable to quantify (a useful discussion is given by D'Hulster, 2009). International research has not found it to be a very informative early warning indicator in previous financial crises (e.g. Guimaraes et al. 2013), so we exclude it from our index.

4 Choice of filtering method and sample period

Our choice of variables for the leading indicator is broadly in line with similar indicators developed by the BIS, the ECB, and Norges Bank, among others. We do normalize house prices by the CPI rather than by disposable income, but in our sample, the effect of this switch on the EWI is small. Where we do differ more substantially from indicators developed elsewhere is in how we filter the data prior to their aggregation into an index. These choices have a very strong impact on the EWI, and we therefore discuss them at length.

4.1 Trending ratios and the HP filter

Good quality data for our EWI are available from 1980 in Sweden. Over this period, several ratios show a clear upward trend, a feature shared by many other countries. Alan Taylor has described this worldwide phenomenonas “the great leveraging”. Others refer to it as “financial deepening”. “Leveraging” and “deepening” describe the same data but imply quite different interpretations. The implications for an appropriate choice of filter are also different.

It is beyond doubt that the financial sector and the total level of private debt are larger than ever in recorded history (Taylor 2014). The wide spread availability of mortgage credit to households is the most distinguishing feature of the great leveraging period (The starting date of the great leveraging is arbitrary, but 1980 is a reasonable choice in most countries, including Sweden). Household debt the great driver of the trend in the credit-to-GDP ratio. Faced with trending series and wanting to work with stationary series, supervisory authorities and academics, starting with a series of influential papers by the BIS, have opted to pass trending series through the HP filter, with a large penalization parameter (λ = 400000) to reflect the notion that financial cycles have much longer duration than business cycles (Drehmann and Juselius, 2013). We have three objections to the choice of the HP filter for our series.

First limitation of the HP filter: mean reversion may require a longer sample. Financial cycles have very long durations. Drehmann and Juselius estimate an average duration four time longer than for the business cycle using data from 1980, or roughly 20-25 years. A sample dating 1980-2015 can therefore be expected to contain one to three complete financial cycles. It is a useful approximation to say that the sample has one to three observations of the phenomenon we wish to investigate, and misleading to think in terms of 140 quarterly data points. Trying to infer a trend from such limited data is obviously problematic. (And even more so when the results are presented conditioning on a point estimate of the trend). At present, it is possible that we are somewhere near the peak of a financial cycle, and that adding 10-20 years of data will reveal a significant amount of mean reversion in credit aggregates. History provides several cases of credit series that showed very long trends but eventually mean reverted (at least to a large degree). For example, the non-financial business sector in the US was more leveraged at the pre-Great Depression peak (as a share of GDP) than ever before or after, not with standing decades of trending growth after WW2. In Australia, non-financial business debt-to-GDP peaked in the early 1890 after three decades of growth, to then decline for another three decades. The 1890 peak has only recently been matched there. (Total private credit is much higher today due to the explosion in household credit compared to 1890). Japanese property prices are currently around 40% of their 1990 peak. None of this implies that sizable mean reversion is certain. What it does imply is that any trend that may be apparent in thirty or so years of data is estimated with huge uncertainty. The common practice of fitting a trend or filter and then removing it from the data would only be appropriate if the estimation uncertainty were very small.

Second limitation of the HP filter: it implies an interpretation as 100% “deepening”, 0% “leveraging”. The world is more financialized than ever before. Let’s assume that this phenomenon is here to stay, and that credit-to-GDP has shifted to a higher mean compared to the 1980s and 1990s. From a purely time-series perspective, this would call for some type of mean-adjustment or trend fitting (see Giordani et al., 2011 for a review of some useful models for the purpose), if the goal was to forecast credit-to-GDP. But if the goal is to build a financial fragility index, this procedure implies an interpretation as “deepening”, that is, that higher levels of credit can be sustained without increasing financial fragility. The more conservative interpretation is to assume that increased credit-to-GDP implies at least some measure of increased “leveraging”, making the financial system more fragile. Schularick and

Taylor (2012) interpret their empirical results as "*some quantitative evidence to back up the claim that larger, more complex financial systems may be inherently more risky*".

Third limitation of the HP filter: it is an implausible time series model for credit-to-GDP and house prices-to-income (or house prices-to-CPI). The filter proposed by Hodrick and Prescott (1981) is written as the solution to

$$\min_{\mu_{1:T}} \sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda\,(\Delta\mu_t - \Delta\mu_{t-1})^2,$$

where λ is a parameter which penalizes changes in the growth rates μ_t but, importantly, not the growth rate $\Delta\mu_t$ itself. This is asymptotically equivalent to the state space model first proposed by Akaike (1980)

$$y_t = \mu_t + \epsilon_t,\ \epsilon_t \sim NID(0, \sigma^2_\epsilon)$$

$$\mu_t = \mu_{t-1} + \beta_{t-1}$$

$$\beta_t = \beta_{t-1} + \xi_t,\ \xi_t \sim NID(0, \sigma^2_\xi)$$

with $\lambda = \sigma^2_\epsilon / \sigma^2_\xi$. The model is designed to capture a smoothly changing trend, and in continuous time becomes itself equivalent to a cubic spline (Wecker and Ansley, 1983).

The most common use of such filters in statistics and engineering is to eliminate the IID noise ϵ_t and keep μ_t for subsequent analysis. By contrast, economists typically throw away the trend μ_t and keep ϵ_t for subsequent analysis. This demands that they do not estimate λ using any standard method, as common in other disciplines, since estimation would attempt to make ϵ_t an uncorrelated process, but rather impose a higher λ which produces a highly auto correlated ϵ_t. This procedure is then motivated as a quick-and-dirty alternative to a frequency domain filter, where $\lambda = 1600$ (400000) tends to cut out frequencies corresponding to periods above 10 (40) years.

The first problem in the context of EWI is that trying to cut out frequencies corresponding to periods above 40 years, when the sample is also around 40 years, necessarily gives large estimation errors, which are then forgotten by conditioning on a single path of the trend. In other words, the EWI will behave as if the trend was certain where as it is estimated very, very imprecisely even if the model is correct. An important consequence is that the HP filter will be very unstable in real time, as commonly observed, and very sensitive to extensions of the sample.

The second problem for a EWI is that the HP filter places no penalization on the steepness of the trend, and projects the trend observed at the end of the sample to continue in the future. Using $\lambda = 400000$ often delivers a fairly straight line. The HP filter does not penalize its steepness and projects it to continue indefinitely. This is not a reasonable assumption for credit-to-GDP or almost any variable used in the EWI literature. Even if the trend in credit-to-GDP observed in sample was due to a structural change that will not mean revert, it is extremely improbable that credit-to-GDP will double again in the next thirty years. In any case, such strong assumptions need to be made as explicit and transparent as possible, since they can have a very large impact on the results and cannot be left entirely to the data to decide. (As there are not enough data.)

4.2 The local level filter for early warning indicators

The HP filter was originally designed for series, like GDP, which are naturally thought of as trending, possibly with a time-varying trend. Ratios like credit-to-GDP are, we believe, better thought of as not trending, but rather reverting around a possibly time-varying mean. We want to allow for increased financialization or higher real property prices to have taken place in sample, but not to extrapolate in-sample growth out of sample and allow credit-to-GDP or house prices-to-per capita GDP to grow indefinitely.

One option would be to model the time series process of the shifts explicitly, as for example in Giordani et al. (2011). The requirement of a high degree of transparency in our EWI however suggests a simpler approach. We use a very simple model for the trend with a long tradition in econometrics and a record of good forecasting performance for economic time series, the local level model. Specifically, we suggest to set μ_t to solve the minimization problem

$$\min_{\mu_{1:T}} \sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda_{LL} (\Delta\mu_t)^2,$$

where λ_{LL} now penalizes changes in the local mean (local level) μ_t. This is asymptotically equivalent to the local level model (see Harrison and West 1989):

$$y_t = \mu_t + \epsilon_t,\ \epsilon_t \sim NID(0, \sigma_\epsilon^2)$$

$$\mu_t = \mu_{t-1} + u_t,\ u_t \sim NID(0, \sigma_u^2)$$

where $\lambda_{LL} = \sigma_\epsilon^2 / \sigma_u^2$. The one-sided version of the filter is a simple exponential moving average, so that

$$\tilde{\mu}_1 = y_1$$

$$\tilde{\mu}_t = \delta\tilde{\mu}_{t-1} + (1 - \delta)\, y_t,$$

where asymptotically $\lambda_{LL} = \delta/(1-\delta)^2$. For $\lambda_{LL} \longrightarrow \infty$, μ_t becomes a constant (the sample mean).

To set λ_{LL}, we recommend thinking in terms of either the half-life of the process or of the equivalent sample size. Having set H, a desired half-life for the process, expressed in number of periods (e.g. 40 for 10 years of quarterly data), we solve for λ_{LL} (or, equivalently, δ), to satisfy $0.5 = \delta^H$. The equivalent sample size can be thought of as the solution to $\Sigma_{i=0}^{\infty} \delta^{t-i}$, which is $\delta/(1-\delta)$.

The equivalent sample size is roughly 1.5 times the half-life. For example, setting the equivalent sample size at fifteen years can be thought of as approximately using fifteen years of data to estimate μ_t. The approach closest to ours is in Aikman et al. (2015), who detrend series using a ten-year, one-sided moving average (not exponential).

The policy maker can then set a half-life or equivalent sample size and compute the corresponding EWI. In suggesting a reasonable range of parameters, we need to remember that financial cycles are long. A range of ten to thirty years of equivalent sample size seems an appropriate starting point,and were commend computing the EWI at several different values to appreciate the role of this most important assumption.

Does the choice of filter matter in practice? We have argued that the LL (local level) filter is more suitable than the HP filter for our EWI. But does the choice matter in practice for Swedish data? In short, yes, particularly right now, as documented in the next section. We expect the local level filter to perform better, but it is simply impossible to “let the data speak” as there is not enough information in them. What we can hope is to have provided a tool to force the users to make their assumptions more explicit, and then visualize their implications.

5 The early warning indicator for Sweden: pseudo real-time performance and current outlook

5.1 Computing the indicator

The formula for our EWI is

$$\text{EWI}(d) = (2 \times \text{credit gap} + \text{house price gap} + \text{funding gap})/4,$$

where each variable, prior to its inclusion in the EWI, is detrended using the (two-sided) local level filter with equivalent sample size *d* and standardized. Of course, the EWI can also be computed using the HP filter for comparison. The credit gap is the deviation from trend of log credit-to-GDP, the house price gap is the deviation from trend of log house price-to-CPI (with an option to use house price-to-GDP instead), and the funding gap is the deviation from trend of the log unstable funding to stable funding ratio. We consider a default equivalent sample size of ten years. Data for all variables are available from 1980q4 to 2016q2.

The credit-to-GDP gap is given twice the weight compared to the other variables, reflecting its fairly consistent performance as the best single indicator in a wide variety of studies. We make no attempt to estimate the weights econometrically. As the next section demonstrate, major improvements in forecasting accuracy are more likely to come from the right choice of filtering procedure.

5.2 Pseudo real-time performance at the end of 1989 and 2007

The value of our EWI does not give a formal probability of a crisis, nor a formal prediction of the consequences of a crisis. The most informative and intuitive way of judging a number of the EWI is to compare it with its history, particularly ahead of known crises. We now look at how the indicator would have looked in (pseudo) realtime ahead of the crises of 1990 and 2008. Figure 3 shows the EWI estimated with data up to 1989q4. With such a short sample, the local level trends are nearly constant. The EWI performs well, rising steadily starting around 1986. Good performance is also observed with data up to 2007q4, with the EWI's value slightly above the 1990 level clearly sounding an alarm bell. For comparison, Figures 5 and 6 show the same exercise but using the HP filter (which, again,we do not recommend). The indicator is then high in 1989q4, but no higher than in 1981, which would have been puzzling to any user, whereas in 2007q4 it gives only a timid signal.

5.3 Current outlook

The EWI with an equivalent sample size of ten years is shown in Figure 7. The value of the EWI is currently roughly as high as in 1990 and 2008. Longer equivalent sample sizes imply flatter filters and strengthen the conclusion of high fragility.

Figure 3. EWI with local level filter (default), equivalent sample size 10 years.
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 1989q4.

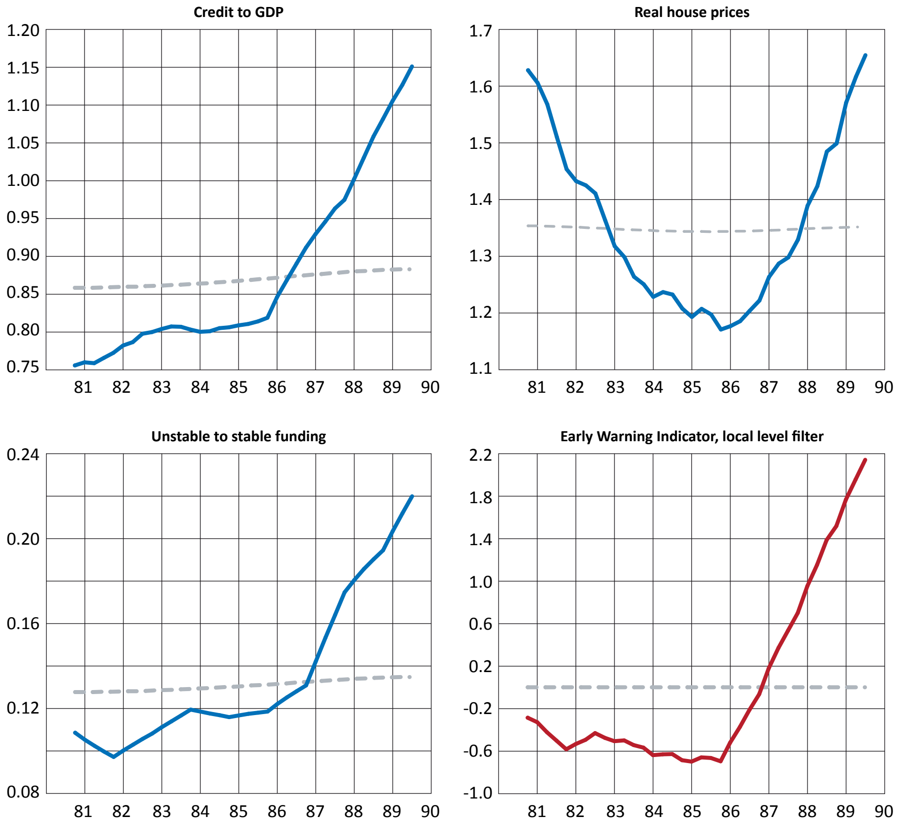


Figure 4. EWI with local level filter (default), equivalent sample size 10 years.
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 2007q4.

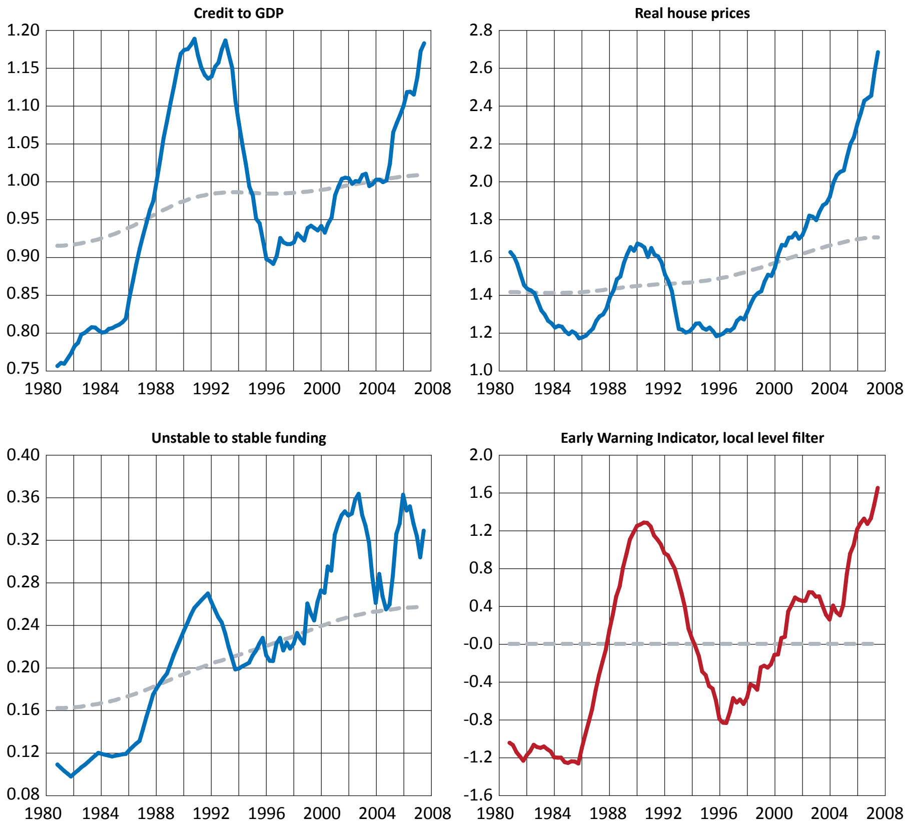


Figure 5. EWI with HP filter (not recommended, presented only for comparison).
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 1989q4.

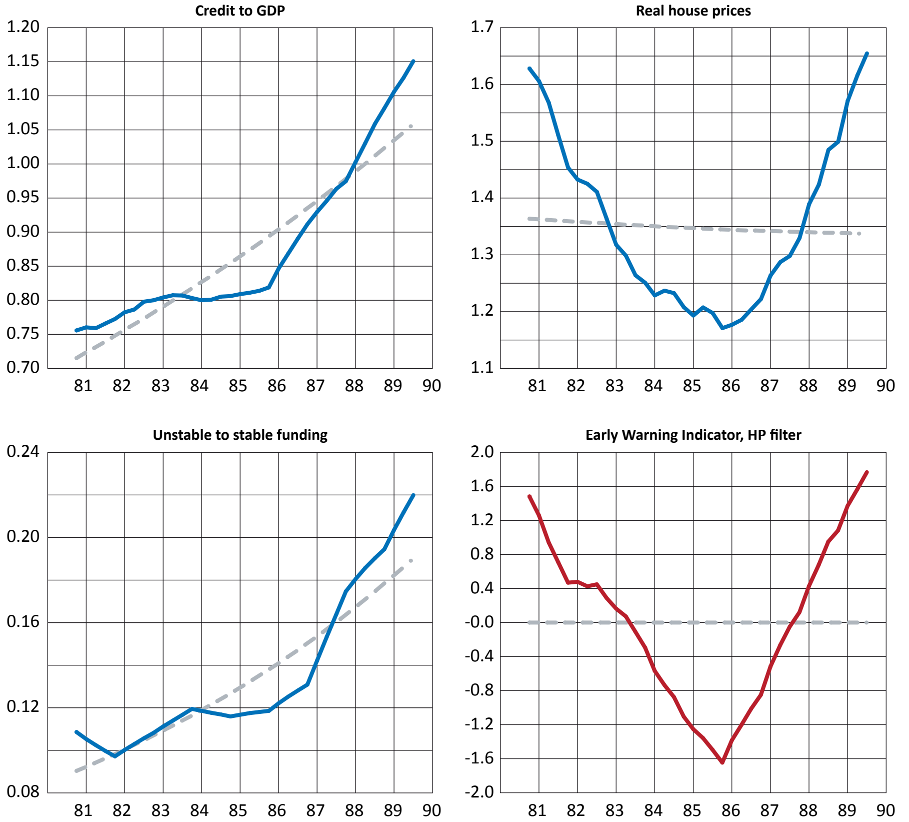


Figure 6. EWI with HP filter (not recommended, presented only for comparison).
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 2007q4.

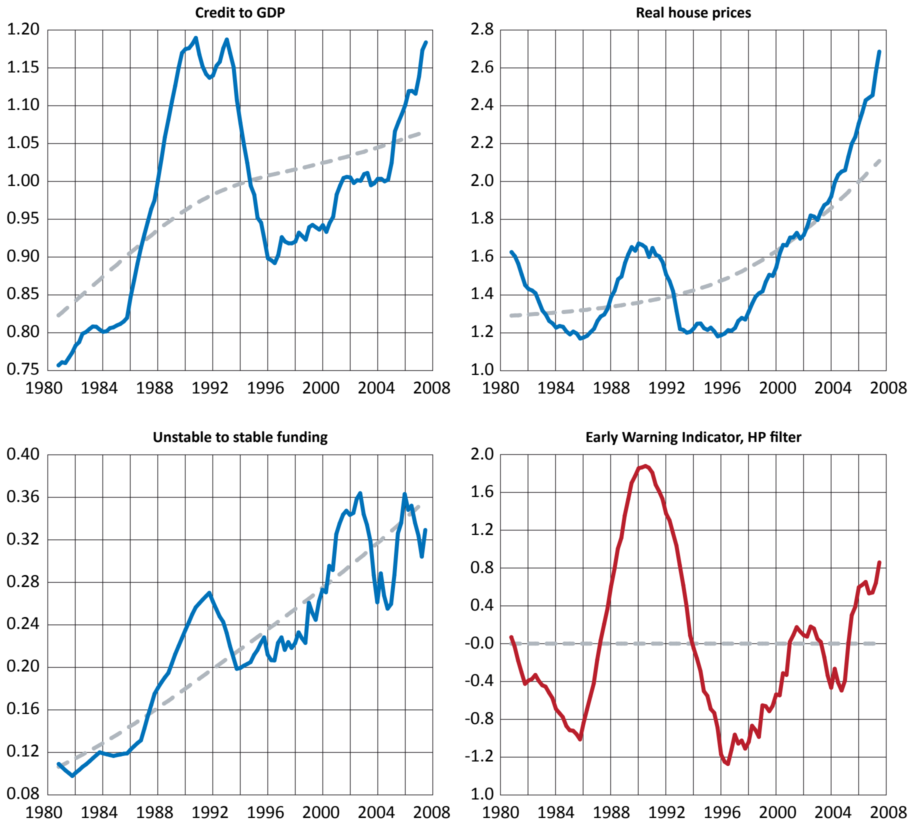
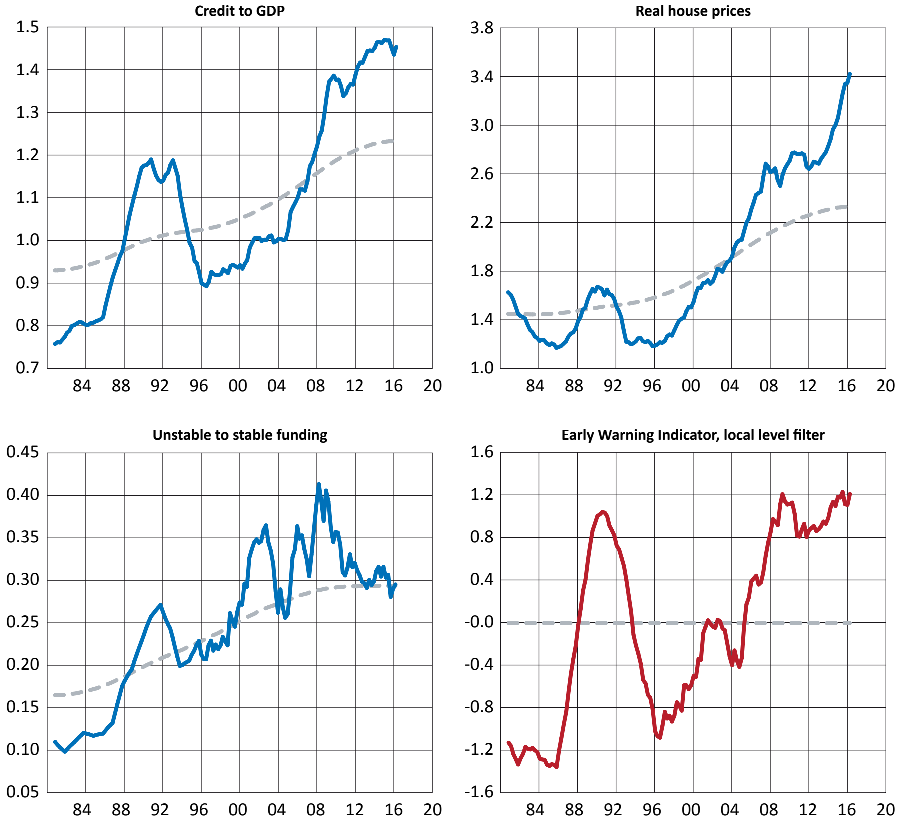


Figure 7. EWI with local level filter (default), equivalent sample size 10 years.
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 2016q2.



The results using house prices divided by disposable income, shown in Figure 8, are very similar. We consider an equivalent sample size of ten years to be at the lower range of admissible parameters: inspecting Figure 7, a fair amount of the trend in each component variable is attributed to a change in mean which, by construction, is interpreted as sustainable.

This is a good point to remind the reader that this EWI measures financial fragility in a very broad sense, and it is not a formal stress test of banks balance sheets. A very high value does not necessarily imply a high probability of crippling bank losses. What a high value does predict is an increased probability of persistent reductions in new loans and aggregate credit volumes, which historically have coincided with persistently lower GDP growth. For comparison, we also compute the EWI with the HP filter (which we do not recommend), with the standard value $\lambda = 400000$. This gives a completely different picture and suggests below-average levels of fragility at present, highlighting the crucial role of assumptions on the trending process.

Figure 8. House prices divided by GDP per capita rather than CPI.
EWI with local level filter (default), equivalent sample size 10 years. Data up to 2016q2.

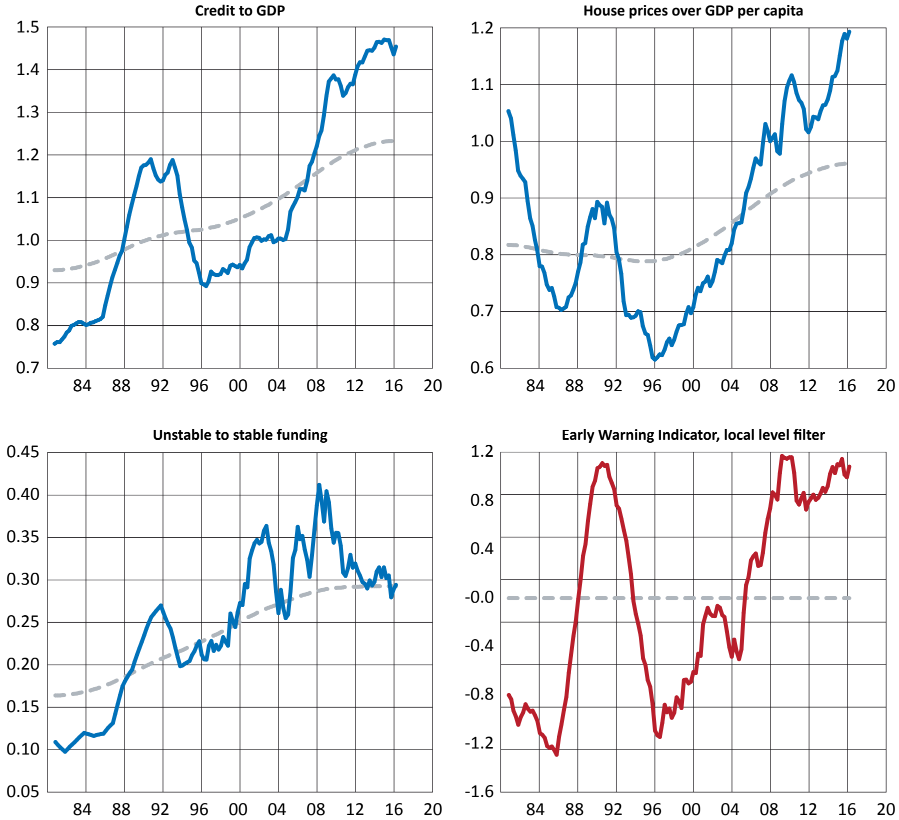
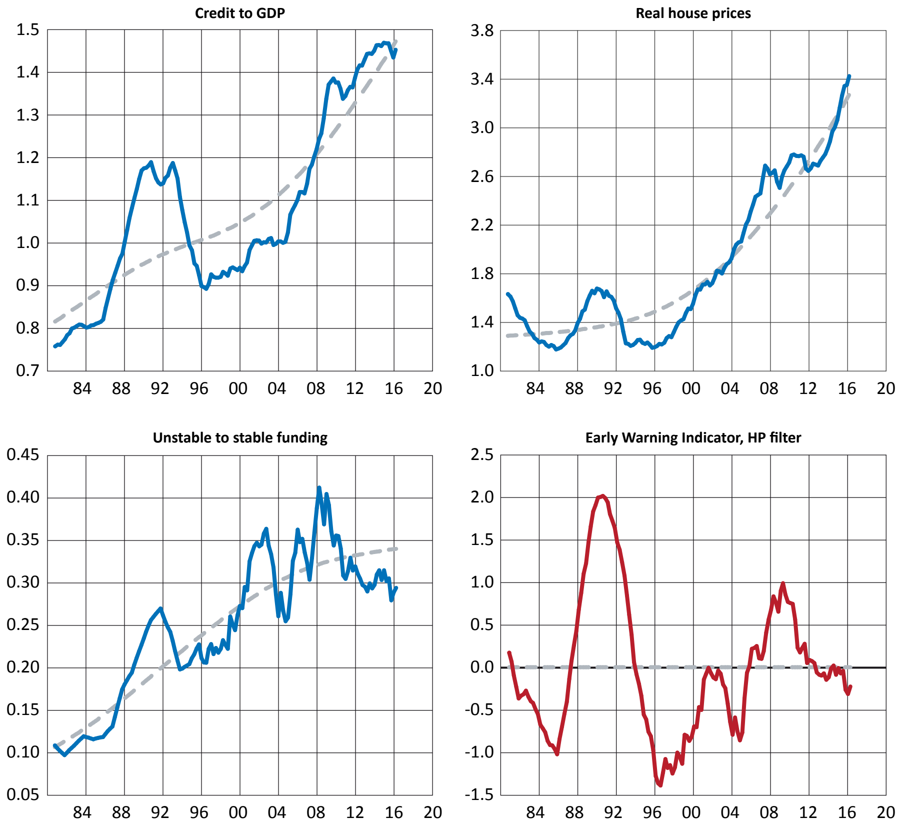


Figure 9. EWI with HP filter (not recommended, presented only for comparison).
The first three plots show the filter components and the estimated trend. The trend is estimated on logs of the shown variable and then exponentiated in the graphs. Data up to 2016q2.



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