A Semi-Structural Framework for Measuring Credit Cycles in Europe*

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Abstract

We develop a framework for evaluating the accumulation of cyclical systemic risk using an unobserved component model of credit to the private sector. The structure of the model is derived from theory where the latent component are lending standards given prices and quantities of collateral in the economy. The credit cycle is then driven by fluctuations in lending standards. Computations are carried out using only the information available to the policymaker when deciding on a policy stance. It depends only on a small set of variables that are usually available with a sufficiently long length. Its leading properties regarding the detection of systemic financial crises are tested against the Basel gap for several European countries. The evaluation exercise relies on a set of metrics commonly used in the context of early-warning systems of crises and is performed both in-sample and out-of-sample. The latter exercise allows us to assess the usefulness of including our measure in a risk monitoring system designed to be used regularly by policymakers. We conclude that our proposed model-based indicator ranks well when compared to the Basel gap, even in the most demanding out-of-sample exercise.

Keywords: Credit cycle; Financial Crises; Forecasting; State space; Bayesian Methods

JEL Classification: E30; E37; E60; G01

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1 Introduction

Surges in lending have often been associated with the onset of financial stress and with increased severity of recessions both in the theoretical (Lorenzoni, 2008; Bianchi and Mendoza, 2010; Bianchi, 2011;) and in the empirical literature (Borio et al., 2001; Drehmann et al., 2012; Schularick and Taylor, 2012; Ziemann, 2012). This relationship has been at the centre of recent efforts by policymakers and institutions aimed at curbing the build-up of vulnerabilities in the financial sector (BCBS, 2010a; ESRB, 2014). In fact, the countercyclical capital buffer (CCyB), a recently introduced capital-based macroprudential policy instrument, aims at increasing bank capital requirements in periods of increased lending to absorb losses and prevent credit supply restrictions during bad times (BCBS, 2010b).

However, in practice, not all peaks in the so-called credit cycle coincide with financial stress (Drehmann et al., 2012) and the extent of overborrowing in the economy is difficult to identify (Bianchi and Mendoza, 2010). This creates a tradeoff for policymakers given that *ex-ante* restrictions imposed on economic agents are costly, but so are missed crisis signals, which may lead to severe recessions in investment and consumption. Thus, accurate and timely information on the phase of the credit cycle and the likelihood of a financial crisis is key when deciding on a policy stance. Another important aspect for creating a policy stance is the need to have credit cycle measures that allow the identification of the underlying drivers.

In this paper, we investigate the leading properties of a credit cycle indicator for the detection of financial systemic crises by measuring the difference between observed credit in the economy and a reference level derived from theory (Kiyotaki and Moore, 1997; Iacoviello, 2005) in which the quantity of credit depends on the expected value of collateral and the repayment effort exerted by borrowers. This reference level is obtained from an unobserved components model estimated with Bayesian methods, using a Gibbs sampling framework and the algorithm by Carter and Kohn (1994). A Bayesian approach has the advantage of performing better with short samples relative to classical methods. In addition, some of the identification problems that may arise under classical estimation are more easily overcome when resorting to these methods.

We test the properties of our proposed measure by using a novel dataset on financial crises in European countries (Lo Duca et al., 2017) and a set of metrics commonly used in the context of crises early-warning systems (Kaminsky et al., 1998; Alessi and Detken, 2011; Drehmann and Juselius, 2014).[1] The signalling properties regarding systemic financial crises are assessed both in-sample and out-of-sample, as a good real-time performance is paramount for policymaking purposes. The credit-to-GDP gap, known as the Basel gap and proposed by Borio and Lowe (2002), is defined as the competing benchmark early-warning indicator. This choice is grounded in the fact that this is one of the best univariate early-warning indicator regarding systemic financial crises (Dekten et al., 2014) and its use is prescribed in the EU current regulatory toolkit concerning macroprudential policy instruments.

We find that our proposed model-based credit cycle measure compares well with the Basel gap, especially in out-of-sample exercises. In particular, the signalling regarding systemic financial crises provided by our measure occurs in a timely and persistent manner, allowing for a gradual implementation of preemptive macroprudential policy actions with time to become effective.

In addition, the small scale nature of the multivariate model and the use of widely available time series with a sufficient time span implies that it can be applied to a wide variety of countries. Its derivation from theory allows policymakers to assign an economic interpretation to the early-warning signals. As such, we argue that there are compelling arguments and evidence that suggest the usefulness of including our measure in a risk monitoring system designed for macroprudential policy purposes.

[1]The benchmark crisis definition used in this paper is the set of systemic crisis which are not purely foreign in origin, and have macroprudential relevance.

Literature. Our paper is related to the literature on the measurement of the financial/credit cycle, starting with Claessens et al. (2011), Drehmann et al. (2012), and Aikman et al. (2015). Several authors have built on this work to cover different sets of countries or testing the robustness of those findings to different methods (e.g.: Hiebert et al., 2015; Galati et al., 2016; Rünstler and Vlekke, 2017). More recently, Durdu and Zhong (2021) analyse the extent to which the drivers of the bank credit cycle differ from those of the nonbank credit cycle.

We contribute to this literature in two ways: First, we propose a notion of the credit cycle derived from theory, allowing us to interpret changes in our measure as variations in lending standards. Second, we conduct a (pseudo) real-time computation of our proposed measure. The credit cycle observed at each point in time uses only available information in each quarter. The choice for this approach is motivated by Duprey and Klaus (2021) that provide evidence that the predictivity power of early-warning indicators may change over time. However, this contrasts with much of the literature, which uses two-sided filtering techniques, implicitly assuming that future data is available to the policymaker. This situation partially explains the good leading properties of many of indicators used in this context.

Our paper is also related to the early-warning system literature (e.g., Alessi et al., 2015; Coudert and Idier, 2016). This literature typically uses a large set of indicators to estimate the probability that a financial crisis occurs within a given horizon. Those indicators are often aggregated into a single composite index, which inherits the leading properties of its components, such as proposed by Lang et al. (2019). The drawback of these methods is that, although they may be attractive in quantitative terms due to their high success rate in predicting financial crises, they are frequently difficult to interpret and explain in the context of defining a policy stance. We contribute to this stream by developing a credit cycle indicator with a straightforward economic interpretation.

Finally, this paper is related to the literature on defining a reference level of credit in the economy. In contrast to a purely statistical approach (e.g. the Basel Gap), Buncic and Melecky (2014) and Albuquerque et al. (2014) set up linear regression models that explain credit to the private non-financial sector using variables such as potential GDP, the unemployment rate, and financial development indicators. In the same vein, Galán and Mencia (2018) propose to extract a credit cycle using an unobserved components model.

A drawback of these approaches is that model construction and variable choice is often based on heuristics, rather than on a formal derivation of the equations. In alternative, Drehmann and Juselius (2015) use a multivariate, co-integration approach to estimate a model of leverage and debt service, based on the work of Kiyotaki and Moore (1997). Our paper is closest to Lang and Welz (2018), who use the theoretical framework of Eggertsson and Mehrotra (2014) to derive an equation for the trend of household credit. They then estimate credit cycles for a set of European countries with a state space formulation and use those estimates as early-warning indicators of systemic financial crises. We complement their work by considering a model of total credit rather than household credit, given that this is one of the target variable related to the implementation of the countercyclical capital buffer.

Layout. Our paper is organized as follows. Section 2 presents the theoretical background, the empirical model to be estimated and our measure of the credit cycle. Section 3 provides an overview of the data used in estimation and discusses the transformations used. Section 4 presents the results from model estimation and performance tests of our measure relative to the Basel gap. Section 5 concludes

2 A model of the credit market

In this section, we describe the theoretical structure that underpins our measurement of the credit cycle. To define a reference quantity of credit, we start from a theory of credit to the private sector from Iacoviello (2005) and derive a state-space formulation that can be estimated from aggregate data. In the economy of Iacoviello (2005) the level of aggregate debt is constrained by the availability and value of collateral. While in the original version of the model lending standards are fixed, in our formulation we allow them to vary, given that they are often understood to be at the heart of credit market dynamics that drive boom and bust cycles (Greenwald, 2016; Greenwald and Guren, 2019; Mian and Sufi, 2021).

The goal is to measure the distance between the aggregate quantity of credit to the private sector and a reference level that reflects the level of interest rates in the economy or available collateral. At any point in time, the level of actual credit may deviate from the reference level due to changes in lending standards. These may be driven by both long-run changes in institutions, such as a greater ability by banks to screen borrowers or more stringent supervisory standards, or cyclical factors, such as momentary changes in the risk appetite of investors or depositors.

To define the reference quantity of credit, we start from a theory of equilibrium credit drawn from Iacoviello (2005) and derive a state-space formulation that can be estimated from aggregate data. In the economy of Iacoviello (2005) the level of aggregate debt is constrained by the availability of collateral, and a key source of macroeconomic fluctuations are the shocks that affect its value.

Specifically, the existence of collateral in Iacoviello (2005) stems from the need to overcome a limited commitment problem, as in Kiyotaki and Moore (1997). Because agents cannot commit to repayment in advance, lenders are given a claim on the borrowers' assets, which generally take the form of a durable good. Thus, the quantity of credit in the model is a constant fraction of the value of the capital stock. In our state-space casting of this framework, the fraction of the capital stock that can be posted as collateral is modeled as an unobserved component with trend and cycle features.

Our formulation is as follows. We assume that there is a continuum of borrowers in the private sector of the economy with measure 1. Each period, agents start with a given level of assets, k_t, which can be used as collateral to obtain loans. Thus credit is limited by the value of collateral:[2]

$$R_t c_t \leq M k_t \mathbb{E}_t \left[q_{t+1} \right], \tag{1}$$

where c_t is the amount of credit borrowed by an agent, R_t is the gross nominal interest rate, M is the loan-to-value (LTV) ratio, q_{t+1} is the asset price next period, and k_t is the quantity of collateral. This expression implies that the value of repayment cannot exceed a faction of the expected value of the asset provided as collateral. If it did, the borrower would simply default on its obligations and keep the funds. Thus, we are assuming that there is no mechanism to make either firms or households in the economy to credibly commit to use their future cash-flows to repay debt, as they can threaten to withdraw their efforts in order to force a reduction in the value of repayment after the contract has been signed (see Kiyotaki and Moore, 1997 for a discussion).

In a setting without uncertainty, Kiyotaki and Moore (1997) show that 1 holds with equality in equilibrium, i.e., agent borrow up to the maximum. Iacoviello (2005) argues that 1 holds with equality in a stationary equilibrium if uncertainty is small enough such that agents do not need to engage in precautionary saving. We need not make this assumption, and simply view M_t as the average LTV ratio in the economy at a point in time. Integrating 1 over all agents, rearranging the resulting expression and dividing both sides by the price of consumption goods, P_t, we can express the observed level of debt as a function of debt service and the expected relative price of collateral:

$$\frac{C_t}{P_t} = \frac{M_t K_t}{R_t} \mathbb{E}_t \left[\frac{Q_{t+1}}{P_t} \right], \tag{2}$$

where capital letters indicate aggregate values. Furthermore, note we allow the loan-to-

[2] Individual subscripts are suppressed because all agents are assumed to be identical.

value, M, to change across time in order to capture changes in the credit cycle. We take the natural logarithm of 2 and arrive at the following equation for aggregate credit at constant prices:

$$\ln\left(\frac{C_t}{P_t}\right) = \ln M_t + \ln K_t - \ln R_t + \ln\left[\mathbb{E}_t\left(\frac{Q_{t+1}}{P_t}\right)\right] + \epsilon_t. \tag{3}$$

We assume that the natural log of the LTV ratio, $\ln M_t$, may be decomposed into a trend and a cycle component, specify 3 as an unobserved components model, and recast it in a state-space structure with the following form:

$$\ln\left(\frac{C_t}{P_t}\right) = \mu_t^M + c_t^M + \ln K_t - \ln R_t + \ln\left[\mathbb{E}_t\left(\frac{Q_{t+1}}{P_t}\right)\right] + \epsilon_t, \tag{4}$$

$$c_t^M = \sum_{i=1}^{h} \rho_i c_{t-i}^M + \varepsilon_t^M, \tag{5}$$

$$\mu_t^M = \mu_{t-1}^M + \nu_{t-1}^M + \xi_t^M, \tag{6}$$

$$\nu_t^M = \nu_{t-1}^M + \zeta_t^M, \tag{7}$$

where μ_t^M and c_t^M are, respectively, the trend and cycle components of $\ln M_t$. This specification follows the structural time series model introduced by (Harvey, 1991) where equation 4 is the observation or measurement equation that relates the vector of observed variables to state unobserved variables, explanatory variables and a measurement error. Equations 5 to 7 are the state or transition equations.

The cycle component in 5 is modelled as an autoregressive process of order h with parameters ρ_i, $i = 1, ..., h$. The stochastic trend component is defined as a random walk process with a slope where equation 6 models the trend level and equation 7 models the trend slope as a random walk process. Both the level and the slope of the trend are allowed to vary over time to easily accommodate any structural changes occurring in the trend of credit limits.

Implicitly, we assume that credit will differ from its reference level for a combination of three reasons: (i) measurement error, ϵ_t; (ii) trend changes in credit limits, μ_t^M; and (iii) cyclical changes in credit limits, c_t^M. All innovations in the model are assumed to be jointly normally distributed, with zero mean and variance-covariance matrix:

$$\text{Var}\left(\begin{bmatrix} \epsilon_t \\ \varepsilon_t^M \\ \xi_t^M \\ \zeta_t^M \end{bmatrix}\right) = \begin{bmatrix} \sigma_\epsilon^2 & 0 \\ 0 & R \end{bmatrix}, \tag{8}$$

where σ_ϵ^2 is the variance of the measurement error, ϵ_t, and R is the 3×3 covariance matrix of state variable innovations. We assume all innovations are serially uncorrelated and independent of each other.

Iacoviello (2005) interprets the loan-to-value ratio, M_t, as a parameter of the economy for implementability reasons. With the present framework, we are able to define the loan-to-value as a time-varying unobserved component and to estimate it using the Kalman filter. Critically, movements in the estimate for M_t can indicate changing credit standards or changes in the precautionary behavior of borrowers, reflecting shifts in the supply or demand for credit. In particular, periods associated with low lending standards (i.e., high LTV) may preface the occurrence of foreclosure crises in housing markets, for example, as argued in Corbae and Quintin (2015) and Kaplan et al. (2020).

To reduce the number of parameters to be estimated and keep close to the structure imposed by the mode, we set unit coefficients on the amount of collateral that may be posted, the gross interest rate, and on the expected relative price of collateral. The reason for this choice is the assumption that the framework in Iacoviello (2005) is a reasonable description of the behavior of agents in credit markets in a stationary equilibrium, and that any deviation of observed credit from the reference credit level is either due to observational error or changes in the willingness to lend/borrow, which are orthogonal to observable fundamentals.

To estimate 4, we require a series of one-step ahead forecasts for the price of collateral, Q_t. We assume that it can be decomposed into a trend-cycle process as proposed by Harvey (1991), which we write in state space form as:

$$\begin{aligned}
Q_t &= \mu_t^Q + c_t^Q + \epsilon_t^Q, \\
c_t^Q &= \sum_{i=1}^{h} \phi_i c_{t-i}^Q + \varepsilon_t^Q, \\
\mu_t^Q &= \mu_{t-1}^Q + \nu_{t-1}^Q + \xi_t^Q, \\
\nu_t^Q &= \nu_{t-1}^Q + \zeta_t^Q,
\end{aligned} \tag{9}$$

where c_t^Q and μ_t^Q are the time-varying unobserved components of asset prices (trend and cycle, respectively). Again, the cycle component is modelled as an autoregressive process of order h, where ϕ_i are the corresponding autoregressive parameters. The trend component is defined as a first-order autoregressive process with stochastic level and slope. As in equations 4 to 7, all innovations are assumed to be Gaussian, with zero mean and a covariance matrix of the form:

$$\text{Var}\left(\begin{bmatrix} \epsilon_t^Q \\ \varepsilon_t^Q \\ \xi_t^Q \\ \zeta_t^Q \end{bmatrix}\right) = \begin{bmatrix} \sigma_{\epsilon^Q}^2 & 0 \\ 0 & V \end{bmatrix}, \tag{10}$$

where $\sigma_{\epsilon^Q}^2$ is the variance of the observational error, ϵ^Q, and V is the 3×3 covariance matrix of state variable innovations. All innovations are serially uncorrelated and independent of each other.

We assume that agents use this model to form expectations about future collateral prices. Thus, we use it to generate forecasts to estimate the system in equations 4 to 7. In the Appendix we present the state space formulation of model equations 4 to 7 and 9 in matrix form.

We use Bayesian methods, namely the Carter and Kohn (1994) algorithm, to estimate the parameters in 4 to 7 and 9 and the Kalman filter to obtain estimates of the unobserved components of the models. These methods have the advantage of working well in the context of short time series samples.

Estimation and filtering is performed using only past and contemporaneous information (pseudo real-time) to mimic as much as possible the information set available to policymakers in each period. This procedure yields a distribution of estimates of the cycle in credit standards, c_t^M, where the median of those estimates in each period is denoted by $c_{t|t}^M$. The credit cycle indicator (CCI) is then defined as:

$$\mathrm{CCI}_t = c_{t|t}^M. \tag{11}$$

The CCI is a measure of changes in credit standards, which are usually suggested in the literature as a driver of many of the historical systemic financial crises preceded by credit booms (Dell'Ariccia et al., 2012; Corbae and Quintin, 2015; Kaplan et al., 2020).

On the practical side, this framework has advantages with respect to the Basel Gap and other purely statistical measures of the credit cycle: (i) it provides an economic interpretation for credit cycle developments; and (ii) its linear formulation allows to easily decompose the results along theoretically grounded driving factors.

3 Data sources

We estimate the model described in the previous section for 13 European countries, covering the sample period 1970Q1 - 2017Q3.[3] However, data availability varies across countries. Table 1 summarizes the data used in the estimation of the model and the

[3]The countries are Austria, Belgium, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, the Netherlands, and Portugal.

performance tests, as well as its sources.

Table 1: Data overview

Variable	Description	Source
State-space model		
Credit (C_t)	Total credit to the non-financial private sector	Quarterly Sector Accounts, Eurostat
Prices (P_t)	Harmonised index of consumer prices (2015=1)	Main Economic Indicators, OECD
Capital (K_t)	Capital at constant 2015 prices, structures	Penn World Table version 9.0
Investment	Investment in dwellings and other structures	World Economic Outlook, OECD
Interest rate (R_t)	Gross 3-months money market rate	Financial Market Data, ECB - SDW
		Main Economic Indicators, OECD
House prices (Q_t)	Residential property price index	Residential Property Price Index Statistics, ECB - SDW
Performance tests		
Basel gap	Real time HP-filtered credit to GDP ($\lambda = 400,000$)	Authors' calculations
Systemic financial crisis	Binary variable (=1 during pre-crisis periods)	Lo Duca et al. (2017)

Note: SDW stands for Statistical Data Warehouse.

The measure of credit in the economy is total credit, including both loans and securities, granted by all sectors to the domestic non-financial private sector. Lending to governments and financial institutions is excluded from the credit aggregate given that they are not modelled in our framework.[4] This variable is then deflated using the harmonised index of consumer prices (HICP), given that consumption is the numeraire good in the theoretical model.

We use the stock of structures in the economy as a proxy for the amount of collateral available in each year. We use data from the Penn World Table (PWT), which have annual frequency and are only available until 2014. We linearly interpolate the series in order to obtain quarterly data and extend it to 2017Q3 using quarterly data on investment in dwellings and other structures.

The choice to restrict attention to structures instead of the entirety of the capital stock is made for a number of reasons: (i) the major role of housing in lending to households; (ii) the link between housing and credit booms (Dell'Ariccia et al., 2012); and (iii) the fact that structures are often a significant component of firm assets and are more easily repossessed in case of default when compared to other assets which can be moved or

[4] Furthermore, lending dynamics to these sectors are not considered when deciding on CCyB stance.

have high depreciation rates, such as electronic equipment or perishable inventories.

Note that we are not assuming that banks demand collateral on every loan or that collateral is correctly valued at all times. Rather, our reasoning is that a banking system which is more stringent in terms of collateral requirements is more resilient in case of widespread counterpart defaults, all else equal.[5] A corollary is that credit market dynamics should follow closely those of collateral markets, which forms the basis for our measurement of reference credit.

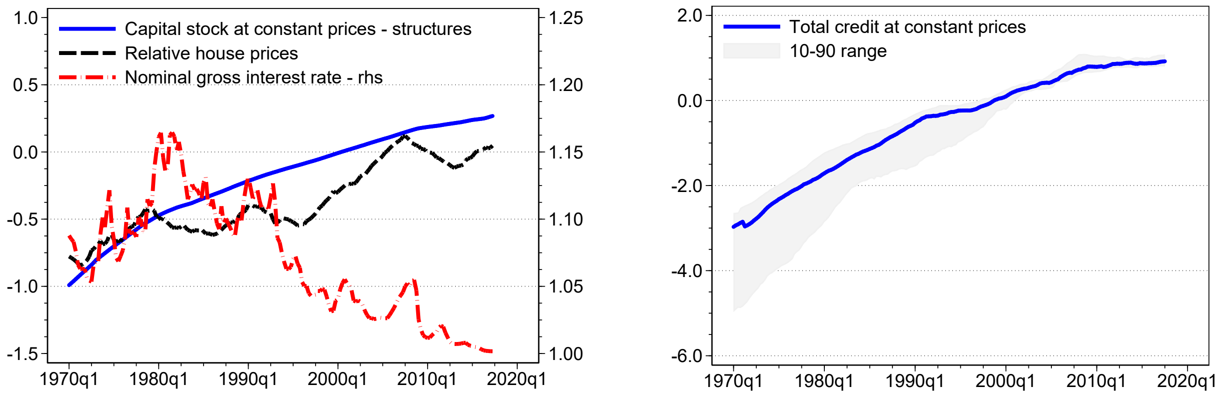
We use the gross 3-month money market rate as a proxy for the nominal repayment rate of borrowers, due to the availability of long time series and to its role as a reference for interest rate fixing of both household and firm lending.

We use the residential property price index as a proxy for collateral prices. Whenever possible the index is backcasted using the price of structures from the PWT, which is linearly interpolated to obtain a series with quarterly frequency. We then deflate the index using the HICP.

Figure 1 shows the behaviour of the data used in estimation over the sample period. Viewing Figure 1b in light of the proposed model indicates that the median reference credit in the sample trends upwards for three reasons: (i) increase in the availability of collateral in the economy, as suggested by the steady climb in the stock of structures; (ii) growth in relative house prices, indicating that collateral has become more valuable and can thus be posted for a greater amount of credit; and (iii) the drop in the nominal interest rate since the 1980s, which implies that the repayment effort has been substantially reduced for borrowers. Furthermore, the apparent cyclical behaviour of relative house prices is coherent with boom and bust cycles, which motivates the framework we have presented.

[5] In the run-up to the financial crisis, only 35% of all NFC loans by US commercial banks were secured by collateral (data from FRED). This feature is related with the business of short-term lending, which is often unsecured. However, Duval et al. (2017) find evidence that US firms with higher roll-over risk suffered greater productivity slowdowns in the aftermath of the financial crisis. This implies both that banks which are more heavily exposed to this type of lending are more vulnerable and that over-reliance on short-term funding by firms amplifies the effects of unforeseen credit constraints.

Figure 1: Cross-country data



(a) Collateral and interest rates

(b) Credit

Notes: The stock of capital, the relative house prices and total credit were normalized with respect to their 2000Q4 value for each country and then log-transformed. Total credit is the total credit granted to households and non-financial corporations. The charts show the yearly cross-sectional median of each series. The 10-90 range on chart 1b is the interval between the 10$^{\text{th}}$ and the 90$^{\text{th}}$ percentiles of the yearly cross-sectional distribution.

4 Using the credit cycle indicator for crisis prediction

In this section, we describe the results of the estimation of the state-space model and measure the ability of our credit cycle indicator to predict the onset of systemic financial crises. We also compare our indicator to benchmark indicators in the literature which can be computed in real time.

4.1 Estimation details and assumptions

To obtain the CCI estimates by country, as given in equation 11, we estimate the unobserved components $c_t^M, \mu_t^M, \nu_t^M, c_t^Q, \mu_t^Q$ and ν_t^Q, the variances σ_ϵ^2 and $\sigma_{\epsilon^Q}^2$, the covariance matrices V and R and the set of parameters ϕ_i and ρ_i.

We begin by estimating the model given by equations 9, and 4 to 7 using Bayesian methods, which perform better in short samples when compared with the classical approach. Furthermore, Bayesian estimation can help to overcome identification problems that may arise in the maximization of the likelihood function.[6]

Table 2: Prior distributions

Collateral prices model					
Parameter	**Equation**	**Distribution**	**l.b**	**u.b**	**Parameters**
ϕ_1	State	Normal	$-\infty$	$+\infty$	mean: $\phi_1^{\hat{OLS}}$, std: $\hat{\sigma}_{\phi_1}^{2,OLS}$
ϕ_2	State	Normal	$-\infty$	$+\infty$	mean: $\phi_2^{\hat{OLS}}$, std: $\hat{\sigma}_{\phi_2}^{2,OLS}$
$\sigma^2_{\varepsilon^Q}$	State	Inv. Wishart	0	$+\infty$	scale: 1, df: 5
$\sigma^2_{\xi^Q}$	State	Inv. Wishart	0	$+\infty$	scale: 1, df: 5
$\sigma^2_{\zeta^Q}$	State	Inv. Wishart	0	$+\infty$	scale: 1, df: 5
$\sigma^2_{\epsilon^Q}$	Obser.	Inv. Gamma	0	$+\infty$	scale: 1, df: 3
Real total credit model					
Parameter	**Equation**	**Distribution**	**l.b**	**u.b**	**Parameters**
ρ_1	State	Normal	$-\infty$	$+\infty$	mean: $\rho_1^{\hat{OLS}}$, std: $\hat{\sigma}_{\rho_1}^{2,OLS}$
ρ_2	State	Normal	$-\infty$	$+\infty$	mean: $\rho_2^{\hat{OLS}}$, std: $\hat{\sigma}_{\rho_2}^{2,OLS}$
$\sigma^2_{\varepsilon^M}$	State	Inv. Wishart	0	$+\infty$	scale: 1, df: 5
$\sigma^2_{\xi^M}$	State	Inv. Wishart	0	$+\infty$	scale: 0.001, df: 5
$\sigma^2_{\zeta^M}$	State	Inv. Wishart	0	$+\infty$	scale: 0.001, df: 5
σ^2_{ϵ}	Obser.	Inv. Gamma	0	$+\infty$	scale: 1, df: 3

Note: L.b. stands for lower bound and u.b. stands for upper bound.

Priors and initialization. Table 2 summarizes the priors in the estimation procedure, which are common across all countries. We assume an inverse Gamma prior distribution for the variances of the observation errors (σ^2_ϵ and $\sigma^2_{\epsilon^Q}$) and an inverse Wishart for the covariance matrices of the state variable innovations (V and R). In the latter case, we impose that the standard deviation of trend shocks is lower than the standard deviation of cyclical shocks by a factor of 0.001 (Rünstler and Vlekke, 2017 and Melolinna and Tóth, 2019). In the case of matrix V, the scale matrix of the prior distribution is set to the identity matrix. Degrees of freedom are set to 5 for R and V to guarantee that the prior distributions are proper.

[6] As pointed out by Primiceri (2005) and Melolinna and Tóth (2019), the application of classical estimation to state space models might imply likelihood functions which have a flat surface, complicating the optimization problem, or multiple peaks, some of which not feasible from a policymaker's perspective.

This choice of scale matrices defines the parameter space in which we believe the covariance matrix should reside. Choosing a small value for the degrees of freedom implies uniformative priors, i.e., prior distributions that have a negligible influence in the estimated parameters.[7]

For of the inverse Gamma prior distributions, we impose a value of 1 for the scale parameter and 3 for the degrees of freedom. The values for the distribution's hyperparamenters are the ones commonly used to specify uninformative and proper priors The initial values for the variances of the observation errors and for the covariance matrices of the state variable innovations are set, respectively, to the scale parameters and matrices of the respective prior distributions.

Prior distributions are chosen on the basis of the range of admissible values for the parameters. They follow standard practice in the literature (among others, Melolinna and Tóth, 2019 and Tóth, 2021) as they are conjugate priors to the likelihood functions. This property facilitates the use of the Gibbs sampling algorithm, as in our case.

We assume a multivariate Normal prior distribution for the autoregressive parameters of the cyclical component of real total credit and collateral prices. For the ϕ_i parameters, the prior mean is set to the vector of OLS coefficient estimates obtained from fitting an AR(h) process to a cycle estimate, obtained from computing the difference between observed collateral prices and a Hodrick-Prescott trend (filter with a smoothing parameter of 1,600) using the first 39 sample observations. The covariance matrix of the normal prior is set to the estimated version of the covariance matrix of OLS coefficient estimates.

The same approach is used to define the hyperparameters of the prior distribution for the ρ_i parameters in the real total credit equation. We choose an AR(2) model for the credit cycle equation (Rünstler and Vlekke (2017), Lang and Welz (2018) and Galán and

[7]The inverse Wishart distribution (inverse-Gamma distribution is the univariate version) is defined by the scale matrix that positions the distribution in the desirable parameter space and the degrees of freedom that set the certainty about the information in the scale matrix. Thus, the higher the degrees of freedom the more informative is the prior (see Schuurman et al., 2016).

Mencia (2018)). The works by Claessens et al. (2012), Hiebert et al. (2015) and Rünstler and Vlekke (2017) find evidence of similar cyclical dynamics between collateral prices and credit. Hence, in both models we set $h = 2$.[8] The initial values for the parameters of the cyclical components are set to equal the prior means.

Finally, the cyclical components are initialised at zero. The initial value for the trend level is set equal to the first sample observation of collateral prices or real total credit. The initial value for the trend slope is set to the first value of the times series that results from taking the first differences of either collateral prices or real total credit. The initial state covariance matrix is assumed to be the identity matrix in both unobserved components models.

Estimation algorithm. With initial values and prior distributions defined, we estimate the posterior parameter distributions by drawing from the conditional posterior using the Gibbs sampling algorithm with 5,000 replications and rejecting the first 2,000 draws. The procedure is as follows.

First, the Kalman filter is used to recursively obtain the unobserved components of both models. Next, the backward recursion algorithm described in Carter and Kohn (1994) is used to obtain the mean and variance of the distribution of the latent state variables that will feed into the conditional posterior distribution of the parameters. Finally, conditional on the state variables, we draw the matrices V and R from an inverse Wishart distribution, σ^2_ϵ and $\sigma^2_{\epsilon Q}$ from an inverse Gamma and the ϕ_i and ρ_i parameters from a Normal distribution. In the latter case, random draws from the Normal posterior conditional distribution are taken until a stationary cyclical component is obtained, given our prior that the cyclical components are stationary. In addition, to guarantee that the cyclical component has an oscillating movement, the random draws also have to fulfill the requirement of delivering complex roots.

[8] For the cases of Austria and Portugal we did not obtain a stationary cycle with $h = 2$ in the model for real total credit. Thus, we increased the lags of the cyclical component until convergence to a stationary cycle. This happened when we set $h = 3$ for both countries.

Finally, one of our main contributions to the literature is to provide a real time estimate of the credit cycle indicator. This means that

4.2 Performance test design

Benchmark indicators. In the performance tests, we compare our new credit cycle measure to the Basel gap, the debt service ratio, and the house price to income ratio. As proposed by Borio and Lowe (2002), the Basel gap is a real-time estimate of the credit cycle as the ratio between total credit to the non-financial private sector and GDP using the one-sided Hodrick-Prescott filter with a smoothing parameter of 400,000. The debt service ratio is XXX. The house price to income ratio is XXXX.

The rationale for comparing our credit cycle measure with the Basel gap is its prominent use as a signalling indicator of cyclical imbalances and in guiding the setting of CCyB rates for dealing with excessive credit.[9] It is the recommended indicator in the CCyB guidance provided by the Basel Committee of Banking Supervision (BCBS, 2010b), and its use is inscribed in European Union law (European Parliament and Council of the European Union, 2014).

The relative performance of the CCI is assessed on the basis of two evaluation exercises that comprise a set of commonly used metrics. The early-warning properties of the CCI for signalling systemic financial crises are evaluated both in-sample and out-of-sample. For that we use a binary indicator of systemic financial crises, drawn from a database of financial crises in European Union countries by Lo Duca et al. (2017). The details on the metrics are provided below in Section 4. This framework follows current practice for early-warning of financial crises exercises (Lang and Welz, 2018; Aikman et al., 2018).

In our analysis, only systemic financial crises with macroprudential relevance are

[9]The Basel gap is considered one of the best univariate signalling indicators for systemic financial crises, as discussed in Borio and Lowe (2002) and Dekten et al. (2014)

considered. This set of crisis events is divided in two categories. One that only considers crises with a domestic origin and another that considers crises with a domestic or foreign origin. In total there are 15 crisis events with a domestic origin and 19 crisis events with a domestic or foreign origin in our sample. These crises are described in detail in Lo Duca et al. (2017) but one feature is their clustering around the Great Financial Crisis.

The use of a signalling approach to study the early-warning properties of indicators regarding crisis events was first introduced by Kaminsky et al. (1998) and Kaminsky and Reinhart (1999) in the context of currency crises.[10] This approach assumes a non-linear relationship between the indicator and the crisis event variable and has been frequently used in the aftermath of the Great Financial Crisis as a tool to assess which indicators are better suited to signal in a timely manner that a systemic financial crisis is imminent (among others Dekten et al., 2014, Lo Duca et al., 2017).

In our case, the early-warning properties of the CCI and the Basel gap for signalling systemic financial crises are assessed individually, in-sample and out-of-sample for a pooled set of countries in terms of the following standard metrics.

AUROC. The Area Under the Receiver Operating Characteristic (AUROC) curve is a summary measure of the signalling performance of an indicator. The receiver operating curve plots the noise ratio (false positive rate) against the signal ratio (true positive rate) for every possible signalling threshold. The AUROC varies between 0 and 1. A value of 0.5 indicates an uninformative indicator (i.e., no better than a coin toss) and a value of 1 indicates a perfect early-warning indicator. The AUROC allows ranking indicators according to their ability to predict crises without the need to specify a threshold.

The AUROC is computed assuming two prediction horizons.[11] The first one consid-

[10] According to this approach, an indicator signals an incoming crisis event if it is above/below a certain threshold within a specific period prior (vulnerable period) to the crisis.

[11] A prediction horizon is defined as the set of quarters prior to a crisis start within which an indicator is expected to have the ability to signal that a systemic financial crisis is likely to occur in the future. The binary variable is set to 1 in the quarters within the prediction horizon, to missing in the quarters before a crisis event and for the crisis period, to account for post-crisis and crisis bias as proposed by Bussiere and Fratzscher (2006), and to 0 otherwise.

ers a 12 to 5 quarters window prior to crisis start and the second one a 20 to 5 quarters window prior to crisis start.

These choices are motivated by two sets of reasons. First, lags in data availability which prevents a timely detection of risk buildup. Second, the lags in implementation of macrocprudential tools and the speed of adjustment of institutions to those policies. For example, the CCyB has a 1 year implementation lag to allow institutions to conform to the new capital buffer requirement, which they may adjust to at different speeds. Both reasons require the use of an indicator that detects the emergence of cyclical systemic risk early on.

Relative usefulness. The relative usefulness of an indicator is defined in Alessi and Detken (2011) as $U = \frac{min(\theta,1-\theta)-L}{min(\theta,1-\theta)}$, where L represents a policymaker loss function defined as $L = \theta\,(\text{Type I error}) + (1-\theta)\,(\text{Type II error})$ and θ the policymaker preference for not missing a crisis (risk aversion or relative preferences parameter).[12] It quantifies the usefulness of considering the signal issued by an indicator versus disregarding it. In our analysis, the preference parameter takes the values of 0.5 (policymaker has balanced preferences) or 0.7 (policymaker prefers not to miss a crisis).

The balanced preferences scenario is the most commonly used in the related literature, as it does not privilege either of the two types of error. However, Borio and Drehmann (2009) and Betz et al. (2014), among others, argue that policymakers may be more averse to missing a crisis, especially after the Global Financial Crisis, since the costs of a crisis may be higher than the costs of taking preemptive measures even in the case of a false alarm. The higher is the relative usefulness the better the indicator and, according to Lo Duca et al. (2017), a good early-warning indicator should present a relative usefulness of at least 0.25.

False negative rate and false positive rate. The false negative rate is the share of missed

[12] Type I error is the percentage of vulnerable periods that are not correctly predicted (missed vulnerable periods) and type II error (false vulnerable periods) is the percentage of non-vulnerable periods incorrectly signalled as vulnerable periods.

vulnerable periods (type I error rate) and the false positive rate is the share of false alarms of vulnerable periods (type II error rate). For very low values of the signalling threshold the rate of false negatives will be low while the rate of false positives will be high. The opposite will occur if the signalling threshold is very high.

The optimal threshold level is defined as the one that maximizes the relative usefulness for a grid of indicator values and for a specific value of the policymaker preference parameter. The policymaker knows it's impossible to detect in advance all crisis events but its credibility is also questioned if these two error rates are deemed too high. The goal is to strike a balance between the two rates while assuring that their magnitude is acceptable from a policy perspective. Following Lo Duca et al. (2017), we define as acceptable for a good early-warning indicator if type I error and type II error rates are below 0.5 and 0.6, respectively.

P(Vuln | signal)-P(Vuln). Difference between the probability of being in a vulnerable period conditional on a signal issued by the indicator and the unconditional probability of being in a vulnerable period. If the indicator anticipates systemic financial crisis then the conditional probability should be higher than the unconditional probability.

Lead time. Following Kaminsky et al. (1998), the lead time of an indicator is measured as the average number of quarters in which the first signal is issued. While useful for assessing the indicator's ability to anticipate a financial crisis, the above metrics are uninformative on timeliness. As macroprudential policy is preventive in nature, a good early-warning indicator should signal a crisis a reasonable number of quarters ahead to allow the prompt deployment of available instruments to maintain financial stability.

Persistence. This metric complements the previous one to the extent that it measures the persistence of the signals issued by the indicator during a vulnerable period relative to normal periods. A value above one means that the signals are more persistent within the vulnerable period than in non-vulnerable periods. This provides information to the policymaker on how well the indicator performs in disentangling vulnerable periods from normal periods.

4.3 Early-warning signalling performance

Indicator performance exercises are conducted both in and out-of-sample. In the former, we define a threshold and compute performance metrics based on the full sample information. In the latter, the signalling threshold is determined using a smaller sample, and performance tests are calculated for a non-overlapping window of the full sample.[13]

Following Lo Duca et al. (2017), all metrics defined in the previous section are computed for each quarter t with all available information up to that point considering a data lag of 3 years.[14] The recursive procedure starts in the first quarter of 2000 and ends in the second quarter of 2017. From a policy perspective, it can be argued that the out-of-sample signalling performance of the indicator should receive more weight on balance as it mimicks a situation more close to that faced by policymakers.

The results of the early-warning signalling performance exercise are presented in Table 3. Panel (a) displays the evaluation metrics for the in-sample exercise and panel (b) the evaluation metrics for the out-of-sample exercise.

[13] This is the so-called "quasi-real time" exercise, where lags in the publication of the indicators are not considered.

[14] A data lag of 3 years is considered due to choice of using a prediction horizon between 12 and 5 quarters ahead of the crisis (information used to compute the indicators).

Table 3: Results for the in-sample and out-of-sample signalling performance exercises

	Only crises with domestic origin				*All systemic crises*			
Panel (a): In-sample exercise	**Basel gap**	**CCI**	**Debt service ratio**	**House price to income**	**Basel gap**	**CCI**	**Debt service ratio**	**House price to income**
AUROC: 12 to 5 horizon	0.70	0.71	0.78	0.75	0.66	0.68	0.69	0.72
AUROC: 20 to 5 horizon	0.67	0.58	0.74	0.73	0.66	0.55	0.67	0.71
Balanced preferences ($\theta = 0.5$)								
Relative usefulness	0.32	0.39	0.38	0.44	0.27	0.32	0.31	0.36
False negative rate	0.20	0.32	0.30	0.34	0.52	0.30	0.37	0.02
False positive rate	0.47	0.30	0.32	0.22	0.21	0.38	0.32	0.62
P(Vuln | signal)-P(Vuln)	0.06	0.10	0.10	0.15	0.12	0.09	0.10	0.06
Persistence	1.68	2.30	2.21	2.97	2.26	1.83	1.98	1.58
Lead time (quarters)	12	10	11	12	12	10	11	12
Unbalanced preferences ($\theta = 0.7$)								
Relative usefulness	0.06	0.24	0.27	0.33	0.06	0.18	0.06	0.33
False negative rate	0.00	0.08	0.07	0.00	0.00	0.08	0.00	0.02
False positive rate	0.94	0.58	0.57	0.67	0.94	0.64	0.94	0.63
P(Vuln | signal)-P(Vuln)	0.01	0.05	0.05	0.04	0.01	0.05	0.01	0.06
Persistence	1.06	1.60	1.63	1.49	1.06	1.45	1.07	1.55
Lead time (quarters)	12	12	11	12	12	12	12	12

Panel (b): Out-of-sample exercise	**Basel gap**	**CCI**	**Debt service ratio**	**House price to income**	**Basel gap**	**CCI**	**Debt service ratio**	**House price to income**
AUROC (mean): 12 to 5 horizon	0.70	0.73	0.74	0.71	0.69	0.70	0.63	0.69
AUROC (mean): 20 to 5 horizon	0.65	0.55	0.70	0.70	0.68	0.53	0.61	0.68
Balanced preferences ($\theta = 0.5$)								
Relative usefulness	0.07	0.37	0.20	0.21	-0.04	0.22	0.22	0.11
False negative rate	0.38	0.18	0.28	0.00	0.51	0.24	0.30	0.00
False positive rate	0.56	0.46	0.52	0.79	0.53	0.54	0.48	0.89
P(Vuln | signal)-P(Vuln)	0.02	0.10	0.05	0.04	-0.01	0.06	0.07	0.02
Persistence	1.13	1.80	1.39	1.27	0.92	1.40	1.45	1.12
Lead time (quarters)	12	11	11	12	12	11	11	12
Unbalanced preferences ($\theta = 0.7$)								
Relative usefulness	-0.29	0.05	0.26	0.09	-0.65	-0.13	0.04	0.05
False negative rate	0.28	0.18	0.00	0.00	0.41	0.24	0.00	0.00
False positive rate	0.65	0.54	0.74	0.91	0.70	0.57	0.96	0.95
P(Vuln | signal)-P(Vuln)	0.02	0.07	0.04	0.01	-0.03	0.05	0.01	0.01
Persistence	1.11	1.53	1.35	1.10	0.84	1.33	1.04	1.05
Lead time (quarters)	12	11	12	12	11	11	12	12

4.4 In-sample results

The AUROC values for the two indicators are above 0.5 for the two prediction horizons and sets of crises, meaning that they are both useful in anticipating systemic financial crises. For the prediction horizon of 12 to 5 quarters, the AUROC values are virtually the same across indicators whereas for the prediction horizon of 20 to 5 quarters the Basel gap slightly outperforms our model-based indicator.

As such, the signalling properties of the model-based indicator seem to be concentrated in a prediction horizon that is close to the materialization of the crisis but still 3 to 1 years ahead. In fact, Lo Duca et al. (2017), among others, focus their univariate early-warning signalling performance exercises in this prediction window.

As the CCI is more volatile than the Basel gap, due to the fact that the trend of the CCI adjusts more rapidly to recent developments, it is not surprisingly that, when a 20 to 5 quarters prediction horizon is considered, the early-warning properties of the CCI tend to decrease close to a point in which the indicator is no longer informative. When crises with a foreign origin are also considered, the signalling power of both indicators tends to deteriorate, implying that the indicators seem better suited to anticipate systemic financial crises driven by domestic imbalances.

For both indicators, the relative usefulness and the difference between the conditional and unconditional probability of being in a vulnerable period are always positive meaning that they provide additional information to the policymaker's decision process. However, the relative usefulness of the model-based indicator is always higher than that of the Basel gap, especially in the case of unbalanced preferences.

In terms of the false negative rate, it seems that the CCI leads to a slightly higher share of missed vulnerable periods (at most 32%) than the Basel gap in the case of balanced policymaker preferences. Opposite results are obtained in the case of unbalanced preferences. However, the CCI issues less false alarms than the Basel gap. The exception being the case in which only crises with domestic origin and unbalanced preferences are considered. For most scenarios, the two indicators verify the guiding values put forward by Lo Duca et al. (2017) to deem an indicator as an acceptable early-warning indicator.

Overall in terms of average leading time, the two competing indicators exhibit leading properties regarding crisis as desirable. Under the scenario of balanced preferences of the policymaker, the Basel gap issues the first signal regarding a crisis before the CCI, but we argue that the difference is not substantial. On average and considering the crises with domestic origin, the two indicators issue the first signal around 3 years before crisis start. The average lead time is somehow shorter, between 10 and 11 quarters, for the larger set of systemic financial crisis. Nevertheless, we argue that this difference is not worrisome from a policy perspective to the extent that it does not preclude the implementation of preemptive measures, even though they may have to be implemented at a slightly higher pace. Under the scenario of unbalanced preferences, the indicators show the same average leading time.

In terms of persistence of the signals, the CCI ranks above the Basel gap for the majority of the cases, the exception being the scenario in which only domestic crises and unbalanced policymaker preferences are considered. But even in this case the difference in the metric between indicators is the lowest across all scenarios. Overall, the signals issued by the two indicators are between 1 and 2 times more persistent in periods that precede crisis than in the so-called normal periods.

4.5 Out-of-sample results

Overall the signalling properties of the indicators become weaker in a setting that resembles more closely the decision environment faced by policymakers. The deterioration in the relative usefulness and in the difference between the conditional and unconditional probability of being in a vulnerable period of the Basel gap is evidence that its good in-sample signalling properties seem not hold in a out-of-sample performance exercise.

In constrast, the in-sample signalling properties of the model-based indicator seem to be confirmed by the out-of-sample exercise. The performance of the Basel gap in terms of issuing bad signals, either in terms of missing crisis or issuing false alarms, declines. For the CCI the results are less clear-cut but in most cases there is also a deterioration in the share of bad signals issued.

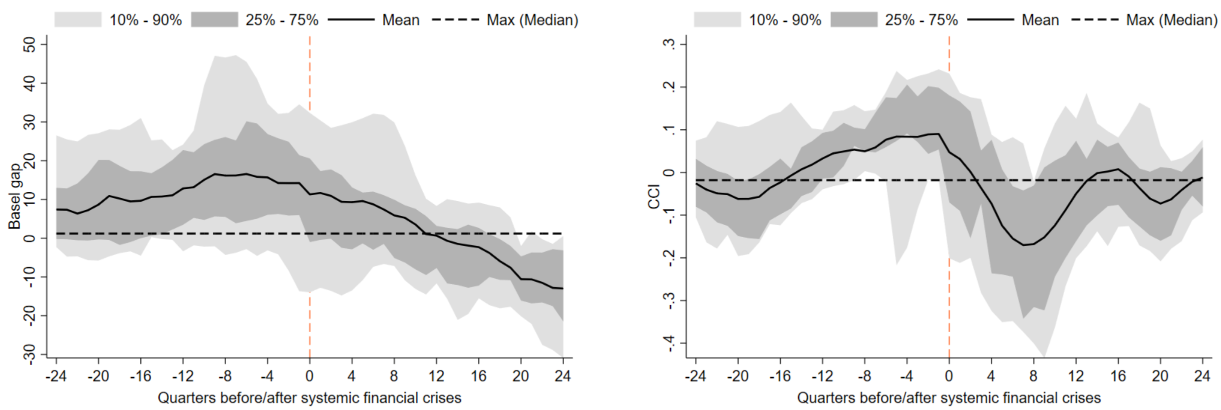
Nonetheless, in terms of the AUROC, most of the conclusions drawn from the in-sample exercise are still valid. The Basel gap seems to marginally outperform the CCI in most scenarios and the AUROC values of both indicators seem to deteriorate when crises with a foreign origin are also considered in the analysis. Also, unchanged in comparison to the in-sample exercise is the fact that the two indicators send the first signal around 3 years before a crisis start, a desirable property from a policymaker perspective if he wants to consider the implementation of preemptive measures. The persistence of the signals issued by the indicators in advance of crises deteriorates only slightly, implying that the indicators are still useful for antecipating crises in a real-time scenario. However, there is an exception. When all crises are considered, the signal persistence of the Basel gap seems to be higher in tranquil periods than in vulnerable periods.

The main conclusion from this analysis is that our proposed model-based indicator ranks very well in comparison with one of the most used univariate early-warning indicator, more so in the most demanding out-of-sample exercise. But the CCI has the advantage of being a small scale multivariate indicator embedding the orthodox view that financial crises result from mutually reinforcing forces that drive the financial sector and the real sector of the economy (Kindleberger, 2000 and Minsky, 1982). As a result, it allows policymakers to assign an economic interpretation to early-warning signals and build a narrative about the drivers of a systemic financial crisis. Notice that the comparison between the two indicators is extremely fair to the extent that both indicators are computed in real time and their early-warning signaling performance is evaluated both in-sample and out-of-sample, the latter mimicking as close as possible the environment in which policymakers are called to take a decision on deploying policy instruments. We argue that this is not always the case in related literature in which it is not possible to disentangle whether the better properties of an indicator come from the fact that unknown information to the policymaker at the decision time is used in the computation of the indicator. Another take away from this analysis is the fact that the signaling regarding systemic financial crises provided by the CCI occurs in a timely and persistence manner that may allow for preemptive and better informed policy actions.

Panels (a) and (b) of Figures 2 and 3 show the dynamics of the Basel gap and CCI before and after systemic financial crisis events for the two sets of crises considered in this analysis. On average, the Basel gap is positive more than four years prior to the start of a systemic financial crisis and tends to consistently increase until two years prior to the start of a systemic financial crisis. This is particularly true when only crises with a domestic origin are considered. One year ahead of the crisis the gap seems to stabilize and once the crisis event occurs a long deleveraging period takes place lasting on average more that four years. The CCI shows a similar dynamic for the two sets of crises considered. The CCI steeply increases in the 16 to 1 quarter window prior to a systemic financial crisis start, implying that there seems to be information content regarding the signalling of systemic financial crises. After that point, the CCI decreases in line with the ajustment process that usually takes place after a crisis. In contrast with the Basel gap, the CCI returns to positive values more rapidly, a result that mimics the different recovery paces across countries. For both indicators, positive and increasing values are observed during the quarters that precede systemic financial crises, meaning that is the combination of the level with the change in the indicator that provides information about future crisis events. For the vast majority of countries these results hold even though there is evidence of some cross country heterogeneity.

Overall, both indicators seem useful in identifying periods in which cyclical systemic risk starts to accummulate, providing time to implement preemptive macroprudential measures either to mitigate risk or to increase financial system resilience against shocks. The CCI should be seen as an additional model-based indicator for the assessment of cyclical systemic risk and as such its use for creating a policy stance should be complemented by additional information provided by other indicators of credit cycle. This is in line with the findings of Galán and Mencia (2018) and with the guidance provided by the ESRB Recommendation on setting countercyclical buffer rates.

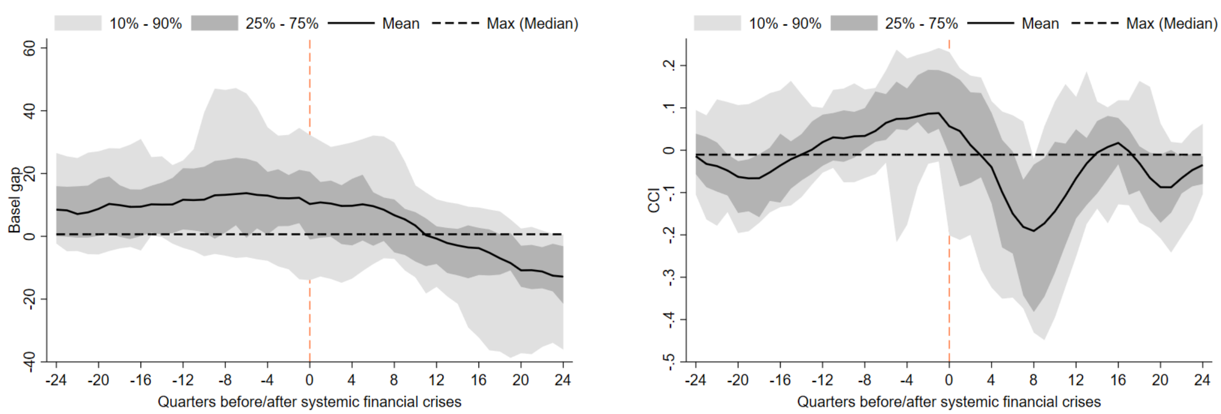
Figure 2: Distribution around systemic financial crises with domestic origin.



(a) Basel gap

(b) CCI

Figure 3: Distribution around systemic financial crises with domestic/foreign origin.



(a) Basel gap

(b) CCI

5 Conclusion

In this paper we develop a framework for evaluating the accumulation of cyclical systemic risk using a set of unobserved component models of credit to the private sector. The structure of these models is derived from theory to assign an economic interpretation to the early warning signals issued by our proposed indicator. This indicator is computed using only the information available to the policymaker when deciding on a policy stance. It depends only on a small set of variables that are usually available with a sufficiently long length. Its leading properties regarding the detection of systemic financial crises are tested against the Basel gap for several European countries. The evaluation exercise relies on a set of metrics commonly used in the context of early-warning systems of crises and is performed both in-sample and out-of-sample. The latter exercise allows us to assess the usefulness of including our measure in a risk monitoring system designed to be used regularly by policymakers. We conclude that our proposed model-based indicator ranks well when compared to the Basel gap, even in the most demanding out-of-sample exercise. A promising avenue of future work in this line of research is the

APPENDIX

A State space representations

This appendix provides an overview of the models in state space form. Consider the following general state space model consisting of an observation equation and a state equation:

$$Y_t = H\beta_t + AZ_t + e_t,$$
$$\beta_t = \mu + F\beta_{t-1} + v_t,$$

with $e_t \sim \mathrm{N}(0, R)$, $v_t \sim \mathrm{N}(0, Q)$ and $Cov(e_t, v_t) = 0$. Y_t is a $k_1 \times 1$ vector of observed data, H is a $k_1 \times k_2$ coefficient matrix of the state variables in the observation equation, β_t is a $k_2 \times 1$ vector of state variables, A is a $k_1 \times k_3$ coefficient matrix of the exogeneous variables in the observation equation, Z_t is a $k_3 \times 1$ vector of exogenous variables, μ is a $k_2 \times 1$ vector of constants and F is a $k_2 \times k_2$ coefficient matrix of the state equation. The observation error, e_t, and the state error, v_t, are normally distributed with zero mean and covariance matrices R and Q, respectively. In both equations the vector of state variables, β_t, needs to be estimated. In addition, in the observation equation the unknown parameters are the elements of the coefficient matrices H and A and the non-zero elements of matrix R. In the state equation the unknown parameters are the elements of μ, F and Q.

For the model in equations 4 to 7 with h set to 2 the observation equation has the following matrices:

$$\ln\left(\frac{C_t}{P_t}\right) = \begin{bmatrix}1 & 1 & 0 & 0\end{bmatrix}\begin{bmatrix}c_t^M \\ \mu_t^M \\ \nu_t^M \\ c_{t-1}^M\end{bmatrix} + \begin{bmatrix}1 & -1 & 1\end{bmatrix}\begin{bmatrix}\ln K_t \\ \ln R_t \\ \ln\left[\mathbb{E}_t\left(\frac{Q_{t+1}}{P_t}\right)\right]\end{bmatrix} + \epsilon_t \tag{A-1}$$

and the state equation has the following matrices:

$$\begin{bmatrix}c_t^M \\ \mu_t^M \\ \nu_t^M \\ c_{t-1}^M\end{bmatrix} = \begin{bmatrix}\rho_1 & 0 & 0 & \rho_2 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}c_{t-1}^M \\ \mu_{t-1}^M \\ \nu_{t-1}^M \\ c_{t-2}^M\end{bmatrix} + \begin{bmatrix}\varepsilon_t^M \\ \xi_t^M \\ \zeta_t^M \\ 0\end{bmatrix} \tag{A-2}$$

For the model in equation 9 with h^Q set to 2 the observation equation has the following matrices:

$$Q_t = \begin{bmatrix}1 & 1 & 0 & 0\end{bmatrix}\begin{bmatrix}c_t^Q \\ \mu_t^Q \\ \nu_t^Q \\ c_{t-1}^Q\end{bmatrix} + \epsilon_t^Q \tag{A-3}$$

and the state equation has the following matrices:

$$\begin{bmatrix}c_t^Q \\ \mu_t^Q \\ \nu_t^Q \\ c_{t-1}^Q\end{bmatrix} = \begin{bmatrix}\phi_1 & 0 & 0 & \phi_2 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}c_{t-1}^Q \\ \mu_{t-1}^Q \\ \nu_{t-1}^Q \\ c_{t-2}^Q\end{bmatrix} + \begin{bmatrix}\varepsilon_t^Q \\ \xi_t^Q \\ \zeta_t^Q \\ 0\end{bmatrix} \tag{A-4}$$

B Priors

The conjugate priors distribution for the variance parameters ($\sigma^2_{\varepsilon M}, \sigma^2_{\xi M}, \sigma^2_{\zeta M}, \sigma^2_{\epsilon}, \sigma^2_{\varepsilon Q}, \sigma^2_{\xi Q}$, $\sigma^2_{\zeta Q}, \sigma^2_{\epsilon Q}$) belong to the inverted gamma distribution family. The random variable X follows an inverted gamma distribution with shape parameter α and scale parameter β, $X \sim IG(\alpha, \beta)$, if:

$$f(x) = \frac{1}{\Gamma(\frac{\alpha}{2})(\frac{2}{\beta})^{\frac{\alpha}{2}}} x^{-\frac{1}{2}(\alpha+2)} e^{-\frac{\beta}{2x}}, \qquad x > 0 \tag{A-5}$$

where $\Gamma(\dot{)}$ is the gamma function. The mean (μ) and variance (σ^2) are given by:

$$\mu = \frac{\beta}{\alpha - 2} \quad \alpha > 2, \qquad \sigma^2 = \frac{2\mu^2}{\alpha - 4} \quad \alpha > 4 \tag{A-6}$$

The conjugate priors distribution for the covariance matrices of the state variable innovations (V and R) are inverse Wishart. The random matrix $\mathbf{X}_{p\times p}$ (positive definite) follows and inverse Wishart distribution with scale matrix $\mathbf{\Psi}_{p\times p}$ (positive definite) and degrees of freedom $\vartheta > p - 1$, $\mathbf{X} \sim W^{-1}(\mathbf{\Psi}, \vartheta)$, if:

$$f(\mathbf{x}) = \frac{|\mathbf{\Psi}|^{\frac{\vartheta}{2}}}{2^{\frac{\vartheta p}{2}} \Gamma_p(\frac{\vartheta}{2})} |\mathbf{x}|^{-\frac{(\vartheta+p+1)}{2}} e^{-\frac{1}{2} tr(\mathbf{\Psi}\mathbf{x}^{-1})} \tag{A-7}$$

where $\Gamma(\dot{)}$ is the multivariate gamma function. The mean and variance are given by:

$$\mu = \frac{\mathbf{\Psi}}{\vartheta - p - 1} \quad \vartheta > p + 1 \tag{A-8}$$

$$Var(x_{ii}) = \frac{2\psi_{ii}^2}{(\vartheta - p - 1)^2 (\vartheta - p - 3)} \tag{A-9}$$

$$Cov(x_{ij}, x_{kl}) = \frac{2\psi_{ij}\psi_{kl} + (\vartheta - p - 1)(\psi_{ik}\psi_{jl} + \psi_{il}\psi_{kj})}{(\vartheta - p)(\vartheta - p - 1)^2 (\vartheta - p - 3)} \tag{A-10}$$

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