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

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April 28, 2022

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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 cyclical component are lending standards given prices and quantities of collateral in the economy. Computations are carried out using only the information available to the policymaker when deciding on a policy stance. Our measure depends on the availability of only 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 benchmark real-time indicators 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 against other measures, 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

*We thank members of the ECB Cyclical Risk Analysis Group, and seminar participants at the Lisbon Macro Workshop and the Joint BdP/ECB/ESRB Workshop 2018 for helpful comments and suggestions. We thank Jan Hannes Lang and Cosimo Izzo for providing us with their early-warning performance routines.

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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 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 signaling 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 one of the three competing benchmark early-warning indicators. 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. Also, it is computed on a real-time fashion, which ensures the fairness of the comparison exercise.

The other competing benchmark early-warning indicators, selected from the set of measures computed in real-time, are the non-financial private sector debt service ratio and the house price to income ratio. Duprey and Klaus (2021) conduct an extensive investigation of the early-warning properties of several indicators and show that these two indicators are also among the best predictors of systemic financial crises. We focus solely on indicators which can be computed in real time, to accurately reflect the information set that policy makers possess when they are called on to make a decision and thus to make a fair comparison to our own measure.

We find that our proposed model-based credit cycle measure compares well with alternative measures, especially in out-of-sample exercises. In particular, the signaling regarding systemic financial crises provided by our measure occurs in a timely and per-

[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.

sistent 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.

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. This choice 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. (2019a). 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 non-financial 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

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

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-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:

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

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:

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

where $\sigma^2_{\epsilon^Q}$ 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 A 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:

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

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, conditional on data availability.[3] Table 1 summarizes the data used in the estimation of the model and the 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 ($\lambda = 400,000$)	Bank for International Settlements (BIS)
Debt service ratio	Debt service to income of households and non-financial firms	BIS
House price to income	Real residential property price index to income	OECD
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 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 modeled in our framework.[4] This variable is then deflated using the harmonised

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

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

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

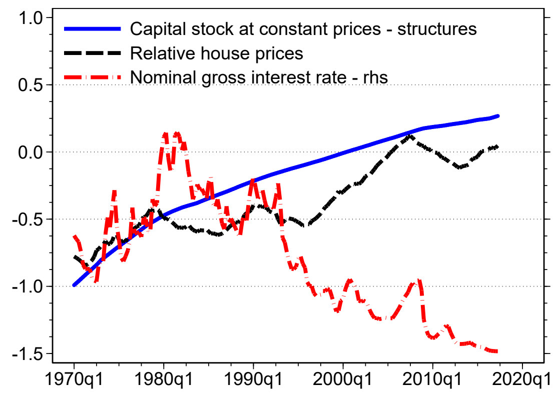
Note that we are not assuming that banks demand collateral on every loan or that it is correctly valued at all times. Rather, our reasoning is that an economy where credit grows faster than the value of the stock of assets which can be repossessed is more vulnerable to widespread defaults, all else equal. 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.

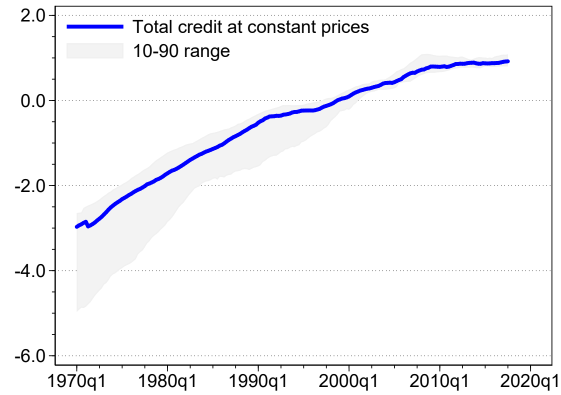
We use the residential property price index as a proxy for collateral prices. Whenever possible the index is backcasted using the price of structures from the PWT, which is linearly interpolated to obtain a series with quarterly frequency. We then deflate the index using the HICP.

Figure 1 shows the behavior of the data used in estimation over the sample period.

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.

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 behavior of relative house prices is coherent with boom and bust cycles, which motivates the framework we have presented.

In section 4.3 we quantify the performance of our credit cycle indicator in detecting systemic financial crises, as identified in Lo Duca et al. (2017). In a nutshell, a period of financial stress is defined as a systemic crisis if it fulfills one of the following criteria. First, the financial sector originated or played a significant role in amplifying negative shocks, and there was a contraction of financial intermediation or funding to the economy. Second, market infrastructures were dysfunctional or there were bankruptcies among significant financial institution. Third, policies were adopted to preserve financial stability, such external support or extraordinary provision of central bank liquidity.

We compare the performance the CCI to benchmark early-warning indicators in the literature. For this purpose, we choose the Basel Gap, the non-financial private sector debt service ratio, and the house price to income ratio. Duprey and Klaus (2021) conduct an extensive investigation of the early warning properties and show that the latter two indicators are among the best predictors of financial crises, using the dating scheme by Lo Duca et al. (2017). The Basel Gap is included given its widespread use in the literature and explicit inclusion in the CCyB legal framework as a minimum requirement for monitoring the accumulation of vulnerabilities.

A common feature of all these indicators, including the CCI, is the ability to calculate these measures in real-time, which ensures the fairness of the exercise. Indicators such as the one in Lang et al. (2019b) have not been computed in real-time and thus cannot be compared directly to our measure in performance terms.

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, as described in the previous section.

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.[5]

Table 2: Prior distributions

Collateral prices model					
Parameter	**Equation**	**Distribution**	**l.b**	**u.b**	**Parameters**
ϕ_1	State	Normal	$-\infty$	$+\infty$	mean: $\phi_1^{\hat{O}LS}$, std: $\hat{\sigma}^{2,OLS}_{\phi_1}$
ϕ_2	State	Normal	$-\infty$	$+\infty$	mean: $\phi_2^{\hat{O}LS}$, std: $\hat{\sigma}^{2,OLS}_{\phi_2}$
$\sigma^2_{\varepsilon^Q}$	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: $\rho_1^{\hat{O}LS}$, std: $\hat{\sigma}^{2,OLS}_{\rho_1}$
ρ_2	State	Normal	$-\infty$	$+\infty$	mean: $\rho_2^{\hat{O}LS}$, std: $\hat{\sigma}^{2,OLS}_{\rho_2}$
$\sigma^2_{\varepsilon^M}$	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

[5] 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.

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.

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.[6]

For 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.

[6]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).

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 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 $h = 2$.[7] 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. Second, 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

[7] 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.

our prior that the cyclical components are stationary. In addition, to guarantee that the cyclical component has an oscillating movement, only the random draws that deliver complex roots are kept.

Finally, one of our main contributions to the literature is to provide a real time estimate of the credit cycle indicator. This means that the approach just described to obtain the unobserved state variables and the unknown parameters considers each time only the information available up to period t. As such, the approach is recursive and repeated from $t = 40, \ldots, T$, where T is the sample length.

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 rationale for comparing our credit cycle measure with the Basel gap is its prominent use as a signaling indicator of cyclical imbalances and in guiding the setting of CCyB rates for dealing with excessive credit.[8] 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), along with other indicators.

The debt service ratio and the house price to income ratio are also added to the set of competing indicators given that they are identified by Duprey and Klaus (2021) as possessing good early-warning signaling properties. In addition, by being computed in real-time, as discussed in section 3, they contribute to ensure the fairness of the compar-

[8] The Basel gap is considered the benchmark univariate signaling indicators for systemic financial crises, as discussed in Borio and Lowe (2002) and Dekten et al. (2014)

ison exercise.

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 signaling systemic financial crises are evaluated both in-sample and out-of-sample (description below). For that we use a binary indicator of systemic financial crises from Lo Duca et al. (2017). The details on the metrics are provided below. 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 considered. This set of crisis events is divided in two categories. One that only considers crises with a domestic origin and another that includes those with both domestic and foreign origin. In total there are 15 crisis events with a domestic origin and 18 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 Global Financial Crisis.

The use of a signaling 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.[9] 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 Global 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 indicators are assessed individually, in-sample and out-of-sample for a pooled set of countries in terms of the following standard metrics.

[9] 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.

AUROC. The Area Under the Receiver Operating Characteristic (AUROC) curve is a summary measure of the signaling 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 signaling 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.[10] The first one considers 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 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:

$$U = \frac{\min(\theta, 1-\theta) - L}{\min(\theta, 1-\theta)}, \tag{12}$$

[10] 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.

where L represents a policymaker loss function defined as:

$$L = \theta\,(\text{Type I error}) + (1-\theta)\,(\text{Type II error}), \tag{13}$$

and θ is the policymaker preference for not missing a crisis (risk aversion or relative preferences parameter).[11] 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. Finally, the determination of the relative usefulness implies setting a signaling threshold to compute type I and II error rates. How we set this threshold in our analysis is discussed further below in this section.

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.

Error rates. The false negative rate is the share of missed vulnerable periods (type I error rate) and the false positive rate is the share of false alarms of vulnerable periods

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

(type II error rate). To obtain the error rates, one has to set a signaling threshold. If in a particular period the indicator value is above the signaling threshold level then that period is flagged as vulnerable. As non-vulnerable otherwise.

For very low values of the signaling threshold the false negative rate will be low while the false positive rate will be high, given that the indicator will constantly issuing signals. The opposite will occur if the signaling threshold is very high. The goal is to find an appropriate a balance between the two rates while assuring that their magnitude is acceptable from a policy perspective.

In the majority of the related literature, the signaling threshold level is tipically 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. In our study, we follow also this approach to determine the error rates and 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, following Lo Duca et al. (2017).

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, conditional on the choice of horizons. As macroprudential policy is preventive in nature, a good early-warning indicator should signal a crisis some quarters ahead of its materialization 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.[12] 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

[12]The persistence is computed as the average number of signals in vulnerable periods over the average number of signals in non-vulnerable periods.

policymaker on how well the indicator performs in disentangling vulnerable periods from normal periods. An indicator that sends an intermittent signal during a vulnerable period might not be credible when used in practice, as it can muddle the communication of the macroprudential authority.

4.3 Early-warning signaling performance

Even though all the indicators being tested for early-warning properties are computed in "pseudo-real time", the indicator performance exercises are conducted both in and out-of-sample.[13] In the former, we define a threshold and compute the performance metrics based on the full sample information, i.e. using information that spans from the third quarter of 1980 until the second quarter of 2017. In the latter, the signaling threshold is determined using an expanding window that grows as more information becomes available to the policymaker. Following Lo Duca et al. (2017), this procedure starts in the first quarter of 2000 and ends in the second quarter of 2017. In particular, for each quarter t within this time interval, the signalling threshold is determined using all available information up to $t-12$.[14]. This threshold is then used in period t to retrieve a signal from the indicator. The same procedure is performed for the next quarter, $t+1$, until the end of the sample.

From a policy perspective, it can be argued that the out-of-sample signaling performance of the indicator should receive more weight on balance as it mimics a situation more close to that faced by policymakers.

The results of the early-warning signaling 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. For illustration purposes, Figures

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

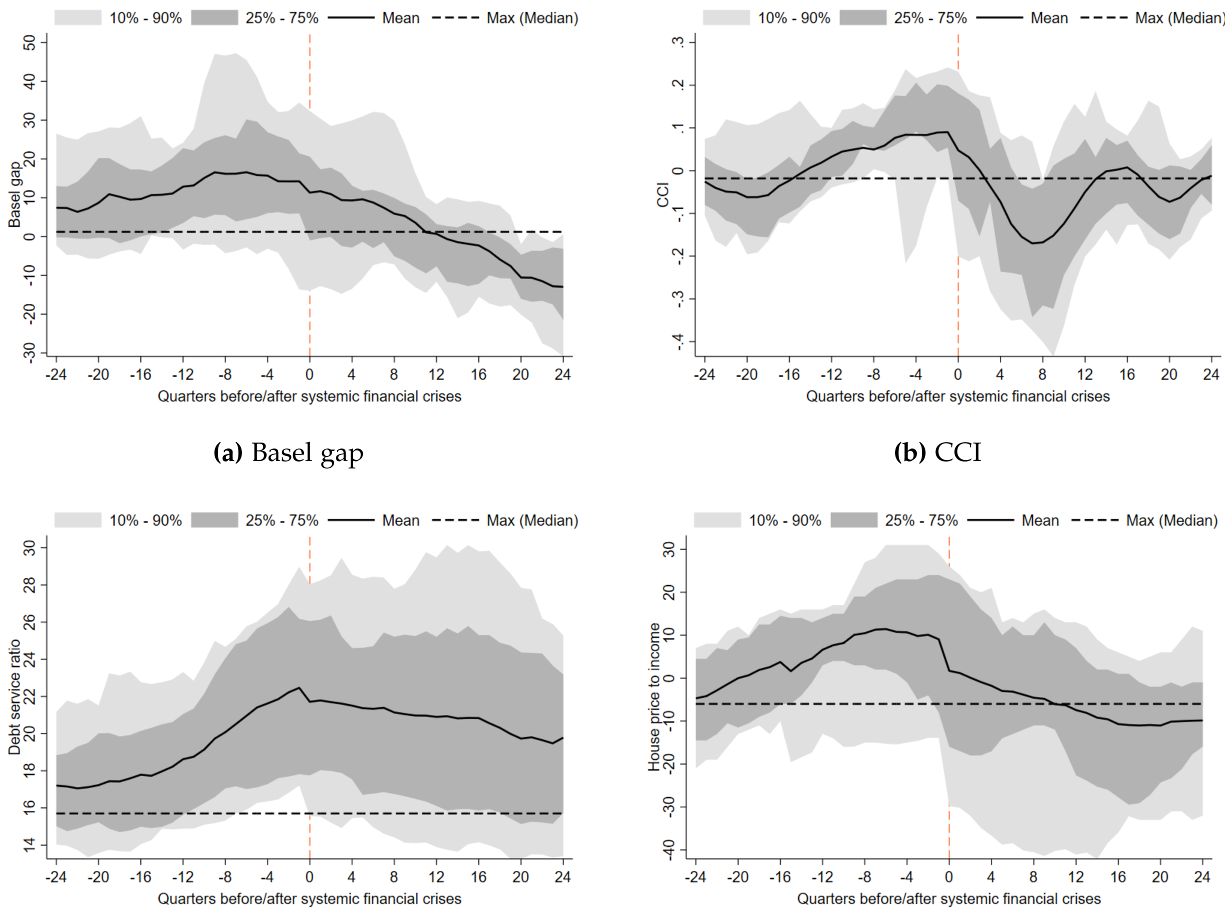
[14] A 12-quarters data lag is considered because vulnerability periods can't be classified as such for the last 12 quarters of a particular sample of information. This follows from the choice of using a prediction horizon between 12 and 5 quarters ahead of the crisis.

2 and 3 show the behavior of the indicators around systemic financial crises.

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

	Only crises with domestic origin				*Crises with domestic/foreign origin*			
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

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



(a) Basel gap

(b) CCI

(c) Debt service ratio

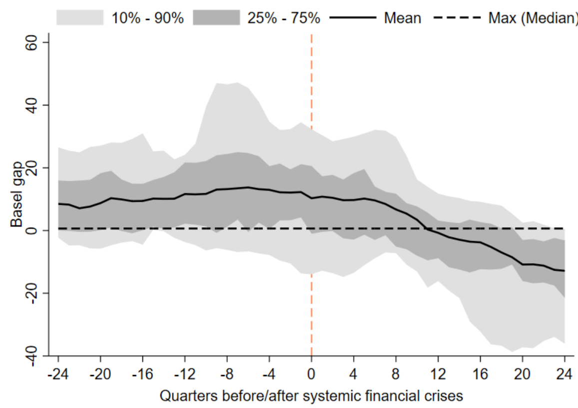
(d) House price to income ratio

4.4 In-sample

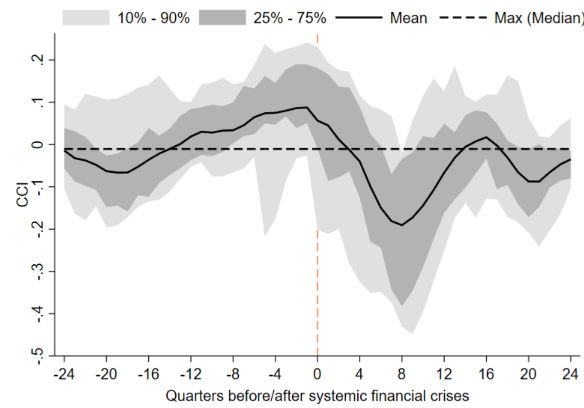
AUROC. In the 12 to 5 quarters horizon, the CCI has a performance comparable to the Basel Gap. The two indicators have AUROC values above 0.5 for both sets of crises, implying that they are both useful in anticipating systemic financial crises. However, the two indicators trail the predictive ability of the debt service ratio and the house price to income ratio, more so in the detection of crises of domestic origin.

In the 20 to 5 quarters horizon, the CCI has a reduced performance compared to the alternative indicators. This is due to a much lower persistence of the CCI compared

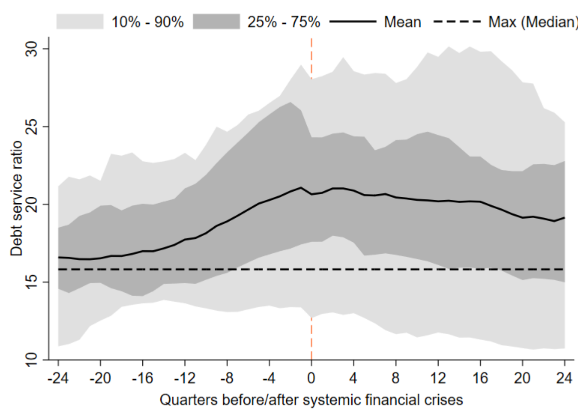
Figure 3: Distribution around systemic financial crises with domestic/foreign origin.



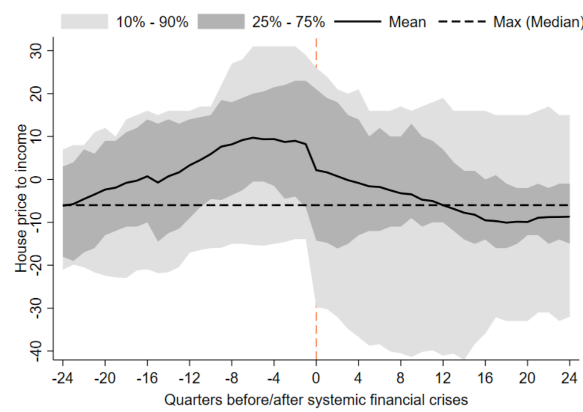
(a) Basel gap



(b) CCI



(c) Debt service ratio



(d) House price to income ratio

with the other alternatives, as can be gauged in Figures 2 and 3. This is a consequence of the modeling assumptions made. One desirable property of signaling indicators is not only that they are able to perform well in signaling past crises, but also that they adjust to new conditions sufficiently fast. Hence, the CCI reverts to values close to zero quite fast when compared the other indicators, especially after systemic events. This low persistence has the effect of reducing the horizon at which the indicator emits a signal before a systemic financial crisis. In contrast, slow moving indicators like the Basel Gap predict past crises earlier but linger in negative territory for quite a while after a crisis has materialized.

Thus, the signaling properties of the CCI are concentrated in a prediction horizon that is close to the materialization of the crisis but still 3 to 1 years ahead. Lo Duca et al. (2017), among others, focus their univariate early-warning signaling performance exercises in this prediction window.

Relative usefulness. For a policymaker who is indifferent between issuing a false alert (type I error) and missing a crisis (type II error), the CCI is a competitive indicator, taking up second place in the early warning exercises for both sets of crises, only behind the house price to income ratio. This is the result of a lower false positive rate when compared to the Basel Gap, even though it comes at the cost of a higher false negative rate.

In case the policymaker puts a higher weight on not missing systemic crises the CCI fares well relative to other indicators but maintains the second place with respect to the house price to income ratio. This follows from the fact that the CCI is able to achieve low levels of false negative rates compared to other indicators while maintaining a low false positive rate. In contrast, the Basel gap is only able to achieve a false negative rate of zero in both cases by way of constantly emitting alerts and leading to a false positive rate of close to 100% for both sets of crises. The debt service ratio suffers from the same problem when detecting systemic crises of all origins.

P(Vuln | signal)-P(Vuln). In this metric, the CCI again stands out as one of the most competitive indicators for both types of preferences and both types of crisis. On average, the probability there is a systemic crisis in the near future given that a signal was issued is higher by between 5 to 10 percentage points with respect to the unconditional probability.

Error rates. In the case of balanced preferences, the CCI is able to produce a reasonably low value of error rates, especially compared to the Basel gap and the debt service ratio. For the case in which the policymaker prefers not to miss a crisis, the CCI is not as effective as the other indicators. However, the low type II error rate that makes the other indicators more attractive is often times achieved at the cost of a much higher type I error rate. Overall, we find that the CCI verifies the guiding values put forward by Lo Duca et al. (2017) to establish whether an indicator has acceptable early-warning properties.

Lead time. In terms of average leading time, the CCI has lower average number of quarters between the first period where a signal is issued and the onset of a systemic financial crises than competing indicators, especially in the case of balanced preferences. However, on average and considering the crises with domestic origin, all indicators issue the first signal close to three years before the crisis start.

Persistence. In terms of persistence of the signals, the CCI ranks well with respect to other indicators. Overall, the signals issued by the CCI are between 1.4 and 2.3 times more persistent in periods that precede crises than in the normal periods.

In summary, our in-sample analysis shows that the CCI ranks well with respect to the Basel gap and the debt service ratio, but is only better than the house price to income ratio in some cases. Still, our indicator allows for a consistent economic interpretation of the evolution of the credit market and quickly adapts to new circumstances, such as changes in interest rates or in the stock of structures in the economy. In our view, this is a major advantage of our framework when compared with simpler indicators.

However, the core of the analysis we have conducted in this sub-section is based on finding an optimal signaling threshold, subject to a number of restrictions, in order to emit an early-warning of eminent systemic financial crisis based on an indicator breaching that threshold. To find that value, we used all periods in the sample.

In the next section, we use data up to 1999Q4 to determine the signaling threshold for each early-warning indicator. We then rerun the performance tests for a non-overlapping window of the full sample.

4.5 Out-of-sample

In this sub-section, we use a sub-sample until 1999Q4 to determine the signaling threshold for each early-warning indicator. The early-warning exercise is then carried out for the 2000Q1-2017Q2 period. In practice, this implies dropping the Global Financial Crisis from the training sample and testing the ability of each early-warning indicator to detect it. Overall the signaling properties of the indicators become weaker in a setting that resembles more closely the decision environment faced by policymakers. Interestingly, this is not true for the CCI at shorter horizons, which either maintains its performance or enhances it. Our conclusion is that the CCI is very competitive in this setup, though only for the shorter horizons.

AUROC. The CCI shows one of the highest AUROC scores for the 12 to 5 quarter horizon for both sets of crises. It is beaten by the debt service ratio for the set of domestic crises but only marginally so. On the other hand, it performs poorly for longer horizons when compared to the other early-warning indicators, a property it retains when compared to the in-sample exercise.

Relative usefulness. The CCI stands out in terms of relative usefulness: It has the highest value for balanced preferences for all sets of crises. This is the result of a more attractive trade off between false positive and false negative rates when compared with the most competitive of the other indicators. For example, the house price to income indicator correctly identifies the occurrence of systemic financial crises in the 2000s only at the expense of issuing a much greater number of false alarms.

However, when the policymaker puts a larger weight on not missing crises, the CCI does not retain these properties. It issues signals less frequently and produces a higher rate of false negatives when compared with the debt service ratio or the house price to income ratio. Yet, it remains a very attractive alternative to the Basel gap, whose early-warning score significantly deteriorates with respect to the in-sample exercise.

P(Vuln | signal)-P(Vuln). In this metric, the CCI trumps all other indicators on all exercises except for the debt service ratio in the case of the detecting crisis of both domestic an foreign origin. On average, it presents a 6 p.p. greater probability of detecting a vulnerable period given that a signal was issued, compared with the unconditional probability.

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 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.

When conducting performance exercises, we limit our scope to indicators which are computed in real time. Thus, their early-warning signaling performance, evaluated both in-sample and out-of-sample, reflects as close as possible the information set which policymakers possess at the time they are called on to make a decision on deploying policy instruments. We argue that this is not always the case in the literature in which future information is often used to compute systemic risk measures.

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:

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

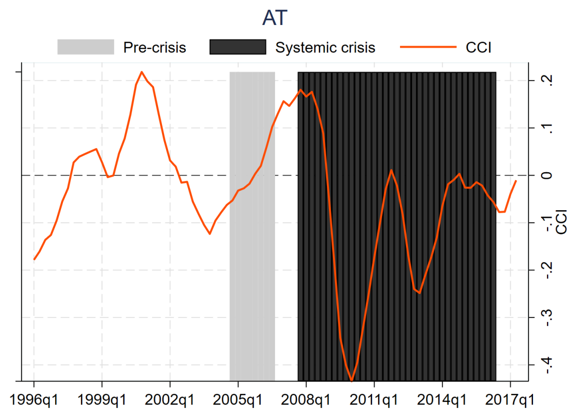
$$Var(x_{ii}) = \frac{2\psi_{ii}^2}{(\vartheta - p - 1)^2(\vartheta - p - 3)} \tag{A-9}$$

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

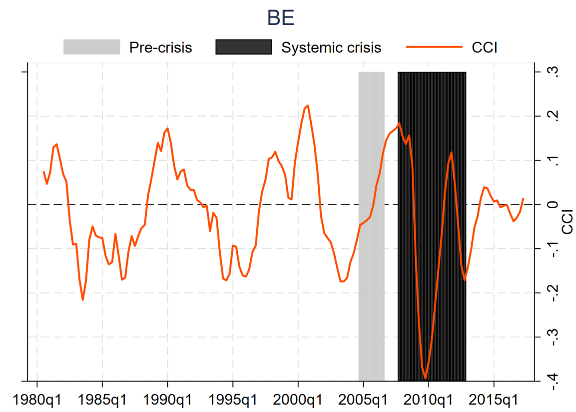
C CCI by country

This section shows the estimated credit cycle indicator by country, together with pre-crisis periods and domestic systemic crises.

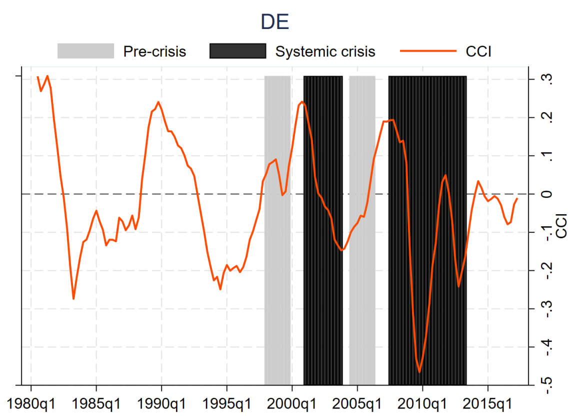
Figure C.1: Credit cycle indicator by country.



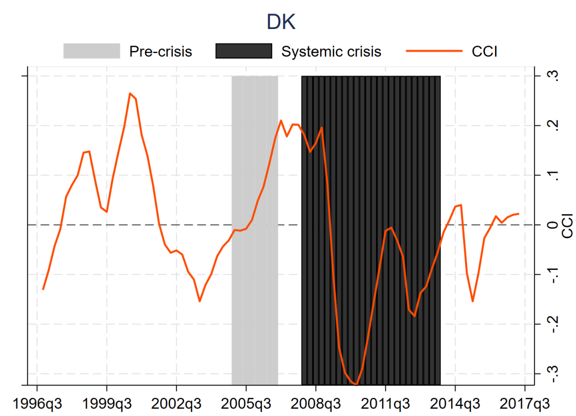
(a) Austria



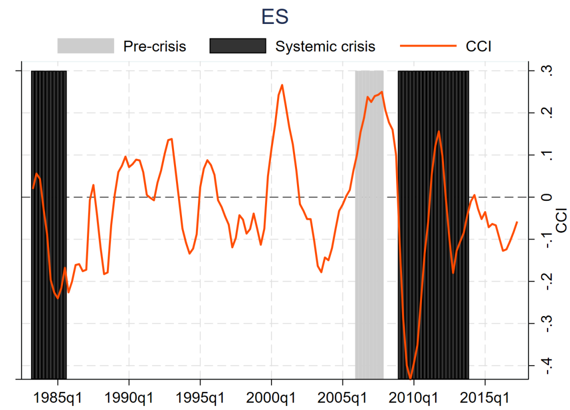
(b) Belgium



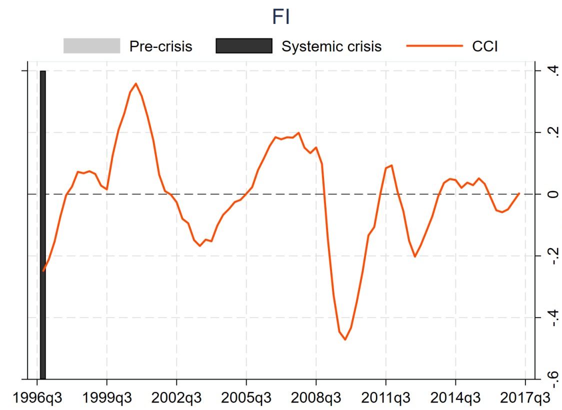
(c) Germany



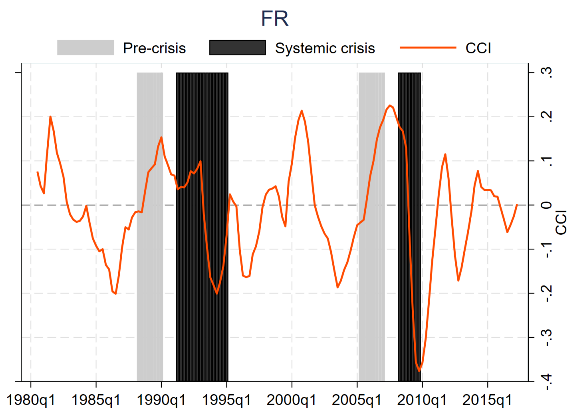
(d) Denmark



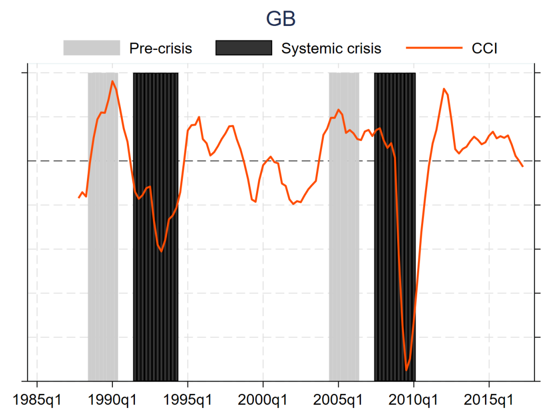
(e) Spain



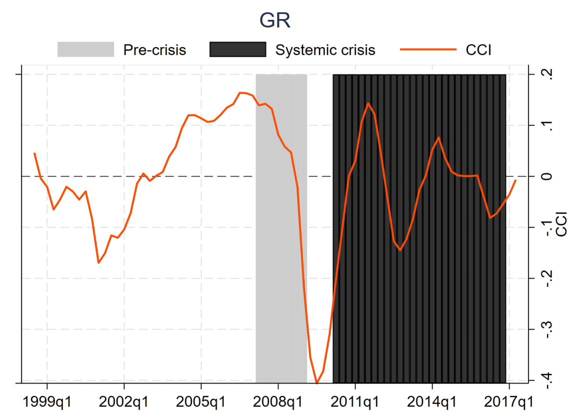
(f) Finland



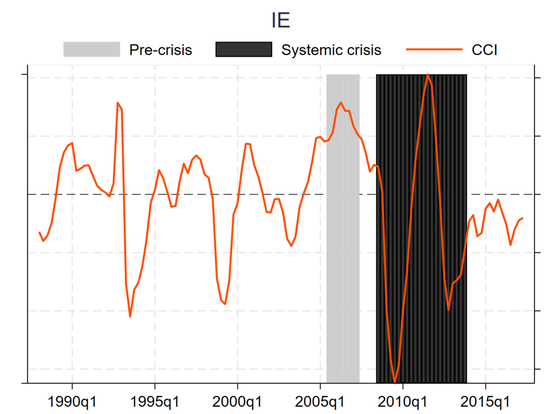
(g) France



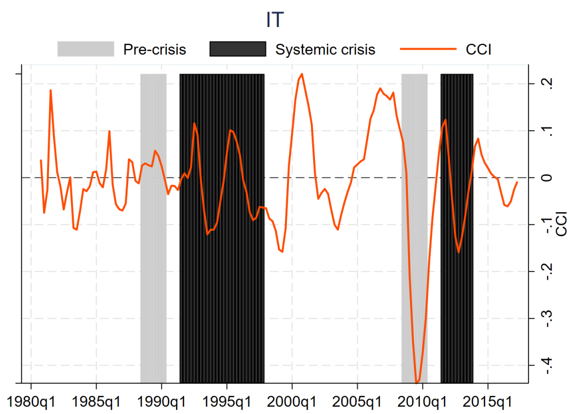
(h) United Kingdom



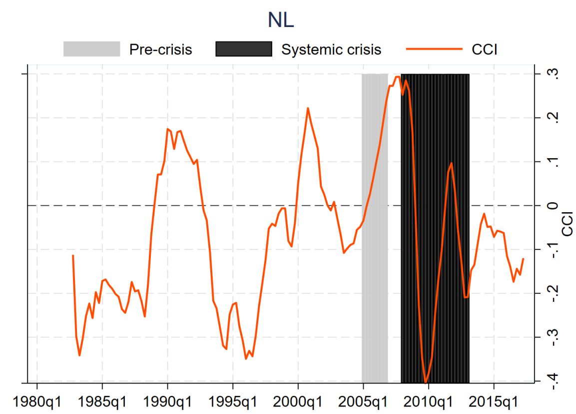
(i) Greece



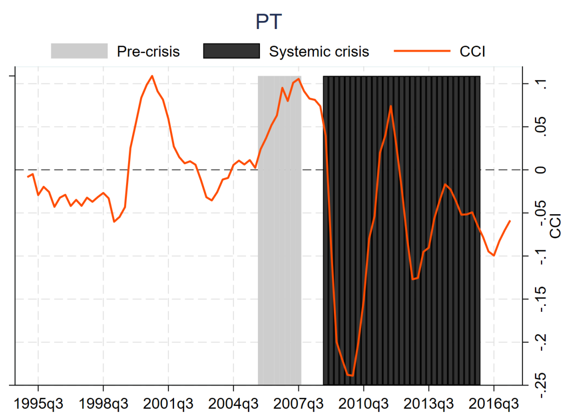
(j) Ireland



(k) Italy



(l) Netherlands



(m) Portugal

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