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Abstract

The credit-to-GDP gap, as proposed by the Basel methodology, has become the reference measure for the activation of the Countercyclical Capital Buffer (CCyB) due to its simplicity and good predictive power for future systemic crises. However, it presents several shortcomings that could lead to suboptimal decisions in many countries if it were used as an automatic rule for the activation of the CCyB. We study to what extent the purely statistical nature of the Basel methodology is responsible for these undesired effects by considering potential complementary credit gap measures that incorporate economic fundamentals. Specifically, we analyse the performance of two alternative (semi-) structural models that may account for these factors. We assess the proposed measures using time series data from the 70's for six European countries and compare them to the Basel gap. We find that the proposed models provide more accurate early warning signals of the build-up of cyclical systemic risk than the Basel gap, as well as lower upward and downward biases after rapid changes in fundamentals. Nonetheless, results evidence heterogeneity in the ability from different models and specifications across countries to forewarn about future crises. This result evidences the differences in the financial cycles and their drivers across countries, and shows the importance in macroprudential policy of considering flexible approaches that adapt to national specificities.

Keywords: Credit imbalances, cyclical systemic risk, early-warning models, macroprudential policy, model-based indicators.

JEL classification: C32, E32, E58, G01, G28.

Resumen

La brecha crédito-PIB, calculada según la metodología de Basilea (brecha de Basilea), es actualmente el indicador de referencia para la activación del colchón de capital anticíclico (CCA), debido a su simplicidad y capacidad predictiva sobre futuras crisis sistémicas. Sin embargo, este indicador presenta ciertas limitaciones que pueden producir decisiones subóptimas en muchos países si se utiliza de manera automática para la activación del CCA. La naturaleza puramente estadística de la metodología de Basilea puede estar detrás de estas limitaciones. En este estudio proponemos como medidas complementarias de desequilibrio de crédito dos modelos semi-estructurales desarrollados para aprovechar relaciones económicas entre las variables. Estos modelos son evaluados utilizando datos de seis países europeos con información desde 1970. En comparación con la brecha de Basilea, los modelos propuestos tienden a proporcionar señales más precisas de la acumulación de riesgo cíclico, y reaccionan de forma más estable ante cambios muy rápidos en el crecimiento del crédito o en otras relaciones económicas. No obstante, los resultados muestran heterogeneidad entre países en la capacidad de estos modelos para anticipar crisis sistémicas. Esto evidencia las diferencias existentes entre países en los ciclos financieros y las variables vinculadas a estos, así como la importancia de considerar enfoques flexibles que se adapten a las especificidades nacionales en la formulación de políticas macroprudenciales.

Palabras clave: desequilibrios de crédito, indicadores basados en modelos, modelos de alerta temprana, política macroprudencial, riesgo sistémico cíclico.

Códigos JEL: C32, E32, E58, G01, G28.

1. Introduction

After the last global financial crisis, excessive credit has been put on the focus of attention and identified as one of the most important sources of imbalances and financial instability. The role of credit growth in the building-up of systemic risk has been evidenced in many countries, preceding several systemic events (See Borio and Drehmann, 2009; Drehmann et al., 2011; Schularik and Taylor, 2012, for international evidence). This has been one of the motivations for setting-up the Countercyclical Capital Buffer (CCyB), which could prevent or mitigate systemic risk derived from excessive credit growth during booms while increasing resilience of banks during busts (BIS, 2011).

The activation and calibration of the CCyB requires guiding indicators that provide useful information for policy decisions. In that context, the Basel Committee for Banking Supervision (BCBS) adopted the credit-to-GDP gap as the standardized guiding indicator of excessive credit growth (BIS, 2010). The methodology adopted for its calculation is simple and based on a purely statistical decomposition of the trend of the credit-to-GDP ratio, so that deviations from this long-run trend might be interpreted as imbalances. The credit-to-GDP gap as proposed by the Basel methodology (Basel gap) has become the main standard indicator used to guide countercyclical instruments in many countries and the one recommended in the international regulation and European Union (EU) legislation (BIS, 2010; EU CRR/CRD-IV[2]).

The Basel gap has been found to have a good predictive performance in the past (Drehmann et al., 2010; Detken et al., 2014; Drehmann and Tsatsaronis, 2014). Its simplicity ensures that it can be easily computed, verified and replicated by external observers. The fact that it does not rely on any particular model is another reason why the Basel gap has been chosen as the main reference criteria for the activation of the CCyB. However, it presents several shortcomings and limitations that could lead to misleading signals for the activation of the CCyB if it were used as an automatic rule. The purely statistical nature of the methodology is potentially behind the main drawbacks, mainly derived from the great inertia of the trend when major or sudden changes in the observed ratios are presented, as it was the case from the onset of the last financial crisis in many countries. The main implication of this situation for the use of the Basel gap in the future is that it might provide very late signals of excessive credit during the next cycle. Castro et al. (2016) provide evidence of this situation after simulating the performance of this indicator in Spain under different credit growth scenarios in the next years. These problems have been recognized in the legislation. This is why the European Systemic Risk Board (ESRB) recommends using the Basel gap as the main reference, but considering complementary information to tackle situations in which the Basel gap does not issue the right signal.[3]

Besides the large persistence of the trend computed under the Basel methodology, other previous identified limitations of the Basel gap include the cases where either the credit (numerator) increases or the GDP (denominator) declines much faster than the other term of the ratio. In the former case, it could lead to overestimation of credit gaps in situations in which credit growth might be justified by financial deepening, in particular in developing economies. In the latter case, the ratio might increase due to a fast GDP contraction and provide conflicting signals (see Repullo and Saurina, 2011).

Complementary statistical-based methods have been proposed before. However, it might be desirable to estimate credit gap measures that are able to better distinguish between

[2] EU Regulation 575/2013 and EU Directive 2013/36/EU.
[3] Recommendation ESRB/2014/1.

sustainable and unsustainable credit developments. For instance, some events may erroneously appear unsustainable from a simple univariate historical perspective, but they may turn out to be fully explained by changes in economic fundamentals captured by other variables. In this context, some of the most used methods for analysing financial cycles in the literature, such as unobserved components models (UCM) and vector autoregressive models (VAR), could also be used for macroprudential policy purposes. In particular, with the aim of obtaining measures of credit imbalances associated to the build-up of systemic risk that may overcome the limitations of the Basel gap. However, literature on the assessment of the performance of these types of models for these purposes is still scarce.

Thus, this study pretends to contribute to this incipient literature by comparing empirically the performance of (semi-) structural model-based indicators of cyclical systemic risk. In particular, our aim is to identify those models and specifications providing the more accurate early warning signals of excessive credit growth leading to financial crises. For this purpose, we propose some variants of UCM and vector error correction models (VEC) that account for a relationship between credit and other macro-financial variables. We use quarterly data from France, Germany, Italy, the Netherlands, Spain, and the United Kingdom from 1970 to 2016 and compare the results against the Basel gap.

Results evidence large heterogeneity in the estimations obtained from different models across countries. In particular, unobserved component models perform better in Germany and the Netherlands, while VEC models tend to exhibit better performance in Spain, France, Italy and the United Kingdom. This suggests the difficulty of finding a unique method that performs equally well in every country. Differences in the financial cycles of the countries and their drivers become evident even in this framework to model the financial cycle where only credit, GDP, interest rates and house prices are included as macro-financial variables. In particular, accounting for house prices is found to be very relevant in those countries where the real estate sector has played a major role explaining previous crises, such as Spain and France. On the other hand, specifications omitting house prices may provide better results in countries such as Germany and Italy. Hence, our results show that it is essential that models adapt to national specificities to achieve their maximum potential performance.

Nevertheless, at least one of the models and specifications analysed outperform the Basel gap in each of the countries in the sample. Moreover, if the best performing model and specification is chosen in each country, the aggregate results obtained improve importantly with respect to using the same model for all the countries. Overall, these results suggest that relatively simple (semi-) structural models may be very useful for the identification of credit imbalances and the decision-making process of macroprudential policies at national level. However, choosing a unique model for all countries would be very difficult given country-specificities. This would suggest that these models may perform better as complements rather than substitutes of the Basel gap.

Besides this introduction, the rest of the paper is organized in four additional sections. Section 2 presents a brief literature review. Section 3 presents the assessed models and the proposed specifications. Section 4 describes the data and sample. Section 5 analyses the estimations results and the performance of the models on providing early warning signals of the build-up of cyclical systemic risk. Section 6 presents some robustness exercises. Finally, section 7 concludes the paper.

2. Brief empirical literature review

Literature on measuring the financial cycle is still scarce though increasing in recent years. We can find mainly two types of methodologies. One is purely statistical, mainly through the use of filters which allow extracting a cyclical component from a financial series. The second one is more structural, through the estimation of models which relate credit to fundamental variables.

From the statistical methods, turning point analysis, frequency- and model-based filters are the most common methods.[4] Turning point analysis characterizes cycles in terms of peaks and troughs. Using this method, Claessens et al. (2011, 2012) find that financial cycles are more ample than business cycles and that credit and house prices are highly synchronized. Under frequency-based filters, the most common are the Hodrick-Prescott filter employed in the construction of the Basel gap, and band-pass filters (Baxter and King, 1999; Christiano and Fitzgerald, 2003). Recently, Aikman et al. (2015) apply a Christiano and Fitzgerald (CF) type of band-pass filter to long time series from a large set of countries, finding out high correlation between credit excess periods and subsequent financial crises as well as longer financial cycles compared to business cycles. Drehmann et al. (2012) also apply a CF band-pass filter combined with turning point analysis to a sample of developed countries, and find that financial cycles tend to last between 8 and 30 years. Finally, model-based filters extract cycles from unobserved components time series using the Kalman filter (Harvey, 1989), and avoid imposing predetermined cycle lengths. Galati et al. (2016) apply this method recently to the US and some Euro Area countries finding that the amplitude and duration of the cycles differ among countries and that credit and house prices follow very similar cycles, which supports the convenience of accounting for house prices when analysing financial cycles.

Recently, model-based filters have been extended towards structural specifications for using UCM. A proposal in Lang and Welz (2017) models the trend component of household credit as a function of fundamental variables related to potential GDP, long-term interest rates, population and institutional quality. It is found that the cyclical component extracted from this model may exhibit less inertia than the Basel gap. However, excluding credit to non-financial companies from the analysis would run the risk of missing unsustainable credit developments under the scope of the CCyB that are not sufficiently correlated with household credit. This study do not account for house prices either, which could be particularly relevant when modelling household credit given the importance of mortgages within this type of credit.

Moving to more structural models in the empirical literature, we can find some proposals from panel regressions to VAR and VEC models. Castro et al. (2016) propose a panel regression with fixed effects where the credit-to-GDP ratio is explained by potential GDP per capita and short-term interest rates using a sample of 20 advanced economies. Authors find that this model captures the structural change experienced in Spain after joining the Euro and does not overreact to the great bust presented from the onset of the crisis. However, the study does not carry out a cross-country comparison of the performance of the model, and it lacks an assessment of the impact of including house prices. VAR models have also been recently used to estimate the relationships between macroeconomic and financial variables, in particular the effects of credit shocks in GDP (Hristov et al., 2012; Duchi and Elbourne, 2016). The estimation of long-run relationships between financial and business variables is useful for the purpose of credit equilibrium levels. Juselius et al. (2016) propose a VEC model where credit, expenditure,

[4] However, other methods have been also proposed before. Kauko (2012) proposes using moving averages of the output; Alessandri et al. (2015) propose a two-sided Hodrick-Prescott filter with forecasted data; and Schuller et al. (2015) find that financial cycle indicators might also be useful as alternative measures of credit imbalances.

assets prices, inflation and interest rates are accounted for. The authors propose a measure of financial equilibrium in terms of a leverage and a debt-service gap, which are estimated from the VEC system by adding constraints in the cointegrating relationships. However, the authors did not have in mind a macroprudential application in their paper. For this reason, this paper lacks an empirical assessment of the early warning properties of the proposal.

Finally, in terms of the variables used for the analysis of the financial cycle there is still no consensus in the literature either. Some studies focus on credit to the non-financial private sector, either total or bank credit (Aikman et al., 2015; Dell'Ariccia et al., 2016). Total credit to the non-financial private sector is often used, since it is part of the definition of the Basel gap (Drehmann et al., 2012). In particular, in countries where the importance of non-bank credit is high such as the US, accounting for total credit instead of only bank credit has been identified to be very relevant in explaining financial crises (Dembiermont et al. 2013). Narrow definitions of credit have also been used. Lang and Welz (2017) focuses on household credit, which is found to provide better early warning signals of financial crises in some countries. Nonetheless, credit to non-financial companies has been closely related to financial crises in the past in some countries, and is part of the definition of the type of credit targeted when setting the CCyB (ESRB/2014/1; EU CRR-CRD-IV). Interest rates as the price of credit has also been modelled often. Castro et al. (2016) find interest rates to be a key determinant of the credit-to-GDP ratio. Several other studies have identified the importance of modelling real estate prices along with credit given that both variables share relevant cyclical similarities (Claessens et al., 2012; Shuller et al., 2015; Galati et al., 2016; Rünstler and Vlekke, 2017). The use of debt service ratios has also been identified to have important early warning properties (Drehmann and Juselius, 2012) and to resemble adequately the financial cycle when analysed along credit and asset prices (Juselius et al., 2016).

3. Empirical specifications of model-based cyclical risk measures

As it was mentioned above, we propose two variants of UCM and VEC models that are able to yield estimates of credit equilibria justified by macro-financial fundamental variables. The main variable of interest used for the analysis is total credit to the non-financial private sector. We prefer using this broad measure of credit due to three main reasons. First, this is the credit definition used for the Basel gap, which allows comparing different approaches under the same conditions. Second, our approach also has a policy justification, since the purpose of countercyclical macroprudential instruments is intended to prevent and mitigate systemic risk derived from excessive credit from any source (banking and non-banking) and to any type of borrower (households and non-financial corporations). And third, although for some countries banking credit to households has been highly related to the occurrence of previous crises, this is not the case in all the countries and there is no guarantee that this is going to be the case in the future.[5] Based on the previous studies described in Section 2, we consider structural specifications for credit in which observed GDP, long-term interest rates and house prices are the main drivers.

[5] For instance, in Spain, although bank credit to households has been much related to crises, the key trigger in the past has been mainly credit to real estate companies.

3.1. *Unobserved Components Models (UCM)*

As our first model, we propose a semi-structural UCM, in which credit is split into a trend and a cyclical component. Both terms are unobserved. The trend follows a structural specification driven by macro-financial variables, while the cycle, in turn, follows and autoregressive univariate process. This model is similar in spirit to the one proposed in Lang and Welz (2017), except for three main differences. First, this is an empirical-based model where the trend of credit is driven by exogenous variables related to the demand of credit and its price in the long run. In particular, we use real GDP and the real long-run interest rates as the key variables explaining the credit long run level. Second, we model total credit to the non-financial private sector instead of only household credit as justified above. And, third, we account for house prices and link them to the credit cycle, following previous findings on the importance of this variable when modelling financial cycles. Thus, the general specification is the following:

$$\begin{aligned}
c_t &= \tau_t + \psi_t \\
\tau_t &= \alpha + \beta_y y_t + \beta_r r_t + \eta_t \\
\psi_t &= \rho_1 \psi_{t-1} + \rho_2 \psi_{t-2} + \kappa_t,
\end{aligned} \tag{1}$$

where, c_t is the log of real total credit and represents the observed equation, which is composed of two unobserved components: trend (τ_t) and cycle (ψ_t). The former is determined by a constant term (α); the log of real GDP (y_t); long-term real interest rates (r_t); their corresponding estimated coefficients (β_y) and (β_r); and an error term (η_t) capturing other shocks. The cycle component is modelled to follow an autoregressive process of order 2 where, $\rho_1$and ρ_2 are the corresponding autoregressive parameters and κ_t is an error term.[6] We assume that in the long-run a stable relationship can only be preserved between GDP and credit if β_y is constrained to be equal to 1. This is done in order to maintain an exact one-to-one relationship between credit and output, which is behind the motivation of measures such as the credit-to-GDP gap. In general, a one-to-one relationship between credit and GDP assures that differences in equilibrium credit levels between two economies sharing exactly the same macro-financial conditions are proportional to their size. Additionally, in terms of the model estimation, adding a constraint improves the identification of the parameters.

Furthermore, we also consider an additional equation to model the relationship between house prices and the credit cycle. In particular, the empirical evidence shows that the cyclical component of house prices resembles the credit cycle in some proportion (Claessens et al., 2012; Shuller et al., 2015). In order to allow for this relationship, we include house prices as an additional observed equation within the state space structure represented in (1), as follows:

$$hp_t = \gamma_0 + \gamma_1 hp_{t-1} + \gamma_2 \psi_t + \varepsilon_t, \tag{2}$$

where, hp_t represents the real house prices, γ_0 is a constant term, γ_1 is the coefficient for the first lag of house prices, γ_2 is the coefficient linking the effect of the credit cycle to house prices, and ϵ_t is an error term.

[6] Previous studies have identified financial cycles to follow AR(2) processes and to be a fair assumption for modeling credit gaps (Rünstler and Vlekke, 2017; Lang and Welz, 2017). In general, this is derived from the standard assumption in the literature on measuring output gaps where output is modeled as a local linear trend with an AR(2) component for the cycle (see Clark, 1987).

The model specification in (1) encloses other types of unobserved component models and trend specifications by constraining some parameters. The general model is formulated as a state space model (Harvey, 1989) and solved through quasi-maximum likelihood estimators using a diffuse Kalman filter for non-stationary series (Chang et al., 2009).[7] Finally, the credit trend and cycle components are estimated by filtering using only past and contemporaneous information.

3.2. *Vector Error Correction Models (VEC)*

Our second proposal is to estimate a vector autoregressive model with error correction in which some of the underlying variables are cointegrated. This model allows estimating a common long-run stochastic trend for non-stationary time series. The model specification is as follows:

$$\begin{aligned} \Delta \boldsymbol{Y}_t &= \boldsymbol{\delta} + \textstyle\sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{Y}_{t-i} + \boldsymbol{\alpha}\widetilde{\boldsymbol{u}}_{t-1} + \boldsymbol{\epsilon}_t; \\ \widetilde{\boldsymbol{u}}_{t-1} &= \boldsymbol{\mu} + \boldsymbol{\beta}\mathbf{Y}_{t-i}, \end{aligned} \tag{2}$$

where Δ represents the first difference of the variables; $\mathbf{Y}_t = (c_t, y_t, r_t, hp_t)$ is a vector of endogenous variables including the log of real credit, the log of real GDP, long-term real interest rates, and real house prices; $\boldsymbol{\delta}$ is a vector representing the intercepts of each equation; $\boldsymbol{\Gamma}_i$ represents *p-1* matrices of parameters of lagged underlying variables, where *p* is the lag order of the VAR in levels; $\boldsymbol{\alpha}$ is a matrix of adjustment coefficients of long-run deviations containing one vector for each of the variables $(\boldsymbol{\alpha}_c, \boldsymbol{\alpha}_y, \boldsymbol{\alpha}_r, \boldsymbol{\alpha}_{hp})$ of dimension *m*, where *m* represents the number of cointegrating relations; and, $\widetilde{\boldsymbol{u}}_{t-1}$ represents a vector of long-run relationships; where $\boldsymbol{\mu}$ is a vector of constant parameters and $\boldsymbol{\beta}$ is a matrix of parameters composed of four vectors $(\boldsymbol{\beta}_c, \boldsymbol{\beta}_y, \boldsymbol{\beta}_r, \boldsymbol{\beta}_{hp})$ of dimension *m*.

Regardless of the number of cointegrating equations identified, we can add constraints to the equations by imposing restrictions to the estimated coefficients of vector $\boldsymbol{\beta}$. In particular, if we restrict the coefficients associated to credit and GDP to be equal to 1 in the first cointegrating relation, then we end-up with a long-run relationship that estimates deviations from the credit-to-GDP ratio (or aggregate leverage) with respect to a constant, long-term interest rates and house prices as follows:[8]

$$leverage\ gap = (c_t - y_t) - \left(\mu + \beta_r r_t + \beta_{hp} hp_t\right), \tag{4}$$

where μ is a constant term that would represent the long-run equilibrium level of the credit-to-GDP ratio, and β_r and β_{hp} are coefficients representing the proportion of aggregate leverage that would be linked to the levels of long-term interest rates and house prices, respectively.

[7] A general state-space model can be specified as: $y_t = \boldsymbol{D}\boldsymbol{z}_t + \boldsymbol{E}\boldsymbol{z}_t + \boldsymbol{v}_t;\ \boldsymbol{z}_t = \boldsymbol{A}\boldsymbol{z}_t + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{\epsilon}_t;\ \boldsymbol{v}_t \sim N(0, \boldsymbol{R}); \boldsymbol{\epsilon}_t \sim N(0, \boldsymbol{Q})$, where the equations for $\boldsymbol{y}_t$ represent the observation equations and those for $\boldsymbol{z}_t$ represent the state equations; $\boldsymbol{w}_t$ and $\boldsymbol{x}_t$ represent vectors of exogenous variables and $\boldsymbol{v}_t$ and $\boldsymbol{\epsilon}_t$ are error terms assumed to be zero mean, normally distributed, serially uncorrelated, and uncorrelated with each other where $\boldsymbol{R}$ and $\boldsymbol{Q}$ represent their corresponding covariance matrixes.

[8] We borrow the denomination of leverage gap to this cointegrating relationship from Juselius et al (2016), who decompose characterisations of the financial cycle into structural components by embedding cointegrating relationships into a VAR system. Although the aim of the authors is to link the impact of monetary policy on output and interest rates through the financial cycle, they propose this cointegrating relationship to identify a long-run equilibrium for the credit-to-GDP ratio. The main difference besides the inclusion of other macro-financial variables in the system is that the authors constrain all coefficients in the leverage gap relationship to be zero except for the one on asset prices. The authors also propose a second cointegrating relationship with respect to the lending rate on outstanding debt. However, this relationship is more intended to capture a debt service gap.

Therefore, the full VEC system follows the specification in Equation (3) but restricting the long-run relationship represented by $\tilde{u}_{t-1}$ to be equal to the leverage gap defined in Equation (4). As mentioned above, constraining the credit and GDP coefficients to be 1 and -1 respectively, assures a one-to-one relationship of credit to output and improves the identification of unknown parameters.

The estimation of the model is performed through maximum likelihood, the number of lags is selected following the Akaike Information Criteria (AIC), and the number of cointegrating relations is determined using the trace statistics method (Johansen, 1995). Post-estimation tests for the validity of the restrictions and the stability conditions are also performed. The model is estimated recursively by using an initial window of 40 quarters and adding one period each time. Credit deviations from the long run estimates are then computed at each period.

3.3. *Comparison criteria*

Given that our final purpose is to identify credit excess periods associated to financial crises, we use the AUROC (Area Under the Receiver Operating Characteristics Curve) as performance comparison criteria of the different models. This method has been widely used to assess the performance of early-warning indicators and in particular those used to guide the CCyB (Castro et al., 2016; Detken et al., 2014; Giese et al., 2014). This method assesses the relationship between the false positive rate and the true positive rate for every probability threshold. In this context, the AUROC is a measure of the probability that the model predictions are correct.[9] We compare the predictive power of the models by considering several time periods ahead of the systemic events. These periods are 20 to 5 quarters, 16 to 5 quarters, and 12 to 5 quarters before the crises. Hence, models should be able to issue signals at least 5 quarters before a crisis outbreak in order to qualify as truly early warning. This is convenient for practical purposes, since signals that are too close to the beginning of a crisis may arrive too late for an activation of the CCyB with the potential to have meaningful effects. We also identify whether or not AUROC values are significantly different from those obtained using the Basel gap by computing confidence intervals using the non-parametric approach proposed by DeLong et al. (1998).

We also compare the performance of the models in terms of the accuracy of the signals of imbalances in the past and its correlation with the severity of previous crises. In particular, we identify missing crises, false alarms, too-early warnings, as well as the correlation with output losses and unemployment rates. We compare the performance between the different methods and with respect to the Basel gap.

4. Data

The data set comprises quarterly time series for six different European countries: France, Germany, Italy, the Netherlands, Spain, and the United Kingdom.[10] The sample period is from 1970Q1 to 2016Q4. The data sources are the Bank of International Settlements (BIS) for credit, house prices, and deflator; the ECB Statistical Data Warehouse for GDP and the OECD for long-

[9] A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment.

[10] The following country abbreviations are used in tables and figures: France (FR), Germany (DE), Italy (IT), Spain (ES), the Netherlands (NL), and the United Kingdom (UK).

term interest rates. Table 1 presents a summary statistics of the pooled data and Table A1 in the Annex presents it by country.

Table 1. Summary Statistics

Variable	Mean	Median	S.D.	Min	Max
Real credit (millions)	1,641,974	1,536,639	905,709	334,432	3,936,050
Real GDP (millions)	1,384,927	1,399,170	651,396	236,772	2,842,465
Real house prices growth (%)	1.17	0.96	2.22	-7.05	12.64
Long-term real Interest rates (%)	4.70	4.69	2.93	-2.84	11.65
Credit-to-GDP ratio (%)	126.78	117.07	47.04	51.70	247.00
Basel gap (pp)	1.20	1.51	11.93	-49.49	43.94
Systemic crises events (grouped by country)	2.83	3	0.41	2	3

Note: Monetary values are expressed in euros and in real terms of year 2010.

We use the dates and definitions reported by countries in the ECB/ESRB crises database recently published in Lo Duca et al. (2017). Based on the information in that study, it is possible to classify systemic events between systemic crises and residual financial stress events. Systemic crises are defined as complex events that reflect the materialisation of a combination of several different risks with broad impact in the financial system that prolongs usually for periods longer than one year, while residual financial stress events have usually a narrower impact in the financial system and a shorter duration over time. However, residual events can also be classified as relevant for macroprudential purposes if these events could be addressed through the use of macroprudential cyclical instruments. Systemic events can also be classified by the type of event (e.g. currency, sovereign, banking, among others). In particular, we consider all those crises and residual financial stress events considered to be relevant from a macroprudential perspective. Since our goal is exclusively related to the potential activation and calibration of the CCyB, this definition encompasses all the key events. In any case, in Section 6.3 we consider several robustness checks to assess the performance of the models to different definitions of systemic events.

5. Empirical Estimations and Results

5.1. *Unobserved components model*

We estimate two specifications of the unobserved components model. Our baseline model (Model I) includes all the observed and state equations in (1) and (2) where house prices are linked to the credit cycle. The second specification (Model II) omits house prices and then only accounts for the observed equation of total credit and the state equations for its trend and cycle in Equation (1). As mentioned above, the coefficient associated to real GDP is constrained to be equal to one.

Table 2 reports the estimation results of the two models by country. In general, the effect of long-term interest rates on the credit trend is negative and significant for almost all countries in at least one of the specifications. In the cases of Spain, France, the Netherlands and the United Kingdom, it is significant when house prices are accounted for. It is precisely in these countries where a significant relationship between the credit cycle and house prices is identified. Specifically, only for these four countries the coefficient on ψ_t in the house price equation turns out to be significant. This would indicate that, in these countries, house prices have been closely related to the credit cycle in the past and that the price of long-term loans is only relevant when credit is linked to the prices of the residential real estate sector. The link between the credit cycle and house prices seems to be especially high in Spain. These results support previous evidence on the relevance of house prices during past credit cycles in Spain (Castro et al., 2016) and the United Kingdom (Giese et al., 2014). In the cases of Germany and Italy, house prices do not seem to have a relevant link with the credit cycle. Results also show high persistence of the credit cycle in all the countries.

Table 2. Estimation results by country - UCM

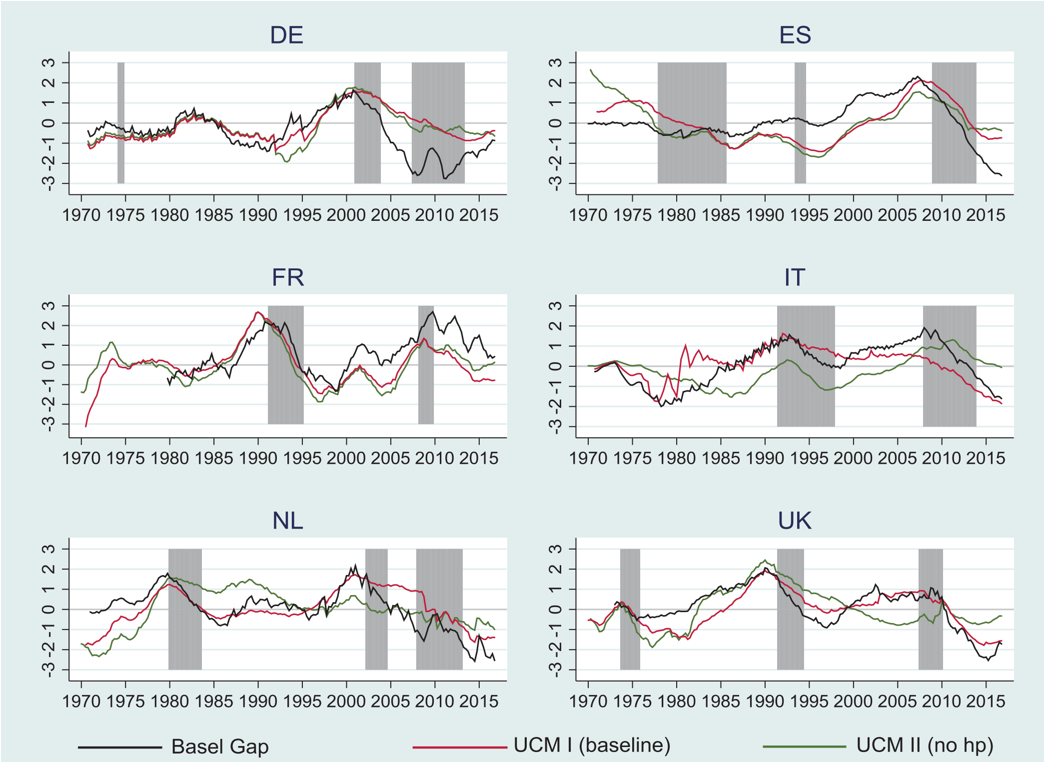
		credit			*hp*			
Country	**Model**	α	β_y	β_r	γ_0	γ_1	γ_2	**Obs.**
DE	Model I (baseline)	0.751***	1	-0.031	1.76	0.135***	0.390	187
	Model II (no *hp*)	0.703***	1	-0.110***				188
ES	Model I (baseline)	0.606***	1	-0.035***	1.218***	0.462***	0.949***	187
	Model II (no *hp*)	-0.13	1	-0.003				188
FR	Model I (baseline)	0.529***	1	-0.086***	1.851	0.142***	0.524***	187
	Model II (no *hp*)	0.154***	1	-0.001				188
IT	Model I (baseline)	0.144	1	-0.015	1.566	0.070***	0.404*	156
	Model II (no *hp*)	-0.036	1	-0.001				156
NL	Model I (baseline)	0.810***	1	-0.083***	1.418	0.118***	0.557***	187
	Model II (no *hp*)	0.268***	1	-0.012***				188
UK	Model I (baseline)	0.836***	1	-0.033***	1.185	0.209***	0.690***	187
	Model II (no *hp*)	0.622***	1	-0.010				188

*,**,*** represent that the coefficient is statistically significant at a confidence level of 90%,95% and 99%, respectively.

Figure 1 plots the credit disequilibria estimations from the two specifications of the UCM, and compares them to the Basel gap. To facilitate the comparison, all disequilibria measures are standardized by subtracting the mean and dividing by its standard deviation. In all the figures we represent the dates of the systemic events as defined in Section 4. We observe that the two specifications of the UCM provide credit imbalances estimations which follow similar trends to the Basel gap but different amplitudes. This is also true when comparing the baseline specification against the one omitting house prices. It is also observed that these models present lower biases than the Basel gap after rapid changes in fundamentals such as those experienced in some countries, both upward in the early 2000's after the launch of the monetary union, and downward after the last financial crisis. In particular, in the case of Spain it has been documented before that part of the leveraging process undergone by the Spanish economy from 1995 to 2004 can be explained as a convergence towards the deeper financial development already existing in more advanced European countries (see Castro et al., 2016).

Table 3 shows the predictive performance of the credit gap measures in terms of their AUROC, distinguishing by three different periods ahead of the crises events as described in Section 3.3 AUROC values which are greater than those from the Basel gap are highlighted in bold, and those which are significantly different from the Basel gap at different confidence levels are marked with stars. In general, it is observed that, for Germany and Italy, models omitting house prices perform better. However, in countries where the real estate sector has played a relevant role in previous crises, the specification including house prices performs better and outperforms the Basel gap. Nonetheless, in Italy and the United Kingdom these models are not able to improve the predictive performance provided by the Basel gap, which seems to perform particularly well in these countries. In fact, the credit-to-GDP gap has been previously identified as providing particularly accurate and timely signals of the build-up of cyclical systemic risk in the United Kingdom (see Giese et al., 2014). Finally, the superior AUROC values of the model-based specifications turn out to be statistically significant for Germany, France, and the Netherlands.

Figure 1. Credit gaps estimated with unobserved components models



Note: The dark grey shaded areas represent macroprudential relevant financial crises s as identified by countries in ESRB/ECB (2017).

Table 3. Country comparison of performance by AUROC: UCM and the Basel gap (12-5, 16-5 and 20-5 quarters ahead of crises)

	UCM I - Base			UCM II No HP			Basel Gap		
Country	12-5	16-5	20-5	12-5	16-5	20-5	12-5	16-5	20-5
DE	**0.79*****	**0.80****	**0.77**	**0.77*****	**0.83*****	**0.82****	0.63	0.68	0.73
ES	**0.74**	**0.74**	**0.75**	0.65	0.67	0.69	0.73	0.72	0.71
FR	**0.65**	**0.65****	**0.68*****	0.61	**0.60**	**0.60**	0.64	0.55	0.52
IT	0.60	0.59	0.59	0.69	0.69	0.71	**0.81**	**0.78**	**0.76**
NL	**0.81***	**0.85****	**0.84****	0.67	0.63	0.60	0.76	0.74	0.76
UK	0.75	0.74	0.73	0.64	0.62	0.63	**0.84**	**0.84**	**0.87**

Note: Values in bold represent that the AUROC of the model is higher than the one of the Basel gap given the corresponding period of quarters ahead of crises. *,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively computed using the non-parametric approach in DeLong et al. (1998).

5.2. *VEC models*

We estimate two different specifications of VEC models under the same spirit that those in the previous subsection. Model I (baseline model) corresponds to the full specification in (3), while Model II omits house prices. After selecting the number of lags using the AIC and testing for the number of cointegrating equations using the trace statistics method, we find that the number of lags varies between 3 and 4 depending on the country and specification, and that only one cointegrating relation should be included for all countries.[11] This equation is the one defined as the leverage gap in Equation (4), where the coefficients for the log of credit and GDP are constrained to be equal to 1.

Table 4 reports the estimation results for the coefficients of the cointegrating equation, including the adjustment coefficients, by country. We observe that interest rates have a significant positive effect on the leverage gap in all the countries and specifications, implying that increases in the interest rates lead to decreases in total credit. Regarding house prices, the effect is significant for Spain, France, the Netherlands and the United Kingdom. This is consistent with the results obtained with UCM's, confirming the importance of real estate developments in the credit cycle of these countries. For these four countries we obtain a negative coefficient on real estate prices, which implies that increases in house prices lead to increases in credit over the long run.

Table 4. Estimation results for the cointegrating equation of VEC models by country

Country	Model	β_c	β_y	β_r	β_{hp}	μ	α_c	α_y	α_r	α_{hp}	obs
DE	Model I (baseline)	1	-1	0.057***	0.125	-0.113	-0.000***	0.000	0.001*	0.000	184
	Model II (no *hp*)	1	-1	0.034***		-0.279	-0.026***	-0.005**	0.498*		184
ES	Model I (baseline)	1	-1	0.018	-0.495***	-0.614	-0.000***	0.001***	0.005	0.015***	184
	Model II (no *hp*)	1	-1	0.038**		-0.167	-0.012**	-0.002	0.199		184
FR	Model I (baseline)	1	-1	0.043***	-0.247***	-0.909	-0.000***	0.012***	0.085*	0.019***	184
	Model II (no *hp*)	1	-1	0.072***		-0.793	-0.000**	0.000**	0.053***		184
IT	Model I (baseline)	1	-1	0.034*	0.187	-0.105	-0.000**	0.000***	0.003	0.000	152
	Model II (no *hp*)	1	-1	0.042***		-0.055	-0.035**	-0.007***	0.684		152
NL	Model I (baseline)	1	-1	0.024	-0.378***	-0.743	-0.027***	-0.005**	0.200	0.023*	184
	Model II (no *hp*)	1	-1	0.084***		-0.841	-0.013***	-0.005***	0.190		184
UK	Model I (baseline)	1	-1	0.016***	-0.0183*	-0.912	-0.004**	0.002	0.514***	0.031***	184
	Model II (no *hp*)	1	-1	0.021***		-0.857	-0.002**	-0.001**	0.211***		184

*,**,*** represent that the coefficient is statistically significant at a confidence level of 90%,95% and 99%, respectively.

It is also interesting to analyse the estimated adjustment coefficients. In the case of $\boldsymbol{\alpha_c}$ the negative and significant coefficients obtained for all the countries imply that when credit deviates from its long-run equilibrium, it tends to adjust back to interest rates and house prices levels in the next periods. In general, the speed of adjustment seems to be faster in countries such as Germany and the Netherlands than in France and the United Kingdom. It is also identified that interest rates tend to rise following increases in the leverage gap, although this adjustment is only significant in Germany, France and the United Kingdom. As regards the coefficient on house prices, the positive and significant figures obtained for Spain, France, the Netherlands and the United Kingdom imply that house prices tend to increase when the leverage gap becomes positive.

Figure 2 plots the credit disequilibria estimations from both VEC specifications, together with the Basel gap for comparison purposes. We observe that the full specification tends to signal vulnerabilities ahead of crises better than the specification excluding house prices in most

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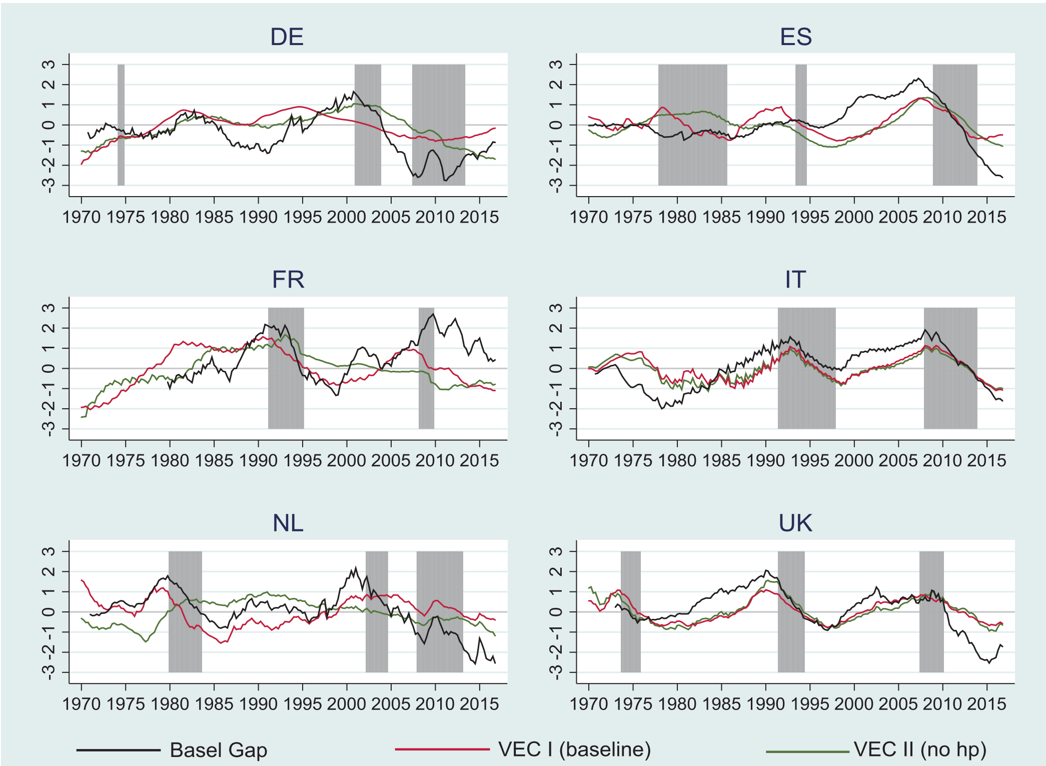
[11] Table A2 in the Annex presents the results for the lags and the trace statistics for determining the number of cointegrating relations. It is also worth mentioning that after applying the Dickey-Fuller GLS test for the presence of unit roots, variables are identified to be integrated of order one in levels for all countries. Additionally, eigenvalues stability conditions are checked after estimations, the greatest moduli is reported also in Table A2, where all values are found to be strictly lower than 1. This suggests that the number of cointegrating equations are not misspecified and that they are stationary. Finally, the table includes the likelihood ratio test of identifying restrictions. Results suggest that restrictions are valid in all the cases.

of the countries. The exception is Germany, probably due to the specificities of its real estate sector, which has been historically low correlated to cyclical systemic crises. In the case of Italy, which is the other country besides Germany where the coefficient on house prices is found to be non-significant, the estimated gaps are very similar between both specifications. VEC models also link credit developments experienced in Italy, Spain and the United Kingdom during the early 2000's to fundamentals. In the case of Spain, this has been argued before due to the new conditions implied after joining the Euro (see Castro et al., 2016). Finally, VEC models also provide estimates of negative gaps which present lower downward bias after the last financial crisis than the Basel gap.

Figure 2. Credit gaps estimated with VEC models



Note: The dark grey shaded areas represent macroprudential relevant financial crises and financial stress periods as identified by countries in ESRB/ECB (2017).

Table 5. Country comparison of performance by AUROC: VEC models and the Basel gap
(12-5, 16-5 and 20-5 quarters ahead of crises)

	VEC I - Base			VEC II - No HP			Basel Gap		
Country	12-5	16-5	20-5	12-5	16-5	20-5	12-5	16-5	20-5
DE	**0.65**	0.64	0.61	**0.64**	**0.69**	**0.74**	0.63	0.68	0.73
ES	**0.82*** **	**0.85*** **	**0.83*** **	0.72	0.70	0.69	0.73	0.72	0.71
FR	**0.85*** **	**0.81*** **	**0.77*** **	**0.68**	**0.68** **	**0.69*** **	0.64	0.55	0.52
IT	0.73	0.77	**0.79**	0.79	**0.81**	**0.81***	**0.81**	0.78	0.76
NL	**0.87*** **	**0.82** **	**0.78**	0.67	0.66	0.65	0.76	0.74	0.76
UK	**0.86**	**0.85**	**0.89**	**0.84**	0.83	0.81	0.84	0.84	0.87

Note: Values in bold represent the highest AUROC by row given the corresponding period of quarters prior to the crisis.
*,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%, 95% and 99%, respectively computed using the non-parametric approach in DeLong et al. (1998).

Table 5 compares the performance of the VEC models against the Basel gap in terms of AUROC. We observe that at least one VEC specification outperforms the Basel gap in each country. This difference becomes statistically significant in Spain, France and the Netherlands, especially when house prices are accounted for. Similarly to the results obtained with UCM's, accounting for house prices is relevant and improves the predictive performance in those countries where the real estate sector has been closely related to systemic crises in the past. If the best VEC specification is chosen for each country, then VEC models exhibit greater AUROC values than the Basel gap in all the countries.

5.3. Aggregate performance comparison

In our view, from a macroprudential policy perspective the country-by-country results should be the main criteria to choose the best complementary indicators for the activation of the CCyB. The CCyB addresses national credit imbalances, which explains why national specificities and the ability of models to adapt to these circumstances matter the most. However, an aggregate performance comparison may still be worth considering. Specifically, it may be useful to assess whether broader lessons can be obtained beyond purely national results. Furthermore, as the number of crises in the sample for specific countries is limited to 2 or 3 in most cases, it may be useful to check the stability of results when the imbalances estimations and the crises events of all countries are aggregated.

Table 6. Aggregate performance comparison: UCM's and Basel gap

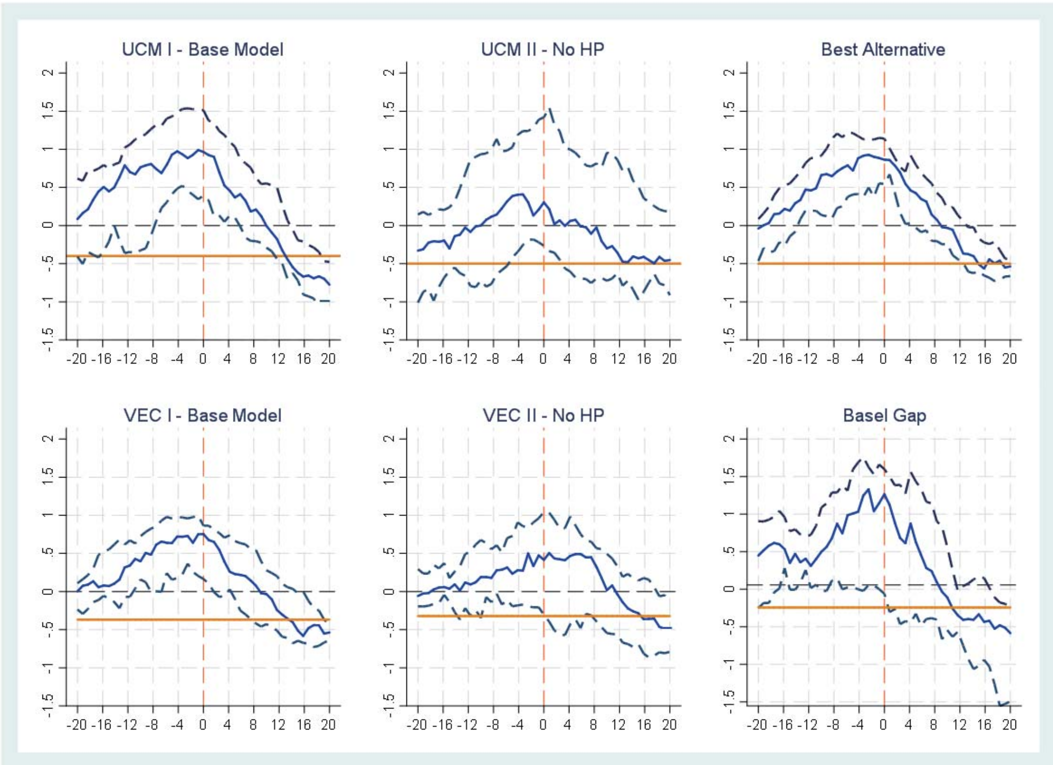
	UCM I Base	UCM II No HP	Best UCM	VEC I Base	VEC II No HP	Best VEC	Best Alternative	Basel Gap
Pool AUROC$_{16\text{-}5q}$	**0.73**	0.66	**0.75**	**0.76**	**0.73**	**0.78**	**0.82**	0.70
Pool AUROC$_{16\text{-}5q}$ (out-of-sample) [1]	**0.67***	**0.61**	**0.70****	**0.71****	**0.67***	**0.72*****	**0.75*****	0.61
Average AUROC (12-5q, 16-5q, 20.5q)	**0.74**	0.68	**0.75**	**0.79**	**0.73**	**0.80**	**0.84**	0.72
Best indicator by AUROC$_{16\text{-}5q}$ (# of countries)	4	2	4	3	4	**6**	**6**	0
AUROC$_{16\text{-}5q}$ significantly greater than that of the Basel gap (# of countries)	**3**	1	**3**	**3**	1	**3**	**4**	
Systemic events missed[2] - Type I error (%)	**25.4%**	**32.7%**	**27.3%**	**22.0%**	**30.9%**	**14.6%**	**13.7%**	33.2%
False alarms[3] – Type II error (%)	**34.9%**	**37.2%**	**33.9%**	**38.6%**	**38.9%**	**36.3%**	**30.0%**	39.4%
Too early signals[4] (%)	**32.1%**	**33.5%**	**30.3%**	**34.3%**	**34.9%**	**32.3%**	**26.1%**	35.2%
Correlation with output losses[5]	**19.0%**	**15.8%**	**22.3%**	**19.4%**	**16.5%**	**21.1%**	**20.1%**	13.5%
Correlation with unemployment5	**23.7%**	19.0%	**26.0%**	**30.4%**	**21.0%**	**29.0%**	**23.8%**	19.6%
Countries for which the model is the best alternative	**NL**	**DE**		**ES, FR, UK**	**IT**			

Note: 1 Estimations up to 1998QIV, AUROC assessed for the period 1999QI – 2016QIV. 2 Percentage of quarters with non-positive gap estimations 16-5q before crises. 3 Percentage of quarters with positive gap estimations without the occurrence of crises during the following 16q. 4 Percentage of positive gap estimations earlier than 20q ahead of crises. 5 Correlations with 2 years ahead quarterly variations in GDP and unemployment rate, respectively. Best UCM, VEC and alternative refer to selecting the best performing specification in each country according to their average AUROC using three different periods ahead of crises (20-5q, 16-5q, 12-5q). In the case of best UCM and VEC, these are the best specifications of each type of model, while the best alternative refers to the best of the four options. Values in bold represent better performance than the Basel gap by criterion. *,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively, computed using the non-parametric approach in DeLong et al. (1998).

Table 6 reports an overall summary of the performance of the two models, and their different specifications by comparing the performance of all the approaches for the group of six countries in our sample as a whole, instead of the country-by-country analysis performed in the previous subsection. Since the results have shown the heterogeneous early warning performance of the different approaches, three columns are added comparing the cases in which the best performing specification and type of model is selected for each country. In general, VEC type models exhibit a greater AUROC than the UCM, both when averaging individual results and when pooling the sample.[12] In turn, the AUROC's obtained from both model-based approaches are generally greater than the one computed from the Basel gap. As a consequence, when selecting the best VEC specification in each country, aggregate results improve the most. The improvement of the model-based indicators is more notorious when the out-of-sample AUROC is computed.

Overall, although the VEC seems to perform the best in aggregate terms (especially the baseline specification including house prices), the heterogeneous results at country level show that the best performing model differs across countries. The UCM base model is the best alternative for the Netherlands. The same type of model but omitting house prices exhibits the best performance in Germany. The full VEC model specification performs the best in Spain, France, and the United Kingdom, while the VEC model omitting house prices is the best alternative in Italy. As a result of this heterogeneous performance, it is only when the best of the four model-specification alternatives is selected for each country that the performance improves significantly with respect to the Basel gap. In fact, not only AUROC values increase up to 0.82 using the pooled sample and 0.84 on average, but the number of type I and type II errors, as well as too-early signals diminishes notoriously.

Figure 3. Cross-country distributions of the estimations of credit imbalances around crises with different models



Note: The blue solid line represents the mean of the credit disequilibria estimation around crises. The blue dashed lines represent the 25th and 75th percentile of the credit disequilibria estimations around crises. Horizontal axis represents the number of quarters before and after systemic crises. The vertical dashed line represents the beginning of the systemic crises. The orange horizontal line represents the median of the credit disequilibria indicator in normal times (out of the range -20 to 20 quarters around systemic crises).

[12] Pool AUROC is computed after pooling the data for the left-hand side variable (crises events) and the right-hand side variable (imbalances estimations) in a logit model with clustered errors by country.

The behaviour of the estimations of credit imbalances around systemic crises can be observed graphically in Figure 3, where the mean and the interquartile range of these estimates are plotted for a period including 20 quarters before and after the beginning of the systemic crises, and compared to the median value of the estimations out of these range (which can be considered as a normal times period). The mean estimates for all the models exhibit increases between 16 and 4 quarters ahead of crises and rapid reductions from the onset of the systemic events that lead to negative values around 12 quarters after the beginning of crises. However, the most interesting conclusions in terms of the desirable predictive performance of the models can be derived from the behaviour of the distribution earlier than 4 quarters ahead of crises. In this context, both the UCM and VEC baseline specifications including house prices exhibit estimated values consistently positive and above normal times around 3 years before a crisis in more than 75% of such situations in the data. Under those same circumstances, the signals issued by the specifications omitting house prices are less evident.

In general, UCM's tend to estimate rapid increases of positive gaps from 8 to 12 quarters ahead of the crises, while VEC models estimate slow increases in most cases but starting earlier, from 16 to 20 quarters before systemic events. Another desirable feature of the credit imbalances estimates from the proposed models is that they exhibit lower downward bias after the onset of the crises than the Basel gap. In fact, it is observed that the negative gap computed from the Basel methodology continue decreasing 20 quarters after the start of the crises, and even accelerates for the 25th percentile.

6. Robustness checks

6.1. *Other statistical-based indicators: Band-pass filtering*

Given that the purpose of this study is to identify structural relationships in the long-run between credit and other fundamental variables, we have focused on model-based indicators of credit imbalances rather than on statistical-based indicators. However, it would be useful to check if the performance results obtained from these models are robust when compared to statistical-based indicators other than the Hodrick-Prescott filtering technique used to compute the Basel gap. In particular, we compare the results of our models to those obtained from the use of Christiano-Fitzgerald band-pass filters, which have been previously found to be useful identifying differences in the length between business and financial cycles (Aikman et al., 2012; Drehmann et al., 2012). In particular, Drehmann et al. (2012) find that financial cycle's length may vary in a range between 8 and 30 years. We apply these values for the filter application and estimate it recursively using an initial window of 40 quarters.

Table 7 reports the performance in terms of the AUROC compared to those obtained from previous models. In general, we find that CF band-pass filters perform worse than the Basel gap in all countries except the Netherlands. However, in all the cases we find that at least one of the proposed models performs better than the CF band-pass filter as it is the case when they are compared to the Basel gap. Interestingly, the relatively bad performance of the CF band-pass filter with respect to the Basel gap confirms that the choice of the Basel gap as the reference for the activation of the CCyB is backed by its relatively good performance among other alternative statistical-based indicators. In fact, the Basel gap has been found previously to be one of the performers among single indicators and other non-model based and easily reproducible measures (Detken et al., 2014; Giese et al., 2014).

Table 7. Country comparison of performance by AUROC: CF band-pass filters, structural models and Basel gap (16-5 quarters ahead of crises)

Country	UCM I Baseline	UCM II No HP	VEC I Baseline	VEC II No HP	CF band-pass	Basel gap
DE	**0.80****	**0.83*****	0.64	**0.69**	0.63	0.68
ES	**0.74**	0.67	**0.85*****	0.70	0.71	0.72
FR	**0.65****	**0.60**	**0.81*****	0.68**	0.55	0.55
IT	0.59	0.69	0.77	**0.81**	0.51	0.78
NL	**0.85****	0.63	**0.82****	0.66	0.81	0.74
UK	0.74	0.62	**0.85**	0.83	0.63	0.84

Note: Values in bold represent the highest AUROC by row given the corresponding window of quarters prior to the crisis.
*,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively, computed using the non-parametric approach in DeLong et al. (1998).

6.2. *Autoregressive Distributed Lags Models with Error Correction (ARDL-EC)*

We also propose to check the robustness of our results to the use of an alternative structural model which can be seen as a univariate version of the VEC model. ARDL models, introduced by Pesaran and Shin (1999), allow estimating univariate time series in terms of their own lags and those of explanatory variables of different orders. These models also allow identifying long-run relationships and to separate them from the short run effects by including cointegration terms (Hassler and Wolters, 2006). ARDL-EC present several advantages in the case of the presence of one cointegrating vector, such as a unified framework for testing and estimating cointegration relations, and not requiring pretesting unit roots. The aim is to use these models to identify long-run relationships between credit and the other variables included in the study (GDP, long-term interest rates and house prices) through cointegrating equations, without specifying the dynamics of all the involved variables through a large dimensional VEC. The general specification is as follows:

$$\begin{aligned}\Delta c_t &= \delta + \textstyle\sum_p \rho_p \Delta \mathrm{c}_{t-p} + \sum_{q1} \lambda_{yq1} \Delta \mathrm{y}_{t-q1} + \sum_{q2} \lambda_{rq2} \Delta \mathrm{r}_{t-q2} + \\ &\quad + \textstyle\sum_{q3} \lambda_{hpq3} \Delta \mathrm{hp}_{t-q3} + \alpha \tilde{u}_{t-1} + \epsilon_t; \\ \tilde{u}_{t-1} &= \mathrm{c}_{t-1} - \mu - \beta_1 \mathrm{y}_{t-1} - \beta_2 \mathrm{r}_{t-1} - \beta_3 \mathrm{hp}_{t-1}, \end{aligned} \tag{5}$$

where, Δ represents the first difference of the variables, c_t is the log of real credit; δ is a constant term; ρ_i are the estimated autoregressive coefficients of order *p* of the log of real credit; y_t is the log of real GDP; r_t represents the long-term real interest rates; hp_t represents real house prices; $\lambda_{yq1}, \lambda_{rq2}, \lambda_{hpq3}$ are their corresponding autoregressive coefficients of different orders q_1, q_2, q_3, which are determined optimally using the AIC; α is the adjustment coefficient of long-run deviations; $\tilde{u}_{t-1}$ represents the long-run relationship; and, $\mu, \beta_1, \beta_2, \beta_3$ are the constant term, and the estimated coefficients in the cointegrating equation, where β_1 is constrained to be equal to 1 as it is done for the UCM and VEC models.

Table 8 presents the results in terms of AUROC for the same two types of specifications assessed before (with and without house prices), and compared to the UCM and VEC models as well as to the Basel gap. The ARDL baseline specification exhibits a greater AUROC than the Basel gap in three countries (ES, FR, and NL), but only in Spain the difference is significant. However, results do not improve when compared to the two types of models proposed previously. In the case of France and the Netherlands, both the UCM and the VEC model perform better and provide significantly greater AUROCs than the Basel gap. In the case of Spain, the VEC specification is slightly better. Regarding the specification without house prices, the AUROC obtained with the ARDL-EC model is lower in all the cases to any other model and specification in all the countries. This is true also when compared to the Basel gap, except in Italy, where it is slightly greater.

Overall, results from the UCM and VEC models provide better results than ARDL specifications. This is especially remarkable when contrasted to the VEC model, which can be seen as its multivariate extension, which suggests that the univariate specification is not able to provide better information on credit imbalances ahead of crises.

Table 8. Country comparison of performance by AUROC: ARDL-EC models, UCM's, VEC models and Basel gap (16-5 quarters ahead of crises)

Country	UCM I - Baseline	UCM II - No HP	VEC I - Baseline	VEC II - No HP	ARDL I - Baseline	ARDL II - No HP	Basel gap
DE	**0.80****	**0.83*****	0.64	**0.69**	0.60	0.64	0.68
ES	**0.74**	0.67	**0.85*****	0.70	**0.82****	0.62	0.72
FR	**0.65***	**0.60**	**0.81*****	0.68**	**0.62***	**0.58**	0.55
IT	0.59	0.69	0.77	**0.81**	0.55	0.63	0.78
NL	**0.85****	0.63	**0.82****	0.66	**0.75**	0.57	0.74
UK	0.74	0.62	**0.85**	0.83	0.67	0.60	0.84

Note: Values in bold represent the highest AUROC by row given the corresponding window of quarters prior to the crisis.
*,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively, computed using the non-parametric approach in DeLong et al. (1998).

6.3. *Definition of systemic events*

An important issue when assessing the performance of systemic risk indicators is the definition used to classify an event as systemic and their specific dates. Given the aim of our study, the definition of the events should be consistent with the occurrence of episodes of systemic magnitude related to the materialization of cyclical risk derived from excessive credit growth periods. As described in Section 4, our definition of systemic events and their dates are based on the classification reported by countries in the EU crises database (Lo Duca et al., 2017). In particular, we use all systemic crises and residual financial stress events classified as macroprudentially relevant. Nonetheless, different definitions can be obtained from these classifications and robustness of the proposed models to other definitions become relevant As Gadea and Perez-Quiros (2015) have shown, dating crises is a difficult task: potential concerns may arise due to the fact that the relevant dates are typically chosen once the crises are over and not in real time. In this context, it is essential to assess the robustness of the results to different dating approaches, even though the start and end dates from different crises databases do not generally differ much in practice. Specifically, we assess the performance of the models providing early warning signals of the occurrence of the following four definitions of systemic events: i) systemic crises, ii) residual financial stress events, iii) systemic crises and residual financial stress events of macroprudential relevance, which corresponds to the definition used along this study; and, iv) all systemic crises and residual financial stress events. In order to explore potential differences in the signals derived from the proposed models and the Basel gap, we compare their performance in terms of the ability of anticipating each of the four classifications of events.

Table 9 presents the results in terms of the AUROC distinguishing by type of systemic stress event for the three types of models. In general, models seem to be robust to the use of different definitions of systemic events. This is particularly evident with VEC models, which perform better than the Basel gap for almost all definitions of systemic events. However, it can be observed that UCM's tend to do a better job anticipating residual financial stress events in Spain, Italy, and the United Kingdom; while VEC models tend to perform better anticipating systemic crises in Germany and the Netherlands. Similarly to what was identified in terms of the models before, it is also noticeable that there is at least one definition of systemic event for which the models outperform the Basel gap in each country.

Table 9. Comparison of AUROC by type of systemic event - UCM's, VEC models and the Basel gap (16-5 quarters ahead of systemic events)

Country	Event	UCM I Baseline	UCM II No HP	VEC I Baseline	VEC II No HP	Basel Gap
DE	Systemic crises	**0.80****	**0.83*****	0.64	**0.69**	0.68
	Residual financial stress events	**0.78****	**0.79****	0.52	0.63	0.66
	MP relevant crises and stress events	**0.80****	**0.83*****	0.64	**0.69**	0.68
	All crises and stress events	**0.67****	**0.68****	**0.57**	**0.68****	0.54
ES	Systemic crises	**0.80**	0.68	**0.78**	0.74	0.75
	Residual financial stress events	**0.81*****	**0.70***	**0.89*****	0.55	0.60
	MP relevant crises and stress events	**0.74**	0.67	**0.85*****	0.70	0.72
	All crises and stress events	**0.74**	0.67	**0.85*****	0.70	0.72
FR	Systemic crises	**0.65***	**0.60**	**0.81*****	**0.68****	0.55
	Residual financial stress events	**0.58**	**0.60***	**0.67*****	**0.70*****	0.52
	MP relevant crises and stress events	**0.65***	**0.60**	**0.81*****	**0.68****	0.55
	All crises and stress events	**0.55**	**0.55**	**0.66*****	**0.58**	0.54
IT	Systemic crises	0.54	0.64	0.78	**0.85**	0.84
	Residual financial stress events	0.50	**0.70****	0.50	0.50	0.59
	MP relevant crises and stress events	0.59	0.69	0.77	**0.81**	0.78
	All crises and stress events	**0.60***	**0.69*****	**0.70*****	**0.72*****	0.52
NL	Systemic crises	**0.91*****	**0.88*****	**0.87*****	**0.77*****	0.53
	Residual financial stress events	0.68	**0.76**	**0.80**	0.57	0.76
	MP relevant crises and stress events	**0.85****	0.63	**0.82****	0.66	0.74
	All crises and stress events	0.51	0.57	**0.86*****	0.62	0.69
UK	Systemic crises	0.74	0.62	0.83	**0.85**	0.84
	Residual financial stress events	**0.85***	**0.87****	0.71	**0.76**	0.76
	MP relevant crises and stress events	0.74	0.62	**0.85**	**0.83**	0.84
	All crises and stress events	0.58	0.60	**0.73***	**0.72**	0.64

Note: Values in bold represent the highest AUROC by row given the corresponding window of quarters prior to the crisis.
*,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively, computed using the non-parametric approach in DeLong et al. (1998).

In principle, we should only care about those events that are truly systemic or at least relevant for macroprudential purposes. In practice, though, we can observe that the AUROC's do not differ too much between systemic and residual events, regardless of whether macroprudentially relevant crises are considered or not, these results show the difficulty of distinguishing between different kinds of crises, which in fact are classified through a mainly judgemental procedure.

6.4. *The great financial crisis and the Euro*

Recent studies assessing performance of cyclical systemic risk indicators tend to give a great importance to the last financial crisis. This is not only because of its large magnitude, but also because it accounts for half of the total number of systemic crises in the pool sample. This may bias the aggregate results towards the performance of the models signalling this crisis. Also, the type of imbalances leading to the last financial crises may differ from those related to previous crises, in particular those before the launch of the monetary union in Europe in 1999, which could imply important changes to fundamental macro-financial variables in many countries. Thus, it would be relevant to check the robustness of the proposed models to the characteristics of the financial cycles in both periods. For this purpose, we split the sample into two periods: the first one (from 1970 to 1998) is used for the estimations of the different models, and the second one (from 1999 to 2016) is used for predictions.

Table 10. Robustness of AUROC to the estimated sample period - UCM's, VEC models and the Basel gap (16-5 quarters ahead of systemic events)

Country	UCM I - Baseline		UCM II - No HP		VEC I - Baseline		VEC II - No HP		Basel Gap
	Full sample	Split sample	Full sample	Split sample	Full sample	Split sample	Full sample	Split sample	Full sample
DE	**0.80****	**0.72**	**0.83*****	**0.76****	0.64	0.58	**0.69**	0.62	0.68
ES	**0.74**	0.63	0.67	0.54	**0.85*****	**0.78***	0.70	0.60	0.72
FR	**0.65***	**0.59**	**0.60**	0.54	**0.81*****	**0.74*****	**0.68****	**0.61***	0.55
IT	0.59	0.50	0.69	0.59	077	0.70	**0.81**	0.75	**0.78**
NL	**0.85****	**0.80***	0.63	0.57	**0.82****	**0.76**	0.66	0.60	0.74
UK	0.74	0.68	0.62	0.57	**0.85**	0.78	0.83	0.77	**0.84**

Note: Values in bold represent the highest AUROC by row given the corresponding window of quarters prior to the crisis.
*,**,*** represent that the AUROC value is significantly different from that estimated for the Basel gap at a confidence level of 90%,95% and 99%, respectively.

Table 10 presents the AUROC results of the different models after splitting the sample. In general, robustness is observed in terms of the best performing model and specification in each country with respect to the conclusions obtained from the performance of the models using the whole sample. Thus, these results supports evidence on the real time robustness of the models when used for systemic crises predictions. Nonetheless, in countries where changes in the evolution of credit with respect to GDP were more evident after the launch of the monetary union such as Italy and Spain, the performance of UCM's decreases more than in other countries or with the use of VEC models.

7. Conclusions

The credit-to-GDP gap is the main standard indicator used to guide countercyclical instruments in many countries and the one recommended in the international regulation and EU legislation (BIS, 2010; EU CRR/CRD-IV). This indicator has been selected mainly because of providing useful signals of credit imbalances leading to systemic crises in the past, and being simple and easy to compute and communicate (Detken et al., 2014; Drehmann and Tsatsaronis, 2014; Giese et al., 2014). However, the Basel credit-to-GDP gap exhibits some limitations mainly associated to the inertia of its long-run trend, which may take long time to incorporate new information from fast and large variations of the credit-to-GDP ratio or structural changes. This is particularly evident in countries that experienced large credit growth rates before crisis and deep deleveraging processes after the last financial crisis. This may have implications for future signals of the building-up of systemic risk during the next credit cycle if credit recovers rapidly in the upcoming years (see, Castro et al., 2016). This issue is not exclusive of the Basel gap but is a general limitation of statistical-based indicators, since it is only possible to extract a long-run equilibrium level of credit from historical values. Thus, complementary indicators based on structural models that link credit developments to fundamental variables may provide useful estimations of credit imbalances that may help macroprudential authorities in the decision-making processes on the activation of the CCyB. In fact, the Basel credit-to-GDP gap is considered as an initial reference that should be complemented with information from other individual and model-based indicators (ESRB/2014/1).

In this study we assess two different (semi-) structural methods in terms of their ability to identify cyclical systemic risk periods leading to financial crises and compare them against the Basel credit-to-GDP gap. We propose two easy-to-implement models that have been used before in the analysis of financial cycles: a semi-structural unobserved components model and a vector error correction model. We use quarterly data from six major European countries (France, Germany, Italy, the Netherlands, Spain and the United Kingdom) from 1970 to 2016. This relatively long sample period is a useful testing ground, as it includes several crises for most countries in the sample.

Results evidence heterogeneity in the performance of the models across countries, which suggests the difficulty in finding a unique method that fits equally well for all countries. In particular, unobserved component models are found to perform better in Germany and the Netherlands, while VEC models tend to exhibit better performance in Spain, France, Italy and the United Kingdom. The inclusion of house prices is also found to provide heterogeneous results. In particular, in those countries where the real estate sector has played a major role explaining previous crises (Spain, France, the Netherlands, and the United Kingdom), including house prices improves the performance of the models. In fact, previous studies have found indicators related to residential real estate prices to perform particularly well providing signals of the build-up of cyclical risk leading to systemic crises in some of these countries (see Castro et al., 2016 and Giese et al., 2014, for an empirical analysis in Spain and the United Kingdom, respectively). On the other hand, specifications omitting house prices may provide better results in countries such as Germany and Italy.

Nevertheless, at least one of the models and specifications analysed outperform the Basel gap in each of the countries of the sample. Moreover, if the best performing model and specification is selected in each country, the aggregate results obtained improve importantly with respect to using the same model for all the countries. Overall, these results suggest that simple (semi-) structural models may complement the Basel gap and be very useful for the identification of credit imbalances and the decision-making process of macroprudential policies at national level. The proposed models seem to be particularly useful in providing lower biased signals after rapid changes in fundamentals. Thus, these models may provide convenient information in situations in which the signals derived from the Basel gap are less useful or inconsistent with other complementary information. However, choosing a unique model for all countries would be very difficult given country-specificities.

Results of the proposed models are found to be robust to different definitions of systemic crises. Nonetheless, some of these models are found to perform better for identifying only financial crises while others seem to perform better in identifying also residual financial systemic stress events. The two models assessed in this study are also found to perform better than other alternative statistical and model-based indicators. Finally, the best performing models are found to be robust to the characteristics of the financial cycle before and after the introduction of the Euro as legal currency, which marked important structural changes in some countries.

A potential implementation of these models for policy purposes should also consider some advantages and limitations of using these models in practice. As the main advantages we can consider that these models allow for economic interpretation, yield estimates of equilibrium levels of credit justified by economic fundamentals, capture country specificities, provide low volatile signals, are robust to real-time estimations, and present both higher early-warning performance and lower biases after rapid changes in the credit-to-GDP ratio than the Basel gap. On the other hand, limitations may include that these models are not easy to communicate to the general public, may be sensitive to the addition of other macro-financial variables, and are not easy to replicate or being assessed in countries with short time series.

The results obtained are expected to be useful for macroprudential policy authorities in their decision-making process on the activation of the CCyB, as well as to contribute to the incipient literature on assessing empirical models for macroprudential decisions. This is an open area where more research is still needed. Comparing other types of structural models and methods of estimation such as using Bayesian inference; assessing the usefulness of accounting for other macro-financial variables related to the credit cycle; and, considering alternative models distinguishing by type of borrower (households and non-financial companies) are some interesting research lines for further research.

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ANNEX

Table A1. Summary statistics by country

Country	Variable	Mean	Median	S.D.	Min	Max
DE	Real credit (millions)	2,497,141	2,635,328	515,739	1,533,305	3,118,053
	Real GDP (millions)	2,095,839	2,209,792	497,083	1,113,360	2,842,465
	Real house prices growth (%)	0.39%	0.20%	0.78%	-1.02%	2.27%
	Long-term real Interest rates (%)	6.43	6.99	2.38	2.41	10.13
	Credit-to-GDP ratio (%)	111.52	109.45	10.05	91.90	131.10
	Basel gap (pp)	-2.64	-3.55	5.52	-13.70	8.20
ES	Real credit (millions)	1,116,728	663,304	723,081	416,419	2,348,237
	Real GDP (millions)	808,505	776,850	215,310	498,500	1,124,300
	Real house prices growth (%)	1.67%	1.50%	2.91%	-5.33%	12.64%
	Long-term real Interest rates (%)	4.93	4.86	2.56	0.18	10.44
	Credit-to-GDP ratio (%)	125.51	89.70	52.13	73.41	217.79
	Basel gap (pp)	3.42	1.09	21.09	-49.49	43.94
FR	Real credit (millions)	2,261,173	2,002,697	863,831	1,025,629	3,936,050
	Real GDP (millions)	1,627,901	1,622,746	335,602	1,118,129	2,123,186
	Real house prices growth (%)	1.15%	1.05%	1.96%	-4.03%	5.98%
	Long-term real Interest rates (%)	5.17	5.11	1.65	0.76	7.85
	Credit-to-GDP ratio (%)	132.93	125.95	24.88	99.90	184.30
	Basel gap (pp)	2.76	2.60	4.25	-5.70	11.50
IT	Real credit (millions)	1,212,066	1,007,440	522,812	503,623	2,005,907
	Real GDP (millions)	1,468,667	1,508,912	130,320	1,218,665	1,687,142
	Real house prices growth (%)	1.35%	0.99%	2.14%	-2.18%	10.81%
	Long-term real Interest rates (%)	5.08	4.25	2.90	-1.48	11.65
	Credit-to-GDP ratio (%)	82.99	71.95	25.85	51.70	127.30
	Basel gap (pp)	3.17	4.95	8.42	-16.10	17.70
NL	Real credit (millions)	955,192	885,623	455,893	334,432	1,579,898
	Real GDP (millions)	480,475	493,907	138,471	236,772	674,864
	Real house prices growth (%)	0.85%	0.98%	2.10%	-7.05%	5.97%
	Long-term real Interest rates (%)	4.20	3.41	3.45	0.12	10.03
	Credit-to-GDP ratio (%)	181.14	176.45	49.29	105.70	247.00
	Basel gap (pp)	-0.94	0.20	9.01	-22.30	18.80
UK	Real credit (millions)	1,809,546	1,529,211	918,835	429,916	3,206,427
	Real GDP (millions)	1,828,174	1,841,882	432,245	1,185,025	2,569,879
	Real house prices growth (%)	1.63%	1.80%	2.58%	-6.84%	12.36%
	Long-term real Interest rates (%)	2.40	2.89	2.76	-2.84	6.43
	Credit-to-GDP ratio (%)	126.60	117.70	40.44	55.90	191.90
	Basel gap (pp)	2.13	5.60	12.25	-28.90	23.50

Note: Monetary values are expressed in euros and in real terms of year 2010.

Table A2. Pre- and post-estimation tests of VEC models

Country	Model	Lags (#)[1]	Maximum rank (trace-stat)[2]	Modulus - eigenvalue stability condition[3]	LR test of identifying restrictions[4]
DE	Baseline	4	1 (28.16)	0.9103	0.167
	No HP	4	1 (11.34)	0.8764	0.467
ES	Baseline	3	1 (29.30)	0.9063	0.714
	No HP	3	1 (15.19)	0.9187	0.112
FR	Baseline	4	1 (27.56)	0.9213	0.211
	No HP	3	1 (14.88)	0.9286	0.113
IT	Baseline	4	1 (25.14)	0.9118	0.137
	No HP	4	1 (13.44)	0.9233	0.367
NL	Baseline	4	1 (27.96)	0.9056	0.426
	No HP	3	1 (12.54)	0.9247	0.202
UK	Baseline	3	1 (23.23)	0.9152	0.145
	No HP	4	1 (13.28)	0.9258	0.532

Note: 1 The number of lags is selected following the AIC criterion. 2 For the trace statistic test, the critical values corresponding to rank equal to 1 at 5% confidence level are 29.68 for the baseline model and 15.41 for the model without house prices. 3 Modulus eigenvalue strictly lower than 1 assure stationary of the cointegrating equation and correct number of cointegration relations. 4 p-value of the chi-square statistic of the LR test where the null hypothesis is that the restrictions imposed are valid.

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