MEASURING CREDIT-TO-GDP GAPS. THE HODRICK-PRESCOTT FILTER REVISITED

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(*) This paper is the sole responsibility of its author. The views represented here do not necessarily reflect those of the Banco de España or the Eurosystem.

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Abstract

The credit-to-GDP gap computed under the methodology recommended by Basel Committee for Banking Supervision (BCBS) suffers of important limitations mainly regarding the great inertia of the estimated long-run trend, which does not allow capturing properly structural changes or sudden changes in the trend. As a result, the estimated gap currently yields large negative values which do not reflect properly the position in the financial cycle and the cyclical risk environment in many countries. Certainly, most countries that have activated the Countercyclical Capital Buffer (CCyB) in recent years appear not to be following the signals provided by this indicator. The main underlying reason for this might not be only related to the properties of statistical filtering methods, but to the particular adaptation made by the BCBS for the computation of the gap. In particular, the proposed one-sided Hodrick-Prescott filter (HP) only accounts for past observations and the value of the smoothing parameter assumes a much longer length of the credit cycle that those empirically evidenced in most countries, leading the trend to have very long memory. This study assesses whether relaxing this assumption improves the performance of the filter and would still allow this statistical method to be useful in providing accurate signals of cyclical systemic risk and thereby inform macroprudential policy decisions. Findings suggest that adaptations of the filter that assume a lower length of the credit cycle, more consistent with empirical evidence, help improve the early warning performance and correct the downward bias compared to the original gap proposed by the BCBS. This is not only evidenced in the case of Spain but also in several other EU countries. Finally, the results of the proposed adaptations of the HP filter are also found to perform fairly well when compared to other statistical filters and model-based indicators.

Keywords: credit-to-GDP gap, cyclical systemic risk, early-warning performance, macroprudential policy, statistical filters.

JEL classification: C18, E32, E58, G01, G28.

Resumen

La brecha crédito-PIB calculada con la metodología recomendada por el Comité de Supervisión Bancaria de Basilea (BCBS, por sus siglas en inglés) presenta importantes limitaciones, debido principalmente a la alta inercia de la tendencia de largo plazo estimada, que no permite capturar de manera apropiada cambios estructurales o rápidos en la tendencia. Como resultado, la brecha estimada presenta actualmente en muchos países valores muy negativos, que no reflejan de un modo adecuado el entorno de riesgo cíclico ni su posición en el ciclo financiero. Esto ha llevado a que la gran mayoría de los países que han activado recientemente el Colchón de Capital Anticíclico (CCA) no estén siguiendo las señales derivadas de este indicador. La principal razón de estas discrepancias entre las señales del indicador y la actual posición en el ciclo financiero de muchos países puede estar relacionada no solo con las propiedades de los métodos de filtrado estadístico, sino también con la adaptación específica del filtro de Hodrick-Prescott (HP) recomendada por el BCBS para el cálculo de la brecha. En particular, el parámetro de suavización del filtro HP propuesto asume una duración del ciclo de crédito mucho mayor que la evidenciada empíricamente en la mayoría de los países, lo que lleva a que la tendencia de largo plazo estimada tenga una memoria muy larga. Este estudio evalúa si una relajación de este supuesto mejora la capacidad predictiva del indicador y su utilidad para identificar señales de riesgo sistémico cíclico que permitan informar adecuadamente sobre decisiones de política macroprudencial en los próximos años. Los resultados sugieren que adaptaciones del filtro HP que asumen una menor duración del ciclo de crédito, más coherente con la evidencia empírica, mejoran la capacidad predictiva del indicador y corrigen el sesgo negativo tras los eventos de crisis, en comparación con la brecha calculada con la metodología propuesta por el BCBS. Esto se evidencia no solo en el caso de España, sino también en otros países de la Unión Europea. Finalmente, se encuentra que los resultados obtenidos con las diferentes adaptaciones del filtro HP presentan una capacidad predictiva superior a la de otros métodos de filtrado estadístico y comparable con la obtenida con modelos econométricos.

Palabras clave: brecha crédito-PIB, filtros estadísticos, indicadores de alerta temprana, política macroprudencial, riesgo sistémico cíclico.

Códigos JEL: C18, E32, E58, G01, G28.

CONTENTS

1 Introduction

Excessive credit growth is often cited as one of the main drivers of systemic risk in the run-up to financial crises. Certainly, international evidence has confirmed that periods of high credit growth rates have preceded the occurrence of systemic crises between 2 and 5 years after these events materialize (Borio and Drehmann, 2009; Drehmann et al., 2011; Schularik and Taylor, 2012). This evidence is behind the idea of the implementation of countercyclical macroprudential instruments, such as the Countercyclical Capital Buffer (CCyB) as proposed by the Basel Committee for Banking Supervision (BCBS) (see BIS, 2011). The aim of this instrument is to increase the resilience of the banking sector in a financial downturn through the accumulation of capital during the expansionary phase of the credit cycle. In addressing this aim the CCyB also help to lean against the build-up phase of the cycle. The accumulation of buffers in good times to be used in bad times was also behind the dynamic provisioning system adopted in 2000 by Banco de España (see Saurina and Trucharte, 2017), which has been proved to benefit banks during the last downturn (Jiménez et al., 2017).

The implementation of the CCyB is closely linked to the identification of periods of excessive credit growth. Thus, it would not be sufficient to identify high credit growth rates in absolute terms, but to identify whether the observed growth is excessive or not. In that context, quantitative indicators may provide useful information to policy makers on the build-up of cyclical systemic risk. The BCBS proposes a credit-to-GDP gap computed using a statistical method, as a standardised indicator of credit imbalances (BIS, 2010). This indicator, widely known as the Basel gap, is based on the decomposition of the credit-to-GDP ratio into a long-run trend and a cyclical component using a statistical filter. In particular, the Basel methodology proposes the use a real-time (one-sided) version of the Hodrick–Prescott filter (HP), which is widely used for macroeconomic series (Hodrick and Prescott, 1997). The Basel gap has become the standard indicator used not only to identify credit imbalances but also to calibrate CCyB rates across BCBS jurisdictions, including European Union countries (BIS, 2010; EU CRR/CRD-IV[1]).

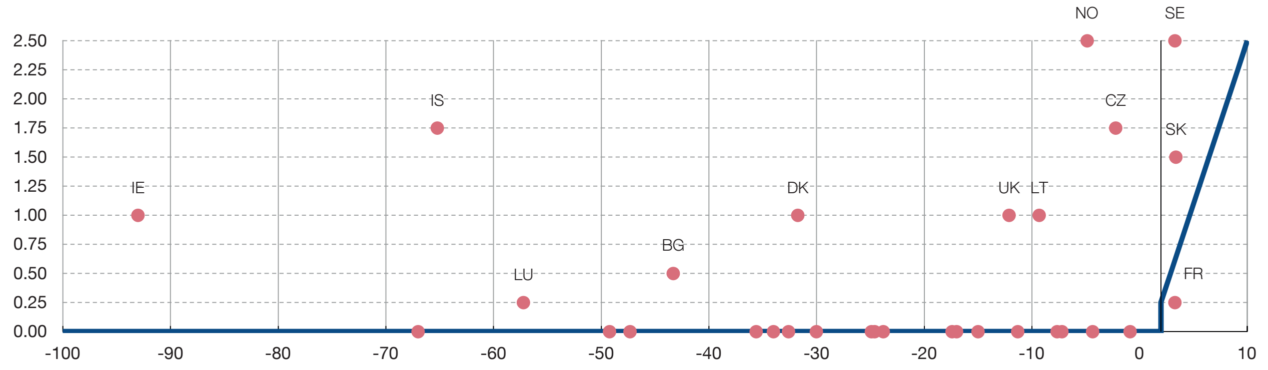
The Basel gap has been selected among different indicators due to its simplicity in terms of easiness to be computed, replicated and communicated, and to its relatively good performance. In fact, the performance of the Basel gap as an early warning indicator of the build-up of cyclical systemic risk related to excessive credit growth has been found to be fairly good in the past (Drehmann et al., 2010; Detken et al., 2014; Drehmann and Tsatsaronis, 2014). However, the Basel gap presents several limitations, some of which have recently become the focus of attention. One of its main limitations is related to the large negative values that it currently estimates for many countries that have undergone a severe credit contraction in the recent past, even after several years from the end of the last crisis. The main negative implication of this situation is that it will not provide prompt 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. This is one of the reasons behind the fact that most of countries activating the CCyB in recent years are not following the signals issued by the Basel gap (see Chart 1).

1 EU Regulation 575/2013 and EU Directive 2013/36/EU. The use of this indicator to guide the CCyB decisions in the EU is detailed in Recommendation ESRB/2014/1 of the European Systemic Risk Board (ESRB).

BASEL GAP VS. CCYB RATES IN COUNTRIES OF THE EUROPEAN ECONOMIC AREA

CHART 1

Most countries with positive CCyB rates are not following the BCBS recommended buffer guide (red line). Even some countries with the largest negative gaps have recently activated the instrument.



SOURCES: ESRB and BCBS. Own elaboration.
NOTE: The y-axis represents the announced CCyB rate as to December 2018. The x-axis represents the Basel credit-to-GDP gap in pp. The red line represents the BCBS recommended rule for the setting CCyB rates linked to values of the Basel gap. The grey dashed line represents the 2pp threshold recommended by the BCBS as point of activation of the CCyB (BCBS, 2010; ESRB/2014/1).

The downward bias problem of this indicator has been identified to be particularly important when large changes in the credit-to-GDP ratio are presented. Repullo and Saurina (2011) discuss the limitations of the Basel gap when either credit increases or GDP decreases faster than the other term of the ratio. In particular, the indicator is not able to distinguish situations where credit growth might be justified by financial deepening or when a fast GDP contraction provides conflicting signals.

The inability of incorporating structural changes and link equilibrium levels of the credit-to-GDP ratio to fundamental variables is a general limitation of statistical methods. This has led to recent proposals of methods based on models that may incorporate this information. Galán and Mencía (2018) recently discuss the advantages of these methods and propose two (semi-) structural models that outperform the Basel credit-to-GDP gap using a sample of six EU countries. Other recent studies propose similar methods, which have been found to perform better than the Basel gap (see Lang and Welz, 2018, for a semi-structural method applied to a large sample of EU countries).

Nonetheless, adaptations of the specific filtering method proposed in Drehmann et al. (2010) and adopted by the BCBS, may still provide useful information and avoid some of the main limitations of the Basel gap. In particular, addressing the use of a one-sided HP filter and the specific parameterisation adopted in the calculation of the Basel gap may improve the performance of the indicator. In an application to Italy, Alessandri et al. (2015) propose a method to correct deviations between the one- and two-sided versions of the HP filter using forecasted data. In fact, a two-sided filter is able to capture changes in trends more properly. Nonetheless, the need of forecasted data may introduce biases and makes the estimations dependent on the quality of the forecasts. Recently, Martínez and Oda (2018) addresses the problem of the large value of the smoothing parameter assumed in the computation of the Basel gap. The authors find that lowering this value improves the performance of the indicator in Chile.

Certainly, the use of a large value for the smoothing parameter (400,000) is responsible for the large inertia of the filter. This value assumes that the length of the credit cycle is around 30 years (see Drehmann et al., 2010), which empirically seems to be unrealistic for many countries. Recently, Bedayo et al. (2018) identify that the average frequency of systemic crises over the 1880-2017 period in Spain is around 17 years, which is almost half of the frequency implicitly assumed by the Basel gap. Using broad samples of advanced countries and emerging economies, Drehmann et al. (2011) and Drehmann et al. (2012) identify average lengths of credit cycles between 15 and 25 years, with cases around 30 years being at the tail of the distributions.

Moreover, the length of credit cycles may present large heterogeneity across countries and assuming a fixed and common duration of the cycle can be very restrictive. On this regard, Galati et al. (2016) identify that the amplitude and length of the cycles largely differ among countries after applying Kalman filtering methods to the US and some euro area countries. Thus, although there is some consensus in the literature on the fact that credit cycles have longer duration than business cycles (see Claessens et al. 2011, 2012; Aikman et al., 2015), assuming that its length is around 30 years seems empirically to be an upper bound rather than a representative number.

In this context, the aim of this study is whether the one-sided HP filter, in which the Basel gap indicator is based on, is still a useful indicator of credit imbalances in the future if the filter is allowed to have shorter memory. In particular, I propose two different adaptations of the one-sided HP filter for these purposes. The first one is to use lower values for the smoothing parameter, and the second one is to discard older information than a certain time horizon through the use of rolling windows. Martínez and Oda (2018) performs a similar analysis for Chile and find that adapting the Basel gap to assume a shorter length of the credit cycle improves significantly the performance of the indicator. Also, the performance of two alternative common statistical filters is explored. I use quarterly data of the credit-to-GDP ratio in Spain spanning more than half a century: from 1965Q1 to 2018Q3. Finally, I also explore as robustness the performance of some of these variants in a sample of 13 EU countries.

The paper is organized in four sections besides this introduction. Section 2 briefly describes the performance criteria assessed. Section 3 presents the results of the proposed exercises using the one-sided HP filter. Section 4 presents some robustness exercises including an assessment of the performance of other alternative statistical filters, a comparison with model-based indicators, and the application of some of the proposed alternatives to a large sample of EU countries. Finally, section 5 concludes the paper.

2 Assessment criteria

I compare the predictive performance of the proposed adaptations of the HP filter within a reasonable period before the onset of systemic events. In particular, I assess conditional probabilities, the probabilities of missing a crisis (Type I error) and issuing false alarms (Type II error), and the Area Under the Receiver Operating Characteristics Curve (AUROC). The AUROC has become a useful method 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) because it does not require to select a specific probability threshold. The AUROC assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct.[2] In order to obtain these measures, I estimate logit regressions of the different versions of the credit-to-GDP gap on a variable signalling the occurrence of a systemic event 5 to 12 quarters ahead.[3] This range is convenient for policy purposes, since too-early signals may have unintended consequences on credit supply and too-late signals reduce the effectiveness of the policy, mainly due to the one-year long phase-in period of the CCyB requirement for banks following the announcement of the rate by the macroprudential authority. The conditional probability of a crisis, and Type I and II errors are computed at relevant thresholds (2pp and 10pp). The 2 percentage point threshold is the reference for the activation of the CCyB under the BCBS Guidance (BIS, 2010) and ESRB Recommendation 2014/1, and the 10pp gap corresponds to the maximum value at which automatic reciprocity is mandatory between EU members. Although these thresholds could be optimized for the specific adaptations of the HP filter proposed, I hold these reference values in order to focus the analysis on the effects of adapting the filter.

2 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.

3 For the computation of the AUROC, the case of signals within 5 to 16 quarters ahead of the occurrence of systemic events is also considered.

3 The Hodrick-Prescott Filter

The methodology proposed by the BCBS for computing the credit-to-GDP gap is based on the use of a trend-removal statistical technique. In particular, the HP filter was selected for this purpose given the good properties and wide use of this technique on the identification of business cycles. This method, firstly proposed by Hodrick and Prescott (1997) is a high-pass type of filter, which has the property of making stationary processes of integrated orders 1 up to 4. The BCBS proposes to use a one-sided version of the filter, where only past and current observations are used to compute the trend at each moment of time. This allows obtaining real-time estimations of the gap but limits the ability of the filter to incorporate changes in the trend. In contrast, a two-sided filter incorporates these changes more properly since all past and future observations are used for identifying the trend. However, in order to obtain useful estimations for policy purposes from a two-sided filter, forecasted data is required. This may introduce biases related to the quality of the forecasts.

The HP filter requires defining only one parameter, denoted as λ, which is related to the smoothness of the trend. In general, the smoother the trend (larger values of λ), the wider the amplitude of the cycle and the longer its duration. Ravn and Uhlig (2002) recommended to use a value of 1,600 for quarterly data when analyzing business cycles. This value assumes implicitly a cycle frequency of around 7.5 years, which is appropriate given the empirical evidence on the length of business cycles in advanced economies. In fact, business cycles have been identified to range from 4 to 8 years in OECD countries, with a mean of around 5 years (see e.g. Cotis and Coppel, 2005).

This assumption seems to be very reasonable for business cycles; however, credit cycles have been identified to be longer (Claessens et al. 2011, 2012; Aikman et al., 2015), and its length to be heterogeneous across countries (Galati et al., 2016). Drehmann et al. (2010) argues that a good approximation is the length between two systemic crises. These authors analyze a sample of G20 and OECD countries excluding transition economies and identify that this length ranges between 5 and 20 years with a median around 15 years. Drehmann et al. (2011) identify a longer occurrence of systemic crises (20-25 years on average) using a sample of 36 developed and emerging economies. International evidence shows not only large heterogeneity in the length of credit cycles across countries, but also that in very few cases this length is longer than 25 years.

Despite of this evidence, Drehmann et al., (2010) propose a smoothing parameter equal to 400,000 for the HP filter, which is equivalent to assume a length of around 30 years. Interestingly, the authors identify that using a smoothing parameter equal to 25,000 presents the best early warning properties at gaps within a range between 2pp and 4pp. Moreover, they find that for gaps between 5pp and 8pp, a smoothing parameter equal to 125,000 presents equal performance than using 400,000. However, the authors conclude in favor of the highest smoothing parameter because it preserves a good performance for gaps beyond 9pp. This criterion implicitly favors the indicator with the largest upward deviations before historical crises,

COUNTRIES USING DIFFERENT ADAPTATIONS OF THE HP FILTERING METHOD FOR IDENTIFYING CREDIT-TO-GDP GAPS

TABLE 1

Adaptation of the Basel gap methodology	Countries
Adjusted by GDP decrease	Germany
Adjusted by historical deviations between one- and two-sided filters	Italy
Combining one- and two-sided filters	Japan
Adjusted by projections	Norway
Adjusted by currency fluctuations	Brazil, Russia
Adjusted using a rolling window	Chile, Korea
Range of smoothing parameters	Denmark

SOURCES: BCBS (2017) and Martínez and Oda (2018).

which also implies the largest inertia of the long-run trend and the largest downward biases after crises. This study influenced the BCBS adoption of this indicator for guiding the calibration of the CCyB. Nonetheless, it is important to remark than in 2010, neither the BCBS nor the authors were able to realize that the last financial crisis could become so deep and long, that the large deviations that they considered desirable during the booms, could become so negative and persistent in many countries and for so many years.

The implications of computing the HP filter with such a high smoothing parameter have been identified as uninformative by many national authorities after the last crisis. In fact, most of countries activating the CCyB in recent years are not following the signals issued by the Basel gap (see Chart 1). Moreover, several countries have decided to adapt either the computation of the HP filter or the buffer guide in order to correct this bias and to incorporate country specificities. Table 1 presents a summary of the main adaptations of the Basel gap methodology recently made by BCBS countries in order to take decisions on macroprudential cyclical instruments. Germany adjusts the guide so that decreases in GDP will not imply higher buffer rates, avoiding raising the CCyB during an economic downturn (see Repullo and Saurina, 2011 for a discussion on this issue). Brazil and Russia adapt the gap by currency fluctuations given the implications of the exchange rate over credit in foreign currency. Japan combines the information provided by the one-sided and the two-sided HP filters in their analysis. Italy incorporates implicitly the signals from the two-sided HP filter by adjusting the one-sided filter for historical deviations between both alternatives (see Alessandri et al., 2015). Norway adjusts the one-sided HP filter by including projections of data. Finally, Chile, Korea and Denmark use either rolling windows or lower smoothing parameters in order to shrink the duration of the estimated cycle. Since my main concern with the usefulness of the Basel gap in Spain is derived from this assumption, I assess below the effects of these two specific adaptations the HP filter.

3.1 The smoothing parameter

As aforementioned, empirical evidence in Spain has shown that the length of the credit cycle is on average around 17 years (Bedayo et al., 2018). This would be between 2 and 3 times the

VALUES OF CORRESPONDING SMOOTHING PARAMETERS GIVEN THE LENGTH OF THE CYCLE

TABLE 2

Length of the cycle (years)	Times the business cycle	λ	λ (standard approximation)
7.5	1	1,600	1,600
15	2	25,600	25,000
22.5	3	129,600	125,000
30	4	409,600	400,000

SOURCE: Drehmann et al. (2010).

median of the business cycle assumed with a value of λ=1,600 (7.5 years). The formula for the parameter λ in terms of the length of the business cycle is the following (Drehmann et al., 2010):

$$\lambda = (\textit{times the business cycle})^4 * 1{,}600$$

Following this formula, the corresponding values for the λ parameter given the different assumptions for the length of the financial cycle with respect to the business cycle are summarized in Table 2.

Using the four approximated values of the smoothing parameters above, I compute the HP filter for the quarterly credit-to-GDP ratio in Spain from 1965Q1 to 2018Q3.[4] The gap estimations are presented in Chart 2. In general, it is observed that the higher the value assumed for λ, the higher the estimated gaps and the greater their variance. On the one hand, assuming a smoothing parameter equal to 1,600, as it is assumed for the business cycle, estimates too-short credit cycles and very small gaps that would difficult the identification of clear signals of imbalances. On the other hand, a λ equal to 400,000 introduces too much inertia to the long-run trend leading to too-late signals of imbalances. In fact, the Basel gap misses 2 out of 3 systemic events identified in Spain since 1970. Intermediate values of the smoothing parameter signal correctly the systemic event presented during the 90's, yield lower deviations after the last financial crisis, and adapt more quickly to a change in the trend in the last two years. In the case of λ equal to 25,000, the signals are clearer for the 90's systemic event, and the drop after the last crisis is lower than using a parameter of 125,000.

Table 3 also presents a comparison of the performance of the HP filter using the four different values of the smoothing parameter. In general, the filter using the lowest value for λ presents even lower performance than the Basel gap. However, the intermediate values outperform the Basel gap both in terms of AUROC and of Type I/II errors, being the gap using a λ of 25,000 the one presenting the best performance.

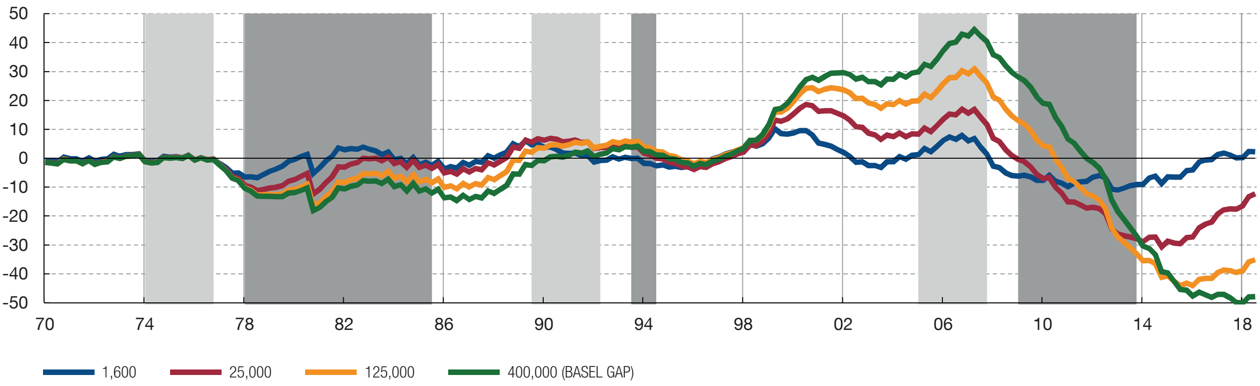
Chart 3 plots the early warning performance of the different HP filter alternatives, as measured by the AUROC, at different quarters ahead of the systemic crises. It is observed that the Basel gap presents the lowest predictive performance among the four alternatives 16 to 9 periods ahead of the crises, and only get close to the AUROC values of the best alternatives

4 The gaps are computed starting at 1970Q1 with information from 1965Q1.

ESTIMATION OF THE CREDIT-TO-GDP GAP USING THE HP FILTER WITH DIFFERENT VALUES OF THE SMOOTHING PARAMETER λ

CHART 2

The lower the λ, the lower the estimated gaps and their variance. Gap s estimated with λ equal to 25,000 and 125,000 signal properly the systemic event occurred in the 90's.



SOURCE: Banco de España. Own elaboration.
NOTE: The dark grey shaded areas denote three financial stress periods identified in Spain since 1970, corresponding to two periods of systemic banking crises (1978-Q1 to 1985-Q3; 2009-Q1 to 2013-Q4) and one idiosyncratic event (1993-Q3 to 1994-Q3). The light grey shaded areas represent the period from 5 to 16 quarters ahead of the onset of the systemic events, when it is desirable to identify risk signals for macroprudential policy purposes.

PERFORMANCE COMPARISON OF THE CREDIT-TO-GDP GAP UNDER DIFFERENT SMOOTHING PARAMETERS

TABLE 3

The gap estimated using a λ equal to 25,000 presents the best predictive performance and the lower errors.

λ	AUROC 12-5	AUROC 16-5	Type I error at 2pp	Type II error at 2pp	Conditional probability at 2pp	Conditional probability at 10pp
1,600	0.70	0.72	9.76%	87.50%	12.67%	38.78%
25,000	0.80	0.81	5.10%	77.46%	10.06%	23.88%
125,000	0.79	0.79	5.33%	79.49%	9.41%	15.51%
400,000	0.77	0.75	8.81%	85.51%	9.27%	12.85%

SOURCE: Own elaboration.
NOTE: For comparability, the thresholds used for the computation of type I/II errors and conditional probabilities are the reference values recommended for the Basel gap (BCBS, 2010). Nonetheless these thresholds could be optimized for each of the alternatives.

between 8 and 5 quarters before the crises. The gap using the lowest λ (1,600) performs relatively well up to 9 periods before the systemic events but its performance decreases very fast and becomes almost completely uninformative 5 quarters ahead of the onset of the crises. On the other hand, the performance of the gaps using λ values of 25,000 and 125,000 is relatively good and stable during all the pre-crises periods analysed, reaching their maximum signalling power 9 quarters ahead of the onset of the systemic events.

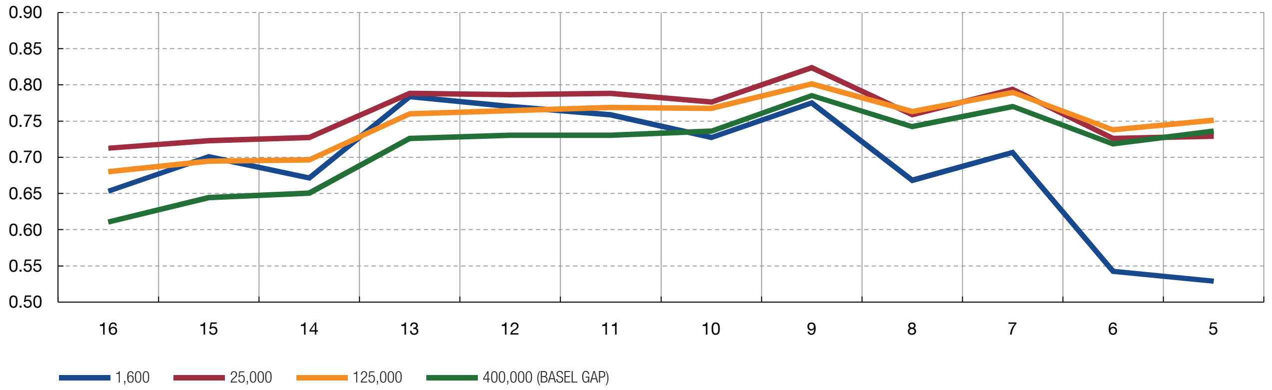
3.2 Rolling windows

The computation of the HP filter is not only sensitive to the value of the parameter λ, but also to the length of the horizon for which it is computed. This can be adjusted by means of a rolling window, which allows discarding old observations that may not provide useful or proper

AURoC OF THE CREDIT-TO-GDP GAPS ASSUMING DIFFERENT VALUES OF THE SMOOTHING PARAMETER (λ) FOR THE HP FILTER AT EACH QUARTER AHEAD OF CRISES (5-16 QUARTERS).

CHART 3

The gaps estimated with λ's equal to 25,000 and 125,000 outperform the Basel gap in terms of predictive performance. The difference is especially high between 8 and 16 quarters ahead of the onset of the systemic events.



SOURCE: Own elaboration.
NOTE: The vertical axis represents AUROC values and the horizontal axis represents the number of quarters before the occurrence of systemic events in Spain.

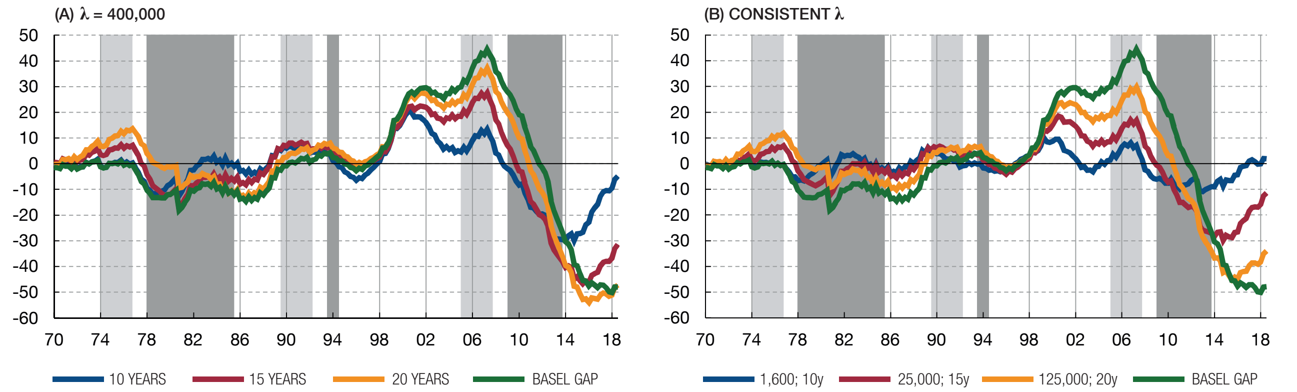
information for current estimations of the long-run trend. The use of a rolling window assures that the memory of the trend is shorter than the window set. Martínez and Oda (2018) apply this adaptation of the HP filter to estimate credit-to-GDP gaps in Chile and find that a rolling window of 10 years provides the best results.

The length of the window can be adjusted in order to assume shorter lengths of the credit cycle. Thus, I assess three different lengths of windows, which represent approximately the lengths of the credit cycle assumed by the use of the smoothing parameters analyzed above (for simplicity I use rolling windows equal to 10, 15 and 20 years). Chart 4 presents the estimations of the gap using these different windows along with the standard Basel method, where the complete time horizon of available data for Spain is used.[5] Although using a smoothing parameter that assumes a longer cycle than the window may still imply a large inertia of the trend, first I hold the smoothing parameter fixed at 400,000, as suggested by the Basel methodology, in order to check only the effect of shortening the horizon. As in the case of lower smoothing parameters, the HP filters with shorter horizons issue correct signals of credit imbalances before the systemic event in the 90's and currently exhibit an upward trend of the gaps. Nonetheless, the amplitude of the cycles estimated using rolling windows of 15 and 20 years is not very different than the one using the full sample. The reason is that in all the cases, the smoothing parameter is hold fixed at 400,000, which introduces a high persistence to the long-run trend estimation. These results suggest that shortening the horizon of observed data may capture inflection points on the cycle earlier, while it may have less effects on reducing potential biases.

5 In all the cases information starting at 1965 is used. Nonetheless, the length of the window avoids real-time estimations shorter than the initial window. That is, for the 10, 15 and 20-year windows, the first gaps are reported at 1975Q1, 1980Q1 and 1985Q1, respectively. For the Basel gap, only estimations starting at 1970Q1 are reported in order to allow the 1-sided HP filter to provide informative real-time estimations.

ESTIMATION OF THE CREDIT-TO-GDP GAP USING THE HP FILTER WITH DIFFERENT TIME HORIZONS AND SMOOTHING PARAMETERS. CHART 4

Reducing the time horizon for which the filter is computed allows incorporating changes in the trend more quickly. Nonetheless, if the λ is not adjusted consistently, the inertia of the trend continue to be large.



SOURCE: Banco de España. Own elaboration.
NOTE: The grey shaded areas denote three financial stress periods identified in Spain since 1970, corresponding to two periods of systemic banking crises (1978-Q1 to 1985-Q3; 2009-Q1 to 2013-Q4) and one idiosyncratic event (1993-Q3 to 1994-Q3). The light grey shaded areas represent the period from 5 to 16 quarters ahead of the onset of the systemic events, when it is desirable to identify risk signals for macroprudential policy purposes. In Panel (a) a smoothing parameter equal to 400,000 is used in all the cases. In Panel (b) three combinations of smoothing parameters and rolling windows consistent in terms of the length of the credit cycle are presented. When rolling windows of 15 and 20 years are used, it is not possible to obtain estimations before the late 70's crisis given that using data from 1965 lead to observe the first real-time estimations at 1980 and 1985, respectively.

Theoretically, the smoothing parameter should be consistent with the time horizon used for computations. Thus, adapting the filter in both dimensions, i.e. simultaneously lowering the smoothing parameter and shortening the horizon would be more consistent and may yield better results. This would imply approximate λ values of 1,600, 25,000 and 125,000 when using rolling windows of 10, 15 and 20 years, respectively. The results of these alternatives are presented in Chart 4 panel (b). In general, it is observed that shortening the horizon in combination with lowering the smoothing parameter estimate both lower amplitude of the cycles and earlier inflection points.

Shortening the time horizon while holding constant the smoothing parameter improves the predictive performance of the estimated gaps, except for the 10-year rolling window, which seems to assume a too-short length of the credit cycle (see Table 4). In general, using a rolling window equal to 15 years provides the best performance at any value of the smoothing parameter. These results are also consistent when analyzing type I and II errors (see Table A1 in the Annex). It is important to remark that using smoothing parameters that assume credit cycles longer than the rolling window provide very similar estimations, given that the memory of the long-run trend implied by the filter cannot be longer than the time horizon. The same is true when rolling windows longer than the length assumed by the smoothing parameter are used. This is evident when other combinations of rolling windows and λ values are plotted (see Chart A1 in the Annex).

These results are consistent throughout all the period between 5 and 16 quarters ahead of systemic events, where it is observed that the alternatives using a rolling window equal to 15 years provide the best results, and reach the maximum predictive performance around 9 periods before the beginning of the crises (see Chart 5). As it was identified above, when a very low value of the smoothing parameter (1,600) is used, the performance decreases rapidly from 8 quarters before the events.

AUROC COMPARISON OF THE CREDIT-TO-GDP GAP USING DIFFERENT COMBINATION OF ROLLING WINDOWS AND SMOOTHING PARAMETERS

TABLE 4

Using a rolling window of 15 years provides the best performance results.

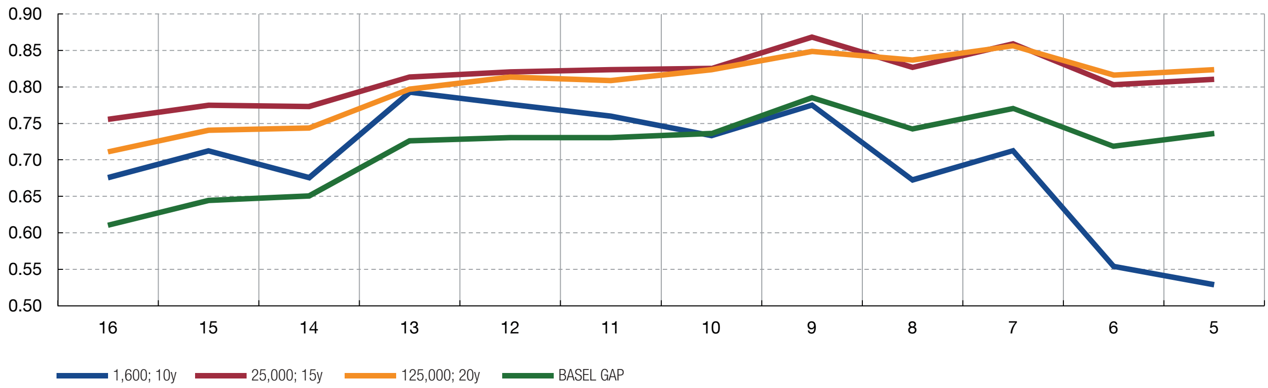
Time horizon	λ = 1,600	λ = 25,000	λ = 125,000	λ = 400,000
10	0.75	0.79	0.79	0.77
15	0.78	0.87	0.88	0.88
20	0.78	0.84	0.82	0.81
Full sample	0.72	0.81	0.79	0.75

SOURCE: Own elaboration.
NOTE: The AUROC 16-5 quarters ahead of systemic events is presented. For the alternatives using rolling windows of 15 and 20 years, it is not possible to obtain estimations before the late 70's crisis given that the first real-time estimations are obtained in 1980 and 1985, respectively. For comparability, the thresholds used for the computation of type I/II errors and conditional probabilities are the reference values recommended for the Basel gap (BCBS, 2010). Nonetheless these thresholds could be optimized for each of the alternatives.

AUROC OF THE CREDIT-TO-GDP GAP USING THE HP FILTER USING DIFFERENT ROLLING WINDOWS AND CONSISTENT VALUES OF THE SMOOTHING PARAMETER (λ), AT EACH QUARTER AHEAD OF CRISES (5-16 QUARTERS)

CHART 5

The alternatives using rolling windows of 15 and 20 years outperform the Basel gap consistently throughout the whole pre-crises periods in terms of predictive performance.



SOURCE: Own elaboration.
NOTE: The vertical axis represents AUROC values and the horizontal axis represents quarters before the occurrence of systemic events in Spain. For the alternatives using rolling windows of 15 and 20 years, it is not possible to obtain estimations before the late 70's crisis given that the first real-time estimations are obtained in 1980 and 1985, respectively.

4 Robustness

4.1 Other alternative filters

Although, the HP is one of the most commonly used filters for macroeconomic series, there are other statistical filters with properties that may be adequate for extracting the cyclical component of a time series. The most popular types of filters are high-pass and band-pass filters. High-pass filters characterises for allowing signals with a frequency higher than a certain cut-off. The HP and the Butterworth filters are the most popular. On the other hand, band-pass filters remove stochastic cycles outside of a specific band or length of the cycle, for which frequencies are unwanted. The Baxter and King and the Cristiano-Fitzgerald filters are the most common band-pass type filters. The main characteristics of each of these filters are summarized in Table 5.

As it was aforementioned, the HP filter is a trend-removal technique that estimates the trend by minimizing its distance to the actual series, and its time variation, where the smoothing parameter defines the weight of the time variation component. In general, the HP filter can be seen as a specific case of the Butterworth filter.

The Butterworth filter (Butterworth, 1930; Pollock, 2000) is a signal-processing filter widely applied by engineers and macroeconomists because of its main property of having a frequency response as flat as possible in the pass-band. This filter estimates the components driven by stochastic cycles at specified frequencies when the original series is non-stationary. The mechanism of the Butterworth filter is to discard the stochastic cycles of higher periodicities than a determined period or cutoff. Thus, the filter requires specifying two parameters: the order of the filter, which determines the slope of the gain function, and the cutoff frequency. Implications and derivations of the most adequate orders for given cutoffs have been studied before by Pollock (2000). I follow these proposals for selecting proper orders for the frequencies assessed.

COMPARISON OF CHARACTERISTICS OF THE MOST COMMON STATISTICAL FILTERING METHODS — TABLE 5

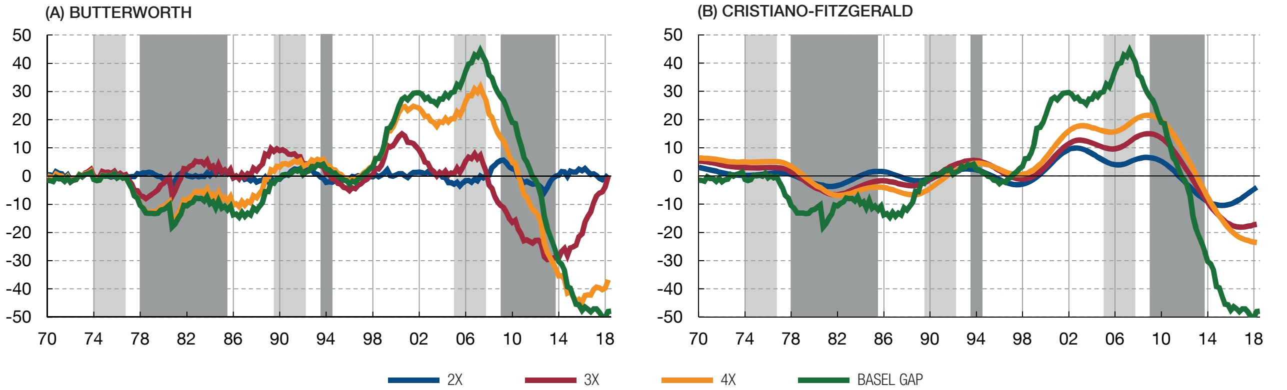
	Hodrick-Prescott	Butterworth	Cristiano-Fitzgerald	Baxter and King
Filter class	High-pass	High-pass	Band-pass	Band-pass
Parameters (#)	(1): Smoothing	(2): Order of filter and cut-off frequency	(1): Range of frequencies	(2): Number of leads/lags and range of frequencies
Symmetry	None	Symmetric	Asymmetric	Symmetric
Loss function	Weighted function of the difference between actual values and trend, and time changes of trend	Approximation of the order to the ideal filter around the cut-off frequency	Mean squared error between the estimated and true components	Error between filter coefficients and the ideal band-pass filter
Series	Integrated processes of orders 1 up to 4	Non-stationary	Random-walk process	Covariance-stationary process

SOURCE: Martínez and Oda (2018) and own elaboration.

ESTIMATION OF THE CYCLE COMPONENT USING THE BUTTERWORTH AND THE CRISTIANO-FITZGERALD FILTERS ASSUMING DIFFERENT LENGTHS OF THE CREDIT CYCLE

CHART 6

The alternative filters assuming a similar length for the credit cycles (black lines) exhibit lower variance of the gap estimations compared to the Basel gap. These filters also seem to be more sensitive to assuming lower lengths for the cycle.



SOURCE: Banco de España. Own elaboration.
NOTE: The grey shaded areas denote three financial stress periods identified in Spain since 1970, corresponding to two periods of systemic banking crises (1978-Q1 to 1985-Q3; 2009-Q1 to 2013-Q4) and one idiosyncratic event (1993-Q3 to 1994-Q3). The light grey shaded areas represent the period from 5 to 16 quarters ahead of the onset of the systemic events, when it is desirable to identify risk signals for macroprudential policy purposes.

Chart 6 panel (a) plots the gap estimations using the Butterworth filter for cutoffs equivalent to 16, 24, and 30 years, which correspond to assumptions of lengths of credit cycles around two, three and four times the business cycle, respectively.[6] It is observed that the Butterworth filter assuming a length of around 30 years (as the Basel methodology assumes for the HP filter) estimates very similar values to the Basel gap, although deviations are slightly lower. The filter assuming a length of the cycle around 16 years is very volatile and comparable to the case of the HP filter with λ equal to 1,600, which assumes shorter cycles (around 7.5 years). The most appropriate frequency of the filter would be the one assuming that the credit cycle has a length of 24 years (around three times the business cycle). In this case, the filter signals correctly the systemic event occurred during the 90's and generates much lower deviations from the long-run trend. In fact, this alternative currently estimates a gap close to 0, which has rapidly recover from the minimum at the end of the crisis. However, it also issues relatively low signals of imbalances during the pre-crisis period. In terms of performance, Table 6 summarizes the AUROC values for different periods ahead of the systemic events. It can be observed that this last alternative is the only one improving from the Basel gap. However, the best predictive performance of this filter seems to be very close to the onset of the crises, which also brings a problem to be considered for policy purposes.

The Cristiano-Fitzgerald filter (Christiano and Fitzgerald, 2003) is a band-pass type of filter that separates stochastic cycles at periods smaller and greater than a determined range while assuming that the underlying variable follows a random-walk process. Under this assumption, the filter minimizes the mean squared error between an estimated component and a true component. This filter has been previously applied to the analysis of financial cycles. Recently, Aikman et al. (2015) apply this type of band-pass filter to long time series from a large set of countries, finding

6 In particular, cutoffs in terms of quarters equal to 64, 96 and 120 periods are used. The corresponding orders of the filter used are 6, 3, and 2, following Pollock (2000). The case assuming a length of the credit cycle equivalent to that of the business cycle (around 7.5 years) cannot be estimated due to problems regarding the high value of the optimal order combination. In any case, assuming a length of 16 years already provide very volatile estimations of the gap.

AUROC COMPARISON OF THE CREDIT-TO-GDP GAP USING THE ALTERNATIVE FILTERS — TABLE 6

The Butterworth filter provide similar predictive performance than the Basel gap. Nonetheless, its version assuming a credit cycle length equal to three times the business cycle presents the best performance. In contrast, the Cristiano-Fitzgerald filter underperforms the Basel gap.

	Butterworth filter (times the business cycle)			Cristiano-Fitzgerald filter (times the business cycle)			Basel gap
	2X	3X	4X	2X	3X	4X	
AUROC 12-5	0.54	0.79	0.77	0.66	0.67	0.66	0.77
AUROC 16-5	0.57	0.78	0.76	0.63	0.65	0.64	0.75
Lag with highest AUROC	3	1	4	3	1	4	9

SOURCE: Own elaboration.

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 Cristiano-Fitzgerald filter to a sample of developed countries, and find that financial cycles tend to last between 8 and 30 years. This range assumes a credit cycle up to 4 times the business cycle. Since our interest is to check potential improvements of assuming shorter lengths, I assess the Cristiano-Fitzgerald filter by changing the upper bound to be equivalent to 16, 24, and 30 years, which assumes credit cycles up to twice, three and four times the business cycle, respectively.[7] The gap estimations obtained for the cycle component are presented in Chart 6 panel (b). In general, the estimations using this filter tend to be as persistent as the Basel gap. Only the alternative assuming a length of the cycle around 16 years clearly estimates lower deviations than the Basel gap and an increasing trend in the last few years. However, the signals issued before the two previous systemic events are not clear under this alternative. In fact, the predictive performance of the different versions of this filter is lower than that of the Basel gap (see Table 6). Moreover, similarly to the Butterworth filer, CF filters tend to provide improve their performance too-close to the occurrence of the crises.

Finally, the Baxter and King filter (Baxter and King, 1999) is a symmetric moving average filter that estimates the cyclical component using a weighted average of the leads and lags of the series. This property is related to its main drawback. In particular, there is a trade-off between choosing an enough large number of periods (leads/lags) that minimizes the difference between the coefficients in the filter and the ideal band-pass filter, and the consequent increase in missing observations. This is an important limitation from a policy perspective, since it would require to use forecasted data for a potentially large number of periods. Therefore, I do not assess this filter in this study.

4.2 Model-based credit gap estimations

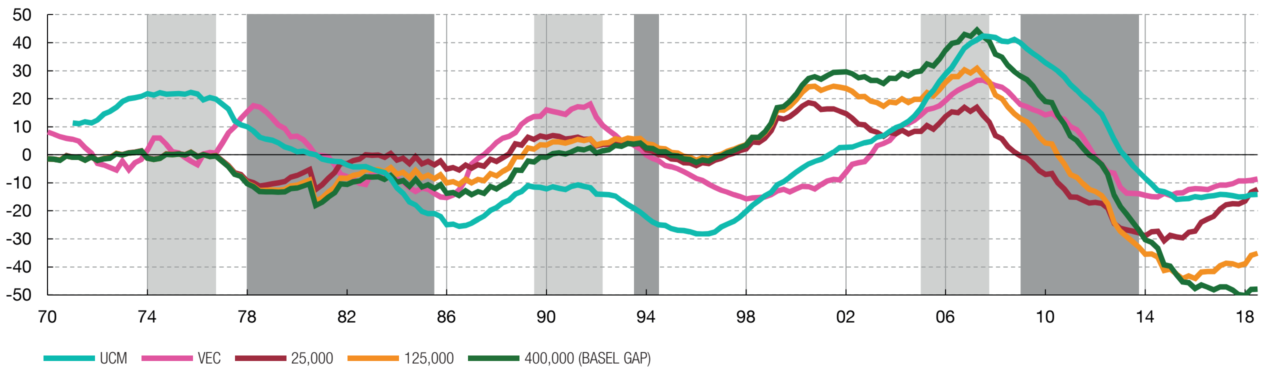
One of the main critiques to the use of statistical methods for the estimation of credit gaps is that these methods are unable to incorporate information from fundamental variables that may justify the equilibrium level of credit. On this regard, Castro et al. (2016) identified that joining the Euro implied a structural change in Spanish fundamentals that had effects on credit equilibrium

7 In terms of quarters the upper bounds are set to 64, 96 and 120 quarters, respectively. As in the case of the Butterworth filter, the case of assuming a cycle length equal to that of the business cycle is not assessed given that it would imply changing the lower bound, which already takes this length into consideration.

ESTIMATION OF CREDIT GAPS USING MODEL-BASED INDICATORS AND THE HP FILTER WITH DIFFERENT VALUES OF THE SMOOTHING PARAMETER (λ)

CHART 7

Model-based indicators tend to exhibit clearer signals before the first two systemic events, and justify the credit growth observed around 2000. These indicators also present a lower downward bias after the last crisis. Nonetheless, their estimated deviations are currently very similar to that of the credit-to-GDP gap estimated using the HP filter with λ equal to 25,000.



SOURCE: Banco de España and Galán and Mencía (2018). Own elaboration.
NOTE: The grey shaded areas denote three financial stress periods identified in Spain since 1970, corresponding to two periods of systemic banking crises (1978-Q1 to 1985-Q3; 2009-Q1 to 2013-Q4) and one idiosyncratic event (1993-Q3 to 1994-Q3). The light grey shaded areas represent the period from 5 to 16 quarters ahead of the onset of the systemic events, when it is desirable to identify risk signals for macroprudential policy purposes. Gaps estimated from UCM and VEC models represent deviations of the observed credit level as a percentage of the long-run estimated equilibrium. In the case of the statistical filters, these values represent the credit-to-GDP gap in percentage points as in previous figures.

levels, which are not able to be captured by statistical methods in due time. In order to account for these factors, recent studies have proposed the use of models linking credit to other macrofinancial fundamental variables. Juselius et al. (2016) propose a measure of financial equilibrium in terms of a leverage and a debt-service gap, which are estimated from a VEC system that accounts for interest rates and asset prices. Several other studies have identified the importance of accounting for real estate prices when estimating credit given the relevant cyclical similarities that both variables share (Schüler et al., 2015; Rünstler and Vlekke, 2017). Lang and Welz (2018) propose a semi-structural unobserved components model for household credit that account for long-term interest rates and institutional quality. Galán and Mencía (2018) propose an unobserved components and a VEC model for estimating long-run equilibrium levels of total credit accounting for GDP, long-term interest rates and house prices. The authors find that these methods outperform the Basel gap in terms of early warning performance, present lower deviations from long-run equilibrium levels after rapid variations of credit, and may deal better with structural changes in a sample of six EU countries.

Chart 7 presents the estimated gaps using the HP filter and the model-based indicators. It is observed that, model-based indicators provided clearer signals of imbalances previous to the systemic events occurred in the late 70's and early 90's, although each model identifies properly only one of these events. It is also remarkable that both models recognize the first stage of credit growth observed after Spain joined the Euro in 1999, as justified by macro-financial fundamentals. After the last financial crisis, both models exhibit lower negative deviations than the statistical-counterparts. Nonetheless, the statistical adaptations of the HP filter with lower smoothing parameters evidence clearer a change in the trend of the deviations. Also, the current deviations of credit from the estimated long-run equilibria are similar between these models and the HP filter using a smoothing parameter equal to 25,000.

PERFORMANCE COMPARISON OF ALTERNATIVE HP FILTERS VS MODEL-BASED INDICATORS — TABLE 7

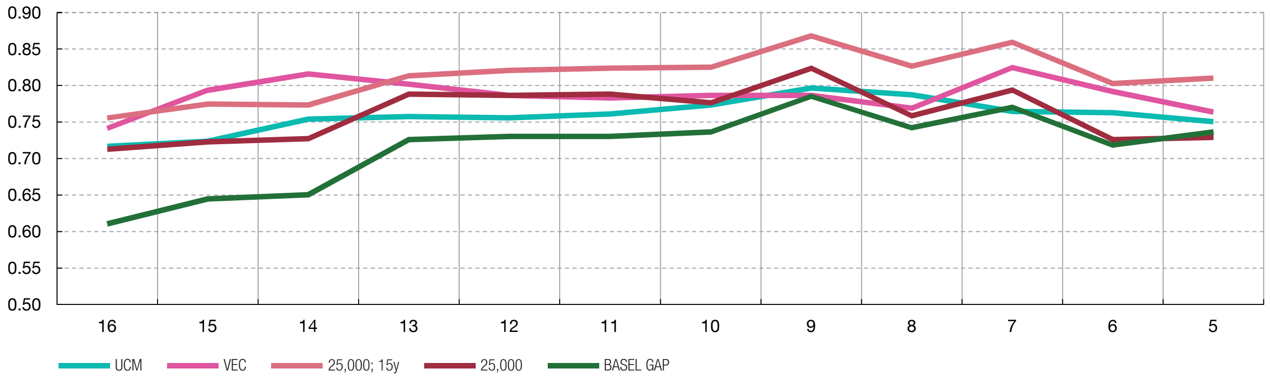
The performance of the best HP filter alternatives is comparable to that of model-based estimations.

Indicator	AUROC 12-5	AUROC 16-5	Lag with highest AUROC	Type I error at 10% conditional probability	Type II error at 10% conditional probability
UCM	0.75	0.76	9	5.5%	78.9%
VEC	0.82	0.86	7	4.7%	73.7%
HP (λ = 25,000)	0.80	0.81	9	5.1%	77.5%
HP (λ =125,000)	0.79	0.79	9	5.3%	79.5%
HP (λ = 25,000; 15 years)	0.85	0.87	9	0.0%	71.8%
HP (λ = 125,000; 20 years)	0.84	0.82	7	0.0%	75.3%

SOURCE: Galán and Mencía (2018) and own elaboration.
NOTE: For the alternatives using a rolling windows of 15 years, it is not possible to obtain estimations before the late 70's crisis given that the first real-time estimations is obtained in 1980. For comparability, the thresholds used for the computation of type I/II errors and conditional probabilities are the reference values recommended for the Basel gap (BCBS, 2010). Nonetheless these thresholds could be optimized for each of the alternatives.

AUROC OF ALTERNATIVE HP FILTERS VS MODEL-BASED INDICATORS AT EACH QUARTER AHEAD OF CRISES (5-16 QUARTERS) — CHART 8

The predictive performance of the best HP filter adaptations is similar to that of model-based indicators along the whole pre-crises period.



SOURCE: Own elaboration and Galán and Mencía (2018).
NOTE: The vertical axis represents AUROC values and the horizontal axis represents quarters before the occurrence of systemic events in Spain. For the alternative using a rolling windows of 15 years, it is not possible to obtain estimations before the late 70's crisis given that the first real-time estimations is obtained in 1980.

It is also interesting to check whether or not the adaptations of the HP filter proposed in this study are outperformed by model-based indicators in terms of predictive performance. Table 7 presents this comparison against the four best alternatives of the HP filter analyzed above. Interestingly, the performance of the models is not very different from that of the adaptations of the HP filter assuming a lower length of credit cycle.[8] This is also observed when the AUROC by quarter before the crises is computed (see Chart 8). While the VEC model performs better in predicting crises around four years before the events, its performance is similar to that of the alternative HP filters for later periods.

8 Nonetheless, it is important to notice that, although the HP filter adaptation using a rolling window of 15 years presents the best AUROC values, the window length used in this case avoid assessing the performance before the first systemic crisis. If the AUROC of the VEC model is computed only from 1980, its results improve to 0.95 and 0.96 for 5-12 and 5-16 quarters ahead of systemic events, respectively.

4.3 *Is this valid only for Spain?*

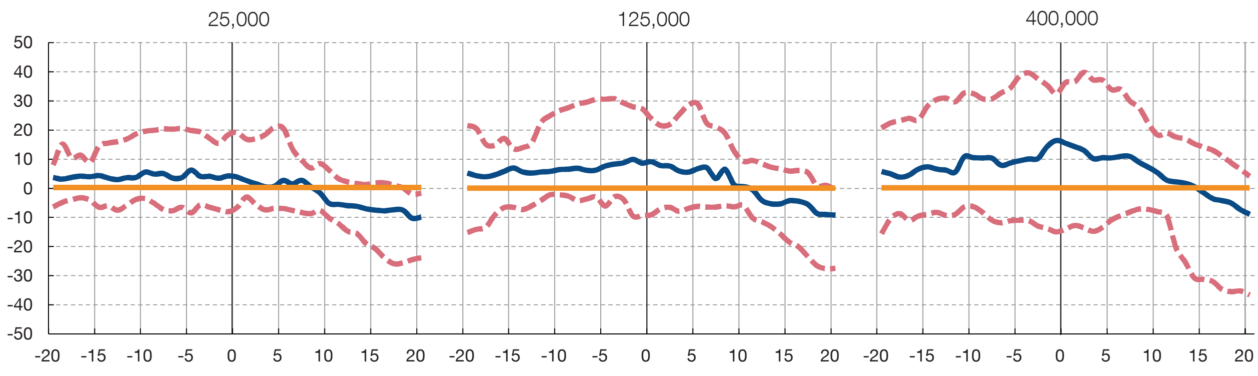
The specific characteristics of the last credit cycle in Spain may be behind the main limitations of the Basel gap in providing useful signals of credit imbalances in the near term. In fact, the magnitude of credit growth after joining the euro, which lasted almost up to the onset of the crisis, and the subsequent deep drop, exacerbated the deviations introduced by the long-memory of the HP filter computed as in the Basel methodology. Thus, it is interesting to check if lowering the smoothing parameter also improves from the Basel gap in other EU countries. In fact, empirical studies have identified lower lengths of the credit cycle (between 15 and 25 years) in samples that cover several EU countries (see Drehmann et al., 2010; Drehmann et al., 2011). In order to check this, I use a sample of 13 EU countries with available series on the credit-to-GDP ratio beginning before 1975. I collect data from the ECB and the dates and definitions reported by countries in the ECB/ESRB crises database recently published in Lo Duca et al. (2017).[9] In particular, I estimate the HP filter for the 13 countries using smoothing parameters equal to 25,000 and 125,000 in addition to the Basel gap.

Chart 9 plots the results for the median and the 10th and 90th percentiles of the pooled distributions of the gap estimates in a range of 20 quarters around the onset of systemic crises. Results show that the higher the smoothing parameter, the greater the estimated gaps both positive and negative. Before crises all alternatives evidence signals of imbalances in more than 50% of the systemic events. However, the 10th percentile exhibits negative values of the gap during pre-crises periods, which are more evident under the filter based on the Basel methodology. Nonetheless, the differences between the different alternatives are more evident after the crises. It is observed that the lower the smoothing parameter, the earlier

9 All crises and residual financial stress events considered to be relevant from a macroprudential perspective are included. The length of the series varies across countries with the longest starting at 1970Q1 and the shortest starting at 2005Q1.

CREDIT-TO-GDP GAP AROUND CRISES IN EU COUNTRIES UNDER DIFFERENT SMOOTHING PARAMETERS OF THE HP FILTER. 10TH, 50TH, AND 90TH PERCENTILES OF THE POOL DISTRIBUTIONS **CHART 9**

Using lower λ values for the HP filter also improve the predictive performance of the estimated gaps in other EU countries. Lower λ values tend to correct both the absence of early warning signals and the post-crises downward biases in a proportion of previous systemic events in the EU.



SOURCE: Own elaboration.
NOTE: The blue solid line represents the median and the dashed lines represent the 10th and 90th percentile of the credit-to-GDP gap around crises, respectively. The horizontal axis represents the number of quarters before and after systemic crises. The vertical dashed line signals the beginning of systemic crises. The horizontal line represents the median of the credit-to-GDP gap in normal times (out of the range -20 to 20 quarters around systemic crises).

AUROC COMPARISON OF THE CREDIT-TO-GDP GAP IN EU COUNTRIES USING DIFFERENT SMOOTHING PARAMETERS (λ) — TABLE 8

Adapting the HP filter to assume lower length of the credit cycle also improves the predictive performance in other EU countries.

	25,000	125,000	400,000
AUROC 12-5	0.71	0.69	0.67
AUROC 16-5	0.72	0.70	0.67
Lag with highest AUROC	9	8	6

SOURCE: Own elaboration.

the gaps decrease recognizing faster the downturn of the cycle. In particular, the median gap turns negative 8, 12 and 16 quarters after the onset of crises using values of λ equal to 25,000, 125,000 and 400,000, respectively. The 10th percentile also evidences that the higher the smoothing parameter, the steeper and more pronounced the decreases in the gaps after crises. In fact, in the case of the Basel gap the 10^{th} percentile decreases more than 30pp between 2 and 4 years after the crises and it stays at those low values even 5 years after the onset of the events.

Table 8 presents the AUROC values for two different ranges of quarters ahead of the onset of the events, as well as the quarter of maximum AUROC. It is observed that the predictive performance ahead of crises improves when lowering the smoothing parameter, being the highest when λ is equal to 25,000. This alternative also provides the best signals earlier than the Basel gap. These results suggest that adapting the HP filter in terms of the smoothing parameter for estimating the credit-to-GDP gap may also be a better alternative for providing faster signals of imbalances during the next cycle in several other countries in Europe besides Spain.

5 Concluding remarks

The Basel gap is the reference indicator proposed by the BCBS and recommended by the ESRB at the European level to guide the decisions on the activation, calibration and release of the CCyB. The indicator presents advantages in terms of its simplicity, which makes it easy to compute and communicate, and also in terms of its relatively good performance as an early warning indicator of previous systemic crises. However, the Basel gap also features some limitations, which have become more evident after the last financial crisis. In particular, after intense credit contractions it suffers of downward biases leading to the estimation of large negative values for the gap in many countries, even currently after several years from the end of the crisis. The main negative implication of this situation is that it will take a long time for the indicator to provide accurate signals of the build-up of cyclical systemic risk during the next cycle. Due to this situation, most countries activating the CCyB in recent years are not following the signals issued by the Basel gap. The main reason behind this problem is the large inertia of the long-run trend estimated using the Basel methodology. In particular, the BCBS proposes to use a one-sided HP filter with a smoothing parameter equal to 400,000. This value was recommended in Drehmann et al. (2010) after assuming that the length of a credit cycle is as long as four times that of a business cycle (i.e. around 30 years). Nonetheless, this assumption is far from being realistic for many countries. Empirical studies have identified lengths of the credit cycle ranging on average between 15 and 25 years in samples that cover developed and emerging economies (see Drehmann et al., 2011; Drehmann et al., 2012). In particular, the empirical evidence for Spain suggests that financial cycles have historically a length of 17 years on average (see Bedayo et al., 2018 for an analysis stretching back to 1880).

This paper assesses whether the performance of the HP filter improves when it is allowed to introduce assumptions in line with empirical evidence on the length of the credit cycle. This improvement is measured not only in terms of early warning signals but also in terms of the magnitude of deviations around crises. In particular, I assess the effects of using lower values of the smoothing parameter as well as rolling windows that allow dropping old information. Results suggest that changing the smoothing parameter has primarily an effect on lowering the amplitude of the estimated gaps, which may avoid exacerbating the deviations from the long-run trend after large variations of the ratio. The use of rolling windows tend to have a more important effect on the speed of incorporating changes in the trends of the estimated gaps, which would allow earlier identification of potential risk signals.

In particular, in the case of Spain, using a smoothing parameter equal to 25,000 appears to improve the early warning performance of the indicator significantly compared to the Basel definition. This value of the smoothing parameter is equivalent to assuming a length of the credit cycle of around 15 years, which is very close to the empirical evidence for Spain. Importantly, the computation of the filter with this smoothing parameter seems to address more properly biases after periods of large variations in the credit-to-GDP ratio, as those observed in Spain during the last financial cycle.

Similar results are obtained when selecting a rolling window equal to 15 years. In this case the early warning performance improves the most among the assessed alternatives. This alternative also provides estimations with lower deviations than the Basel gap. In general, when using rolling windows, the sensitivity to the use of large smoothing parameters is low. Overall, current estimations of the gap with HP filters assuming a shorter length of the credit cycle are more consistent with the last definition of the macroprudential stance and the analysis of other cyclical risk indicators presented by Banco de España (BdE, 2018).

Regarding the use of other alternative statistical filters, I find that they are also sensible to changes in their parameters that would imply different assumptions regarding the length of the financial cycle. The performance of these indicators is found to improve with respect to the Basel gap under certain specifications. Nonetheless, the alternative HP filters proposed outperform these other filtering methods. I also find that the proposed adaptations of the HP filter provide similar performance than model-based indicators of credit imbalances. Finally, I identify that although the length of the financial cycles is heterogeneous among countries, assuming a lower length (between 15 and 22 years) corrects potential biases in several EU countries.

Overall, our results suggests that statistical methods and, in particular, the HP filter still deserves a chance as an early warning indicator of cyclical systemic risk once the assumption on the length of the cycles is relaxed. This adjustment can be justified by empirical evidence on the length of the cycles in each country. Nonetheless, it is important to remark that the characteristics of the financial cycles change over time, and that these assumptions may not necessarily be valid in the future. Thus, complementing the information provided by statistical methods with individual indicators, structural models and qualitative information is of great importance in the assessment of cyclical systemic risk and the calibration of the CCyB.

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Annex 1

COMPARISON BY PERFORMANCE CRITERION OF THE CREDIT-TO-GDP GAP USING DIFFERENT COMBINATIONS OF ROLLING WINDOWS AND SMOOTHING PARAMETER (λ)

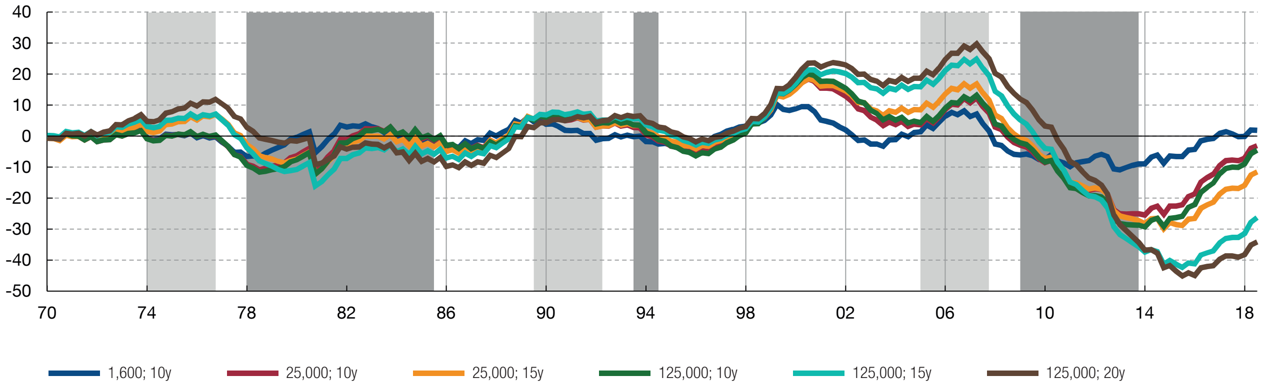
TABLE A1

Time horizon	Performance criterion	λ = 1,600	λ = 25,000	λ = 125,000	λ = 400,000
10	AUROC	0.75	0.79	0.79	0.77
	Type I error	9.6%	5.4%	5.3%	5.3%
	Type II error	87.1%	79.8%	79.5%	79.5%
15	AUROC	78.0%	87.0%	88.0%	88.0%
	Type I error	7.0%	0.0%	0.0%	0.0%
	Type II error	81.7%	71.8%	73.9%	74.5%
20	AUROC	78.0%	84.0%	82.0%	81.0%
	Type I error	6.8%	0.0%	0.0%	0.0%
	Type II error	80.6%	71.8%	75.3%	76.5%
Full sample	AUROC	72.0%	81.0%	79.0%	75.0%
	Type I error	9.8%	5.1%	5.3%	8.8%
	Type II error	87.5%	77.5%	79.5%	85.5%

SOURCE: Own elaboration.
NOTE: The AUROC 16-5 quarters ahead of systemic events is presented. Type I and II errors are computed at a threshold equivalent to a 2pp gap.

ESTIMATED GAPS USING ALTERNATIVE COMBINATIONS OF ROLLING WINDOWS AND SMOOTHING PARAMETER (λ)

CHART A1



SOURCE: Banco de España. Own elaboration.
NOTE: The grey shaded areas denote three financial stress periods identified in Spain since 1970, corresponding to two periods of systemic banking crises (1978-Q1 to 1985-Q3; 2009-Q1 to 2013-Q4) and one idiosyncratic event (1993-Q3 to 1994-Q3).). The light grey shaded areas represent the period from 5 to 16 quarters ahead of the onset of the systemic events, when it is desirable to identify risk signals for macroprudential policy purposes.

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