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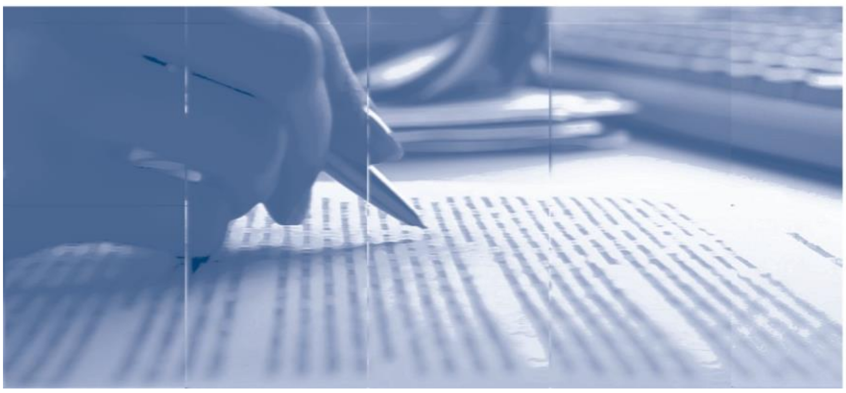

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Countercyclical Capital Buffers: bayesian estimates and alternatives focusing on credit growth[*]

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Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central do Brasil.

We re-evaluate the proposed framework of the Basel Committee on Banking Supervision (BCBS) to look into the credit-to-GDP gap as a leading indicator related to the Countercyclical Capital Buffer (CCB) and propose an alternative approach focusing at credit-to-GDP growth. We follow earlier work that the HP filter, especially with the proposed smoothing factor calibration, HP(400k), could possibly create spurious cycles. Moreover, it would not properly fit short credit series. With that in mind, we estimate Bayesian STMs for 34 countries and evaluate on-line (one-sided) estimates of their state components as well as other variables derived from their joint posterior distributions to anticipate crisis. The probabilities associated with the slope of the credit-to-GDP estimated using a one-sided STM have lower noise-to-signal ratios (NS) than the credit-to-GDP gap, especially considering a robustness exercise comprise of short series. The slope of the one-sided HP(150), which is simpler but closely related to our STM in its gain function, also performs better in anticipating crisis both in short and long series when compared to the credit-to-GDP gap. Finally, we put forward an exercise of CCB using the last available data point and our five leading indicators in all 34 countries.

Keywords: financial cycle, bayesian STM, Countercyclical Capital Buffer (CCB), banking crisis, noise-to-signal (NS)

JEL Classification: E44, E51, E32, C11, C22

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1. Introduction

Since the U.S. Subprime Meltdown and the ensuing global credit crunch and economic recession, regulators have looked into alternatives to minimize the probability and severity of such events. Time-varying regulatory capital buffers for banks are among these tools. Embedded in the Basel III framework, the Countercyclical Capital Buffer (CCB) is about to phase-in starting in 2015. However, at least two questions remain: 1) the effectiveness of such instrument – even as a simple layer of protection to withstand future losses; and 2) the decision-making process, i.e., the timing for accumulation (and release) of the capital buffer.

In this paper, we focus on the latter. Following Drehmann et al. (2011), we evaluate the credit-to-GDP as a leading indicator that could anticipate disrupting events for the banking industry within a three-year window. We look into 34 countries and 40 crises and calibrate thresholds for several state estimates of Structural Time Series Models (STM) and other simpler alternatives in order to maximize their anticipating power over crises and minimize noise surrounding activation signals for the CCB.

Even though the one-sided credit-to-GDP gap, as proposed by the Basel Committee, does perform well as an early warning tool, the slope component is less noisy and predicts just as many crises. The slope of the credit-to-GDP estimated using the Hodrick Prescott (HP, $\lambda^{HP} = 150$) filter also has a good performance and the advantage of being easier to apply and simpler to communicate. Moreover, the credit-to-GDP gap fails a robustness check in short series. In this paper, we use a database similar to Drehmann et al. (2011) and evaluate our results following the same methodology and, as an alternative, following Kaminsky and Reinhart (1999) more closely.

2. Literature Review

Time-varying countercyclical capital requirements are a new instrument mostly built on the ideas of Borio et al. (2001), Borio and Lowe (2002) and Borio (2003). The authors argue that procyclicality comes from risk measurement itself and agency issues amplified by collective undesirable outcomes emerging from bank individual actions. The Basel Committee on Bank Supervision embraced such view in the aftermath of the Subprime Meltdown (BCBS, 2010a and 2010b), putting forward the Countercyclical Capital Buffer (CCB).

When analyzing the CCB, one must grapple with two related concepts: 1) a sustainable level of financial intermediation whose positive deviations may represent pockets of systemic risk (materialized in downturns – see Borio, 2009); and 2) a financial and periodic cycle that is represented as the deviations from such sustainable (or natural) level of financial intermediation.

More generally, assessing sustainability of credit growth as deviations from a long-term trend is being carried out both through a purely statistical perspective, e.g. Gourinchas et al. (2001), Tornell and Westermann (2002) and Coudert and Pouvelle (2010), and as a function of other economic fundamentals (Cotarelli et al., 2005, Boissay et al, 2005).

The existence of a financial cycle, longer than the business one and whose swings supervisors would like to alleviate or, at least, to have banking capital leaning against (BCBS, 2010b) is the conceptual foundation of CCB. Important critics are drawn by Repullo and Saurina (2011), who believe this type of policy may be indeed more procyclical as it misses the business cycle.

Claessens et al. (2009 and 2011) and Mendoza and Terrones (2008) draw work on main characteristics of financial cycles and its interactions with the business one. Lown and Morgan (2006) take an alternative approach describing the financial cycle around opinion surveys from loan officers. Drehmann et al. (2012) document financial cycles averaging 16 years and by splitting the sample in two, before and after 1998, finds an increase from 11 to 20 years.

Drehmann et al. (2010) also define the cycle as the distance between credit crises. In that respect, Bordo and Haubrich (2009), Laeven and Valencia (2008, 2010), Reinhart and Rogoff (2009) and Drehmman et al. (2011) identified the periods of credit distress usually related to busts.

Dell'Ariccia et al. (2012) evaluate policy responses to credit booms and Che and Shinagawa (2014) are concerned with financial stability across different stages of the financial cycle.

Drehmann et al. (2011) look into several indicators that could proxy a financial cycle, their predictive power and behavior around crises. These indicators comprise macroeconomic, banking sector activities and cost of funding. The leading one in terms of anticipating crises is the credit-to-GDP gap estimated using the Hodrick and Prescott (1997) filter with a λ^{HP} smoothing factor of 400,000, i.e., HP(400k). Drehmann and

Juselius (2014) also find that debt service ratio (DSR) perform well as a short-term early warning indicator, while the credit-to-GDP gap is better in the long-run.

This stream of the literature is particularly interesting because it connects CCB, the definition of financial cycle, and the systemic risk through crises anticipation. It also creates a straightforward strategy to evaluate indicators that could anchor Macroprudential Policy and are connected to its main purpose. The Basel Committee on Bank Supervision elected the credit-to-GDP gap estimated using HP(400k) as an anchor for CCB precisely following this rationale (BCBS, 2010a and 2010b).

This paper relates closely to the work of Drehmann et al. (2011) and Drehmann and Juselius (2014). We take credit-to-GDP as a leading indicator, but explore other properties of this indicator estimating Bayesian Structural Time Series Models (STM) for 34 countries and evaluating the predictive power of the related state equations. We also evaluate HP alternatives mostly related to the slope of credit-to-GDP, i.e., the growth rate that can proxy a sustainable level of credit growth. In this paper, we take the credit and financial cycles as equivalents.

The main motivation to evaluate such alternatives comes from Harvey and Jaeger (1993) and Harvey and Trimbur (2003, 2008) that report spurious cycles when the λ^{HP} smoothing factor is not properly set and favors direct estimation of the frequency parameter λ using STM. When Drehmann et al. (2011) proposes HP(400k), based on Ravn and Uhlig (2002) conversion formula (1), it is implicit that the credit cycle is four times longer than the business one in all countries.[1]

Setting HP(400k) has other implications though. An *ad hoc* cut-off period (T) of 39.5 years is implied. Thus, only extremely low frequency components are indeed cut-off by the filter, as most countries do not even have such long series (see Iacobucci and Noullez, 2004 and formulas 1 and 2[2]).

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[1] See (1 and 2)

$$\lambda_s^{HP} = s^4 \cdot \lambda_q^{HP} \tag{1}$$

$$T = \frac{\left(\frac{\pi}{4}\right)}{\arcsin\left(\frac{\lambda^{HP^{-1/4}}}{2}\right)} \tag{2}$$

where $\lambda_q = 1600$ is the value for quarterly sampled series (suggested by Hodrick and Prescott, 1997 for the US GDP) and s is the new sampling frequency relative to one quarter (e.g., 1/4 for annual and 3 for monthly samples). That is to say, s is no longer 1 but 4 leading to $\lambda_s = 4^4 \cdot 1600 = 400k$ (Drehmann et al., 2010 and 2011).

[2] Formula 2 is obtained as the point where the frequency response of HP filter reaches 0.5 (Iacobucci and Noullez, 2004).

3. Data and Methodology

The data we use for credit aggregates is the same provided by and publicly available from the BIS website (Dembiermont et al., 2013). The quarterly GDP is obtained from the OCDE database[3]. Following BCBS (2010a) and Dembiermont et al. (2013), we use a broader definition of credit to account for risks that may be originated outside the banking system. The data is very similar to the one in Drehmann et al. (2011), but updated to 2013. Our sample is comprised of 34 countries and 40 crises. We follow Drehmann et al. (2011) on crisis dates for greater comparability (see details on Appendix A).

We estimate Harvey et al. (2007) Bayesian Structural Time Series Model (STM) to further explore its state components and its related information extracted from the joint posterior densities. Early warning exercises are then carried out on these one-sided state estimates as well as on one-sided HP estimates. We also provide a robustness check using shorter series.

Bayesian STM

Structural Time Series Models could be formulated directly in terms of its unobserved components (Koopman et al., 2009). Harvey and Jagger (1993) strongly suggest the use of these models to both represent stylized facts about macroeconomic series and assess limitations of alternative *ad hoc* methods. The authors demonstrate that the HP filter can easily create spurious cycles and also illustrate how structural time series analysis can be used to detect cyclical, trend, and seasonal components (Harvey, Jaeger, 1993; Harvey, Trimbur, 2008). We use a similar approach to estimate trend and cycle components.

The full model of this paper can be found in Harvey et al. (2007), as described in terms of a measurement equation (3) and the state equations (4 to 6), where μ_t represents a local level, ψ_t the cyclical state vector, and ε_t a white noise process:

$$y_t = \mu_t + \psi_t + \varepsilon_{t,} \ \varepsilon_t \sim NID(0, \sigma_\varepsilon^2) \tag{3}$$

[3] For Brazil, we use quarterly GDP available at Central Bank of Brazil website. We also construct the broad credit to non-financial private sector series using data available at the same source.

The state vector (4) represents the trend component and (5) the slope component that feeds into the trend component, where β_t represents the slope, η_t a white noise for local level and ζ_t the slope vector residual. Observe that σ_η^2 is set to zero, because we decide to use a smooth trend (see more on Koopman et al., 2009).

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_{t,}\ \eta_t \sim NID\left(0, \sigma_\eta^2 = 0\right) \tag{4}$$

$$\beta_t = \beta_{t-1} + \zeta_{t,}\ \zeta_t \sim NID\left(0, \sigma_\zeta^2\right) \tag{5}$$

In our model, the cyclical state component (6) is of order $k = 2$, specified as $\psi_t = \psi_t^{(k)}$. In this case, for $j = 1, 2$ (See Harvey and Trimbur, 2003):

$$\begin{bmatrix} \psi_t^{(j)} \\ {\psi_t}^{*(j)} \end{bmatrix} = \rho \begin{bmatrix} cos\lambda_c & sin\lambda_c \\ -sin\lambda_c & cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(j)} \\ {\psi_{t-1}}^{*(j)} \end{bmatrix} + \begin{bmatrix} \psi_t^{(j-1)} \\ {\psi_t}^{*(j-1)} \end{bmatrix}, \text{where} \tag{6}$$

$\begin{bmatrix} \psi_t^{(0)} \\ {\psi_t}^{*(0)} \end{bmatrix} = \begin{bmatrix} \kappa_t \\ {\kappa_t}^{*} \end{bmatrix}$ are two mutually uncorrelated white noise disturbances with zero means and common variance σ_κ^2 and λ_c is the frequency in radians, in the range [0, π]. The cycle period is $2\pi/\lambda_c$ and this stochastic cycle becomes an AR(1) if λ_c is 0 or π (Trimbur, 2006). It is important to highlight that the cycle is stochastic only in terms of amplitude.

A higher k leads to more pronounced cut-offs of the band-pass gain function at both ends of the range of cycle frequencies centered at λ_c, rendering smoother cycles. We follow Harvey and Trimbur (2003) and Harvey et al. (2007) and test several k orders of the cycle for robustness.

The q_c ratio (signal-to-noise) in this model is expressed in (7) (Harvey and Trimbur, 2008):

$$q_c = \frac{\sigma_\zeta^2}{\sigma_\varepsilon^2 + \sigma_\psi^2} \tag{7}$$

where σ_ψ^2 is the variance of the state component ψ, closely related to σ_κ^2 and ρ.

As demonstrated by Hodrick and Prescott (1996), the estimated q-ratio (8) is related to the HP smoothing factor, λ^{HP}.

$$\lambda = \lambda^{HP} = \frac{1}{q} \tag{8}$$

The q-ratio (8) from an estimated model without cycle is fully comparable to the one of the HP filter, but the q-ratio (8) is not comparable to the q-ratio (7) of an estimated model with a cycle. However, the cut-off frequency of the estimated STM and HP filter can be matched in their gain functions, so that these two filters render approximate results (Harvey and Trimbur, 2008). See more on Appendix C.

Bayesian estimations are carried out for five of these parameters (Harvey et al., 2007) $\theta = \{\sigma_\zeta^2, \sigma_\kappa^2, \sigma_\varepsilon^2, \rho, \lambda_c,\}$ and the posterior distribution can be accessed using (9):

$$p(\theta|y) = L(\theta; y)p(\theta) \tag{9}$$

where the likelihood function $L(\theta; y)$ is evaluated using the Kalman Filter.

Similarly, the marginal likelihood $M(y)$ is (10):

$$M(y) = \int L(\theta; y)p(\theta)d\theta \tag{10}$$

Markov Chain Monte Carlo (MCMC) methods are a convenient way to sample parameter drawings from the posterior. Two great advantages in adopting a bayesian framework in STM are: 1) avoid fitting implausible models and 2) investigate parameter uncertainty in the posterior distribution of the cycle and trend components. In this work, we follow the same computational procedure of Harvey et al. (2007) (see also, Durbin and Koopman, 2002, Koop and Van Dijk, 2000 for details on the simulation smoother).

For the financial cycle, we rely on Drehmann et al. (2010) and set the prior mode of λ_c to meet the median distance between crises, 15 years, i.e. $2\pi/60$. However, as the degree of uncertainty around the cycle frequency is expressive, we choose a wide prior so that the proportional spread, the relation between the standard deviation and the mode of the beta distribution, $\sigma_y/\hat{\mu}_y$, is 100% (see more on Harvey et al., 2007). The wide prior is set in a way that could (if necessary) encompass the business cycle. We set non-informative flat distributions to all other four parameters. The parameter ρ is also truncated to lay in the interval $[0,1]$ as expected in the model.

A great advantage of this methodology is that one-sided estimates can be assessed straightforwardly, reflecting information available to the policy-maker at the time of the crisis and, therefore, are directly comparable to those of the one-sided HP filter.

A framework for crisis early-warning

After estimating this model on the credit-to-GDP series of 34 countries, we proceed to evaluate the early-warning properties of the state components and other related information (indicators) for the build-up phase that could trigger the Countercyclical Capital Buffer (CCB). Our approach maintains the same spirit as that of Drehmann et al. (2011) and we look to a similar dataset.

Basically, if the value of one indicator is above a threshold, a signal is issued. To access the performance of these indicators, we follow both Drehmann et al. (2011) framework (BCBS Approach) and Kaminsky and Reinhart (1999) (KR Approach). There are some important differences. Additionally, we follow Drehmann and Juselius (2014) for indicators classification using receiver operating characteristic (ROC) curves and the area under the curve (AUC), also distinguishing between BCBS and KR approaches.

The BCBS approach

In this Approach, we follow the exactly same method of Drehmann et al. (2011). In details, there are two types of forecast errors:

- Type 1 error: no signal is issued and a crisis occurs in a three years window before the crisis;
- Type 2 error: a signal is issued and no crisis occurs in a three years window before the crisis;

Both are summarized by the *noise-to-signal* ratio (NS) calculated as (11):

$$NS = \frac{T_2}{1 - T_1} \tag{11}$$

Where T_1 is the fraction of type 1 errors relative to all crises dates and T_2 is the fraction of type 2 errors relative to non-crises dates. Signals in the two years period after the beginning of a crisis (crisis included) are not considered. Also, if a crisis occurs in the first three years of a series, we consider only data two years after this crisis date. An important point is that if the indicator issues a signal in the three years window before a crisis, this crisis is considered predicted, *even if the indicator does not issue other signals all over this period.*

The Kaminsky and Reinhart (KR) approach

Kaminsky and Reinhart (1999) illustrate their approach using the following matrix:

	Crisis occurs in the following 3 years	No crisis occurs in the following 3 years
Indicator issues a signal	A	B
Indicator does not issues a signal	C	D

Table 1: NS as in Kaminsky and Reinhart (1999), adapted.

At each point in time:

- if the indicator issues a signal and a crisis occur in the next 3 years, A is increased by one unit;
- if the indicator issues a signal and NO crisis occur in the next 3 years, B is increased by one unit;
- if the indicator DOES NOT issues a signal and a crisis occur in the next 3 years, C is increased by one unit;
- if the indicator DOES NOT issues a signal and NO crisis occur in the next 3 years, D is increased by one unit.

In other words, A counts correct positive signals, B counts false positives, C counts false negatives and D correct negative signals. Signals in the two years period after the beginning of a crisis are not considered, for the same reasons of the BCBS Approach. The *noise-to-signal* ratio (NS) is the ratio of false positives (B) to all possible false positives (B+D) divided by the ratio of correct positive signals (A) to all possible positive signals (A+C), that is:

$$NS = \frac{B}{(B+D)} \times \frac{(A+C)}{A} \tag{12}$$

Noise-to-signal ratio: KR x BCBS approach

To improve comparability with the BCBS Approach, we clarify this aspect a little bit more.

In (12), C represents the type 1 errors and B represents the type 2 errors. The total of crisis dates is represented by A+C while the total of no-crisis dates is represented by B+D. Substituting these figures in (11), we have (13).

$$T_1 = \frac{C}{(A+C)} \text{ and } T_2 = \frac{B}{(B+D)}. \tag{13}$$

However, there is an interpretation issue worth noticing. In the KR Approach, A+C represents *all possible correct signals*, which is different from the BCBS interpretation that this represents *all crisis dates*. In the BCBS Approach, if a series has 2 crisis, A+C = 2, and in the KR Approach A+C = 24 (for quarterly data and 3 years window), which is the number of *points in time* for which a correct signal is possible. As an example, consider the following situation:

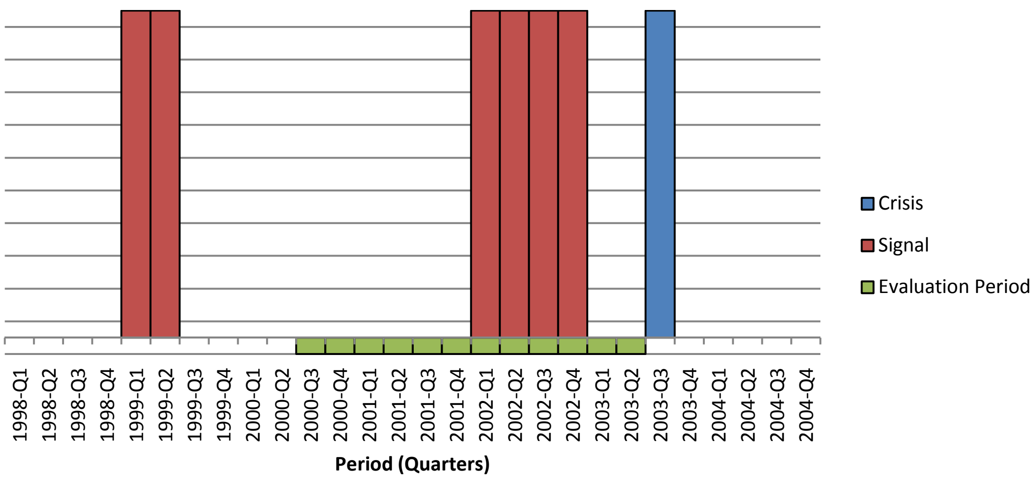

Figure 1: Signal before a crisis.

In Figure 1, the blue bar represents the beginning of a crisis (here 2003-Q3), the red bars represents signals by the indicator (1999-Q1 to 1999-Q2 and 2002-Q1 to 2002-Q4) and the green bars below the horizontal axis represents the 3 years window before the crisis (evaluation period).

The BCBS Approach considers this crisis predicted so that there are no Type 1 errors. As we have one crisis, $T_1 = 0/1 = 0$. Also, there are two Type 2 errors, and we have $T_2 = 2/10 = 0.2$ (the denominator 10 is the number of data points where there is no crisis in the next 3 years, discarding the two years window after a crisis).

In this example, $NS = \frac{T_2}{1-T_1} = 20\%$.

The KR Approach considers the following:

I. A = 4, corresponding to the four correct signals inside the evaluation period;
II. B = 2, corresponding to the two false alarms outside the evaluation period;
III. C = 8, corresponding to the eight points inside the evaluation period where there are no signals;
IV. D = 8, corresponding to the eight points outside the evaluation period where there are no signals (discarding the two years period after the crisis).

These figures imply a NS of 60%, according to (12). The KR and BCBS Approach results are very different, thus not directly comparable. We evaluate all our estimates in both of these frameworks, but we consider KR a more conservative choice.

The rationale lays in the fact that the BCBS Approach considers a crisis predicted even if the indicator signals only once inside the evaluation period. Therefore, there is a positive bias towards the prediction rate that tends to underestimate NS as compared to KR, especially in the case of a volatile indicator. As an illustration, consider the following situation:

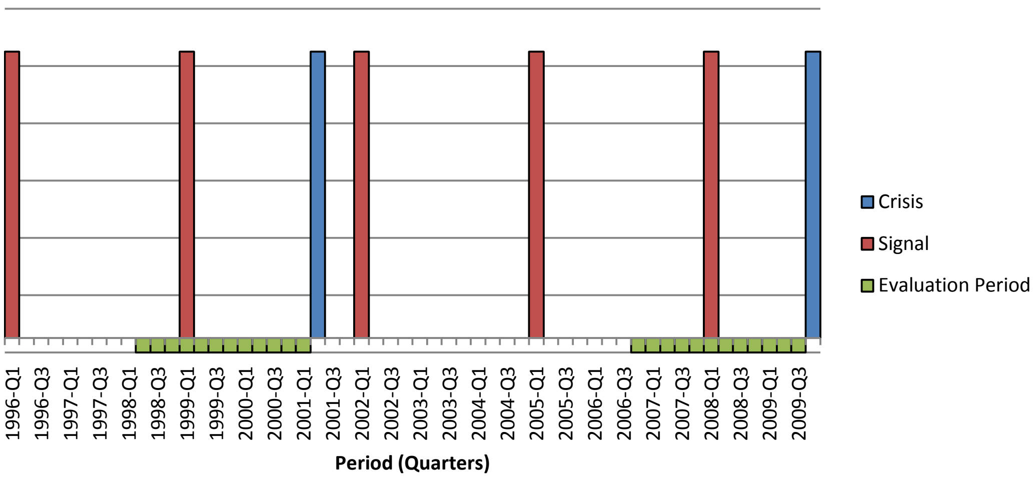

Figure 2: Pulse train indicator.

In Figure 2, the indicator is a pulse train, a periodic signal with a 3 years period. By the BCBS approach, both crises where predicted (prediction rate of 100%) and the $NS = 8.7\%$. In the KR Approach, $NS = 104\%$.

Now consider a more informative indicator for the same situation. In Figure 3, the BCBS approach points to a predicting rate of 100% with a NS of 8.7%, i.e., the same predicting power of the pulse train. However, KR assigns a NS of 11% for this indicator, more precisely discriminating between the informative indicator and the pulse train.

This phenomenon is a consequence of the Type 1 error interpretation of the BCBS approach. Not considering false negatives inside the evaluation period as Type 1 errors leads to an overestimation of the prediction power of an indicator that signals erratically over time.

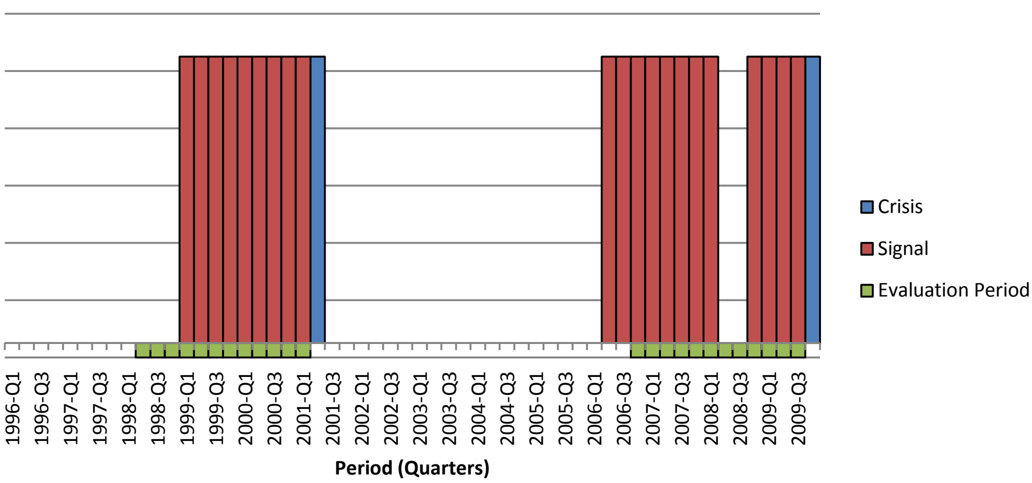

Figure 3: “More informative” indicator.

Most variables in Drehmann et al. (2011) are relatively continuous over time, keeping the main conclusions of the paper untouched. However, we face more volatile indicators in our analysis. The leading indicators usually perform well under both approaches.

ROC curves and AUCs

This technique is an attempt to circumvent the problem of evaluating costs and benefits for policy makers. These issues were addressed in Drehmann et al. (2011) by choice of criteria for NS minimization given at least 2/3 of crises predicted and, later, fixing NS to maximize prediction rates.

In ROC analysis, a range of possible utility functions are implicitly evaluated as all thresholds are evaluated. As in Drehmann and Juselius(2014), we calculate ROC curves based on false positive rates (type 2 errors) and true positive rates (one minus type 1 errors) obtained varying the thresholds for BCBS and KR approaches.

The idea is to choose the best indicator evaluating the area under the ROC curve (AUC), obtained by trapezoidal rule (Fawcett, 2006) as it contains information of all possible thresholds.

Robustness check: shorter series exercise

Some countries have limited datasets for the construction of the broad credit series and, consequently, the credit-to-GDP ratio. With less data and considering the cut-off period of 39.5 years implied in the HP(400k), we hypothesize that HP(400k) is not a good choice in these countries. For short series, a 400k smoothing parameter implies an almost linear trend, and the one-sided estimate of the trend becomes relatively rigid, bringing some issues, like the difficulty with structural breaks and occasionally spurious estimates.

For this reason, we make a short series exercise, to assess the robustness of the early warning indicators using limited information. We choose a relatively short series as a benchmark and artificially create other short series from the longer ones. We also exclude from our sample those series shorter than the benchmark. The procedure is as follows:

1. We choose the Brazilian series as our benchmark for series length. Its length is 73 data points (dp) (18¼ years). Czech Republic, Hungary and Poland have series of about the same size, 76 data points;

2. For each series whose length is longer than 73 dps we take the last 73 points as the first artificial short series. (Most series end in 2013Q4). To create the second series, we cut the last 37 points[4] (from the series end) and repeat the procedure taking new 73 dps until the beginning of the series is reached. In other words, we take half of the first short series to create the second and so on. If the remaining series has length slightly longer than 73, we take the last 73 points of the original one. Following this procedure, we have created 122 "artificial countries" for which we estimated 122 models. The short series are listed in Appendix B.

In this procedure, most countries will contribute with more than one short series. Argentina, India, Indonesia and Luxembourg are excluded though, as they do not meet the 73 dps length criteria we impose.

The purpose of this exercise is to evaluate the predictive power of our model, of the proposed BCBS indicator, HP(400k), and also of some other indicators with incomplete information.

The overall list of indicators we evaluate and descriptions is presented in Table 2:

[4] The rationale to choose 37 data points is that this is approximately half of the short series size. In a situation where there is a crisis in the beginning of the short series, this crisis may be excluded from the sample by the procedures of NS evaluation. However, moving back just half of the short series size, we guarantee that this crisis is accounted for in the next short series detached from the same country.

Indicator	Notation	Description
Cycle Change Median	$D\tilde{\psi}_{2,t}$	Median of the 2nd order cycle change, $\tilde{\psi}_{2,t}$, sampled from the posterior distribution of $D\psi_{2,t}$. With an approximated solution in discrete time (Harvey et al, 2007), $D\psi_{2,t}$ measures the rate of change in the cycle, an interesting indicator to evaluate turning-points. The approximation is: $$D\psi_{2,t} = (log\rho)\psi_{2,t} + \lambda_c\psi^*_{2,t} + \rho^{-1}(\psi_{1,t}cos\lambda_c - \psi^*_{1,t}sin\lambda_c)$$
Cycle Median	$\tilde{\psi}_{2,t}$	Median of the cyclical state component, $\tilde{\psi}_{2,t}$, sampled from the posterior distribution of ψ_2 in *t*.
Simple Slope	Δ	First difference of the credit-to-GDP series, $\Delta(\frac{credit}{GDP})$.
Moving average of Simple Slope	MOVAV(Δ)	1 year moving average of $\Delta(\frac{credit}{GDP})$, $$\sum_{i=0}^{3}\Delta(\frac{credit_{t-i}}{GDP_{t-i}})\ /4$$
Pulse train	Pulse train	Pulse train with 3 years period.
Gap using HP(400k)_0.10	Gap HP(400k)_0.10	Credit-to-GDP gap estimated using an HP filter with $\lambda = 400k$, HP(400k), i.e., the irregular additive component referred to as cycle. This is the benchmark of this paper, because it is the leading indicator proposed by BCBS (2010) and Drehmman et al. (2011). The authors suggest the fixed threshold of 10% to best anticipate crises.
Gap using HP(400k)	Gap HP(400k)	Same as before, but we optimize the threshold to better fit our data. This is the **benchmark** in all following tables.
Probability of Cycle Change	$P(D\psi_{2,t}) > 0$	Probability that the cycle change is positive.
Probability of (positive) Cycle	$P(\psi_{2,t}) > 0$	Probability that the cycle state is positive.
Probability of (positive) Slope	$P(\beta_t) > 0$	Probability that the slope state is positive.
Probability of growth over median	$P(\beta_t - \bar{\beta}_t\ ) > 0$	Probability that the slope is greater than its on-line (one-sided) mean. The online mean is the sample mean of the slope estimate to the point of the assessment of the indicator. It is an on-line proxy for the "long run growth" of the credit-to-GDP ratio. $$P\left[\beta_t - \sum_{i=1}^{t}\beta_t/t\right] > 0$$
Slope Median	$\tilde{\beta}_t$	Median of the slope state component, $\tilde{\beta}_t$, sampled from the posterior distribution of β in *t*.
Slope using HP(150)	$\Delta\mu^{HP(150)}$	Consider that the effect of applying an HP filter (with $\lambda = 150$) on a certain series *y* results on two additive components, usually referred to as trend, μ^{HP} and a residual. The indicator comprises of the first difference of μ^{HP} component, i.e., $\Delta\mu^{HP}$. This indicator is created to match the results of STM (Appendix C).

Table 2: List of indicators and descriptions.

4. Results

In this session, we present our findings over the one-sided indicators in Table 2. First, we estimate the optimum thresholds for every variable in three cases, two related to the BCBS approach and one related to KR. Second, we present our results for these three criteria, considering, in all cases, the optimized thresholds. Third, we show the AUCs extracted from ROC analysis for BCBS and KR approaches. Fourth, we follow the same scheme for the robustness check session with short series and, finally, we present an illustrative panel of the state of CCB over our sample considering the last available data point.

The procedures we apply to estimate the optimum threshold for every indicator in the BCBS framework consists of:

- minimizing NS for all countries given that the indicator predicts at least 2/3 of the sample crisis, as in Drehmann et al. (2011);
- maximizing the prediction rate for thresholds that keep the NS lower than 16%. We do that because in Drehmann et al. (2011) the best indicator reaches a 16% NS;

In the KR framework, the optimum threshold is based only on the first criterion, because the second is meaningless, given the different scales of the NS as compared to the BCBS Approach. The AUCs are estimated applying trapezoidal rule over ROC curves obtained by threshold variation over a large range both in KR and BCBS approaches. In other words, we evaluate five cases, but we focus our analysis on KR. The best variables are usually the same, except for the robustness check exercise.

Table 3 presents the first case. The results are ordered from the lowest NS subject to a minimum of 2/3 of crises predicted (BCBS approach). Naturally, it is impossible to optimize the prediction rate and NS at the same time as one usually comes at the expense of the other.

First thing to be noted is the BCBS indicator, credit-to-GDP gap calculated using HP(400k), the **benchmark**, with a threshold set to 10% did not predict 67% of the crises. Naturally, our sample is slightly different than the original and our optimized threshold would be a bit lower, 9.1%, but close to the original one. In this last case, the benchmark predicts 67% of the crises (the minimum prediction rate), figuring as our 7th best indicator. This NS figure of 22% is worse than the original performance presented in Drehmann et al. (2011) where NS is 16%. The slope or slope related components present the best results.

#	Indicator	NS	Predicted	Threshold
1	Pulse Train[5]	9%	100%	0.001
2	Simple Slope	12%	69%	0.032
3	Probability of (positive) Slope	15%	69%	0.989
4	Probability of growth over mean	15%	69%	0.945
5	Slope using HP(150)	15%	69%	0.021
6	Moving average of Simple Slope	18%	68%	0.017
7	**Benchmark**	**22%**	**67%**	**0.091**
8	Probability of Cycle Change	22%	77%	0.557
9	Probability of (positive) Cycle	24%	74%	0.593
10	Slope Median	26%	80%	0.012
11	Cycle Change Median	30%	71%	0.002
12	Cycle Median	37%	71%	0.002

Table 3: Lowest NS given at least 2/3 of crisis predicted. BCBS approach. Complete series.

An authority in charge of CCB may naturally favor less noise to prediction rates. This is, in a sense, the rationale of Table 3. In Table 4, the noise tolerance is fixed and the prediction rate is maximized. In this case, the authority would set more conservative thresholds for indicators that perform better (in noise sense) in the first case. We ordered variables by prediction rate.

Table 4 presents the second case, where the prediction rate is maximized given at most 16% of NS.

#	Indicator	NS	Predicted	Threshold
1	Pulse Train	9%	100%	0.001
2	Simple Slope	16%	77%	0.026
3	Probability of (positive) Slope	16%	71%	0.987
4	Slope using HP(150)	15%	69%	0.021
5	Probability of growth over mean	15%	69%	0.945
6	Moving average of Simple Slope	14%	62%	0.02
7	Probability of (positive) Cycle	14%	54%	0.654
8	**Benchmark**	**16%**	**52%**	**0.129**
9	Slope Median	13%	51%	0.021
10	Cycle Median	13%	49%	0.007
11	Probability of Cycle Change	15%	34%	0.619

Table 4: Highest prediction rate given at most 16% of NS. BCBS Approach. Complete series.

[5] As noted in the methodology, we present the pulse train results to point out the limitation of the BCBS approach to volatile indicators. The pulse train was the best indicator, followed by the informative indicators Probability of excess of credit-to-GDP growth, credit-to-GDP growth and Probability of credit-to-GDP growth.

In Table 4, the benchmark threshold ended up being increased to 12.9, because it was already above 16%. As a consequence, its prediction rate decreased to 52%. The slope indicators are still the preferred ones. The best four slope variables already presented NS figures close to 16% in Table 3. In these cases, increasing NS also increases the prediction rate. The rationale of the exercise still remains and illustrates that authorities utility function may influence their thresholds justifying a complementary technique to jointly evaluate indicators on the basis of all possible thresholds with ROC curves and AUCs (Drehmann and Juselius, 2014).

Table 5 presents the AUCs through BCBS approach:

#	Indicator	AUC
1	Pulse Train	96%
2	Simple Slope	92%
3	Probability of Cycle Change	88%
4	Slope using HP(150)	87%
5	Moving average of Simple Slope	87%
6	Probability of (positive) Cycle	87%
7	Probability of (positive) Slope	86%
8	Probability of growth over mean	86%
9	Cycle Change Median	86%
10	Slope Median	85%
11	Cycle Median	84%
12	**Benchmark**	**82%**

Table 5: AUCs for each indicator. BCBS Approach. Complete series.

Here, the benchmark shows the worst performance. But, it may be pointed out that results are relatively close, with the exception of first placed indicators. As confidence intervals for AUCs were not computed, it is difficult to state that the ordering of close indicators in Table 5 is rather rigorous. Slope related indicators also show better performance, with the notable exception of Probability of Cycle Change and Probability of (positive) Cycle.

Table 6 presents results for the KR approach. The criterion is minimum NS for at least 2/3 of crisis predicted as in Table 3. As noted in the methodology session, NS increases substantially for all variables, which is a consequence of KRs conservativeness.

Some things are worth noticing in Table 6. First, the pulse train is correctly deemed a bad indicator, because KR does not suffer the BCBS' drawbacks. However, this aspect highlights how stable is the benchmark as opposed to several other indicators appraised insofar. The best indicator in the previous approach, Simple Slope, is now at 6th position, because it proved too unstable in the evaluation window.

#	Indicator	NS	Predicted	Threshold
1	Probability of (positive) Slope	28.6%	66.7%	0.989
2	**Benchmark**	**29.0%**	**67.6%**	**0.091**
3	Probability of growth over mean	29.2%	66.7%	0.945
4	Slope using HP(150)	30.7%	67.6%	0.021
5	Moving average of Simple Slope	33.1%	66.7%	0.016
6	Simple Slope	40.1%	67.6%	0.03
7	Slope Median	43.4%	80.6%	0.012
8	Probability of (positive) Cycle	58.1%	66.7%	0.601
9	Cycle Median	75.6%	86.1%	0.001
10	Probability of Cycle Change	91.2%	100.0%	0.368
11	Pulse Train	96.6%	97.2%	0.001
12	Cycle Change Median	99.4%	94.4%	0.001

Table 6: Lowest NS given at least 2/3 of crisis predicted. KR Approach. Complete series.

The benchmark reached the second best position in terms of NS, but so closely paired to the probability of positive growth that they may be considered equivalent. All other variables up to 7th position are still slope related.

Table 7 presents the AUCs through KR approach:

#	Indicator	AUC
1	**Benchmark**	**72%**
2	Slope Median	68%
3	Moving average of Simple Slope	68%
4	Probability of (positive) Slope	67%
5	Slope using HP(150)	67%
6	Probability of growth over mean	66%
7	Simple Slope	60%
8	Probability of (positive) Cycle	56%
9	Cycle Median	56%
10	Pulse Train	50%
11	Cycle Change Median	50%
12	Probability of Cycle Change	49%

Table 7: AUCs for each indicator. KR Approach. Complete series.

Notice that unstable indicators are adequately punished, and the benchmark reaches 1st place. The Probability of Cycle Change and Probability of (positive) Cycle are now almost completely uninformative, as compared with Table 5, because they are actually too volatile to be useful. Slope indicators still dominate, but the order is diverse from Table 6. Actually, the figures for best indicators are so closely matched that one might consider they render the same results.

Gonzalez et al.(2015) argues that the estimated slope component is possibly more informative than the cycle and could be considered a more effective CCB indicator. This exercise reinforces such hypothesis as most leading variables are slope or slope related proxies. However, the benchmark is as consistent as the others.

Exploring the rationale

If one is to define the stable path of credit growth as that of the same magnitude as GDP growth, the leading variables in Table 6 are an attempt to capture deviations from this stable path. We call the point where GDP and nominal credit growth are equal "sustainable credit growth". In other words, credit-to-GDP growth should be of negligible magnitude in fully developed financial systems. In our sample, 3.0% excess of growth in a particular quarter (Simple Slope) or 1.6% average excess of growth during the last year (Moving average of Simple Slope), issues an early warning signal that anticipates around 67% of crises. However, the benchmark and Bayesian probability estimates are less noisy thus preferable.

Slope Median $\tilde{\beta}_t$ and cycle estimates $\tilde{\psi}_{2,t}$ issue more false alarms than the benchmark indicator, credit-to-GDP gap HP(400k). See Table 6. However, Slope Median showed good performance in AUC exercises. Besides its noisiness related to a fixed threshold, it is less sensitive to threshold variability (Table 7). Cycle estimates has proved a low quality early warning indicator. A possible explanation is that there are too many differences of growth and cycle estimates across countries to find an effective common threshold. The same goes for the cycle change that, on the top of that, is too volatile.

However, probabilities extracted from posterior densities are preferable because they are both less noisy and cleared of the level issues. The probability of a positive figure on the credit-to-GDP slope component, $\mathrm{P}(\beta_t) > 0$, is highly informative, and makes the concept of sustainable credit growth operational and probabilistic. When 98.9% of posterior estimates are in the positive side, a signal is issued. According to our model, this is the point where sustainable long-term credit growth has very confidently been surpassed and this is the best indicator in KR approach (Table 6).

A "caught up" process referred to as financial deepening is arguably expected as a consequence of financial inclusion, especially among Developing Economies (see Coudert and Pouvelle, 2010). In other words, in some countries a more aggressive credit growth could be a natural phenomenon and not necessarily unsustainable. With that in mind, we created a sustainable financial deepening proxy that could be more suitable for those cases; $\beta_t > \overline{\beta_t}$, is the excess of credit/GDP growth as compared not to zero but to its own (one-sided) mean. In these cases, the variable of interest is not the slope but excessive historical growth relative to an adaptive trend. This sustainable financial deepening proxy, probability of growth over mean, $P(\beta_t - \overline{\beta_t}) > 0$, has a smaller threshold (0.945) but shows a very close performance to its simpler counterpart, probability of a positive slope component, $P(\beta_t) > 0$. This is the third best indicator in Table 6.

The slope of HP(150), $\Delta\mu^{HP(150)}$, our HP proxy to the slope of the model we estimate, also performs well (Table 6). See Appendix C for more details on how STM gain function is matched to HP(150).

Nonetheless, estimates are still very close to each other in terms of NS and prediction ratio. From Table 7, we also notice that, while slope indicators have more rigid thresholds, the benchmark is less sensitive to threshold variability. It is in the robustness check session that one can see more clearly the benefits of the slope components when compared to the credit-to-GDP gap.

Robustness check: Short series

In this session, we create 122 synthetic series with 73 continuous quarters from the original data. After re-estimating STM in all these synthetic countries, we calculate the same indicators and thresholds for all cases and present results of the early warning exercise. The rationale is to evaluate the predictive power of these indicators with incomplete information. We argue that the results of this exercise are more valuable to countries facing data limitations, especially those whose datasets hardly meet 20 years.

As in previous session, Table 8,Table 9 and Table 10 present results for BCBS approach in three cases: the lowest NS given a 2/3 prediction rate, the higher prediction rate given a NS < 16%, and the AUCs estimations, respectively.

Again, Simple Slope and all slope indicators are on top in the list, but, as we explained before, the BCBS approach tends to misrepresent volatile indicators.

Two things are very worth observing in Table 8. First, thresholds are usually set in more conservative levels, as compared to Table 3. Second, the benchmark indicator is now far from noise-to-signal of 16% to 22% and becomes one of the worst indicators in the sample, with a NS of 34.2%, twice as much as the leading variables.

#	Indicator	NS	Predicted	Threshold
1	Short Pulse Train	8.4%	100.0%	0.001
2	Short Simple Slope	12.8%	68.0%	0.032
3	Short Slope using HP(150)	17.9%	70.6%	0.019
4	Short Probability of (positive) Cycle	19.7%	71.4%	0.586
5	Short Probability of Cycle Change	20.7%	68.6%	0.552
6	Short Moving average of Simple Slope	22.0%	66.7%	0.016
7	Short Probability of growth over mean	22.8%	74.3%	0.823
8	Short Probability of (positive) Slope	24.0%	68.6%	0.954
9	Short Slope Median	29.8%	74.3%	0.012
10	Short Cycle Change Median	33.2%	85.7%	0.001
11	**Short Benchmark**	**34.2%**	**68.6%**	**0.044**
12	Short Cycle Median	34.4%	82.9%	0.001

Table 8: Lowest NS given at least 2/3 of crisis predicted. BCBS Approach. Short series.

The rationale is embedded in the nature of using a filter with such a low cut-off frequency, $(1/\lambda^{HP} = 1/400{,}000)$, when such frequencies cannot be found in the data. In other words, there is too much information in the residual or gap component and some of which reflects misspecification bias. Alternatively, the slope of credit-to-GDP when we use the "proper" λ^{HP}, i.e. HP(150) does a better job, especially because the slope is more sensitive to the current data.

Table 9 can be directly compared to Table 4, reflecting an attempt of maximizing prediction rate limiting NS. The results are very similar to those of Table 3. Table 10 shows the results for AUCs. Notice that in this case, the benchmark shows the worst performance.

#	Indicator	NS	Predicted	Threshold
1	Short Pulse Train	8.4%	100.0%	0.001
2	Short Simple Slope	14.3%	70.0%	0.03
3	Short Probability of growth over mean	14.1%	62.9%	0.909
4	Short Slope using HP(150)	14.5%	61.8%	0.022
5	Short Probability of (positive) Cycle	15.5%	60.0%	0.607
6	Short Moving average of Simple Slope	15.8%	57.8%	0.02
7	Short Probability of (positive) Slope	10.3%	57.1%	0.988
8	Short Slope Median	14.6%	54.3%	0.021
9	Short Cycle Median	13.6%	31.4%	0.005
10	**Short Benchmark**	**14.3%**	**28.6%**	**0.138**
11	Short Probability of Cycle Change	9%	6%	0.685

Table 9: Highest prediction rate given at most 16% of NS. BCBS Approach. Short series.

#	Indicator	AUC
1	Short Pulse Train[6]	96%
2	Short Simple Slope	91%
3	Short Probability of Cycle Change	88%
4	Short Probability of (positive) Cycle	88%
5	Short Moving average of Simple Slope	87%
6	Short Probability of (positive) Slope	87%
7	Short Slope using HP(150)	87%
8	Short Probability of growth over mean	85%
9	Short Slope Median	85%
10	ShortCycleChangeFlatMediana1s	84%
11	Short Cycle Median	83%
12	**Short Benchmark**	**78%**

Table 10: AUCs for each indicator. BCBS Approach. Short series.

Table 11 and 12 present the robustness check results for KR approach. We focus most of our analysis in these results, for the same reasons we stated before.

#	Indicator	NS	Predicted	Threshold
1	Short Moving average of Simple Slope	44.3%	69.1%	0.014
2	Short Slope using HP(150)	47.3%	70.5%	0.013
3	Short Probability of (positive) Slope	48.6%	72.7%	0.913
4	Short Slope Median	49.2%	72.7%	0.011
5	Short Simple Slope	52.9%	69.0%	0.025
6	**Short Benchmark**	**66.6%**	**70.5%**	**0.022**
7	Short Probability of growth over mean	67.5%	68.2%	0.709
8	Short Probability of (positive) Cycle	73.1%	72.7%	0.564
9	Short Cycle Median	83.0%	79.5%	0.001
10	Short Probability of Cycle Change	90.8%	100.0%	0.429
11	Short Pulse Train	95.6%	86.4%	0.001
12	Short Cycle Change Median	114.4%	81.8%	0.001

Table 11: Lowest NS given at least 2/3 of crisis predicted. KR Approach. Short series.

First thing to be noticed is that the more volatile Simple Slope indicator is replaced by its smoothed counterpart, Moving Average of Simple Slope, as the leading indicator for short series in Table 11. Additionally, the probability of exceeding sustainable credit growth – proxied as probability (of positive) slope, $P(\beta_t) > 0$ – is almost as good in short series as it was in the long series exercise. The matched model,

[6] Table 8, Table 9 and Table 10 shows volatile indicators on top, and the uninformative Pulse Train is the best performer overall. Its 96% AUC means an almost perfect indicator, a completely misleading result. We present this result to highlight an important limitation of the BCBS Approach.

slope of HP(150), also renders good results in short series both considering a fixed threshold (Table 11) and AUCs (Table 12).

#	Indicator	AUC
1	Short Slope Median	67%
2	Short Probability of (positive) Slope	67%
3	Short Slope using HP(150)	66%
4	Short Moving average of Simple Slope	65%
5	**Short Benchmark**	**61%**
6	Short Simple Slope	58%
7	Short Probability of growth over mean	58%
8	Short Cycle Median	53%
9	Short Probability of (positive) Cycle	53%
10	Short Pulse Train	50%
11	Short Cycle Change Median	49%
12	Short Probability of Cycle Change	49%

Table 12: AUCs for each indicator. KR Approach. Short series.

Naturally, NS increases dramatically when using limited information. Another interesting feature is the higher AUC values implied in BCBS Approach. This is a consequence of Type 1 error interpretation and its consequent bias towards prediction rate, as explained before.

General conclusions

Table 13 shows the best five indicators for complete and short series exercise for three cases:

- BCBS Pred > 66% represents methodology of Table 3. It was chosen because this is the choice of Drehmann et al. (2011);
- KR Pred > 66% represents methodology of Table 6. This is the preferable approach, because it works properly with volatile indicators;
- KR AUC represents AUCs calculated through KR Approach. As said before, KR is our preferred approach for prediction calculations, and AUCs have the advantage of indirectly considering a set of possible utility functions for the policy maker as all possible thresholds are tested to rank indicators (Drehmann and Juselius, 2014).[7]

[7] A limitation of this technique is that AUCs are estimated varying thresholds over a full range, even possibly meaningless thresholds. An alternative to overcome this is to use partial AUCs (McClish, 1989), but we leave this for future work.

	Complete Series			Short Series		
Pos	**BCBS Pred > 66%**	**KR Pred > 66%**	**KR AUC**	**BCBS Pred > 66%**	**KR Pred > 66%**	**KR AUC**
#1	Simple Slope	Probability of (positive) Slope	Benchmark	Simple Slope	Moving average of Simple Slope	Slope Median
#2	Probability of (positive) Slope	Benchmark	Slope Median	Slope using HP(150)	Slope using HP(150)	Probability of (positive) Slope
#3	Probability of growth over Mean	Probability of growth over Mean	Moving average of Simple Slope	Probability of (positive) Cycle	Probability of (positive) Slope	Slope using HP(150)
#4	Slope using HP(150)	Slope using HP(150)	Probability of (positive) Slope	Probability of Cycle Change	Slope Median	Moving average of Simple Slope
#5	Moving average of Simple Slope	Moving average of Simple Slope	Slope using HP(150)	Moving average of Simple Slope	Simple Slope	Benchmark

Table 13: Best five indicators for selected methodologies and series length.

We consider Probability of (positive) Slope, slope of HP(150), and the benchmark as the best univariate indicators for long series. They outperform all other indicators for long series[8]. Probability of (positive) Slope has proved to be marginally better than Benchmark in our sample considering the preferred methodology (KR Pred > 66%), but was outpaced in AUCs.

Moreover, the "matched model" for the slope component, Slope of HP(150); Moving Average of Simple Slope; as well as Probability of (positive) Slope renders great results when considering complete series and incomplete information. The benchmark does not perform well in short series, which leads to the discussion of whether this should be the BCBS choice. This is an important result and suggests that countries facing data limitations should consider a focus on slope components to make decisions regarding CCB. Our more conservative thresholds presented in Table 11 could be a starting point for these countries' authorities.

Our financial deepening proxy, probability of growth over mean, also proves to be very volatile in short series. Perhaps, $\overline{\beta_t}$ did not have enough time to capture the "caught up" process as it did in the long series exercise. A second analysis comprised only of developing countries could be a nice way of checking how the indicator performs. However, there are not enough crises events in these countries to carry out properly this robustness exercise.

[8] Simple Slope is first placed in BCBS approach only. We believe this is so because it is volatile but not highly informative.

Examples

For illustration, we take United Kingdom. We focus on 1990Q2 crisis (Table A.1, appendix A) and look into time span called United Kingdom_3 (See Table B2 in appendix B). Figure 4 shows benchmark versus Slope HP (150) for complete series and optimized thresholds from Table 6. The benchmark has been signaling since 1983Q2, when the 0.091 threshold is exceeded. This is seven years before the crisis, more than two times the evaluation window (shaded area). The Slope HP (150) signals two years before the crisis, inside the evaluation period and with a good anticipation. We would say that both indicators signaled the crisis in the second quarter of 1990, but Slope HP (150) is less noisy and, in this case, issues fewer false alarms than the benchmark.

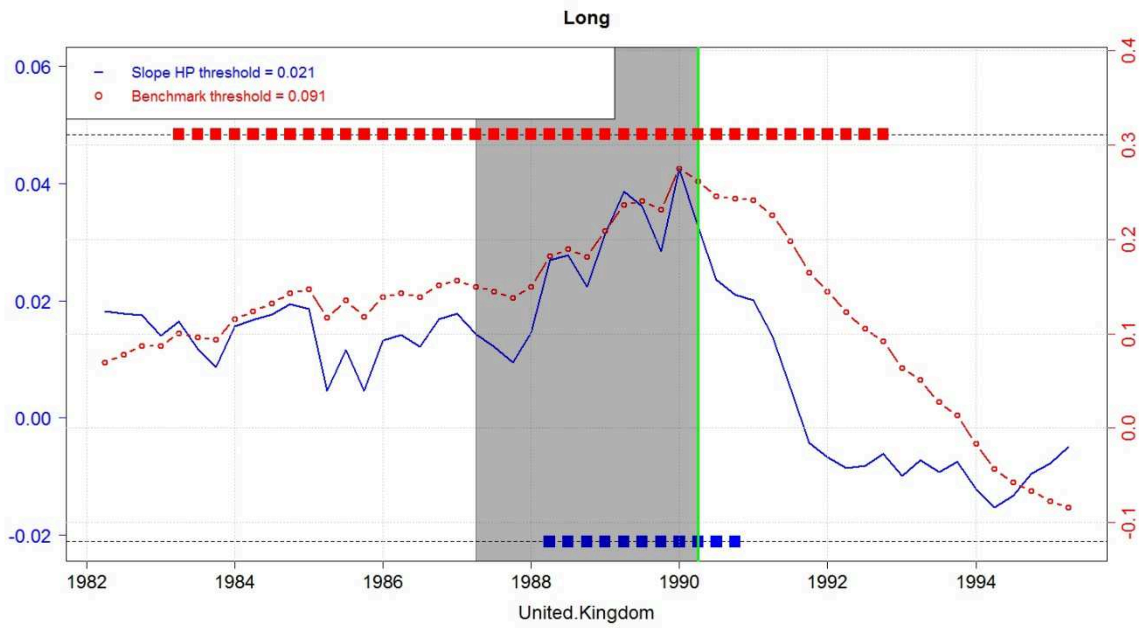

Figure 4 - Slope HP (150) indicator for United Kingdom. Blue squares at the bottom are crisis signals issued by $\Delta\boldsymbol{\mu}^{HP(150)}$, the green vertical line is 1990Q2 crisis, shaded area represents the 3 years evaluation window and red squares at the top are crisis signals issued by the benchmark. Thresholds from Table 6.

Figure 5 presents the performance of both indicators using incomplete information and thresholds suggested by complete series. In this example, only data available from 1977Q2 to 1995Q2 is used to calculate the indicators. In this case, the Benchmark signals the crisis one year before it, and Slope HP (150) signals just one quarter before the complete series case. The robustness to series length variation of Slope HP (150) using the same threshold is evident, and here its signals are practically the same. On the other hand, the benchmark showed strong variation of behavior under limited information. As one notices from Table 12, the benchmark is not as robust to thresholds variability under incomplete information as it is under complete information (Table 6).

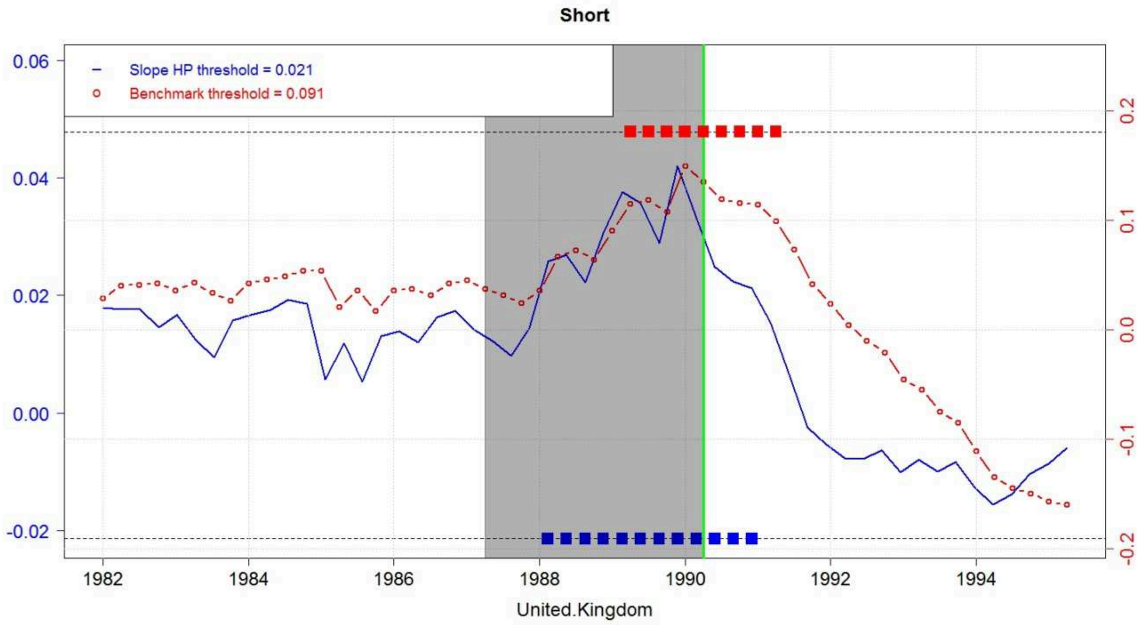

Figure 5 - Slope HP (150) indicator for United Kingdom in the short series exercise with complete series thresholds. Blue squares at the bottom are crisis signals issued by $\Delta\boldsymbol{\mu}^{\boldsymbol{HP(150)}}$, green vertical lines are crisis dates, shaded areas are 3 years evaluation windows and red squares at the top are crisis signals issued by the benchmark. Thresholds from Table 6.

Figure 6 presents the same case, but using optimized thresholds to short series from Table 11. In this case, both indicators issue much more false alarms, but Slope HP (150) performs a bit better than Benchmark, because it issues less wrong signals.

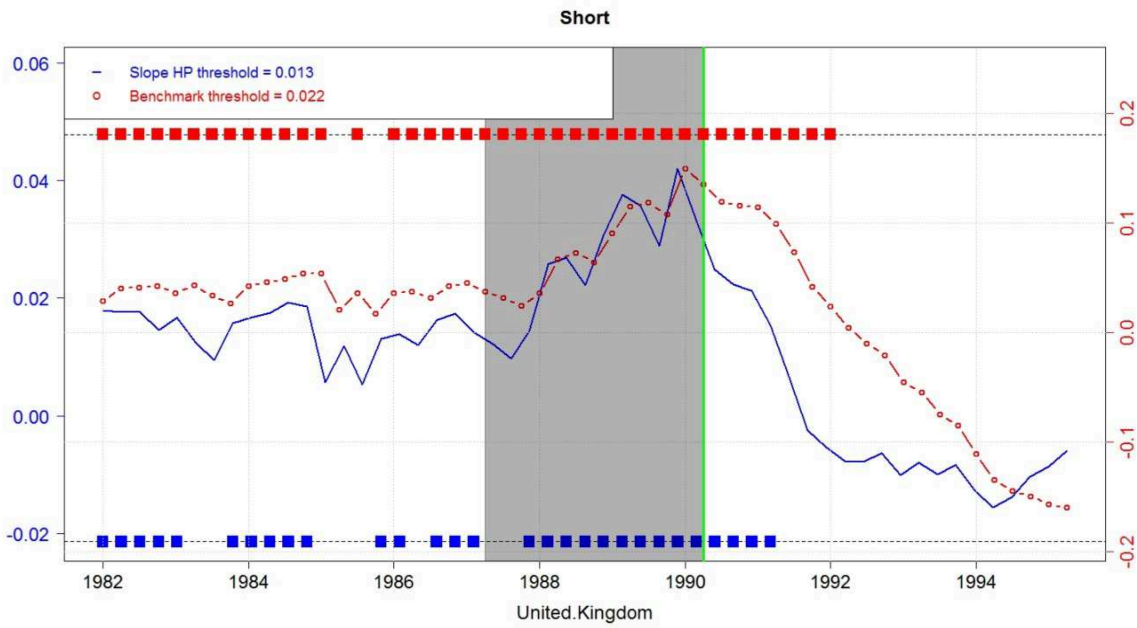

Figure 6 - Slope HP (150) indicator for United Kingdom in the short series exercise with optimized thresholds. Blue squares at the bottom are crisis signals issued by $\Delta\mu^{HP(150)}$, green vertical lines are crisis dates, shaded areas are 3 years evaluation windows and red squares at the top are crisis signals issued by the benchmark. Thresholds from Table 11.

Notice from Table 11 and Table 8 that, by construction, both the short-run threshold for the benchmark and for Slope HP (150) anticipate roughly as many crises. However, even with optimized thresholds for short series, the benchmark noises between 50% and 100% more on average. As Drehmann and Juselius (2014) point out, such result is undesirable because using Macroprudential Policy when not needed is costly for the economy.

The economic rationale of using slope components is appealing because it closely relates to the concept of potential or natural output as a natural long-term anchor for sustainable credit growth. Note that all these indicators focus on the growth of deviations between nominal Broad Credit and GDP. As the growth of one of these aggregates outpaces the other, the Authorities introduce a macroprudential response to facilitate convergence or, at least, build a capital buffer against possible upcoming losses in the best spirit of BCBS(2010a, 2010b).

The probabilistic threshold is also interesting. If figures such as 91.3% (short series) and 98.9% (long series) represent an ultimate red alert, so are intermediate ones that can relate to CCB thresholds. More importantly, this is not a volatile indicator as already mentioned and more promptly captured in KR approach.

We take Sweden as an example (Figure 7). The threshold is 98.9%. Observe that during the second half of 1980s it is possible to come up with intermediate thresholds that would precede the 98.9% signal. For example, it is possible to raise a 1% capital buffer when probability exceeds 95%, another 1% when exceeds 97.5% and the maximum, 2.5%, when the threshold is reached, mimicking BCBS(2010a) intermediate thresholds for the benchmark.

Alternatively, the short series thresholds can also be used as initial thresholds for CCB activation at minimum levels in countries with more data availability. As we illustrate throughout this paper, using more conservative thresholds represent more risk aversion on the part of the Authorities in charge of CCB (see also Drehmann and Juselius, 2014).

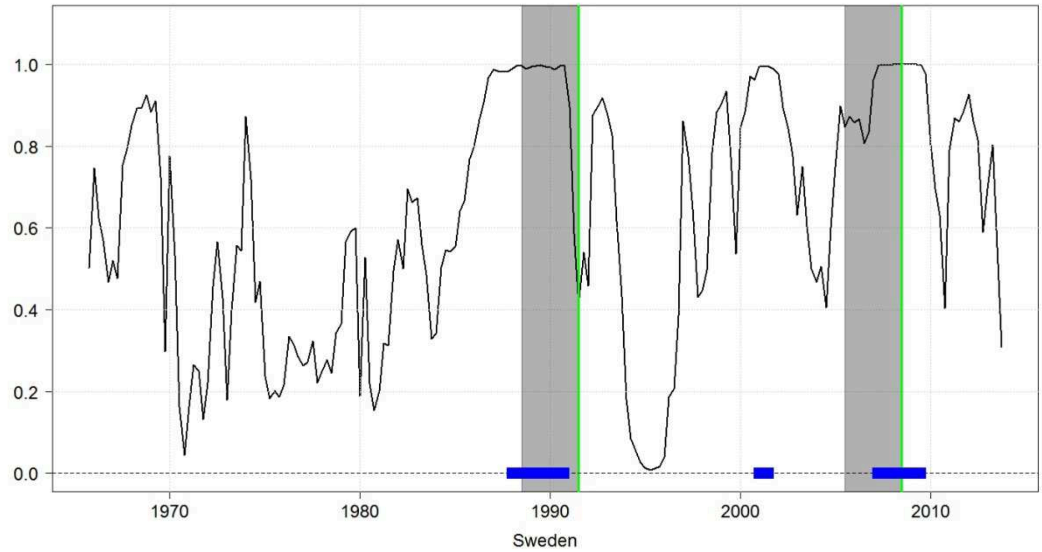

Figure 7: Probability of (positive) Slope indicator for Sweden. Blue squares at the bottom are crisis signals, green vertical lines are crisis dates and shaded areas are 3 years evaluation windows. Crises dates in Sweden are 1991Q3 and 2008Q3.

Illustrative Panel of CCB Application

In this session, we present our estimates for the last available point, i.e., 2014Q1 for Brazil, 2012Q4 for Hong Kong and 2013Q4 for all other countries. We evaluate a possible activation using the Benchmark and our proposed five leading indicators for two different thresholds, KR in long-series and the more conservative threshold, KR in short-series (more suitable for countries facing data limitations)

Table 9 presents some interesting results. The BCBS benchmark suggests activation in Turkey, Switzerland, Hong Kong and Brazil. Most indicators agree that Turkey and Switzerland should consider using Macroprudential Policy instruments. Hong Kong is much above the credit-to-GDP proposed threshold of 0.10 (or 0.091 in our estimates). However, the other indicators would disagree on that (in 2012Q4). The estimated slope median is on 1%, which is below the thresholds, the probability that this figure is above the long term average slope is 51%, whereas 65% is the probability it exceeded the zero boundary that we refer to as sustainable long-term credit growth. Moving average is close to zero and slope using HP(150) is close to -2%. Even though the benchmark is in very high levels, the other estimates picture a credit slowdown, possibly as a consequence of other sectoral macroprudential measures already in place (HKMA, 2011). As noticed before, the benchmark is very rigid and takes a long time to capture more recent events (see also Gonzalez et al., 2015). Nevertheless, Authorities are probably be concerned about the magnitude credit-to-GDP has already achieved as well as property prices and still considered CCB activation in 2015 (HKMA, 2015).

Luxembourg is possibly the counter-example. Two of our slope indicators point to thresholds being exceeded. However, the benchmark and some of the slope indicators would disagree. Apparently, they are capturing a fast recovery process. The probability that the sustainable level is exceeded is in 55%, but the benchmark is still on negative figures.

	Moving average of Simple Slope	Benchmark	Probability of (positive) Slope	Probability of growth over Mean	Slope Median	Slope using HP(150)
Argentina	0.00	0.01	0.65	0.67	0.00	0.00
Australia	0.01	-0.07	0.85	0.55	0.01	0.01
Austria	-0.01	-0.07	0.29	0.05	0.00	-0.01
Belgium	-0.01	-0.03	0.70	0.30	0.01	0.00
Brazil	0.01	0.11	**0.95**	**0.80**	0.01	0.01
Canada	0.01	0.05	0.87	0.65	0.01	0.01
Czech Republic	0.00	0.08	0.63	0.57	0.00	0.00
Denmark	-0.02	-0.17	0.10	0.02	-0.02	-0.02
Finland	0.00	0.03	0.42	0.25	0.00	0.00
France	0.00	-0.01	0.64	0.31	0.00	0.00
Germany	-0.01	-0.10	0.14	0.05	0.00	0.00
Greece	0.00	-0.03	0.47	0.12	0.00	0.00
Hong Kong	0.00	0.17	0.65	0.51	0.01	-0.02
Hungary	-0.03	-0.30	0.22	0.06	-0.02	-0.04
India	0.00	-0.03	0.71	0.23	0.00	0.00
Indonesia	0.01	0.08	0.68	0.68	0.01	0.01
Ireland	-0.01	-0.22	0.09	0.04	-0.04	-0.05
Italy	-0.01	-0.07	0.26	0.12	0.00	-0.01
Japan	0.00	0.04	0.52	0.37	0.00	0.01
Korea	0.01	0.03	0.75	0.47	0.01	0.01
Luxembourg	**0.06**	-0.53	0.55	0.48	**0.01**	**0.03**
Mexico	0.00	0.04	0.79	0.69	0.00	0.00
Netherlands	0.00	-0.13	0.38	0.03	0.00	0.00
Norway	0.00	-0.02	0.53	0.35	0.00	0.00
Poland	0.00	-0.03	0.50	0.17	0.00	0.00
Portugal	-0.04	-0.17	0.04	0.01	-0.03	-0.04
Russia	**0.01**	0.02	0.84	0.57	0.01	**0.02**
South Africa	0.00	-0.03	0.58	0.49	0.00	0.00
Spain	-0.03	-0.27	0.01	0.00	-0.03	-0.03
Sweden	-0.01	-0.08	0.31	0.19	-0.01	-0.02
Switzerland	0.01	0.14	**0.98**	**0.91**	**0.02**	**0.01**
Turkey	**0.03**	0.18	**1.00**	**0.99**	**0.02**	**0.03**
United Kingdom	-0.02	-0.22	0.05	0.01	-0.02	-0.02
United States	0.00	-0.13	0.36	0.15	0.00	0.00
Threshold Short	**0.014**		**0.913**	**0.709**	**0.011**	**0.013**
Threshold Long	0.016	0.091	0.989	0.945	0.012	0.021

Table 9. Illustrative Panel of CCB. Bold Figures exceed the more conservative KR short time threshold and shaded areas the KR long series threshold

In the case of Brazil, the benchmark is above the BCBS threshold and probabilities (considering short-term thresholds) would agree with CCB activation. However, the other three slope indicators, the quicker ones, would disagree. As Hong Kong, Brazil introduced sectorial macroprudential instruments in 2010 and 2011, a credit expansion peak period (AFANASIEFF, T. et al., 2015, MARTINS and SHECHTMAN, 2013, SILVA, L. and HARRIS, R., 2012). Moreover, a credit slowdown led by private banks risk aversion is in place since June, 2011 (BCB, 2015). In other words, it may be the case that potential imbalances, if still in place, are unwinding without the need for additional macroprudential policy intervention.

5. Final remarks

This work focuses on alternatives to credit-to-GDP gap proposed by the Basel Committee as the leading indicator to Countercyclical Capital Buffers. We estimate Bayesian Structural Time Series Models (STM) in 34 countries and evaluate their state components and posterior densities as early warning indicators. The credit-to-GDP growth, i.e., the estimated median slope component and, more importantly, the probabilities extracted from its posterior distribution are the best indicators in our analysis, providing results as accurate as those of the BCBS indicator (benchmark), the credit-to-GDP gap using HP(400k), to anticipate crises. However, they highly outperform the credit-to-GDP gap, minimizing noise in a robustness check on short series. We argue that the framework we propose is a better choice for countries facing limited data. It is also an interesting alternative to the credit-to-GDP gap for all countries as it also performs well on longer series. As a simpler choice, we state that the slope of credit-to-GDP estimated using HP(150) and even a one-year moving average of the first difference of credit-to-GDP render very good results and should be preferable to the credit-to-GDP gap for the same reasons. We also provide an illustrative panel considering the use of the BCBS indicator (benchmark) and the ones we propose.

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Appendix A. Crises Dates

Country	Crises dates
Argentina	1980Q1, 1989Q4, 1995Q1, 2001Q4
Australia	1989Q4
Austria	2008Q3
Belgium	2008Q3
Brazil	NA
Canada	NA
Czech Republic	1996Q4
Denmark	1987Q4, 2008Q3
Finland	1991Q3
France	1994Q1, 2008Q3
Germany	2007Q3
Greece	2008Q3
Hong Kong	NA
Hungary	1991Q3
India	1993Q3
Indonesia	1997Q4
Ireland	2008Q3
Italy	1992Q3
Japan	1992Q4
Korea	1997Q3
Luxembourg	2008Q3
Mexico	1981Q3, 1994Q4
Netherlands	2008Q3
Norway	1990Q4
Poland	1992Q3
Portugal	2008Q3
Russia	1998Q3
South Africa	1977Q4, 1989Q4
Spain	1977Q4, 1993Q4, 2008Q3
Sweden	1991Q3, 2008Q3
Switzerland	1991Q3, 2007Q3
Turkey	1982Q2, 2000Q4
United Kingdom	1973Q4, 1990Q2, 2007Q3
United States	1990Q2, 2007Q3

Table A1:Crises dates for all countries.

Appendix B. Complete and Short Series

	Series	Start	End
1	Argentina	2004Q1	2013Q4
2	Australia	1960Q1	2013Q4
3	Austria	1960Q1	2013Q4
4	Belgium	1970Q4	2013Q4
5	Brazil	1996Q1	2014Q1
6	Canada	1960Q1	2013Q4
7	Czech Republic	1995Q1	2013Q4
8	Denmark	1960Q1	2013Q4
9	Finland	1970Q4	2013Q4
10	France	1969Q4	2013Q4
11	Germany	1960Q1	2013Q4
12	Greece	1960Q1	2013Q4
13	Hong Kong	1978Q4	2012Q4
14	Hungary	1995Q1	2013Q4
15	India	1996Q2	2013Q4
16	Indonesia	2000Q1	2013Q4
17	Ireland	1971Q2	2013Q4
18	Italy	1960Q1	2013Q4
19	Japan	1964Q4	2013Q4
20	Korea	1970Q1	2013Q4
21	Luxembourg	2003Q1	2013Q4
22	Mexico	1980Q4	2013Q4
23	Netherlands	1961Q1	2013Q4
24	Norway	1960Q1	2013Q4
25	Poland	1995Q1	2013Q4
26	Portugal	1960Q1	2013Q4
27	Russia	1995Q2	2013Q4
28	South Africa	1965Q1	2013Q4
29	Spain	1970Q1	2013Q4
30	Sweden	1961Q1	2013Q4
31	Switzerland	1960Q1	2013Q4
32	Turkey	1987Q4	2013Q4
33	United Kingdom	1963Q1	2013Q4
34	United States	1952Q1	2013Q4

Table B1: Complete series time span.

	Series	Start	End
1	Australia 1	1995Q4	2013Q4
2	Australia 2	1986Q3	2004Q3
3	Australia 3	1977Q2	1995Q2
4	Australia 4	1968Q1	1986Q1
5	Australia 5	1960Q1	1978Q1
6	Austria 1	1995Q4	2013Q4
7	Austria 2	1986Q3	2004Q3
8	Austria 3	1977Q2	1995Q2
9	Austria 4	1968Q1	1986Q1
10	Austria 5	1960Q1	1978Q1
11	Belgium 1	1995Q4	2013Q4
12	Belgium 2	1986Q3	2004Q3
13	Belgium 3	1977Q2	1995Q2
14	Belgium 4	1970Q4	1988Q4
15	Brazil 1	1996Q1	2014Q1
16	Canada 1	1995Q4	2013Q4
17	Canada 2	1986Q3	2004Q3
18	Canada 3	1977Q2	1995Q2
19	Canada 4	1968Q1	1986Q1
20	Canada 5	1960Q1	1978Q1
21	Czech Republic 1	1995Q4	2013Q4
22	Czech Republic 2	1995Q1	2013Q1
23	Denmark 1	1995Q4	2013Q4
24	Denmark 2	1986Q3	2004Q3
25	Denmark 3	1977Q2	1995Q2
26	Denmark 4	1968Q1	1986Q1
27	Denmark 5	1960Q1	1978Q1
28	Finland 1	1995Q4	2013Q4
29	Finland 2	1986Q3	2004Q3
30	Finland 3	1977Q2	1995Q2
31	Finland 4	1970Q4	1988Q4
32	France 1	1995Q4	2013Q4
33	France 2	1986Q3	2004Q3
34	France 3	1977Q2	1995Q2
35	France 4	1969Q4	1987Q4
36	Germany 1	1995Q4	2013Q4
37	Germany 2	1986Q3	2004Q3
38	Germany 3	1977Q2	1995Q2
39	Germany 4	1968Q1	1986Q1
40	Germany 5	1960Q1	1978Q1
41	Greece 1	1995Q4	2013Q4
42	Greece 2	1986Q3	2004Q3

	Series	Start	End
43	Greece 3	1977Q2	1995Q2
44	Greece 4	1968Q1	1986Q1
45	Greece 5	1960Q1	1978Q1
46	Hong Kong 1	1994Q4	2012Q4
47	Hong Kong 2	1985Q3	2003Q3
48	Hong Kong 3	1978Q4	1996Q4
49	Hungary 1	1995Q4	2013Q4
50	Hungary 2	1995Q1	2013Q1
51	Ireland 1	1995Q4	2013Q4
52	Ireland 2	1986Q3	2004Q3
53	Ireland 3	1977Q2	1995Q2
54	Ireland 4	1971Q2	1989Q2
55	Italy 1	1995Q4	2013Q4
56	Italy 2	1986Q3	2004Q3
57	Italy 3	1977Q2	1995Q2
58	Italy 4	1968Q1	1986Q1
59	Italy 5	1960Q1	1978Q1
60	Japan 1	1995Q4	2013Q4
61	Japan 2	1986Q3	2004Q3
62	Japan 3	1977Q2	1995Q2
63	Japan 4	1968Q1	1986Q1
64	Japan 5	1964Q4	1982Q4
65	Korea 1	1995Q4	2013Q4
66	Korea 2	1986Q3	2004Q3
67	Korea 3	1977Q2	1995Q2
68	Korea 4	1970Q1	1988Q1
69	Mexico 1	1995Q4	2013Q4
70	Mexico 2	1986Q3	2004Q3
71	Mexico 3	1980Q4	1998Q4
72	Netherlands 1	1995Q4	2013Q4
73	Netherlands 2	1986Q3	2004Q3
74	Netherlands 3	1977Q2	1995Q2
75	Netherlands 4	1968Q1	1986Q1
76	Netherlands 5	1961Q1	1979Q1
77	Norway 1	1995Q4	2013Q4
78	Norway 2	1986Q3	2004Q3
79	Norway 3	1977Q2	1995Q2
80	Norway 4	1968Q1	1986Q1
81	Norway 5	1960Q1	1978Q1
82	Poland 1	1995Q4	2013Q4
83	Poland 2	1995Q1	2013Q1

	Series	Start	End
84	Portugal 1	1995Q4	2013Q4
85	Portugal 2	1986Q3	2004Q3
86	Portugal 3	1977Q2	1995Q2
87	Portugal 4	1968Q1	1986Q1
88	Portugal 5	1960Q1	1978Q1
89	Russia 1	1995Q4	2013Q4
90	Russia 2	1995Q2	2013Q2
91	South Africa 1	1995Q4	2013Q4
92	South Africa 2	1986Q3	2004Q3
93	South Africa 3	1977Q2	1995Q2
94	South Africa 4	1968Q1	1986Q1
95	South Africa 5	1965Q1	1983Q1
96	Spain 1	1995Q4	2013Q4
97	Spain 2	1986Q3	2004Q3
98	Spain 3	1977Q2	1995Q2
99	Spain 4	1970Q1	1988Q1
100	Sweden 1	1995Q4	2013Q4
101	Sweden 2	1986Q3	2004Q3
102	Sweden 3	1977Q2	1995Q2
103	Sweden 4	1968Q1	1986Q1
104	Sweden 5	1961Q1	1979Q1
105	Switzerland 1	1995Q4	2013Q4
106	Switzerland 2	1986Q3	2004Q3
107	Switzerland 3	1977Q2	1995Q2
108	Switzerland 4	1968Q1	1986Q1
109	Switzerland 5	1960Q1	1978Q1
110	Turkey 1	1995Q4	2013Q4
111	Turkey 2	1987Q4	2005Q4
112	United Kingdom 1	1995Q4	2013Q4
113	United Kingdom 2	1986Q3	2004Q3
114	United Kingdom 3	1977Q2	1995Q2
115	United Kingdom 4	1968Q1	1986Q1
116	United Kingdom 5	1963Q1	1981Q1
117	United States 1	1995Q4	2013Q4
118	United States 2	1986Q3	2004Q3
119	United States 3	1977Q2	1995Q2
120	United States 4	1968Q1	1986Q1
121	United States 5	1958Q4	1976Q4
122	United States 6	1952Q1	1970Q1

Table B2: Short series time span.

Appendix C. Matching the gain functions of STM and Hodrick-Prescott (HP) Filter

Suppose a stochastic trend in a model without cycle such as (C.1):

$$y_t = \mu_t + \varepsilon_{t,}\ \varepsilon_t \sim NID(0, \sigma_\varepsilon^2)\ ,$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_{t,}\ \eta_t \sim NID\left(0, \sigma_\eta^2 = 0\right) \tag{C.1}$$

$$\beta_t = \beta_{t-1} + \zeta_{t,}\ \zeta_t \sim NID\left(0, \sigma_\zeta^2\right)$$

where μ_t is a local level, ε_t is a white noise, β_t represents the slope, η_t a white noise for local level and ζ_t the slope vector residual and σ_ε^2, σ_η^2 and σ_ζ^2 are the respective variances. σ_η^2 is set to zero, because we decided on a smooth trend (see more on Koopman el al., 2009).

The gain function $w(\lambda)$ to extract this trend can be obtained from the Wiener-Kolmogorov (WK) filter and expressed in (C.2), where λ is the frequency in radians and lays in the interval $0 \leq \lambda \leq \pi$ and q is the signal-to-noise in a model without cycle $(\sigma_\zeta^2/\sigma_\varepsilon^2)$ and can be directly estimated in a model such as C.1 using the Kalman Filter (Harvey and Trimbur, 2008).

$$w(\lambda) = \frac{1}{1 + q^{-1}2^4 \sin^4(\lambda/2)} \tag{C.2}$$

The cut-off frequency is the frequency for which the gain, $w(\lambda)$, equals 0.5, $\lambda_{0.5}$. For instance, when $\lambda_{0.5}$ = 0.1583, q = 1/1600, the usual HP specification for the business cycle. From formula (2), $\lambda_{0.5}$ = 0.1583 translates into 39.70 quarters (9.93 years).

However, models with cycle have different gain functions, $w_c(\lambda)$, (C.3), and their signal-to-noise ratios (q_c) also include the variance of the cyclical component, σ_ψ^2 as in formula (7).

$$w_c(\lambda) = \left[1 + \frac{1}{q_c}\frac{(2-2cos\lambda)^2(1+\rho^2-2\rho cos\lambda_c cos\lambda)(1-\rho^2)}{1+\rho^4+4\rho^2\cos^2\lambda_c - 4(\rho+\rho^3)cos\lambda_c cos\lambda + 2\rho^2 cos2\lambda}\right]^{-1} \quad \text{(C.3)}$$

As illustrated in Harvey and Trimbur (2008), when the gain functions are matched at the cut-off frequency point, i.e. $w(\lambda) \cong w_c(\lambda) = 0.5$, these gain functions render very close results. Even though they are not identical, differences evaluated using the Simpson's rule are negligible.

The minimum figure we could estimate for q_c in our sample is 0.02, using long-series and all data (i.e. two-sided estimates). If we match the gain function of HP filter to the STM parameters that rendered q_c= 0.02 at the point where gain equals 0.5, we arrive at q=0.006567 or HP(152.27). For simplicity, HP(150). Figure C1 presents these gain functions and also HP(1600) and HP(400k) for comparison. As mentioned in the introduction, HP(400k) is "cutting out" only extremely low frequencies of over 39.5 years (sometimes inexistent in the series) leaving most information in the residuals (gap). In STM and HP(150), we take the slope component (the filtered frequencies) as informative and are "cutting out" mostly noise.

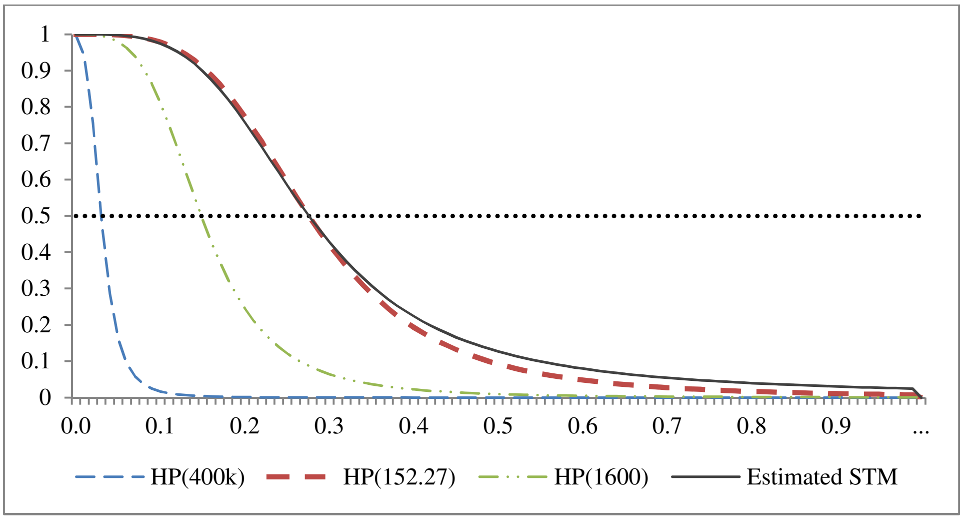

Figure C1. Gains for an estimated STM with q_c=0.02,ρ=0.6 and λ_c=0.154; HP(400k); HP(1600) and our "matched" HP(152.27)