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## How Should Credit Gaps Be Measured? —An Application to European Countries—

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I N T E R N A T I O N A L M O N E T A R Y F U N D

**IMF Working Paper**

European Department

**How Should Credit Gaps Be Measured? An Application to European Countries**

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Authorized for distribution by Enrica Detragiache

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**Abstract**

Assessing when credit is excessive is important to understand macro-financial vulnerabilities and guide macroprudential policy. The Basel Credit Gap (BCG) – the deviation of the credit-to-GDP ratio from its long-term trend estimated with a one-sided Hodrick-Prescott (HP) filter—is the indicator preferred by the Basel Committee because of its good performance as an early warning of banking crises. However, for a number of European countries this indicator implausibly suggests that credit should go back to its level at the peak of the boom after the credit cycle turns, resulting in large negative gaps that might delay the activation of macroprudential policies. We explore two different approaches—a multivariate filter based on economic theory and a fundamentals-based panel regression. Each approach has pros and cons, but they both provide a useful complement to the BCG in assessing macro-financial vulnerabilities in Europe.

JEL Classification Numbers: C33, C51, E32, E44, E51, G20, G28

Keywords: Credit Cycle, Credit Gap, Countercyclical Capital Buffer, Macroprudential Policies

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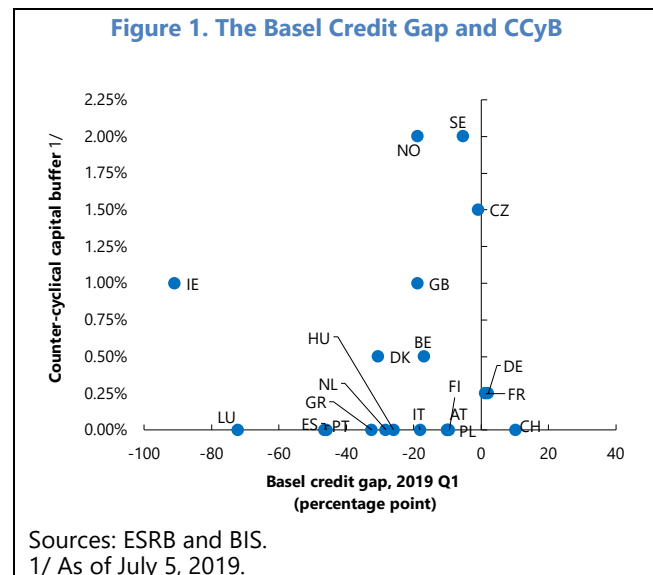
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## I. INTRODUCTION

To prevent systemic financial crises or mitigate their impact, policymakers need to identify the build-up of macro-financial risks with an adequate leading time so that they can act in a counter-cyclical manner. The build-up of these risks often occurs when stress levels in the financial system seem low, financial conditions are loose, and the cost of raising bank capital is also relatively low. These are periods in which capital buffers should be built, specifically by activating the countercyclical capital buffer (CCyB) or other macroprudential instruments, so that they can be released when financial conditions tighten, banks need capital to absorb losses, and fire sales and contagion threaten macroeconomic and financial stability. Similarly, after a boom deflates, policymakers need to assess whether the downward correction in credit has overshoot its desirable level or more adjustment is still needed.

As in many areas of economics, there is no widely-agreed method for measuring when credit is excessive, partly reflecting the lack of a “canonical” theoretical macroeconomic model of financial excesses. Nonetheless, the Basel Committee on Banking Supervision (BCBS) recommended as a common starting reference point the so-called Basel Credit Gap (BCG), i.e., the difference between the credit-to-GDP ratio and its HP-filtered value. The Fund is also using the BCG in its country surveillance, its External Balance Assessment, and in some cases in Financial Sector Assessment Programs (FSAPs).<sup>2</sup> However, as the use of the BCG has expanded, difficulties with its use have come to the fore (ECB 2017, 2019). For instance, in many European countries the BCG measure is currently large and negative, implying that credit should return to close to the levels of its previous cyclical peak. Yet with output gaps positive, interest rates exceptionally low, and financial conditions supportive, policymakers see risks building up and lean toward tightening rather than loosening macroprudential settings. Indeed, a number of European countries currently have positive CCyB even though the BCG is negative (Figure 1), suggesting that they are considering a broader set of indicators when deciding on the CCyB (Annex II).

This paper reviews the key limitations of the BCG and proposes two alternative approaches that can complement the BCG when assessing credit excesses or deciding whether to activate the CCyB. The first approach jointly estimates the credit gap and other standard indicators of



<sup>2</sup> In countries where external imbalances are assessed with the so-called EBA-Lite methodology, credit growth is used to capture cyclical considerations as data limitations preclude the use of BIS-type credit gaps and the need to take into account large financial deepening needs. For more detail, see IMF (2019).

cyclical conditions, i.e., the output gap, real interest rate gap, and unemployment gap, using a multivariate filtering method. This approach identifies the gap as the cyclical component of credit, which is assumed to be related to the cycle in economic activity and the level of interest rates. It provides a useful perspective for macroprudential policy setting given that financial instability is more likely to build up when credit growth occurs while the economy is over-heating and interest rates are low. The second approach estimates the trend in credit as the level of credit that is consistent with long-term fundamentals (i.e., income level, demography, financial deepening, and interest rate) in a panel of countries using an error-correction model. Analysis of the residuals of these regression is then be used to inform the assessment of the credit gap.

We show that both methodologies yield credit gaps that turn positive ahead of crises (similar to the BCG) but, unlike the BCG, do not remain negative for an extended period following the burst of a large and prolonged credit boom. We do not test the crisis early warning properties of these two measures because, as the experience with the BCG indicates, focus on these properties may produce a measure that performs poorly in other phases of the credit cycle. Having an indicator that can produce a view of the position of the economy over the entire financial cycle may inform recommendations of broader macroeconomic policy, beyond the decision on the CCyB.

The structure of the paper is as follows. Section II reviews the BCG and its key limitations. Section III provides a brief literature survey on measuring credit gaps. Section IV describes the two approaches that can complement the BCG when assessing credit and deciding whether to activate the CCyB. Section IV concludes the paper.

## **II. THE BASEL CREDIT GAP AND ITS LIMITATIONS**

### ***What is the BCG?***

The BCG became prominent in the context of the Basel III reforms. In December 2010, the Basel Committee on Banking Supervision (BCBS) published “Basel III: A global regulatory framework for more resilient banks and banking systems,” introducing new global standards on bank capital adequacy and liquidity. The CCyB was introduced as part of these reforms. To help policymakers lean against the credit cycle, the CCyB should be raised during the build-up phase of the cycle and released during downturns, when banks need more capital to absorb losses without cutting back lending.

To guide the practical implementation of the framework, the Basel III document recommends using as a “common reference guide” to set the CCyB the BCG, defined as the difference between the aggregate credit-to-GDP ratio and its long-term Hodrick-Prescott (HP) filtered trend CCyB. This indicator was chosen because of its good performance as an early warning of banking crises (BCBS 2010).<sup>3</sup> The guidelines state that the CCyB should be activated when the BCG is above a top threshold (i.e., 2 percentage points), should continue to

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<sup>3</sup> Jokivuolle et al. (2015) also argues that the BCG provides a good basis for CCyB decision based on an analysis of a nonlinear effect on banks’ loan losses of output shocks during high private indebtedness regimes (as measured by the BIS methodology of identifying excessive indebtedness) in selected European countries.

increase until a maximum is reached, and should be released when the BCG falls below a bottom threshold. This means that the BCG should be able to gauge the state of the credit cycle both in its build-up and its deflation phases, while early-warning properties only reflect the ability of an indicator to correctly signal forthcoming relatively rare extreme adverse events. The BCBS (2010) itself acknowledges that the BCG does not always work well in all jurisdictions or at all times, and therefore calls for judgment coupled with proper communications as an integral part of the regime (Annex I).

The BCG is calculated as the difference between the credit-to-GDP ratio and its long-term trend. Credit is defined as total credit to the non-financial private sector, including credit extended by nonbanks and foreign entities.<sup>4</sup> The long-term trend is estimated with a one-sided HP filter with the smoothing parameter ( $\lambda$ ) of 400,000 applied to quarterly data, based on the assumption that credit cycles range about 30 years, about four times longer than typical business cycles.

A number of limitations of the BCG have become evident over time (see ECB, 2017 and 2019, or Drehmann and Yetman, 2018, for instance). In practice, BCBS member countries, especially Europe, use a range of additional indicators to guide their decision on the CCyB (Annex II).

### *What are the key weaknesses of the BCG?*

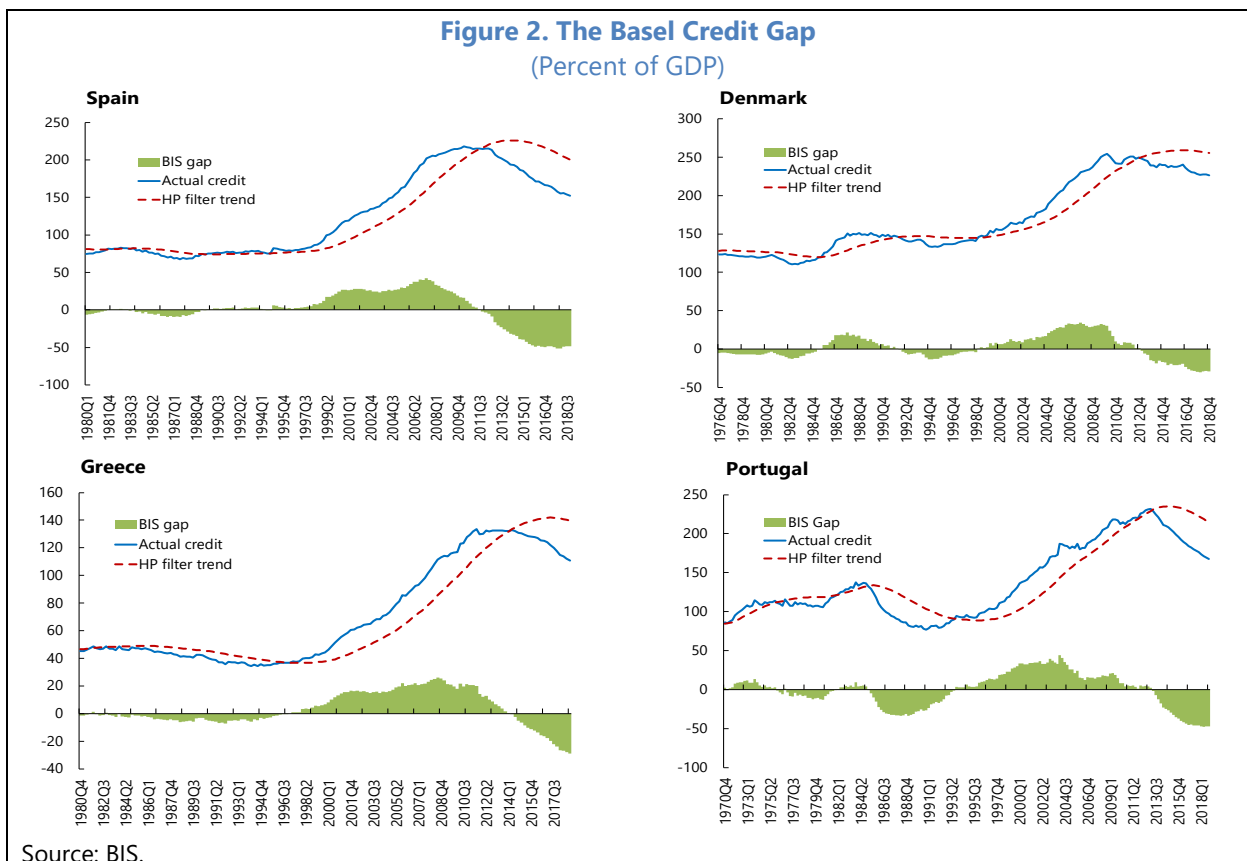
- **Excessive credit vs. financial deepening.** Periods in which credit growth exceeds GDP growth could reflect healthy growth in financial intermediation (financial deepening) and not necessarily excessive risk taking. In fact, not all credit booms end in financial crises or even adverse macroeconomic developments (Dell’Ariccia et al. 2012 and 2019). Booms may be the result of policy changes such as domestic financial liberalization or the dismantling of capital controls that aim at increasing financial intermediation. In these cases, a rising credit-to-GDP ratio may be the intended consequence of a policy change. Even in these cases, of course, credit expansion may go too far and reflect imprudent lending practices and excessive risk taking. To guide macroprudential policies, therefore, it is necessary to sort out the benign booms from the more dangerous sort. To this end, more in depth information about bank lending practices and lending standards, household and corporate balance sheets, housing and other asset prices, and changes in bank funding profile could help.
- **Countercyclicality.** The credit-to-GDP ratio sometimes moves countercyclically with GDP growth (Repullo and Saurina 2011). More specifically, when GDP declines because of a negative shock, credit tends to decline less than one-for-one with it because credit is a stock variable that adjusts more slowly than GDP (a flow variable). This results in an increase in the credit-to-GDP ratio and hence a widening of the gap. A positive credit gap, therefore, can arise not only in periods of rapid credit expansion but also in

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<sup>4</sup> Public sector credit exposures should not be included in the credit gap as their inclusion would significantly weaken the performance of the guide in a statistical sense. However, it is also recommended that the authorities pay attention to the behavior of public debt as excessive growth in public debt can contribute to a growth in financial system-wide risk.

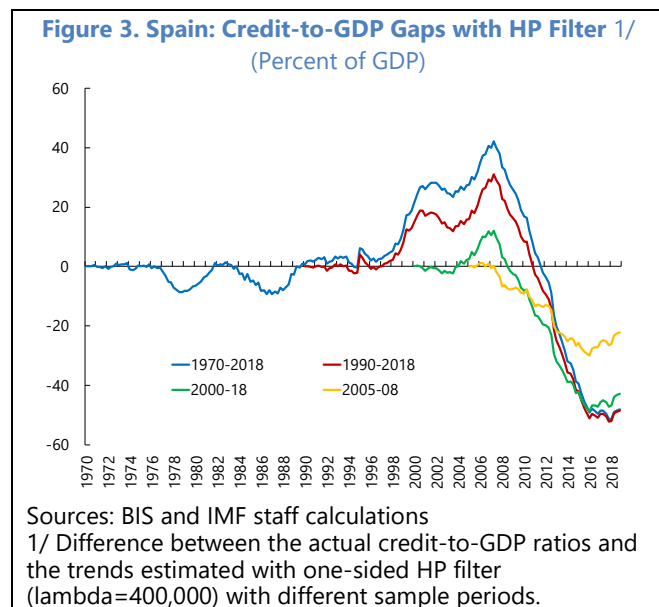
economic downturns. Thus, the BCG could signal to tighten macroprudential policies in an economic downturn potentially propagating a negative shock, just the opposite of what the framework aims to achieve. Drehmann and Tsatsaronis (2014) indeed find a negative correlation between the credit gap and real GDP growth using a panel data for 53 countries over the period 1980-2013, though the degree of correlation is small. This criticism indicates that it is important to examine whether the BCG becomes positive because credit growth accelerates or because GDP growth slows down temporarily. In the latter case, the emergence of a positive gap may not signal excessive credit growth but simply the slower adjustment of the credit stock to the deceleration in output. To avoid this problem, some studies scale credit with a more stable denominator than GDP, for instance population (see, for instance, Jordà et al. 2016).

- Large credit booms in the past.** In countries that experience a very pronounced credit boom-bust cycle, instead of filtering out the long credit cycle as intended, the BCG filter appears to track the boom with a few years' lag (Figure 2). As a result, while the BCG correctly signals growing vulnerabilities as the boom builds up and therefore performs well as an Early Warning System, it remains large and negative for an extended period after the bust even as credit growth and other indicators of financial activity such as housing prices recover to normal levels, implying that credit should return to its peak levels during the boom. Thus, in the years after a prolonged boom-bust cycle the BCG may fail to identify cases in which credit has normalized or is starting to become excessive again. Similar issues can arise when countries' credit cycles are significantly shorter than the 30 year cycle assumed by the BCG methodology (see below).



- **General problems with HP filters.** The BCG suffers from measurement issues arising from its reliance on statistical filtering in general and HP filtering in particular. These issues are familiar from the literature on output gap measurement.
- The end-point of the sample has a strong influence on the estimate of the underlying trend (and therefore of the cyclical component of the series). The BCG is calculated using a one-sided (real time) HP filter, namely it extracts a cycle using only backward-looking data, and the filter is run recursively with an expanding sample each period. While this avoids the problem arising from two-sided filters which use artificially generated forecast values, it still is affected by the end-point problem. Indeed, Edge and Meisenzahl (2011) find that for the U.S. ex-post revisions to credit gaps do not reflect data revisions but mainly the end-point problem. For European countries, the ECB (2018) finds that real-time estimates usually identify the phase of the financial cycle correctly but underestimate the size of the boom-bust.

- As is the case with other estimation techniques, the HP filter is sensitive to length of the time series (ECB 2019). For example, the timing and size of positive credit gaps before the global financial crisis (GFC) are estimated to differ greatly depending on the length of time series used (Figure 3).



- In addition, there is no consensus on the duration of the credit cycle, which in principle should guide the choice of the smoothing parameter ( $\lambda$ ) in the HP filter (Ravn and Uhlig 2002). Several studies (Aikman et al. 2015, Claessens et al. 2012 and 2012, Drehmann et al. 2012 and 2014) document that financial/credit cycles have greater amplitude and duration than fluctuations in economic activity, but others find that cycle duration varies greatly among countries and even over time (e.g., Galati et al 2016, Rünstler and Vlekke 2016, Galán 2019), calling for a country-specific approach in choosing the  $\lambda$ . In a comprehensive study of OECD countries, Jordà et al. (2016) finds that credit cycles have similar length to GDP cycles, significantly shorter than the 30 years assumed by the BCG. Indeed, Galán (2019) criticizes the great inertia embedded in the BCG and finds that reducing the  $\lambda$  from 400,000 to 25,000 in the case of Spain improve the indicator's early warning performance. Similarly, Kauko and Tölö (2019) also find that the optimal size of the  $\lambda$  is much smaller than 400,000. As indicated by ECB (2019), results of the HP filter are also sensitive to the length of time series data applied.

- **Lack of sectoral detail.** The BCG is constructed using a broad credit aggregate. This may hide imbalances that develop within narrower segments, for instance the residential mortgage market, but have the potential to spread more widely. Ignoring sectoral developments may also make it more difficult for policymakers to identify the appropriate policy response. Some studies find that a credit gap based on a narrower credit aggregate than the BCG approach, e.g., bank credit, performs better than the BCG at signaling banking crises at some horizons and for some specifications (Detken et al. 2014, Aldasoro et al. 2018). Furthermore, the BCG's credit data do not consolidate intra-company loans, which would be desirable to assess financial stability risks.

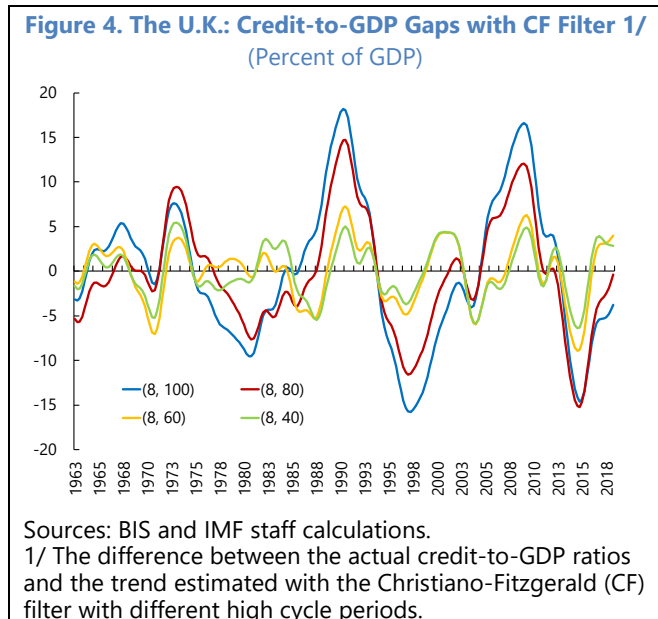
### III. BRIEF LITERATURE REVIEW ON CREDIT GAPS

The literature on measuring credit gaps generally comprises two strands of methodologies. The first takes a purely statistical approach, mainly using filters that allow to extract a cyclical component from credit data itself (univariate) or from other indicators (multivariate). The other strand takes a structural approach, estimating a model that relates credit to fundamental variables.

#### Statistical approaches

Univariate statistical filtering approaches, including the HP filter, belong to a class of frequency-based methods. Widely-used filters aside from the HP filter include bandpass methods proposed by Baxter and King (BK) (1999) and Christiano and Fitzgerald (CF) (2003). The BK and CF approaches extract frequencies within a predetermined range. By allowing for a range of frequencies, the BK and CF are more flexible regarding the priors for credit cycles compared to the HP filter.<sup>5</sup> However, these filters can still provide a wide range of credit gaps depending on the assumed length of credit cycles (Figure 4).

Hamilton (2017) proposes a linear projection approach as an alternative to the HP filtering. Specifically, he defines the trend value of variable  $y$  at  $t+h$  as the value that would have been forecasted at  $t$  on the basis of the past  $x$  realizations of that variable. For standard macroeconomic quarterly series, he recommends  $h=8$  and  $x=4$  (or preceding 8, 7, 6, and 5 quarters). For



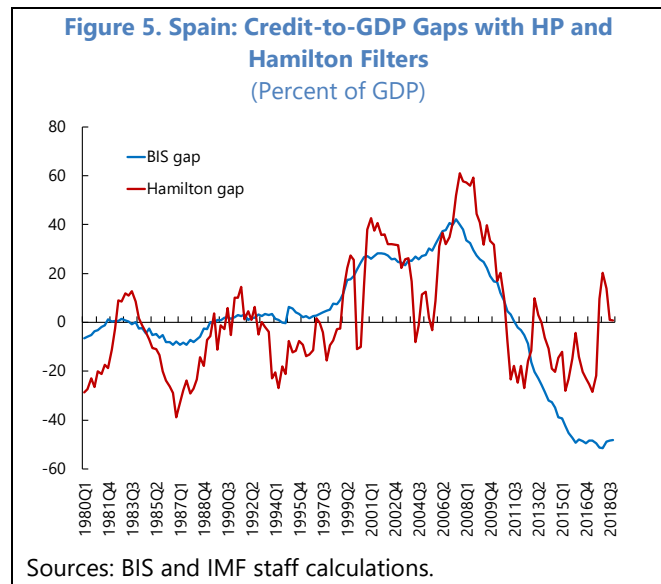
<sup>5</sup> Studies that use the bandpass methods included Aikman et al. (2015), who apply the CF filter to long-time series (1880-2008) for 14 advanced economies, finding a high correlation between credit excess periods and subsequent financial crises.



credit cycles, given the long-lasting nature of credit shocks and the length of available samples, he recommends  $h=20$  and  $x=4$  (or preceding 20, 19, 18, and 17 quarters). Figure 5 shows the credit gaps computed for Spain with the HP and Hamilton approaches.

Hamilton approach overcomes the end-point problem of the HP filter.

However, the estimated credit gaps are volatile with frequent sign changes, making them difficult to use for policymakers. Drehmann and Yetman (2018) criticize the Hamilton approach because it performs poorly as an early-warning indicator of crises. The approach is applied with more success by Richter et al. (2017). They identify credit booms by applying the Hamilton approach with  $h=6$  and  $x=4$  (or preceding 3, 4, 5, and 6 years) to annual panel dataset for 17 countries over 150 years. They then find that booms accompanied by increasing loan-to-deposit ratios in the banking system and housing price boom are significantly more likely to end in crises.



Lastly, an alternative statistical approach is the statistical multivariate model. A strand of this literature applies the Kalman filter to unobserved components models (Harvey 1989, Durbin and Koopman 2012) to estimate jointly trend and cyclical components for GDP, credit, and house prices. One of the main advantages of these models is that the length of the cycle can be estimated from the data. The main drawback of these approaches is that they do not use structural relationships derived from economic theory, while they can become rather difficult to estimate as more variables are included in the estimation.

### Structural model approaches

An alternative approach is to estimate the trend in credit by regressing credit on its fundamental determinants and take the residuals from this regression as credit gaps. Compared to statistical filters, a model-based approach can explicitly capture factors that move the trend of credit over time and across countries, such as income levels, financial reforms, changes in the real interest rate, or demographic developments. Galán and Mencia (2018) consider a vector error correction (VEC) model for total private credit, where real GDP, the real long-run interest rates, and real house prices are used as fundamentals. The model outperforms the BCG as an early warning indicator for some countries (Spain, France, Italy, and the U.K.) but not others, suggesting the difficulty in finding a unique method that fits equally well for all countries. Also, treating housing prices as exogenous to credit is problematic. Lang and Welz (2017) estimate the trend in credit by regressing real household credit on real potential output, quality of institutions, the equilibrium real interest rate, and a demographic variable related to savings (the share of middle-aged population in total population). An application along these lines can also be found in IMF (2015), which

regresses per-capita private debt on per-capita GDP and the nominal interest rate using an autoregressive-distributed lag (ADL) model on panel data for 36 European countries during 1995-2013. The approach allows the analysis to distinguish the long-run relationship from the short-run one.

This approach is subject to important limitations, however. Specifically, the residuals from the reduced form regressions may be sensitive to changes in model specification, sample composition, or estimation techniques, so the credit gaps may not be robust. Residuals may also not necessarily reflect distortions or vulnerabilities, as they may capture omitted fundamentals, for instance. Accordingly, even a model-based approach, if adopted, should be complemented by the analysis of supplementary indicators that cast additional light on the situation in the credit market.

#### **IV. TWO APPROACHES TO COMPLEMENT THE BCG**

In this section, we propose two structural approaches that can potentially complement the BCG. The first approach jointly estimates the cyclical component of credit and other macroeconomic variables using a multivariate filtering method. This approach assumes that credit is affected by economic activity and the level of interest rates, and vice versa. The second approach estimates the trend in credit using long-term fundamentals, then takes the deviation of actual credit from the underlying credit as a *prima facie* indicator of the credit gap. For both approaches, we use real credit, or real credit per capita, to avoid the dividing a stock variable (credit) by a flow variable (GDP).

##### **A. Multivariate Filtering Approach Based on Economic Theory**

The multivariate filter (MVF) model is in the spirit of Krznar and Matheson (2017), which is a variant of the model in Carabenciov et al. (2008), and similar to the approaches in Benes et al. (2010), Andrieu et al. (2014), Maria (2016). These papers use semi-structural, forward looking models to estimate the cyclical component of credit (i.e., the credit gap) and include equations for output (IS curve), inflation (Phillips curve), the policy interest rates (Taylor rule), real interest rates (Fisher equation), and the real exchange rate to allow for a better identification of trends and cycles than univariate filtering, an approach originally suggested by Laxton and Tetlow (1992). The approach focuses on modeling the credit gap and relies on country-by-country Bayesian estimation with quarterly data.

We develop two versions of the model, one for economies in a currency union and one for other economies, with different modeling of interest rates and the exchange rate.<sup>6</sup> The credit gap equation is:<sup>7</sup>

$$c_t = \theta_y y_{t-1} + \theta_{lag} c_{t-1} + \theta_r r_{t-1} + \varepsilon_t^c$$

where the credit gap  $c_t$  is affected by the lagged output gap  $y_{t-1}$  and its own lag  $c_{t-1}$  and the deviation of the real interest rate from its trend  $r_{t-1}$ . The intuition is that (new) credit flows are affected, in the short-term, by economic activity and the prevailing interest rate, while the stock of credit slowly adjusts reflecting repayments of outstanding loans.

The model incorporates a feedback from the credit gap to aggregate demand by including a credit shock in the equation of the output gap:

$$y_t = \beta_{lead} y_{t+1} + \beta_{lag} y_{t-1} - \beta_r r_t + \beta_{y^e} y_t^e + \beta_z z_t + \beta_{\varepsilon^c} \varepsilon_t^c + \varepsilon_y$$

where the output gap ( $y_t$ ) is affected by its value in a period ahead ( $y_{t+1}$ ), its lagged value ( $y_{t-1}$ ), the real rate gap ( $r_t$ ), the credit shocks (i.e., changes in lending behavior) ( $\varepsilon_t^c$ ), the output gap in the foreign economy ( $y_t^e$ ), and the real exchange rate gap ( $z_t$ ). Because the credit shock does not directly affect inflation, the model is consistent with observing growing credit and output without the build-up of inflation (Borio et al. 2013 and 2014).

The data used in the estimation are provided in Appendix II. The models and the details of the Bayesian estimation methods used as well as the main estimated parameters are provided in Appendix III.

There are both advantages and disadvantages from using an MVF. One of the key advantages is that we can model explicitly the linkages between credit gaps and other macroeconomic variables. This allows to better understand the drivers of the unobserved credit gaps in terms of measurable macroeconomic variables (Andrle 2013). The MVF has also been shown to provide more stable estimates of the unobserved components compared to univariate filters (Benes et al. 2010), which is important for policymakers. Finally, the MVF can be estimated without making prior assumptions regarding the length of the credit cycle, which, as discussed before, could be highly heterogenous across countries. At the same time, there are two main disadvantages. First, as any filter, it does not resolve the end-point bias (Andrle 2013). However, a comparison of the revision properties of the MVF versus HP filter for the

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<sup>6</sup> See Appendix I for the model specifications.

<sup>7</sup> In Krznar and Matheson (2017) the credit gap is a function of lagged credit and lagged business cycle. Their model also includes a ‘financial cycle’ to capture the linkages between financial conditions (an index of sovereign spreads, money-market spreads, interest rates, real exchange rates and stock prices) and economic activity.

estimated credit gaps shows that the MVF reduces the problem considerably (Appendix IV). Second, as any model, it assumes that certain macroeconomic relationships hold for the country that is analyzed, but the empirical validity of these relationships needs to be tested and assessed through extensive validation exercises. This also allows to assess how sensitive the results are to initial parametrization.

## B. Results

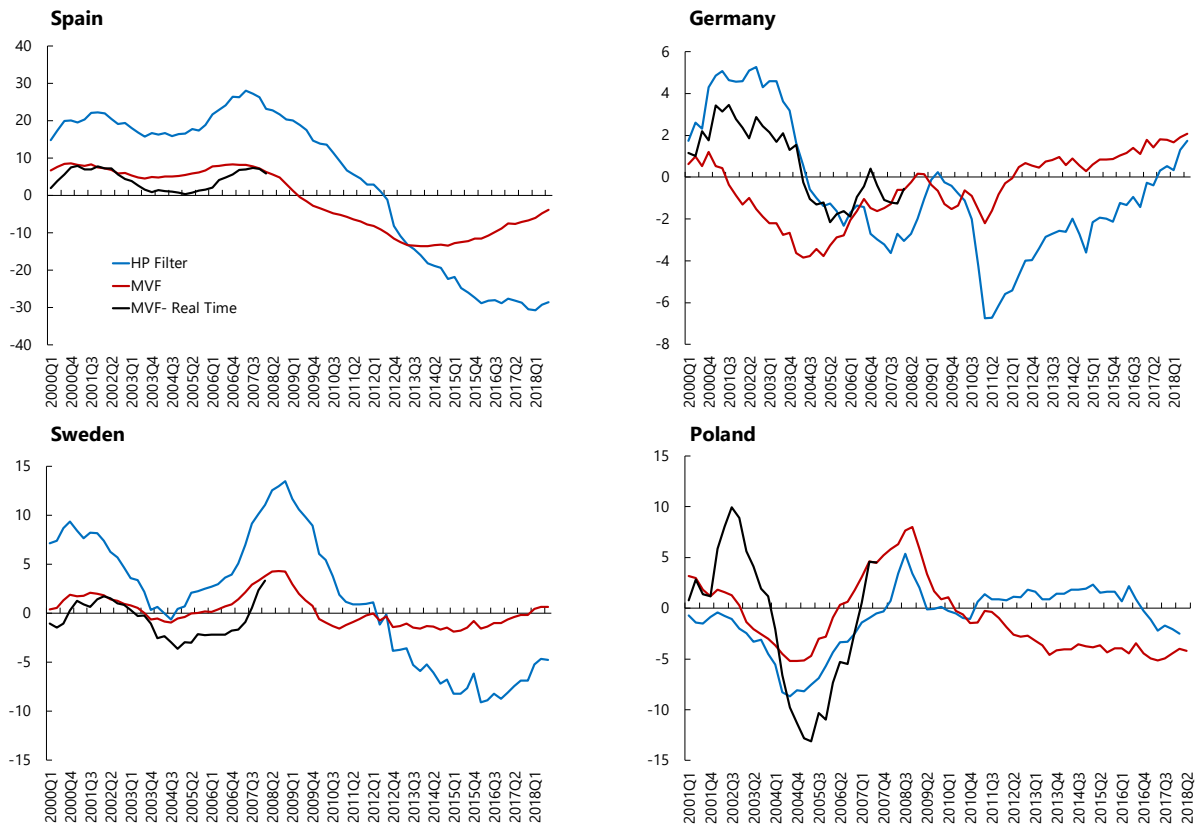
We estimate the model for two countries inside the euro area (Germany and Spain) and two countries with floating exchange rates and independent monetary policy (Poland and Sweden) to demonstrate how the MVF can be applied to different contexts. The main results are presented in Figures 6 and 7. In figure 6, we compare the real credit gaps estimated with the MVF (red lines) using the Kalman filter<sup>8</sup> with the credit gaps obtained using a one-sided HP filter with smoothing value of 400,000 (blue lines) as suggested by the BCBS. We also add (black lines) the credit gaps estimated using the Kalman smoother but using only the data up to end-2007 (pseudo real-time). In Figure 7 we compare the credit-to-GDP ratio implied by the MVF with the BCG.

The results show that the credit gaps estimated with the MVF have on average lower volatility and a shorter cycle than HP gaps. The MVF-implied cycle is typically less than 15 years (e.g., equivalent to a smoothing factor roughly below 25,000 in the HP filter). While the turning points are often similar between the two filters, the amplitudes of the cycles are different. The real credit gap from the MVF is less volatile than the credit-to-GDP gap. In addition, the plots show that the MVF using real credit avoids the countercyclicality problem highlighted by Repullo and Saurina (2011), a problem particularly acute during the 2009 recession. The real time estimates obtained with data prior to the GFCs also show a widening of positive credit gaps ahead of the GFC (Figure 6, black lines). The revision properties of the credit gaps estimated with the MVF (Appendix IV) confirms the results from the literature on output gaps (Benes et al. 2010, Andrieu 2013), which show that estimates from the MVF have better revisions properties than the HP. In the case of Germany, the negative credit gap closed before the GFC. Finally, the MVF does not show the large negative gaps following the bust phase of the cycle as is the case for the BCG, as evidenced by the charts for Spain and Sweden. In the latter cases, the real credit gap is closing at a faster pace than what is implied by the BCG.

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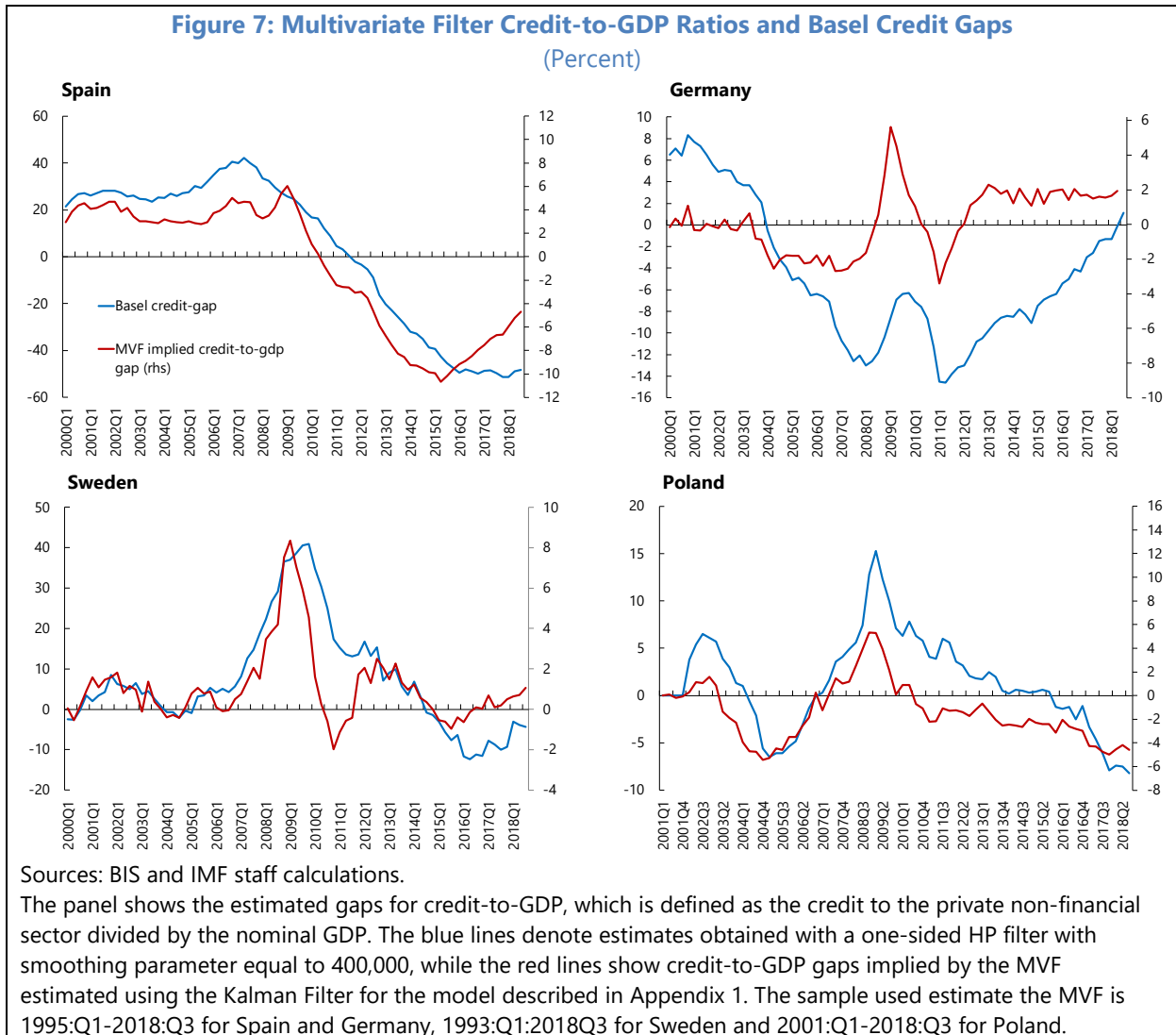
<sup>8</sup> The Kalman filter produces one-sided estimates using only contemporaneous data, to assess credit gaps at time  $t$ . In contrast, the Kalman smoother uses the entire sample to estimate the gaps.

**Figure 6: Real Credit Gaps Estimated with the Multivariate Filter**  
(Percent)



Source: IMF staff calculations.

The panel shows the estimated gaps for real credit, which is defined as the credit to the private non-financial sector deflated by the GDP deflator. The red lines denote estimates of the real credit gap obtained with a one-sided filter (calculated using the Kalman filter for the model described in Appendix 1), the blue lines denote estimates of the real credit gap using a one-sided HP filter (calculated using a smoothing factor of 400,000), and the black lines denotes estimates of the real credit gap obtained with a two-sided filter (calculated using the Kalman smoother for the model described in Appendix 1) on a sample ending in 2007:Q4. The sample used estimate the MVF is 1995:Q1-2018:Q3 for Spain and Germany, 1993:Q1-2018:Q3 for Sweden and 2001:Q1-2018:Q3 for Poland. The sample used for the HP filter is 1980:Q1-2018:Q3 for Sweden and Spain, 1970:Q1-2018:Q3 for Germany and 1995:Q4-2018:Q3 for Poland.



### C. Empirical Models of Credit Consistent with “Fundamentals”

Another complementary approach to the BCG is to estimate an empirical model of underlying credit that is consistent with fundamentals and then analyze the model residuals to form a view of the credit gap. The approach is similar to the one used for a panel of European countries by IMF (2015) and in a single country setting by Buncic and Melecky (2014) and Galán and Mencía (2018) among others. An advantage of this approach is that it separates long-term and short-term effects of fundamental variables on credit levels. Furthermore, using a panel dataset allows to estimate long-run elasticities for a heterogeneous sample of advanced and emerging market economies, increasing the chance of isolating steady-state relationships from credit-boom dynamics. On the other hand, assuming identical regression coefficients across sample countries and over time may be a strong assumption if cycles are heterogeneous. In addition, the results can be sensitive to the choice of countries considered and the length of time series available.

## Model Specification

We estimate the following error-correction (EC) model using an unbalanced panel of data for 40 European countries:

$$\Delta \ln \frac{CR}{Pop}_{it} = \alpha_i + \beta \left( \ln \frac{CR}{Pop}_{it-1} - \sum_{q=1}^Q \delta_q X_{it-1}^q \right) + \sum_{s=1}^S \gamma_s \Delta X_{it-1}^s + \varepsilon_{it}$$

where the dependent variable is the change in log credit per capita,  $\alpha_i$  is a country fixed effect, and  $X_{it}$  is a vector of “fundamental variables” explaining credit trends for country  $i$  at time  $t$ . The term in parenthesis is the EC term, which represents deviations of credit from its estimated long-term equilibrium level,  $\beta$  is the speed of adjustment to the long-term equilibrium, and  $\Delta X_{it-1}$  represent the impacts of the explanatory variables in the short-term. The fundamentals include GDP per capita, which proxies the economy’s opportunities and capacity to borrow (or repay) and affects both the demand and supply of credit positively. Unlike the regressions using the credit-to-GDP ratio as the dependent variable, the use of GDP per capita as an explanatory variable does not restrict the elasticity of credit to GDP to be unity.<sup>9</sup> Total bank deposits per capita is included to capture financial deepening.<sup>10</sup> The real interest rate affects credit supply negatively and credit demand positively. The choice of the real interest rate is rooted in theory from an extensive literature of on real macro-financial linkages and financial accelerator models, including with pecuniary externalities (Bernanke and Gertler 1987, Kiyotaki and Moore 1997, Jermann and Quadrini 2010, Bianchi and Mendoza 2018, and several others). The old-age dependency ratio is expected to affect credit demand negatively given life-cycle borrowing needs of the old-age population. On the other hand, increased life expectancy of recent old-age cohorts could partially offset the life-cycle channel.

The dataset consists of annual data for an unbalanced panel of 40 advanced and emerging European countries over 1970-2017.<sup>11</sup> The length of the time series varies across country and ranges between 5 and 47 years, with advanced economies having relatively longer series due to better data availability. Credit is defined as total credit to the private sector including bank loans and debt securities, as well as credit extended by nonbanks and foreign entities. Credit, GDP and bank deposits are all expressed as per capita in 2010 U.S. PPP terms. All variables,

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<sup>9</sup> One limitation of this approach is that GDP may itself be affected by the financial cycle.

<sup>10</sup> Household deposits are a better proxy for financial deepening, which are less susceptible to credit booms that can lead to unsustainable credit booms. However, we use total deposits for our analysis because of the substantially better data availability regarding the length of time series and country sample. Using household deposits in a more limited sample does not materially change the coefficients.

<sup>11</sup> The sample consists of Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Israel, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and United Kingdom.

except interest rates, are expressed in logarithm. Statistical tests support the existence of cointegrating relationships among the relevant variables. The data sources are summarized in Appendix II.

We use both the dynamic fixed effect estimation (DFE) technique and pooled-mean group (PMG) estimation technique of Pesaran et al. (1997). The DFE assumes common coefficients across all panels both for the long-run and short-run equations, including those for the error-correction term. Meanwhile, the PMG allows for country-specific short-term dynamics while restricting the long-run elasticities to be equal across panels (the estimated coefficients for the short-term equations in Table 1 are the mean value of country-by-country coefficients). Imposing fewer restrictions is generally preferred, yet the Hausman test—assessing if the DFE is an efficient and consistent estimator compared to the PMG—does not reject the use of the restrictions employed by the DFE. We include country fixed effects in all the specifications presented in the paper to capture time-invariant country characteristics, such as institutional quality and the steady-state level of per capita credit.<sup>12 13</sup>

## Regression Results

Regressions results show that most of the fundamental variables have their expected signs in both the long-run and short-run equations. The first column of Table 1 reports estimation results for a simple fixed-effects panel model of the short-term relationship between credit growth and its fundamentals. Columns 2 through 4 report the error-correction DFE regression results for the full sample, advanced economies, and emerging market economies, respectively. The DFE standard errors are clustered within panel and are heteroscedasticity robust. Columns 5 through 7 present the results using the PMG estimator for the entire sample, advanced economies, and emerging markets economies, respectively.

- The coefficients on GDP per capita and per capita deposits are generally statistically and economically significant with expected signs for both the DFE and PMG estimators. The coefficients for real interest rate and old-age dependency ratio are statistically and economically significant for the PMG estimator but not always for the DFE estimator. Nonetheless, the signs of the coefficients of the old-age dependency ratio are consistent with theoretical priors for both estimators while those of real interest rate are also in line with priors except for the DFE estimator for the full sample and for emerging markets. Interestingly, the coefficient on the old-age dependency ratio is larger for emerging markets economies than for advanced economies. One possible explanation is that faster aging in European emerging markets economies has been driven by the emigration of the

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<sup>12</sup> Even within a monetary union, there could be a wide dispersion of business models, leading to a broad range of credit per capita levels consistent with financial stability.

<sup>13</sup> The inclusion of the country fixed effect term can be somewhat misleading if the time series is short relative to credit cycles.

(continued...)



working-age population, leading to a reduced appetite for investment and lower per capita credit.

- The PMG estimator, which allows the short-run coefficients to differ across countries, results in smaller standard errors for the long-run coefficients than the DFE estimator. However, it also results in smaller elasticities for GDP per capita except for emerging economies. At the same time, the magnitudes of the coefficients for the real interest rate and old age dependency become larger with the PMG estimator, and the coefficients become statistically significant.<sup>14</sup>
- The coefficients for the error-correction term indicate a speed of adjustment of between around 13 and 20 percent per year for deviations of credit from its long-term equilibrium. This means that it takes roughly 5-8 years for credit to return to its long-term equilibrium. Advanced economies adjust more slowly (12 percent per year) than emerging economies (20 percent per year).
- Short-run estimates are also consistent with theoretical priors; credit grows more rapidly with higher GDP growth, higher deposit growth, and slower aging. The coefficient on the change in real interest rates is generally positive across specifications, possibly suggesting that credit supply factors dominate credit demand in the short run. These results generally hold for different country groupings and for the different estimators, though the magnitudes vary.

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<sup>14</sup> Some of the coefficients for emerging markets economies estimated with the PMG approach are implausibly large. This may be due to the relatively short sample periods.

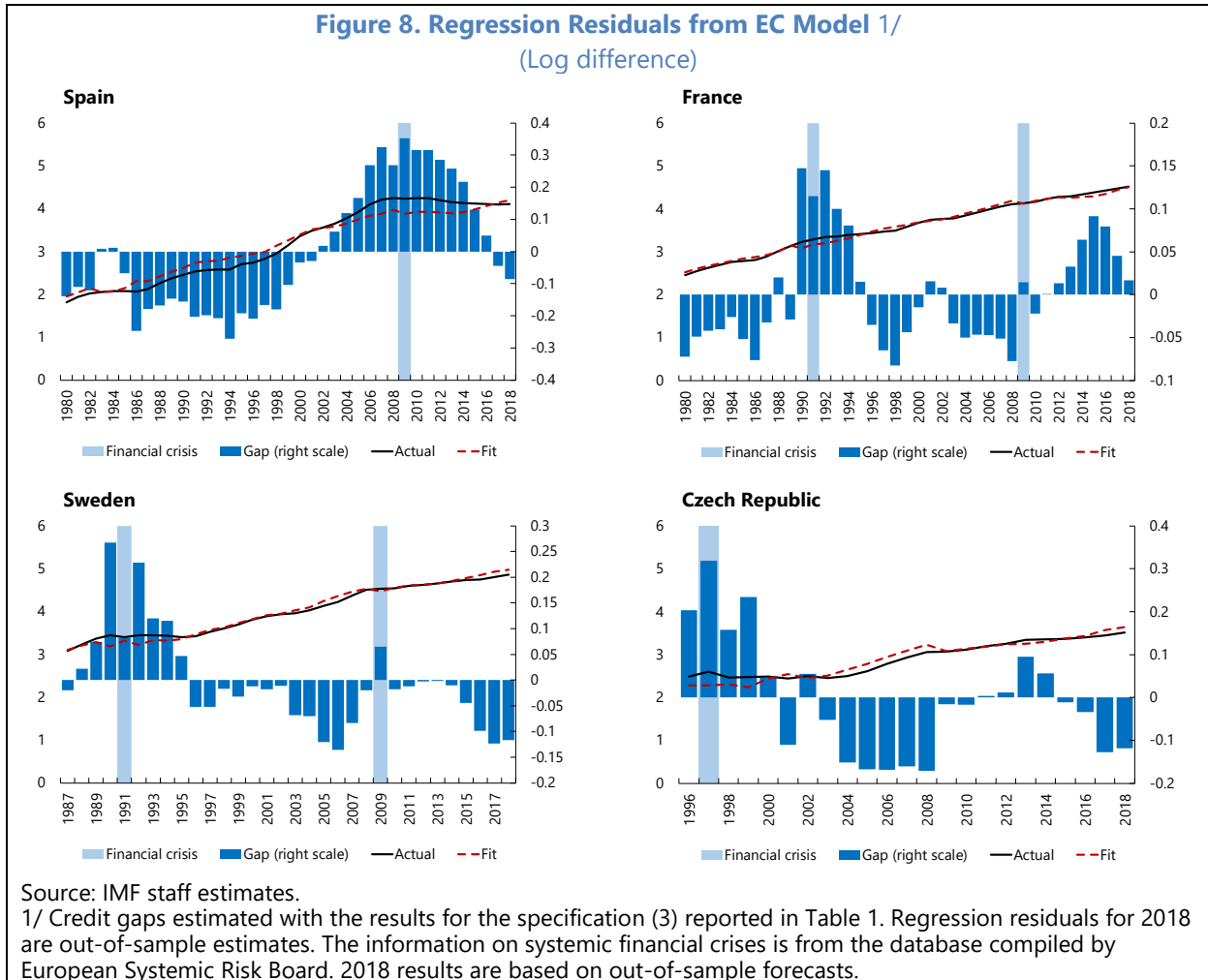
Table 1. Long-term and Short-term Equations for Credit per Capita in Europe							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fixed effects		Error-correction				
	Dynamic Fixed Effects			Pooled Mean Group			
	All	Advanced	Emerging	All	Advanced	Emerging	
Error correction term		-0.136*** (0.023)	-0.127*** (0.029)	-0.199*** (0.051)	-0.205*** (0.033)	-0.201*** (0.038)	-0.194*** (0.063)
Long-run relation							
GDP per capita (log)		1.010*** (0.308)	0.789** (0.399)	1.984** (0.887)	0.738*** (0.085)	0.725*** (0.086)	2.648*** (0.374)
Deposit per capita (log)		0.429** (0.215)	0.549* (0.291)	0.086 (0.450)	0.458*** (0.048)	0.456*** (0.049)	0.250 (0.182)
Real interest rate		0.008 (1.190)	-1.810 (1.815)	0.306 (1.343)	-0.592** (0.257)	-0.716*** (0.290)	-0.840** (0.386)
Old age dependency (log)		-0.068 (0.443)	-0.242 (0.424)	-0.415 (1.010)	-1.212*** (0.151)	-1.139*** (0.155)	-5.253*** (0.862)
Δ Lagged credit per capita (log)	0.238*** (0.029)	0.260*** (0.047)	0.233*** (0.049)	0.239** (0.111)	0.200*** (0.039)	0.249*** (0.047)	0.110 (0.081)
Δ GDP per capita (log)	0.704*** (0.107)	0.533*** (0.102)	0.612*** (0.081)	0.229 (0.195)	0.771** (0.331)	0.866* (0.444)	0.567* (0.344)
Δ Deposit per capita (log)	0.370*** (0.049)	0.257*** (0.078)	0.179* (0.091)	0.477*** (0.134)	0.137 (0.127)	0.016 (0.150)	0.460** (0.197)
Δ Real interest rate	0.086 (0.105)	0.121 (0.126)	0.383 (0.251)	-0.001 (0.057)	0.318* (0.182)	0.334 (0.248)	0.376** (0.148)
Δ Old age dependency (log)	-0.691** (0.324)	-0.492 (0.438)	-0.062 (0.440)	-2.453*** (0.800)	0.720 (1.542)	2.127 (2.098)	1.476** (0.593)
Constant	0.010 (0.008)	-0.200 (0.180)	-0.116 (0.174)	-0.339 (0.526)	0.497*** (0.125)	0.371*** (0.144)	2.194*** (0.759)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maximum time span	1980-2017	1980-2017	1980-2017	1994-2017	1980-2017	1980-2017	1994-2017
Num of observations	894	907	705	189	881	705	176
Num of countries	40	40	27	13	38	27	11
R-squared	0.299						

Source: IMF Staff estimations.  
Notes: Standard errors, clustered by country, are reported in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Figure 8 plots estimation residuals from the long-term relationship, which correspond to the error-correction term and can be interpreted as a *prima facie* measures of the credit gap. In general, the credit gap appears to signal financial crises reasonably well.<sup>15</sup> In addition, for Spain, which experienced a large and prolonged period of credit boom and bust, the positive credit gap has been closing in recent years and is around zero at the end of the sample. This contrasts with the BCG, which shows large negative credit gaps for Spain in 2018. The gap for France, while negative in the late 1990s and early 2000s, is positive in recent years,

<sup>15</sup> The real-time signaling property of this approach is not tested due to data limitations.

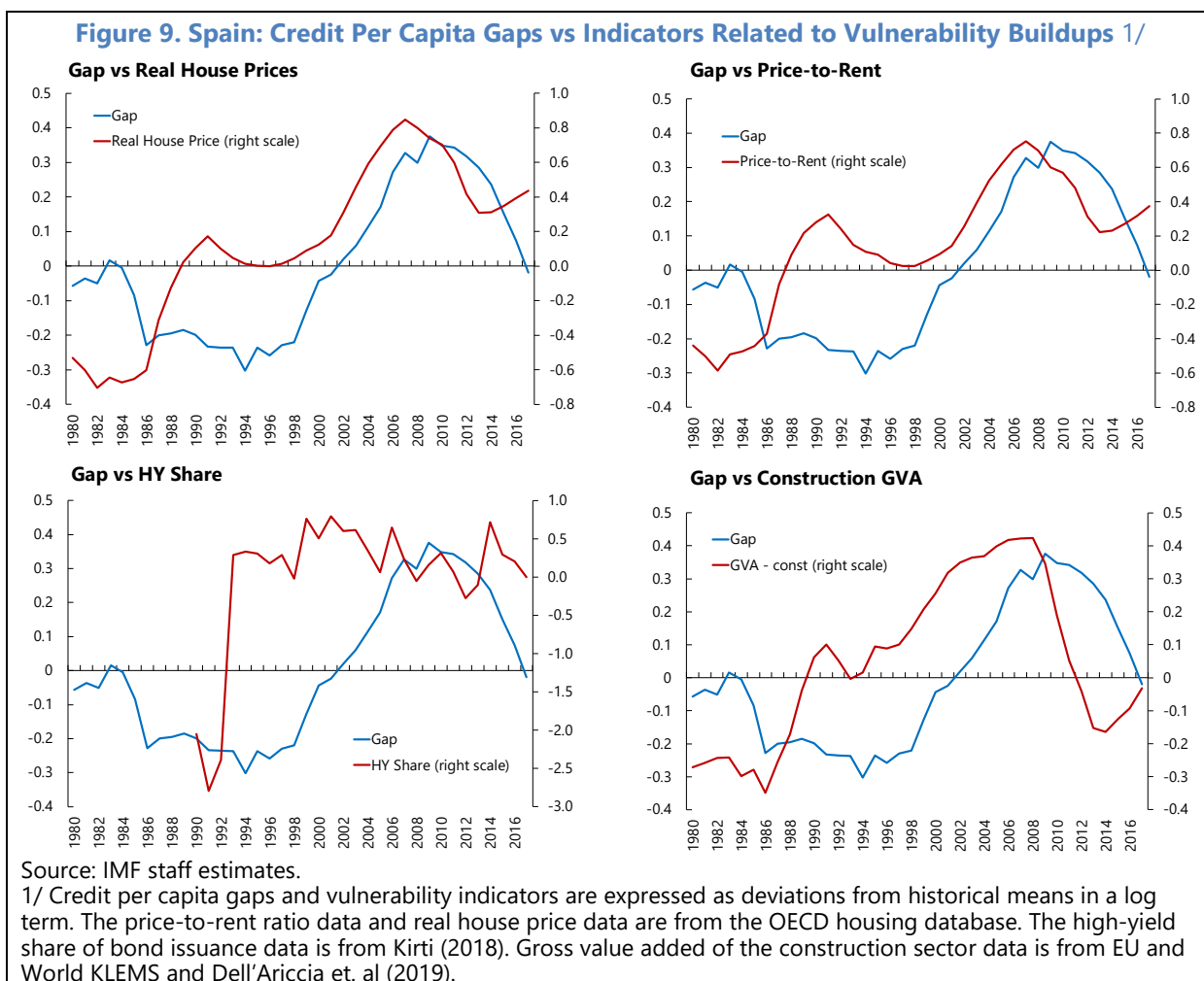
reflecting the growth in debt in the corporate non-financial sector. For Sweden, the gap was positive around the past financial crises. Sweden's recent credit upswing—with higher credit growth than predicted by the short-term relationship of the model (Figure 10)—has not yet translated into positive gaps.



## Interpreting the Gaps and Trends

To help interpreting estimation residuals as credit gaps, the use of supplementary indicators that can signal a build-up of financial vulnerabilities can be helpful. Estimation residuals can be driven by a range of factors, including estimation errors and omitted variables, therefore there is not prior estimation residuals should be correlated with such supplementary indicators. Figure 9 uses Spain as an illustration of how this can be done in practice. In each panel, the estimated credit gaps are plotted against a variable that the literature has identified as related to systemic financial vulnerabilities, i.e., the house price-to-rent ratio, the real house price, share of high-yield corporate bonds in total corporate bond issuance, and valued-

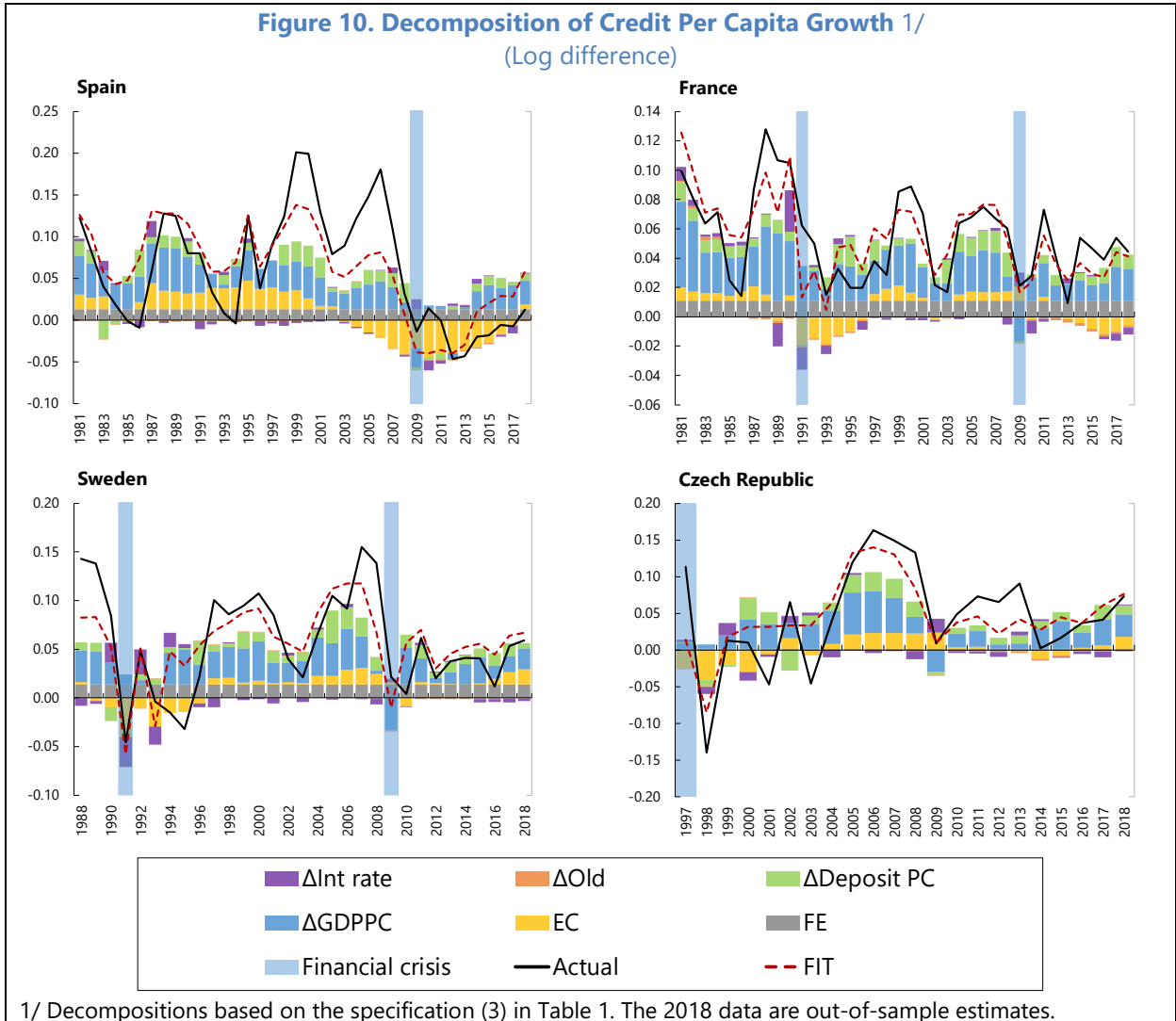
added in the construction sector.<sup>16</sup> If positive credit gaps are accompanied by high values—for some of these variables, it could be a signal that credit is excessive and vulnerabilities are building up. In contrast, positive credit gaps when other indicators do not signal concerns may just reflect model misspecification, sampling variation, or random factors. In the case of Spain, the emergence of positive credit gaps in the mid-2000s was accompanied by a high and rising LTD ratio, as well as increasing housing prices and construction-sector activity, signaling excessive credit and a buildup of vulnerabilities.



Analyzing credit growth in the short-term relation is also informative in understanding the role of each fundamental variable and interpreting trends. The error-correction model allows the decomposition of credit growth (as opposed to credit level) into (1) adjustments to the

<sup>16</sup> Kirti (2018) finds that credit booms with deteriorating lending standards (rising HY share) tend to be followed by lower GDP growth in the subsequent three to four years. Meanwhile, Dell’Ariccia et al (forthcoming) argue that an unusually rapid expansion of the construction sector can help discriminate bad booms from good booms.

long-term level (the EC term) and (2) contemporaneous developments in the other fundamental variables, such as GDP, deposit, demography, interest rates (as in the form of changes in log terms). As Figure 10 illustrates, in Spain, after a period of excess credit, equilibrium credit growth had been subdued to allow credit to adjust to its long-term level. With the credit gap closing at the end of the sample, and reflecting pickups in GDP and deposit growth, equilibrium credit growth has accelerated in recent years.



## V. CONCLUSIONS

Measuring credit gaps properly is important to assess macro-financial vulnerabilities and guide policymakers in the setting macroprudential policy. Rapid credit growth and high leverage are often key indicators of periods in which financial risks are building up, yet there is no widely-agreed method for measuring when credit is excessive. The BCG was chosen by the Basel Committee as the “reference indicator” of excessive credit in the decision to activate the CCyB, but this measure suffers several weaknesses. In particular, the BCG tends to become persistently negative after a pronounced credit boom deflates, implausibly indicating that credit should return to its cyclical peak. This poses questions about the usefulness of the BCG as a guide for macroprudential policy settings over the full credit cycle.

In this paper, we have propose two approaches to measure credit gaps that can complement the BCG, have applied these approaches to selected European countries, and have discussed their advantages and disadvantages.

The first approach, the model-based multivariate filter, identifies the cyclical conditions of credit and macroeconomy jointly. This provides a useful perspective for macroprudential policy setting given the financial instability is more likely to build up when credit growth occurs as the macroeconomy is overheating. The second approach, the fundamental-based EC model, seeks to explicitly identify long-term fundamental determinants of credit. Regression residuals are then examined in conjunction with other variables related to systemic financial vulnerabilities to assess whether they should be interpreted as “gaps” that require a policy response. Both approaches have the advantage of not imposing exogenously a specific duration to the credit cycle, consistent with evidence that such a duration is not uniform. Also, unlike the BCG these methods produce sensible estimates of credit gaps in countries that have experienced large booms and busts, as is the case for several European countries. At the same time, these approaches have some disadvantages. Importantly, the end-point bias remains a problem for the model-based multivariate filter, just as with any filter, even though the bias is much smaller than with the BCG. In addition, the coefficients for the fundamentals-based EC model are sensitive to the choice of countries considered and the length of time series available. Nonetheless, these methods show promise in complementing the BCG and help guide policymakers’ judgement in assessing the position of the economy in the credit cycle and calibrating the macroprudential stance. In addition, using different methods to estimate credit gaps can be useful to identify the range of plausible assessments of credit excesses. When this range is large, policymakers may need to conduct a deeper analysis of potential imbalances to make policy decisions.

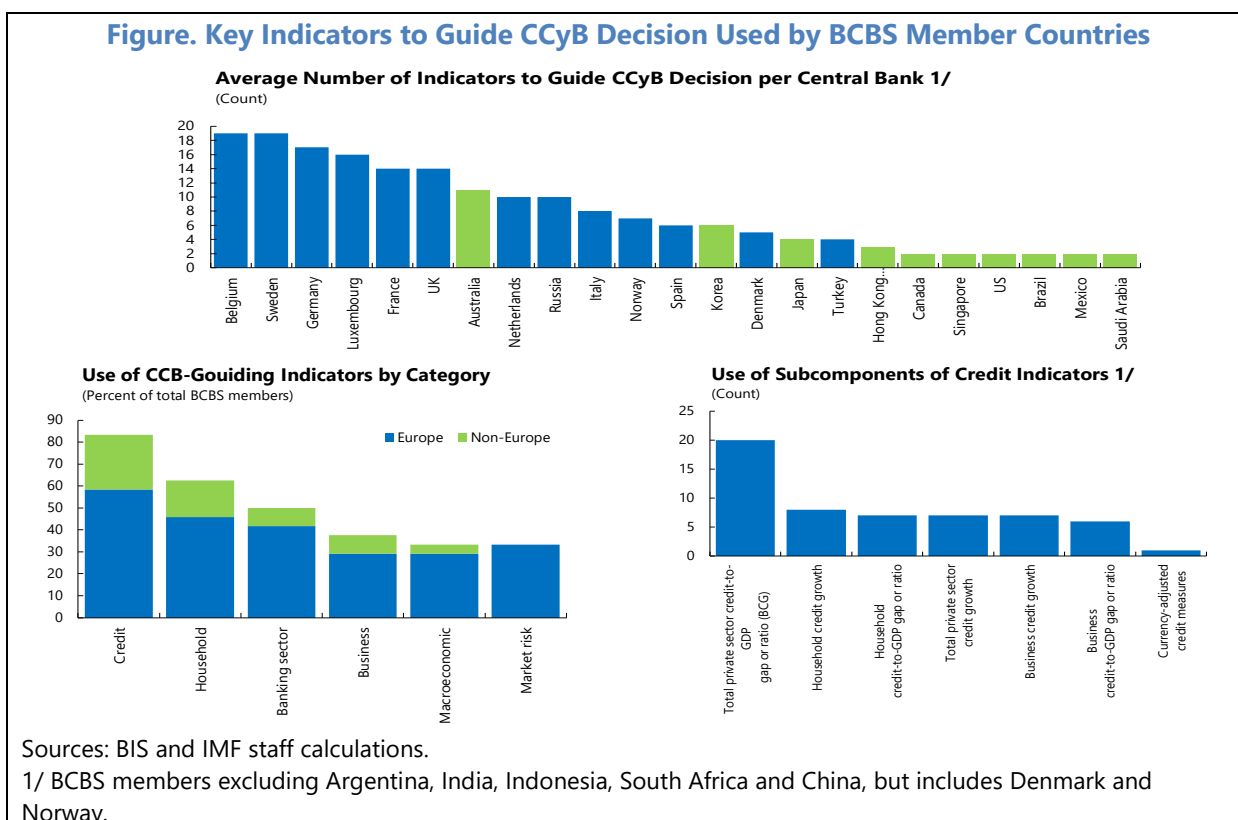
## Annex I. BCBS Operational Guidance for the Countercyclical Capital Buffer

- The primary aim of the CCyB regime is to use capital buffer to achieve the broader macroprudential goal of protecting the banking sector from periods of excess aggregate credit growth that have often been associated with the build-up of system-wide risk. In addressing the such an aim, the CCyB regime may also help to lean against the build-up phase of the cycle in the first place.
- The common reference guide is based on the aggregate private sector credit-to-GDP gap. The guide, however, does not always work well in all jurisdictions. Therefore, judgment coupled with proper communications is an integral part of the regime.
- Rather than rely mechanistically on the credit gap guide, authorities are expected to apply judgment in setting the buffer in their jurisdiction after using the best information available to gauge the build-up of system-wide risk. It is crucial that the use of such judgment is anchored to a clear set of principles. The following principles have been formulated by the BCBS to guide authorities in the use of judgment in this framework.
  - **Principle 1 (Objectives):** Buffer decisions should be guided by the objectives to be achieved by the buffer, namely to protect the banking system against potential future losses when excess credit growth is associated with an increase in system-wide risk.
  - **Principle 2 (Common reference guide):** The credit gap guide is a useful common reference point in taking buffer decisions. However, it does not need to play a dominant role in the information used by authorities to take and explain buffer decisions. Authorities should explain the information used, and how it is considered in formulating buffer decisions.
  - **Principle 3 (Risk of misleading signals):** Assessments of the information contained in the credit/GDP guide and any other guides should be mindful of the behavior of the factors that can lead them to give misleading signals.
  - **Principle 4 (Prompt release):** Promptly releasing the buffer in times of stress can help to reduce the risk of the supply of credit being constrained by regulatory capital requirements.
  - **Principle 5 (Other macroprudential tools):** The CCyB is an important instrument in a suite of macroprudential tools at the disposal of the authorities, therefore when excess aggregate credit growth is judged to be associated with a buildup of system-wide risks, authorities should deploy the CCyB, possibly in tandem with other macroprudential tools.

## Annex II. Indicators Used by Country Authorities to Guide the CCyB Decision

**BCBS member countries, especially European countries, use a range of indicators of systemic to guide their CCyB decision.** Such indicators range from a wide array of credit indicators, sectoral indicators, market risk indicators, to macroeconomic indicators. European members tend to use a wider set of indicators—the median number of indicators of nine—than their non-European counterparts (Figure, top panel). This holds for both advanced and emerging market economies.

- Credit-related indicators are mostly frequently used (Figure, bottom left panel).** About 80 percent of the BCBS members—100 percent of European BCBS members—use at least one of the credit-related indicators. About 2/3 of the BCBS members also look at indicators on the financial health of households, followed by those on the health of banking sector, which 1/2 of the members use. Only 1/3 of members use indicators on the financial health of businesses, market risks, and macroeconomics. Interestingly, none of the non-European members use indicators on market risks.
- Several members also pay attention to subcomponents of credit (Figure, bottom right panel).** All the members that use credit-related indicators use the BCG is mostly commonly used, but About 80 percent of the BCBS members—100 percent of European BCBS members—use at least one of the credit-related indicators. About 1/3 of BCBS members also look at the growth of total private credit and indicators on household credit or business credit. Emerging markets economies—e.g., Brazil and Russia—also look at currency-adjusted credit measures.





## Appendix I. Detailed Overview of the Multivariate Filter

This Appendix provides a detailed overview of the models used in the main section of the paper. The model presented here are variations of Carabenciov et al. (2008), Andrieu et al. (2014), Maria (2016), and Krznar and Matheson (2017). We develop two versions: a version for a euro area economy (slightly modified for Germany) and a version for a small open economy outside the euro area. In terms of notation: lower case letters denote deviation of variables from trends; the lower-case letters with the symbol \* denote trends and upper-case letters denote the variable itself, i.e.  $x = X - x^*$ . We use the letter  $e$  to mark the foreign economy variables.

### A. Domestic Economy

**Output** The output gap is defined as the deviation of output from its long-term trend:

$$y_t = Y_t - y_t^* \quad (0.1)$$

where  $Y_t \equiv 100 \cdot \ln(GDP)$ ,  $GDP$  is the quarterly actual real Gross Domestic Product<sup>17</sup> and  $y_t^*$  is the trend real GDP (potential output). Potential output depends on potential growth ( $g_t$ ):

$$y_t^* = y_{t-1}^* + \frac{1}{4} g_t + \varepsilon_t^{y^*} \quad (0.2)$$

real potential growth converges toward a steady state value:

$$g_t = \rho_g g_{t-1} + (1 - \rho_g) g_{ss} + \varepsilon_t^g \quad (0.3)$$

The output gap ( $y_t$ ) is affected by its value next period ( $y_{t+1}$ ), its lagged value ( $y_{t-1}$ ) the real rate gap ( $r_t$ ) the credit shock ( $\varepsilon_t^c$ ) the output gap in the foreign economy ( $y_t^e$ ) and the real exchange rate gap ( $z_t$ ):

$$y_t = \beta_{lead} y_{t+1} + \beta_{lag} y_{t-1} - \beta_r r_t + \beta_{y^e} y_t^e + \beta_z z_t + \beta_{\varepsilon^c} \varepsilon_t^c + \varepsilon_y \quad (0.4)$$

**Inflation** A Phillips curve drives the inflation dynamics. In the euro area model, the current headline inflation ( $\pi_t$ ) is linked to its value next period ( $\pi_{t+1}$ ), its lagged value ( $\pi_{t-1}$ ) the output gap and the difference between the euro area aggregate annual inflation ( $\pi_t^{eA}$ ) and the annual domestic inflation ( $\pi_t^A$ ):

$$\pi_t = \lambda_{lead} \pi_{t+1} + \lambda_{lag} \pi_{t-1} + \lambda_y y_t + \lambda_z (\pi_t^{eA} - \pi_t^A) + \varepsilon_t^\pi \quad (0.5)$$

<sup>17</sup> See the Data section in the main text for details on the data sources.

where the annual inflation is calculated for both the foreign and domestic economy is calculated as follows:

$$\pi_t^A = 1/4 * (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3}) \quad (0.6)$$

In the non-euro area model, we substitute the inflation differential with the change in the real exchange rate:

$$\pi_t = \lambda_{lead} \pi_{t+1} + \lambda_{lag} \pi_{t-1} + \lambda_y y_t + \lambda_z (z_t - z_{t-1}) + \varepsilon_t^\pi \quad (0.7)$$

**Credit** The credit shock featured in equation (1.4) is derived from the equation for the credit gap ( $c_t$ ), which is assumed to be driven by the lagged output gap, its own lagged value ( $c_{t-1}$ ) and the lagged real rate gap:

$$c_t = \theta_y y_{t-1} + \theta_{lag} c_{t-1} - \theta_r r_{t-1} + \varepsilon_t^c \quad (0.8)$$

The credit gap is defined as the difference between the real credit  $C_t \equiv 100 * \ln(CRED / CPI_{core})$  and its trend ( $c_t^*$ ):

$$c_t = C_t - c_t^* \quad (0.9)$$

where ( $CRED$ ) is credit to the private non-financial sector as a share of core price inflation index ( $CPI_{core}$ ). The trend credit is determined by the following equation:

$$c_t^* = c_{t-1}^* + \frac{1}{4} g_t^c + \varepsilon_t^{c^*} \quad (0.10)$$

and trend credit growth is subject to shocks and converges toward a steady state potential credit growth:

$$g_t^{c^*} = \rho_{g^{c^*}} g_{t-1}^{c^*} + (1 - \rho_{g^{c^*}}) g_{ss}^{c^*} + \varepsilon_t^{g^{c^*}} \quad (0.11)$$

**Unemployment** The unemployment rate is determined by a dynamic Okun's law, where the unemployment gap ( $u_t$ ) is a function of its own lagged value ( $u_{t-1}$ ) and the output gap:

$$u_t = \alpha_1 u_{t-1} + (1 - \alpha_1) \alpha_2 y_t + \varepsilon_t^u \quad (0.12)$$

The variable  $u_t$  is the unemployment gap, defined as actual quarterly unemployment  $U_t$  minus the equilibrium unemployment rate  $u_t^*$  (NAIRU):

$$u_t = U_t - u_t^* \quad (0.13)$$

where the latter is determined by its steady state value  $u_{ss}$  and its growth rate  $g_t^{u^*}$  according to the following equations:

$$u_t^* = (1 - \alpha_3)u_{t-1}^* + (\alpha_3)(u_{ss} + g_t^{u^*}) + \varepsilon_t^{u^*} \quad (0.14)$$

$$g_t^{u^*} = (1 - \alpha_4)g_{t-1}^{u^*} + \varepsilon_t^{g^{u^*}} \quad (0.15)$$

## B. Foreign Economy

**Output** The foreign economy's output gap ( $y_t^e$ ) is also determined by a trend and a cycle, estimated jointly with the other cyclical components:

$$y_t^e = Y_t^e - y_t^{e^*} \quad (0.16)$$

where  $Y_t^e \equiv \sim 100 * \ln(GDP^e)$  and  $GDP^e$  is the observed quarterly real GDP of the foreign economy.<sup>18</sup> The variable  $y_t^{e^*}$  is the endogenously determined potential output, whose dynamics are given by:

$$y_t^{e^*} = y_{t-1}^{e^*} + \frac{1}{4} g_t^{e^*} + \varepsilon_t^{y^{e^*}} \quad (0.17)$$

$$g_t^{e^*} = \rho_{g^e} g_{t-1}^{e^*} + (1 - \rho_{g^e}) g_{ss}^{e^*} + \varepsilon_t^{g^e} \quad (0.18)$$

where  $g_{ss}^{e^*}$  is the steady-state growth rate of the foreign economy.

For the determination of the output gap, we assume that the domestic economy is small and so its output does not affect the foreign economy<sup>19</sup>:

$$y_t^e = \beta_{lead}^e y_{t+1}^e + \beta_{lag}^e y_{t-1}^e - \beta_r^e r_t^e + \varepsilon_t^e \quad (0.19)$$

We relax this assumption for the case of Germany, for which we assume that the domestic output gap affects also the euro area output gap.

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<sup>18</sup> In our estimation, we use the euro area aggregate. See Data Appendix.

$$y_t^e = \beta_{lead}^e y_{t+1}^e + \beta_{lag}^e y_{t-1}^e - \beta_r^e r_t^e + \beta_y y + \varepsilon_t^e \quad (0.20)$$

**Inflation** We assume foreign inflation is driven by the following Phillips curve:

$$\pi_t^e = \lambda_{lead}^e \pi_{t+1}^e + \lambda_{lag}^e \pi_{t-1}^e + \lambda_{y^e} y_t^e + \varepsilon_t^{\pi^e} \quad (0.21)$$

### C. Interest Rates

The determination of interest rates differs depending on whether the economy belongs or not to a currency union.

**Domestic economy outside a currency union** The nominal interest rate is determined by a Taylor-type monetary policy rule:

$$i_t = \gamma_i i_{t-1} + (1 - \gamma_i) [r_t^* + \pi_{t+1}^{tar} + \gamma_\pi (\pi_{t+4}^A - \pi_{t+4}^{A,tar}) + \gamma_y y_t] + \varepsilon_t^i \quad (0.22)$$

where the central bank aims to set a policy rate ( $i_t$ ) that is close to the equilibrium rate and the announced inflation target ( $r_t^* + \pi_{t+1}^{tar}$ ) while adjusting the rate in response to deviation of the expected annual inflation rate ( $\pi_{t+4}^A$ ) from its annualized target<sup>20</sup> ( $\pi_{t+4}^{A,tar}$ ) and the output gap ( $y_t$ ). The inflation target converges toward a steady state level ( $\pi_{ss}^{tar}$ ):

$$\pi_t^{tar} = \rho_{\pi^{tar}} \pi_{t-1}^{tar} + (1 - \rho_{\pi^{tar}}) \pi_{ss}^{tar} \quad (0.23).$$

The real interest rate is defined as the difference between the nominal rate ( $i_t$ ) and the next period expected inflation ( $\pi_{t+1}$ ):

$$R_t = i_t - \pi_{t+1} \quad (0.24)$$

while the real interest rate gap is defined as the difference between the real rate ( $R_t$ ) and its trend ( $r_t^*$ ) plus a risk premium ( $\phi_t$ ):

$$r_t = R_t - r_t^* + \phi_t \quad (0.25)$$

where the trend real rate converges toward a steady-state value ( $r_{ss}$ )

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<sup>20</sup> The annualized inflation target ( $\pi_{t+4}^{A,tar}$ ) is measured as in (1.6).

(continued...)

$$r_t^* = \rho_r r_{t-1}^* + (1 - \rho_r) r_{ss} + \varepsilon_r \quad (0.26)$$

while the risk premium follows an autoregressive process<sup>21</sup>:

$$\phi_t = \rho_\phi \phi_{t-1} + (1 - \rho_\phi) \phi_{ss} + \varepsilon_\phi \quad (0.27)$$

**Foreign Economy** The interest rate  $i_t^e$  also follows a forward-looking Taylor-type rule:

$$i_t^e = \gamma_i i_t^e + (1 - \gamma_i) [r_t^e + \pi_{t+1}^{e^{tar}} + \gamma_\pi (\pi_{t+4}^e - \pi_{t+4}^{A,tar}) + \gamma_y y_t^e] + \varepsilon_t^i \quad (0.28)$$

with the inflation target  $\pi_t^{e^{tar}}$  modeled as:

$$\pi_t^{e^{tar}} = \rho_{\pi^{e^{tar}}} \pi_{t-1}^{e^{tar}} + (1 - \rho_{\pi^{e^{tar}}}) \pi_{ss}^{e^{tar}} \quad (0.29)$$

The real rate is determined by the following equation:

$$R_t^e = i_t^e - \pi_{t+1}^e \quad (0.30)$$

The real rate gap  $r_t^e$  is determined by:

$$r_t^e = R_t^e - r_t^{e^*} \quad (0.31)$$

where the trend real rate converges toward a steady state value ( $r_{ss}^e$ ):

$$r_t^{e^*} = \rho_{r^{e^*}} r_{t-1}^{e^*} + (1 - \rho_{r^{e^*}}) r_{ss}^e + \varepsilon_t^{r^{e^*}} \quad (0.32)$$

**Domestic economy in a currency union** We assume in this case that the nominal interest rates is the sum of the common nominal rate plus a risk premium ( $\phi_t$ ):

$$i_t = i_t^e + \phi_t \quad (0.33)$$

where the latter follows (1.27). The real rate gap ( $r_t$ ) is then specified as the model implied real rate minus the currency union common trend real rate ( $r_t^{e^*}$ ):

$$R_t = i_t - \pi_{t+1} \quad (0.34)$$

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<sup>21</sup> The model assumes the risk premium is exogenous. For similar specification see for example Andrle et al. (2014) and Maria (2016).

$$r_t = R_t - r_t^e \quad (0.35)$$

#### D. Exchange Rates

**Currency Union** In a currency union, the nominal exchange rates are irrevocably fixed. Therefore, the real exchange rate is given by:  $Z_t = 100 * (\log(CPI^*) - \log(CPI))$ . The real exchange rate gap ( $z_t$ ) in both cases is the difference between the real exchange rate and its long-term trend:

$$z_t = Z_t - z_t^* \quad (0.36)$$

and the gap and the trend evolve according to:

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z \quad (0.37)$$

$$z_t^* = \rho_z^* z_{t-1}^* + (1 - \rho_z^*) z_{ss}^* + \varepsilon_t^{z^*} \quad (0.38)$$

where  $z_{ss}^*$  is a steady-state value.

**Non Currency Union** Outside the currency union the real exchange rate is defined as  $Z_t = 100 * (\log(s * CPI^* / CPI))$  where  $s$  is the nominal real exchange rate,  $CPI^*$  and  $CPI$  are the foreign and domestic price indices. We assume an interest parity condition:

$$z_t = z_{t+1}^e - (r_t - r_t^e - \rho_t^*) / 4 + \varepsilon_t^z \quad (0.39)$$

As in Berg et al. (2006) we allow rational expectation for the exchange rate:

$$z_{t+1}^e = \delta_z z_{t+1} + (1 - \theta_z) z_{t-1} \quad (0.40)$$

We define the equilibrium risk-premium to be:

$$\rho_t^* = 4 * (z_t^* - z_{t+1}^*) + (r_t^* - r_t^{*e}) \quad (0.41)$$

The gap follows (1.36) and the trend real exchange rate follows (1.38).

## APPENDIX II. Data Sources

### The Multivariate Filter (Quarterly Data)

#### ***Domestic Economy***

Real GDP	Federal Reserve Bank of St. Louis
Credit to the private nonfinancial sector	Federal Reserve Bank of St. Louis
Headline inflation	Federal Reserve Bank of St. Louis
Unemployment rate	Federal Reserve Bank of St. Louis
10-year government bond yield	Federal Reserve Bank of St. Louis
Nominal Exchange Rate	Federal Reserve Bank of St. Louis
3-Month nominal rate	Federal Reserve Bank of St. Louis

#### ***Euro Area***

Real GDP	Euro Area Wide Model Database
Headline inflation	Euro Area Wide Model Database
10-year benchmark yield	Euro Area Wide Model Database
3-Month nominal rate	Euro Area Wide Model Database

### The Fundamentals-Based Approach

GDP	World Economic Outlook
PPP Exchange Rate vs USD	World Economic Outlook
Population	World Economic Outlook
Credit to the private nonfinancial sector	International Finance Statistics, BIS
GDP deflator	International Finance Statistics
Deposits	International Finance Statistics
Interest Rates	ECB, Eurostat, OECD, IFS

### APPENDIX III. Estimated Parameters and Shocks for the Multivariate Filter

#### Estimation

The MVF flexibly uses a mixture of calibration and estimation. The calibration is done bearing in mind available evidence from other studies, ensuring the model properties are robust, meaning the impulse response functions are economically plausible and the 8 quarters step-ahead projections are good. We rely on Bayesian estimation instead for the model shocks. In the estimation, to help with the identification of the shocks, we rely on “system priors” (Andrle and Plasil 2016). System priors impose a penalty on the estimation process when the estimates are not consistent with a prior on the model behavior. In our case, we impose that the length of the business cycle should not be longer than 40 quarters. For sake of exposition, the following tables present only the estimated coefficients.

#### I. GERMANY

#### Estimated Parameters

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\beta_{lead}$	beta	0.200	0.010	0.200	0.010
$\beta_{lag}$	beta	0.500	0.100	0.497	0.119
$\beta_r$	gamma	0.060	0.020	0.053	0.019
$\beta_{y^c}$	gamma	0.100	0.100	0.152	0.092
$\beta_{\epsilon^c}$	gamma	0.100	0.050	0.075	0.043
$\beta_z$	gamma	0.070	0.020	0.064	0.019
$\lambda_{lag}$	gamma	0.150	0.100	0.116	0.088
$\lambda_y$	beta	0.500	0.100	0.491	0.102
$\lambda_z$	beta	0.050	0.010	0.048	0.010
$\theta_y$	beta	0.100	0.050	0.076	0.047
$\theta_{lag}$	beta	0.700	0.100	0.723	0.105
$\theta_r$	gamma	0.050	0.010	0.048	0.010



### Estimated Shocks

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\sigma^y$	invgamma	0.500	<i>Inf</i>	0.145	0.074
$\sigma^g$	invgamma	0.100	<i>Inf</i>	0.044	0.021
$\sigma^{y^*}$	invgamma	0.100	<i>Inf</i>	0.036	0.023
$\sigma^\pi$	invgamma	0.500	<i>Inf</i>	0.144	0.076
$\sigma^c$	invgamma	0.500	<i>Inf</i>	0.166	0.096
$\sigma^{c^*}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^{g^{c^*}}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^u$	invgamma	0.500	<i>Inf</i>	0.166	0.096
$\sigma^{u^*}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^{g^{u^*}}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^\phi$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{\pi^{e^{tar}}}$	invgamma	0.300	<i>Inf</i>	0.100	0.057
$\sigma^{y^e}$	invgamma	0.500	<i>Inf</i>	0.124	0.054
$\sigma^{g^e}$	invgamma	0.100	<i>Inf</i>	0.052	0.024
$\sigma^{y^{e^*}}$	invgamma	0.100	<i>Inf</i>	0.037	0.025
$\sigma^{\pi^e}$	invgamma	0.500	<i>Inf</i>	0.159	0.093
$\sigma^i$	invgamma	0.500	<i>Inf</i>	0.164	0.093
$\sigma^{r^{e^*}}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^z$	invgamma	1.000	<i>Inf</i>	0.330	0.190
$\sigma^{z^*}$	invgamma	1.000	<i>Inf</i>	0.332	0.192

## II. SPAIN

## Estimated Parameters

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\beta_{lead}$	beta	0.250	0.010	0.250	0.010
$\beta_{lag}$	beta	0.700	0.020	0.702	0.020
$\beta_r$	gamma	0.030	0.020	0.017	0.015
$\beta_{y^c}$	gamma	0.250	0.100	0.209	0.091
$\beta_{c^c}$	gamma	0.100	0.050	0.075	0.044
$\beta_z$	gamma	0.100	0.020	0.095	0.020
$\theta_y$	beta	0.200	0.100	0.160	0.104
$\theta_{lag}$	beta	0.850	0.050	0.865	0.049
$\theta_r$	gamma	0.150	0.050	0.133	0.047

## Estimated Shocks

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\sigma^y$	invgamma	0.500	<i>Inf</i>	0.143	0.079
$\sigma^g$	invgamma	0.010	<i>Inf</i>	0.042	0.011
$\sigma^{y^*}$	invgamma	0.010	<i>Inf</i>	0.003	0.002
$\sigma^\pi$	invgamma	0.500	<i>Inf</i>	0.131	0.068
$\sigma^c$	invgamma	1.000	<i>Inf</i>	0.263	0.151
$\sigma^{c^*}$	invgamma	0.500	<i>Inf</i>	0.066	0.038
$\sigma^{g^{c^*}}$	invgamma	0.500	<i>Inf</i>	0.066	0.038
$\sigma^u$	invgamma	0.300	<i>Inf</i>	0.097	0.054
$\sigma^{u^*}$	invgamma	0.300	<i>Inf</i>	0.075	0.042
$\sigma^{g^{u^*}}$	invgamma	0.100	<i>Inf</i>	0.033	0.018
$\sigma^\phi$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{\pi^{c^{tar}}}$	invgamma	0.300	<i>Inf</i>	0.099	0.057
$\sigma^{y^c}$	invgamma	0.500	<i>Inf</i>	0.166	0.096
$\sigma^{g^c}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^{y^{c^*}}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{\pi^c}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^i$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{r^{c^*}}$	invgamma	1.000	<i>Inf</i>	0.321	0.186
$\sigma^z$	invgamma	1.000	<i>Inf</i>	0.328	0.191

## III. SWEDEN

## Estimated Parameters

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\beta_{lead}$	beta	0.200	0.100	0.157	0.096
$\beta_{lag}$	beta	0.700	0.100	0.713	0.085
$\beta_r$	gamma	0.040	0.010	0.037	0.010
$\beta_{y^c}$	gamma	0.200	0.030	0.199	0.030
$\beta_{\epsilon^c}$	gamma	0.070	0.020	0.064	0.019
$\beta_z$	gamma	0.010	0.010	0.001	0.000
$\lambda_y$	gamma	0.100	0.050	0.072	0.039
$\lambda_{lag}$	beta	0.300	0.100	0.276	0.104
$\lambda_z$	beta	0.040	0.010	0.038	0.010
$\theta_y$	beta	0.200	0.100	0.153	0.099
$\theta_{lag}$	beta	0.800	0.100	0.846	0.100
$\theta_r$	gamma	0.050	0.010	0.048	0.010
$\delta_z$	beta	0.700	0.100	0.723	0.106
$\rho_{gz}$	beta	0.800	0.100	0.846	0.100
$\tau_1$	normal	1.000	0.100	0.999	0.100
$\tau_2$	normal	0.800	0.100	0.807	0.097
$\tau_3$	normal	0.100	0.100	0.100	0.100
$\tau_4$	normal	0.100	0.100	0.100	0.100

## Estimated Shocks

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\sigma^y$	invgamma	0.800	<i>Inf</i>	0.232	0.132
$\sigma^{y^*}$	invgamma	0.200	<i>Inf</i>	0.059	0.026
$\sigma^g$	invgamma	0.200	<i>Inf</i>	0.063	0.033
$\sigma^\pi$	invgamma	0.800	<i>Inf</i>	0.277	0.151
$\sigma^c$	invgamma	0.800	<i>Inf</i>	0.267	0.154
$\sigma^{c^*}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{g^{c^*}}$	invgamma	0.500	<i>Inf</i>	0.167	0.097
$\sigma^u$	invgamma	0.300	<i>Inf</i>	0.174	0.097
$\sigma^{u^*}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^{g^{u^*}}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^\phi$	invgamma	0.800	<i>Inf</i>	0.267	0.154
$\sigma_{z^*}$	invgamma	1.000	<i>Inf</i>	0.334	0.193
$\sigma_z$	invgamma	0.500	<i>Inf</i>	0.167	0.097
$\sigma^{\pi^{tar}}$	invgamma	0.500	<i>Inf</i>	0.168	0.097
$\sigma^{\pi^{c^{tar}}}$	invgamma	0.500	<i>Inf</i>	0.114	0.049
$\sigma^{y^c}$	invgamma	0.500	<i>Inf</i>	0.152	0.080
$\sigma^{g^c}$	invgamma	0.500	<i>Inf</i>	0.165	0.095
$\sigma^{y^{c^*}}$	invgamma	0.800	<i>Inf</i>	0.269	0.155
$\sigma^{\pi^c}$	invgamma	1.000	<i>Inf</i>	0.332	0.191

## IV. POLAND

## Estimated Parameters

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\beta_{lead}$	beta	0.200	0.100	0.150	0.094
$\beta_{lag}$	beta	0.700	0.100	0.694	0.085
$\beta_r$	gamma	0.040	0.010	0.038	0.010
$\beta_{y^e}$	gamma	0.200	0.030	0.199	0.031
$\beta_{\epsilon^c}$	gamma	0.070	0.020	0.064	0.019
$\beta_z$	gamma	0.010	0.010	0.001	0.000
$\theta_y$	beta	0.200	0.100	0.150	0.097
$\theta_{lag}$	beta	0.800	0.100	0.846	0.100
$\theta_r$	gamma	0.100	0.050	0.075	0.043
$\delta^z$	beta	0.700	0.100	0.723	0.105

## Estimated Shocks

Parameter	Distribution	Prior		Posterior	
		Mode	St. Dev.	Mode	St. Dev.
$\sigma^y$	invgamma	0.800	<i>Inf</i>	0.243	0.139
$\sigma^{y^*}$	invgamma	0.200	<i>Inf</i>	0.053	0.019
$\sigma^g$	invgamma	0.200	<i>Inf</i>	0.059	0.027
$\sigma^\pi$	invgamma	0.800	<i>Inf</i>	0.285	0.160
$\sigma^c$	invgamma	0.800	<i>Inf</i>	0.269	0.156
$\sigma^{c^*}$	invgamma	0.200	<i>Inf</i>	0.067	0.039
$\sigma^{g^{c^*}}$	invgamma	0.200	<i>Inf</i>	0.067	0.039
$\sigma^u$	invgamma	0.300	<i>Inf</i>	0.100	0.058
$\sigma^{u^*}$	invgamma	0.300	<i>Inf</i>	0.114	0.059
$\sigma^{g^{u^*}}$	invgamma	0.100	<i>Inf</i>	0.033	0.019
$\sigma^\phi$	invgamma	0.800	<i>Inf</i>	0.267	0.154
$\sigma_{z^*}$	invgamma	1.000	<i>Inf</i>	0.336	0.195
$\sigma_z$	invgamma	0.500	<i>Inf</i>	0.164	0.094
$\sigma^{\pi^{tar}}$	invgamma	0.500	<i>Inf</i>	0.167	0.097
$\sigma^{\pi^{c^{tar}}}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{y^e}$	invgamma	0.500	<i>Inf</i>	0.106	0.038
$\sigma^{g^e}$	invgamma	0.500	<i>Inf</i>	0.159	0.089
$\sigma^{y^{e^*}}$	invgamma	0.500	<i>Inf</i>	0.167	0.096
$\sigma^{\pi^e}$	invgamma	0.500	<i>Inf</i>	0.172	0.101
$\sigma^{i^e}$	invgamma	0.500	<i>Inf</i>	0.167	0.096

#### APPENDIX IV. Revision Properties of the MVF compared with the HP

A common issue concerning the use of filters is that the arrival of new information leads to revision of past estimates of the unobserved components (Andrle 2013). In the output gap literature, a typical test of the performance of two filters is to compare the difference between the nowcasts and final estimates obtained using data over the entire period (Benes et al. 2010). We quantify the size of the revision by comparing the mean absolute error (MAE), the average absolute deviation of the difference between nowcasts and final estimates. In the Table below, we show the results for each of the four country in our sample.

**Table: Real Time Properties of MVF vs. HP**

	MAE	
	HP	MVF
ESP	21.2	5.4
DEU	6.3	1.7
SWE	6.7	1.4
POL	8.1	4.1

The MAE of the MVF is typically much smaller than the MAE for the HP, reducing the MAE by as much as 80 percent. Yet, compared to the literature on output gap, the MAE of the credit gaps are larger. This suggests that further refined to the MVF could be implemented using different data and/or further specification of the cycle equation. The latter is an exercise we leave for future research.

## References

- Adrian, T., He, D., Natalucci F., and Liang, N. forthcoming. "Macrofinancial Linkages and Global Financial Stability." IMF Staff Discussion Note.
- Aikman, D, A Haldane and B Nelson. 2015. "Curbing the credit cycle." *The Economic Journal*, Volume 125, Issue 585, Page 1072-1109. Bank of England.
- Aldasoro, Inaki, Borio Caludio, and Mathias Drehmann. 2018. "Early Warning Indicators of Banking Crises: Expanding the Family." *BIS Quarterly Review*, March 2018.
- Andrle, Michal. 2013. "What Is in Your Output Gap? Unified Framework & Decomposition into Observables." IMF Working Papers 13/105, International Monetary Fund.
- Andrle, Michal, Roberto Garcia-Saltos, and Giang Ho. 2014. "A Model-Based Analysis of Spillovers; The Case of Poland and the Euro Area." IMF Working Papers 14/186, International Monetary Fund.
- Andrle, Michal, Miroslav Plašl. 2016. "System Priors for Econometric Time Series." IMF Working Papers 16/231, International Monetary Fund.
- Basel Committee on Banking Supervision. 2010. "Guidance for national authorities operating the countercyclical capital buffer." Bank for International Settlements, December 2010.
- Baxter, Marianne, and Robert. G. King. 1999. "Measuring business cycles: Approximate band-pass filters for economic time series." *The Review of Economics and Statistics* 81(4), 575-593.
- Benes, J., K. Clinton, R. Garcia-Saltos, M. Johnson, D. Laxton, P. Manchev, and T. Matheson. 2010. "Estimating Potential Output with a Multivariate Filter." IMF Working Papers 10/285, International Monetary Fund.
- Berg, A., P. Karam, and D. Laxton, 2006, "A Practical Model-Based Approach to Monetary Policy Analysis: Overview", IMF Working Paper 06/080, International Monetary Fund.
- Bernanke, Ben, and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review* 79 (1), pp. 14-31
- Bianchi, Javier, and Enrique Mendoza. 2018. "Optimal Time-Consistent Macroprudential Policy." *Journal of Political Economy* 126 (2), pp. 588-634

- Buncic, Daniel and Martin Melecký. 2014. "Equilibrium credit: The reference point for macroprudential supervisors." *Journal of Banking & Finance*, vol. 41, issue C 135-154.
- Carabenciov, Ioan, Igor Ermolaev, Charles Freedman, Michel Juillard, Ondra Kaminek, Dmitry Korshunov, and Douglas Laxton. 2008. "A Small Quarterly Projection Model of the U.S. Economy." IMF Working Paper No. 08/278, International Monetary Fund.
- Christiano, Lawrence J., and T. J. Fitzgerald. 2003. "The band pass filter," *International Economic Review* 44(2), 435-465.
- Claessens, Stijn, Ayhan M. Kose, and Marco E. Terrones. 2011. "Financial Cycles: What? How? When?" IMF Working Paper 11/76, International Monetary Fund.
- Claessens, Stijn, Ayhan M. Kose, and Marco E. Terrones. 2012. "How Do Business and Financial Cycles Interact?" *Journal of International Economics* 87 (2012) 178–190.
- Dell’Ariccia, Giovanni, Deniz Igan, Luc Laeven, and Hui Tong. 2012. "Policies for macro-financial stability: Dealing with credit booms and busts." Staff Discussion Note 12/06, International Monetary Fund.
- Dell’Ariccia, Giovanni, Ehsan Ebrahimi, Deniz Igan, and Damien Puy. 2019. "Discerning Good from Bad Credit Booms: The Role of Construction." Staff Discussion Note, International Monetary Fund, *forthcoming*.
- Detken Carsten, Olaf Weeken, Lucia Alessi, Diana Bonfim, Miguel M. Boucinha, Christian Castro, Sebastian Frontczak, Gaston Giordana, Julia Giese, Nadya Jahn, Jan Kakes, Benjamin Klaus, Jan Hannes Lang, Natalia Puzanova. And Peter Welz. 2014. "Operationalizing the Countercyclical Capital Buffer." ESRB Occasional Paper, no 5.
- Drehmann, Mathias, Claudio Borio, and Kostas Tsatsaronis. 2012. "Characterising the financial cycle: don't lose sight of the medium term!" BIS Working Papers No 380, June 2012.
- Drehmann, Mathias, and Mikael Juselius. 2014. "Evaluating early warning indicators of banking crises: Satisfying policy requirements." *International Journal of Forecasting* Volume 30, Issue 3, July–September 2014, Pages 759-780.
- Drehmann, Mathias, and Kostas Tsatsaronis. 2014. "The Credit-to-GDP Gap and Countercyclical Capital Buffers: Questions and Answers." *BIS Quarterly Review*, March 2014.
- Drehmann, Mathias, and James Yetman. 2018. "Why You Should Use the Hodrick-Prescott Filter—At Least to General Credit Gaps." BIS Working Papers No 744, September 2018.

- Durbin, James, and Siem Jan Koopman. 2012. "Time series analysis by state space methods (2nd ed.)" Oxford University Press.
- Edge, Rochelle M., and Ralf R. Meisenzahl. 2011. "The Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers." *International Journal of Central Banking*, vol. 7(4), pages 261-298, December.
- European Central Bank. 2017. "Financial Stability Review," May 2017.
- \_\_\_\_\_. 2018. "Real and financial cycles in EU countries: Stylised facts and modelling implications." Occasional Paper Series, No 205, January 2018.
- \_\_\_\_\_. 2019. "Anticipating the bust: a new cyclical system risk indicator to assess the likelihood and severity of financial crises." Occasional Paper Series, No 219, February 2019.
- Galán, Jorge E., and Javier Mencía. 2018. "Empirical Assessment of Alternative Structural Methods for Identifying Cyclical Systemic Risk in Europe." Documentos de Trabajo No. 1825, Banco de España.
- Galán, Jorge E. 2019. "Measuring Credit-to-GDP Gaps. The Hodrick-Prescott Filter Revisited." Documentos de Trabajo No. 1906, Banco de España.
- Galati, Gabriele, Irma Hindrayanto, Siem Jan Koopman, and Marente Vlekke. 2016. "Measuring Financial Cycles with a Model-Based Filter: Empirical Evidence for the United States and the Euro Area." Tinbergen Institute Discussion Papers 16-029/III, Tinbergen Institute.
- Hamilton, James. 2017. "Why You Should Never Use the Hodrick-Prescott Filter." NBER Working Paper No 23429 (and Review of Economics and Statistics, forthcoming).
- Harvey, Andrew. 1989. "Forecasting, Structural Time Series Models and the Kalman Filter." Cambridge University Press.
- International Monetary Fund. 2015. "Central, Eastern, and Southeastern Europe. Mind the Credit Gap." Regional Economic Issues, May 2015, International Monetary Fund.
- \_\_\_\_\_. 2019. "The Revised EBA-Lite Methodology." July 2019, International Monetary Fund.
- Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic Effects of Financial Shocks." *American Economic Review* 102 (1), pp. 238-71



- Jokivuollea, Esa, Jarmo Pesola, and Matti Viren. 2015. "Why is credit-to-GDP a good measure for setting countercyclical capital buffers?" *Journal of Financial Stability* 18 (2015) 117-126
- Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2016. "Macrofinancial History and The New Business Cycle Facts." NBER Working Paper No 22743.
- Kauko, Karlo, and Eero Tölö. 2019. "On the long-run calibration of the credit-to-GDP gap as a banking crisis predictor." Bank of Finland Research Discussion Papers 6/2016.
- Kirti, Divya. 2018. "Lending Standards and Output Growth." IMF Working Paper 18/26, International Monetary Fund.
- Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy*, 105 (2), pp. 211-48
- Krznar Ivo, Troy D. Matheson. 2017. "Financial and Business Cycles in Brazil." IMF Working Papers 17/12, International Monetary Fund.
- Lang, Jan Hannes, Peter Welz. 2017. "Semi-Structural Credit Gap Estimation." ECB mimeo.
- Laxton, Douglas, and Robert Tetlow. 1992. "A Simple Multivariate Filter for the Measurement of Potential Output." Technical Report no. 59 (Ottawa: Bank of Canada).
- Maria, José R. 2016. "Portugal: Trends, cycles, and instability in output and unemployment over 2008-2012." *Economic Studies*, Vol II, No. 3, Banco de Portugal.
- Pesaran, Hashem M., Shin Yongcheol, and Smith Ronald. 1997. "Pooled Estimation of Long-run Relationships in Dynamic Heterogeneous Panels." Cambridge Working Papers in Economics.
- Ravn, Morten O., and Harald Uhlig. 2002. "On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations." *Review of Economics and Statistics*.
- Repullo, Rafael, and Jesús Saurina. 2011. "The Countercyclical Capital Buffer of Basel III: A Critical Assessment." Working Ppaers wp 2011\_1102, CEMFI.
- Richter, Björn, Moritz Schularick, and Paul Wachtel. 2017. "When to Lean Against the Wind." CEPR Discussion Paper No. 12188.
- Rünstler, Gerhard, and Marente Vlekke. 2016. "Business, Housing, and Credit Cycles." ECB Working Paper Series No 1915, European Central Bank, June 2016.