AN ITALIAN TAKE ON THE CREDIT-TO-GDP GAP

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1. Introduction

The global financial crisis has shown that banks' procyclical behaviour can greatly exacerbate the impact of adverse financial shocks. Policy makers and regulators have responded by introducing in the Basel III package a "countercyclical capital buffer" (CCyB) aimed at strengthening the resilience and limiting the procyclicality of the banking sector. The CCyB should rise in good times, when credit is above equilibrium, and fall in bad times, when it is scarce, with the twin objective of protecting the banking sector from periods of excess aggregate credit growth and 'leaning against the financial cycle' so to keep the supply of credit stable over time.[2]

The implementation of the CCyB poses a great empirical challenge: how should good and bad times be identified? More specifically, how can the aggregate 'credit gap' be measured, and how much trust can policy makers put in such estimates?

BCBS (2011) and ESRB (2014) recommend calculating the credit-to-GDP gap (or simply 'credit gap' or 'credit cycle' – we use these terms as synonyms) by applying a one-side Hodrick-Prescott (HP) filter to the ratio between total credit and GDP. The trend-cycle decomposition based on this filter for the 1970-2012 period is displayed in figure 1.[3] Figure 2 shows the associated CCyB based on ESRB (2014). The grey band identifies the banking crisis of 1994-1995. The credit gap is virtually always positive from the mid-80s onwards. The average duration of the upturns is about 49 quarters, well above the estimates obtained for other countries, which typically range between 8 and 22 quarters (Claessens et al., 2012; Drehmann et al., 2012). The CCyB rate peaks long before the 1994 crisis and remains positive for over ten years from the late 1990s onwards. In short, the indicator raises more questions than it answers, and its numerous 'false positives' might arguably lead to an overly restrictive capital buffer policy.

In this contribution we (i) propose a simple refinement for the estimation methodology, (ii) exploit the depth of the Italian data – where aggregate credit series are available since the end of the XIX century – to test the usefulness of the indicators in forecasting financial crises, and (iii) discuss their use in real-time policy making. The discussion is based on Alessandri et al. (2015), which we henceforth refer to as ABFS.

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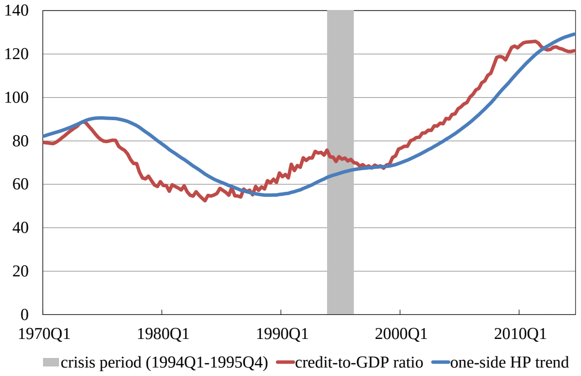
[2] After the approval of the European Directive 2013/36/EU, also known as CRD IV, CCyB frameworks are now active in all European countries and the European Systemic Risk Board (ESRB) is responsible for a harmonized implementation of the new policy across Europe. Its key recommendations are discussed in ESRB (2014).

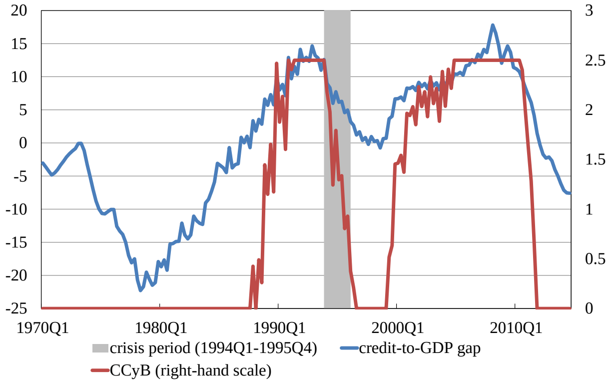
[3] Credit is measured as nominal total credit to the domestic non-financial private sector, available from the Bank for International Settlements (Dembiermont et al., 2013; Dekten et al., 2014). Annual GDP is seasonally and working day adjusted. Both series are expressed in nominal terms.

Figure 1. Credit-to-GDP ratio
(*per cent*)



Source: elaborations on BIS and Eurostat data.

Figure 2. Credit-to-GDP gap and CCyB rate
(*percentage points*)



Source: elaborations on BIS and Eurostat data.

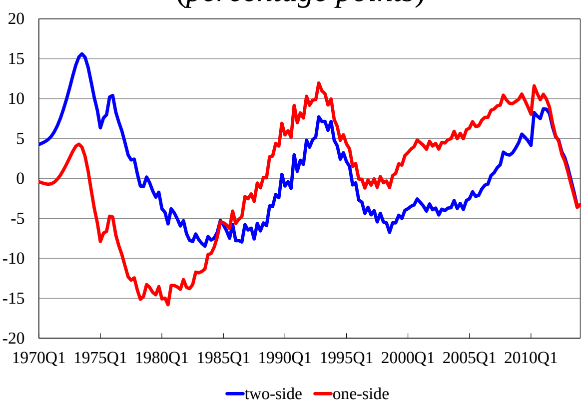
2. One-side or two-side?

Some of the questionable conclusions that emerge from figures 1 and 2 are a mere by-product of using short series to estimate a low-frequency phenomenon. In the case of Italy, by switching from total to bank credit it is possible to push the estimation back as far as 1861. Once post-war data is included, the filter estimates a -15% credit trough at the end of the 1970s and a much more conservative assessment of the subsequent boom phase (see ABFS). This delivers the first, somewhat obvious message that one should be wary of short samples.[4] Yet this is not the only issue. The one-side HP filter (1*S*) forms an estimate of the cycle at time *t* using exclusively information available until then, while the two-side HP filter (2*S*) employs the full sample information – i.e. it includes the observations which become available in the following periods. Hence, a comparison between the two filters gives a direct measure of whether and how the estimate of the credit gap is revised when more data becomes available. We carry out this comparison in figure 3.a. In both cases we use data from 1950 and a smoothing parameter λ set to 400,000, in accordance with ESRB (2014).

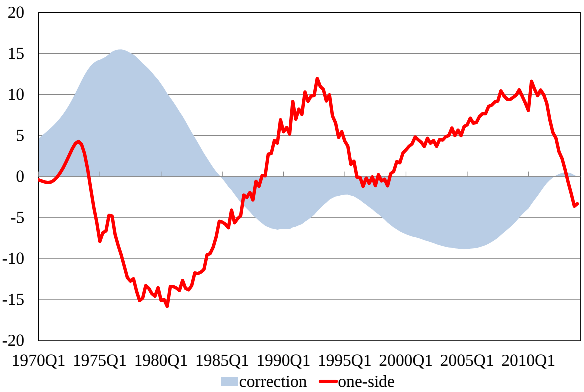
The differences are stark. 2S drastically reduces the 1980 trough and then delays the beginning of the booms of the 1990s and 2000s compared to 1*S*. In the case of the 2000s cycle, the expansion is estimated to start in early 2007, almost two years before the outbreak of the financial crisis.

Figure 3. Credit-to-GDP gap: two-side and one-side filtering

(a) Credit-to-GDP gap
(*percentage points*)



(b) One-side estimate and two-side correction
(*percentage points*)



Source: elaborations on BIS, De Bonis et al. (2012), and Eurostat data.

[4] We stick to bank credit for the remainder of the analysis in order to fully exploit the length of our dataset.

More generally, the cycles estimated using 2S are less volatile, with shorter and less pronounced booms than those estimated with 1S. In other words, 1S tends to 'overshoot' relative to its full-sample counterpart. These features do not reflect accidental factors driving the dynamics of credit over the last two decades, as ABFS find that they are also apparent in the 1861-1950 sample.

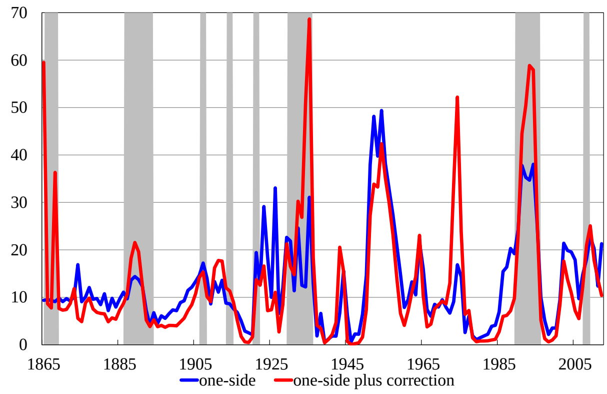
Figure 3.b shows the difference between 2S and 1S. Besides being large, this difference ('correction' or $Corr$ from now on) is highly persistent and negatively correlated to the *1S* estimate. This issue is not new in the filtering literature (Orphanides and Van Norden, 2002), and it opens the way to the possibility of forecasting the 1S filtering error and adjusting the estimate accordingly. We examine this possibility in Section 4. Before doing that, we check more formally whether the exercise is worth undertaking – i.e. whether, going beyond the visual inspection of figure 3, the 2S estimates also allow for more accurate predictions of financial crises.

3. A crisis prediction exercise

Is the 2S estimate of the credit gap a good predictor of financial crises? Or, more precisely, is the additional information provided by 2S relative to 1S valuable from a forecasting perspective? These questions can be answered with a *pseudo*-forecasting exercise. The question is whether – if the 'true' 2S cycle were hypothetically available in real time – it would allow policy makers to obtain more accurate warning signals on future crises. Drehmann et al. (2011) argue that in general the answer is negative: their cross-country evidence suggests that the credit gap estimated using a 1S is often a better crisis predictor than that based on 2S. If confirmed for the case of Italy, this result would heavily tilt the policy-maker's preferences towards using 1S despite the fact that *2S* provides a more convincing narrative of financial cycles.

The Logit model estimated in ABFS exploits the 1861-2012 period and a total of eight banking crises (see ABFS for details). Crises and model-based crisis probabilities are depicted in figure 4. The inclusion of *Corr* as an explanatory variable substantially improves the predictive performance of the model. If we assume that an early warning is issued when the probability of a crisis is above 30%, including *Corr* increases the true positives from 30.8% to 53.9% at a very low cost in terms of false positives. The predictive performance of the model is enhanced both in the earlier part of the sample (i.e. around the 1890 and 1935 crises) and in later years (mid-1990s crisis).[5]

Figure 4. Crisis probabilities based on Logit models (1)
(*percentage points*)



(1) Predicted probabilities generated by the models in Equations 5 and 6.
Source: elaborations on BIS, De Bonis et al. (2012), and Eurostat data.

[5] The interpretation of the 'false positive' in 1975 is not straightforward (see ABFS).

4. Estimating the credit gap in real time

Since 2*S* provides *by construction* a more accurate estimate of the cycle than a 1*S*, the power of *Corr* in predicting crises does not come as a surprise. But is this result of any use in real time, when the 'true' 2*S* cannot be calculated? The answer is yes, to some extent. Since *Corr* is large and persistent, the policy maker can learn from history and use past observations on *Corr* to adjust his current estimate of the credit gap.

ABFS run extensive Granger-causality tests and find that the 1*S* cycle predicts *Corr*: in other words, real-time estimates provide information on whether and how the cycle will be revised when new observations are added to the sample. This is consistent with the 'overshooting' phenomenon displayed in figure 3. In addition, *Corr* predicts the 1*S* cycle: knowing its past "mistakes", one can predict the future evolution of the one-side filter itself. Given the dynamic setting of the VAR model used for the test, this also implies that *Corr* has a strong autoregressive component and that the information contained in past 2S estimates could be used to improve the current estimate of the cycle, in line with Gerdrup et al. (2013).

Since *Corr* is not known in real time, it must be estimated. To do so ABFS proceed in four steps. First, they estimate 1*S* and 2*S* up to time *t*, calculating the associated series of *Corr*. Second, they discard the last *h* observations of *Corr*, which are known to be biased. Third, they estimate a predictive model and use it to generate $E_t Corr_t$, essentially a "nowcast" of the correction term. In the final step a new real-time estimate of the cycle is constructed as $\widehat{2S_t} = 1S_t + E_t Corr_t$. Intuitively, this process fine-tunes the estimate suggested by the Basel framework using a guess on the adjustment to that estimate that would ultimately emerge in a full-sample filtering process.

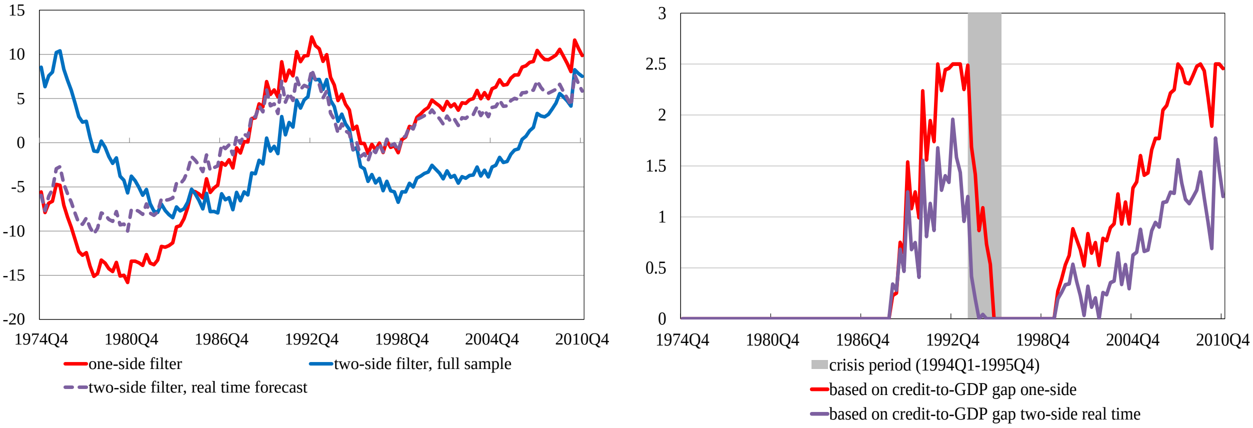
In order to implement this procedure ABFS consider forecasting horizons between 4 and 16 quarters and compare three naïve predictive models for *Corr*: a random walk (a standard benchmark in forecasting), a univariate dynamic equation and a bivariate VAR that includes 1*S* and *Corr*. Results show that all three models have acceptable performances at short horizons. The random walk generates the best predictions: its average root mean square error is 6%, corresponding to roughly ¼ of the range of the target variable. The message is that (a model as simple as) a random walk can generate sensible forecasts for *Corr*.

To shed more light on how useful these forecasts would be in practice, ABFS use them to compute real-time estimates of the two-side credit gap ($\widehat{2S_t}$) and derive the associated CCyB ratios. These are presented respectively in figure 5.a and 5.b. To aid the interpretation of the results, in figure 5.a we reproduce (i) the unadjusted 1*S* cycle (red); (ii) the 2*S* cycle, i.e. what we would ideally like to use, but do not observe in real time (blue); (iii) our real-time estimate of the *2S* cycle (dashed line). The success of the procedure thus depends on whether and how it allows us to move from the red line towards the blue line.

The results are promising. The quality of the predictions changes of course over time, but the forecast is always better than the 1*S* estimate, with one exception in the period 1983-1987. Relative to 1*S* the forecast would have suggested shaving two to three percentage points off the "boom" in the late 1980s, and up to five percentage points in the late 2000s. These are clearly economically significant numbers. The pattern followed by the CCyB remains qualitatively similar to the benchmark case, but the new estimates lead to a generally more gradual and cautious approach by the policy maker.

Figure 5: Adjusting the credit gap estimate in real time

(a) Credit-to-GDP gap (*percentage points*) (b) Countercyclical capital buffer rate (*percentage points*)



Source: elaborations on BIS, De Bonis et al. (2012), and Eurostat data.

The random-walk adjustment gives good results in the case of the total credit series too, suggesting that the erratic performance of 1*S* and the predictability of its filtering errors might be a common feature of credit-to-GDP ratios (the results are available in ABFS).

5. Conclusions

Obtaining a reliable estimate of the aggregate credit gap in the economy has become an important objective for macroprudential authorities after Basel III. In this contribution we discuss some of the technical issues associated to this task and present a simple strategy to improve the standard methodology suggested by BCBS (2011) and ESRB (2014). Our method can be implemented using the same data and the same econometric tools. In the case of Italy, it generates credit gap estimates that are more plausible, less volatile and more accurate in forecasting financial crises.

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