



BANCA D'ITALIA  
EUROSISTEMA

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of a Countercyclical Capital Buffer in Italy

by Piergiorgio Alessandri, Pierluigi Bologna, Roberta Fiori and Enrico Sette

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ISSN 1972-6627 (print)

ISSN 1972-6643 (online)

*Printed by the Printing and Publishing Division of the Bank of Italy*

# A NOTE ON THE IMPLEMENTATION OF THE COUNTERCYCLICAL CAPITAL BUFFER IN ITALY

by Piergiorgio Alessandri\*, Pierluigi Bologna\*, Roberta Fiori\*, Enrico Sette\*

## Abstract

This paper analyzes the challenges posed by the implementation of the countercyclical capital buffer framework in Italy and proposes ways of meeting them. In the first part of the analysis we review the limitations of the standardized Basel III credit-to-GDP gap; we then propose possible solutions, which while remaining in the spirit of Basel, can better capture the state of the credit cycle in real time. In the second part of the paper we propose a step by step approach for reducing the uncertainty that may arise when looking at the indicators which, in addition to the credit-to-GDP gap, are designed to help authorities take decisions about the buffer rate; we also analyze the relationship between the selected indicators and a continuous variable of banking system riskiness. While the analysis is conducted with reference to Italian data, the proposed analytical framework is applicable to any country.

**JEL Classification:** E32, G01, G21, G28.

**Keywords:** countercyclical capital buffer, financial cycle, credit cycle, macroprudential policy, capital requirements, banks, banking crises.

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## 1. Introduction

The global financial crisis has highlighted that one of the elements that exacerbated the impact of the crisis has been the procyclical behavior of the banking system following a shock. The regulatory response by policy makers and regulators has been aimed at strengthening the resilience of the banking system and limiting its procyclicality. The countercyclical capital buffer (CCyB) has therefore been introduced as part of the Basel III package as the main macroprudential tool to protect the banking sector from periods of excess aggregate credit growth that have often been associated with the accumulation of system-wide risk. In addressing this primary aim, the CCyB regime may also help to ‘lean against the financial cycle’, by raising the cost of credit and thus dampening its demand during the build-up phase and vice versa during the release phase.

The European Directive 2013/36/EU – also known as CRD IV – requires members states to have an operational framework for the CCyB in place by March 2016. The implementation of the framework poses, however, a number of challenges related to: a) the difference in credit cycles across countries which goes against a one-size-fits-all type of approach, particularly in the context of an overall still limited knowledge of the features of financial cycles; b) the lack of systemic crises in several countries to test the significance of early warning indicators; c) the lack of empirical macro-models to support decision making in the macroprudential sphere.

In light of these uncertainties the aim of this paper is to propose an operational framework that, within the degrees of freedom allowed by the Basel approach and the European regulation, aims to address the challenges related to the application of the CCyB in Italy. In particular, we (i) study the credit cycle using the longest time series of credit and GDP available in Italy; (ii) propose a way to improve the real-time estimation of the state of the financial cycle, or in other words of the credit-to-GDP gap;<sup>1</sup> (iii) propose an approach to select a set of additional macro-financial indicators that should complement the credit-to-GDP gap in guiding decision making on the CCyB.

The paper proceeds as follows. In Section 2 we review the European Systemic Risk Board (ESRB) recommendation which aims at guiding member states in the operationalization of the CCyB. In Section 3 we study the credit-to-GDP gap on Italian data, propose an alternative approach to the standardized estimation of the gap, testing its usefulness in forecasting financial crises and discussing its applicability in real-time policy making. In Section 4 we propose a way to select a core set of additional indicators that could usefully complement the credit-to-GDP gap in setting the CCyB. Section 5 concludes.

## 2. The ESRB Recommendation on the countercyclical capital buffer

The CRD IV introduced the Basel III package in Europe and delegated the European Systemic Risk Board (ESRB) to guide member states in the operationalization of the countercyclical capital buffer. In June 2014, the ESRB issued a Recommendation (ESRB, 2014) for a harmonized implementation of the CCyB across the EU. The Recommendation consists of four sub-recommendations, dealing respectively with: “Principles” (A); “Guidance on the measurement and calculation of the credit-to-GDP gap, calculation of the benchmark buffer rate and the buffer guide” (B); “Guidance on variables that indicate the build-up of system-wide risk associated with periods of excessive credit

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<sup>1</sup> In the macroeconomic literature on filtering, the difference between a variable and its trend is commonly referred to as “cycle” rather than “gap”: in the remainder of the paper, we use the two terms as synonyms.

growth” (C); and “Guidance on variables that indicate that the buffer should be maintained, reduced or fully released” (D). Despite the very detailed guidance by the ESRB, the framework provided applies the principle of “guided discretion”, hence no automatism is foreseen in setting the CCyB rate.

To put in context our analysis it is useful to recall the main contents of Recommendations B, C and D which deal with the issues addressed in the remainder of the work.

### 2.1 Recommendation B

This Recommendation requires authorities to measure and publish, on a quarterly basis, a standardized credit-to-GDP gap which, in accordance with Basel Committee on Banking Supervision (2011), is defined as

$$GAP_t = Ratio_t - Trend_t \quad (1)$$

where

$t$  = the end of each quarter;

$$Ratio_t = \left( \frac{Credit_t}{GDP_t + GDP_{t-1} + GDP_{t-2} + GDP_{t-3}} \right) \times 100\%;$$

$GDP_t$  = gross domestic product at time  $t$ ;

$Credit_t$  = broad measure of the stock of domestic credit to the private non-financial sector outstanding at the end of quarter  $t$ ;<sup>2</sup>

$Trend_t$  = long-term trend of  $Ratio$  computed with a one-side (recursive) Hodrick-Prescott filter with the smoothing parameter  $\lambda = 400,000$

The Recommendation allows authorities to use additional measures of the credit-to-GDP gap if the standardized one does not adequately reflect the specificities of national economies. In this case, they are requested to justify the need to deviate from the standardized credit-to-GDP gap.

The credit-to-GDP gap is then translated in a percentage of the bank risk-weighted assets by calculating a benchmark buffer rate which, following BCBS (2011), is equal to

$$\text{zero if } GAP_t \leq L \quad \text{with } L = 2 \text{ percentage points} \quad (2)$$

$$2.5\% \text{ if } GAP_t \geq H \quad \text{with } H = 10 \text{ percentage points} \quad (3)$$

$$0.3125 \times GAP_t - 0.625 \quad \text{if } L \leq GAP_t \leq H \quad (4)$$

According to this specification the buffer rate increases linearly with the credit-to-GDP gap for values of the gap between 2 and 10 percentage points, while it is zero when the gap is below the lower threshold  $L$  and is 2.5 per cent when the gap is above the upper threshold  $H$ .

<sup>2</sup> It includes all credit by both banks and non-bank financial institutions.



Authorities can also calculate a buffer rate with a methodology different from the one described by Equations 2, 3 and 4, either on the base of the standardized credit-to-GDP gap, or by using an alternative credit-to-GDP gap. Hence, Recommendation B introduces a substantial degree of flexibility as it allows authorities to use alternatives to the standardized credit-to-GDP gap and its translation into the benchmark buffer rate.

## *2.2 Recommendation C*

Recommendation C introduces further discretion in the guidance on the set of additional variables that should signal the build-up of system-wide risks associated with periods of excessive credit growth, and recommends authorities to periodically reassess the performance of the indicators and exercise their judgment when setting the buffer.

When looking at additional indicators of risk, authorities should take into consideration both qualitative and quantitative information and may combine them with the credit-to-GDP gap in the context of multivariate models.

Provided that authorities can select the set of indicators they deem more appropriate to capture the build-up of risks, the additional indicators should in all cases include measures of:

- a) potential overvaluation of property prices (e.g. commercial and residential real estate price-to-income ratios, price gaps and growth rates);
- b) credit developments (e.g. real total credit or real bank credit growth, the deviation from trend in deflated M3);
- c) external imbalances (e.g. current account balances as a ratio to GDP);
- d) the strength of bank's balance sheets (e.g. leverage ratios);
- e) private sector debt burden (e.g. debt-service to income ratios);
- f) potential mispricing of risk (e.g. real equity price growth);
- g) models output that combine the credit-to-GDP gap and a selection of the above measures

Authorities are recommended to publish quarterly at least one of the measures in each of the above categories, where available (and relevant), to accompany their decisions on the level of the CCyB.

## *2.3 Recommendation D*

Recommendation D provides guidance on the information relevant to decide whether the buffer should be maintained, reduced or fully released. To this end, authorities should take into account both quantitative and qualitative information. As part of the quantitative information the following set of variables should be monitored:

- a) measures of stress in bank funding markets (e.g. the LIBOR-OIS spread, bank CDS premia);
- b) measures that indicate general systemic stress (e.g. composite indicators of systemic stress in the financial system at the national or EU level, such as the European Central Bank CISS indicator).

In general, market-based indicators seem to display good signaling properties with regard to the materialization of risks. However, due to the limited availability of sufficiently long time series for the above mentioned variables, the scope for empirical analyses of the release phase of the CCyB is more limited than for the build-up phase. Therefore authorities need to exercise even greater judgment for the purpose of this Recommendation.

### 3. The credit-to-GDP gap: an application to Italian data

#### 3.1 The standardized Basel framework

In this section we study the BCBS (2011) credit-to-GDP gap for Italy, starting from the “minimum requirement” stated by the ESRB (2014) Recommendation. As a measure of credit, similarly to Dekten et al. (2014), we use nominal total credit to the domestic non-financial private sector available from the Bank for International Settlements (Dembiermont et al., 2013). As for the annual GDP we use the sum of four quarters of nominal GDP, seasonally and working day adjusted. To estimate the credit-to-GDP gap, differently from Dekten et al. (2014) who study the measure for a pool of 28 European countries using data from 1970, we make full use of the BIS data for Italy, which range from 1950Q1 to 2014Q3.<sup>3</sup>

Dekten et al. (2014) and the work carried out at the ESRB considered – as target variable for the purpose of CCyB implementation – episodes of systemic banking crises associated with excessive credit growth and leverage. Banking crises were detected according to one of the following criteria: i) bank runs in a number of relevant institutions; ii) significant losses in the banking sector, as measured by NPL ratio above 20 per cent or bank closures of at least 20 per cent of banking assets; iii) significant public intervention. Based to these criteria Italy experienced only one crisis episode, starting in 1994Q1 and ending in 1995Q4, after the strong recession of 1992-1993. In the episode several banks from southern Italy – all owned by the general government and affected by allocative and cost inefficiencies – were severely hit when Italy was forced to leave the European Monetary System.<sup>4</sup>

The one-side HP filtered trend, the credit-to-GDP gap and the CCyB buffer rate are computed as of 1950Q4 but for the sake of comparability with previous studies estimates are presented from 1970Q1 onward. Figure 1 shows the level and trend of the credit-to-GDP ratio and Figure 2 presents the credit-to-GDP gap and the CCyB buffer rate. The standardized credit-to-GDP gap is virtually always positive from the mid-80s on, in other terms, the credit-to-GDP ratio is almost always above its trend during the same period.

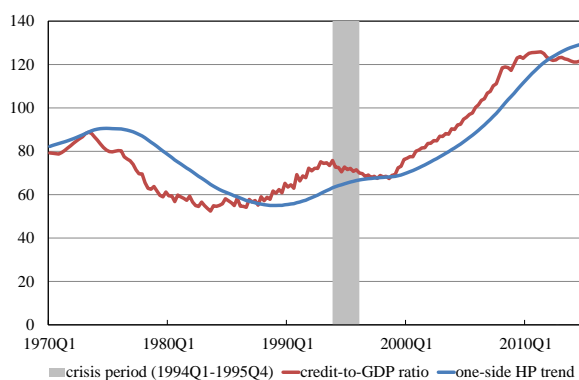
According to these measures, the average duration of the upturns of the credit-to-GDP cycles is about 49 quarters, much longer than what has been documented by the existing literature for credit cycles: according to Claessens et al. (2012) the average length of the upturns of credit cycles is eight quarters while according to the medium-term cycle definition introduced by Drehmann et al. (2012) the median length of the expansionary phase of the credit-to-GDP ratio is 22 quarters.

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<sup>3</sup> Calculating the gap with nominal credit and GDP data is in line with the recommendation by the ESRB (2014) and with the current practice by national and international authorities. Inflation does not distort the statistic insofar as it influences both credit and GDP in a similar way.

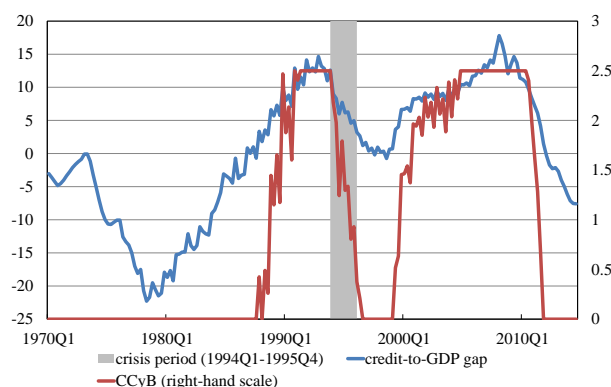
<sup>4</sup> The crisis was solved by favouring mergers, acquisitions and privatisations. From the second half of the 1990s Italy did not register any major banking crises, in contrast to what happened in most of the OECD countries during the global economic and financial crisis erupted in 2008 with the failure of Lehman Brothers. In Italy the global financial instability did not have disruptive consequences on the banking system. Also after the outbreak of the sovereign debt crisis in 2011 the government support to troubled banks was very limited (see Banca d’Italia (2014) for a comparison of the government’s supports to banks in different European countries following the global financial and economic crisis).

**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.

The BCBS (2011) suggests that the accumulation period of the CCyB should be such that (i) the buffer rate is at the maximum prior to a major crisis and (ii) banks are given one year to build-up the CCyB.<sup>5</sup> Dekten et al. (2014) add that the CCyB should not reach the maximum too early and operationalize this concept by saying that the buffer rate (i) should reach the maximum one year prior to a crisis (so to have one year to build up capital) and (ii) should not start to accumulate any time before five years prior to a crisis.<sup>6</sup> By these criteria, the standardized credit-to-GDP gap gives several false positive signals in the case of Italy: as shown in Figure 2, the CCyB rate reaches the maximum for the first time more than three years before the crisis, after an accumulation period that exceeds that suggested by Dekten et al. (2014). Furthermore, the rate would have been positive and rising for more than ten years from the late 1990s onwards, with a second sustained plateau at 2.5 percentage points between 2004Q4 and 2010Q2.

Overall the behavior of the standardized gap and the benchmark buffer rate for Italy do not fulfill the requirement of the CRD IV according to which the buffer rate should reflect, in a meaningful way, the credit cycle and the risks due to excessive credit growth. ESRB (2014) recognizes that the measurement and calculation suggested by BCBS (2011) may result, at least in some countries, in a credit-to-GDP gap that does not perform well in signaling the build-up of risks that precede financial crises. According to ESRB (2014) national specificities, such as “differences in the structure and degree of the development of the financial system, and in the quality and availability of credit data”, suggest that authorities may use alternative methods for calculating a credit-to-GDP gap that may exhibit stronger signaling properties. In the next sections we explore this avenue.

### 3.2 A step forward: extending the length of the credit-to-GDP time-series

A first way to possibly improve the estimates of the long run credit trend and cycle is by using a longer series of data. It may allow us to estimate the credit cycle more accurately thanks to its greater informative content, and has the additional benefit of allowing to test the predictive power of early warning models given that most of the Italian banking crises episodes occurred before 1950s (see Section 3.4).

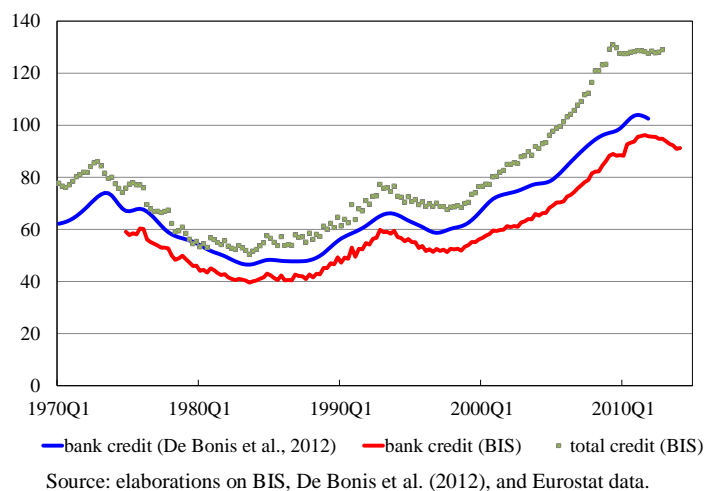
<sup>5</sup> The BCBS calibration criteria are implicitly based on the presumption that the activation of CCyB would have not prevented the crises or altered their timing (in other words, the crises are taken to be exogenous with respect to the policy instrument).

<sup>6</sup> Similarly, Drehmann and Juselius (2014) assess the appropriate timing of an early warning indicator if a signal is issued between 20 and 6 quarters prior to a crisis.

De Bonis et al. (2012) provide historical time series of credit in Italy since the union of the country in 1861. The series have been reconstructed through a careful work of data collection from historical statistical sources.<sup>7</sup> The historical time series by De Bonis et al. (2012) refers to the bank credit to the domestic non-financial private sector while the one used in Section 3.1 and by Dekten et al. (2014) refers to the total credit to the domestic non-financial private sector. The use of the former definition of credit instead of the latter is not problematic in light of the structural feature of the Italian financial system, which is largely and steadily represented by banks. Over the period 1974Q4-2012Q4 bank credit accounted on average for 75 per cent of the total credit to the domestic non-financial private sector, with standard deviation of 3.6 percentage points (the minimum of 68.0 per cent has been in 2008Q1 and the maximum of 84.4 per cent in 1979Q3). On these grounds we submit that the exclusion of non-bank credit is more than compensated by the possibility of trebling the length of our dataset. Figure 3 shows the credit-to-GDP ratios computed from different data sources and with different definitions of credit; in the remainder of the paper we use bank credit unless otherwise stated.

Some differences also exist between the bank credit series by De Bonis et al. (2012) and that available from the BIS; these reflect a number of factors – importantly, loans issued by branches of foreign banks are included in the former but not in the latter. Nonetheless the dynamics of the two series are similar, as implied by credit-to-GDP ratios based on the two sources of data and shown in Figure 3, thereby reassuring us on using the longer time series.

**Figure 3. Credit-to-GDP ratio:  
comparing different data sources and definitions**  
(per cent)



Despite the close co-movements, the credit-to-GDP ratio based on credit data from De Bonis et al. (2012) and the credit-to-GDP ratio based on BIS data still differ in levels. So to be able to use the more recent information from the BIS, as in Dekten et al. (2014), while extending the length of the time series backward leveraging on De Bonis et al. (2012), we construct a new bank credit-to-GDP series as follows:

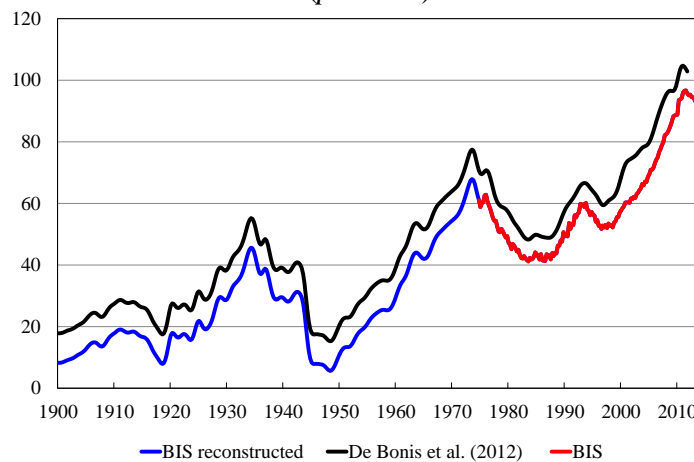
- i) we interpolate data from De Bonis et al. (2012) by cubic spline to get quarterly frequency from the original annual frequency;

<sup>7</sup> More in particular, the dataset includes short-term loans (i.e. with a duration of less than 18 months) and long-term loans (i.e. with a duration of more than 18 months), securities other than shares (or debt securities held), shares and other equity, fixed assets, deposits, debt securities issued, capital and reserves.

ii) we merge the data from the BIS with the interpolated data from De Bonis et al. (2012) using a level dummy in the fourth quarter of 1974. This approach assumes a constant difference between the two series from 1861 to the third quarter of 1974. For robustness, we also employ a proportional adjustment, which assumes a constant percentage difference between the two series, based on the observed percentage difference in the fourth quarter of 1974. The results are essentially unchanged, since the two series are approximately the same in terms of post-1970 cycles.<sup>8</sup>

The results of the performed adjustment are shown in Figure 4.

**Figure 4. Credit-to-GDP ratio:  
merging different sources of data**  
(per cent)



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

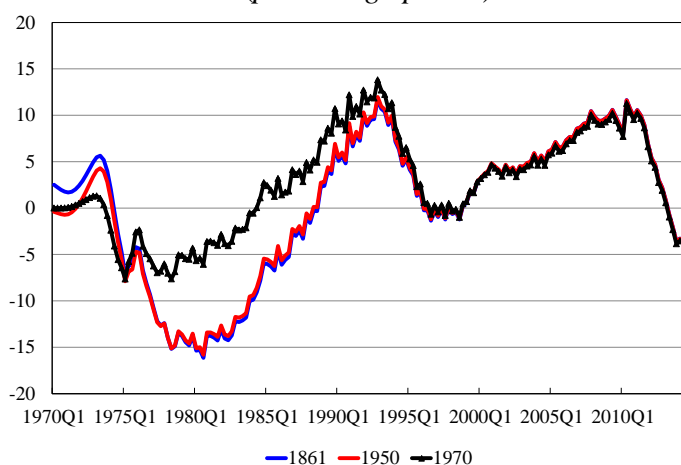
Relying on such a long time series may nevertheless pose some issues. First, the structure of the Italian economy, and of its financial system, evolved considerably over time. Then, the time span between 1861 and today also features two extreme events such as the World Wars which had a dramatic impact on all major economic and financial indicators. With these caveats in mind, we estimate two credit-to-GDP gaps: the first using all the information contained in the series from 1861 and the second by restraining ourselves to the information contained in the series from 1950, which excludes the two world war episodes.

Figure 5 shows the estimated credit cycles using the two starting points mentioned above, plus 1970, as in the study by Dekten et al (2014). The estimation follows the ESRB recommendation and is performed using a one-side HP filter setting  $\lambda$ , the parameter which gauges the sensitivity of the trend to short-term fluctuations, to 400,000.<sup>9</sup>

<sup>8</sup> Furthermore, in an HP decomposition any mechanical adjustment to the data based on fixed proportions or level shifts is captured by the trend component, leaving the cycle unaffected. Hence the problem of how to adjust the data becomes relatively unimportant given our objective.

<sup>9</sup> While  $\lambda$  can be potentially set at different levels from what is suggested by the regulation, results are not particularly sensitive to different parameter settings.

**Figure 5. Credit-to-GDP gap:  
estimates with alternative starting points**  
(percentage points)



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

Figure 5 provides two reassuring messages: first, the cycle estimated using the whole data back to 1861 is essentially the same as the cycle estimated using data from 1950 only; second, and more importantly, if a longer time series is used the credit cycle of the 1980s is more than halved. HP filters are known to be subject to a ‘starting point’ problem: the initial observations may significantly distort the estimates of trend and cycle, and it may take up to 20 years of quarterly data for the bias to be reabsorbed (Geršl and Seidler, 2012; Drehmann and Tsatsaronis, 2014). The data confirm that the estimation of the 1980s cycle is affected by this issue if, as in the analysis discussed in section 3.1, the sample is too short. Moving forward the benefits of using longer time series fade out, with the credit cycles of the early 2000s very similarly estimated across specifications.

Hence, since the additional benefits of going further backward than 1950 are negligible in terms of improved estimation of the post-1970 credit cycle we focus the rest of the analysis of the credit cycle on the period after 1950. This allows us to substantially enlarge the length of the time series with respect to the BIS bank credit data, while at the same time limit the concerns of using a too-long time series related to the evolution of the economic and financial structure of the country.

### *3.3 Two-side versus one-side HP filter: a qualitative re-assessment on Italian data*

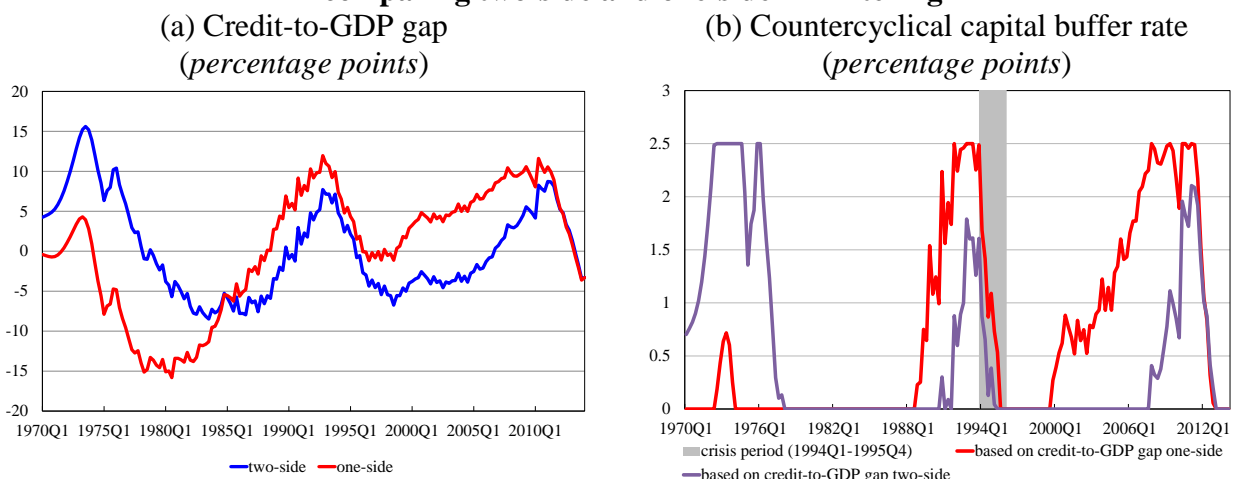
Despite being based on a large sample, the cycles displayed in Figure 5 are arguably still controversial to some extent: for instance, one could conceivably question whether credit was 15 per cent below trend in 1980, or whether the boom that led to the recent crisis began as early as 1999, lasting for over a decade.

We show below that these features depend to a large extent on the limitations of the one-side HP filter, which forms an estimate of the cycle at time  $t$  using exclusively information available until then. As an alternative, we estimate trend and cycle using a two-side HP filter that employs the full sample information at each point in time, including the observations which become available in the following periods. The benefits of using a two-side HP filter can be shown to be substantive from both a visual and an empirical perspective.

Figure 6 (panel *a*) compares the credit cycles estimated using a one-side and a two-side HP filter based on the same sample and parameterisation (both estimates use data from 1950 and a  $\lambda$  parameter set to 400,000).

The two-side HP filter identifies the cycles of the 1990s and 2000s, but in both cases it delays the beginning of the boom compared to the one-side filter. 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. In this respect, the two-side filter appears to strike a good balance between foreseeing crises while at the same time avoiding the long series of ‘false positives’ that characterize the one-side filter. Compared to the latter, the two-side filter also detects a boom in the early 1970s and a less pronounced contraction in the early 1980s. These phenomena may be due to the fact that the one-side filter effectively only uses 20 years of data when estimating the state of the cycle in the 1970s. The differences between the two filters over the last decade are remarkable and show clearly that using a one-side filter is not a neutral modelling choice.<sup>10</sup>

**Figure 6: Credit-to-GDP gap and CCyB:  
comparing two-side and one-side HP filtering**



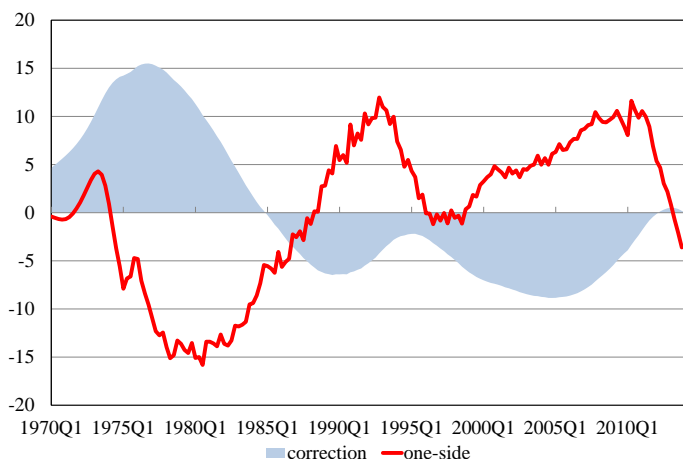
The credit cycles estimated using the two-side HP filter are generally less volatile and with shorter and less pronounced booms than those estimated with the one-side filter. In other words, the one-side HP filter tends to ‘overshoot’ relative to its full-sample counterpart. These features do not reflect accidental factors driving the dynamics of credit over the last two decades: they are also apparent in the 1861-1950 sample, and they partly reflect the structural differences between the two filters (one uses more data than the other). Hence the two-side filter could be generally expected to reduce the risk of issuing false positive signals, which are indeed costly.

Furthermore Figure 6 (panel *b*) shows that using the two-side HP filter measure of the credit-to-GDP gap would have a material impact on the buffer rate, which reaches the maximum of 2.5 per cent in the 1970s but remains well below that both in the 1990s and 2000s. In the latter case, in particular, the delayed beginning of the expansion phase delays the increase in the buffer rate, which begins to build up in 2007Q4 and peaks in 2011Q1, just before the outburst of the sovereign tensions in Italy.

<sup>10</sup> It should be recognized, however, that the latest data include the most recent years of economic recession and have therefore a large informative content.

Another way to look at the two estimated cycles is by taking the difference between the two-side HP filter and the one-side HP filter estimates of the credit cycles, as shown in Figure 7.

**Figure 7. Credit-to-GDP gap:  
correction from one-side HP filtering  
(percentage points)**



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

This difference (“correction” from now on) is very large, and importantly, it is persistent and negatively correlated to the one-side filter. This evidence, which could have relevant implications for policy making as we will discuss in Section 3.5, is confirmed also by estimating the credit cycles using all the available historical data going back to 1861, thereby suggesting that it is a structural feature of the estimates. This issue is not new in the filtering literature; Orphanides and Van Norden (2002) show for instance that the *ex post* revisions of the one-side estimates of the output gap in the US are of the same order of magnitude as the gap itself and are highly persistent – a situation analogous to that displayed in Figure 7.

### 3.4 Two-side versus one-side HP filter in the prediction of financial crises

We now turn to assess whether – besides providing a more intuitive picture of historical credit dynamics – the two-side HP filter would be a good predictor of financial crises or, more precisely, whether the additional information it provides relative to the one-side filter is valuable from a forecasting perspective. To do so, we compare the performance in forecasting crises of the “standard” one-side HP filter with that of the one-side HP filter augmented with the additional information provided by the two-side HP filter, as measured by the correction shown in Figure 7. This is clearly a *pseudo* forecasting exercise: the two-side estimate of the credit cycle is based on full-sample information and, as such, it is not available to forecasters in real time. The question we aim to answer is a hypothetical one: if that information were available, would it allow us to extract more accurate ‘warning’ signals? This question is interesting because Drehmann et al. (2011) argue that in general the answer is “no”: their cross-country evidence suggests that the credit gap estimated using a one-side filter often turns out to be a better crisis predictor than that based on an two-side filter. If confirmed for the case of Italy, this (surprising) result would heavily tilt the policy-maker’s preferences towards using a plain one-side filter even in cases, like ours, where the two-side filter provides a more convincing narrative of financial cycles.

We run this test on the annual data from the longer dataset dating back to 1861. Using a longer time series allows us to increase the number of crisis episodes available. In fact, between the 1970s and the early 2000s Italy featured only one banking crisis according to Dekten et al. (2014), the ESRB



and Reinhart and Rogoff (2009), and an additional borderline case in 2008 according to Laeven and Valencia (2012) which we treat as a crisis. Nine more crises occurred however before World War II (WWII) according to Reinhart and Rogoff (2009), and these can be exploited in the econometric exercise with longer time series.<sup>11</sup> Crises are defined using a slightly modified version of the dating proposed by Reinhart and Rogoff (2009) and Laeven and Valencia (2012). In fact, following the argument by Gigliobianco and Giordano (2012) and De Bonis and Silvestrini (2013), we consider some of the crisis episodes closely linked to each other and as such we treat them as single episodes.<sup>12</sup> As a result, our dataset includes eight crises episodes from 1861 to 2012, of which six occurred before WWII.

On this dataset we estimate the Logit models given by Equations 5 and 6:

$$Prob(C_t = 1) = \mathbf{F}(\alpha + \sum_{i=1}^4 \beta_i 1S_{t-i}) \quad (5)$$

$$Prob(C_t = 1) = \mathbf{F}(\alpha + \sum_{i=1}^4 \beta_i 1S_{t-i}, \sum_{i=1}^4 \gamma_i Corr_{t-i}) \quad (6)$$

where  $F$  denotes the cumulative distribution function for the logistic distribution and the dependent variable  $C_t$  is a crisis dummy.

In the explanatory variables, Equation 5 includes  $1S_{t-i}$ , which is the credit-to-GDP gap estimated through a one-side HP filter, with lags from 1 to 4, and Equation 6 includes  $1S_{t-i}$  plus the correction variable  $Corr_{t-i} = (2S_{t-i} - 1S_{t-i})$ , both with lags from 1 to 4.

Results shown in Table 1 indicate that the inclusion of the correction substantially improves the performance of the model. If we assume, as shown in top panel of Table 1, that an early warning is issued when the probability of a crisis is above 30 per cent, including the correction term increases the true positives from 30.8 per cent to 53.9 per cent. Even though an increase of the false positives is observed (from 7.4 to 12.3 per cent) the inclusion of the correction provides an economically and statistically significant effect since it increases the fraction of true positives by 75 per cent. The dominance of model in Equation 6 is confirmed if the warning threshold is raised to 50 per cent (Table 1, bottom panel). The relative performance of the two models is depicted in Figure 8.

The one-side credit-to-GDP cycle plus the correction term provides a stronger signal for the 1890 and 1935 crises. It provides also a stronger but slightly delayed signal for the 1990 crisis, the exact dating of which, however, is debatable. If the crisis is assumed to start back in 1992, when the Italian Lira exited the European Monetary System, then the one-side cycle plus correction issues a timely warning. There is also a potentially false positive around 1975 as this period is not officially classified as an episode of banking crisis in any of the sources available. Notably, however, during the financial tensions at the global level following the 1973 oil crisis and the related fast increase in interest rates, a subsector of the Italian banking system was hit by the turmoil but a spreading to the entire system was avoided also thanks to the institutional segmentation that existed at the time.<sup>13</sup>

<sup>11</sup> Reinhart and Rogoff (2009) list ten episodes of banking crises in Italy since 1800: 1866-1868, 1887, 1891, 1893, 1907, 1914, 1921, 1930-1931, 1935, 1990-1995. De Bonis and Silvestrini (2013) confirm this chronology but treat some of the crises as a single episode (1866-1868, 1887-1893, 1930-1935).

<sup>12</sup> In particular, the 1887, 1891 and 1893 crises are considered as one episode (1887-1893), and so are the 1930-31 and 1935 crises (1930-1935).

<sup>13</sup> Before the Amato-Carli Law n. 218/1990 which introduced the universal banking model, banking in Italy was institutionally segmented between those banks operating on the short-term only and those operating on the medium-long term only. Mortgage and construction lending was allowed only to the latter group of institutions which were not allowed to collect deposits and had to finance their assets with medium-term liabilities. In this context there was very

**Table 1. Forecast evaluation for the Logit models (1)**

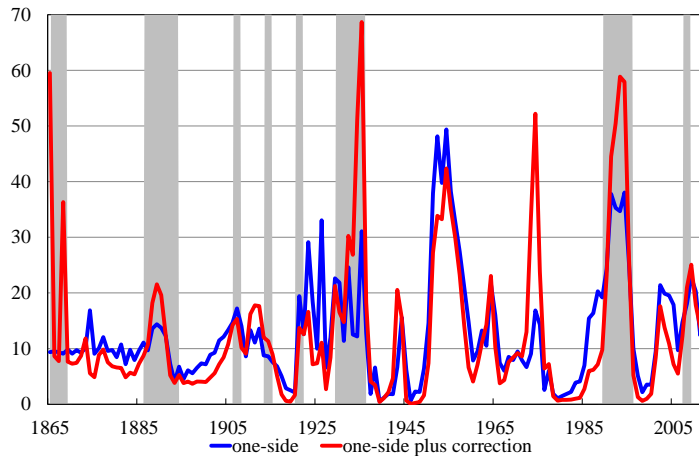
	1S			1 S + CORR			INTERCEPT ONLY		
	No Crisis	Crisis	Total	No Crisis	Crisis	Total	No Crisis	Crisis	Total
P(Dep=1)≤30%	113	18	131	107	12	119	122	26	148
P(Dep=1)>30%	9	8	17	15	14	29	0	0	0
Total	122	26	148	122	26	148	122	26	148
Correct	113	8	121	107	14	121	122	0	122
% Correct	92.62	30.77	81.76	87.7	53.85	81.76	100	0	82.43
% Incorrect	7.38	69.23	18.24	12.3	46.15	18.24	0	100	17.57
Total Gain*	-7.38	30.77	-0.68	-12.3	53.85	-0.68			
Percent Gain**	-	30.77	-3.85	-	53.85	-3.85			
P(Dep=1)≤50%	119	26	145	119	18	137	122	26	148
P(Dep=1)>50%	3	0	3	3	8	11	0	0	0
Total	122	26	148	122	26	148	122	26	148
Correct	119	0	119	119	8	127	122	0	122
% Correct	97.54	0	80.41	97.54	30.77	85.81	100	0	82.43
% Incorrect	2.46	100	19.59	2.46	69.23	14.19	0	100	17.57
Total Gain*	-2.46	0	-2.03	-2.46	30.77	3.38			
Percent Gain**	-	0	-11.54	-	30.77	19.23			

(1) The first (second) column refers to the Equation 5 (6).

\* Change in "% Correct" from default (constant probability) specification.

\*\* Percent of incorrect (default) prediction corrected by equation.

**Figure 8. 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.

Further diagnostic tests confirm the usefulness of the correction term: the Likelihood Ratio test rejects the exclusion of *Corr* from the Logit model (Table 2).<sup>14</sup>

limited interconnection between the short-term credit institutions and the medium-term ones. So when the soundness of the medium-term institutions was threatened (Zamagni, 2008) there were no major spill-overs to the rest of the banking system and the crisis remained a sectoral one.

<sup>14</sup> These results hold if use one-year lagged regressors.

**Table 2. Likelihood ratio test for the exclusion of the variable *Corr* from Equation 6**

<i>Corr</i> : <i>n</i> of lags omitted	one	two	three	four
LR Statistic	13.096	19.163	21.283	21.462
Probability	0.0003	0.0001	0.0001	0.0003

Overall, this evidence point to: a) the need to use longer time series than in Dekten (2014) to have more stable estimates of the credit cycle; and b) the usefulness of using an augmented one-side HP filter to estimate the credit cycle in Italy.

### 3.5 Two-side HP filter cycle and real-time policy making

A two-side HP filter provides *by construction* a more accurate estimate of trend and cycle than a one-side filter. The reason is intuitive: any given increase or decrease in the target variable (in our case the credit-to-GDP ratio) can be better put in context by a model that, having ‘seen the future’, knows whether the observed change is temporary, persistent or indeed permanent.<sup>15</sup> The assessment carried out in Section 3.3 confirms that the two-side filter generates a qualitatively more plausible estimate of the credit cycle. We have also shown in Section 3.4 that the correction provided by the two-side filter significantly improves the early warning signaling power of the credit-to-GDP gap.

Yet, these benefits may be of little use in real-time analyses: as one moves towards the end of the available sample, the informational advantage of the two-side filter vanishes and the filter converges to the one-side case (this convergence is apparent in Figures 5 and 6). In principle, this could make the comparison between one- and two-side filter irrelevant: if the latter is unavailable in real time, policy makers have no choice but to use the former. In this section we show that this is not the case. It is of course true that the two-side filter is unavailable in real time, but since its divergence from the one-side filter is large and persistent, the policy maker can learn from history and use past observations on such divergence to adjust his current estimate of the credit gap.<sup>16</sup> Such a forecasting exercise essentially aims at forming a view of how the release of new observations on credit and GDP in the future is likely to affect the estimate of the cycle suggested by the one-side filter today.

We first explore the predictability of the two-side correction by testing for Granger-causality. The test is based on a bivariate VAR model that includes the one-side cycle and the correction. The VAR has the following form:

$$Y_t = c + \sum_{i=1}^p B_i Y_{t-i} + e_t \quad (7)$$

where  $Y_t = (1S_t, Corr_t)$ ,  $Corr_t = (2S_t - 1S_t)$ , and  $1S$  and  $2S$  denote the credit-to-GDP gap estimated respectively via a one-side and a two-side HP filter. Like the Logit of Section 3.4, this is

<sup>15</sup> We are comparing one-side and two-side filters *taking as given all remaining Basel prescriptions*, which include the data, the type of filter (HP) and the smoothing parameter ( $\lambda=400000$ ) to be used. Subject to these, the two-side filter generates by definition our best guess on the state of the credit cycle, and the problem of how to approximate it in real time becomes interesting. However, the trend-cycle decomposition could of course be implemented in a number of different ways; we do not take a stance on how accurate (one- or two-sided) HP filters are relative to such alternatives.

<sup>16</sup> Alternatively, one could forecast the credit-to-GDP ratio and then apply a two-sided filter to a series that combines data and forecast. We plan to explore this possibility in the future.

an in-sample exercise, in the sense that (a) the model is estimated using all available observations and (b), more importantly,  $Corr_t$  is assumed to be known at time  $t$ . This means that the test assumes, counterfactually, that the patterns displayed in Figure 7 are known at all points in time.

We estimate the VAR model separately on the original De Bonis-Silvestrini annual dataset, using a lag length of  $p=2$ , and on the (interpolated) quarterly series, using a lag length of  $p=4$ .<sup>17</sup> In the former case we exploit the full depth of the time series, while in the latter we focus on the post-1950 sample, which, as we discussed in Section 3.3, is large enough to guarantee the stability of the one-side estimate of the cycle. In both cases we look at separate subsamples in order to check the robustness of any predictive relations uncovered by the tests. Results are shown in Tables 3 and 4. Each table reports the chi-squared statistic and the p-value for the null hypothesis of no Granger-causality, or lack of predictability, both from  $IS$  to  $Corr$  (left column) and from  $Corr$  to  $IS$  (right column). The key finding is that the one-side cycle predicts the correction: in other words, real-time estimates of the cycle 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 and the dynamics displayed in Figure 7, which show that booms (contractions) are typically revised downwards (upwards) when more information is available. We also find that the correction predicts the one-side cycle: by learning about the past “mistakes” of the filter, it is possible to predict the future evolution of the one-side cycle itself. Given the dynamic setting of the VAR, this also implies that the correction has a strong autoregressive component, so that it can be used to predict its future movements (in line with the persistence observed in Figure 7).

**Table 3. VAR-based Granger causality test**  
(annual data,  $p=2$ )

Sample	$H_0$ : IS does not G-cause Corr	$H_0$ : Corr does not G-cause IS
1861-2011	82.63 ***	216.56 ***
1900-2011	62.61 ***	161.52 ***
1950-2011	35.28 ***	82.07 ***
1950-2008	38.61 ***	81.97 ***

\*\*\*, \*\*, \* significance levels at 1, 5 and 10 per cent respectively.

**Table 4. VAR-based Granger causality tests**  
(quarterly data,  $p=4$ )

Sample	$H_0$ : IS does not G-cause Corr	$H_0$ : Corr does not G-cause IS
1950q1-2014q1	65.25 ***	34.33 ***
1950q1-2008q4	78.14 ***	33.85 ***
1950q1-1980q4	39.87 ***	15.85 ***
1981q1-2014q1	5.85	22.05 ***
1981q1-2008q4	12.70 **	19.10 ***

\*\*\*, \*\*, \* significance levels at 1, 5 and 10 per cent respectively.

The results are remarkably robust across datasets and subsamples. A partial exception is the 1981-2014 subsample, for which we cannot reject the null hypothesis that the one-side cycle does not predict the correction.<sup>18</sup> However, this is due to the fact that the correction converges to zero at the end of the sample (when one-side and two-side filters are forced to rely essentially on the same dataset), and in this specific subsample the last observations – with large swings in the credit-to-

<sup>17</sup> The number of lags is selected using the Schwarz information criterion; the resulting specifications are in both cases sufficiently rich to generate serially uncorrelated residuals.

<sup>18</sup> The period 1981-2014 has been examined because it divides the post-war sample into two equally sized sub-samples; the early 1980s also mark the beginning of the “great moderation” period.

GDP ratio – have a significant weight. Indeed, if we truncate the sample in 2008, so that the least informative observations on the correction are excluded, the predictive power of the one-side cycle is restored (the p-value on the null hypothesis of no Granger causality drops to around 1 per cent).

This evidence is important because it suggests that in principle the information contained in past estimates of the cycle (based on a two-side filter) could be used to improve the current estimate of the cycle. This is in line with the similar approach proposed by Gerdrup et al. (2013) for Norway. We note that we conducted our predictability tests in a very restrictive set up where the only relevant predictors for the correction term are assumed to be the correction itself and the one-side estimate of the cycle. It is possible, and indeed highly likely, that a number of additional macro-financial indicators, including those examined in the last part of this paper, also have useful predictive power for the correction term, in which case one could set up a better forecasting model than the bivariate VARs examined above.

When moving to real-time applications, the main difficulty is of course that  $Corr_t$  is not known at time  $t$ : at that point, the forecaster does not observe *any* of the points under the blue area in Figure 7. In order to revise the one-side estimate of the cycle, he must then proceed in four steps. First, he estimates one-side and two-side filters up to time  $t$ , calculating the associated series of corrections  $Corr_{1,...,t}$ . Second, he discards the last  $h$  observations of  $Corr$ , which are known to be biased. Third, using the cleaned sample, he estimates a statistical model and uses it to generate  $E_tCorr_t$ . This is essentially a “nowcast” of the correction term, because it is a prediction of its current value based on its lags up to time  $t-h$  and on any additional predictors available as of time  $t$  (including the one-side estimate of the cycle,  $IS_t$ ). In the fourth and final step, a new real-time estimate of the cycle can be constructed as  $\widehat{2S}_t = 1S_t + E_tCorr_t$ . In essence, this process aims at fine-tuning the one-side estimate suggested by the Basel framework using (our best guess on) the adjustment to that estimate that would ultimately emerge in a full-sample filtering process.

In order to implement this procedure, specific choices must be made on (i) the number of observations to be discarded in the second step (i.e. the horizon  $h$ ), and (ii) the forecasting model to be used in the third step. We consider horizons ranging from 4 to 16 quarters and look at three simple forecasting models. The first one is a random walk

$$Corr_t = Corr_{t-h} + \varepsilon_t \quad (8)$$

The second one is a dynamic equation of the form

$$Corr_t = \alpha + \sum_{i=1}^4 \beta_i 1S_{t-i} + \sum_{i=1}^4 \gamma_i Corr_{t-h-i} + \varepsilon_t \quad (9)$$

The third one is the bivariate VAR used for the Granger-causality tests (Equation (7)). The random walk, which represents a standard benchmark in forecasting, simply assumes the correction to remain constant at the last ‘valid’ observation  $Corr_{t-h}$ . Dynamic equation and VAR exploit a larger information set (they use the history of both  $IS$  and  $Corr$ ). They differ from one another mostly in how the forecast is constructed: the VAR forecast is recursive ( $Corr_t$  is calculated using estimates of all intermediate values  $Corr_{t-h+1}, \dots, t-1$ ) while the dynamic equation forecast is direct (the model predicts directly  $h$  steps ahead, ignoring all intermediate values). Needless to say, the space of models that could be explored is much larger and the comparison we propose mostly illustrative.

Table 5 below shows the root mean square error (RMSE) for the three models at different horizons. The error is measured by the gap between the nowcast  $E_tCorr_t$  and the full-sample estimate  $Corr_t$ , which is assumed to identify the ‘right’ correction and is consequently used as a target. We evaluate the model forecasts over the 1974Q1-2010Q4 time window (using more recent data would make it

impossible to evaluate forecasts at horizons of 12 or 16 quarters). The HP filters and the three models are estimated recursively, starting from an initial 1950Q1-1973Q4 sample and then adding one observation at a time and repeating both estimation and forecasting at each step.

To put the figures in Table 5 in perspective, it is useful to keep in mind that over the evaluation period *Corr* has a range of roughly 24 percentage points, from -9 per cent to about 15 per cent (see Figure 7). In this respect, an average 6, 12 or 24 per cent RMSE imply respectively that the model’s prediction may get “3/4 of the correction right”, “1/2 of the correction right”, or the correction “entirely wrong”.

**Table 5: Root mean square errors**  
(percentage points)

	Horizon (quarters)						
	4	6	8	10	12	14	16
Random Walk	6.62	6.25	6.06	6.04	6.17	6.38	6.66
Single Equation	7.94	8.11	8.22	8.37	8.38	8.42	8.27
VAR	7.27	7.07	13.66	35.23	86.04	203.30	483.96

Random Walk:  $CORR(t+h)$  is assumed to be constant at the value estimated in  $t$ . Single Equation:  $CORR(t+h)$  is the direct forecast from a single-equation model based on *CYCIS* and *CORR*. VAR:  $CORR(t+h)$  is forecast recursively using the bivariate VAR introduced in this section. All models are evaluated over the period 1974Q-2010Q4.

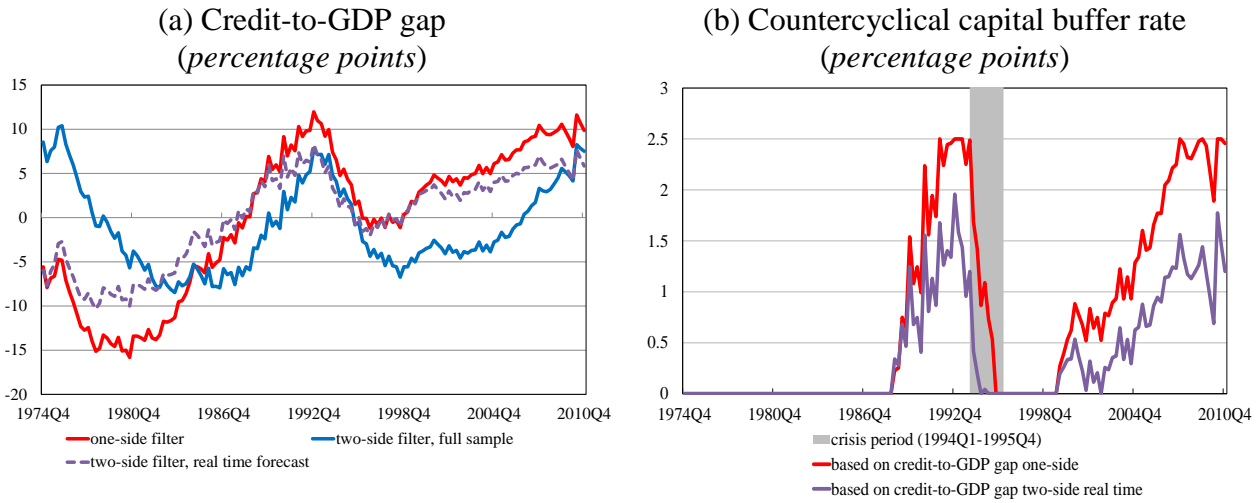
All models have acceptable performances at short horizons. The random walk generates the most accurate predictions, with errors of the order of 6 per cent. The single equation model is a close second. The VAR is in the same ballpark with  $h=4, 6$ , but its performance deteriorates rapidly and significantly as the horizon grows longer. Since neither the random walk nor the single equation have this problem, this deterioration is a clear sign that with large  $h$  the recursive nature of the VAR forecast takes its toll, and prediction errors are compounded over the forecast horizon.

The main message from the Table 5, however, is that (a model as simple as) a random walk can generate sensible forecasts for *Corr*, allowing us to improve the real-time estimate of the credit gap. To shed more light on how material and useful such improvement would be in practice, we use the forecasts of  $Corr_t$  from the random walk to obtain the real-time estimate of the 2-side HP filter credit-to-GDP gap ( $\widehat{2S}_t = 1S_t + E_t Corr_t$ ), and then look at the resulting CCyB.

Figure 9 shows the model-based estimate of the credit cycle (panel *a*) and the corresponding capital buffer (panel *b*). To aid the interpretation of the results, in the left panel we reproduce together (i) the *1S* cycle, *i.e.* what we would use for CCyB without any adjustment (red); (ii) the *2S* 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 based on the random walk model (dashed line; for simplicity we focus on the  $h=8$  case). The overall success of the procedure is thus measured by 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 raw *1S* estimate, with the only exception of the period between 1983 and 1987. Furthermore, relative to *1S* the forecast would have suggested shaving 2 to 3 percentage points off the “boom” in the late 1980s and up to 5 percentage points in the late 2000s. These are clearly economically significant numbers. Panel (*b*) of the chart shows the implications of these adjustments for the CCyB ratio. The pattern followed by the CCyB over time remains in many ways similar to the initial one, but the new estimates lead to a more cautious approach by the policy maker as the buffer never reaches the 2.5 per cent cap.

**Figure 9: Adjusting the credit gap estimate in real time**

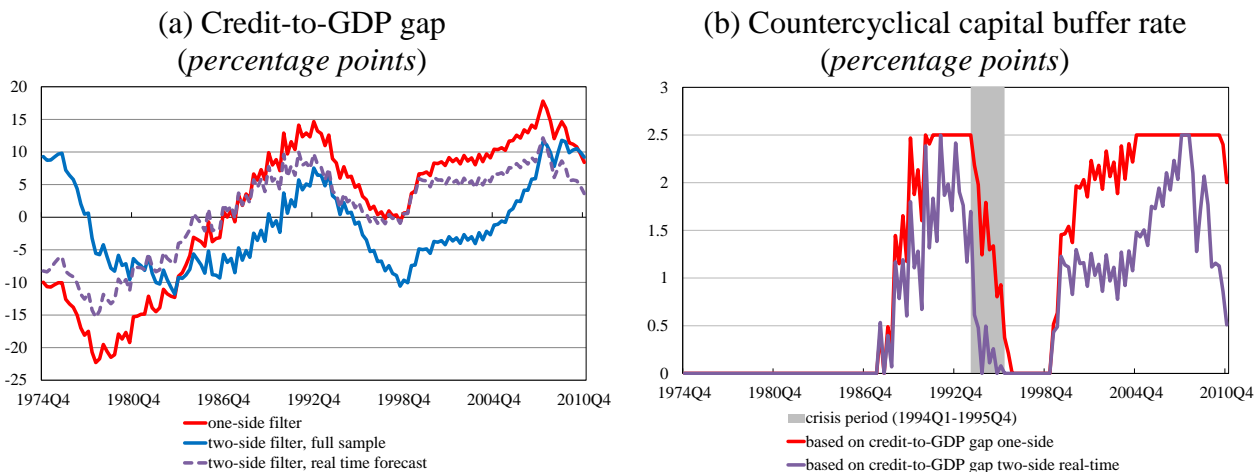


Source: elaborations on BIS, De Bonis et al. (2012), and Eurostat data.

To further strengthen the empirical evidence we repeat the forecasting exercise with the random walk using data on total credit rather than on bank credit. This allows us to obtain results directly comparable with the standardized credit-to-GDP gap and CCyB computed according to the ESRB (2014) Recommendation and already shown in Figure 2. The results, presented in Figure 10, broadly confirm those in Figure 9: the model calls for a downward revision of the one-side estimate of the gap in both the 1990s and the 2000s expansionary phases, and these real-time adjustments are consistent with the *ex post* (full sample) estimate of the gap itself (panel *a*). Relative to the case of bank credit, the buffer based on total credit (panel *b*) follows a more conservative pattern both ahead of the 1990s crisis and in the late 2000s; the rule also suggests a prompt release of the buffer at the turn of the cycle.

Overall, this evidence confirms the improvements achieved with the real time estimate of the cycle relative to the one-side filtered gap.

**Figure 10: Adjusting the credit gap estimate in real time based on total credit data**



Source: elaborations on BIS and Eurostat data.

## 4. The additional risk indicators for the activation of the countercyclical capital buffer

In this section we assess the early warning power of a set of additional indicators that would be available to policymakers on a quarterly basis for their policy decisions regarding the CCyB.

Additional indicators should be used for both the build-up and the release of the CCyB, but the relevant indicators are likely to be different depending on whether authorities are considering a tightening or a loosening of the tool.

In this analysis we study the additional indicators only for the build-up phase of the CCyB. We leave those relevant for the release phase, for which the literature is still relatively scarce, for future analyses and research. To proxy for financial distress we use the ratio of bad loans to total loans. In section 4.1 we argue that this variable is closely associated with the type of systemic risk the CCyB is meant to mitigate. Then, in Section 4.2, we study the signalling properties of a set of potential indicators in explaining the dynamics of the bad loans ratio. We collect a large set of macro-financial variables, including the bad loans ratio, and use principal component analysis (PCA) to identify the combination(s) of indicators that best explains the aggregate variance of the data. These combinations represent by construction the key driving forces behind financial cycles in Italy. The significance of their association with the riskiness in the banking system, as proxied by the bad loans ratio, is then tested with a regression analysis. The statistically significant variables have the potential to be interpreted as systemic risk indicators and be exploited to adjust the CCyB.

### *4.1 The definition of a measure of financial distress*

To identify a measure of financial distress (or crisis) we cannot rely, as in the previous sections, on the banking crises identified by Reinhart and Rogoff (2009) and Laeven and Valencia (2012). The explanatory variables (the potential indicators) are broadly available only from the 1970s and the very few crisis episodes from the 1970s hamper the use of standard Early Warning Models in which the dependent variable is a binary indicator of crisis periods, to assess the signalling properties of the macro variables.

As a consequence, to measure financial distress, we use a continuous measure of the banking system's riskiness, given by the ratio of bad loans to total loans, rather than a crisis/not-crisis dichotomous variable.<sup>19</sup> The choice of the bad loans to total loans ratio as a target variable is based on the following considerations: first, credit risk is the main source of concern for the Italian banking sector as Italian banks' business model is largely focused on loan intermediation;<sup>20</sup> second, the funding structure of non-financial firms in Italy is strongly skewed towards bank financing, especially that of SMEs;<sup>21</sup> third, past evidence shows that when credit risk is high, and the prospects of potential borrowers uncertain, a tightening in credit conditions has negative consequences on economic growth, which in turn magnifies credit risk causing a negative feedback loop for the financial sector.

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<sup>19</sup> Bad loans are defined on a customer basis and include all the outstanding credit extended by a bank to a borrower considered insolvent. Under Italian regulations, banks are asked to classify as bad loans outstanding exposures to borrowers who are not expected to meet their obligations.

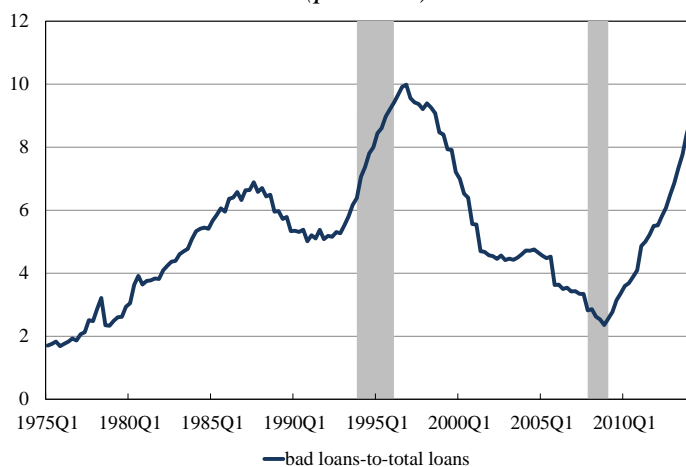
<sup>20</sup> Loans to customers accounted for more than 60 per cent of the Italian banking system assets in 2013.

<sup>21</sup> The share of bank debt to total financial debt in Italy was 64.2 per cent in 2013, compared 45.5 per cent in the euro area and 29.1 per cent in the US.



This argument can be verified in the data. Looking at the ratio of bad loans to total loans we can identify two periods of strong credit risk acceleration (Figure 11): the first is between 1993 and 1997, when the ratio peaks at about 10 per cent, is broadly coincident with the 1990-1995 crisis identified by Dekten et al. (2014) and Reinhart and Rogoff (2009); the second between 2009 and 2014 stems from the two recessions experienced by the Italian economy in 2008-2009 and in 2012-2013, and is broadly in line with the latest crisis tentatively identified by Laeven and Valencia (2012) as starting in 2008.<sup>22</sup>

**Figure 11. Ratio of bad loans to total loans**  
(per cent)



Source: elaborations on Bank of Italy data.

#### 4.2 Identifying early warning indicators

An effective early warning indicator should signal the build-up of systemic risk in a timely fashion, when threats to financial stability begin to heighten, in advance of the materialization of a financial crisis. The capacity to signal risk well in advance is of paramount importance for an effective use of the CCyB: the capital buffer should be raised during a boom, when systemic risks are building up, and released in times of stress so as to help banks absorb potential losses, reduce the risk of a credit crunch and preserve financial stability.

In practice, however, such indicators are not easy to develop. Two main approaches are available in the existing literature to identify systemic risks: the reduced-form and the structural approach.<sup>23</sup> Both approaches have pros and cons. The strength of the reduced-form approach is that it is based on actual historical correlations, but it runs the risk of potential breakdowns in historical correlation and usually falls short of explaining the fundamental drivers of observed economic phenomena.<sup>24</sup> The structural approach on the hand focuses less on statistical analysis and more on theoretical models, but it may prove inadequate to provide a reasonable picture of the empirical evidence.

<sup>22</sup> Since 2008, the cumulative fall of Italian GDP has been nine percentage points.

<sup>23</sup> The reduced-form approach focuses on finding variables that have been useful in signalling financial crises in the past. Such an approach is usually agnostic about the actual mechanisms of the build-up of systemic risk and the causal structures and focuses on the ability of indicators to predict crises based on historical correlations. The structural approach on the other hand focuses on the understanding of systemic risk and underlying causal structures.

<sup>24</sup> In other words, indicators that would have been helpful in identifying systemic risks in a past financial crisis might be no longer able to do so in a future crisis due to changes in the economic and financial environment. This means that the indicators selected according to this approach are dynamic in nature and need to be periodically reassessed as conditions and correlations change.

In this paper we follow a reduced-form approach, while also taking into account some of the key insights provided by the literature on structural analysis (e.g. IMF, 2011) in selecting ex-ante the set of indicators.<sup>25</sup>

We examine all the main indicators that have been found promising for the build-up phase in the existing literature and have been suggested by the ESRB. In addition to the credit-to-GDP gap, these include other credit-related variables<sup>26</sup>, macro-financial variables<sup>27</sup>, real estate variables, signals of potential overvaluation of property prices, financial asset price variables signalling potential mispricing of risk<sup>28</sup>, the loans to deposits ratio as a measure of banks' exposure to structural funding risk. Table 6 provides a detailed description of all the variables considered and Figures A1 to A5 in the Appendix presents plot of some the variables together with the target variable defined in the previous paragraph. For all indicators we use quarterly data over the period 1976Q1-2013Q4. To account for possible non-stationarity, data are taken either as annual growth rates or as first difference year-on-year, with the exception of gap measures which have not been adjusted.

We proceed in two steps. First, we use principal components analysis (PCA) to isolate from a time-t dataset the factors (components) that are responsible for the bulk of the overall fluctuations in our macro-financial indicators, i.e. the factors that are most directly responsible for 'financial cycles' (in a loose sense, because we do not focus on specific frequencies). We apply the PCA to all the indicators other than our measure of financial distress and the credit-to-GDP gap. Second, we pick the variables that have the highest loadings on the factors and study their power in predicting the bad loan ratio using standard regression analysis. This process is similar in spirit to the forecasting method proposed by Stock and Watson (2002).<sup>29</sup>

The results of the PCA analysis are shown in Tables 7 and 8. Table 7 summarises that six latent factors have been retained<sup>30</sup>, explaining almost 83 per cent of total variation. Table 8 shows the factor loadings<sup>31</sup> which provide information on the additional indicators that best explain each latent factor and that as such could contribute more effectively than others to signal potential vulnerabilities in the credit cycle.

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<sup>25</sup> Structural approaches suggest that credit growth, when accompanied by asset price growth, typically anticipates the outburst of a financial crisis. This appears to be especially true in environments characterized by low interest rates and narrow risk premia, when risk appetite across the financial system tend to increase (the so called 'search for yield' phenomenon) and credit standards tend to be relaxed.

<sup>26</sup> As in Repullo and Saurina (2011), and Schularick and Taylor (2012).

<sup>27</sup> As in Borge et al. (2009), Borio and Drehmann (2009), Barrell et al. (2010), Drehmann et al. (2010 and 2011), Babecky et al. (2011), and Kauko (2012a).

<sup>28</sup> Riiser (2005), Mendoza and Terrones (2008), Borio and Drehmann (2009), Barrell et al. (2010), Drehmann et al. (2010 and 2011), and Claessens et al. (2011, 2012).

<sup>29</sup> The analogy is loose, however, because our exercise is conducted 'in sample' and we use (subsets of) the underlying variables, rather than the estimated factors, to produce the forecasts. Using the factors would presumably improve the accuracy of the forecasts at the cost of transparency, as it may not be possible to give an economic interpretation of the factors.

<sup>30</sup> The most widely used criterion for determining the number of factors suggests to retain those factors with eigenvalues equal or higher than 1 (Kaiser criterion).

<sup>31</sup> Factor loadings measure the pairwise correlations between the indicators in the original dataset and each latent factor and represent the contribution of each indicator to the variance of each factor. The higher the load the higher the role of the indicator in defining the factor's dimensionality. A negative value indicates an inverse impact of the indicators on the factor.

**Table 6: Dataset on additional risk indicators**

Category	Variable	Mnemonic	Variable Transformation
Credit market developments	M3 Stock growth, real	M3_real	y-o-y growth rate
	M3 Stock growth, nominal	M3_nom	y-o-y growth rate
	Bank credit-to-GDP	Bank_credit_to_GDP	first difference
	Total credit-to-GDP	Tot_credit_to_GDP	first difference
	Bank credit growth to private non-financial sector, nominal	Bank_credit_nom	y-o-y growth rate
	Bank credit growth to private non-financial sector, real	Bank_credit_real	y-o-y growth rate
	Total credit growth to households, nominal	Credit_hh	y-o-y growth rate
	Total credit growth to non-financial corporations, nominal	Credit_nfc	y-o-y growth rate
Macroeconomic variables	Real GDP growth	GDP	y-o-y growth rate
	Unemployment rate	U	first difference
	Slope of the yield curve (Long-term interest rate on gov. bond - Short-term interest rate)	Slope	level
	Sovereign spread (IT 10y government bond yields - DE 10y government bond yields)	Spread	first difference
Potential overvaluation of property prices	Gap of the residential property price index (based in 2010, nominal)	HP_nom_gap	One-side HP filter (lambda of 400,000)
	Gap of the residential property price index (based in 2010, real)	HP_real_gap	One-side HP filter (lambda of 400,000)
	Two-year growth rate of residential property price index (based in 2010, nominal)	HP_nom_2y	2-year growth rate
	Two-year growth rate of residential property price index (based in 2010, real)	HP_real_2y	2-year growth rate
	Ratio of nominal house prices to nominal disposable income (index based in 2010)	PTI	first difference
	Ratio of nominal house prices to rent prices (index based in 2010)	PTR	first difference
Potential mispricing of risk	MSCI Italy Stock price index	MSCI	y-o-y growth rate
Strenght of banks' balance sheets	Bad loans to total loans	Bad_loans	first difference
	Loans to deposits ratio	LTD	first difference

Source: Bank of Italy and ECB.

**Table 7: Principal component analysis of the additional risk indicators: summary results**

Factor	Eigenvalue	Difference	Percentage proportion of variance explained by each factor	Cumulative percentage proportion of variance explained
Factor1	6.038	2.264	0.302	0.302
Factor2	3.774	1.181	0.189	0.491
Factor3	2.593	0.797	0.130	0.620
Factor4	1.796	0.541	0.090	0.710
Factor5	1.255	0.137	0.063	0.773
Factor6	1.118	0.315	0.056	0.829

**Table 8: Principal component analysis of the additional risk indicators: factor loadings**

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
M3_real	0.273	0.210	-0.113	<b>-0.716</b>	-0.135	0.525
M3_nom	0.489	<b>-0.594</b>	0.217	-0.470	-0.100	0.266
Bank_credit_nom	<b>0.838</b>	-0.390	-0.108	0.016	-0.155	-0.143
Bank_credit_real	0.629	0.477	<b>-0.510</b>	-0.014	-0.179	-0.049
HH_credit	0.580	-0.467	-0.409	-0.018	-0.078	0.018
NFC_credit	0.686	<b>-0.514</b>	-0.051	-0.135	-0.051	-0.231
U	<b>-0.580</b>	-0.277	0.284	-0.119	0.225	-0.131
GDP	0.392	<b>-0.506</b>	-0.330	0.253	-0.281	0.107
Bank_credit_to_GDP	0.336	0.723	-0.399	-0.107	-0.048	-0.181
Tot_credit_to_GDP	0.336	<b>0.784</b>	-0.361	-0.086	-0.063	-0.175
PTI	0.516	0.444	0.327	0.409	-0.078	0.386
PTR	<b>0.620</b>	0.230	0.387	0.384	-0.248	0.389
MSCI	0.045	-0.340	-0.313	0.471	0.479	0.351
Slope	<b>-0.515</b>	0.564	0.334	0.090	-0.072	0.105
LTD	0.231	-0.024	<b>-0.616</b>	0.438	0.269	-0.003
Spread	0.272	-0.055	0.489	0.287	-0.486	-0.364
Houes_price_nom	0.704	-0.317	0.503	0.089	0.204	-0.125
Houes_price_real	0.728	0.310	0.392	0.100	0.241	-0.089
Houes_price_gap_nom	<b>0.734</b>	0.135	0.098	-0.304	0.415	-0.094
Houes_price_gap_real	0.704	0.380	0.332	-0.134	0.380	-0.076

We use the results of the PCA to identify the variables to be included in a regression with the bad loans ratio as dependent variable instead of using the latent factors directly, as these cannot be given an economic interpretation and would be difficult to communicate for policy making purposes.

Each variable needs to satisfy a set of criteria to be included in the regression. First, it has to contribute to explain the variance of at least one latent factor, with a loading equal or higher, in absolute value, than  $\pm 0.5$ . Second, its unconditional correlation with the other variables satisfying the first criteria needs to be lower than  $\pm 0.6$  in absolute value. If the correlation between two variables satisfying the first criteria is higher than  $\pm 0.6$ , the variable with the higher factor loading is chosen (pairwise correlations are shown in Table 9).

As a result of these steps we select the following variables: the nominal bank credit growth to the private non-financial sector (*Bank\_credit\_nom*), unemployment rate (*U*), price-to-rent ratio (*PTR*) and the gap of the nominal residential house price index (*HP\_nom\_gap*) from the first latent factor; real GDP growth (*GDP*) and bank credit to GDP (*Bank\_credit\_to\_GDP*) from the second factor; loans to deposits ratio (*LTD*) and growth of the stock of M3 real (*M3\_real*), from the third and fourth factor respectively.

The selected variables are included in a regression together with the credit-to-GDP gap, proxied alternatively by the variables *1S* and *2S* previously defined. We also include an autoregressive term in some specifications as a robustness check. All variables enter the model with a lag of eight quarters ( $t-8$ ) since they need to signal future risks well ahead of the possible onset of a crisis, as is also for the credit-to-GDP gap, so that policymakers have enough time to take actions to enhance bank resilience (in the case of the CCyB banks should be given at least one year to meet an additional capital requirement). Using lagged explanatory variables also allows us to limit the scope for endogeneity concerns.

Therefore, we estimate the following model:

$$Bad\ loans_t = c + \alpha IS_{t-8} + \beta M3\_real_{t-8} + \gamma Bank\_credit\_nom_{t-8} + \delta Bank\_cr\_to\_GDP_{t-8} + \theta U_{t-8} + \mu GDP_{t-8} + \pi PTR_{t-8} + \tau LTD_{t-8} + \varphi House\_price\_nom_{t-8} + \varepsilon_t \quad (10)$$

where all variables are in changes, or in growth rates. Standard errors are estimated using the Newey-West methodology to account for serial correlation.<sup>32</sup> Results are shown in Table 10.

First and foremost the estimates confirm, even in a different econometric setting and with a different dependent variable, the results of the analysis carried out in the Section 3, in which the two side HP filtered credit-to-GDP gap (2S, very significant in the specifications *sub* (iii) and (iv)) substantially outperforms the gap estimated with the one side HP filter (IS, never significant in specifications *sub* (i) and (ii)).<sup>33</sup> Second, the results show that, albeit with a different degree of significance, the AR(1) term of the dependent variable improves the estimation in a material way, having by far the larger coefficient among the set of regressors considered.

Among the other potential indicators, the growth of bank credit in nominal terms is always significant and with the expected sign in all the specifications. Furthermore, its significance improves in the regressions including the two side HP filter credit-to-GDP gap *sub* (iii) and (iv). The results are broadly similar for the GDP growth which has the expected sign and while being marginally or not significant in the regressions shown in column (i) and (ii), it becomes highly significant in the specifications shown in column (iii) and (iv). The evidence is different for the change in the unemployment rate whose coefficient has expected sign but is statistically significant only when the AR(1) term is omitted.

As for the PTR ratio, significant in three out of four specifications, the evidence might suggest that an increase in house prices relative to rents - by making a buy-to-let strategy by homeowners more profitable - might improve the servicing capacity and hence be associated with a decrease in the ratio of bad loans to total loans. Vice versa, a fall in housing prices relative to rent prices is associated with an increase of the bad loans ratio which suggests that losses might be materialising for homeowners when housing prices decline. While the analysis does not provide insights about the causality of the nexus between house prices and bad loans, this evidence appears to be broadly consistent with the possibility of an inverse causation between house prices and lending (and by extension bad loans) that has been discussed in Panetta (2014).

The negative sign of the highly significant LTD ratio, albeit possibly counterintuitive *prima facie*, might be driven by banks more reliant on wholesale funding which, being more reactive to changes in market conditions, are likely to become more selective about borrowers to avoid experiencing tensions on the funding side.

These findings are broadly robust to the lag structure used (as shown in Table A.1 in the Appendix, by estimating Equation 10 with a lag of four quarters instead of eight).

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<sup>32</sup> The Newey – West (1987) variance estimator allows to produce consistent estimates in the case of autocorrelation and possible heteroskedasticity.

<sup>33</sup> This evidence is fully confirmed by a univariate estimation of the dependent variable on the two measures of the credit-to-GDP gap.

**Table 9 Pairwise correlation matrix**

Variable	cycle_is	M3_real	M3_nom	Tot_credit_nfs	Bank_credit_nfs	HF_credit	NFC_credit	U	GDP	Bank_cr_to_GDP	Tot_cr_to_GDP	PTI	PTR	MSCI	Slope	LTD	Spread	HPN_2y	HPN_gap	HPR_gap	
cycle_is	1																				
M3_real	0.201	1																			
M3_nom	-0.607	0.497	1																		
Bank_credit_nom	-0.383	0.080	-0.086	1																	
Bank_credit_real	0.494	0.348	0.480	0.678	1																
Credit_HH	-0.434	0.112	0.461	0.328	0.189	1															
Credit_NFC	-0.502	0.035	0.633	0.802	0.328	0.757	1														
U	-0.187	-0.211	-0.026	-0.362	-0.592	-0.297	-0.226	1													
GDP	-0.398	-0.047	0.329	0.596	0.257	0.461	0.350	-0.330	1												
Bank_credit_to_GDP	0.705	0.277	-0.336	0.043	0.728	0.086	0.025	-0.407	-0.197	1											
Tot_credit_to_GDP	0.765	0.284	-0.342	0.096	0.807	-0.004	-0.101	-0.380	-0.221	0.871	1										
PTI	0.229	0.093	-0.029	0.195	0.356	0.017	0.024	-0.329	-0.028	0.296	0.331	1									
PTR	0.033	0.127	0.189	0.366	0.314	0.141	0.204	-0.424	0.138	0.146	0.170	0.893	1								
MSCI	-0.309	-0.222	-0.002	0.089	-0.087	0.311	0.074	0.071	0.264	-0.149	-0.194	0.060	0.033	1							
Slope	0.399	-0.071	-0.479	-0.640	-0.222	-0.623	-0.639	0.139	-0.526	0.058	0.124	0.120	-0.009	-0.294	1						
LTD	-0.009	-0.147	-0.164	0.247	0.379	0.286	0.104	-0.295	0.317	0.174	0.205	0.032	-0.010	0.410	-0.260	1					
Spread	-0.063	-0.241	0.127	0.291	-0.025	-0.017	0.196	-0.027	0.138	-0.058	-0.019	0.269	0.429	-0.219	-0.046	-0.196	1.000				
HPN_2y	-0.442	-0.080	0.564	0.671	0.018	0.337	0.630	-0.147	0.205	-0.196	-0.184	0.332	0.475	0.043	-0.332	-0.013	0.356	1			
HPN_gap	0.169	0.086	0.145	0.420	0.398	0.103	0.286	-0.386	-0.024	0.285	0.304	0.581	0.590	-0.126	-0.049	0.048	0.234	0.765	1		
HPR_gap	0.209	0.320	0.352	0.469	0.400	0.240	0.397	-0.350	0.101	0.294	0.299	0.261	0.261	-0.015	-0.372	0.062	0.062	0.507	0.609	1	
HPR_gap	0.369	0.241	0.191	0.342	0.382	0.020	0.244	-0.335	-0.080	0.360	0.402	0.512	0.463	-0.106	-0.093	-0.005	0.193	0.560	0.789	0.885	1

**Table 10: The relation between bad loans and risk indicators**

Bad_loans <sub>t</sub>	(i)	(ii)	(iii)	(iv)
1S <sub>t-8</sub>	0.029 (0.035)	0.019 (0.033)		
2S <sub>t-8</sub>			0.086*** (0.022)	0.073*** (0.022)
Bad_loans <sub>t-8</sub>		0.472*** (0.176)		0.286* (0.154)
M3_real <sub>t-8</sub>	-0.014 (0.032)	0.008 (0.026)	-0.010 (0.023)	0.003 (0.021)
Bank_credit_nom <sub>t-8</sub>	0.804* (0.043)	0.082** (0.040)	0.070*** (0.016)	0.074*** (0.015)
Bank_credit_to_GDP <sub>t-8</sub>	-0.008 (0.072)	0.043 (0.077)	-0.011 (0.039)	0.016 (0.044)
U <sub>t-8</sub>	0.346*** (0.116)	0.148 (0.118)	0.163** (0.081)	0.071 (0.085)
GDP <sub>t-8</sub>	-0.081 (0.049)	-0.087* (0.047)	-0.102*** (0.037)	-0.104*** (0.034)
PTR <sub>t-8</sub>	-0.017** (0.008)	-0.009 (0.008)	-0.022*** (0.008)	-0.017** (0.008)
LTD <sub>t-8</sub>	-0.044** (0.017)	-0.039*** (0.013)	-0.030*** (0.009)	-0.029*** (0.007)
House_price_gap_nom <sub>t-8</sub>	0.017 (0.032)	0.004 (0.028)	0.017 (0.021)	0.008 (0.018)
c	-0.512 (0.320)	-0.617** (0.271)	-0.243 (0.179)	-0.357*** (0.177)
Observations	144	144	144	144

OLS estimates of equation 10. Newey-West standard errors in parentheses. \*\*\*, \*\*, \* significance levels at 1, 5 and 10 per cent respectively.

Further insights on the lead-lag relation between the indicators and the bad loan ratio can be gained by examining their correlations over a wide time window which includes, but is not limited to, the two-year or one-year horizons examined in the regressions. To that end, in Figure A7 of the annex we report the cross-correlogram between bad loans and each of the indicators, considering leads and lags of up to 12 quarters. The two-side gap is positively correlated to bad loans at all lags, which suggests that its predictive power should be fairly robust. The correlation turns negative when the bad loan ratio is lagged relative to the gap, which is consistent with spikes in credit losses causing a contraction in credit. One-side gap and credit growth display a similar behavior, but the correlations are lower and their sign is more erratic which, for the one-side gap explains the relative lack of success in the regressions. Among the remaining indicators, output growth, unemployment and the real estate price gap also display a regular pattern that bodes well for their usefulness as risk indicators.

## 5. Conclusions

In this paper we propose an operational approach to overcome some of the challenges posed by the application of the standardized credit-to-GDP gap measurement framework to the Italian financial sector. We also identify a sub-set of macro-financial indicators that explain the dynamics of the financial cycle and as such could complement the credit-to-GDP gap in the decision making process for the activation of the CCyB by the macroprudential authority. Finally, we test their association with a continuous measure of the riskiness of the banking system.

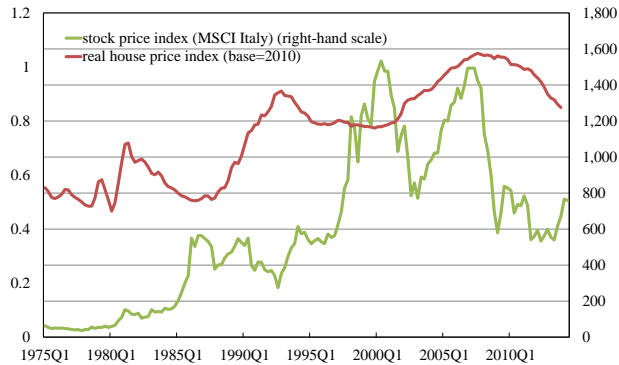
We find that the filtering approach we propose provides a better representation of the financial cycle from an historical perspective (with shorter length of more accurate timing of the cycles than the standardized approach based on the one-side HP filter), performs better in forecasting financial crises, and can be estimated in real-time. The statistical analysis of the additional macro-financial indicators is useful to pin-down a manageable number of variables that could be closely monitored to evaluate the build-up of systemic risk. It also provides preliminary evidence of the signaling properties of the additional macro-financial indicators as early warning indicators for a continuous variable of banking system risk.

This work is the first step for the study of the implementation of the CCyB. Further topics to be investigated in the future could include: the development of a more comprehensive framework for the real time estimation of the financial cycle; a refinement of the analysis of the additional indicators in a forecasting framework, and the analysis of the additional indicators for the release of the CCyB.



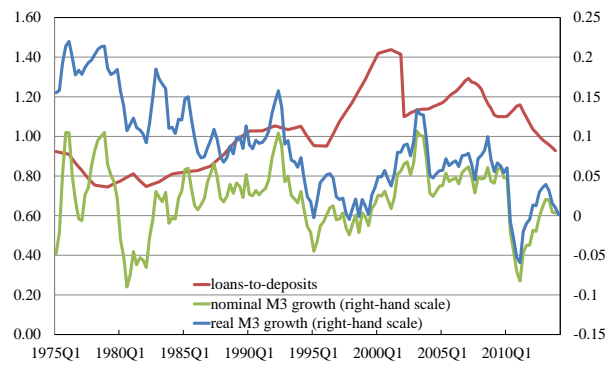
## Appendix

**Figure A1. Asset price growth  
(per cent)**



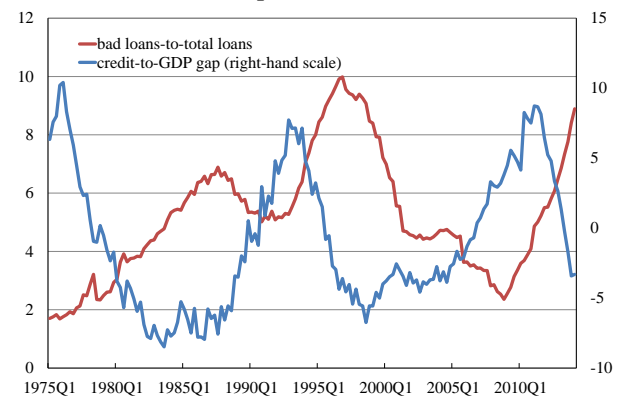
Source: Bank of Italy

**Figure A2. Loans-to-deposits and M3 growth  
(per cent)**



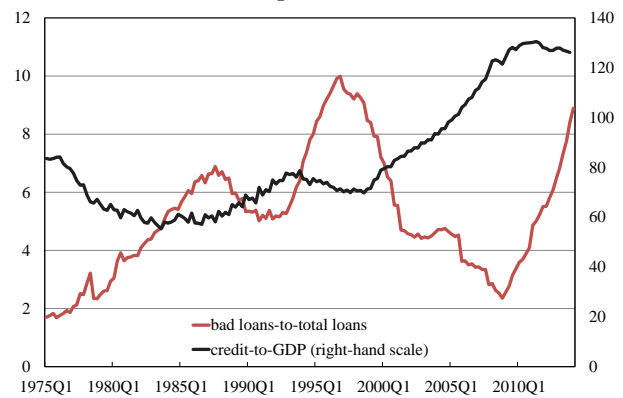
Source: Bank of Italy

**Figure A3. Bad loans-to-total loans  
and credit-to-GDP gap  
(per cent)**



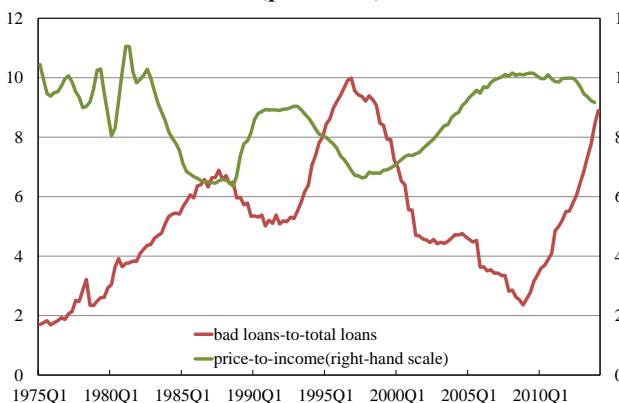
Source: Bank of Italy

**Figure A4. Bad loans-to-total loans  
and credit-to-GDP  
(per cent)**



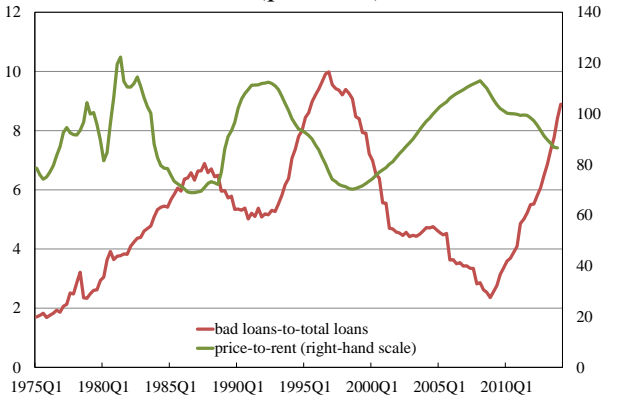
Source: Bank of Italy

**Figure A5. Bad loans-to-total loans  
and price-to-income  
(per cent)**



Source: Bank of Italy and ECB.

**Figure A6. Bad loans-to-total loans  
and price-to-rent  
(per cent)**



Source: Bank of Italy and ECB.

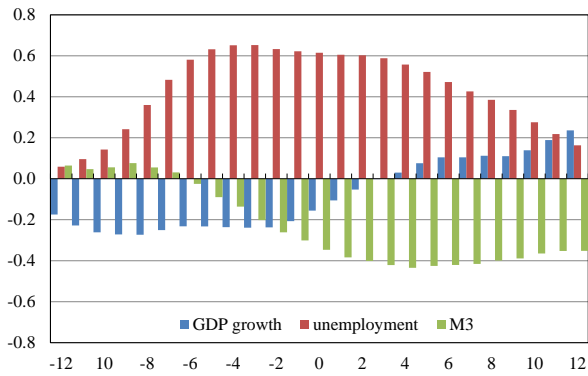
**Table A1: Testing for an alternative lag structure of Equation 10**

Bad_loans <sub>t</sub>	(i)	(ii)	(iii)	(iv)
1S <sub>t-4</sub>	0.036* (0.020)	0.031 0.020		
2S <sub>t-4</sub>			0.064*** (0.016)	0.051*** (0.014)
Bad_loans <sub>t-4</sub>		0.418*** (0.125)		0.299** (0.125)
M3_real <sub>t-4</sub>	-0.023 (0.024)	-0.002 (0.016)	-0.022 (0.019)	-0.008 (0.018)
Bank_credit_nom <sub>t-4</sub>	0.045* (0.024)	0.049** (0.024)	0.023 (0.014)	0.026** (0.013)
Bank_credit_to_GDP <sub>t-4</sub>	-0.072 (0.064)	-0.034 (0.061)	-0.040 0.038	-0.011 (0.037)
U <sub>t-4</sub>	0.605*** (0.101)	0.45*** (0.102)	0.470*** (0.087)	0.386*** (0.096)
GDP <sub>t-4</sub>	-0.017 (0.047)	-0.026 (0.047)	-0.022 (0.039)	-0.025 (0.038)
PTR <sub>t-4</sub>	-0.011* (0.006)	-0.003 (0.005)	-0.014** (0.006)	-0.008 (0.004)
LTD <sub>t-4</sub>	-0.033** (0.014)	-0.029*** (0.011)	-0.024*** (0.008)	-0.023*** (0.007)
House_price_gap_nom <sub>t-4</sub>	0.018 (0.019)	0.004 (0.018)	0.026 (0.016)	0.015 (0.015)
<i>c</i>	-0.277 (0.188)	-0.373** (0.162)	0.012 (0.137)	-0.095 (0.137)
Observations	148	148	148	148

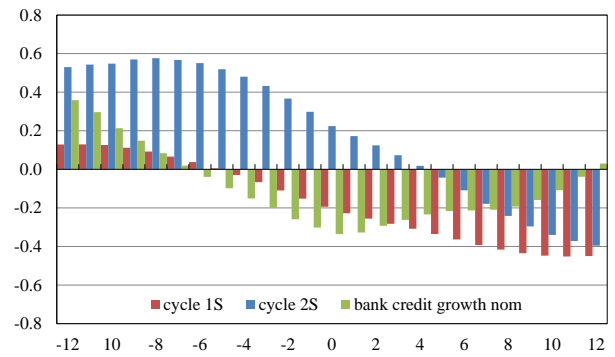
Newey-West standard errors in parentheses. \*\*\*, \*\*, \* significance levels at 1, 5 and 10 per cent respectively.

**Figure A7. Correlograms between the bad loans ratio and the macro-financial indicators**

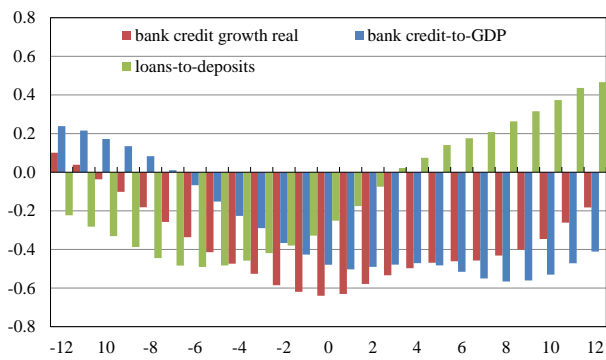
(1)



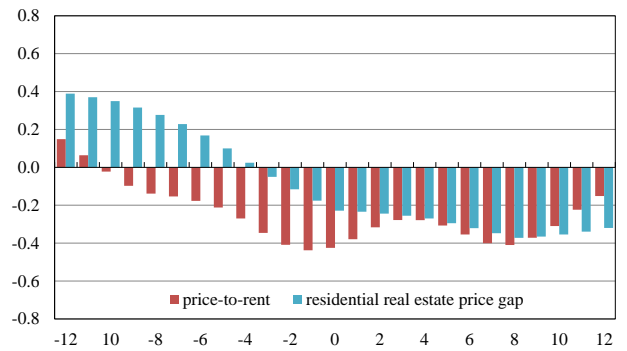
(2)



(3)



(4)



## References

- Babecky J., T. Havranek, J. Mateju, M. Rusnak, K. Smidkova, B. Vasicek, 2011. *Early warning indicators of economic crises: Evidence from a panel of 40 developed countries*, Czech National Bank Working Paper, No. 8
- Banca d'Italia, 2014. Financial Stability Report No. 2, November
- Barrell R., E.P. Davis, D. Karim, I. Liadze, 2010. *Bank regulation, property prices and early warning systems for banking crises in OECD countries*, NIESR Discussion Paper, No. 330
- Basel Committee on Banking Supervision, 2011. *Basel III: A global regulatory framework for more resilient banks and banking systems*, Revised version
- Borgy V., V. Clerc, J.P. Renne, 2009. *Asset-price boom-bust cycles and credit: what is the scope of macroprudential regulation?*, Working Paper Series, No. 263, Banque de France
- Borio C., M. Drehmann, 2009. *Assessing the risk of banking crises – revisited*, BIS Quarterly Review, March, pp. 29- 46
- Claessens S., M.A. Kose, M.E. Terrones, 2011. *Financial cycles: What? How? When?*, IMF Working Paper No. 11/76
- Claessens S., M.A. Kose, M.E. Terrones, 2012. *How do business and financial cycles interact?*, Journal of International Economics, Elsevier, Vol. 87(1), pp. 178-190
- De Bonis R., F. Farabullini, M. Rocchelli, A. Salvio, 2012. *A Quantitative Look at the Italian Banking System: Evidence from a New Dataset since 1861*, Quaderni di storia economica (Economic History Working Papers) 26, Bank of Italy
- De Bonis R., A. Silvestrini, 2013. *The Italian financial cycle: 1861-2011*, Temi di discussione (Economic working papers) 936, Bank of Italy
- Dekten C., O. Weeken, L. Alessi, D. Bonfim, M.M. Boucinha, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J.H. Lang, N. Puzanova, P. Welz, 2014. *Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options*, Occasional Paper Series 5, European Systemic Risk Board
- Dembiermont C., M. Drehmann, S. Muksakunratana, 2013. *How much does the private sector really borrow? A new database for total credit to the private non-financial sector*, BIS Quarterly Review, March, pp. 65-81
- Drehmann M., C. Borio, L. Gambacorta, G. Jimenez, C. Trucharte, 2010. *Countercyclical capital buffers: exploring options*, BIS Working Papers No. 317
- Drehmann M., C. Borio, K. Tsatsaronis, 2011. *Anchoring countercyclical capital buffers: the role of credit aggregates*, International Journal of Central Banking, Vol. 7 (4), pp. 189–240
- Drehmann M., C. Borio, K. Tsatsaronis, 2012. *Characterising the financial cycle: don't lose sight of the medium term!*, BIS Working Papers 380, Bank for International Settlements

- Drehmann M., M. Juselius, 2014. *Evaluating early warning indicators of banking crises: Satisfying policy requirements*, International Journal of Forecasting, Vol. 30(3), pp. 759–780
- Drehmann M., K. Tsatsaronis, 2014. *The credit-to-GDP gap and countercyclical capital buffers: questions and answers*, BIS Quarterly Review, March, pp. 55-71
- European Systemic Risk Board, 2014. Recommendation of the ESRB of 18 June 2014 on guidance for setting countercyclical buffer rates, ESRB/2014/1, OJ 2014/C 293/01
- Gerdrup K., A.B. Kvinlog, E. Schaanning, 2013. *Key indicators for a countercyclical capital buffer in Norway – Trends and uncertainty*, Norges Bank Staff Memo No. 13
- Geršl A., J. Seidler, 2012. *Excessive credit growth and countercyclical capital buffers in Basel III: an empirical evidence from central and east European countries*, Economic Studies and Analyses, No. 6(2)
- Gigliobianco A., C. Giordano, 2012. *Does economic theory matter in shaping banking regulation? A case-study of Italy (1861-1936)*, Accounting, Economics, and Law, 2(1), pp. 1-75
- Hodrick R.J., E.C. Prescott, 1997. *Postwar U.S. Business Cycles: An Empirical Investigation*, Journal of Money, Credit and Banking, Vol. 29(1), pp. 1-16
- International Monetary Fund, 2011. *Towards Operationalizing Macroprudential Policies: When to Act?*, Global Financial Stability Report, September 2011
- Kauko K., 2012a. *External deficits and non-performing loans in the recent financial crisis*, Economics Letter 115, pp. 196-199
- Kauko K., 2012b. *Triggers for countercyclical capital buffers*, Bank of Finland Online 7/2012
- Keller J., 2011. *The BCBS proposal for a countercyclical capital buffer: an application to Belgium*, Financial Stability Review, National Bank of Belgium, pp. 121-132
- Laeven L., F. Valencia, 2012. *Systemic banking crises database: an update*, IMF Working Papers 12/163, International Monetary Fund
- Mendoza E., M. Terrones, 2008. *An anatomy of credit booms: evidence from macro aggregates and micro data*, NBER Working Paper, No. 14049
- Orphanides A., S. van Norden, 2002. *The unreliability of output gap estimates in real time*, The Review of Economics and Statistics, Vol. 84(4), pp. 569-583
- Panetta F., 2014. *On the special role of macroprudential policy in the euro area*, speech at the De Nederlandsche Bank, 10 June
- Reinhart C.M., K.S. Rogoff, 2009. *This Time Is Different: Eight Centuries of Financial Folly*, Princeton University Press
- Repullo R., J. Saurina, 2011. *The countercyclical capital buffer of Basel III: A critical assessment*, CEPR Discussion Papers 8304

- Riiser M., 2005. *House prices, equity prices, investment and credit –what do they tell us about banking crises? A historical analysis based on Norwegian data*, Economic Bulletin, 05 Q3, Norges Bank, pp. 145-154
- Schularick M., A.M. Taylor, 2012. *Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870–2008*, American Economic Review, Vol. 102 (2), pp. 1029-1061
- Stock J.H., M.W. Watson, 2012. *Macroeconomic Forecasting Using Diffusion Indexes*, Journal of Business & Economic Statistics, Vol. 20(2), pp. 147-162, DOI: 10.1198/073500102317351921
- Zamagni V., 2008. *Il credito all'industria*, in Storia d'Italia. La Banca, Annali 23, Einaudi, Torino, pp. 765-784