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Abstract

While the setting of the countercyclical capital buffer (CCyB) is not an automatic decision, insights from indicators, such as the credit-to-GDP gap, are a starting point to inform the policy decision. This paper identifies an optimal rule to map the credit-to-GDP gap adjusted to the guide to set the CCyB. We follow two alternative procedures. First, we apply the criteria suggested by the Basel Committee on Banking Supervision, (BCBS), obtaining 3 percentage points of the adjusted gap as the activation threshold and 8 percentage points as the maximum. Then we depart from the BCBS approach by proposing a procedure based on the maximization of the area under the receiver operating characteristic curve (AUROC), which suggests 1 and 9 percentage points as the minimum and maximum thresholds, respectively. We also explore whether the CCyB, had it been in place, would have mitigated the repercussions of the Great Financial Crisis for the Italian banking system. Based on a stylized exercise, the full release of the CCyB at the outbreak of the crisis would have freed around €40 billion of capital, a value close to the total amount of banks' credit provisions during the three following years.

JEL Classification: E32, G21, G28.
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1 Introduction [*]

The countercyclical capital buffer (CCyB) is one of the instruments introduced by the Basel Committee on Banking Supervision (BCBS) in response to the Great Financial Crisis (GFC) as part of the Basel III framework. The CCyB is a capital layer of up to 2.5 percent of risk-weighted assets (RWA)[1] and is designed to be released during a downturn so that banks may absorb losses while maintaining the flow of credit to the economy. The BCBS issued detailed guidance (henceforth referred also as 'standardized framework') on how to operate the CCyB (BCBS (2011)). It suggests calculating the credit-to-GDP gap using the one-side Hodrick-Prescott (HP) filter and provides a guide (buffer guide) for the decision making by national authorities that explains how the accumulation of the buffer should be linked to the level of the credit-to-GDP gap (hereafter also referred as 'credit gap' or simply 'gap').[2] To translate the credit-to-GDP gap into a percentage of the bank RWA, the BCBS suggests a threshold of 2 percentage points of the credit-to-GDP gap for the activation of the CCyB and of 10 percentage points as a cap at which the maximum buffer requirement should be reached. These thresholds were calibrated to ensure a good signaling property of the one-side HP filter based on the historical banking crises experienced by 25 countries (BCBS (2010)). While the existing literature has extensively studied the reliability of the indicator used to capture the credit cycle (Alessi and Detken (2018), Drehmann and Yetman (2018), Hamilton (2018), among others) and the appropriateness of setting the maximum level of the CCyB rate to 2.5 percent (Aikman et al. (2019), Van Oordt (2018), Faria-e-Castro (2019), among others), only a few studies have called into question the levels of the min-max thresholds. Detken et al. (2014) observe that in 18 EU member states the gap exceeded the 10 percentage points upper bound outside crises, both 5 years before a crisis and when a crisis did not occur, while the minimum threshold of 2 percentage points seems broadly adequate. Starting from this evidence, Wezel (2019) assesses for 27 EU countries whether threshold specifications other than the (2, 10) are more

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[1] While neither the BCBS nor the CRD IV explicitly set a maximum CCyB rate, the reciprocity under Basel and the CRD IV is only mandatory until 2.5% of risk-weighted assets and the calibration rule suggested by the BCBS has 2.5% as maximum.

[2] See Appendix A.1 for more details on the BCBS guidance.

appropriate. They study 9 alternative min-max credit gap combinations and find that the (4,20) pair works better. Therefore, both Detken et al. (2014) and Wezel (2019) suggest that mapping the CCyB in line with BCBS (2010) guidance would unnecessarily lengthen the period during which the buffer is at its maximum, increasing its cost.
While ensuring that the CCyB is built promptly enhances the resilience of the banking system and its capacity to better weather adverse shocks, building capital too soon in the cycle could excessively weigh on credit supply, with possible negative implications on the real economy.[3] The activation threshold should therefore strike the balance between being high enough to avoid repercussions on the real economy from a too early activation and being low enough to allow a gradual accumulation of the buffer along the cycle. At the same time, the threshold at which the buffer would reach its maximum level should be such to ensure that the CCyB can work as intended while avoiding excessive capital constraints on banks.

These evident trade-offs have largely been overlooked in the literature, even though the analysis of the best timing for phasing-in the CCyB through the appropriate settings of the credit gap thresholds should be part of the judgment that is expected in the deployment of the CCyB (Van Norden (2011), Kowalik et al. (2011)). However, the setting of the CCyB is not automatic and expert judgment is a key element of the framework. Indeed, many factors such as the economic situation and the interaction with other policies should be taken into account. Over the next few years, when policymakers will be called to decide on how to rebuild the buffers that have been released to support banks' ability to lend during the COVID-19 crisis, having in place a reliable calibration framework will be a central issue.

This note contributes to inform the setting of the credit gap thresholds for the operationalization of the CCyB. Using the gap *à* la Alessandri et al. (2015) as a measure of the credit cycle, we first calibrate the thresholds for the activation of the

[3]See among others Gropp et al. (2019), Ragnar and Wold (2020), Galardo and Vacca (2021)

CCyB using the same criteria as the one used by BCBS (2010) for the calibration of the standardized framework. Then we depart from this approach by proposing the use of the receiver operating characteristic (ROC), a method commonly adopted in the literature to measure the accuracy of binary early warning indicators (Berge and Jordà (2011) and Drehmann and Juselius (2014)). In particular, we model the area under the ROC curve (AUROC) to deal with a multi-class problem that evaluates the classification ability of different lower and upper bounds of the credit gap, having as dependent variable different levels of financial vulnerability. With this approach, we find that a calibration of the rule for the activation of the CCyB different than the one obtained with the Basel criteria achieves a higher accuracy (i.e. a higher AUROC). In our framework, starting from the distribution of the credit-to-GDP gap estimated *à* la Alessandri et al. (2015), we compute the AUROC for all the combinations of lower and upper thresholds between 0 to 10 percentage points of the credit gap. We find that for Italy the combination of thresholds maximizing the AUROC is (1,9). While we use this approach to map the gap *à* la Alessandri et al. (2015) into a buffer guide, this is a highly flexible evaluation criterion that may in principle be applied to any indicator of the credit cycle.

We also perform a stylized exercise to explore whether the release of the CCyB, if in place, would have helped banks to face the impact of the Great Financial Crisis (GFC). We show that the Italian banking system, *ceteris paribus*, would have faced the GFC with a total regulatory capital to risk-weighted assets ratio equal to 12.9 percent instead of 10.4 percent that it had in the absence of the CCyB. The immediate release of the CCyB at the outbreak of the crisis would have freed around 40 billion euros of capital, a value close to the amount of the banks' new provisions on non-performing loans cumulated during the three years after the beginning of the crisis. While this result takes a step towards the understating of the real implications of the CCyB, it has to be taken with caution. In fact, our exercise implicitly assumes that the accumulation of the CCyB before the crisis would have had no effect on banks' balance sheets but the existing literature shows that an increase in capital requirements does affect banks' risk-taking and lending supply (see among others, Aiyar et al. (2014) and Gropp et al. (2019)).

The remainder of the paper proceeds as follows. The next section describes the Basel calibration framework and the CCyB build-up rule for Italy consistent with the Basel criteria. Section 3 presents the calibration approach based on the ROC curve and section 3.2 presents the actual calibration of the min-max thresholds. In section 4 we explore to what extent the CCyB framework if in place, would have mitigated the impact of the GFC on the Italian Banking system. Section 5 concludes.

2 Calibrating with the Basel criteria

Building on the general principle that the objective of the CCyB is to protect the banking system from the fallout of periods of excess credit growth, BCBS (2010) has provided criteria for setting both: i) the lower threshold of the gap, appropriate for starting to build up the buffer; and ii) the upper threshold of the gap, in correspondence of which the maximum buffer rate would be reached. The lower and upper thresholds are key in determining the timing and the speed of the adjustment of the buffer guide to underlying conditions.

1. Criteria for the minimum threshold (L)
    - L should be low enough so that banks are able to build up capital in a gradual fashion before a potential crisis. As banks are given one year to raise additional capital, this means that the indicator should breach L at least 2-3 years prior to a crisis.
    - L should be high enough so that no additional capital is required during normal times.
2. Criteria for the maximum threshold (H)
    - U should be low enough so that the buffer would be at its maximum prior to major banking crises.

With these guidelines in mind, the BCBS calibrated the CCyB based on the distribution of the credit-to-GDP gap estimated with the one-side HP filter for a

Table 1: Banking crises and adjusted credit-to-GDP gap for Italy

Crises	Years before crisis				
	5	4	3	2	1
1991Q4	2.6	4.1	5.8	7.9	10.0
2008Q3	4.5	5.2	6.4	7.1	8.1
2011Q4	8.2	10.0	6.7	8.5	3.8

Notes: The table reports the developments of the adjusted credit-to-GDP gap, estimated for the total credit to the non-financial private sector, in the five years prior to the outbreak of a banking crisis. The adjusted gap is computed exploiting data since 1950.

large set of countries. The rule stipulates that the CCyB should be activated when the estimated gap exceeds 2 percentage points, and should peak at 2.5 percent of banks' RWA when the gap reaches 10 percentage points (i.e. the level of the gap typically observed before the major systemic crises).[4]

We follow the BCBS approach to identify a lower bound and a pre-crisis maximum to translate the adjusted credit-to-GDP gap *à* la Alessandri et al. (2015) (hereafter also referred as 'adjusted gap') into a CCyB guide.

We start by computing the adjusted credit-to-GDP gap for the Italian banking system using quarterly data on the total credit to the non-financial private sector dating back to 1950. Next, we explore the developments of the indicator around banking crises. Since 1950, Italy featured two crises - one in 1991Q4 and one in 2011Q4 - according to the ESRB crisis database documented by Lo Duca et al. (2017)[5] and an additional crisis - in 2008Q3 - according to Laeven and Valencia (2020).

Table 1 reports the developments of the adjusted gap over the 5 years preceding a banking crisis. Based on its dynamics, the activation and termination thresholds consistent with the BCBS criteria would be, respectively, 3 and 8 percentage points. The piece-wise linear rule for the calculation of the benchmark for the CCyB would be the following:

[4]We refer the reader to BCBS (2010) for details on the identification and the sample used by the Basel Committee on Banking Supervision.

[5]Data are available at `https://www.esrb.europa.eu/pub/financial-crises/html/index.en.html`

- $CCyB_{total,t} = 0$ if $TotalGap_t \leq 3\%$
- $CCyB_{total,t} = 0.5 * TotalGap_t$-1.5 if $3\% < TotalGap_t < 8\%$
- $CCyB_{total,t} = 2.5\%$ if $TotalGap_t >= 8\%$

The combination - narrower than the one proposed by the BCBS - is the result of not only the use of a different measure of the credit gap (i.e. the adjusted credit gap) but also of a country-specific calibration. The utility of a country-specific approach to calibration is confirmed also when the exercise is repeated for the countries participating in the European Single Supervisory Mechanism, as shown in Annex A.2.

The adjusted gap shown in Table 1 signals a continuous increase of credit above its trend before the 1991Q4 and the 2008Q3 crises, and this is consistent with the literature showing that banking crises typically follow credit booms (Boissay et al. (2016)) and that the credit-to-GDP gap can be a powerful predictor of banking crises.[6] At the same time, however, it can be seen that the period before the outbreak of the European sovereign debt crisis is characterized by a hump-shaped pattern of the adjusted gap, which peaks in 2007Q4. This dynamic implies that at the onset of the sovereign crisis the credit cycle was already in its descending phase (Figure 1) and confirms that identifying and dating correctly financial crises is critical for the application of the Basel criteria in calibrating the CCyB. However, the available chronological definition of crisis periods relies on subjective and objective criteria and different databases for financial crises often have different chronologies (e.g. Schularick and Taylor (2012), Lo Duca et al. (2017), Laeven and Valencia (2020), Baron et al. (2021)). This issue is exacerbated when more countries with different credit cycles are considered.

At least two drawbacks need therefore to be addressed to implement the Basel guidance: the first relates to the chronological definition of crisis periods, the second to the fact that the dynamics of the credit cycle is highly heterogeneous

[6]See among others Borio and Drehmann (2009), Drehmann (2013), Alessandri et al. (2015), Alessandri et al. (2020).

across countries (Annex A.2). To partly deal with these challenges in the next section we propose an alternative approach to map any credit cycle indicator into the CCyB. By construction, the proposed approach will provide an accurate calibration rule given the prevailing level of financial distress.

3 Identifying the optimal calibration rule using AUROCs

In this section, we use the receiver operating characteristic to identify the optimal lower and upper bounds of the rule to translate the adjusted credit gap into a CCyB guide.

3.1 The policymaker problem

A crucial component of the macroprudential approach is to address the procyclicality of the financial system by accumulating the buffer in good times so that it can be drawn down in bad times. As already clarified, the CCyB should be raised promptly enough to enhance the resilience of the banking system to adverse shocks down the road, but it should not be increased too early in the cycle to avoid undesirable effects on credit supply that could potentially affect economic growth. Notwithstanding that the policymaker has a reliable indicator to identify the state of the cycle in real-time, she also needs an optimal rule to translate such indicator into a policy decision, i.e. a rule indicating the appropriate values of the credit cycle to initiate and to terminate the buffer accumulation. Based on a general rule mapping the credit-to-GDP gap, G_t^*, into a benchmark buffer rate, $CCyB_t = \mathfrak{B}\{G_t^*, L, H\}$, the policymaker should choose the pair (L, H) so that the CCyB is raised early enough to enhance the resilience of the banking system, but not too soon in the cycle. The pair chosen will determine the speed and timing of the countercyclical capital buffer accumulation, namely the required CCyB rate at any point in the cycle.

To make the decision problem clearer, assume that the banking system can be in one of four states S: a normal state in which no financial vulnerability is detected, a second state when vulnerabilities start to build up, a boom that will end up in a financial crisis, and then the crisis. In these states, the policymaker can either act accumulating the CCyB or not. The higher is the capital requirement the more costly is to implement a given policy, but this cost needs to be weighed against the benefit of reducing economic losses in case of a crisis. The decision problem for the policymaker consists therefore in identifying for any state S the optimal buffer guide $\mathfrak{B}\{G_t^*, L^*, H^*\}$ that translates the signal, G_t^*, into the optimal level of the CCyB (the policy). The policymaker faces the cost-benefit trade-off of implementing a policy action adequate for each state: she wants to maximize the probability of implementing the adequate policy when needed and minimize the probability of a too stringent policy when not needed. This implies that there is the usual trade-off between the rate of true positives and the rate of false positives that can be evaluated by looking at the ROC curve, which plots the entire set of possible combinations of true and false positives.

3.2 Estimating the policy maker problem

We estimate the policymaker problem described in the previous section using an ordered logistic regression that has as a dependent variable the level of financial vulnerability. An issue to deal with is the identification of different levels of accumulated risks; here we use the ratio of bad loans to total loans.[7] The choice of this ratio as a target variable is based on the following considerations: (i) credit risk has been typically the main source of concern for the financial sector in Italy, (ii) the funding structure of Italian non-financial firms is strongly skewed towards bank financing, and (iii) existing 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

[7]The choice of using bad loans, which may materialize with a lag, is due to the unavailability of long enough time series for other more timely indicators of credit quality as non-performing loans.

risk causing a negative feedback loop for the financial sector.[8] We therefore use the quartiles for the distribution of the bad loans ratio to identify four degrees of vulnerability (Figure 2), $FinRisksLevel_t$: no vulnerability for the first quartile ($FinRisksLevel_t = 0$), low vulnerability for the second ($FinRisksLevel_t = 1$), medium vulnerability for the third ($FinRisksLevel_t = 2$), and high for the fourth quartile ($FinRisksLevel_t = 3$).

Consistently to what has been suggested by the Basel Committee, we define the translating rule $\mathfrak{B}\{G_t^*, L, H\}$ using a piece-wise linear rule to map the credit-to-GDP gap, G_t^*, into a benchmark buffer rate, $CCyBt$, ranging from 0 to 2.5 percent. The Basel rule generalized for any pair (L, H) can be written as:

$$CCyB_t = 0 \text{ if } G_t^* \leq L$$

$$CCyB_t = \frac{2.5}{H-L} * G_t^* - \frac{2.5 * L}{H-L} \text{ if } L < G_t^* < H$$

$$CCyB_t = 2.5 \text{ if } G_t^* \geq H$$

where, assuming that G_t^* has been already chosen, the policymaker should choose the optimal pair (L, H). Beyond the piece-wise linear rule suggested by the BCBS, our approach to identify the optimal (L, H) is general enough to be applied to any translating rule.

The accuracy of $\mathfrak{B}\{G_t^*, L, H\}$ is valued by computing the area under the ROC curve. The ROC curve methodology has been largely adopted in economic science as a measure of forecasting accuracy for binary outcomes, particularly in assessing the accuracy of credit risk systems (among others Engelmann et al. (2003), Stein (2005), and Crook et al. (2007)), and of early warning indicators (Berge and Jordà (2011) and Drehmann and Juselius (2014)). The ROC curve has several noteworthy advantages: (i) it is not tied to a specific loss function as it is a map of the entire space of trade-offs for a given classification problem; (ii) it can be estimated non parametrically; and (iii) its summary statistics have large sample

[8]See Alessandri et al. (2015) for more details on the use of the bad loan ratio to identify financial distress.

Gaussian distributions that make formal inference convenient (Berge and Jordà (2011)).

While the convention in economics is to use the ROC curve for binary classification, i.e. crisis or no-crisis, here we model the ROC-based method on a multi-class problem to handle different degrees of financial vulnerability. For problems comparable to ours there are programs directly usable to estimate AUROCs, as Peterson (2010) which is designed for multinomial logit models.[9] In this work, we depart from Peterson (2010) to define a procedure able to handle ordered logit models in a time-series setting. The procedure we use can be summarized as follows:

1. Randomly select 90 percent of the observations of the initial sample, as a new sample Ψ.

2. Use the randomly selected sample Ψ to estimate by ordered logistic regression the following equation:

$$FinRisksLevel_t = \alpha + \beta CCyB_{t-4} \tag{1}$$

   where $FinRisksLevel_t$ is a number from 0 to 3 capturing the level of financial vulnerability, and $CCyB$ is the benchmark buffer rate one year before. Then, use the estimated model $\mathfrak{M}$ to predict the level of financial vulnerability for the periods left out by the random selection and compute the share of states correctly predicted, i.e., the model accuracy. The procedure is flexible to the use of different weights for different states of world and to the imposition of a penalty when the model fails to predict a high vulnerability state. This allows to accomodate the preferences of the policymaker, e.g. to value more the accurate forecast a bed state of the world, i.e. $S_t = 3$.

3. Estimate the ordered logit regression on the sample Ψ modified such that the levels of financial vulnerability are randomly assigned to the periods. Then,

[9] Peterson (2010) model classification accuracy by comparing sample bootstrapped with replacement to left-out cases.

Table 2: AUROCs for different (L,H) pairs.

L/H	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0	0.53	0.63	0.62	0.63	0.66	0.75	0.67	0.81	0.82	0.81
1		0.72	0.67	0.71	0.74	0.76	0.79	0.81	0.87	0.77
2			0.56	0.66	0.68	0.75	0.83	0.79	0.76	0.75
3				0.66	0.74	0.60	0.73	0.64	0.65	0.55
4					0.62	0.55	0.60	0.60	0.38	0.38
5						0.58	0.49	0.45	0.44	0.34
6							0.55	0.43	0.40	0.43
7								0.59	0.50	0.48
8									0.53	0.60
9										0.67

use the estimated model $\mathfrak{M}_{\mathfrak{null}}$ to predict the level of financial vulnerability for the periods left out and compute the share of states correctly predicted, i.e., the null accuracy.

4. Repeat points 1 to 3 for 300 iterations and compute smoothed probability distributions using kernel density estimation for both the accuracy of $\mathfrak{M}$ and $\mathfrak{M}_{\mathfrak{null}}$.

5. Compute the AUROC from the comparison of the accuracy of $\mathfrak{M}$ measuring the true positive rate and the accuracy of $\mathfrak{M}_{\mathfrak{null}}$ the false positive rate.

3.3 Evaluating lower and upper bound

We apply the described approach to evaluate a set of different (L, U) pair combinations. The aim is to identify the combination that maximizes the AUROC, or in other words to identify the calibration that has the higher ability to rightly distinguish the levels of financial vulnerability. Starting from the distribution of the adjusted credit-to-GDP gap for Italy, that in the period 1950-2020 reaches a maximum at around 10 percentage points (Figure 1), we compute the AUROC for all the combinations of (L, U) from 0 to 10, for a total of 100 pairs. Table 2 reports the AUROC estimated for any pair. The maximum (0.87) is reached at the pair (1,9), implying the following transformation rule:

$$CCyB_t = 0 \text{ if } G_t^* \leq 1$$

$$CCyB_t = 0.3125 * G_t^* - 0.3125 \text{ if } 1 < G_t^* < 9$$

$$CCyB_t = 2.5 \text{ if } G_t^* \geq 9$$

Table 2 and Figure 3 show that the pairs with the lower bound L below 2 and the upper bound U above 7 are those with higher values of the AUROCs. The (3,8) pair identified in section 2 by applying the Basel calibration principles would fall outside this area, and hence entail a lower AUROC.[10] While in our preferred approach the four states of vulnerability are valued the same, for the sake of completeness, we provide results also for two alternative approaches where the model outcomes are weighted consistently with the level of vulnerability predicted, and where a penalty is imposed when the mispredicted state is of high risk. For the exercise that includes weights, we use the weighs $W_s = \{0, 1, 2, 3\}$ associated to the states $S_t = \{0, 1, 2, 3\}$, that is $W_s = S_t$.[11] Figure 4 displays that thresholds couples with lower bounds L below 2 and upper bounds U above 7 but below 10 percentage points maximize the AUROC. For the second exercise, we impose a penalty of 1 when the model fails to identify a high vulnerability period. This exercise suggests, as all the previous ones, that the lower bound should be below 2 complemented with an upper bound above 8, as shown in Figure 5. While the surface graph is quite different from Figure 3, the combination of the threshold that maximizes the AUROC remains (1, 9) as for our preferred approach.

Figure 6 compares the buffer guides implied by different approaches. The guides based on the adjusted gap would have suggested starting building up the buffer at the end of the '90s reaching the maximum of 2.5 percent around one year before the crisis, both with the calibration based on the AUROC approach and

[10] Resuts are confirmed increasing the number of iterations to 1000 (Figure 7).

[11] When the correctly predicted state of vulnerability is high ($S_t = 3$) this is weighted three ($W_s == 3$), when it is $S_t = 2$ the weight is $W_s == 2$, and so on.

on the Basel criteria. However, while following the BCBS criteria the CCyB rate would have risen from 2 percent to the maximum from one quarter to the other, based on the AUROC approach the CCyB rate would have reached the maximum more smoothly, being above 2 percent already 2 years before the crises. Applying the standard Basel framework, the CCyB would have reached the maximum well before the crisis, unnecessarily lengthening the period during which the buffer is at its maximum, consistently with the findings of Alessandri et al. (2015) for Italy and Wezel (2019) for 27 EU countries.

4 Would the release of the CCyB have helped banks to weather the 2008 crisis?

The CCyB has the explicit objective to ensure that the financial system does not amplify a downturn in the real economy by being forced to cut back on the supply of credit in a stressed period because of lack of capital (Borio (2003), Hanson et al. (2011), Aikman et al. (2019)). Therefore, the CCyB rate may be lowered or also fully released to counteract the repercussions of a recession or a financial crisis that would increase the systemic credit losses, even when these have not yet occurred but are highly likely to do so in the near future, with the risk of impairing bank lending capacity.

In light of this, we now explore to what extent the immediate release of the CCyB, accumulated as designed in the previous section, would have mitigated the impact of the GFC for Italian banks. At the beginning of the crisis in 2008Q3 the CCyB rate, if in place, would have been at its maximum of 2.5 percent for almost 1 year.

The countercyclical capital buffer is applied to domestic exposures and hence in our case, it is expressed as a percentage of the RWA for the credit towards borrowers resident in Italy. An estimate of the buffer that would have been accumulated by Italian banks can therefore be computed as follows:

$$CCyB = CCyBrate \times RWA \times \beta \tag{2}$$

where β is a domestic lending conversion factor, which accounts for the fact that banks operate also across international boundaries. If the macroprudential framework would have been in place, the CCyB would have been accumulated since 1999 and would have reached its peak almost 1 year before the GFC. At its maximum, it would have accounted for about one-sixth of the Italian banking system total capital ratio (Figure 8) before falling back to zero in 2011. At the end of 2008, the banking system RWA for credit risk exposures were approximately 1,700 billion, of which about 90 percent related to domestic credit.[12] This implies that a full release of the CCyB at the beginning of the crisis would have freed around 40 billion of bank capital. Would have been as much capital sufficient to ensure first the resilience of the banking system and secondly its ability to support the real economy through lending? For a sense of scale, we consider the resources that banks needed to set aside to face expected losses from their problematic exposures to the private sector, i.e. the amount of new provisions on non-performing loans.[13] An increase in provisions affects the profit and loss account and through this has a negative impact on regulatory capital. As such it may have broadly similar implications on credit supply as a decline in the bank's capital ratio.[14] The growth rate of loan loss provisions peaked in 2009 and remained positive until the end of 2015 (Figure 9). The cumulated amount of new provisions in the three years following the GFC, i.e., from 2009 to the end of 2011, was 36 billion. The release of the countercyclical capital buffer at the end of 2008 would have therefore delivered enough capital to cover banks' provisions for the three following years. As simple as this exercise is, it provides also insights into the appropriateness of the 'cap' for the CCyB at 2.5 percent of RWA. Our simulation suggests the adequacy of a buffer rate at 2.5 percent to deal with future credit losses. This means that even though the CCyB has not been explicitly limited by any rule, the 2.5 percent maximum implied by the Basel calibration rule and used as a limit for the mandatory reciprocity are broadly

[12] Data on RWA for credit risk exposures are from the ECB Statistical Data Warehouse (`https://sdw.ecb.europa.eu/`)

[13] The annual stock of provisions is obtained as the difference between gross non-performing loans and net non-performing loans. New provisions refer to the increase in the stock of provisions.

[14] See e.g. Froot and Stein (1998), Gambacorta and Mistrulli (2004), Beltratti and Stulz (2012), and in particularBerger and Bouwman (2013) for the role of capital during crises.

right based on our available evidence. While providing a comparison for the test we pose, this quantification has to be taken with caution as it assumes that the accumulation of the CCyB along the period preceding the crisis would have had no effect on banks' balance sheets other than an increase in capital. This likely would not have been the case, as an increase in capital requirements does not come without a cost. Banks can increase their capital ratios in two different ways: they can increase their level of regulatory capital (the numerator of the capital ratio) or they can shrink their risk-weighted assets (the denominator of the capital ratio) by deleveraging, also through cuts in lending.[15]. In order to meet increases in the countercyclical capital buffer with more capital, the banking system should have therefore the capacity to issue new equity or retain earnings. Between 2005 and the collapse of Lehman Brothers in 2008 the performance of Italian intermediaries was weak compared to other European countries (Albertazzi et al. (2016)). Given the relatively low profitability, the higher capital requirement could have resulted in lower lending, meaning that in 2008 the banking system would have been in a different state from the one we are considering here. At the same time, however, the recent experience of the pandemic period suggests that, even in an environment of very low profitability, banks may have been able to significantly increase their capital ratio if required to do so by not distributing dividends, as they did in the first half of 2020.

5 Conclusions

Financial crises are often anticipated by unsustainable credit booms and are followed by dramatic credit contractions. To mitigate the volatility of the financial sector, regulators have introduced as part of the Basel III reform package a countercyclical capital requirement that should be tightened in good times and relaxed in bad times, to stabilize both bank balance sheets and the supply of credit to the real economy.

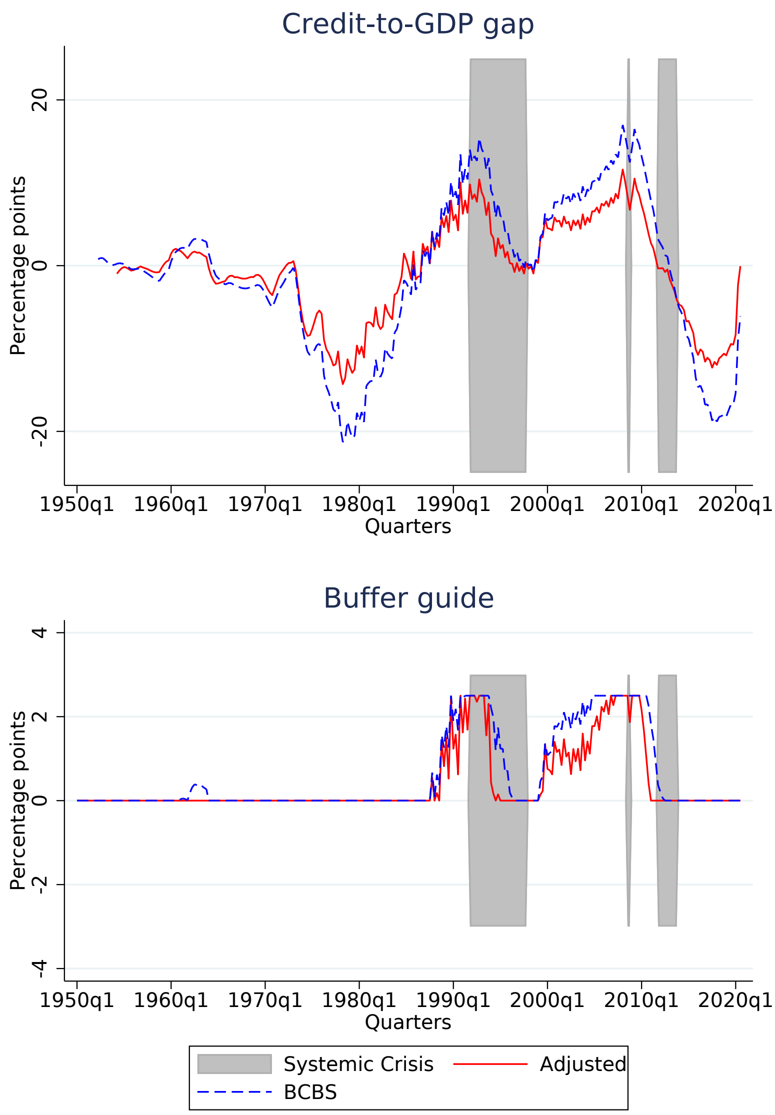
[15]See among others Thakor (1996), Aiyar et al. (2014), Gropp et al. (2019), Bahaj and Malherbe (2020), Galardo and Vacca (2021)

Three relevant issues for the implementation of the CCyB are the selection of indicators to capture the credit cycle, the identification of the maximum level of the cyclical capital add-on, and the best rule for mapping the credit cycle indicator into the buffer guide.

The Basel framework explicitly prescribes the use of the one side HP filter to extract the cyclical component on national credit aggregates, a cap of 2.5 percent for the capital add-on and suggests an activation and termination thresholds of 2 and 10 percentage points, respectively, to map the credit gap into the buffer guide. While the existing literature has extensively studied the reliability of the indicator used to capture the credit cycle (e.g. Alessandri et al. (2020), Aikman et al. (2015), and Edge and Meisenzahl (2011)) and the appropriateness of the 2.5 percent cap (see among others Aikman et al. (2019) and Van Oordt (2018)), only a few studies have called into question the min-max thresholds. The possibility to depart from the standard credit gap based on the one-side HP filter and from the calibration suggested by the BCBS are provided for by the BCBS itself and, in the European context, by the guidelines of the European Systemic Risk Board. This paper starts from the work by Alessandri et al. (2015) that proposes to exploit the filtering errors to adjust real-time the one-side HP filter, and identifies an optimal rule to transform the adjusted credit gap into the guide to set the CCyB. It does so by leveraging on an approach based on the maximization of the AUROC. We identify for Italy an activation threshold when the adjusted credit-to-GDP gap is at 1 percentage point and an upper limit when the adjusted gap is at 9 percentage points. Such a rule, according to the AUROC is more accurate than the one provided by the BCBS.

The CCyB was introduced by the BCBS in response to the GFC, but if already in place before the crisis it would have delivered a buffer requirement that would have mitigated the repercussions of the GFC for the Italian banking system. The release of the CCyB at the onset of the GFC would have freed enough capital to cover banks' provisions for the three following years.

Figure 1: Credit-to-GDP gap and buffer guide



Notes: Systemic crises are identified according to the ESRB crisis database documented by Lo Duca et al. (2017) and Laeven and Valencia (2020). The Adjusted gap is the credit-to-GDP gap computed following the methodology by Alessandri et al. (2015) and Alessandri et al. (2020). The BCBS gap refers to the one-side HP filtered gap computed following the BCBS guidance (See Appendix A.1 for more details on the BCBS guidance).

Figure 2: Defining financial vulnerability

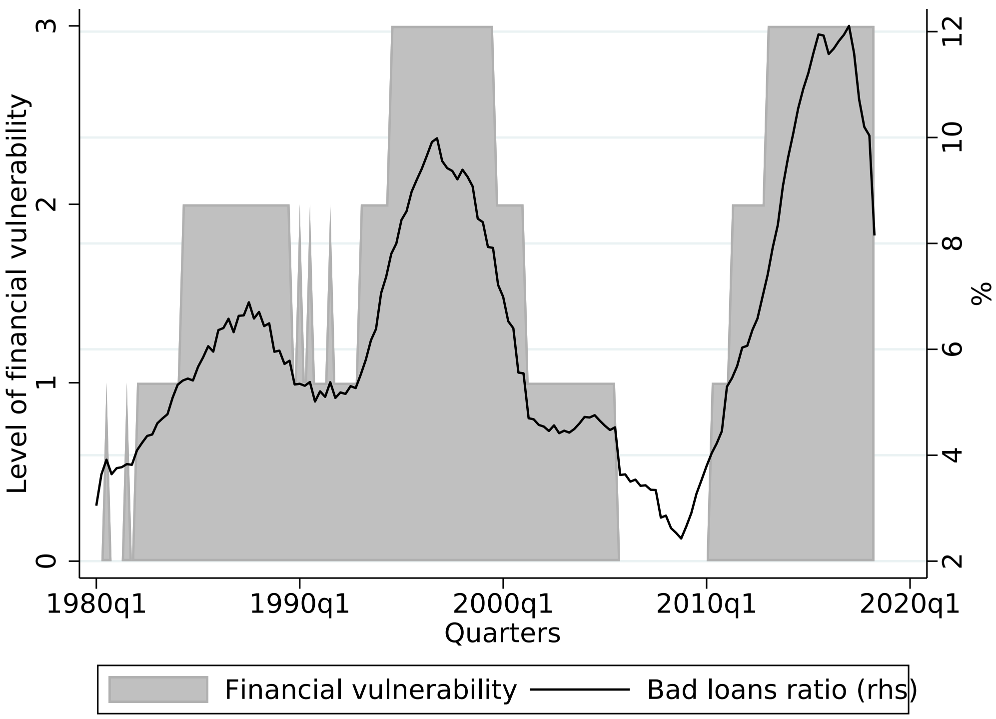
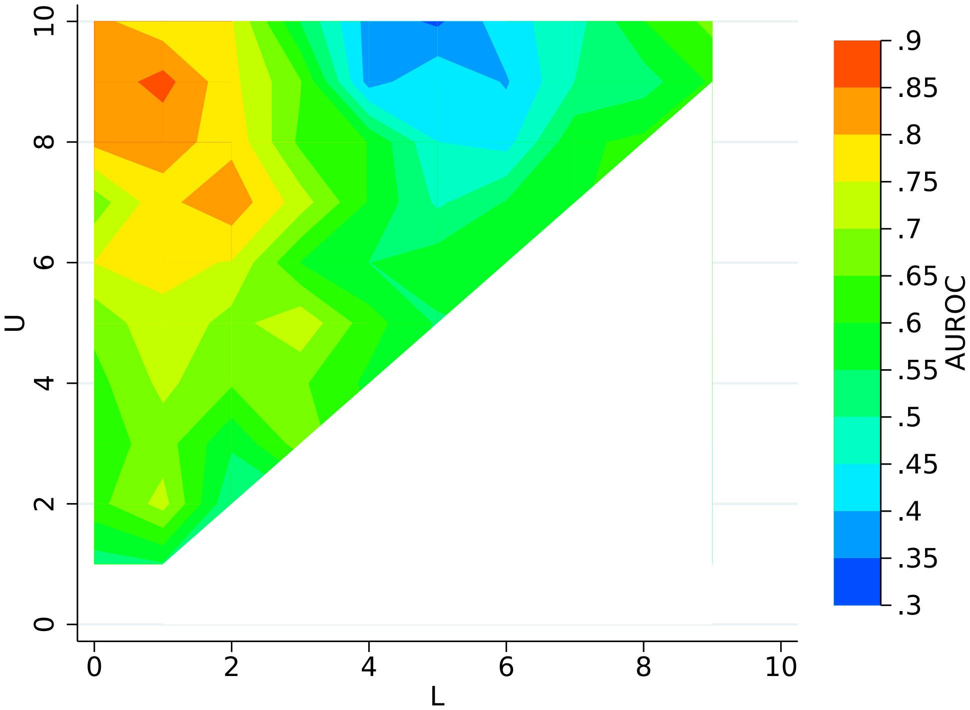
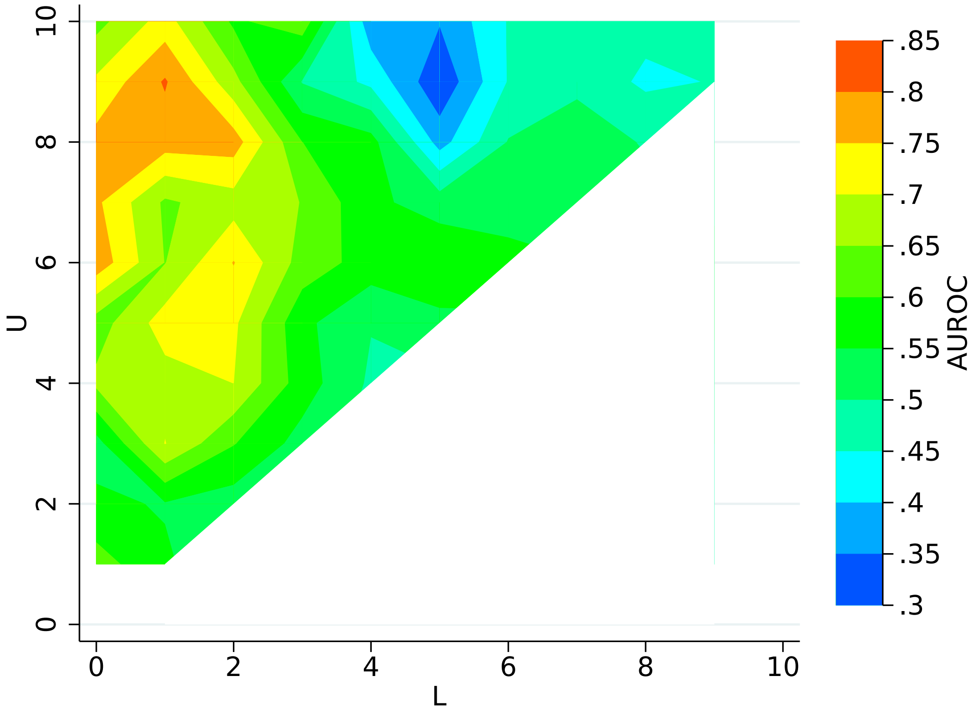


Figure 3: AUROCs



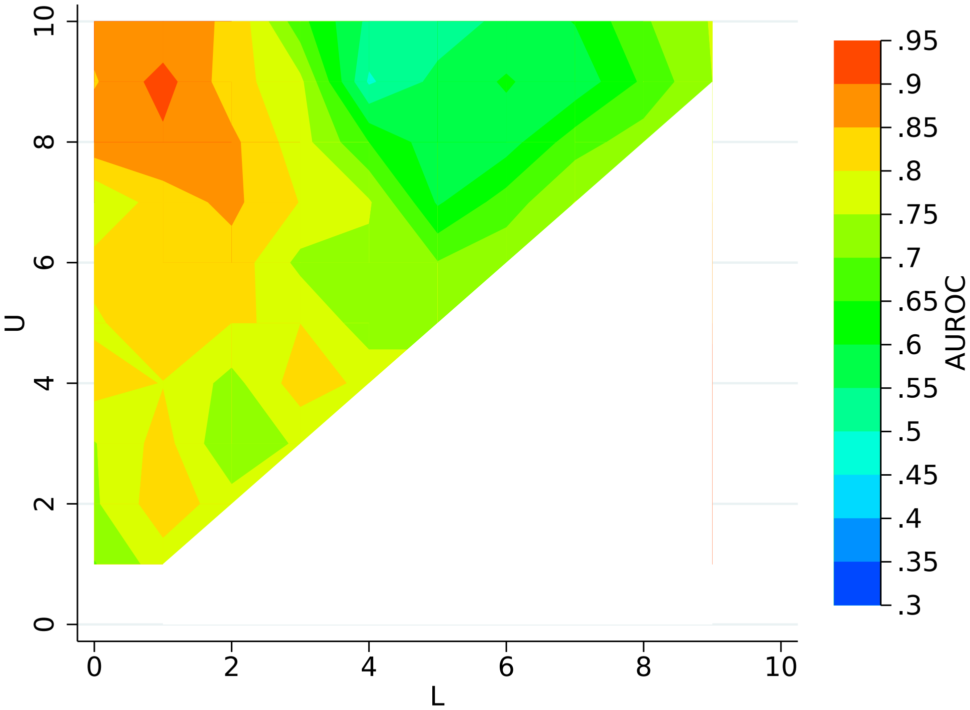
Notes: Estimated AUROCs by comparing randomly selected cases with left-out cases. 300 interactions.

Figure 4: AUROCs using weights



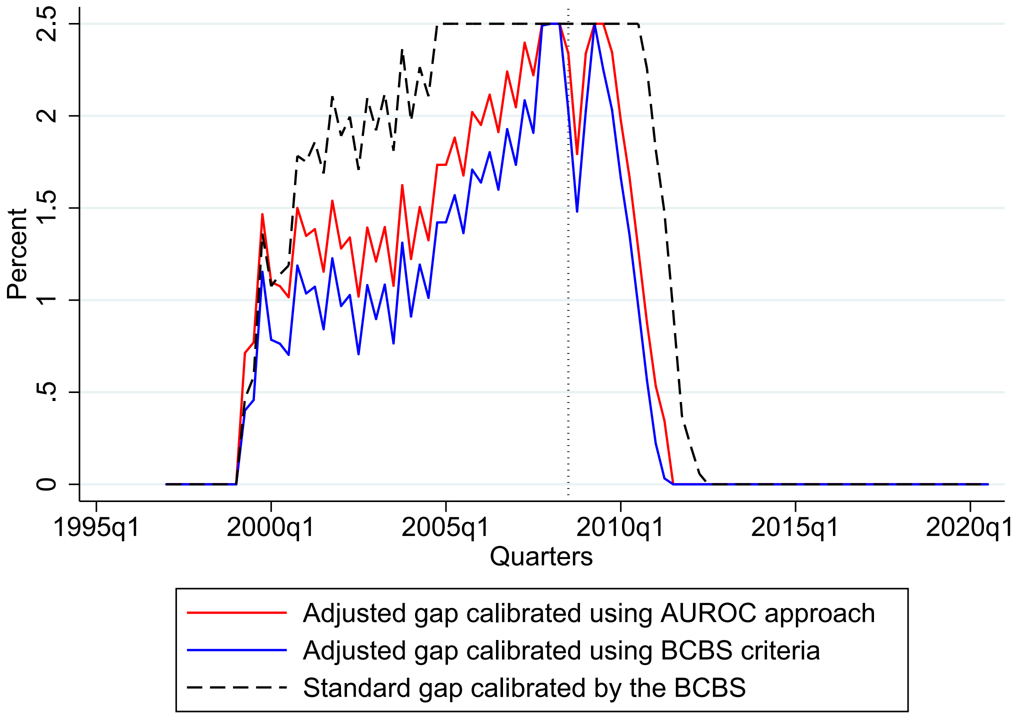
Notes: Estimated AUROCs by comparing randomly selected cases with left-out cases. 300 interactions.

Figure 5: AUROCs imposing the penalty



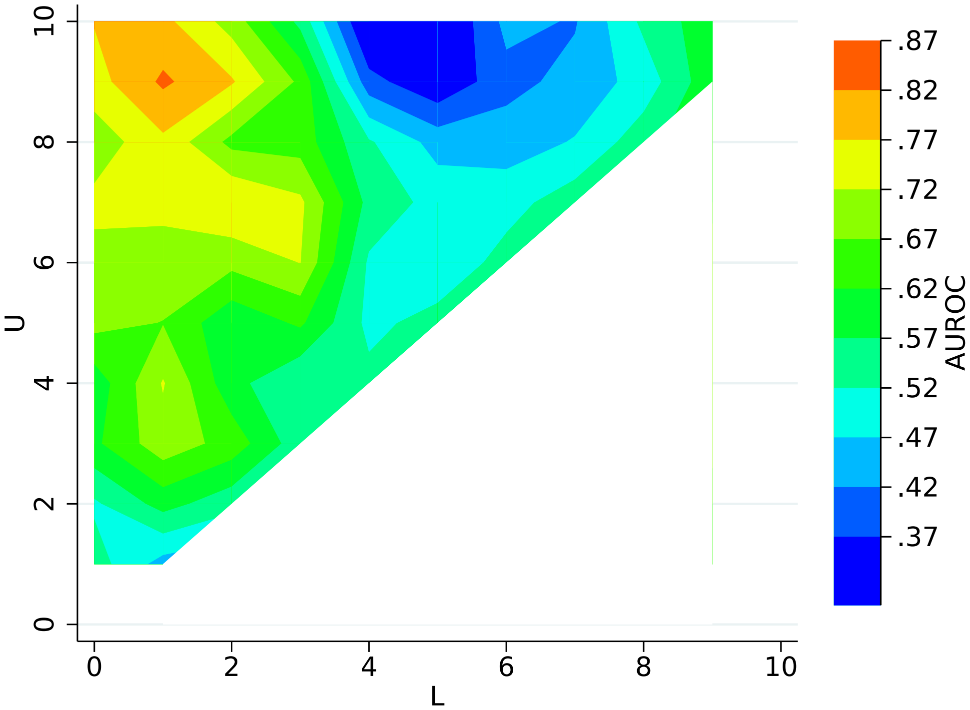
Notes: Estimated AUROCs by comparing randomly selected cases with left-out cases. 300 interactions.

Figure 6: CCyB guide



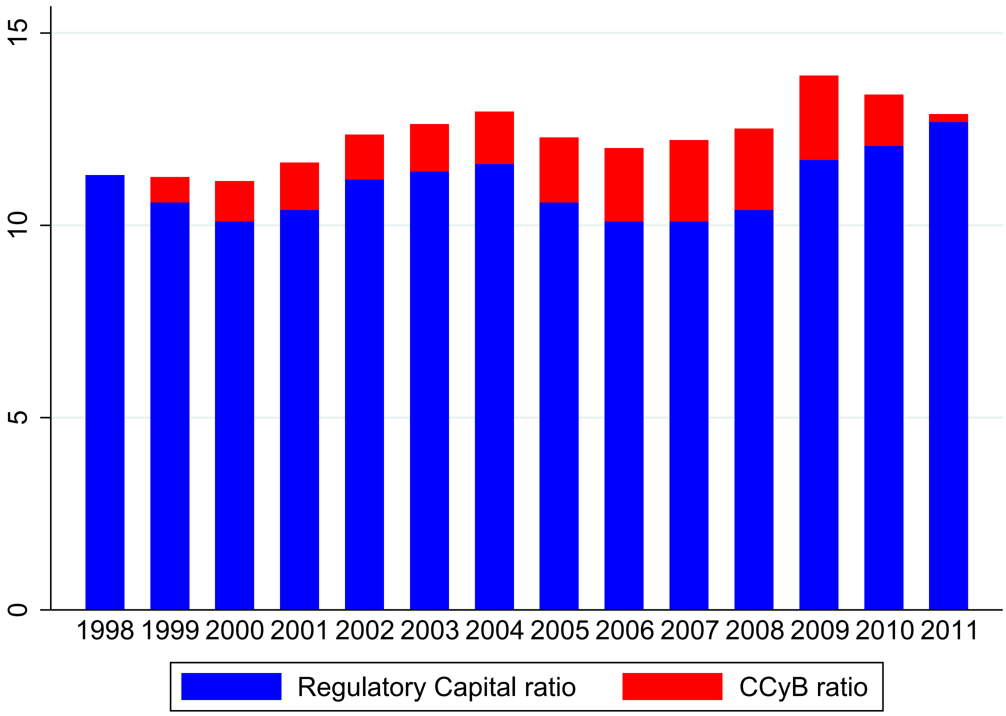
Notes: The vertical dotted line marks the Great Financial Crisis. The red line refers to the buffer guide based on the gap adjusted *à* la Alessandri et al. (2015) and calibrated using AUROCs. The blue line refers to the buffer guide based on the gap adjusted *à* la Alessandri et al. (2015) and calibrated using the BCBS criteria. The black dashed line reports the buffer guide consistent with the Basel guidance (see Appendix A.1 for more details on the BCBS guidance).

Figure 7: AUROCs



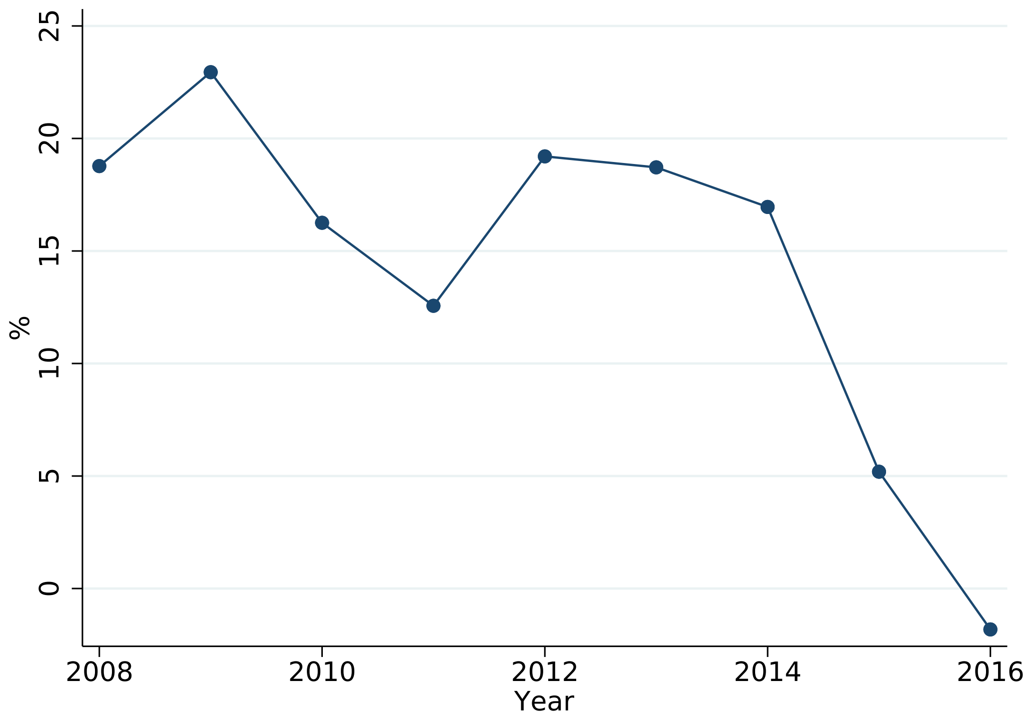
Notes: Estimated AUROCs by comparing randomly selected cases with left-out cases. 1000 interactions.

Figure 8: Regulatory Capital to Risk-Weighted Assets



Sources: World Bank, Bank Regulatory Capital to Risk-Weighted Assets for Italy, retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/DDSI05ITA156NWDB`, and authors' calculation.
Notes: The graph depicts the actual ratio of total regulatory capital to risk-weighted assets (blue bars) and the ratio of the countercyclical capital buffer to risk-weighted assets (red bars) in case the latter instrument was in place before the global financial crisis.

Figure 9: Loan Loss Provision



Sources: Financial Stability Report, No. 2 - 2021, Banca d'Italia, and authors' calculation.
Notes: The graph depicts the growth rate for new loan loss provision of the Italian banking system as a whole. The annual stock of provisions is obtained as the difference between gross non-performing loans and net non-performing loans.

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A Annex

A.1 Basel Committee recommendations on the calculation of the countercyclical capital buffer

According to BCBS (2011) the credit-to-GDP gap is defined as the difference between an economy's aggregate credit-to-GDP ratio and its long-run trend. The long-term trend of the credit-to-GDP ratio is computed with a one-side (recursive) Hodrick-Prescott filter with a smoothing parameter $\lambda = 400,000$. Credit denotes a broad measure of the stock of domestic credit to the private non-financial sector outstanding at the end of quarter t. The credit-to-GDP gap is then translated in a percentage of the bank risk-weighted assets by calculating a benchmark buffer rate based on the piece-wise linear rule:

- $CCyB_t = 0$ if $GAP_t < 2\%$
- $CCyB_t = 0.3125 * GAP_t - 0.625$ if $2\% < GAP_t < 10\%$
- $CCyB_t = 2.5\%$ if $GAP_t > 10\%$

A.2 Calibrating the CCyB for SSM countries

We extend the exercise carried out in section 2 for Italy to explore whether a common rule to calibrate the adjusted credit gap could be defined for countries participating in the European Single Supervisory Mechanism (SSM).[16] To this aim we first compute the adjusted credit-to-GDP gap and then we identify a calibration rule. We use data on total credit-to-GDP ratios from the BIS website (`https://www.bis.org/statistics/index.htm`). To use reasonably long time

[16] All euro area countries participate in European banking supervision. Other EU countries that do not yet have the euro as their currency can choose to participate. To do so, their national supervisors enter into *close cooperation* with the ECB. Bulgaria and Croatia joined European banking supervision through close cooperation in October 2020.

Table A.1: Calibrating the CCyB for SSM countries

	Years before crisis				
Contry	5	4	3	2	1
Austria	-2	-1	-2	0	0
Belgium	6	4	-2	-2	5
Finland	1	4	5	6	8
France	0	0	3	4	5
Germany	0	3	3	2	4
Greece	11	11	13	15	12
Ireland	4	14	20	36	32
Italy	6	7	7	8	7
Netherlands	-7	-8	-7	5	8
Portugal	20	20	8	3	7
Spain	15	18	22	26	21
Average	5	7	6	9	10
P25	0	2	1	3	5
Median	4	4	5	5	7

Notes: The table reports for each country the average development of the adjusted credit-to-GDP gap, estimated on for the total credit to the non-financial private sector, in the five years prior to the outbreak of a banking crisis. The gap is computed exploiting data since 1971.

series we restrict the sample to economies for which data are available for at least 40 years.[17] The resulting dataset covers the eleven main euro area countries over the period 1971-2019.[18] To identify banking crises we rely on the ESRB crisis database and Laeven and Valencia (2020), as we have done for Italy in section 2. Table A.1 reports the development of the adjusted gap over the 5 years preceding a banking crisis for each country in the sample. The level of the adjusted gap one year before a crisis is substantially different from one country to the other as it is also its path leading to a crisis. To ensure that the build-up of the buffer starts around 4 years before a crisis in at least 75 percent of the countries, the activation threshold L has to be set at 2 percentage points, the same level proposed by the

[17]The data published by the BIS don't cover Bulgaria, Malta, Cyprus, Estonia, Croatia, Lithuania, Latvia, Slovenia, Slovakia. While for Luxembourg the series is too short as it starts in 1999.

[18]The countries are Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Netherland, Portugal.

BCBS for the one-side HP filter gap. The upper threshold would be at 7 percentage points, i.e. the median level of the gap observed one year before a crisis. A unique calibration rule for all the SSM countries - similarly to the one proposed by the BCBS for any country - would inevitably result in extending the period during which the buffer is above the required level for some countries while for others the maximum would be never reached. The required coherence between the buffer guide and the outbreak of a crisis is rare (Figure A.10-A.11). At the onset of the GFC, the buffer would have been consistent for a few countries while remaining low or even nil for the majority (Figure A.12). The dynamics of the credit cycle are highly heterogeneous across countries, suggesting that one size doesn't fit all and that country-specific rules would be a better choice.

Figure A.10: Buffer guide

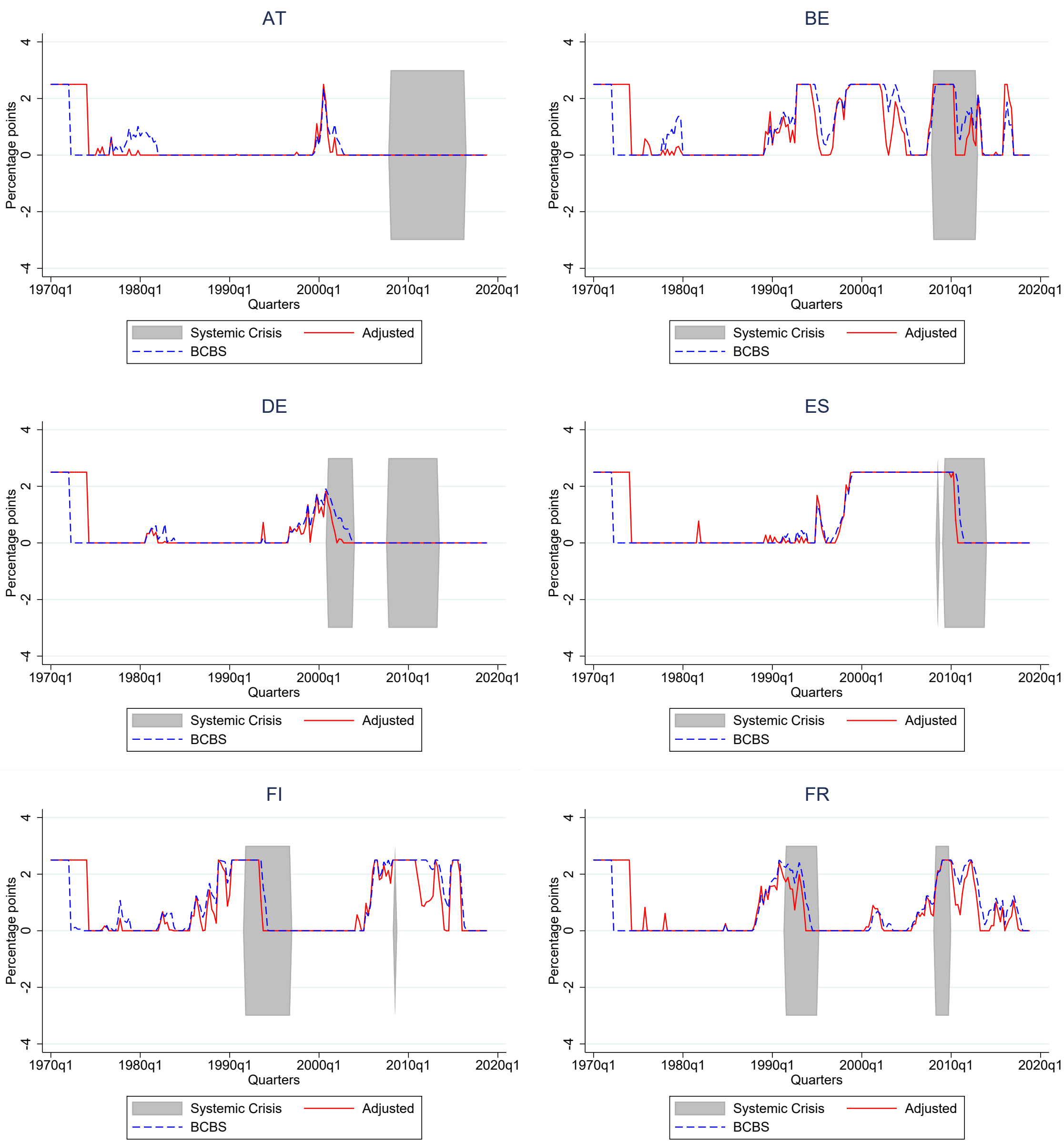


Figure A.11: Buffer guide

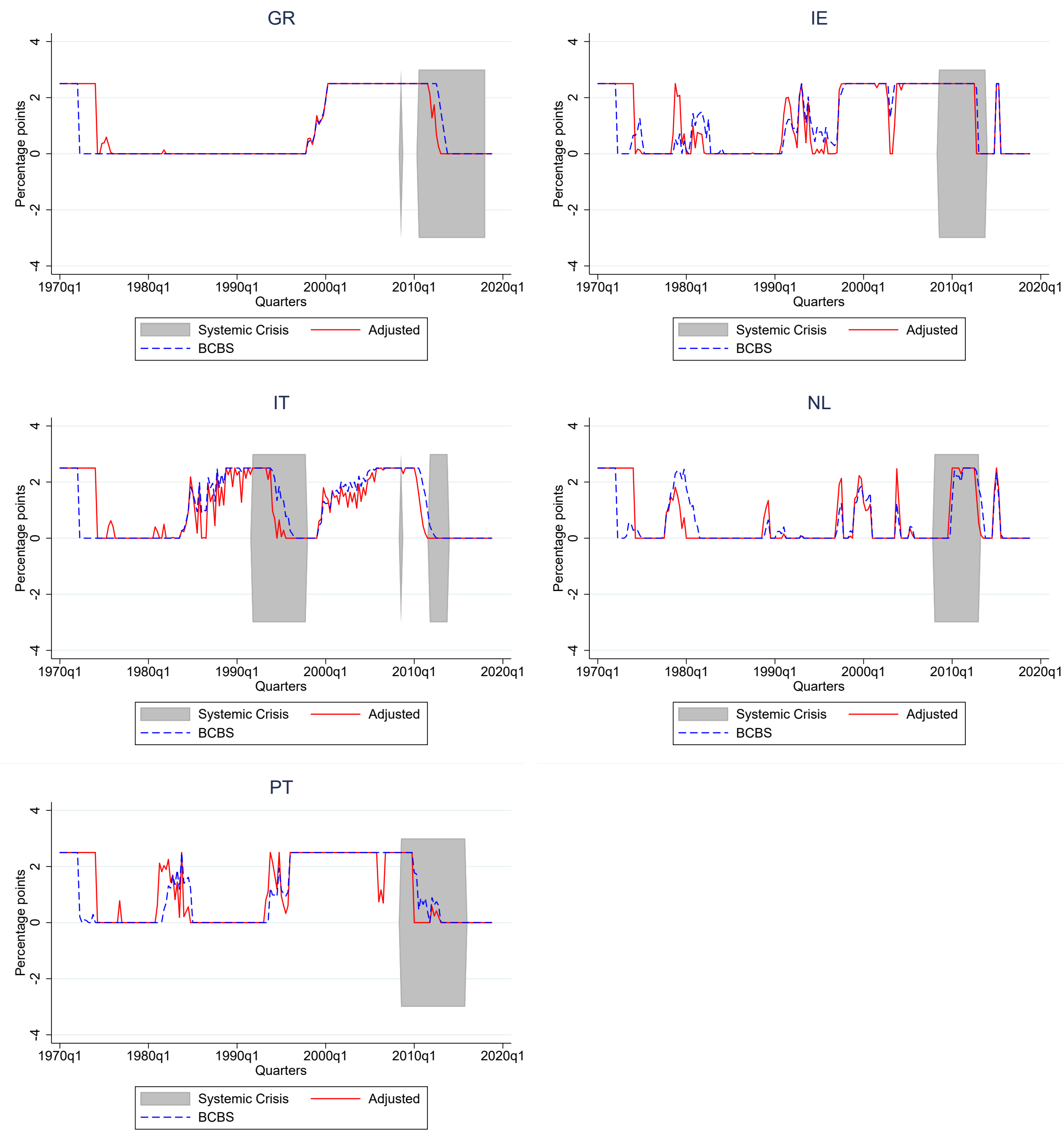
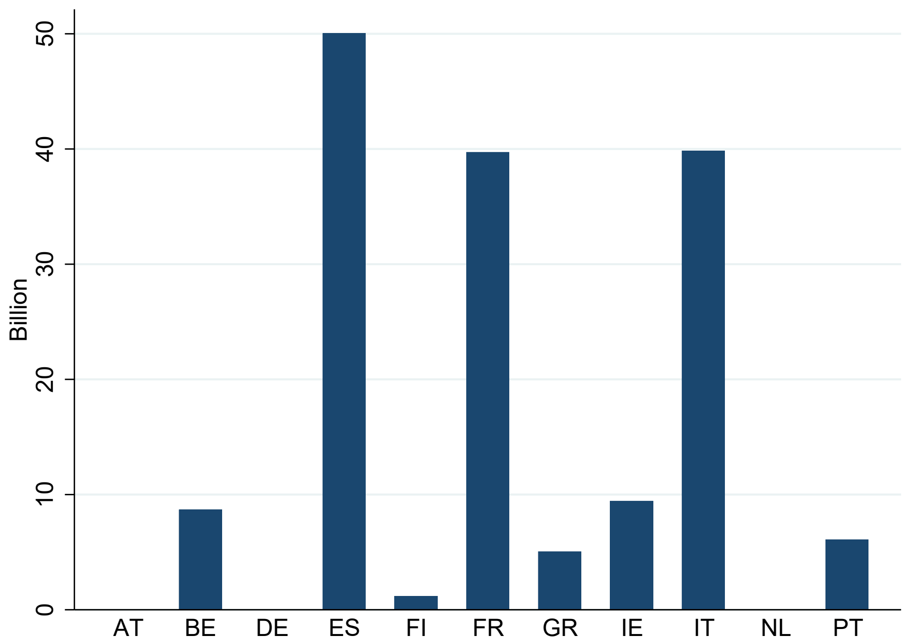


Figure A.12: The CCyB at the outbreak of the Great Financial Crisis



Notes: The graph reports the level of the CCyB for the eleven SSM countries at the end of 2008. The amount of the buffer is calculated multiplying the CCyB rate by the risk weighted assets, assuming that all the exposure are domestic.