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Credit gaps as banking crisis predictors: a different tune for middle- and low-income countries

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Abstract

The aim of this paper is to assess the quality of credit-based variables as early warning indicators of systemic banking crises. The existing literature focuses mainly on developed economies and shows that the best performing indicator is the credit-to-GDP gap computed via one-sided HP filter (the so-called Basel credit gap). The empirical evidence legitimates the use of the credit-to-GDP gap as a key indicator in macro-prudential banking regulation, i.e., in the determination of the countercyclical capital buffer. We take advantage of a new database on bank credit series and credit gaps covering more than 160 countries (Bouvatier, Delatte and Rehault, 2021) to focus specifically on middle- and low-income countries. Our findings suggest that the credit-to-GDP gap remains the single best performing indicator regarding the high-income group while the same does not hold for middle- and low-income countries. This result highlights that a one-size-fits-all approach is not relevant in the design of the operational framework of the countercyclical capital buffer.

JEL classification: G01,G21
Keywords: banking crisis, contercyclical capital buffer, credit gap

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1 Introduction

The countercyclical capital buffer (CCyB) has been included in the Basel 3 regulatory framework to help counter procyclicality in banking activities. More precisely, bank capital requirements should increase (up to 2.5% of risk-weighted assets) during the upswing of the financial cycle to help curb excessive credit growth. Further, with more regulatory capital during the upswing phase of the financial cycle, banks should be more resilient during the downswing of the financial cycle.

The Basel Committee on Banking Supervision (BCBS) proposed an operational framework to set the level of the CCyB (BCBS (2010), Drehmann & Tsatsaronis (2014)). Specifically, quantitative indicators and policymaker judgment are both required to determine the CCyB rate on the basis of guided discretion. Guidance proposed by BCBS (2010) is mainly based on prior research at the Bank for International Settlements (BIS) that accumulated a long-term expertise on procyclicality of the financial system and financial stability (see e.g., Borio et al. (2001), Borio & Lowe (2002)). The main objective of these studies is not to specify an early warning system (EWS) for banking crises but rather to compare, on a univariate basis, the performances of a set of early warning indicators. Particularly, the ongoing objective is to identify the indicator or subset of indicators that is the most effective to measure procyclicality in credit activities and to detect the risk of banking crises. Early warning indicators providing a stable signal that is easy to interpret and early enough before bust periods can then be considered as reliable candidates by national authorities to be used in their guided discretion to set the CCyB rate.

Several empirical investigations implementing, for instance, *horse races* to compare indicators' performance have led to the conclusion that the gap in the credit-to-GDP ratio is an appropriate indicator to capture the risk of banking crises (see, e.g., Drehmann et al. (2010), Drehmann et al. (2011), Drehmann (2013), Drehmann & Juselius (2014)). Further, from a methodological perspective, the gap in the credit-to-GDP ratio should be assessed using the Hodrick & Prescott (1997) (HP) filter with a smoothing parameter set in accordance with the feature of credit cycles.[1] In addition, from an operational perspective, the HP filter is implemented in a one-sided manner so that pseudo-real-time data are used when calculating gaps in the credit-to-GDP ratio. This process of measuring excessive credit activity (i.e., detrending the credit-to-GDP ratio via the one-sided HP filter) corresponds to the so-called Basel Credit Gap (BCG) and can be used to set the CCyB rate according to BCBS

[1] The smoothing parameter (λ) of the HP filter is set to 400,000 for quarterly data so that the trend component captures only low frequencies associated with periodicities higher than 4 decades.

(2010) guidance.[2]

Several critiques have been addressed to the BCG (Baba et al. (2020)). Indeed, the BCG can have difficulty properly capturing some features of periods of excessive credit activity. For instance, disentangling periods of excessive credit activities and financial deepening periods is particularly challenging for statistical approaches such as the BCG. The BCG can also be characterized by long lasting negative gaps following a large credit bust, limiting the identification of the accumulation of new imbalances during post banking crisis periods. Moreover, some critiques directly address the use of the HP filter. For instance, the choice of the smoothing parameter is questionable because the credit cycle duration can be country-specific and even time-specific in the long run. Critiques of the use of the HP filter also concern the introduction of spurious dynamic relations or end-point bias (Hamilton (2018)). These limitations are still an open debate (see, e.g., Drehmann & Yetman (2018, 2020), Hamilton & Leff (2020), Hodrick (2020)).

The BCG remains, however, a key indicator to measure excessive credit activities, to determine the CCyB rate, or more generally to calibrate macroprudential instruments. The implications of the BCG limitations are rather that national authorities can consider a broader set of indicators when deciding on the CCyB rate (BCBS (2017)) and that guided discretion for calibration of macroprudential instruments rarely relies on a single indicator. In addition, complementary methodological approaches to measure credit gaps have been developed to put into perspective assessments obtained by the one-sided HP filter (Drehmann & Yetman (2018), Baba et al. (2020), Bouvatier et al. (2021)).

An important feature of the literature on the BCG is that empirical investigations are based mainly on the BIS database on credit statistics (Dembiermont et al. (2013)). This database contains quarterly credit series that date back to the 1950s.[3] Further, this database covers 43 countries and is composed of mostly high-income countries. As a result, the efficiency of the BCG as an early warning indicator applies mainly to high-income countries. Therefore, an important open question is whether these conclusions and recommendations can be generalized to all countries. More precisely, should middle- and low-income countries also rely on the BCG to elaborate their guided discretion about whether they enforce macroprudential instruments? This question matters because implementation of countercyclical capital requirements, particularly the CCyB, does not concern only BCBS members. For instance, among 100 non-BCBS member jurisdictions surveyed by the Financial

[2] The standard formula to set the CCyB rate is $0.3125 \times BCG - 0.625$ when the BCG $\in [2\%; 10\%]$. The CCyB rate is set to 0% when the BCG is lower than 2% and to 2.5% when the BCG is higher than 10%.

[3] Further, the BIS database contains several credit aggregates; in particular, a narrow credit aggregate (i.e., banking credit) and a broad credit aggregate (i.e., total credit provided to the private sector).

Stability Institute (FSI), more than 75% report that the CCyB implementation is in various stages or under consideration (Hohl et al. (2018)). However, the large adoption of Basel banking standards by non-BCBS member jurisdictions, including some middle- and low-income countries, is not necessarily driven by the good fit of these standards for the management of financial stability risks in these jurisdictions. Concerns about reputation and competition are key drivers, particularly among middle- and low-income countries (Jones & Zeitz (2017), Beck et al. (2018a), Beck et al. (2018b)). Further, middle- and low-income countries receive little guidance for the adoption and adaptation of the Basel banking standards. This situation of standard-taking countries opens numerous research questions. In this paper, we investigate whether BCBC guidance to set the CCyB rate, which promotes the use of the BCG, is tailored for middle- and low-income countries.

The literature on credit booms (see, e.g., Gourinchas et al. (2001), Mendoza & Terrones (2008), Dell'Ariccia et al. (2016)) shows that such episodes have important impacts on macrofinancial stability and can end in banking crises. The BCG is therefore a natural candidate as a leading indicator for banking crises. However, the association between credit booms and banking crises is not systematic. Barajas et al. (2007) introduce the distinction between good and bad credit booms, highlighting that not all credit booms end in banking crises. In addition, the existing literature also shows differences between country groups and regions concerning characteristics of credit booms (Meng & Gonzalez (2017)) or the proportion of bad credit booms (Calderón & Servén (2014), Arena et al. (2015)). Therefore, the performance of the BCG as a banking crisis predictor should be investigated in enlarged samples to properly account for the situation of middle- and low-income countries. The limited existing literature on this question provides mixed results. Drehmann & Tsatsaronis (2014) conclude that the BCG is a valuable banking crisis predictor for emerging countries, even if the performance of this credit metric to detect banking crises is lower than it is in advanced economies. Marchettini & Maino (2015) and Geršl & Jašová (2018) conclude that the BCG performs poorly as an early warning indicator of banking crises outside of advanced economies. However, an important common feature of these papers is data limitations. When empirical investigations rely on quarterly data (Drehmann & Tsatsaronis (2014), Geršl & Jašová (2018)), the number of middle- and low-income countries (and banking crises) considered is rather scarce. When empirical investigations rely on annual data (Marchettini & Maino (2015)), assessment of the BCG can be questioned.[4] Therefore,

[4]A quarterly frequency is more appropriate to assess cyclical movements in credit activities. In addition, the BCG relies on trends estimated from very small samples when annual data are considered. Indeed, the BCG relies on a one-sided HP filter (i.e., on recursive estimates using only pseudo-real-time observations). The common practice is to

no horse race has properly investigated the performance of the BCG as a banking crisis predictor in middle- and low-income countries due to data limitations.

The main contribution of this paper is to overcome data limitations (i.e., the availability of quarterly credit gaps) to accurately investigate whether the BCG remains an efficient early warning indicator when a large set of countries is considered. We take advantage of a new database (Bouvatier et al. (2021)) that provides credit gaps for 163 countries; data are quarterly and date back to the late 1950s. Consequently, we can pay particular attention to middle- and low-income countries to assess the performance of credit-based indicators to detect the risk of banking crises.

We implement a horse race to investigate and compare the performance of credit activity indicators (including the BCG) to detect the risk of banking crises worldwide. In particular, we rely on 3 different methods of trend-cycle decomposition (HP filter, the modified HP filter proposed by Kaiser & Maravall (1999, 2001) and basic SSA) and different credit metrics (expressed in percentage of GDP, in real terms, and in real terms per capita) to consider a large set of credit activity indicators. In addition, the performance of banking crises predictors is assessed with several criteria to cover different aspects of performance. Further, we make the distinction between high-income countries and middle- & low-income countries to investigate differences between income groups. Several robustness checks are considered, concerning, for instance, data sources to identify banking crises periods or the definition of groups of countries.

The main result of the paper is that credit activity indicators, particularly the BCG, are poor banking crisis predictors for middle- & low-income countries. This result is robust in particular to the definition of groups of countries. For instance, when focusing on upper-middle-income countries or emerging countries, the BCG does not fairly predict banking crises, which contrasts with the results obtained for developed countries. In addition, alternative credit metrics, for instance, based on real credit per capita, do not provide better early warning indicators. The main policy implication is that the BCG cannot be considered a key indicator to set the CCyB rate in middle- and low-income countries.

The remainder of the paper is organized as follows: section 2 presents the model and the data; section 3 presents the main results and the robustness checks; section 4 addresses further issues; section 5 concludes the paper.

start to report and to use one-sided credit gaps one decade after credit aggregates become available. This practice translates into only 10 observations when annual data are considered. However, the performance of the one-sided HP filter to identify the trend component is sensitive to the starting point when small samples are considered.

2 Model and data

We implement a horse race to compare the ability of various indicators of credit procyclicality to predict banking crises. In addition, particular attention is paid to middle- and low-income countries. Therefore, we need to (*i*) indicate the data sources to collect banking crisis periods and credit variables ; (*ii*) specify the link function that relates indicators of credit procyclicality to banking crises; (*iii*) define the set of banking crisis predictors; (*iv*) present the set of criteria used to compare banking crisis predictors (i.e., the classifiers).

2.1 Banking crisis periods and credit variables

We use the Laeven & Valencia (2018) database as the primary source to identify banking crisis periods. This database covers banking crises worldwide during the 1970-2017 period. Laeven & Valencia (2018) report 151 systemic banking crisis episodes. For a robustness check, we also rely on the Lo Duca et al. (2017) database and the Reinhart (2010) database (updated by the Behavioral Finance & Financial Stability (BFFS) Project) to identify banking crisis periods (see infra section 3.2).

We use the Bouvatier et al. (2021) database for the credit variables. This database covers an unbalanced panel of 163 countries over the 1957Q1-2018Q4 period. More precisely, the Bouvatier et al. (2021) database reports series on bank credit expressed in real terms and in percentage of GDP.[5] Further, the database provides trend-cycle decompositions based on 3 different methodologies: HP filter, the modified HP filter proposed by Kaiser & Maravall (1999, 2001) and basic SSA. In particular, the latter is not exposed to some of the critiques addressed to the HP filter, such as the introduction of spurious dynamic relations (Hamilton (2018)). All these methodologies are set in accordance with credit cycle properties. Periodicities of credit cycles can reach 2 or 3 decades. Then, the medium-term cyclical component that can characterize credit activities is properly accounted and not included in the long-term secular trend. Last, the 3 different methodologies are implemented from both one-sided and two-sided perspectives.

Table 1 reports descriptive statistics on credit cycles (i.e., gaps in credit-to-GDP ratios). Panel

[5]Bank credit corresponds to a narrow credit definition. A broad credit definition (including, for instance, bond markets and non-bank financial intermediaries) is proposed by Dembiermont et al. (2013) for a limited number of countries due to limited data availability on non-bank credit. However, bank credit accounts for a large share of total credit in most countries. Therefore, relying on bank credit is not detrimental, especially when the main concern is middle- & low-income countries.

A reports descriptive statistics for all countries; then, the distinction between high-income countries (Panel B) and middle- and low-income countries (Panel C) is considered. The size of credit cycles is assessed based on the standard deviation and mean of the absolute values to account for the fact that credit gaps are zero-mean processes. Table 1 shows that the HP filter, modified HP filter and basic SSA lead to similar descriptive statistics. The size of credit cycles assessed as the mean of the absolute values is approximately 5%, but the kurtosis, minimum and maximum indicate that some countries face extreme events. The frequency of such events is higher than that in the Gaussian situation, but the 5th and 95th percentiles show that the range of credit cycles remains moderate in most periods. For instance, the credit cycle measured via one-sided HP filter (variable CY_{gap}^{HPos}) ranges in $[-10.95\%\ ;\ 12.70\%]$ 90% of the time. Further, Table 1 shows that credit cycles in high-income countries have different features than those in middle- and low-income countries. More precisely, descriptive statistics reported for Panel B and Panel C in Table 1 indicate that the size of credit cycles is larger in high-income countries and that extreme events are more often recorded for high-income countries.

2.2 Baseline specification

We use a pooled logit model as the baseline link function:

$$P(Y_{i,t} = 1 | X_{i,t-1}) = \frac{1}{1 + \exp\left[-\alpha - \beta X_{i,t-1}\right]}, \tag{1}$$

where the subscripts refer to country i in period t. The variable $Y_{i,t}$ is a binary variable that is equal to 1 if a banking crisis occurs and 0 otherwise, $X_{i,t}$ is a banking crises predictor, and α and β are parameter estimates. The parameters α and β are estimated by maximum likelihood, and the standard errors, which are obtained from the clustered version (at the country level) of the Huber-White estimator of the variance, are robust to heteroscedasticity. Further, we consider two data treatments to limit bias in the estimates. First, banking crises can occur over the course of several years (corresponding to multiyear events,) but the pooled logit model assumes that observations are independent of each other. Therefore, we follow a common practice: we drop all but the first year of these multiyear events so that yearly observations can be considered as independent of each other. Second, early warning indicators can behave differently during crisis and post-crisis periods (Bussiere & Fratzscher (2006)). Therefore, we follow common practice to manage the post-crisis bias: we drop the two years following the ending year of each banking crisis. These two data management processes reduce the samples size to limit bias; alternative data treatment will be considered in robustness checks.

We consider 8 alternative banking crisis predictors for measuring credit procyclicality to implement the baseline horse race:

- CY_{gap}^{HPos} : gap in the credit-to-GDP ratio assessed by the one-sided HP filter;
- CY_{gap}^{HPts} : gap in the credit-to-GDP ratio assessed by the two-sided HP filter;
- CY_{gap}^{HPMos} : gap in the credit-to-GDP ratio assessed by the one-sided modified HP filter;
- CY_{gap}^{HPMts} : gap in the credit-to-GDP ratio assessed by the two-sided modified HP filter;
- CY_{gap}^{SSAos} : gap in the credit-to-GDP ratio assessed by the one-sided SSA approach;
- CY_{gap}^{SSAts} : gap in the credit-to-GDP ratio assessed by the one-sided SSA approach;
- ΔNC : year-on-year growth rate of nominal credit;
- ΔCY : year-on-year difference in the credit-to-GDP ratio.

Variable CY_{gap}^{HPos} is the reference indicator because the one-sided HP filter applied to the credit-to-GDP ratio is the methodology recommended by the BIS to measure credit procyclicality (i.e., the BCG). We consider variable CY_{gap}^{HPts} to investigate whether relaxing the operational constraint (i.e., the use of pseudo-real-time observations) produces a better measure of credit procyclicality. Variables CY_{gap}^{HPMos}, CY_{gap}^{HPMts}, CY_{gap}^{SSAos} and CY_{gap}^{SSAts} introduce alternative methodologies to generate credit gaps. These variables are meaningful for two reasons. First, they provide robustness checks to assess the performance of credit gap measures to predict banking crises. Second, these variables enable investigation of the performance of the HP filter relative to that of alternative methodologies.

Last, variables ΔNC and ΔCY correspond to basic credit activity indicators that might be relevant to predicting banking crises. These variables are commonly used in the EWS literature that investigates the main determinants of banking crises.

2.3 Criteria

All the variables defined previously are considered as rival binary classifiers. Each classifier provides a predicted probability of a banking crisis (through the estimated logit models). These probabilities are then compared with the observed discrete outcomes of banking crises. We rely on several criteria to measure the performance of each binary classifier because many metrics can be used to assess the performance of a classifier. Specifically, we rely first on criteria that focus only on the relative ranking of the predicted probabilities provided by each classifier; second we rely on criteria that take into account the numerical values of the predicted probabilities. Therefore, we run a broad assessment of performance to cover different aspects of performance.

We rely first on the area under the receiver operating characteristic (AUROC) curve, the standard criterion used for comparison when horse races for banking crisis detection are implemented. The receiver operating characteristic (ROC) curve plots the true positive rate against the false positive rate at various threshold settings. The AUROC curve considers all possible thresholds and provides a summary measure of the classification ability. A high AUROC curve indicates that the binary classifier performs well at predicting zeros as zeros and ones as ones. Realistic values for the AUROC curve range from 0.5 (random ranking) to 1 (perfect ranking). However, the AUROC curve has some limitations.

The AUROC curve assigns the same importance to tranquil periods and crisis periods. However, one might argue that tranquil periods are less relevant than crisis periods, i.e., a lower importance should be given to true negatives than true positives. This issue might be particularly relevant for banking crisis prediction because positive outcomes (i.e., banking crises) are sparse in the dataset. Therefore, the AUROC curve might overstate the overall performance of a classifier when this overall performance is related mainly to the successful prediction of negative outcomes. The area under precision-recall (AUPR) curve is an alternative or complementary metric in such situations of class imbalance (He & Garcia (2009), Saito & Rehmsmeier (2015)). The PR curve plots precision (i.e., the ratio of true positives to overall positives) against recall (i.e., the true positive rate) at various threshold settings. Therefore, we rely on the AUPR curve to eliminate the influence of true negatives in the assessment of the performance of the classifiers in imbalanced data. However, in contrast to the AUROC curve, the AUPR curve does not have an attractive intuitive interpretation.

A more fundamental critique has been addressed to the AUROC curve by Hand (2009, 2010), suggesting that the AUROC curve is not a coherent measure to compare rival classifiers. Therefore, we also rely on the H measure proposed by Hand (2009) as an alternative to the AUROC curve.

The AUROC curve, AUPR curve and H measure focus only on the relative ranking of the predicted probabilities. However, the numerical values of the predicted probabilities may also be considered meaningful. Thus, we use two additional criteria to also measure the accuracy of the predicted probabilities: the Brier (1950) score and the Tjur (2009) R^2. The Brier (1950) score, also called the quadratic scoring rule, is a standard metric to assess and compare the accuracy of binary predictions and is defined as the mean squared error of the predictions. Therefore, a low Brier score indicates that the binary classifier performs well. More precisely, a Brier score approaching 0 is considered ideal (i.e., total accuracy). The Tjur (2009) R^2, also called Tjur's coefficient of discrimination, has intuitive appeal; it is defined as the difference between the mean of the predicted probabilities of positive outcomes and the mean of the predicted probabilities of negative outcomes. Therefore, a high Tjur R^2 indicates that the binary classifier performs well. More precisely, a Tjur R^2 nearing 1 suggests that there is clear separation between the predicted values for zeros and ones.

Furthermore, the predicted probabilities are obtained from a logit model estimated by maximum likelihood. Therefore, we can consider the maximum likelihood and McFadden's pseudo-R^2 to compare the performance of the binary classifiers.

Last, the different credit variables are more or less closely related. Consequently, we do not expect that one credit variable dominates all the others for the whole set of criteria. Rather, we expect to identify a hierarchy in which a subgroup of credit variables is dominated, on average, by some other more efficient credit variables.

3 Results

We run the baseline horse race with annual data because the starting dates for a subset of banking crises are identified only on a yearly basis in the Laeven & Valencia (2018) database. The main point, however, is that credit gaps have been assessed from quarterly data. Therefore, we collapse quarterly credit cycles into annual credit cycles. More precisely, we use the last value of each year (i.e., the value in Q4) to generate the annual credit cycles.[6] We run the baseline horse race for the full sample and for subsamples by income groups (relying on the World Bank classification). We then implement several robustness checks. For instance, we rely on quarterly data to run the horse race, we consider alternative banking crisis databases, or we use alternative classifications of countries for the subsamples analysis.

[6] For a robustness check, annual means have also been used to compute annual credit cycles. We reach similar conclusions for the two alternative ways to collapse the quarterly credit cycles. These results are available upon request.

3.1 Baseline horse race

The results of the baseline horse race for the full sample are reported in Table 2. The same sample is used for all the estimates. Due to data availability, we have an unbalanced sample composed of 146 countries and covering 97 banking crises.[7] Table 2 shows that two-sided credit gaps perform better that one-sided credit gaps according to the 5 criteria (AUROC curve, AUPR curve, H measure, Tjur R^2 and Brier score) and for the 3 methodologies (HP, modified HP and basic SSA). The log-likelihoods and pseudo-R^2 of the estimated models confirm this difference in performance between two-sided and one-sided credit gaps. Therefore, from the operational perspective (i.e., relying only on pseudo-real-time observations), credit gaps loose efficiency to detect banking crises. This result is in line with some critiques addressed to the reliability of one-sided credit gaps (e.g., Edge & Meisenzahl (2011)). For instance, considering credit gaps assessed by HP filter, the AUROC curve decreases from 0.7247 to 0.6018 when the one-sided approach is used instead of the two-sided approach. The general rule of thumb used to assess the quality of a classifier is that an AUROC curve from 0.70 to 0.80 indicates fair discrimination ability while an AUROC curve less than 0.70 indicates poor discrimination ability. Therefore, when the full sample is considered, one-sided credit gaps do not provide acceptable discrimination ability to predict banking crises. Further, Table 2 shows that the differences in performances between HP filter, modified HP filter and basic SSA are slight. Descriptive statistics on credit cycles, discussed previously and reported in Table 1, indicated that the 3 methodologies lead to credit cycles with very similar characteristics. Moreover, Table 2 suggests that their ability to detect banking crises is also very similar. However, the HP filter performs slightly better than the modified HP filter and the basic SSA according to the 5 criteria reported in Table 2. Last, the basic credit activity indicators (i.e., variables ΔNC and ΔCY) do not display better performance to predict banking crises over the full sample than do the one-sided credit gaps (except according to the AUROC curve).

The poor performance of one-sided credit gaps to predict banking crises might be explained by heterogeneity between countries. In particular, Table 1 highlights that credit gaps display different characteristics between high-income countries and middle- & low-income countries. Therefore, we

[7] Data availability is not the same for all predictors. For instance, two-sided credit gaps are available for larger samples than are one-sided credit gaps due to data construction. Therefore, we also run the baseline horse race while relaxing the constraint that the same sample should be used for all the estimates. The number of banking crises covered by the sample reaches 124 when ΔCY is used as the predictor. These results are available upon request and lead to similar conclusions as those obtained from Table 2.

run the baseline horse race for the subsample of high-income countries (Table 3, Panel A) and the subsample of middle- & low-income countries (Table 3, Panel B). The results confirm that two-sided credit gaps perform better than one-sided credit gaps and that the basic credit activity indicators do not outperform one-sided credit gaps. However, the performance of one-sided credit gaps to predict banking crises is higher in high-income countries than in middle- and low-income countries. For instance, considering credit gaps assessed by one-sided HP filter, the AUROC curve is 0.7419 for high-income countries and 0.5150 for middle- and low-income countries. All the other criteria (AUPR curve, H measure, Tjur R^2 and Brier score) confirm this meaningful difference. For instance, considering credit gaps assessed by one-sided HP filter, the Tjur R^2 is 4.70% for high-income countries and 0.16% for middle- and low-income countries. Therefore, the Tjur R^2 indicates that one-sided credit gaps fail to generate higher probabilities of a banking crisis before a banking crisis actually occurs in middle- and low-income countries. Conversely, in high-income countries, predicted probabilities of banking crisis generated by one-sided credit gaps are, on average, 4.70 percentage points higher when a banking crisis does occur than when a banking crisis does not occur.[8] In other words, the poor performance of one-sided credit gaps highlighted in Table 2 is driven mainly by middle- and low-income countries. Figure 1 illustrates the difference between high-income and middle- & low-income countries. Specifically, Figure 1 plots the probability of a banking crisis versus the credit gap (assessed by one-sided HP filter) obtained with the estimated logit model for high-income countries (Fig 1.a) and for middle- and low-income countries (Fig 1.b). The relationship is stronger for high-income countries than for middle- and low-income countries, as suggested by the parameter estimates of the logit models reported in column (1) of Table 3. Further, in high-income countries, the estimated model suggests that the CCyB should be activated (according to the BCBS (2010) guidance) when the probability of a banking crisis is still lower than its long-term (i.e., unconditional) level and that most banking crises occur when the credit gap exceeds 2%.[9] Middle- and low-income countries show different results. Most banking crises occur when the credit gap is relatively low (e.g., lower than the 2% threshold corresponding to the activation rate of the CCyB according to the BCBS (2010) guidance). Therefore, credit gaps generally signal a weak risk of banking crisis (e.g., lower than the

[8]The significance of this magnitude can be appreciated by noting that the unconditional probability of a banking crisis is 2.35% for high-income countries in the sample used in Table 3.

[9]The long-term (i.e., unconditional) probability of a banking crisis is 2.35% for high-income countries and corresponds to the frequency of banking crises in the sample used to estimate the logit model. Further, the probability of a banking crisis is 1.93% when the credit gap equals 2%. For the sample of middle- & low-income countries, the long-term probability of a banking crisis is 2.14%, and the probability of a banking crisis is 2.17% when the credit gap equals 2%.

long-term exposure) when most banking crises occur, highlighting the fact that credit gaps are poor predictors of banking crises in middle- and low-income countries. In other words, numerous banking crises in middle- and low-income countries are not driven by excess credit activities.

Two rationals can explain the results of the horse race. First, some other key influential factors may be in play, for instance, real currency appreciation in emerging economies (Gourinchas & Obstfeld (2012)) or low economic growth and banking system illiquidity in low-income countries (Caggiano et al. (2014)). If such factors are more numerous and diverse in middle- and low-income countries than in high-income countries, the BCG can be a poor banking crisis predictor. Second, excess credit activities alone might not be sufficient to lead to banking crises in developing countries. For instance, capital inflows (Calderón & Kubota (2012), Caballero (2016)), political booms (Herrera et al. (2020)) and the poor financial performance of banks (Fielding & Rewilak (2015)) represent important contextual factors for the occurrence of bad credit booms.

3.2 Robustness checks

We check the robustness of the results obtained with the baseline horse race considering modifications in the time frequency of data, in the timing of the signal prior to a crisis, in data sources used to identify banking crisis periods, and in data sources used to define groups of countries. Further, we pay particular attention to financially underdeveloped countries and to the management of the post-crisis bias.[10]

First, we run the horse race with quarterly data. We use the ESRB database (Lo Duca et al. (2017)) as the primary source to identify banking crisis periods at a quarterly frequency. The ESRB database covers all EU Member States and Norway for the period 1970-2016 and identifies banking crisis dates on a monthly basis. Further, we rely on the Laeven & Valencia (2018) database as a secondary source to identify banking crisis periods in countries not covered by the ESRB database. When the starting dates of banking crises are identified on a yearly basis in the Laeven & Valencia (2018) database, we assume that the banking crises start in Q1.[11] Credit gaps are computed on a quarterly basis, but they are not available since 1970 for all the countries recording banking crises in Lo Duca et al. (2017) and Laeven & Valencia (2018). Due to data availability, we have an unbalanced

[10] Tables containing the results for the horse race with quarterly data are reported in appendix A. Tables associated with the other robustness checks are reported in the web appendix of the paper to save space.

[11] Similarly, when the ending dates of banking crises are identified on a yearly basis, we assume that the banking crises end in Q4. The ESRB database does not have this limitation but focuses on a limited number of countries.

sample composed of 146 countries and covering 106 banking crises. Results are reported in Table A1 in Appendix A. We also consider the sample composed of only countries and banking crises from the ESRB database in order to not mix data sources on banking crises (Table A2). We reach similar conclusions as those obtained with the baseline horse race. One-sided credit gaps are fair predictors of banking crises only in high-income countries. In middle- and low-income countries, they do not perform better than the basic credit activity indicators. In addition, the best performance of one-sided credit gaps is obtained when we consider banking crises from only the ESRB database (i.e., in EU countries plus Norway). For instance, considering credit gaps assessed with the HP filter, the AUROC curve is 0.7535 for one-sided credit gaps and 0.8482 for two-sided credit gaps. This level of performance is in line with the existing literature assessing the ability of one-sided credit gaps to predict banking crises (see, e.g., Drehmann & Tsatsaronis (2014), Drehmann & Juselius (2014), Drehmann & Yetman (2018)).

Second, we investigate the stability of the signal captured by banking crisis predictors. In the baseline horse race (with annual and quarterly data), we consider the signal 1 year prior to a crisis. An effective banking crisis predictor should, however, start to provide a signal earlier than 1 year so that policymakers have time to take corrective actions. In addition, banking crisis predictors should provide a stable signal during several consecutive periods to generate no uncertainty concerning the risk of banking crisis. Therefore, we run the baseline horse race with a forecast horizon up to 5 years (with annual and quarterly data). For each forecast horizon and banking crisis predictor, Figure 2 plots the AUROC curve to highlight the quality of the signals.[12]. Figure 2 enables generalization of the main result obtained from the baseline horse race concerning the difference between high-income and middle- & low-income countries. For all forecast horizons, one-sided credit gaps provide a poor signal to detect banking crises in middle- and low-income countries, and basic credit activity indicators do not perform much better: the AUROC curve rarely exceeds 0.60 in Figures 2-b and d. For high-income countries, Figures 2-a and c show that the one-sided credit gap has valuable properties in terms of stability. This result is in line with Drehmann & Tsatsaronis (2014) and Drehmann & Juselius (2014). For a forecast horizon up to 3 years prior to a banking crisis, the one-sided credit gap displays a stable AUROC curve, slightly higher than 0.70. In addition, Figure 2 shows that two-sided credit gaps do not exhibit the best performance for all forecast horizons. When

[12] We reach similar conclusions if other criteria are considered (i.e., AUPR curve, H measure, Tjur R^2 or Brier score). The AUROC curve is frequently considered in the literature to assess the performance of various banking crisis predictors for different forecast horizons (see, e.g., Drehmann & Tsatsaronis (2014), Drehmann & Juselius (2014))

the latter exceed 2 years, two-sided credit gaps no longer provide the best performance among the different banking crisis predictors.

Third, the Reinhart (2010) database on banking crises (updated by the Behavioral Finance & Financial Stability (BFFS) Project) is considered as an alternative to the Laeven & Valencia (2018) database. This database covers a smaller number of countries than the Laeven & Valencia (2018) database, but the banking crises identified by Reinhart (2010) date back to before 1970. Therefore, we can fully exploit the time dimension of credit series that date back to the late 1950s. In addition, the datation and identification of banking crises can vary slightly between Reinhart (2010) and Laeven & Valencia (2018). We conclude that the results are robust to the choice of data source used to identify banking crises. One-sided credit gaps are poor predictors of banking crises in middle- and low-income countries (results are reported in Table WA.1 in the web appendix).

Fourth, we investigate whether the results are robust to the definition of high-income countries. In the baseline horse race, we rely on a time-invariant classification from the World Bank. For a robustness check, we rely on the Maddison database (Bolt et al. (2018)) to generate a time-varying group of high-income countries. Specifically, we consider real GPD per capita; for each year, countries belonging to the top quartile are classified as high-income countries and other countries are considered middle- and low-income countries. This alternative classification leads to a slightly smaller group of high-income countries. The conclusions obtained from the baseline horse race do not change when this alternative income group classification is considered (results are reported in Table WA.2.1 in the web appendix). Similar conclusions are also obtained when we rely on the country classification provided by the IMF. Credit gaps are fair banking crisis predictors in advanced economies but display poor performance in emerging and developing countries (results are reported in Table WA.2.2 in the web appendix)

Fifth, we investigate whether the poor performance of credit gaps to predict banking crises in middle- and low-income countries is driven by financially underdeveloped countries. The latter can be defined as countries with low credit-to-GDP ratios. The credit dynamics in these countries might be unique due, in particular, to structural characteristics. Indeed, financial deepening might be the main factor explaining episodes of rapid credit expansion in these countries. In such situations, trend-cycle decompositions as the HP filter can face difficulties in properly identifying the cyclical component. Therefore, we drop cases with credit-to-GDP ratios lower than 10%. This threshold is commonly used in the literature (see, e.g., Dell'Ariccia et al. (2016)) and leads to the exclusion of some observations from low-income countries from the analysis. The results show that excluding financially underdeveloped countries does not improve the performance of credit gaps to predict banking crises in the remaining middle- and low-income countries (results are reported in Table WA.3.1 in the web appendix). Further, we consider a more stringent approach to exclude financially underdeveloped countries: we successively run the horse race focusing only on upper-middle-income countries (World Bank classification) and emerging economies (IMF classification). Banking crises driven by credit booms might be a greater concern for these subgroups of countries than for low-income countries (Arena et al. (2015), Meng & Gonzalez (2017)). Most criteria used to assess the performance of credit gaps to predict banking crises improve when upper-middle-income countries or emerging economies are considered while excluding lower-income countries. However, these improvement are rather slight, and all the criteria remain noticeably lower than those observed for developed economies (results are reported in Tables WA.3.2 and WA.3.3 in the web appendix). Overall, the results confirm that one-sided credit gaps are fair banking crisis predictors only in developed countries.

Last, we consider several alternatives in terms of sample management to investigate whether the results are affected by the post-crisis bias. As noted by Bussiere & Fratzscher (2006), during tranquil periods, banking crisis predictors can behave differently than they do during crisis/post-crisis periods. Therefore, considering all periods can affect the performance of banking crisis predictors. In the baseline horse race, we dropped all but the initial years of banking crises that occurred over the course of several years.[13] In addition, we dropped the two years following the ending year of each banking crisis. These two data management processes reduce the samples size but account for the post-crisis bias. For a robustness check, we implement 3 alternative data management approaches. First, we do not drop the two years following the ending year of each banking crisis. Second, we follow Mathonnat et al. (2019) to adopt a more restrictive approach than that in Laeven & Valencia (2018) to measure the duration of banking crises.[14] We then apply the same data treatments for the post-crisis bias management (i.e., dropping all but the initial years of banking crises and dropping the two years following the ending year of each banking crisis). Since the duration of banking crises increases with the more restrictive approach proposed by Mathonnat et al. (2019), more observations are dropped to account for the post-crisis bias. Last, we keep only "vulnerability" periods instead of

[13] Therefore, each banking crisis event is associated with a single year, and observations can be treated as independent of one another.

[14] The datation of the ending year of a banking crisis depends on two indicators: growth rate of GDP per capita and growth rate of banks' credit to the private sector-to-GDP (data are collected from the World Bank's World Development Indicators (WDI) database). Banking crises end the year preceding the simultaneous observation of positive values during at least two consecutive years for the two indicators. In Laeven & Valencia (2018), a banking crisis ends the year preceding the simultaneous observation of positive values for the two indicators.

dropping some crisis and post-crisis periods. We define vulnerability periods as the 5 years preceding each banking crisis (plus the first year of each banking crisis). This approach is the most conservative to account for the post-crisis bias. These 3 robustness checks show that the conclusions obtained from the baseline horse race are not altered when alternative management of the post-crisis bias is considered (results are reported in Tables WA.4.1, WA.4.2 and WA.4.3 in the web appendix).

4 Further issues

4.1 Real credit–based indicators

Real credit can be considered an alternative to the credit-to-GDP ratio to measure credit gaps. In particular, real credit per capita is frequently used in the literature instead of the credit-to-GDP ratio to investigate credit dynamics (see, e.g., Mendoza & Terrones (2012), Arena et al. (2015), Meng & Gonzalez (2017)). The main objective is to not rely on GDP as a scaling variable because cyclical changes in GDP might distort the assessment of credit procyclicality. The Bouvatier et al. (2021) database reports real credit aggregates and trend-cycle decomposition for these credit series (credit gaps are expressed in % of trend). However, real credit per capita series are not available in the Bouvatier et al. (2021) database. Therefore, we collect population data from the World Bank to compute real credit per capita series.[15] Then, we implement HP filter, modified HP filter and basic SSA to generate one-sided and two-sided credit gaps in real credit per capita series.[16]

Consequently, we have two alternative sets of credit indicators based on real credit that can compete with the credit indicators used in the baseline horse race (i.e., based on credit-to-GDP ratio). The results are reported in Appendix B: in Table B1 for real credit per capita and in Table B2 for real credit aggregates. The sample size is slightly smaller than that in the baseline horse race due to the availability of real credit aggregates in the Bouvatier et al. (2021) database. The results in Table B1 (Panel A) show that one-sided credit gaps computed from real credit per capita do not outperform those computed from the credit-to-GDP ratio (Table 3) when the subsample of high-income countries is considered. The 5 criteria used to compare banking crisis predictors support

[15] Population data are not quarterly and have to be interpolated. We rely on a quadratic interpolation that might be more suitable for population variables.

[16] The HP and modified HP filters are applied to the log of real credit per capita to take into account the scaling issue (data are expressed in local currency). Then, credit gaps are defined as the difference between the log of real credit per capita and the log of its trend. Basic SSA does not require such preprocessing. Credit gaps are then computed as the difference between real credit per capita and its trend, divided by the trend.

these results. Similar conclusions are reached when real credit aggregates are considered to generate credit gaps (Table B2, Panel A). Therefore, the results are in line with Drehmann & Yetman (2018): scaling credit by GDP is a good way to generate one-sided credit gaps.

Focusing on two-sided credit gaps in high-income countries, we reach different conclusions: credit gaps based on the credit-to-GDP ratio are not better predictors than credit gaps based on real credit. Indeed, the criteria used to assess the performance of predictors are not all in favor of credit gaps based on the credit-to-GDP ratio. For instance, considering credit gaps computed by two-sided HP filter, two of the 5 criteria reported in Panel A of Tables 3 and B1 suggest that credit gaps based on real credit perform better than credit gaps based on credit-to-GDP ratio (the AUROC curve and the Brier score). Therefore, when credit gaps are assessed ex post (i.e., without relying on pseudo-real-time data), no scaling variable provides a better banking crisis predictor than the others: credit gaps based on the credit-to-GDP ratio or on real credit per capita can be considered equivalent.

Turning to middle- and low-income countries (Panel B of Tables B1 and B2), the results are in line with those obtained from the baseline horse race. One-sided credit gaps are not informative as early warning indicators of banking crises. Therefore, the poor performance of the BCG to predict banking crises in middle- and low-income countries is not explained by the fact that GDP is used as the scaling variable to generate credit gaps.

Last, the credit gaps computed from real credit per capita are very close to those obtained from real credit aggregates. As a result, the criteria reported in Tables B1 and B2 display very similar levels of performance. In other words, scaling by population does not bring much to assess the cyclical component of real credit. Indeed, changes in population are rather smooth and are mostly captured by the trend component. Therefore, the cyclical components (expressed in % of trends) are very similar for real credit aggregate and real credit per capita.

4.2 Frequency of credit series

We rely on the Bouvatier et al. (2021) database that measures credit gaps from quarterly data. Then, the baseline horse race is run with (collapsed) annual data and with quarterly data for a robustness check. This approach provides better coverage of middle- and low-income countries than does the approach proposed by the BIS database on credit statistics (Dembiermont et al. (2013)).

However, since the horse race is run mainly with (collapsed) annual data, the Global Financial Development Database (GFDD) provided by the World Bank might be a valuable alternative data source. This database provides annual credit-to-GDP ratios for a large set of countries, and the series date back to 1960. This database is frequently used in the literature to investigate credit dynamics in large sets of countries (see, e.g., Dell'Ariccia et al. (2016)). Therefore, we can assess credit gaps from annual data relying on GFDD to obtain a new set of credit indicators that can compete with the credit indicators used in the baseline horse race. For simplicity, we focus on only the HP filter since this methodology provided the best performance in the baseline horse race. The main objective is to assess whether credit gaps computed from quarterly data outperform credit gaps computed from annual data.

According to Hodrick & Prescott (1997), the smoothing parameter λ should be set to $1,600$ to capture the business cycle with quarterly data. Hodrick & Prescott (1997) also recommend setting λ to 100 for annual data. However, Ravn & Uhlig (2002) advocate that the smoothing parameter for annual data (λ_A) should follow the formula $\lambda_A = s^n.\lambda_Q$, where s is the ratio of the frequency of observations compared to quarterly data (i.e., $s = 1/4$), $n = 4$, and λ_Q is the smoothing parameter used for quarterly data. Then, for $\lambda_Q = 1,600$, Ravn & Uhlig (2002) recommend $\lambda_A = 6.25$.

Concerning the assessment of credit cycles from quarterly data, Drehmann et al. (2010) recommend setting the smoothing parameter λ_Q to $400,000$.[17] Following the formula of Ravn & Uhlig (2002), we set $\lambda_A = 0.25^4.400,000 \simeq 1,600$ to capture the credit cycle with annual data.[18] Marchettini & Maino (2015) set the smoothing parameter to a similar value to assess credit gaps based on annual data.

The main limitation of this approach is related to small-sample issues. More precisely, the trend-cycle decomposition provided by the HP filter is sensitive to the underlying series' starting point. This starting point problem is not fully fixed even after 10 years of quarterly data (Drehmann & Tsatsaronis (2014)). Consequently, in the context of annual data, one can deduce that the starting point problem can distort the trend-cycle decomposition over more than 4 decades. Further, the size

[17] Drehmann et al. (2010) suggest that credit cycles are between three to four times longer than business cycles. Consequently, λ_Q should be set between $3^4.1,600 = 125,000$ and $4^4.1,600 = 400,000$ to capture credit cycles. Drehmann et al. (2010) conclude that a λ_Q of $400,000$ provides more satisfactory results to detect systemic banking crises than does a value of $125,000$.

[18] The filter parameter can also be set as a function of the frequency cut-off according to the formula:

$$\lambda = \left[2.\sin\left(\pi.\frac{1}{Freq}\right)\right]^{-4},$$

where $Freq$ is the frequency cut-off. For credit cycles, following Drehmann et al. (2010), the frequency cut-off is set to 158 quarters (i.e., 39.5 years). Therefore, $\lambda_Q = \left[2.\sin\left(\pi.\frac{1}{158}\right)\right]^{-4} \simeq 400,000$. For annual data, we obtain $\lambda_A = \left[2.\sin\left(\pi.\frac{1}{39.5}\right)\right]^{-4} \simeq 1,600$.

of the distortion is country-specific, in the sense that its magnitude can be particularly pronounced when the starting point corresponds to a credit cycle's peak or trough.

Results are reported in appendix C (Table C1). We consider in Table C1 both credit gaps computed from quarterly credit-to-GDP ratios (variables CY_{gap}^{HPos} and CY_{gap}^{HPts}) and credit gaps computed from annual credit-to-GDP ratios (variables CYA_{gap}^{HPos} and CYA_{gap}^{HPts}). Considering one-sided credit gaps in high-income countries (Panel A in Table C1), relying on annual data from GFDD instead of quarterly data to generate credit gaps is not detrimental to predict banking crises. There is no clear distinction between the performance of CY_{gap}^{HPos} and CYA_{gap}^{HPos} to predict banking crises; the 5 criteria used to assess the predictors' performance suggest mixed results. The difference is more noticeable when two-sided credit gaps are compared: credit gaps computed from quarterly data outperform those computed from annual data according to all criteria. Further, we also notice in Table C1 from the slope parameter of the logit model (parameter β) and from the pseudo-R^2 that credit gaps computed from quarterly data provide a better fit than credit gaps computed from annual data. Overall, even if quarterly data provide a more accurate signal to predict banking crises, relying on annual data to assess credit gaps, as is commonly done in the literature on credit booms, for instance (see, e.g., Dell'Ariccia et al. (2016)), provides fair results. Therefore, the starting point problem that characterizes the HP filter does not have a detrimental effect, on average.

Turning to middle- and low-income countries (Panel B in Table C1), the results are in line with those obtained from the baseline horse race. Relying on the annual credit-to-GDP ratio from GFDD to assess credit gaps reinforces the conclusion that credit gaps, and particularly the BCG, are not fair predictors of banking crises in middle- and low-income countries.

5 Conclusion

This paper relies on a new database that provides quarterly credit series and trend-cycle decompositions for an unbalanced sample of 163 countries over the period 1957Q1-2018Q4. We investigate whether credit gaps, and particularly the BCG, are good early warning indicators of banking crises. The existing literature concludes that the BCG is a fair banking crisis predictor in developed economies. Our results are logically in line with these empirical findings. However, the existing literature is rather scarce concerning investigations dedicated to middle- and low-income countries due to data limitations. We overcome these data limitations with the Bouvatier et al. (2021) database on credit metrics and show that the BCG is a poor early warning indicator of banking crises in middle- and low-income countries. This result is confirmed by a large number of robustness checks concerning, for instance, alternative data sources used to identify banking crises periods and alternative definitions of groups of countries. Further, we show that the poor performance of the BCG as an early warning indicator for banking crises in middle- and low-income countries is not explained by the fact that GDP is used as the scaling variable to generate credit gaps. Credit gaps based on real credit per capita or real credit aggregates also perform poorly in middle- and low-income countries. Last, we show that assessing credit gaps based on annual data, as is commonly done in the literature on credit booms, for instance, leads to fair results compared to those obtained based on quarterly data.

The main policy implication of our results concerns the implementation of macroprudential frameworks by banking regulators in developing countries. More precisely, our results question the design of the operational framework implemented to set the CCyB. Guidance proposed by the BCBS (2010) is based on strong empirical evidence for advanced economies. Consequently, the BCG is a key indicator used by BCBS members to implement the CCyB (BCBS (2017)). The CCyB is also implemented in various stages or under consideration in numerous non-BCBS member jurisdictions, including some middle- and low-income countries (Hohl et al. (2018)). Our results suggest that no empirical evidence legitimates reliance on the BCG as a key indicator to set the CCyB rate in middle- and low-income countries. Consequently, activation of the CCyB when the BCG signals excess credit activity might be ill-suited to ensure financial stability and might rather be detrimental for the beneficial consequences of good credit booms. Therefore, middle- and low-income countries need to tailor BCBS guidance to local circumstances.

This tailoring opens research perspectives out of the scope of this paper. Banking regulators need early warning indicators that provide a stable signal that is easy to interpret and early enough before the occurrence of banking crises to guide their judgment concerning the build-up of systemic risk. Prediction of bad credit booms is thus a crucial research question. Some characteristics of bad credit booms have been proposed in the existing literature. For instance, bad credit booms have longer duration (Castro & Martins (2020)), and they are a greater concern for countries with a higher level of financial depth (Dell'Ariccia et al. (2016)) and for commodity exporters (Saldarriaga (2018)). Bad credit booms are also associated with surges in gross capital inflows (Calderón & Kubota (2012)) and boom in construction sector (Dell'Ariccia et al. (2020)). However, these empirical findings do not lead to precise guidance to implement the CCyB policy. Therefore, additional empirical investigations are needed to assess whether these characteristics and determinants of bad credit booms can lead to reliable early warning indicators used by national authorities in their guided discretion to set the CCyB rate.

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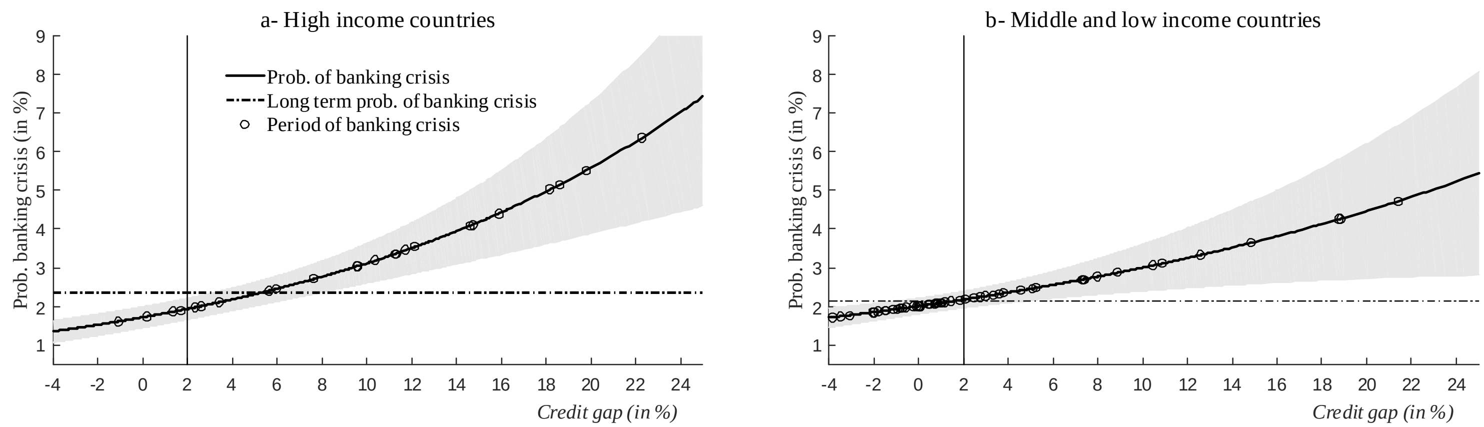
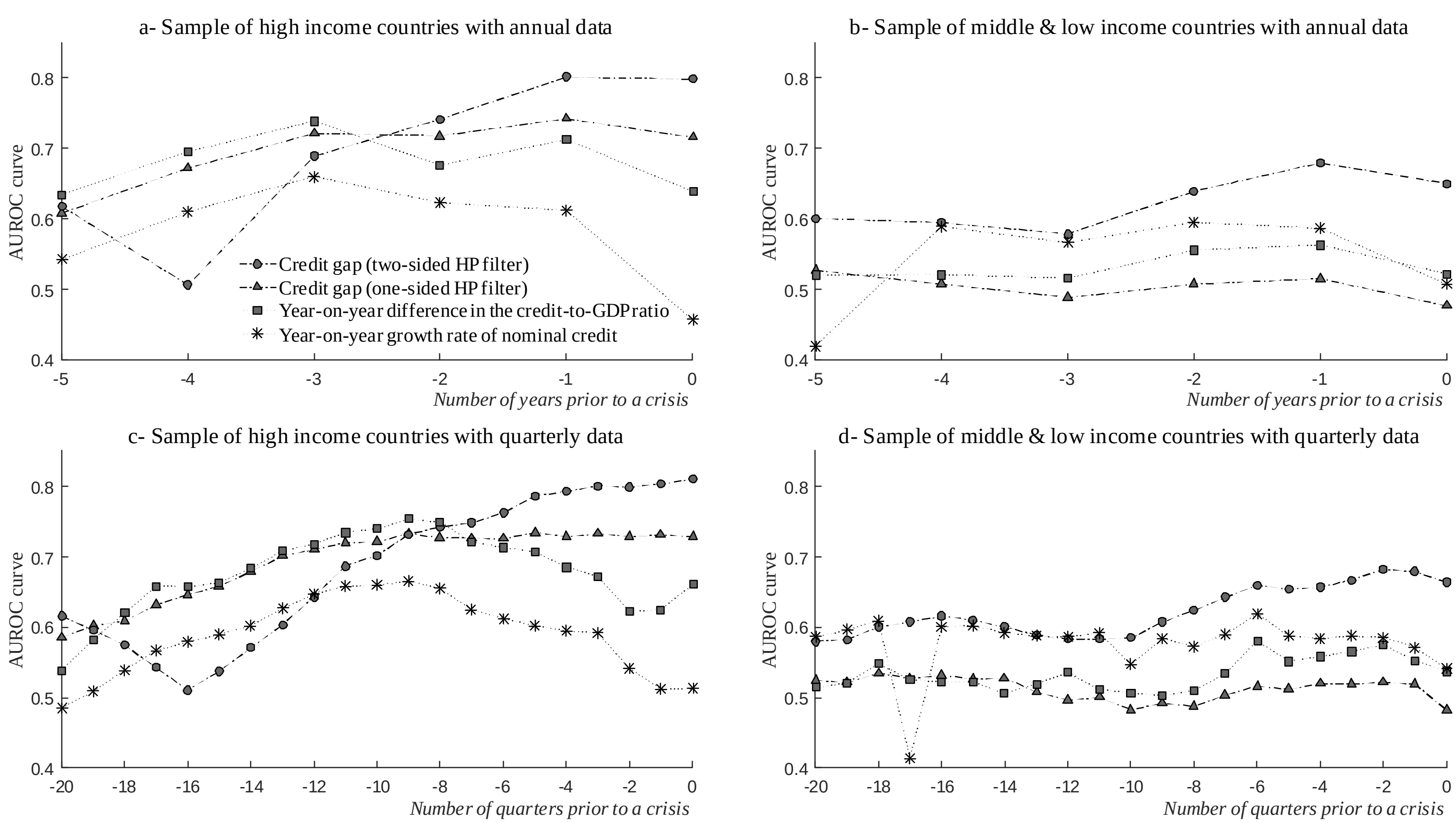
Figure 1: Effect of credit cycle on the probability of banking crisis



Note: The grey area corresponds to the one-standard error band. The vertical line indicates the activation rate of the CCyB.

Figure 2: Performance of banking crisis perdictors for different forecast horizons



Note: Credit gaps obtained by modified HP filter and basic SSA are not considered for a matter of clarity. Credit gaps obtained by HP filter performed slightly better than the ones obtained by modified HP and SSA (see section 3.1).

Table 1: Descriptive statistics

Panel A: Full sample

	CY_{gap}^{HPos}	CY_{gap}^{MHPos}	CY_{gap}^{SSAos}	CY_{gap}^{HPts}	CY_{gap}^{MHPts}	CY_{gap}^{SSAts}
Number of observations	19419	19419	19419	19419	19419	19419
Standard deviation	8.7405	8.7497	9.2431	7.8421	7.7796	7.1915
Mean of absolute values	5.3811	5.3707	5.4014	4.7694	4.7371	4.2409
Kurtosis	19.0168	18.8957	21.2661	27.1648	26.1273	28.2859
Minimum	-75.3833	-75.4781	-100.3126	-49.2176	-50.5012	-72.7827
5th percentile	-10.9508	-10.9677	-14.1946	-10.2211	-10.1302	-9.6968
95th percentile	12.709	12.673	10.7142	11.1912	11.1239	9.3416
Maximum	99.921	98.3969	60.6512	129.7984	128.7478	95.0373
Autocorrelation (order 1)	.9838	.9897	.9876	.9784	.9859	.9886
Autocorrelation (order 4)	.8924	.9014	.9005	.8554	.8649	.8532

Panel B: High income countries

	CY_{gap}^{HPos}	CY_{gap}^{MHPos}	CY_{gap}^{SSAos}	CY_{gap}^{HPts}	CY_{gap}^{MHPts}	CY_{gap}^{SSAts}
Number of observations	6320	6320	6320	6320	6320	6320
Standard deviation	12.3848	12.3066	12.9791	11.2706	11.1828	10.2096
Mean of absolute values	7.8945	7.8318	8.0515	7.1693	7.1197	6.2561
Kurtosis	13.1348	13.303	14.2416	18.0578	17.3631	19.3447
Minimum	-75.3833	-75.4781	-100.3126	-49.2176	-50.5012	-72.7827
5th percentile	-16.7668	-16.6321	-19.023	-15.624	-15.6493	-13.3762
95th percentile	17.5924	17.7291	15.6998	17.603	17.5804	12.1294
Maximum	99.921	98.3969	60.6512	129.7984	128.7478	95.0373
Autocorrelation (order 1)	.9852	.9906	.9891	.9807	.9876	.9905
Autocorrelation (order 4)	.9043	.9095	.9118	.874	.88	.8713

Panel C: Middle & low income countries

	CY_{gap}^{HPos}	CY_{gap}^{MHPos}	CY_{gap}^{SSAos}	CY_{gap}^{HPts}	CY_{gap}^{MHPts}	CY_{gap}^{SSAts}
Number of observations	13099	13099	13099	13099	13099	13099
Standard deviation	6.2659	6.3583	6.7091	5.466	5.4204	5.1165
Mean of absolute values	4.1685	4.1833	4.1227	3.6114	3.5876	3.2686
Kurtosis	10.0094	10.328	14.8044	12.4042	11.8926	14.9734
Minimum	-47.5643	-47.2114	-61.6371	-27.0513	-26.5386	-26.001
5th percentile	-9.2994	-9.262	-10.9406	-8.0496	-7.9392	-7.2859
95th percentile	9.9977	9.9067	8.0998	8.8912	8.7833	7.6069
Maximum	38.6745	38.3686	42.6319	60.6314	52.2669	53.7248
Autocorrelation (order 1)	.9812	.9881	.9848	.9735	.9824	.985
Autocorrelation (order 4)	.8709	.8876	.8806	.8177	.834	.8193

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA.

Table 2: Baseline horse race

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{HPMos}	CY_{gap}^{HPMts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0550***	0.0929***	0.0526***	0.0917***	0.0560***	0.0966***	0.0803***	0.0004***
(σ_β)	(0.0123)	(0.0199)	(0.0109)	(0.0205)	(0.0117)	(0.0225)	(0.0153)	(0.0001)
Log likelihood	-450.3051	-429.1177	-451.4875	-430.3891	-455.8788	-436.3406	-456.0621	-461.6600
Pseudo$-R^2$	0.0329	0.0784	0.0303	0.0756	0.0209	0.0629	0.0205	0.0085
Num. countries	146	146	146	146	146	146	146	146
Num. obs.	4385	4385	4385	4385	4385	4385	4385	4385
Num. crises	97	97	97	97	97	97	97	97
$AUROC$ curve	0.6018	0.7231	0.5893	0.7139	0.5623	0.6988	0.6182	0.5887
$AUPR$ curve	0.0590	0.1060	0.0575	0.1065	0.0492	0.0885	0.0444	0.0374
H measure	0.1127	0.2033	0.1087	0.2001	0.0728	0.1620	0.1022	0.0563
Tjur R^2	0.0162	0.0452	0.0149	0.0446	0.0079	0.0362	0.0058	0.0098
Brier score	0.0214	0.0209	0.0214	0.0208	0.0214	0.0210	0.0216	0.0214

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table 3: Baseline horse race by subsample

Panel A: High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0609***	0.0867***	0.0594***	0.0842***	0.0723***	0.0960**	0.0792***	0.0072***
(σ_β)	(0.0190)	(0.0313)	(0.0177)	(0.0314)	(0.0125)	(0.0412)	(0.0166)	(0.0014)
Log likelihood	-142.5831	-134.2604	-143.3730	-135.2959	-145.2098	-137.8863	-149.9726	-153.0890
Pseudo$-R^2$	0.0877	0.1409	0.0826	0.1343	0.0709	0.1177	0.0404	0.0204
Num. countries	46	46	46	46	46	46	46	46
Num. obs.	1400	1400	1400	1400	1400	1400	1400	1400
Num. crises	33	33	33	33	33	33	33	33
$AUROC$ curve	0.7419	0.8009	0.7214	0.7811	0.6746	0.7799	0.7123	0.6120
$AUPR$ curve	0.1077	0.1855	0.1090	0.1805	0.0971	0.1583	0.0631	0.0615
H measure	0.2754	0.3796	0.2743	0.3582	0.1874	0.3062	0.2010	0.1107
Tjur R^2	0.0470	0.0912	0.0450	0.0882	0.0326	0.0781	0.0116	0.0112
Brier score	0.0224	0.0215	0.0224	0.0215	0.0222	0.0216	0.0231	0.0229

Panel B: Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0412*	0.1041***	0.0366*	0.1042***	0.0213	0.0974***	0.0868***	0.0004***
(σ_β)	(0.0212)	(0.0165)	(0.0200)	(0.0171)	(0.0211)	(0.0178)	(0.0335)	(0.0001)
Log likelihood	-307.3225	-294.4167	-307.5824	-294.5891	-308.6997	-298.4519	-306.0340	-305.5261
Pseudo$-R^2$	0.0062	0.0479	0.0053	0.0473	0.0017	0.0348	0.0103	0.0120
Num. countries	100	100	100	100	100	100	100	100
Num. obs.	2985	2985	2985	2985	2985	2985	2985	2985
Num. crises	64	64	64	64	64	64	64	64
$AUROC$ curve	0.5150	0.6792	0.5097	0.6764	0.4926	0.6489	0.5631	0.5867
$AUPR$ curve	0.0315	0.0534	0.0292	0.0563	0.0242	0.0467	0.0338	0.0313
H measure	0.0510	0.1373	0.0472	0.1440	0.0131	0.1113	0.0630	0.0509
Tjur R^2	0.0016	0.0199	0.0013	0.0206	0.0003	0.0144	0.0027	0.0144
Brier score	0.0209	0.0206	0.0210	0.0206	0.0210	0.0207	0.0209	0.0207

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Appendix A: Baseline horse race with quarterly data

Table A1: Baseline horse race by subsample with quarterly data

Panel A: High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0500***	0.0556***	0.0499***	0.0552***	0.0657***	0.0611***	0.0687***	0.0058***
(σ_β)	(0.0106)	(0.0170)	(0.0105)	(0.0171)	(0.0103)	(0.0184)	(0.0148)	(0.0005)
Log likelihood	-229.6298	-223.4165	-229.7056	-223.5553	-232.0874	-226.8872	-236.8240	-239.7783
Pseudo$-R^2$	0.0589	0.0844	0.0586	0.0838	0.0488	0.0702	0.0294	0.0173
Num. countries	46	46	46	46	46	46	46	46
Num. obs.	5174	5174	5174	5174	5174	5174	5174	5174
Num. crises	42	42	42	42	42	42	42	42
$AUROC$ curve	0.7285	0.7924	0.7304	0.7931	0.6734	0.7906	0.6854	0.5946
$AUPR$ curve	0.0631	0.1169	0.0589	0.1157	0.0596	0.0855	0.0328	0.0234
H measure	0.4367	0.5332	0.4406	0.5331	0.3324	0.4098	0.2761	0.0851
Tjur R^2	0.0141	0.0279	0.0142	0.0278	0.0078	0.0221	0.0032	0.0088
Brier score	0.0081	0.0081	0.0081	0.0081	0.0080	0.0081	0.0081	0.0080

Panel B: Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0348	0.0974***	0.0345	0.0996***	0.0186	0.0918***	0.1103***	0.0007**
(σ_β)	(0.0233)	(0.0161)	(0.0213)	(0.0159)	(0.0215)	(0.0175)	(0.0276)	(0.0003)
Log likelihood	-395.4118	-384.0646	-395.2928	-383.3699	-396.3494	-387.1159	-391.1943	-394.0219
Pseudo$-R^2$	0.0034	0.0320	0.0037	0.0337	0.0010	0.0243	0.0140	0.0069
Num. countries	100	100	100	100	100	100	100	100
Num. obs.	11626	11626	11626	11626	11626	11626	11626	11626
Num. crises	64	64	64	64	64	64	64	64
$AUROC$ curve	0.5196	0.6563	0.5233	0.6635	0.5024	0.6295	0.5581	0.5842
$AUPR$ curve	0.0089	0.0158	0.0084	0.0167	0.0068	0.0129	0.0111	0.0136
H measure	0.0541	0.1281	0.0527	0.1365	0.0206	0.1065	0.0805	0.0772
Tjur R^2	0.0003	0.0060	0.0003	0.0066	0.0001	0.0043	0.0015	0.0021
Brier score	0.0055	0.0054	0.0055	0.0054	0.0055	0.0054	0.0055	0.0055

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table A2: Baseline horse race with the ESRB database on banking crises

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0775***	0.0977***	0.0780***	0.0985***	0.0577***	0.1348***	0.1017***	0.0228**
(σ_β)	(0.0103)	(0.0123)	(0.0104)	(0.0124)	(0.0110)	(0.0203)	(0.0223)	(0.0106)
Log likelihood	-142.0764	-130.4746	-141.9428	-130.2370	-147.4104	-130.8194	-147.6264	-152.8229
Pseudo$-R^2$	0.0776	0.1529	0.0785	0.1544	0.0430	0.1507	0.0416	0.0078
Num. countries	28	28	28	28	28	28	28	28
Num. obs.	2176	2176	2176	2176	2176	2176	2176	2176
Num. crises	29	29	29	29	29	29	29	29
$AUROC$ curve	0.7535	0.8482	0.7546	0.8503	0.6790	0.8479	0.7193	0.5990
$AUPR$ curve	0.0942	0.1782	0.0924	0.1752	0.0866	0.1525	0.0533	0.0233
H measure	0.4966	0.6484	0.4975	0.6503	0.3695	0.5093	0.3306	0.0839
Tjur R^2	0.0167	0.0523	0.0169	0.0527	0.0090	0.0563	0.0058	0.0010
Brier score	0.0130	0.0128	0.0130	0.0127	0.0130	0.0128	0.0131	0.0131

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Appendix B: Horse race with real credit based indicators

Table B1: Credit indicators based on real credit per capita: horse race by subsample

Panel A: High income countries

Predictor :	RCC_{gap}^{HPos}	RCC_{gap}^{HPts}	RCC_{gap}^{MHPos}	RCC_{gap}^{MHPts}	RCC_{gap}^{SSAos}	RCC_{gap}^{SSAts}	ΔRCC
β	0.0287***	0.0557***	0.0289***	0.0556***	0.0205**	0.0990***	0.0288***
(σ_β)	(0.0076)	(0.0083)	(0.0077)	(0.0083)	(0.0093)	(0.0203)	(0.0093)
Log likelihood	-135.2008	-119.1810	-135.2323	-119.2560	-138.3362	-114.5728	-138.3102
Pseudo$-R^2$	0.0309	0.1457	0.0307	0.1452	0.0084	0.1788	0.0086
Num. countries	46	46	46	46	46	46	46
Num. obs.	1325	1325	1325	1325	1325	1325	1325
Num. crises	29	29	29	29	29	29	29
$AUROC$ curve	0.6756	0.8219	0.6737	0.8209	0.6223	0.8503	0.6281
$AUPR$ curve	0.0387	0.1254	0.0386	0.1258	0.0292	0.1599	0.0298
H measure	0.1286	0.3709	0.1311	0.3735	0.0758	0.3927	0.0739
Tjur R^2	0.0066	0.0709	0.0065	0.0706	0.0014	0.0969	0.0014
Brier score	0.0213	0.0204	0.0213	0.0204	0.0214	0.0199	0.0214

Panel B: Middle & low income countries

Predictor :	RCC_{gap}^{HPos}	RCC_{gap}^{HPts}	RCC_{gap}^{MHPos}	RCC_{gap}^{MHPts}	RCC_{gap}^{SSAos}	RCC_{gap}^{SSAts}	ΔRCC
β	-0.0051	0.0245***	-0.0045	0.0250***	-0.0072	0.0227***	-0.0004
(σ_β)	(0.0052)	(0.0064)	(0.0051)	(0.0066)	(0.0062)	(0.0062)	(0.0033)
Log likelihood	-239.0649	-229.5368	-239.1874	-229.4777	-238.8578	-231.9989	-239.6044
Pseudo$-R^2$	0.0023	0.0420	0.0017	0.0423	0.0031	0.0317	0
Num. countries	98	98	98	98	98	98	98
Num. obs.	2421	2421	2421	2421	2421	2421	2421
Num. crises	49	49	49	49	49	49	49
$AUROC$ curve	0.5644	0.6878	0.5575	0.6855	0.5584	0.6934	0.5000
$AUPR$ curve	0.0245	0.0562	0.0239	0.0568	0.0231	0.0512	0.0200
H measure	0.0343	0.2043	0.0280	0.1919	0.0322	0.1918	0.0114
Tjur R^2	0.0005	0.0114	0.0003	0.0117	0.0006	0.0064	0.0001
Brier score	0.0198	0.0196	0.0198	0.0196	0.0198	0.0198	0.0198

Variable definitions: RCC_{gap}^{HPos} = credit gap based on real credit per capita obtained by one-sided HP filter; RCC_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; RCC_{gap}^{MHPos} by one-sided modified HP filter; RCC_{gap}^{MHPts} by two-sided modified HP filter; RCC_{gap}^{SSAos} by one-sided SSA; RCC_{gap}^{SSAts} by two-sided SSA. ΔRCC = year-on-year growth rate of real credit.

Table B2: Credit indicators based on real credit aggregates: horse race by subsample

Panel A: High income countries

Predictor :	RC_{gap}^{HPos}	RC_{gap}^{HPts}	RC_{gap}^{MHPos}	RC_{gap}^{MHPts}	RC_{gap}^{SSAos}	RC_{gap}^{SSAts}	ΔRC
β	0.0313***	0.0570***	0.0317***	0.0569***	0.0230**	0.1030***	0.0305***
(σ_β)	(0.0077)	(0.0084)	(0.0078)	(0.0084)	(0.0100)	(0.0200)	(0.0094)
Log likelihood	-134.5796	-118.2490	-134.5635	-118.3185	-138.1747	-113.5249	-138.1638
Pseudo$-R^2$	0.0354	0.1524	0.0355	0.1519	0.0096	0.1863	0.0097
Num. countries	46	46	46	46	46	46	46
Num. obs.	1325	1325	1325	1325	1325	1325	1325
Num. crises	29	29	29	29	29	29	29
$AUROC$ curve	0.6762	0.8267	0.6756	0.8250	0.6263	0.8485	0.6244
$AUPR$ curve	0.0409	0.1298	0.0409	0.1311	0.0301	0.1661	0.0297
H measure	0.1351	0.3774	0.1349	0.3737	0.0796	0.4026	0.0692
Tjur R^2	0.0083	0.0768	0.0082	0.0763	0.0016	0.1056	0.0017
Brier score	0.0213	0.0203	0.0213	0.0203	0.0214	0.0195	0.0214

Panel B: Middle & low income countries

Predictor :	RC_{gap}^{HPos}	RC_{gap}^{HPts}	RC_{gap}^{MHPos}	RC_{gap}^{MHPts}	RC_{gap}^{SSAos}	RC_{gap}^{SSAts}	ΔRC
β	-0.0046	0.0247***	-0.0025	0.0271***	-0.0066	0.0313***	-0.0001
(σ_β)	(0.0052)	(0.0065)	(0.0053)	(0.0060)	(0.0066)	(0.0069)	(0.0026)
Log likelihood	-239.1567	-229.4254	-239.4786	-227.6156	-239.0745	-226.9302	-239.6064
Pseudo$-R^2$	0.0019	0.0425	0.0005	0.0500	0.0022	0.0529	0
Num. countries	98	98	98	98	98	98	98
Num. obs.	2421	2421	2421	2421	2421	2421	2421
Num. crises	49	49	49	49	49	49	49
$AUROC$ curve	0.5603	0.6894	0.5410	0.7000	0.5483	0.7234	0.4926
$AUPR$ curve	0.0243	0.0571	0.0230	0.0586	0.0225	0.0633	0.0194
H measure	0.0331	0.2015	0.0243	0.1946	0.0284	0.2344	0.0127
Tjur R^2	0.0004	0.0115	0.0001	0.0134	0.0004	0.0127	0.0001
Brier score	0.0198	0.0196	0.0198	0.0196	0.0198	0.0198	0.0198

Variable definitions: RC_{gap}^{HPos} = credit gap based on real credit obtained by one-sided HP filter; RC_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; RC_{gap}^{MHPos} by one-sided modified HP filter; RC_{gap}^{MHPts} by two-sided modified HP filter; RC_{gap}^{SSAos} by one-sided SSA; RC_{gap}^{SSAts} by two-sided SSA. ΔRC = year-on-year growth rate of real credit.

Appendix C: Credit gaps computed from quarterly and annual credit-to-GDP ratios

Table C1: Horse race with credit-to-GDP gaps computed from GFDD

Panel A : High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CYA_{gap}^{HPos}	CYA_{gap}^{HPts}	ΔCYA
β	0.0607***	0.0860***	0.0473**	0.0453*	0.0305
(σ_β)	(0.0190)	(0.0310)	(0.0227)	(0.0254)	(0.0331)
Log likelihood	-141.6109	-133.4685	-146.1433	-144.0980	-154.2297
Pseudo$-R^2$	0.0884	0.1408	0.0592	0.0724	0.0071
Num. countries	45	45	45	45	45
Num. obs.	1361	1361	1361	1361	1361
Num. crises	33	33	33	33	33
$AUROC$ curve	0.7443	0.8013	0.7490	0.7770	0.6977
$AUPR$ curve	0.1093	0.1865	0.0980	0.1305	0.0536
H measure	0.2772	0.3786	0.3176	0.3182	0.1908
Tjur R^2	0.0475	0.0914	0.0167	0.0378	0.0021
Brier score	0.0230	0.0221	0.0239	0.0234	0.0236

Panel B : Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CYA_{gap}^{HPos}	CYA_{gap}^{HPts}	ΔCYA
β	0.0416*	0.1052***	0.0329	0.1036***	0.0881***
(σ_β)	(0.0219)	(0.0181)	(0.0274)	(0.0190)	(0.0231)
Log likelihood	-287.0975	-275.0205	-288.0081	-275.9982	-284.9180
Pseudo$-R^2$	0.0065	0.0483	0.0033	0.0449	0.0140
Num. countries	95	95	95	95	95
Num. obs.	2756	2756	2756	2756	2756
Num. crises	60	60	60	60	60
$AUROC$ curve	0.5121	0.6820	0.4716	0.6529	0.5790
$AUPR$ curve	0.0329	0.0536	0.0404	0.0688	0.0349
H measure	0.0563	0.1394	0.0250	0.1242	0.0730
Tjur R^2	0.0017	0.0205	0.0010	0.0219	0.0034
Brier score	0.0213	0.0209	0.0213	0.0208	0.0212

Variable definitions: CY_{gap}^{HPos} = credit gap based on quarterly credit-to-GDP ratios obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter. CYA_{gap}^{HPos} = credit gap based on annual credit-to-GDP ratios obtained by one-sided HP filter; CYA_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter. ΔCYA = difference in annual credit-to-GDP ratios.

Web Appendix - Not intended for publication

Web Appendix: Robustness checks for the baseline horse race

This appendix reports the results associated with the robustness checks implemented for the baseline horse race. More precisely, we report the results obtained when: (*i*) we modify data sources to identify banking crises periods (Table WA.1); (*ii*) we modify data sources to define income groups (Tables WA.2.1 and WA.2.2); (*iii*) we exclude financially underdeveloped countries (Tables WA.3.1, WA.3.2 and WA.3.3); (*iv*) we modify the management of the post-crisis bias (Tables WA.4.1, WA.4.2 and WA.4.3).

Table WA.1: Baseline horse race by subsample with the Reinhart (2010) database on banking crises

Panel A: High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0739***	0.1060***	0.0720***	0.1032***	0.0748***	0.1229***	0.1017**	0.0057***
(σ_β)	(0.0177)	(0.0203)	(0.0182)	(0.0214)	(0.0109)	(0.0241)	(0.0340)	(0.0010)
Log likelihood	-157.4905	-150.5491	-158.4830	-151.8929	-159.2096	-151.1428	-164.2352	-172.1249
Pseudo$-R^2$	0.0963	0.1361	0.0906	0.1284	0.0864	0.1327	0.0576	0.0123
Num. countries	29	29	29	29	29	29	29	29
Num. obs.	932	932	932	932	932	932	932	932
Num. crises	43	43	43	43	43	43	43	43
$AUROC$ curve	0.7262	0.7425	0.7189	0.7323	0.7030	0.7386	0.6875	0.6181
$AUPR$ curve	0.1791	0.2426	0.1729	0.2350	0.1777	0.2412	0.1372	0.0840
H measure	0.2508	0.2712	0.2491	0.2668	0.2162	0.2637	0.1958	0.0962
Tjur R^2	0.0697	0.1158	0.0645	0.1082	0.0596	0.1117	0.0393	0.0080
Brier score	0.0413	0.0388	0.0415	0.0392	0.0412	0.0389	0.0427	0.0438

Panel B: Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0658*	0.1210**	0.0509	0.1224***	0.0488*	0.1132***	0.1083**	0.0020
(σ_β)	(0.0275)	(0.0376)	(0.0265)	(0.0349)	(0.0246)	(0.0333)	(0.0385)	(0.0014)
Log likelihood	-218.7089	-210.9264	-219.6892	-210.5033	-220.4866	-212.9500	-219.5655	-219.7487
Pseudo$-R^2$	0.0204	0.0552	0.0160	0.0571	0.0124	0.0461	0.0165	0.0157
Num. countries	36	36	36	36	36	36	36	36
Num. obs.	1138	1138	1138	1138	1138	1138	1138	1138
Num. crises	56	56	56	56	56	56	56	56
$AUROC$ curve	0.5780	0.6486	0.5823	0.6493	0.5535	0.6396	0.5824	0.6399
$AUPR$ curve	0.0721	0.1250	0.0725	0.1326	0.0610	0.1080	0.0809	0.0878
H measure	0.0764	0.1523	0.0724	0.1590	0.0516	0.1238	0.0681	0.1125
Tjur R^2	0.0098	0.0390	0.0066	0.0412	0.0047	0.0313	0.0080	0.0175
Brier score	0.0463	0.0448	0.0465	0.0447	0.0466	0.0452	0.0464	0.0460

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.2.1: Baseline horse race by subsample with alternative definition of income groups

Panel A: High income countries based on Maddison database

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0543***	0.0822**	0.0533***	0.0802**	0.0672***	0.0894**	0.0736***	0.0011
(σ_β)	(0.0149)	(0.0349)	(0.0140)	(0.0350)	(0.0123)	(0.0421)	(0.0146)	(0.0010)
Log likelihood	-113.5827	-105.4437	-114.1325	-106.1413	-115.6309	-108.3375	-118.7348	-123.4207
Pseudo$-R^2$	0.0804	0.1463	0.0759	0.1406	0.0638	0.1228	0.0387	0.0007
Num. countries	40	40	40	40	40	40	40	40
Num. obs.	1119	1119	1119	1119	1119	1119	1119	1119
Num. crises	26	26	26	26	26	26	26	26
$AUROC$ curve	0.7293	0.8245	0.7027	0.8048	0.6717	0.8045	0.7033	0.5889
$AUPR$ curve	0.0947	0.1880	0.0959	0.1868	0.0848	0.1501	0.0621	0.0378
H measure	0.2440	0.3913	0.2457	0.3701	0.1894	0.3316	0.1970	0.0761
Tjur R^2	0.0451	0.0973	0.0434	0.0949	0.0271	0.0807	0.0112	0.0001
Brier score	0.0221	0.0212	0.0221	0.0212	0.0220	0.0214	0.0227	0.0227

Panel B: Middle & low income countries based on Maddison database

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0647***	0.1108***	0.0574**	0.1093***	0.0452*	0.1084***	0.1008***	0.0004***
(σ_β)	(0.0171)	(0.0167)	(0.0177)	(0.0170)	(0.0242)	(0.0197)	(0.0294)	(0.0001)
Log likelihood	-324.8105	-309.8374	-325.6838	-310.5639	-328.3536	-315.3929	-325.9796	-327.3080
Pseudo$-R^2$	0.0190	0.0642	0.0164	0.0621	0.0083	0.0475	0.0155	0.0115
Num. countries	110	110	110	110	110	110	110	110
Num. obs.	2953	2953	2953	2953	2953	2953	2953	2953
Num. crises	70	70	70	70	70	70	70	70
$AUROC$ curve	0.5532	0.6926	0.5484	0.6884	0.5200	0.6646	0.5867	0.5902
$AUPR$ curve	0.0434	0.0763	0.0394	0.0775	0.0398	0.0650	0.0409	0.0411
H measure	0.0812	0.1709	0.0764	0.1731	0.0487	0.1300	0.0802	0.0649
Tjur R^2	0.0070	0.0307	0.0055	0.0306	0.0026	0.0228	0.0044	0.0135
Brier score	0.0230	0.0225	0.0230	0.0225	0.0231	0.0227	0.0231	0.0228

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.2.2: Baseline horse race by subsample based on IMF classification

Panel A: Advanced economies based on IMF classification

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0540***	0.0811**	0.0529***	0.0791**	0.0620***	0.0893**	0.0728***	0.0187***
(σ_β)	(0.0150)	(0.0317)	(0.0140)	(0.0317)	(0.0129)	(0.0423)	(0.0154)	(0.0034)
Log likelihood	-111.4492	-102.9084	-112.0054	-103.6329	-114.7359	-106.3424	-117.0060	-119.7918
Pseudo$-R^2$	0.0833	0.1536	0.0788	0.1476	0.0563	0.1254	0.0376	0.0147
Num. countries	34	34	34	34	34	34	34	34
Num. obs.	1040	1040	1040	1040	1040	1040	1040	1040
Num. crises	26	26	26	26	26	26	26	26
$AUROC$ curve	0.7383	0.8331	0.7139	0.8128	0.6524	0.8104	0.6925	0.5918
$AUPR$ curve	0.0991	0.1900	0.1000	0.1867	0.0858	0.1553	0.0644	0.0314
H measure	0.2585	0.4081	0.2566	0.3856	0.1816	0.3398	0.1914	0.0833
Tjur R^2	0.0465	0.1000	0.0447	0.0974	0.0245	0.0827	0.0115	0.0082
Brier score	0.0237	0.0227	0.0237	0.0227	0.0237	0.0230	0.0244	0.0241

Panel B: Emerging & developing economies based on IMF classification

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0582***	0.1076***	0.0523***	0.1069***	0.0459*	0.1020***	0.0935***	0.0004***
(σ_β)	(0.0187)	(0.0170)	(0.0187)	(0.0176)	(0.0238)	(0.0190)	(0.0275)	(0.0001)
Log likelihood	-338.8278	-325.4215	-339.4811	-325.9260	-340.9010	-329.8803	-338.8793	-339.8287
Pseudo$-R^2$	0.0144	0.0534	0.0125	0.0519	0.0084	0.0404	0.0142	0.0115
Num. countries	112	112	112	112	112	112	112	112
Num. obs.	3345	3345	3345	3345	3345	3345	3345	3345
Num. crises	71	71	71	71	71	71	71	71
$AUROC$ curve	0.5409	0.6763	0.5363	0.6726	0.5237	0.6497	0.5875	0.6031
$AUPR$ curve	0.0373	0.0630	0.0338	0.0649	0.0365	0.0551	0.0360	0.0380
H measure	0.0729	0.1453	0.0691	0.1505	0.0485	0.1147	0.0781	0.0686
Tjur R^2	0.0049	0.0243	0.0039	0.0246	0.0024	0.0185	0.0035	0.0134
Brier score	0.0207	0.0203	0.0207	0.0202	0.0207	0.0204	0.0207	0.0205

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.3.1: Baseline horse race without financially underdeveloped countries

Sample: Middle & low income countries with credit-to-GDP ratio>10%

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0438**	0.1040***	0.0387*	0.1042***	0.0226	0.0973***	0.0882***	0.0007*
(σ_β)	(0.0212)	(0.0170)	(0.0200)	(0.0176)	(0.0215)	(0.0181)	(0.0338)	(0.0004)
Log likelihood	-266.9337	-254.9585	-267.2188	-255.1352	-268.4182	-258.6147	-265.8324	-265.0966
Pseudo$-R^2$	0.0077	0.0522	0.0066	0.0515	0.0021	0.0386	0.0118	0.0145
Num. countries	100	100	100	100	100	100	100	100
Num. obs.	2540	2540	2540	2540	2540	2540	2540	2540
Num. crises	56	56	56	56	56	56	56	56
$AUROC$ curve	0.5309	0.6866	0.5263	0.6835	0.5064	0.6588	0.5744	0.6011
$AUPR$ curve	0.0338	0.0567	0.0313	0.0599	0.0256	0.0496	0.0360	0.0319
H measure	0.0561	0.1515	0.0518	0.1611	0.0268	0.1250	0.0703	0.0602
Tjur R^2	0.0020	0.0221	0.0017	0.0229	0.0004	0.0162	0.0032	0.0175
Brier score	0.0215	0.0211	0.0215	0.0211	0.0216	0.0213	0.0215	0.0212

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.3.2: Baseline horse race without financially underdeveloped countries

Sample: Upper middle income countries (World Bank classification)

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0633***	0.0955***	0.0543**	0.0973***	0.0460*	0.0974***	0.1096***	0.0001
(σ_β)	(0.0238)	(0.0207)	(0.0236)	(0.0208)	(0.0243)	(0.0216)	(0.0309)	(0.0002)
Log likelihood	-99.7144	-96.0674	-99.9937	-95.8771	-100.8113	-96.2882	-99.6164	-101.9687
Pseudo$-R^2$	0.0221	0.0579	0.0194	0.0598	0.0114	0.0557	0.0231	0.0000
Num. countries	42	42	42	42	42	42	42	42
Num. obs.	1215	1215	1215	1215	1215	1215	1215	1215
Num. crises	20	20	20	20	20	20	20	20
$AUROC$ curve	0.6336	0.6797	0.6359	0.6783	0.6172	0.6699	0.6312	0.7196
$AUPR$ curve	0.0300	0.0485	0.0272	0.0517	0.0238	0.0494	0.0290	0.0298
H measure	0.1224	0.1860	0.1105	0.1833	0.0839	0.1926	0.1188	0.1530
Tjur R^2	0.0042	0.0284	0.0033	0.0305	0.0015	0.0279	0.0040	0.0000
Brier score	0.0161	0.0156	0.0162	0.0156	0.0162	0.0157	0.0162	0.0162

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.3.3: Baseline horse race without financially underdeveloped countries

Sample: Emerging economies (IMF classification)

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0933***	0.1209***	0.0809***	0.1192***	0.0810***	0.1139***	0.1325***	0.0004***
(σ_β)	(0.0152)	(0.0220)	(0.0182)	(0.0227)	(0.0205)	(0.0233)	(0.0283)	(0.0001)
Log likelihood	-177.3591	-170.6327	-179.0367	-171.3298	-180.6330	-174.1130	-179.8444	-184.4961
Pseudo$-R^2$	0.0587	0.0944	0.0498	0.0907	0.0413	0.0759	0.0455	0.0208
Num. countries	62	62	62	62	62	62	62	62
Num. obs.	1818	1818	1818	1818	1818	1818	1818	1818
Num. crises	39	39	39	39	39	39	39	39
$AUROC$ curve	0.6756	0.7243	0.6682	0.7162	0.6535	0.7054	0.6888	0.7124
$AUPR$ curve	0.0615	0.0924	0.0543	0.0963	0.0574	0.0805	0.0549	0.0539
H measure	0.1785	0.2485	0.1687	0.2587	0.1196	0.2144	0.1711	0.1771
Tjur R^2	0.0223	0.0478	0.0167	0.0481	0.0141	0.0380	0.0106	0.0243
Brier score	0.0205	0.0200	0.0207	0.0200	0.0207	0.0203	0.0210	0.0205

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.4.1: Baseline horse race by subsample with no drop of post-crisis periods

Panel A : High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0618***	0.0844***	0.0603***	0.0819***	0.0723***	0.0953**	0.0813***	0.0066***
(σ_β)	(0.0192)	(0.0290)	(0.0179)	(0.0290)	(0.0121)	(0.0393)	(0.0169)	(0.0011)
Log likelihood	-143.5952	-136.3110	-144.4054	-137.3375	-146.4097	-139.3820	-151.1463	-155.0064
Pseudo$-R^2$	0.0909	0.1370	0.0858	0.1305	0.0731	0.1176	0.0431	0.0187
Num. countries	46	46	46	46	46	46	46	46
Num. obs.	1472	1472	1472	1472	1472	1472	1472	1472
Num. crises	33	33	33	33	33	33	33	33
$AUROC$ curve	0.7477	0.7975	0.7277	0.7774	0.6809	0.7807	0.7188	0.6228
$AUPR$ curve	0.1060	0.1713	0.1075	0.1672	0.0945	0.1502	0.0621	0.0545
H measure	0.2788	0.3689	0.2772	0.3496	0.1880	0.3060	0.2072	0.1131
Tjur R^2	0.0474	0.0859	0.0455	0.0831	0.0319	0.0759	0.0120	0.0087
Brier score	0.0214	0.0205	0.0213	0.0206	0.0212	0.0207	0.0220	0.0219

Panel B : Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0442**	0.1042***	0.0393**	0.1042***	0.0245	0.0983***	0.0891***	0.0004***
(σ_β)	(0.0206)	(0.0159)	(0.0194)	(0.0164)	(0.0206)	(0.0174)	(0.0325)	(0.0001)
Log likelihood	-309.7259	-297.0350	-310.0246	-297.2486	-311.2484	-300.9302	-308.4778	-308.2137
Pseudo$-R^2$	0.0072	0.0479	0.0062	0.0472	0.0023	0.0354	0.0112	0.0120
Num. countries	100	100	100	100	100	100	100	100
Num. obs.	3114	3114	3114	3114	3114	3114	3114	3114
Num. crises	64	64	64	64	64	64	64	64
$AUROC$ curve	0.5227	0.6805	0.5172	0.6777	0.5004	0.6514	0.5682	0.5890
$AUPR$ curve	0.0309	0.0515	0.0286	0.0539	0.0236	0.0450	0.0326	0.0300
H measure	0.0530	0.1376	0.0488	0.1438	0.0266	0.1126	0.0641	0.0515
Tjur R^2	0.0018	0.0194	0.0015	0.0200	0.0004	0.0143	0.0028	0.0144
Brier score	0.0201	0.0198	0.0201	0.0197	0.0201	0.0199	0.0201	0.0198

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.4.2: Baseline horse race by subsample with duration of banking crises measured following Mathonnat et al. (2019)

Panel A : High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0575***	0.0815***	0.0561***	0.0790***	0.0672***	0.0885**	0.0752***	0.0071***
(σ_β)	(0.0171)	(0.0304)	(0.0159)	(0.0303)	(0.0123)	(0.0389)	(0.0158)	(0.0014)
Log likelihood	-137.5243	-129.7104	-138.2635	-130.6772	-140.6215	-133.6460	-143.7559	-146.0974
Pseudo$-R^2$	0.0781	0.1305	0.0732	0.1240	0.0574	0.1041	0.0364	0.0207
Num. countries	45	45	45	45	45	45	45	45
Num. obs.	1262	1262	1262	1262	1262	1262	1262	1262
Num. crises	32	32	32	32	32	32	32	32
$AUROC$ curve	0.7217	0.7857	0.6995	0.7640	0.6502	0.7607	0.6988	0.6045
$AUPR$ curve	0.1069	0.1814	0.1084	0.1767	0.0943	0.1486	0.0649	0.0659
H measure	0.2504	0.3544	0.2482	0.3328	0.1686	0.2760	0.1933	0.1135
Tjur R^2	0.0446	0.0873	0.0426	0.0842	0.0280	0.0719	0.0109	0.0117
Brier score	0.0241	0.0231	0.0240	0.0231	0.0239	0.0234	0.0247	0.0246

Panel B : Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0440*	0.0996***	0.0412*	0.0995***	0.0197	0.0947***	0.0818**	0.0015**
(σ_β)	(0.0225)	(0.0164)	(0.0213)	(0.0169)	(0.0230)	(0.0180)	(0.0333)	(0.0007)
Log likelihood	-284.7787	-274.0140	-284.9258	-274.2531	-286.3599	-277.0829	-283.9911	-282.6145
Pseudo$-R^2$	0.0068	0.0444	0.0063	0.0435	0.0013	0.0336	0.0096	0.0144
Num. countries	100	100	100	100	100	100	100	100
Num. obs.	2656	2656	2656	2656	2656	2656	2656	2656
Num. crises	60	60	60	60	60	60	60	60
$AUROC$ curve	0.5181	0.6671	0.5127	0.6643	0.4913	0.6419	0.5611	0.5987
$AUPR$ curve	0.0336	0.0543	0.0326	0.0572	0.0254	0.0489	0.0351	0.0356
H measure	0.0545	0.1288	0.0529	0.1374	0.0120	0.1134	0.0631	0.0611
Tjur R^2	0.0019	0.0193	0.0017	0.0199	0.0003	0.0146	0.0026	0.0164
Brier score	0.0220	0.0217	0.0220	0.0216	0.0221	0.0218	0.0220	0.0217

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.

Table WA.4.3: Baseline horse race by subsample on vulnerability periods

Panel A : High income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0203***	0.0432**	0.0190***	0.0411**	0.0160*	0.0496*	0.0138	0.0008***
(σ_β)	(0.0062)	(0.0211)	(0.0058)	(0.0195)	(0.0082)	(0.0254)	(0.0126)	(0.0003)
Log likelihood	-86.9482	-81.2783	-87.1931	-81.7832	-88.0672	-82.1131	-88.4707	-88.6088
Pseudo$-R^2$	0.0193	0.0833	0.0165	0.0776	0.0067	0.0738	0.0021	0.0006
Num. countries	29	29	29	29	29	29	29	29
Num. obs.	195	195	195	195	195	195	195	195
Num. crises	33	33	33	33	33	33	33	33
$AUROC$ curve	0.6049	0.7508	0.5896	0.7319	0.5455	0.7428	0.5853	0.5253
$AUPR$ curve	0.2299	0.3610	0.2286	0.3473	0.2114	0.3404	0.2000	0.1802
H measure	0.0904	0.2695	0.0872	0.2500	0.0703	0.2601	0.0664	0.0351
Tjur R^2	0.0200	0.0889	0.0174	0.0830	0.0068	0.0799	0.0017	0.0005
Brier score	0.1379	0.1291	0.1382	0.1299	0.1396	0.1302	0.1404	0.1405

Panel B : Middle & low income countries

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0317*	0.0612***	0.0321*	0.0594***	0.0294	0.0645**	0.0609*	0.0003***
(σ_β)	(0.0173)	(0.0209)	(0.0166)	(0.0193)	(0.0197)	(0.0252)	(0.0345)	(0)
Log likelihood	-167.1369	-163.6405	-167.0954	-163.7372	-167.4163	-163.9908	-166.4989	-166.5310
Pseudo$-R^2$	0.0057	0.0265	0.0059	0.0259	0.0040	0.0244	0.0095	0.0093
Num. countries	53	53	53	53	53	53	53	53
Num. obs.	358	358	358	358	358	358	358	358
Num. crises	64	64	64	64	64	64	64	64
$AUROC$ curve	0.5241	0.6109	0.5188	0.6097	0.5107	0.6097	0.5623	0.4858
$AUPR$ curve	0.2147	0.2627	0.2136	0.2611	0.1915	0.2665	0.2156	0.1667
H measure	0.0449	0.0829	0.0418	0.0892	0.0344	0.0940	0.0446	0.0150
Tjur R^2	0.0059	0.0286	0.0062	0.0284	0.0039	0.0261	0.0093	0.0120
Brier score	0.1459	0.1427	0.1459	0.1427	0.1462	0.1432	0.1455	0.1450

Variable definitions: CY_{gap}^{HPos} = credit gap based on the credit-to-GDP ratio obtained by one-sided HP filter; CY_{gap}^{HPts} indicates credit gap is obtained by two-sided HP filter; CY_{gap}^{MHPos} by one-sided modified HP filter; CY_{gap}^{MHPts} by two-sided modified HP filter; CY_{gap}^{SSAos} by one-sided SSA; CY_{gap}^{SSAts} by two-sided SSA. ΔNC = year-on-year growth rate of nominal credit; ΔCY = year-on-year difference in the credit-to-GDP ratio.