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ARTICLE

Forecast-based credit-to-GDP gaps for macroprudential policy

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Abstract

Banking supervisors rely on a set of indicators, such as the credit-to-Gross Domestic Product (GDP) gap, to evaluate the macro-financial environment and implement the countercyclical capital buffer. This paper proposes two supplementary indicators, based on forecast-based measures of the credit-to-GDP gap: forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps. While the former has already attracted attention from some banking supervisors, the latter represents a novel metric introduced here. These gaps are generated using singular spectrum analysis. We show that forecasting performance varies between countries and depends on credit market conditions. Furthermore, our results indicate that forecast-based credit-to-GDP gaps are effective in predicting the early stages of a credit boom.

Keywords: credit-to-GDP gap; forecasting; singular spectrum analysis

JEL classifications: E51; E58; C53

1. Introduction

Since the Global Financial Crisis, numerous macroprudential measures have been adopted by national authorities, primarily aimed at mitigating systemic risk and countering procyclicality within the financial system. One such measure is the countercyclical capital buffer (CCyB), under which banking sector capital requirements are adjusted over time to reflect changes in the macro-financial environment. National authorities activate CCyB requirements when systemic risk is building up, thereby enhancing the resilience of the banking sector and curbing excessive credit growth. Conversely, these requirements are relaxed when risks materialize or losses occur, allowing banks to better absorb shocks and sustain the flow of credit during downturns. The Basel Committee on Banking Supervision (BCBS) proposed in 2010 an operational framework for setting the CCyB (BCBS (2010)). This framework suggests using the gap in the credit-to-Gross Domestic Product (GDP) ratio, the so-called Basel Credit Gap (BCG), as a key metric for determining the CCyB rate.[1] However, the guidance provided by BCBS (2010) does not advocate focusing on a single quantitative indicator. BCBS (2010) recommends following a wide range of indicators and also relying on policymaker judgment. As a result, national authorities have developed their own operational frameworks for determining the CCyB rate. Each national authority has defined a set of core indicators to account for the macro-financial environment (BCBS (2017), Arbatli-Saxegaard and Muneer (2020), MNB (2020)) and employs a guided discretion approach to set the CCyB rate. While practices differ across countries, they share the same objective: to develop an appropriate policy framework, as the BCG alone does not capture all relevant information. More precisely, national authorities have developed their policy framework in two directions. First, the BCG only focuses on credit activities. Additional indicators are required to properly account for the macro-financial environment, as recommended by BCBS (2010). For

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instance, housing prices are often included in the list of core indicators examined by national authorities (BCBS (2017), Arbatli-Saxegaard and Muneer (2020)). Second, there have been various methodological criticisms raised about the BCG (Edge and Meisenzahl (2011), Hamilton (2018), Baba et al. (2020)). Consequently, national authorities consider additional credit indicators within their policy framework to obtain complementary assessments of the credit cycle. These alternative credit gap metrics differ from the BCG in terms of changes made to the (*i*) definition of the credit-to-GDP ratio, (*ii*) method used for trend-cycle decomposition, or (*iii*) length of the credit cycle being targeted (MNB (2020)).

In this paper, we introduce two additional indicators derived from forecast-based credit-to-GDP gaps. Specifically, we examine two credit metrics that can be integrated into the policy frameworks used by national authorities to determine the CCyB rate: forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps.

Forecast-augmented credit-to-GDP gaps are already considered by several national authorities. The core idea is to extend credit-to-GDP ratios by incorporating forecasted values and then apply a trend-cycle decomposition method to the expanded series to assess the current credit-to-GDP gap. This approach is particularly employed in the CCyB policy frameworks of Lithuania, Norway and Portugal (Arbatli-Saxegaard and Muneer (2020), MNB (2020)). The primary objective of this credit metric is to address a specific criticism directed at the BCG—namely, the end-of-sample problem. In an operational perspective, only real-time data is used to assess credit-to-GDP gaps (i.e., in a one-sided approach). This operational constraint may be perceived as burdensome, because from one period to another, new information can lead to significant revisions in past estimates of credit-to-GDP gaps. More generally, ex-post assessments of credit-to-GDP gaps (i.e., using a two-sided approach) provide valuable information for identifying periods of credit booms and predicting banking crises (Drehmann and Juselius (2014)). Yet for policy purposes, only real-time estimates can be used. In summary, the end-of-sample problem arises due to the lack of information about the future path of the credit-to-GDP ratio. Forecast-augmented credit-to-GDP gaps aim to mitigate this problem.

In this paper, we introduce the predicted credit-to-GDP gaps as a novel credit metric. Specifically, we develop a methodology to predict credit-to-GDP gaps at various time horizons. The primary objective is to provide a forward-looking perspective within the CCyB policy framework.[2] Forecasts are commonly employed by macroeconomic policymakers, such as for the output gap and inflation in the context of monetary and fiscal policies, for example (Wieland and Wolters (2013)). Our aim is to predict the future path of the credit-to-GDP gap to identify potential forthcoming excessive credit activity. Consequently, predicted credit-to-GDP gaps could serve as a supplementary credit metric in policy discussions concerning the CCyB rate.

The credit-to-GDP ratio can contain a long-lasting cyclical component (Drehmann et al. (2012)) captured by the credit-to-GDP gap. These underlying dynamics in credit activity make the implementation of forecast-based credit-to-GDP gaps challenging. Indeed, the underlying model needs to properly account for the medium-to-long run dynamics of the credit-to-GDP ratio. In this paper, we rely on Singular Spectrum Analysis (SSA).[3] SSA is a valuable tool for providing trend-cycle decompositions and is a powerful method for time series forecasting. Therefore, SSA is well-suited for generating forecast-based credit-to-GDP gaps because it is an "all-in-one" method that enables the decomposition and forecasting of time series. In a broader sense, we propose that SSA can serve as a supplementary instrument for the generation of credit gap metrics. The current practice is to rely on the HP filter, but some national authorities also employ alternative methodologies to assess the trend in the credit-to-GDP ratio (Arbatli-Saxegaard and Muneer (2020)). Indeed, the credit-to-GDP gap is inherently unobservable, and each methodology may have inherent limitations. For example, the HP filter is not without its own set of potential shortcomings (Baba et al. (2020)). Therefore, considering multiple methods of trend-cycle decomposition may be a prudent approach to address this uncertainty.

In this paper, we make four main contributions. First, we outline a systematic approach for evaluating forecast-augmented credit-to-GDP gaps using SSA. The forecasting methods currently

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employed by national authorities to generate forecast-augmented credit-to-GDP gaps often fail to adequately account for the persistent cyclical component that characterizes credit-to-GDP ratios. For example, Portugal relies on an $ARIMA(p, 1, 0)$ model to forecast the credit-to-GDP ratio (Banco de Portugal (2020)). Therefore, we propose an approach that explicitly addresses the long-lasting cyclical component when forecasting credit-to-GDP ratios. Moreover, our approach ensures methodological consistency between forecasting the credit-to-GDP ratio and assessing the forecast-augmented credit-to-GDP gap. Second, we introduce a novel credit metric: the predicted credit-to-GDP gaps, which also leverages SSA. More precisely, we propose to successively forecast the trend-cycle component and the trend component of the credit-to-GDP ratio. The difference between these two forecasts yields the predicted credit-to-GDP gaps. This metric holds significant promise for national authorities in the early stages of a credit boom, providing valuable prospective insights into the emergence of excessive credit growth. Third, we investigate the accuracy of forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps. We specifically identify countries where forecasting performance is poor and investigate credit market conditions that influence forecasting accuracy. Finally, we investigate whether forecast-based credit-to-GDP gaps offer valuable information for detecting the early stages of credit booms.

The results reveal substantial heterogeneity across countries in the accuracy of forecast-based credit-to-GDP gaps.[4] The USA, France, India, and Germany exhibit the most robust forecasting performances, consistently excelling in both forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps. Conversely, Malaysia, Thailand, Ireland, and Indonesia record the poorest forecasting performances. Additionally, we demonstrate that forecasting accuracy does not deteriorate during the early stages of a credit boom, when banking supervisors might rely particularly on these credit metrics. Regarding the reliability of forecast-based credit-to-GDP gaps, we demonstrate that these credit metrics offer valuable complementary information for predicting a credit boom.

The remainder of the paper is organized as follows. Section 2 introduces the credit metrics, Section 3 presents the data, Section 4 evaluates the accuracy of forecast-based credit-to-GDP gaps, Section 5 investigates the reliability of these measures, and Section 6 concludes the paper.

2. Measuring credit-to-GDP gaps

2.1 Credit-to-GDP gaps and end-of-sample problem

BCBS (2010) provided guidance to national authorities on implementing the CCyB. Countries are advised to calculate the credit-to-GDP gap using the Hodrick and Prescott (1980, 1997) filter. This filter defines the trend such as to minimize the following penalty function:

$$\underset{\{\tau_t\}_{t=1}^{t'}}{arg\ min} \sum_{t=1}^{t'} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{t'-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 , t' \leqslant T \tag{1}$$

where y_t is the time series (i.e., the credit-to-GDP ratio) and τ_t its trend; λ is the smoothing parameter (the bigger λ is, the smoother the trend). The smoothing parameter used to generate the BCG is set to $\lambda = 400,000$, in accordance with the duration of the credit cycle, which can extend up to four decades (Borio and Lowe (2002), Drehmann et al. (2010), Drehmann and Juselius (2014)). Then, the BCG is given by:

$$BCG_{t'} = y_{t'} - \tau_{t'}. \tag{2}$$

Equation (1) corresponds to the one-sided HP filter. The trend value for a given period $t' < T$ is estimated using data up to period t' (i.e., only with past and current observations) to account for the limited information available in real time.[5] In contrast, the two-sided HP filter uses all past and future values, relative to t', which are available. Consequently, the two-sided approach provides an ex-post trend estimation. Drehmann and Juselius (2014) have shown that, at short horizons,

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the two-sided credit-to-GDP gap outperforms one-sided approach in predicting banking crises. However, from an operational perspective, only the one-sided approach captures the real-time environment that policymakers face when making decisions.

Intrinsically, one-sided estimates face an end-of-sample problem: estimates are subject to ex-post revisions when new data become available. This problem has been extensively discussed in the literature (Canova (1998), Orphanides and van Norden (2002)). Kaiser and Maravall (1999, 2001) find that extending a time series with accurate forecasts reduces the disparity between real-time cycle estimates and their ex-post estimations.

Forecast-augmented credit-to-GDP gaps have thus emerged as a potential solution to mitigate the end-of-sample problem. Gerdrup et al. (2013), Valinskytė and Rupeika (2015), Jokipii et al. (2020) and Škrinjarić (2022) examine Norway, Lithuania, Switzerland and Croatia respectively to investigate the relevance of forecast-augmented credit-to-GDP gaps as credit indicators within the CCyB rate decision-making framework.[6] Gersl and Mitterling (2021) provide a broader analysis considering a panel of 56 countries. The conclusions are rather mixed, as Gersl and Mitterling (2021) conclude that forecast-augmented credit-to-GDP gaps do not provide additional valuable information to predict banking crises in advanced countries but only in emerging countries.

In the existing literature, ARIMA models have traditionally been the primary forecasting method used to generate forecast-augmented credit-to-GDP gaps. However, these models may not adequately account for the long-lasting cyclical components that characterize credit-to-GDP ratio dynamics. In this paper, we turn to SSA, an "all-in-one" method that decomposes and forecasts time series, enabling a more comprehensive consideration of the underlying characteristics of credit-to-GDP ratios. Furthermore, we employ SSA to introduce a new credit metric, termed the predicted credit-to-GDP gaps.

2.2 Singular spectrum analysis: an overview

SSA provides trend-cycle decompositions. In addition, SSA is a powerful tool for time series forecasting. There are two distinct algorithms available for implementing SSA forecasting: recurrent forecasting and vector forecasting (Golyandina and Korobeynikov (2014)). While vector forecasting generally offers more robust forecasts compared to recurrent forecasting, the relative performance of these two algorithms depends on factors such as sample size and forecast horizon (Ghodsi et al. (2018)). In this paper, we conduct forecasting exercises over various horizons, using real-time data (i.e., employing a one-sided approach).[7] This approach involves utilizing different sample sizes. Consequently, we use both forecasting algorithms: recurrent forecasting serves as the baseline, while vector forecasting is employed for robustness checks.

We need first to present the way we proceed to assess credit gaps by SSA. We decompose the time series $\left(y_t\right)_{t=1}^{T}$ (e.g., the credit-to-GDP ratio) into 3 components: the long-term secular trend, the cyclical component and the irregular component. SSA is a 2 stages procedure (see Golyandina et al. (2001) and Golyandina and Zhigljavsky (2013) for details) that can provide such decomposition. Stage 1 corresponds to the decomposition stage. Stage 2 corresponds to the reconstruction stage. Two parameters must be set to implement SSA: (1) the window length L of the trajectory matrix in the decomposition stage and (2) the grouping method of the elementary matrices in the reconstruction stage.

1. The decomposition stage rely on the trajectory matrix of the time series, obtained by mapping $\left(y_t\right)_{t=1}^{T}$ into a sequence of K lagged vectors of size L.[8] Therefore, we have to determine the window length L ($1 < L < T$). We follow the common practice recommended by Elsner and Tsonis (1996), setting $L = T/4$.[9] Then the trajectory matrix is decomposed into L elementary matrices by singular value decomposition (SVD).
2. The reconstruction stage proceed first by grouping the L elementary matrices into 3 components. We proceed as in Bouvatier et al. (2022) for the grouping. The initial elementary

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matrix obtained from the SVD captures the long-term secular trend, representing the general tendency. The irregular component, characterized by high-frequency fluctuations with periodicities of less than 1.5 years (i.e., 6 quarters), is identified through an automatic grouping of elementary matrices (with a frequency cut-off set at $1/6 = 0.1666$). Following this, we deduce the elementary matrices associated with the cyclical component.[10] Last, the reconstruction stage transforms the 3 groups of elementary matrices into 3 time series $\tilde{y}_t^{(j)}$ $(j = 1, 2, 3)$ of length T: the long-term secular trend, the cyclical component and the irregular component.

We implement SSA using real-time data and also apply it in a two-sided setting for comparative purposes. Additionally, we assess the suitability of our selected combination of window length and grouping method in capturing the cyclical component of the credit-to-GDP ratio. First, we examine alternative window lengths, specifically $L = T/3$ and $T/2$. According to Golyandina et al. (2001) and Golyandina and Zhigljavsky (2013), setting $L = T/2$ results in the largest trajectory matrix, thereby providing the most precise decomposition. However, since the trend component is captured by the first elementary matrix, increasing L results in a smoother trend and, in turn, a larger cyclical component. This may lead to the undesirable inclusion of part of the trend within the cyclical component. Following the general recommendation of Elsner and Tsonis (1996), we find that setting $L = T/4$ produces credit-to-GDP gaps with an average magnitude comparable to those obtained using the HP filter (i.e., the Basel credit gap, see Table 1 & Figure 1). By contrast, alternative values ($L = T/3$ and $T/2$) result in larger cycles. We therefore conclude that longer window lengths (e.g., $L = T/3$ or $T/2$) may excessively smooth the trend, potentially reducing the reliability of the decomposition.

Regarding the grouping method, we pay particular attention to the second elementary matrix, which, in our framework, is associated with the cyclical component. For each country, we ensure that the second elementary matrix does not generate a time series component resembling a trend. This matrix captures the medium-term component of the credit-to-GDP gap, which may exhibit different characteristics across countries. In particular, some countries may experience episodes of a large and prolonged medium-term component in the credit-to-GDP gap, as for instance Ireland, Malaysia, Thailand or Indonesia.[11]

2.3 Forecast-based credit-to-GDP gaps

SSA provides trend-cycle decompositions and time series forecasting. Hence, SSA is well-suited for two purposes: (*i*) generating forecast-augmented credit-to-GDP gaps and (*ii*) producing predicted credit-to-GDP gaps.

First, forecast-augmented credit-to-GDP gaps involve extending credit-to-GDP ratio by forecasts for a given horizon k. Then, we implement trend-cycle decomposition for the forecast-augmented credit-to-GDP series to obtain robust credit gaps that mitigate the end-of-sample problem. To accomplish this, we follow a two-step procedure:

1. we conduct recurrent SSA forecasting to predict credit-to-GDP ratios over k periods (considering each sample size employed in the one-sided approach);
2. we perform (one-sided) SSA using the forecast-augmented credit-to-GDP series with a size of $t + k$ to generate credit-to-GDP gaps for period t, as described is subsection 2.2.

We rely on different forecast horizon k ($k = 1, 4, 8, 12, 16, 20$, i.e., up to 5 years) for a matter of comparison. Furthermore, we also execute the same procedure using vector forecasting instead of recurrent forecasting in step 1 to assess robustness.

The main difference between recurrent forecasting and vector forecasting lies in how future values of the time series are generated from the reconstructed structure. Recurrent forecasting

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Table 1. Descriptive statistics on credit-to-GDP gap

Panel A: Credit to the private sector (i.e., broad credit)								
	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	CY_{gap}^{RFA12}	CY_{gap}^{RFA20}	CY_{gap}^{RP1}	CY_{gap}^{RP4}
Num. obs.	6394	7449	6394	7449	6394	6394	6394	6394
STD	13.46	11.49	15.08	11.09	10.44	9.6	19.8	25.6
Mean abs	9.35	8.05	10.05	7.51	6.52	5.65	13.26	15.43
Minimum	−93.4	−93.4	−128.39	−126.67	−132.53	−142.64	−194.68	−316.12
1% percentile	−41.44	−27.18	−48.84	−33.11	−39.45	−37.36	−63.71	−77.18
5% percentile	−20.68	−16.04	−29.39	−15.52	−20.54	−17.16	−36.93	−39.98
95% percentile	20.93	18.03	20.11	15.81	12.13	10.38	27.02	33.24
99% percentile	37.8	38.23	36.97	29.96	23.08	19.95	51.45	64.51
Maximum	79.86	110.59	67.91	59.09	49.47	58.13	106.43	566.48
Panel B: Bank credit (i.e., narrow credit)								
	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	CY_{gap}^{RFA12}	CY_{gap}^{RFA20}	CY_{gap}^{RP1}	CY_{gap}^{RP4}
Num. obs.	6308	7385	6308	7385	6308	6308	6308	6308
STD	10.2	8.62	11.47	8.48	7.96	7.27	14.82	17.77
Mean abs	6.73	5.74	7.1	5.41	4.57	3.95	9.37	10.77
Minimum	−71.95	−36.19	−82.33	−61.54	−63.91	−84.09	−99.84	−149.14
1% percentile	−39.02	−20.55	−47.86	−28.02	−37.08	−31.56	−59.77	−69.02
5% percentile	−14.97	−12.48	−19.87	−11.71	−14.49	−12.59	−25.4	−28.35
95% percentile	13.85	12.23	13.56	10.77	8.27	6.74	17.71	20.12
99% percentile	26.99	30.14	28.58	23.8	17.23	14.9	39.14	44.51
Maximum	42.97	69.82	41.97	53.4	24.94	60.42	58.96	91.67

Variable definitions: CY_{gap}^{HPos} = credit-to-GDP gap computed using a one-sided HP filter; CY_{gap}^{HPts} indicates the credit-to-GDP gap is obtained via two-sided HP filter; CY_{gap}^{SSAos} via one-sided SSA; CY_{gap}^{SSAts} via two-sided SSA. CY_{gap}^{RFA20}: forecast-augmented credit-to-GDP gap generated through recurrent SSA forecasting with a forecast horizon of 20 periods; CY_{gap}^{RP1}: predicted credit-to-GDP gap at horizon 1 computed through recurrent SSA forecasting; CY_{gap}^{RP4}: predicted credit-to-GDP gap at horizon 4.

***Note*:** "STD" is the standard deviation and "Mean abs" is the mean of absolute vaues. Descriptive statistics have been calculated for an unbalanced sample of 43 countries over the period 1970q1–2019q4. We only consider two forecast-augmented credit-to-GDP gaps (with series extended by 10 and 20 periods, respectively) and two predicted credit-to-GDP gaps (at horizons 1 and 4) to save space. Descriptive statistics for the full set of forecast-based credit-to-GDP ratios are available upon request.

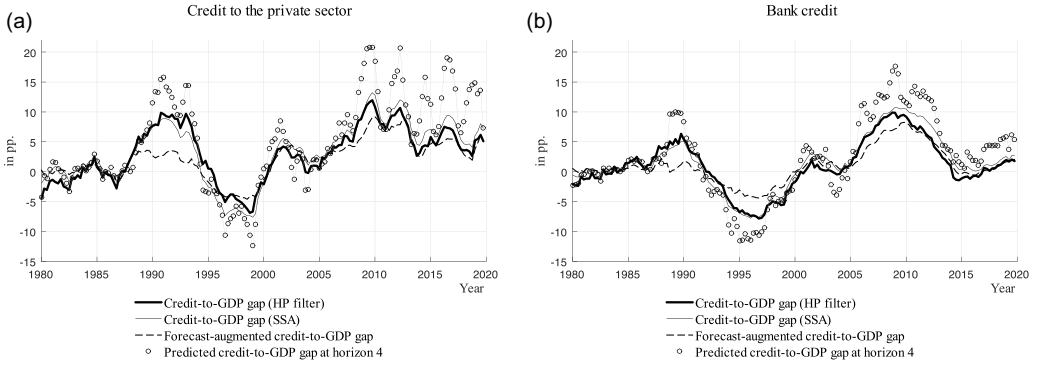


Figure 1. One-sided credit-to-GDP gaps in France (1980q1-2019q4). *Note*: Forecast-augmented and Predicted credit-to-GDP gap are generated through recurrent SSA forecasting. Forecast-augmented credit-to-GDP gap are generated with a forecast horizon of 12 periods.

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is based on Linear Recurrence Relations (LRRs). Formally, $(y_t)_{t=1}^{T}$ satisfies an LRR of order $L-1$ if:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_{L-1} y_{t-L+1}, \quad t = L+1, \ldots, T$$

where parameters $a_1, a_2, \ldots, a_{L-1}$ are derived from the singular values and vectors obtained during the SSA decomposition (Golyandina and Zhigljavsky (2013)). In this approach, the continuation (i.e., the forecast) of the series is performed after the reconstruction stage of SSA by applying the LLR to generate future values step-by-step. In contrast, vector forecasting performs the continuation before the reconstruction step. It works directly in the so-called trajectory space, which represents the time series as a sequence of overlapping vectors. Instead of forecasting one point at a time, vector forecasting extends the trajectory matrix itself into the future. Once this extended matrix is obtained, the standard SSA reconstruction step is applied to recover the forecasted time series values.

Second, we introduce a novel credit metric termed predicted credit-to-GDP gaps. To generate these predicted credit-to-GDP gaps for different horizons k ($k = 1, \ldots, 12$, i.e., up to 3 years), we implement a three-step procedure:

1. we employ (one-sided) SSA to generate both the trend-cycle components and the trend components;
2. we conduct recurrent SSA forecasting to predict both the trend-cycle component and the trend component over k periods (considering each sample size employed in the one-sided approach);[12]
3. we calculate the difference between the predicted trend-cycle component and the predicted trend component to obtain (one-sided) predicted credit gaps up to horizon k.

Additionally, we apply vector forecasting instead of recurrent forecasting in step 2 of the procedure for robustness assessment.

3. Data

We use the BIS database on credit statistics (Dembiermont et al. (2013)). This comprehensive database encompasses an unbalanced panel of 43 countries and offers quarterly credit data dating as far back as the 1950s. Further, the BIS database contains several credit aggregates to compute credit-to-GDP ratios. We both rely on bank credit (i.e., narrow credit) and on total credit provided to the private sector (i.e., broad credit).[13]

To generate credit-to-GDP gaps, we employ one-sided SSA, as elaborated in Section 2.2. Furthermore, we produce forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps, as detailed in Section 2.3. For the sake of comparison, we also compute credit-to-GDP gaps using two-sided SSA; and credit-to-GDP gaps using the Hodrick-Prescott (HP) filter (both using one-sided and two-sided approaches).[14] In summary, we consider two credit aggregates (narrow and broad), two trend-cycle decomposition methods (SSA and HP), and two approaches (one-sided and two-sided), yielding a total of eight distinct assessments of credit-to-GDP gaps. Additionally, the forecasting exercises discussed in Section 2.3 yield forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps for various time horizons.

Table 1 presents descriptive statistics for credit-to-GDP gaps, differentiating between broad credit (Panel A) and narrow credit (Panel B). Both the HP filter and SSA yield credit-to-GDP gaps with notably similar characteristics in terms of their average size and range. For example, when examining two-sided credit-to-GDP gaps for broad credit, Table 1 indicates that the size of credit-to-GDP gaps, given by the mean of absolute values, is 7.51 for SSA and 8.05 for the HP filter. It can be argued that the use of both SSA and HP represents a complementary approach to the assessment of credit gap metrics. In addition, Table 1 shows that broad credit has larger

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credit-to-GDP gaps than narrow credit, and that one-sided credit-to-GDP gaps are larger than two-sided credit-to-GDP gaps. For instance, the mean absolute values of one-sided credit-to-GDP gaps obtained through SSA for broad credit is 10.05, whereas it decreases to 7.51 and 7.10 when considering two-sided credit-to-GDP gaps and narrow credit, respectively. Additionally, Table 1 presents descriptive statistics concerning forecast-based credit-to-GDP gaps. On average, the size of forecast-augmented credit-to-GDP gaps is smaller than that of other metrics. For instance, when analyzing broad credit, Table 1 reveals that the mean of the absolute values of forecast-augmented credit-to-GDP gaps is 6.52 when series have been extended by 3 years (i.e., 12 periods). This suggests that using forecasts to apply the trend-cycle decomposition method to extended credit-to-GDP series results in the identification of smaller credit-to-GDP cycles. When series are extended by 5 years (i.e., 20 periods), Table 1 show that results are not much different. Shifting our attention to predicted credit-to-GDP gaps at horizon 1 and 4, we observe that both the range and size of these gaps increase with the forecasting horizon. These observations imply that the volatility of predicted credit-to-GDP gaps rises as the forecasting horizon extends. As a result, high-horizon predicted credit-to-GDP gaps may not be ideal indicators for operational purposes since new information can lead to significant revisions in the predicted credit-to-GDP gaps.

Figure 1 presents a subset of one-sided credit-to-GDP gaps for a specific country (France) over the period 1980q1 to 2019q4. This figure is intended to complement the descriptive statistics presented in Table 1. First, Figure 1 shows that both the HP filter and SSA provide comparable assessments of one-sided credit-to-GDP gaps. While there may be slight differences between the two methods for a given period, the overall patterns remain very similar. Additionally, Figure 1 indicates that forecast-augmented credit-to-GDP gaps exhibit smaller fluctuations compared to one-sided credit-to-GDP gaps during periods of credit booms and busts. Table 1 shows that forecast-augmented credit-to-GDP gaps are particularly smaller in magnitude than the other metrics. Specifically, during the initial phases of a credit boom (or bust), forecasts of the credit-to-GDP ratio anticipate rapid increases (or decreases) in credit activities for the forthcoming periods. By integrating this broader set of forecast-based information into the trend-cycle decomposition method, more of the fluctuation is allocated to the trend component. Consequently, forecast-augmented credit-to-GDP gaps exhibit fewer oscillations than one-sided credit-to-GDP gaps during credit boom and bust periods. Finally, Figure 1 illustrates that predicted credit-to-GDP gaps exhibit a contrasting pattern compared to forecast-augmented credit-to-GDP gaps. Specifically, during the initial phase of a credit boom or bust, predicted credit-to-GDP gaps anticipate that the rapid expansion or contraction of credit activities will strengthen.[15] Table 1 also shows that predicted credit-to-GDP gaps are notably larger in magnitude than other metrics.

4. Accuracy of forecast-based credit-to-GDP gaps

We investigate the accuracy of forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps.[16] Our analysis delves into heterogeneity across countries to identify the countries with the most accurate forecasting performances. Additionally, beyond the variations observed across countries, we explore credit market conditions that may be linked to poor forecasting performances.

4.1 Forecast-augmented credit-to-GDP gaps

Forecast-augmented credit-to-GDP gaps propose to alleviate the end-of-sample problem that affects one-sided estimates of credit-to-GDP gaps. We first need to define a benchmark to capture the accuracy of forecast-augmented credit-to-GDP gaps. We use forecast-augmented credit-to-GDP gaps derived from perfect forecasts of credit-to-GDP ratios over a 5-year period. In essence, for a given period t, we project the future path of credit-to-GDP ratio over 5 years (i.e., up to

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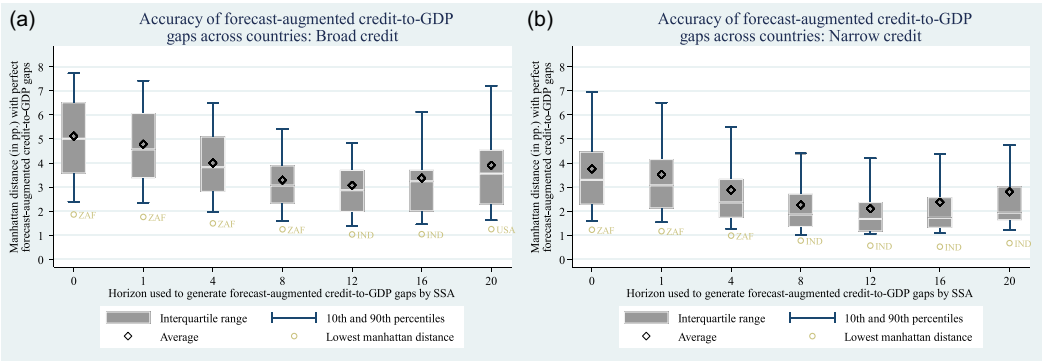


Figure 2. Forecast-augmented credit-to-GDP gaps. *Note*: The top 5 with the lowest Manhattan distances is: 1.IND, 2.USA, 3.ZAF, 4.FRA, 5.DEU. The top 5 with the largest Manhattan distances is: 1.IRL, 2.IDN, 3.THA, 4.MYS, 5.FIN. Top 5 are based on ranking obtained with forecast horizon $k = 12$ (i.e., when the average forecast performance is the best). The perfect forecast-augmented credit-to-GDP gaps are assessed with t + 20 observations. Forecast-augmented credit-to-GDP gaps at horizon 0 are considered for a matter of comparison and correspond to the onesided credit-to-GDP gaps. Note: The top 5 with the lowest Manhattan distances is: 1.IND, 2.USA, 3.FRA, 4.ZAF, 5.AUT. The top 5 with the largest Manhattan distances is: 1.THA, 2.IDN, 3.MYS, 4.HKG, 5.CHN. Top 5 are based on ranking obtained with forecast horizon $k = 12$ (i.e., when the average forecast performance is the best). The perfect forecast-augmented credit-to-GDP gaps are assessed with t + 20 observations. Forecast-augmented credit-to-GDP gaps at horizon 0 are considered for a matter of comparison and correspond to the onesided credit-to-GDP gaps

$t + 20$) and then we evaluate the credit-to-GDP gap at time t using an extended dataset ending at $t + 20$. In this context, we consider forecast-augmented credit-to-GDP gaps generated by SSA forecasting as accurate when they align with forecast-augmented credit-to-GDP gaps obtained with perfect forecasts.[17] It is worth noting that forecast-augmented credit-to-GDP gaps derived from SSA forecasting do not all use a 5-year forecast horizon. We have explored various forecast horizons ($k = 1, 4, 8, 12, 16, 20$) for the sake of comparison, as detailed in Section 2.3.

4.1.1 Country heterogeneity

We have employed a cross-validation procedure, involving an evaluation based on a rolling forecasting origin, to assess the Manhattan distance between forecast-augmented credit-to-GDP gaps obtained through recurrent SSA forecasting and those derived from perfect forecasts.[18] In our view, the Manhattan distance is an appropriate criterion for three reasons. Firstly, the objective is to investigate the factors influencing forecast errors, and therefore imposing greater penalties on larger errors may not be beneficial. Secondly, given that the forecast errors are related to the credit-to-GDP gap, it can be reasonably assumed that controlling for potential scale effects is unnecessary. Lastly, the Manhattan distance has an intuitive appeal.

Figure 2 provides insight into the heterogeneity among countries. The ranges between the 10th and 90th percentiles reveal substantial variations in the accuracy of forecast-augmented credit-to-GDP gaps across countries. At the 90th percentile, Manhattan distances are more than three times larger than those at the 10th percentile. In addition, Figure 2 highlights the impact of the forecast horizon k ($k = 1, 4, 8, 12, 16, 20$) used to generate forecast-augmented credit-to-GDP gaps via SSA forecasting. We have observed that a forecast horizon $k = 12$, on average, yields the best performances. However, there is not a noticeable difference in forecasting performance on average when considering forecast horizons of $k = 8$, 12, 16 or 20. Figure 2 also gauges the advantages of relying on forecast-augmented credit-to-GDP gaps. Forecast horizon $k = 0$, reported on Figure 2, corresponds to the one-sided estimates of credit-to-GDP gaps (i.e., when the end-of-sample problem is the more pronounced). Figure 2 logically shows that forecast-augmented credit-to-GDP gaps

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with forecast horizon $k = 1$ provide results quite similar to those obtained with one-sided credit-to-GDP gaps. Moreover, Figure 2-a shows for broad credit that increasing the forecast horizon from $k = 0$ to $k = 12$ results in a reduction of the median Manhattan distance from 5.01 to 2.79 percentage points, which represents a 44% decrease. Additionally, countries with the best forecasting performance display Manhattan distances close to 1.10 percentage points. A similar pattern is observed in Figure 2-b for narrow credit.[19]

When we extend the forecast horizon beyond 12, the accuracy of forecast-augmented credit-to-GDP gaps does not continue to improve. This result might be explain by the fact that forecast errors in credit-to-GDP ratios logically increase with the forecast horizon. Therefore, we face a trade-off in generating forecast-augmented credit-to-GDP gaps: expanding the credit-to-GDP ratio by forecasts helps to mitigate the end-of-sample problem, but the accuracy of forecasts also matters. Figure 2 suggests that there is no further gain in continuing to expand the credit-to-GDP ratio with more than 12 forecasted observations because additional forecasts are not accurate enough.

4.1.2 Country ranking

We employ a regression model to assess more cautiously heterogeneity across countries. The baseline specification only includes country-fixed effects:

$$dist_{i,\tau} = \alpha_i + \varepsilon_{i,\tau} \tag{3}$$

where $dist_{i,\tau}$ is the average Manhattan distance (between forecast-augmented credit-to-GDP gaps obtained through SSA and those derived from perfect forecasts) for country i during period τ. For the baseline estimate, we consider 5-year periods commencing in 1970q1, where period $\tau = 1$ corresponds to 1965q2-1970q1. Additionally, we narrow down the sample to include countries with data available for at least 2 periods.[20] Subsequently, the baseline specification will be expanded to incorporate covariates aimed at explaining variations in forecasting performance.

Table 2 presents the estimate for broad credit in column (1) of the baseline specification. The coefficient of determination (R^2) stands at 46.42%. Hence, nearly half of the variation in forecasting performance is accounted for by time-invariant country-specific factors. The baseline model will be expanded to investigate whether forecasting performance also varies across different phases of the credit cycle.

The estimate reported in column (1) of Table 2 underscores the significance of country heterogeneity in forecasting performance. However, it's important to note that this estimate is contingent on several methodological choices: the use broad credit; recurrent SSA forecasting with a forecast horizon of $k = 12$, the Manhattan distance metric, a starting date in 1970q1, and 5-year periods. Consequently, the estimated country-fixed effects might be misleading to capture country heterogeneity. To ensure the robustness of our findings, we explore a wide range of alternative specifications. Additionally, we provide descriptive statistics concerning these estimated country-fixed effects. Specifically, the alternative specifications encompass:

- 2 credit variables: broad credit or narrow credit;
- 2 SSA forecasting methods: recurrent or vectorial SSA forecasting;
- 4 forecast horizons used to generate forecast-augmented credit-to-GDP gaps through SSA: $k = 8$, 12, 16 or 20;
- 20 different starting dates: 1970q1, 1970q2,. . ., or 1974q4;
- 6 durations to define periods: 5-year periods, 6-year periods,. . ., or 10 year periods.

These alternative specifications are instrumental in enhancing the robustness and comprehensiveness of our analysis, resulting in a total of 1920 alternative estimates.[21] It's worth noting

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Table 2. Determinants of forecasting performances for forecast-augmented credit-to-GDP gaps

	Estimates with the baseline sample				Robustness checks		
						Mean	Median
	(1)	(2)	(3)	(4)		(5)	(6)
$MBoom_{i,\tau}$		1.74**	1.64**	1.52**	coef	1.06	0.98
		(0.71)	(0.71)	(0.58)	t-sta	1.23	1.18
$LBoom_{i,\tau}$		4.25***	4.10***	3.36***	coef	3.53	3.54
		(1.06)	(1.04)	(0.77)	t-sta	3.36	2.92
$MBust_{i,\tau}$		0.95	1.01*	0.48	coef	0.79	0.67
		(0.65)	(0.59)	(0.54)	t-sta	0.94	0.91
$LBust_{i,\tau}$		4.20***	4.23***	3.77***	coef	5.31	5.04
		(1.15)	(1.10)	(0.96)	t-sta	3.46	3.19
$Peak_{i,\tau}$			1.23**	0.81*	coef	0.43	0.43
			(0.51)	(0.44)	t-sta	1.01	1.03
$Trough_{i,\tau}$			−0.11	0.18	coef	−0.14	−0.17
			(0.29)	(0.32)	t-sta	−0.44	−0.48
$Level_{i,\tau}$				0.03***	coef	0.02	0.02
				(0.01)	t-sta	1.32	1.30
Intercept	2.94***	−0.22	−0.40	−4.59***			
	(0.29)	(0.95)	(0.98)	(1.56)			
Country FE	Yes	Yes	Yes	Yes			
Time FE	No	Yes	Yes	Yes			
Num. countries	35	35	35	35			
Num. obs.	205	205	205	205			
R^2	0.4642	0.6055	0.6351	0.6817			

Variable definitions: the endogenous variable in columns (1) to (4) is the average manhattan distance between forecast-augmented credit-to-GDP gaps obtained through (recurrent) SSA forecasting and those obtained with perfect forecasts for country i during period τ. We consider 5-year periods starting in 1970q1 to compute these average manhattan distances. Period τ=1 corresponds therefore to 1965q2 − 1970q1. Variable *MBoom* is the frequency of medium boom episodes (i.e., one-sided credit-to-GDP gap between 2% and 10%) during period τ; *LBoom* is the frequency of large boom episodes (i.e., one-sided credit-to-GDP gap larger than 10%) during period τ. Variables *MBust* and *LBust* capture the frequency of medium and large bust episodes during period τ, respectively (defined with symmetrical thresholds, i.e., one-sided credit-to-GDP gap between −2% and −10%, and lower that −10% respectively). Variables *Peak* (resp. *Trough*) is a dummy variable equal to 1 if a peak (resp. a trough) in the credit-to-GDP ratio is identified during period τ by the turning point algorithm proposed by Harding and Pagan (2002). Variable *Level* is the level of the trend component of the credit-to-GDP ratio.

***Note*:** ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. Robust standard errors are in brackets. Columns (5) and (6) summarizes the results of the robustness checks, reporting mean and median respectively of coefficients and t-statistics, computed over 3840 alternative specifications (2 credit variables (broad and narrow) x 2 SSA forecasting methods (reccurent and vectorial) x 4 different horizons for generating forecast-augmented credit-to-GDP gaps (8, 12, 16, 20) x 20 different starting dates for the sample (1970q1 to 1974q4) x 6 different durations to define periods (5 to 10 years) x 2 sets of fixed effects (with or without time-fixed effects)).

that the number of countries can vary across these alternative estimates due to data availability, particularly when the duration of periods is extended.

The results are reported in the first columns of Table 3. India, the USA and South Africa display the best performances: the Manhattan distance between forecast-augmented credit-to-GDP gaps obtained through SSA and those derived from perfect forecasts is 1.01pp, 1.11pp and 1.21pp, respectively. Additionally, the accuracy of forecast-augmented credit-to-GDP gaps produced by SSA is noticeable for Germany, Canada, Austia, France, Austalia, Mexico and Italy: the Manhattan distance averages less than 2pp in all of these countries. For these nations, forecast-augmented credit-to-GDP gaps derived from SSA provide a suitable metric for mitigating the end-of-sample problem that affect one-sided credit-to-GDP gaps. However, some countries may not find it

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Table 3. Accuracy of forecast-based credit-to-GDP gaps: country ranking

	Forecast-augmented credit-to-GDP gaps			Predicted credit-to-GDP gaps						
				Horizon:	$k = 2$		$k = 4$		$k = 8$	
Rank	Country	Num. of estimates	Mean	Num. of estimates	Country	Mean	Country	Mean	Country	Mean
1	IND	1920	1.01	480	USA	1.72	USA	2.77	IND	5.07
2	USA	1920	1.11	480	FRA	1.79	FRA	2.91	FRA	5.14
3	ZAF	1920	1.21	480	IND	1.96	IND	3.11	USA	5.20
4	COL	24	1.27	480	DEU	1.99	DEU	3.16	DEU	5.36
5	DEU	1920	1.33	64	COL	2.03	COL	3.34	ZAF	5.40
6	CAN	1920	1.35	480	AUT	2.12	AUT	3.38	AUT	5.74
7	AUT	1920	1.37	480	ZAF	2.13	ZAF	3.57	COL	5.81
8	FRA	1920	1.38	480	CAN	2.23	MEX	3.72	CAN	6.13
9	AUS	1920	1.78	56	BRA	2.42	CAN	3.90	MEX	6.36
10	MEX	1760	1.87	476	MEX	2.47	BRA	4.23	SAU	7.14
11	ITA	1920	1.98	480	AUS	2.48	AUS	4.34	AUS	7.17
12	BEL	1920	2.04	480	GBR	2.99	ITA	4.77	CHE	7.86
13	CHE	1920	2.07	480	ITA	3.09	GBR	4.87	BRA	8.10
14	GBR	1920	2.21	480	BEL	3.13	CZE	5.23	GBR	8.17
15	GRC	1920	2.22	360	TUR	3.16	BEL	5.51	ITA	8.33
16	SAU	192	2.28	176	POL	3.18	GRC	5.63	TUR	8.67
17	NZL	1920	2.30	480	NZL	3.29	NZL	5.72	BEL	8.68
18	NLD	1920	2.41	136	CZE	3.40	POL	5.74	ISR	8.89
19	JPN	1920	2.57	480	GRC	3.62	CHE	5.82	NZL	9.08
20	CHL	1472	2.58	480	NOR	3.62	TUR	5.92	CZE	9.57
21	HUN	1920	2.58	480	CHE	3.67	NLD	6.13	GRC	9.81
22	SGP	1920	2.70	480	NLD	3.77	HUN	6.31	POL	10.03
23	POL	320	2.72	424	CHL	3.95	JPN	6.56	JPN	10.04
24	CZE	192	2.74	136	SAU	4.00	CHL	6.62	NLD	10.16
25	TUR	1088	2.78	480	SWE	4.03	NOR	6.62	SGP	10.97
26	NOR	1920	2.94	480	HUN	4.15	SAU	6.88	HUN	11.42
27	ISR	528	3.05	480	FIN	4.52	ISR	7.25	CHL	11.94
28	SWE	1920	3.10	480	SGP	4.54	SWE	7.32	NOR	12.56
29	KOR	1920	3.20	216	ISR	4.61	SGP	7.50	HKG	13.73
30	CHN	1120	3.73	480	JPN	4.63	FIN	7.95	CHN	13.80
31	ESP	1920	3.79	480	KOR	4.70	KOR	8.12	SWE	13.90
32	ARG	608	3.93	364	CHN	5.26	PRT	8.53	KOR	14.36
33	PRT	1920	3.94	480	DNK	5.42	DNK	9.09	FIN	14.67
34	FIN	1920	4.15	480	PRT	5.68	ESP	9.14	ARG	15.26
35	DNK	1920	4.17	480	ESP	5.71	CHN	9.43	PRT	15.33
36	HKG	1904	4.24	480	HKG	5.85	HKG	9.54	DNK	16.26
37	IRL	1920	6.02	240	ARG	6.84	ARG	10.81	ESP	16.99
38	MYS	1920	6.36	480	MYS	7.66	THA	12.78	IRL	27.61
39	THA	1920	7.97	480	THA	8.14	MYS	13.96	THA	28.26
40	IDN	1920	8.00	480	IRL	8.53	IRL	14.09	MYS	28.52
41				480	IDN	13.55	IDN	26.31	IDN	61.44

***Note*:** The ranking of countries is based on the mean of estimated country-fixed effects computed over the full set of robustness checks (i.e., alternative estimates). The number of alternative estimates can reach 1920 for forecast-augmented credit-to-GDP gaps and 480 for predicted credit-to-GDP gaps. The number of estimates is lower for some countries due to data availability.

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advantageous to rely on forecast-augmented credit-to-GDP gaps. In the bottom of the ranking displayed in Table 3, Finland, Denmark, Hong Kong, Ireland, Malaysia, Thailand, Indonesia exhibit Manhattan distances averaging more than 4pp. In these countries, both one-sided credit-to-GDP gaps and forecast-augmented credit-to-GDP gaps are susceptible to significant revisions when the future path of credit-to-GDP ratios is observed.

Countries at the bottom of the ranking may have experienced large and prolonged booms and/or busts in credit-to-GDP gaps surrounding financial crises. For instance, Malaysia, Thailand, and Indonesia faced sharp credit contractions following the 1997 Asian financial crisis, while Denmark and Ireland experienced both booms and busts around the 2007–2008 Great Financial Crisis. These patterns suggest complex dynamics in credit-to-GDP gaps. Such fluctuations in the medium-term component of credit-to-GDP gaps may contribute to the poor forecasting performance observed for these countries and highlight the need for greater attention to credit market conditions.

4.1.3 Credit market conditions and forecasting performances

The augmented specification introduces time-varying covariates:

$$\begin{aligned} dist_{i,\tau} = {} & \beta_1 MBoom_{i,\tau} + \beta_2 LBoom_{i,\tau} + \beta_3 MBust_{i,\tau} + \beta_4 LBust_{i,\tau} + \beta_5 Peak_{i,\tau} \\ & + \beta_6 Trough_{i,\tau} + \beta_7 Level_{i,\tau} + \delta_\tau + \alpha_i + \varepsilon_{i,\tau} \end{aligned} \tag{4}$$

where variable $MBoom_{i,t}$ is the frequency of medium boom episodes during period τ (defined as one-sided credit-to-GDP gap between 2% and 10%), $LBoom_{i,t}$ is the frequency of large boom episodes during period τ (defined as one-sided credit-to-GDP gap larger than 10%).[22] Variables $MBust_{i,\tau}$ and $LBust_{i,\tau}$ capture the frequency of medium bust and large bust episodes during period τ, respectively (defined with symmetrical thresholds, i.e., one-sided credit-to-GDP gap between −2% and −10%, and lower that −10%, respectively). Variables $Peak_{i,\tau}$ (resp. $Trough_{i,\tau}$) is a dummy variable equal to 1 if a peak (resp. a trough) is identified during period τ using the turning point algorithm proposed by Harding and Pagan (2002).[23] Variable $Level_{i,\tau}$ is the level of the trend component of the credit-to-GDP ratio and serves as an indicator of banking sector development. The augmented specification also includes controls for period-fixed effects (δ_τ).

Table 2 presents the estimates in columns (2) to (4), progressively incorporating covariates into the estimated specifications. We observe an increase in the coefficient of determination (R^2) from 46% in column (1) to 68% in column (4), signifying the influence of credit market conditions on forecasting performance. Particularly, we find that forecasting performance experiences significant deterioration during periods of large credit booms and busts. In column (4) of Table 2, the Manhattan distance between forecast-augmented credit-to-GDP gaps obtained through SSA and those derived from perfect forecasts increases by 3.36pp and 3.77pp during large boom and bust episodes, respectively, compared to periods when the credit-to-GDP gap falls within the range of −2% to 2%. In other words, forecast-augmented credit-to-GDP gaps face challenges in mitigating the end-of-sample problem in the one-sided credit-to-GDP gap during periods of large credit booms or busts. Additionally, forecasting performance mildly deteriorates during medium credit booms, with a 1.52pp increase, but does not exhibit significant deterioration at the 10% level during medium credit busts. Table 2 also indicates that forecasting performances are only lightly mitigated during a peak in the credit-to-GDP ratio; parameter associated with variable $Peak_{i,\tau}$ is 0.81 and significant only at the 10% level. This effect is not symetrical, as the parameter associated with variable $Trough_{i,\tau}$ is not significant at the 10% level.

These results have implications for the reliability of forecast-augmented credit-to-GDP gaps in an operational context. Forecasting performances primarily declines during large boom and bust episodes, i.e., when banking supervisors already have a clear signal concerning the credit market situation. Conversely, outside of these episodes, forecast-augmented credit-to-GDP gaps continue to serve as a reliable complementary metric for banking supervisors to assess the macro-financial

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environment. Performance slightly deteriorates during medium credit booms and during the peak of the credit cycle, but only to a limited extent.

Furthermore, in column (4) of Table 2, we observe that forecasting performances diminishes with increased banking sector development. However, the economic significance of this effect is rather limited: a 10pp increase in trend component of the credit-to-GDP ratio results in a 0.3pp increase in the Manhattan distance ($dist_{i,\tau}$).

When assessing country heterogeneity, the estimates reported in column (4) of Table 2 depends on several methodological choices: we use broad credit; recurrent SSA forecasting with a forecast horizon $k = 12$, the Manhattan distance metric, a starting date in 1970q1, and 5-year periods. Thus, we consider the same alternative specifications as those used in section 4.1.2, along with alternatives that exclude time-fixed effects from the estimated specifications[24] Consequently, we end up with a total of 3840 alternative specifications. Columns (5) and (6) of Table 2 present descriptive statistics for the estimated parameters, confirming the primary findings . It is evident that poor forecasting performances are concentrated during periods of large credit booms and busts. The Manhattan distance increases by an average of 3.53pp and 5.31pp during large boom and bust episodes, respectively, with t-statistics averaging 3.36 and 3.46, respectively, across the full set of alternative estimates. Furthermore, the robustness analysis indicates that medium credit booms and peaks in the credit-to-GDP ratio do not significantly affect forecasting performances, with t-statistics averaging 1.23 and 1.01 for coefficients associated with variables $MBoom_{i,\tau}$ and $Peak_{i,\tau}$, respectively. Similarly, medium credit busts and troughs in the credit-to-GDP ratio do not appear to be detrimental to forecasting performances. Lastly, the robustness analysis does not provide strong evidence supporting a clear connection between banking sector development and forecasting performances. The coefficient associated with variable $Level_{i,\tau}$ averages 0.02, but t-statistic averages only 1.32.

4.2 Predicted credit-to-GDP gaps

Predicted credit-to-GDP gaps provide a forward-looking perspective in the assessment of credit market conditions. For a given period t, we compare predicted credit-to-GDP gaps for horizon k with one-sided credit-to-GDP gaps computed for period $t + k$. We rely on the Manhattan distance between these two metrics to capture the accuracy of predicted credit-to-GDP gaps, for the same reasons as in the previous sub-section. In the present situation, the Manhattan distance corresponds to the mean absolute error (MAE).

4.2.1 Country heterogeneity

We assess the accuracy of predicted credit-to-GDP gaps by a cross-validation procedure. Figure 3 illustrates country heterogeneity for forecast horizons $k = 1$ to 8, both for broad credit and narrow credit. First, Figure 3 shows that forecasting performances deteriote with forecast horizons. MAE is 4.14pp on average for forecast horizon $k = 1$ and increases up to 14.33pp on average for forecast horizon $k = 8$. Second, narrow credit displays better forecasting performances according to MAE than broad credit. However, this difference might be explain by the larger size of credit-to-GDP gaps for broad credit than for narrow credit (see Table 1). Third, Figure 3 shows that country heterogeneity is noticeable. Focusing on broad credit, the range of MAE between the 10th and the 90th percentiles is 5.10pp for forecast horizon $k = 1$ and increases up to 17.73pp for forecast horizon $k = 8$. Further, countries displaying the best forecasting performances exhibit MAE around 2pp for forecast horizon $k = 1$, and up to 5pp for forecast horizon $k = 8$. We consider such average level of errors as substantial relatively to the average size of credit-to-GDP gaps (10.05pp for broad credit for instance, see Table 1).[25]

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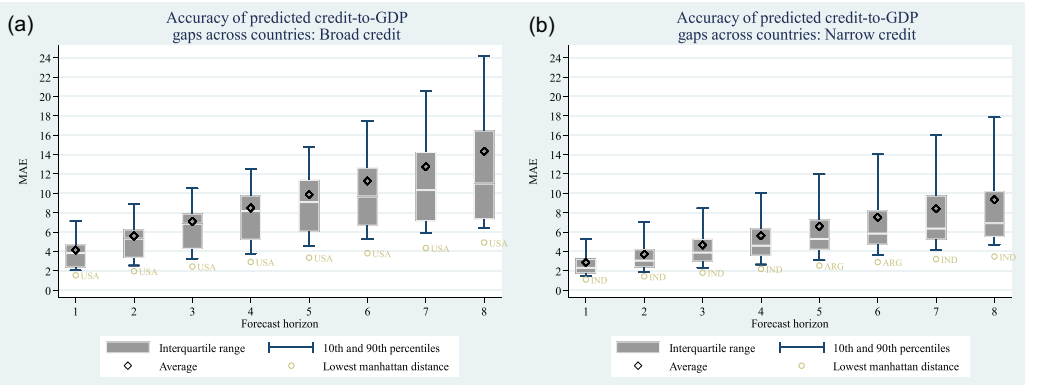


Figure 3. Predicted credit-to-GDP gaps. *Note*: The top 5 with the lowest MAE is: 1.USA, 2.BRA, 3.ZAF, 4.FRA, 5.COL. The top 5 for largest MAE is: 1.IRL, 2.ARG, 3.MYS, 4.THA, 5.ESP. Top 5 are based on the average ranking of each country over the 8 forecast horizons. Note: The top 5 with the lowest MAE is: 1.IND, 2.ARG, 3.ZAF, 4.USA, 5.FRA. The top 5 for largest MAE is: 1.IDN, 2.MYS, 3.THA, 4.HKG, 5.ESP. Top 5 are based on the average ranking of each country over the 8 forecast horizons.

4.2.2 Country ranking

We rely on the same baseline regression model as in section 4.1.2 to assess more cautiously country heterogeneity:

$$dist^{k}_{i,\tau} = \alpha_i + \varepsilon_{i,\tau} \tag{5}$$

where $dist^{k}_{i,\tau}$ is the MAE of predicted credit-to-GDP gaps at horizon k for country i during period τ. We consider 5-year periods in the baseline estimate starting in 1970q1. Table 4 reports estimates for broad credit of the baseline specification in columns (1), (3), (5) for forecast horizons $k = 2, 4, 8$ respectively.[26] R^2 is 35.41% for forecast horizon $k = 2$ and decreases to 28.90% for forecast horizon $k = 8$. Therefore, time-invariant country-specific factors have a substantial importance but do not explain the main part of dispersion in forecasting performances. In addition, time-invariant factors become less important when forecast horizon increases.

We consider the same kind of robustness exercice as in section 4.1.2 to get a more cautious assessment of forecasting performances at the country level. For each forecast horizon, we have 480 alternative estimates of the baseline specification.[27] Results are reported in the last columns of Table 3 only for forecast horizons $k = 2, 4$ and 8 to save space. More precisely, Table 3 reports for forecast horizon $k = 2$: country ranking, the number of estimates per country, and the mean of estimated country-fixed effects. We notice first that the USA, France, India and Germany display the best performances with MAE lower than 2pp on average. Table 3 shows that country ranking does not depend much on forecast horizon. The USA, France, India and Germany always remain in the top 4 for instance. Second, countries in the bottom of the ranking are Malaysia, Thailand, Ireland and Indonesia, whatever the forecast horizon. MAE is already larger than 7pp at forecast horizon $k = 2$ in these countries. Third, Table 3 suggests that the reliability of predicted credit-to-GDP gaps and forecast-augmented credit-to-GDP gaps are not independent. The top and bottom of the rankings are quite similar in Table 3. Austria, South Africa, Canada, Mexico and Austalia are also always well ranked. Last, Table 3 confirms that forecasting performances substantially deteriorate with forecast horizon. MAE is larger than 5pp on average for forecast horizons $k = 8$ in top ranked countries for instance; indicating that MAE is multiplied by more that 2.5 from forecast horizon $k = 2$ to $k = 8$.

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Table 4. Determinants of forecasting performances for predicted credit-to-GDP gaps

	Estimates with the baseline sample						Robustness checks		
Horizon:	$k=2$		$k=4$		$k=8$		$k=2$		
								Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)
$MBoom_{i,\tau}$		0.90		2.87*		7.06**	coef	−0.10	−0.41
		(0.89)		(1.42)		(2.97)	t-sta	−0.22	−0.40
$LBoom_{i,\tau}$		6.55***		10.11***		24.36***	coef	4.54	4.96
		(1.25)		(2.45)		(7.78)	t-sta	2.95	2.72
$MBust_{i,\tau}$		2.84**		4.76***		9.36**	coef	1.37	0.97
		(1.09)		(1.47)		(3.49)	t-sta	1.05	1.04
$LBust_{i,\tau}$		6.80***		10.73***		24.26***	coef	6.62	6.31
		(1.84)		(3.43)		(7.67)	t-sta	2.84	2.75
$Peak_{i,\tau}$		0.68		1.86		7.41	coef	0.24	0.24
		(0.68)		(1.35)		(6.52)	t-sta	0.37	0.46
$Trough_{i,\tau}$		0.45		0.70		1.49	coef	−0.01	−0.06
		(0.70)		(1.13)		(2.09)	t-sta	−0.10	−0.10
$Level_{i,\tau}$		0.05**		0.10***		0.25***	coef	0.03	0.03
		(0.02)		(0.03)		(0.07)	t-sta	1.85	1.83
Intercept	5.71***	−5.55	8.67***	−13.73**	15.00***	−44.19**			
	(0.49)	(4.04)	(0.76)	(5.95)	(1.90)	(17.27)			
Country FE	Yes	Yes	Yes	Yes	Yes	Yes			
Time FE	No	Yes	No	Yes	No	Yes			
Num. countries	39	39	39	39	39	39			
Num. obs.	248	248	248	248	248	248			
R^2	0.3541	0.6512	0.3491	0.6276	0.2890	0.4649			

Variable definitions: the endogenous variable is the MAE of predicted credit-to-GDP gaps obtained by (recurrent) SSA at horizons $k = 2$, 4, 6 or 8 for country i during period τ. We consider 5-year periods to compute MAE in the baseline estimate starting in 1970q1. Period τ=1 corresponds therefore to 1965q2–1970q1. Variable *MBoom* is the frequency of medium boom episodes during period t (defined as one-sided credit-to-GDP gap between 2% and 10%); *LBoom* is the frequency of large boom episodes during period t (defined as one-sided credit-to-GDP gap larger than 10%). Variables *MBust* and *LBust* capture the frequency of medium bust and large bust episodes during period t respectively (defined with symmetrical thresholds, i.e., one-sided credit-to-GDP gap between −2% and −10%, and lower that −10% respectively). Variables *Peak* (resp. *Trough*) is a dummy variable equal to 1 if a peak (resp. a trough) is identified during period t by the turning point algorithm proposed by Harding and Pagan (2002). Variable *Level* is the level of the trend component of the credit-to-GDP ratio.

Note: ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. Robust standard errors are in brackets. Columns (7) and (8) summarizes the results of the robustness checks, reporting mean and median repectively of coefficients and t-statistics, computed over 960 alternative specifications (2 credit variables (broad and narrow) x 2 SSA forecasting methods (reccurent and vectorial) x 20 different starting dates for the sample (1970q1 to 1974q4) x 6 different durations to define periods (5 to 10 years) x 2 sets of fixed effects (with or without time-fixed effects)). Robustness checks concern only forecast horizon k = 2 to save space.

4.2.3 Credit market conditions and forecasting performances

We include the same set of time-varying covariates in the baseline specification (equation (5)) as in equation (4). Table 4 reports estimates for broad credit in columns (2), (4), (6) for forecast horizons $k = 2, 4, 8$ respectively. Focusing on forecast horizon $k = 2$ (columns (1) and (2)), R^2 increases from 35.41% to 65.12% when time-varying covariates are included in the model. Table 4 shows that large boom and bust episodes are the main contributors to this increase in R^2 . Such episodes are particularly detrimental for forecast performances: MAE at forecast horizon $k = 2$ (columns (2)) increases by more than 6.5pp during such episodes for instance. Medium boom and bust episodes have a lower impact of forecasting performances; medium boom episodes can even have no significant effect on MAE at the 10% level for short forecast horizons. Peak and trough

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periods in credit-to-GDP ratio also have no significant effect at the 10% level on forecasting performances, for all forecast horizons. Last, Table 4 shows a positive relationship between banking sector development (captured by variable $Level_{i,\tau}$) and MAE. However, estimated parameters suggest a rather limited effect of financial development on forecasting performances: a 10pp increase in trend component of the credit-to-GDP ratio leads to a 0.5pp increase in MAE.

The robustness of the results reported in Table 4 is investigated by a large set of alternative specifications. The robustness exercice covers 2 credit variables (broad credit or narrow credit); 2 SSA forecasting methods (recurrent or vectorial); 20 starting dates (1970q1, 1970q2,. . ., or 1974q4); 6 durations to define periods (5-year periods, 6-year periods,. . ., or 10 year periods); and 2 set for fixed effects (with or without time-fixed effects). Therefore, we consider 960 alternative specifications per forecast horizons. Results are reported in culumns (7) and (8) of Table 4, only for forecast horizon $k = 2$ to save space. These results confirm the main finding we get from baseline estimates. First, large boom and bust episodes are the two main time-varying drivers that disturb forecasting performances. Large boom and bust episodes magnify MAE for forecast horizon $k = 2$ by 4.54pp and 6.62pp respectively (on average across all the alternative specifications). Second, other characteristics of credit cycle do not mitigate forecasting performances. Medium boom and bust episodes do not significantly affect MAE at the 10% level in most specifications, as peak and trough. Last, banking sector development positively affect MAE at the 10% level in most specifications and then deteriorate forecasting performances. The estimated parameter is 0.03 on average for forecast horizon $k = 2$, suggesting a slightly disruptive effect.

5. Reliability of forecast-based credit-to-GDP gaps

The reliability of one-sided credit-to-GDP gaps is questioned in the literature (see e.g., Edge and Meisenzahl (2011) and Alessandri et al. (2021)). The difference between one-sided and two-sided credit-to-GDP gaps is commonly used to highlight that credit-to-GDP gaps may not be accurately assessed when only real-time data is taken into account. Notably, disparities between one-sided and two-sided credit-to-GDP gaps can exhibit considerable magnitude over a given time span. Edge and Meisenzahl (2011) and Alessandri et al. (2021) put forward that, on average, these disparities are as substantial as the average size of credit gaps. The main objective of forecast-based credit-to-GDP gaps is to provide complementary information available in real time to better capture the build-up of imbalances and to legitimize precautionary measures to ensure financial stability. As a result, our attention is directed towards credit boom episodes identified through the utilization of two-sided credit-to-GDP gaps. Our inquiry seeks to determine whether forecast-based credit-to-GDP gaps offer valuable insights for more accurate predictions of credit boom episodes.[28]

5.1 Prediction of credit booms

We adopt the definitions proposed by Barajas et al. (2007) and Mendoza and Terrones (2008) to identify credit booms (henceforth BDL and MT, respectively).[29] Further, we also rely on a "regulatory" definition of credit booms: credit booms are associated with periods with credit gaps higher than 2%. This aligns with the criteria where the CCyB might be activated, as specified in the BCBS guidelines (BCBS (2010)).[30] We employ these three alternative definitions of credit booms in our analysis to ensure robustness. Table 5 presents descriptive statistics on credit booms, with all three credit boom definitions applied using two-sided credit-to-GDP gaps for both broad credit (Panel A) and narrow credit (Panel B). The MT and BDL definitions yield a relatively similar number of credit booms (76 and 63, respectively, for broad credit, for example). The primary difference lies in the duration of credit booms, with MT averaging 4.17 years, while BDL averages 2.25 years for broad credit, for instance. This implies that, according to the MT and BDL definitions, countries

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Table 5. Identification of credit booms

Panel A: Credit to the private sector (i.e., broad credit)						
	Number of	Number of	Freq. of		Duration (in years)	
Credit booms	countries	booms	booms	Mean	95% pct.	Max.
MT	40	76	.18	4.17	9	12.75
BDL	32	63	.08	2.25	5	5.75
Regulatory	41	135	.35	4.36	9.5	13.25
Panel B: Bank credit (i.e., narrow credit)						
	Number of	Number of	Freq. of		Duration (in years)	
Credit booms	countries	booms	booms	Mean	95% pct.	Max.
MT	36	68	.16	4.31	7.5	11.5
BDL	30	59	.09	2.71	6.25	7.5
Regulatory	41	117	.3	4.45	9.25	13.75

Note: Credit-to-GDP gaps are computed by two-sided SSA. We rely first on Mendoza and Terrones (2008) and Barajas et al. (2007) to identify credit booms, called MT and BDL credit booms respectively. In addition, we define regulatory credit booms as periods with credit-to-GDP gaps higher than 2% during at least 4 consecutive quarters. We consider 41 countries (Luxembourg and Russia are excluded from the initial sample of 43 countries due to limited data availability) with samples ending in 2019q4. The number of countries reported in the table corresponds to countries (over 41) that experienced at least one credit boom. Freq. of booms is the proportion of time countries spend in credit booms.

experience credit booms for approximately 18% and 8% of the time, respectively. In contrast, the regulatory definition of credit booms results in a more lenient identification of such periods. We identify 135 credit booms for broad credit, with an average duration of 4.36 years, signifying that countries experience credit booms for approximately 35% of the time.

We shift our focus to a more specific event: the probability of entering a credit boom. We employ a pooled logit model as the link function:

$$P(CB_{i,t}^{ts}=1)=\frac{1}{1+\exp\left[-\alpha-\beta CY_{i,t}^{os}-\gamma FBCY_{i,t}^{os}\right]}, \tag{6}$$

where the subscripts refer to country i in period t. The variable $CB_{i,t}^{ts}$ is a binary variable that is equal to 1 if a credit boom identified with two-sided credit-to-GDP gap occurs and 0 otherwise, $CY_{i,t}^{os}$ is the one-sided credit-to-GDP gap, $FBCY_{i,t}^{os}$ is an indicator (or a set of indicators) derived from forecast-based credit-to-GDP gaps.[31] Parameters α, β and γ are estimated by maximum likelihood, with standard errors computed via the clustered version (at the country level) of the Huber-White estimator for robustness against heteroscedasticity. Further, credit booms often extend over multiple quarters, constituting multiquarter events. However, the pooled logit model assumes independence between observations. To address this, we apply a common data treatment by retaining only the initial period of these multiperiod events. This allows us to consider observations as independent from each other.

We consider two categories of indicators derived from forecast-based credit-to-GDP gaps to represent the variable $FBCY_{i,t}^{os}$. Firstly, we examine difference between the one-sided credit-to-GDP gap and the forecast-augmented credit-to-GDP gap ($CY_{i,t}^{os}-CY_{i,t}^{RFA12}$). The end-of-sample problem associated with the one-sided credit-to-GDP gap implies that rapid increases in credit activities in the near future are not anticipated. As a result, these increases are not factored into the assessment of the trend-cycle decomposition. Consequently, the current trend in credit-to-GDP ratio may be underestimated, with a significant portion of the credit expansion allocated to the cyclical component. This effect may become particularly pronounced when the trend dynamics are exceptionally smooth. The forecast-augmented credit-to-GDP gap is designed to address this end-of-sample problem. Consequently, during credit boom periods, one-sided credit-to-GDP gap and forecast-augmented credit-to-GDP gap may diverge, with the one-sided credit-to-GDP

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Table 6. Prediction of credit booms

	MT credit booms				BDL credit booms				Regulatory credit booms			
	Broad credit		Narrow credit		Broad credit		Narrow credit		Broad credit		Narrow credit	
	1.a	2.a	3.a	4.a	1.b	2.b	3.b	4.b	1.c	2.c	3.c	4.c
$CY^{os}_{i,t}$	0.07***	0.08***	0.01	0.07***	0.01	0.05***	−0.00	0.07***	0.04***	0.08***	0.08***	0.11***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)
$CY^{os}_{i,t}-CY^{RFA12}_{i,t}$	0.05		0.24***		0.15***		0.28***		0.12***		0.11*	
	(0.04)		(0.04)		(0.02)		(0.04)		(0.03)		(0.06)	
$CY^{RP4}_{i,t}-CY^{os}_{i,t}$		0.01		0.06***		0.04***		0.07***		0.03***		0.04***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
Log likelihood	−288.27	−288.86	−252.82	−254.02	−264.96	−267.82	−243.09	−245.39	−472.98	−474.45	−425.94	−425.16
Pseudo−R^2	0.1243	0.1225	0.1240	0.1198	0.1105	0.1009	0.1096	0.1012	0.1113	0.1086	0.1179	0.1195
Num. countries	41	41	41	41	41	41	41	41	41	41	41	41
Num. obs.	5357	5357	5407	5407	5907	5907	5786	5786	4254	4254	4479	4479
Num. booms	60	60	51	51	52	52	47	47	116	116	101	101
AUROC curve	0.8288	0.8273	0.8317	0.8369	0.7832	0.7801	0.8165	0.8205	0.7864	0.7853	0.8073	0.8139
AUROC test	1.31	0.88	3.62	5.45	9.79	8.32	3.94	5.43	3.59	3.66	3.66	7.68
$p-value$	0.25	0.35	0.06	0.02	0.00	0.00	0.05	0.02	0.06	0.06	0.06	0.01
Robustness checks (average over 80 alternative specifications)												
AUROC curve ($CY^{os}_{i,t}$ only)	0.8263	0.8263	0.8016	0.8016	0.6544	0.6544	0.6588	0.6588	0.8041	0.8041	0.8209	0.8209
AUROC curve (Full model)	0.8413	0.8360	0.8434	0.8368	0.7699	0.7532	0.8036	0.7892	0.8247	0.8174	0.8403	0.8360

Variable definitions: CY^{os}: credit-to-GDP gap obtained through one-sided SSA; CY^{RFA12}: forecast-augmented credit-to-GDP gap (with forecasts extending by 12 periods); CY^{RP4}: predicted credit-to-GDP gap at horizon 4. These forecast-based credit-to-GDP gaps are derived using recurrent SSA forecasting.

Note: ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. Robust standard errors are in brackets. We calculate credit-to-GDP gaps using SSA. Credit booms are identified using two-sided credit-to-GDP gaps. Specifically, MT and BDL refer to credit booms identified with definitions based on Mendoza and Terrones (2008) and Barajas et al. (2007), respectively. We define regulatory credit booms as periods where credit-to-GDP gaps remain above 2% for at least four consecutive quarters. We consider an unbalanced sample ending in 2019q4 for the baseline analysis. The bottom lines in the table summarize the results of the robustness checks, reporting the average AUROC curve computed over 80 alternative specifications when the model only includes the one-sided credit-to-GDP gap and when forecast-based credit-to-GDP gaps are also added. The alternative specifications encompass 2 filters (SSA and HP) x 2 forecasting methods (reccurent and vectorial) x 4 forecast horizons for generating forecast-based credit-to-GDP gaps x 5 different end dates (q4 of 2015 to 2019) for the sample.

gap potentially exceeding the forecast-augmented credit-to-GDP gap during the initial phase of a credit boom.[32]

Secondly, we consider the difference between the predicted credit-to-GDP gap at horizon 4 and the one-sided credit-to-GDP gap ($CY^{RFor4}_{i,t}-CY^{os}_{i,t}$). The primary purpose of this variable is to ascertain whether larger imbalances are expected in the forthcoming periods. Positive differences signify an anticipation of cyclical credit activities expanding over the next year. This information can be valuable for predicting the onset of a credit boom episode in the economy.

The estimates are presented in Table 6.[33] The predictive power of the model is assessed by the AUROC curve. For broad credit, the AUROC curve values are around 0.82 for MT credit booms and 0.78 for BDL and regulatory credit booms. These results suggest that the predictive power of one-sided credit gaps can be considered excellent for MT credit booms and acceptable for BDL and regulatory credit booms. Additionally, the forecast-augmented credit-to-GDP gap, especially its difference with the one-sided credit-to-GDP gap, provides valuable information for predicting credit booms. The coefficient associated with the variable ($CY^{os}_{i,t}-CY^{RFA12}_{i,t}$) is significant at the 1% or 10% level in the estimated models reported in Tables 6, except when both broad credit and MT credit booms are considered. Furthermore, the AUROC test (DeLong et al. (1988)) shows that including the variable ($CY^{os}_{i,t}-CY^{RFA12}_{i,t}$) in the model can significantly enhance the AUROC curve.

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Predicted credit-to-GDP gaps also offer valuable information for predicting credit booms. The coefficient associated with the variable $(CY_{i,t}^{RFor4} - CY_{i,t}^{os})$ is significant at the 1% level in most estimated specifications in Table 6, with the exception of when both broad credit and MT credit booms are considered. In addition, the AUROC test shows that including the variable $(CY_{i,t}^{RFor4} - CY_{i,t}^{os})$ can significantly improve the predictive power of the model. The difference between the predicted credit-to-GDP gap at horizon 8 and the predicted credit-to-GDP gap at horizon 4 $(CY_{i,t}^{RFor8} - CY_{i,t}^{RFor4})$ has also been added for robustness checks to include a second indicator based on predicted credit-to-GDP gaps. However, the additional information provided by this variable was rarely significant at the 10% level. Therefore, a single indicator based on predicted credit-to-GDP gaps performs well in accounting for future expected expansions in credit market imbalances.

5.2 Robustness checks

We investigate the robustness of these results by considering a large set of alternative specifications. In baseline estimates of equation (6) reported in Table 6, we rely on SSA to derive the variable $CY_{i,t}^{os}$, and we rely on recurrent SSA forecasting to generate the $FBCY_{i,t}^{os}$ indicators. In addition, forecast-augmented credit-to-GDP gaps are derived from series extended by 12 periods; and we focus on predicted credit gaps at horizon 4. Last, the sample ends in 2019q4 in our baseline estimates. However, two-sided credit-to-GDP gaps are also exposed to the end-of-sample problem. Thus, some of the later periods may be excluded to mitigate this problem.

For our robustness checks, we explore two distinct filters for generating the variable $CY_{i,t}^{os}$ (SSA and HP), two forecasting methods (reccurent and vectorial) to compute the $FBCY_{i,t}^{os}$ indicators, 4 different horizons for generating forecast-augmented credit-to-GDP gaps (8, 12, 16, 20), 4 different horizons for predicted credit-to-GDP gaps (2, 4, 6, 8), and 5 different end dates (q4 of 2015 to 2019). As a result, we encompass a total of 80 alternative specifications for forecast-augmented credit-to-GDP gaps and an additional 80 alternative specifications for predicted credit-to-GDP gaps. These comprehensive robustness checks are conducted for the two credit agregate (broad and narrow) and the 3 credit boom definitions (MT, BDL and regulatory). At the bottom of Table 6, we report the average AUROC curve when the model only includes the one-sided credit-to-GDP gap and when forecast-based credit-to-GDP gaps are also added. These robustness checks validate our key findings, demonstrating that forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps consistently provide supplementary valuable information for detecting credit booms.[34] The average AUROC curve consistently increases when indicators computed from forecast-based credit-to-GDP gaps are incorporated into our estimated specifications.

5.3 Illustration

Figure 4 illustrates the behavior of the one-sided credit-to-GDP gap (Figure 4-a) and indicators derived from forecast-based credit-to-GDP gaps (Figure 4-b & c) in the periods leading up to a credit boom. To model the behavior of these variables, we employ restricted cubic spline functions.[35] We focus on BDL credit booms and broad credit in Figure 4 to save space. Figure 4-a illustrates why the one-sided credit-to-GDP gap serves as a reliable predictor of credit booms. This metric starts to exhibit notable growth well in advance of the credit boom's commencement, surging to over 3% in the year preceding the credit boom. As demonstrated in Table 6, the difference between the one-sided credit-to-GDP gap and the forecast-augmented credit-to-GDP gap offers valuable additional insights into predicting a credit boom. Figure 4-b highlights that this indicator gradually increases several years prior to a credit boom, eventually surpassing a 2-percentage-point threshold. In other words, the one-sided credit-to-GDP gap overshoots the forecast-augmented credit-to-GDP gap by more than 2 percentage points before a credit boom.

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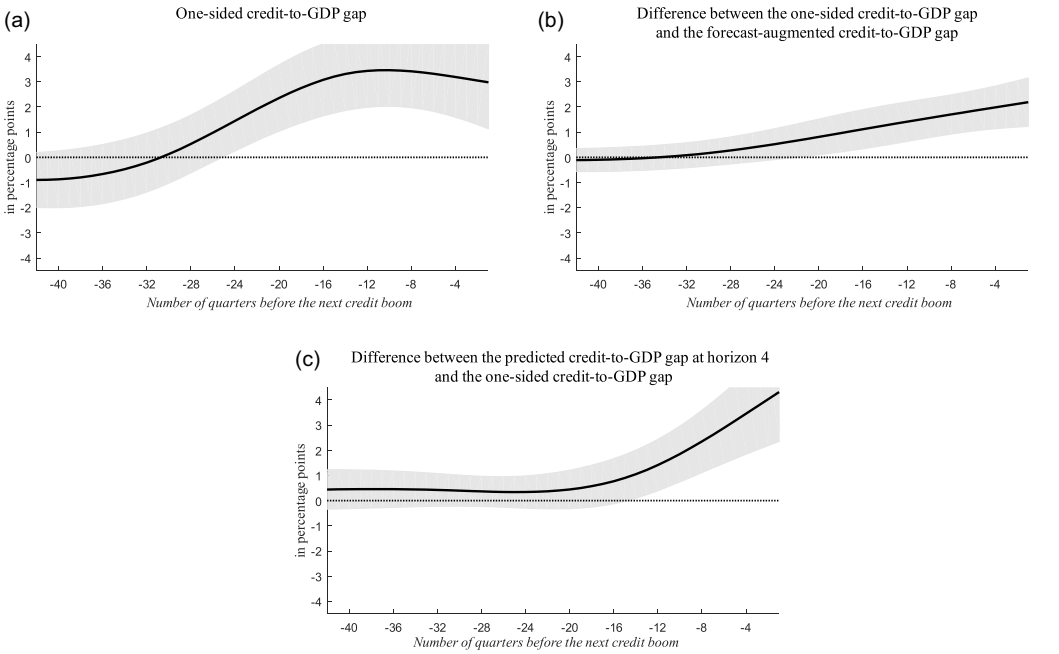


Figure 4. Behavior of credit-to-GDP gaps before a credit boom. *Note*: the gray area corresponds to the one-standard error band.

The difference between the predicted credit-to-GDP gap at horizon 4 and the one-sided credit-to-GDP gap (Figure 4-c) exhibits a more pronounced change before a credit boom. The predicted credit-to-GDP gap at horizon 4 experiences rapid growth and becomes 4 percentage points higher than the one-sided credit-to-GDP gap prior to a credit boom. Consequently, the predicted credit-to-GDP gap captures the fact that credit activities are set to continue expanding rapidly, with the peak yet to come.

From a macro-prudential standpoint, Figure 4 suggests that banking supervisors should rely on both the forecast-augmented credit-to-GDP gap and the predicted credit-to-GDP gap to identify shifts in the macro-financial environment. The risk of a credit boom becomes evident when the one-sided credit-to-GDP gap exceeds 3%. This signal becomes notably more reliable if the one-sided credit-to-GDP gap overshoots the forecast-augmented credit-to-GDP gap by more than 2 percentage points, and if the predicted credit-to-GDP gap indicates that the credit-to-GDP gap will increase by more than 4 percentage points in the upcoming year.

6. Conclusion

For over a decade, banking supervisors in BCBS member countries have been developing their operational frameworks to detect shifts in their macro-financial environments and subsequently adjust the CCyB rate accordingly. Credit metrics, and particularly one-sided credit-to-GDP gaps play a pivotal role in these operational frameworks. Moreover, several banking regulators have recognized the potential value of forecast-augmented credit-to-GDP gaps and have incorporated this credit metric into their core set of indicators. The primary goal of forecast-augmented credit-to-GDP gaps is to address the end-of-sample problem faced by one-sided credit-to-GDP gaps.

In this paper, we propose to leverage SSA to derive forecast-augmented credit-to-GDP gaps. SSA serves as an "all-in-one" method that enables both the decomposition and forecasting of time series. Additionally, we introduce a novel credit metric: the predicted credit-to-GDP gaps.

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The fundamental aim of this credit metric is to introduce a forward-looking perspective into the CCyB policy framework.

First, we evaluate the accuracy of these two forecast-based credit-to-GDP gaps. Our findings indicate that forecasting accuracy varies significantly across countries. For example, the USA, France, India, and Germany exhibit robust forecasting performances, while Malaysia, Thailand, Ireland, and Indonesia show the poorest forecasting performances. In addition, we show that forecasting accuracy is time-varying and depends on credit market conditions. Large boom and bust periods are associated with reduced forecasting accuracy, although such declines are not evident during the early stages of a credit boom.

Second, we establish that both forecast-augmented credit-to-GDP gaps and predicted credit-to-GDP gaps provide valuable insights for identifying the early stages of a credit boom. During this period, the one-sided credit-to-GDP gap naturally becomes prominent. Additionally, we find that before a credit boom: (i) the predicted credit-to-GDP gap effectively captures the acceleration of credit expansion, and (ii) the forecast-augmented credit-to GDP gap is overshot by the one-sided credit-to-GDP gap.

Our findings hold substantial value for banking supervisors seeking to strengthen their CCyB policy framework. The one-sided credit-to-GDP gap, often known as the BCG, requires complementary credit metrics to detect macro-financial environment shifts effectively. Forecast-based credit-to-GDP gaps, obtained through SSA, can provide valuable supplementary information, significantly improving the identification of imbalances in credit dynamics. Moreover, the accuracy and reliability of forecast-based credit-to-GDP gaps are relevant to a broader audience beyond BCBS members. According to a survey conducted by the Financial Stability Institute (FSI) among 100 non-BCBS member jurisdictions, more than 75% of them are in various stages of CCyB implementation or are considering it (Hohl et al. (2018)). Consequently, all these countries must establish their CCyB policy framework and grapple with the end-of-sample problem when assessing credit-to-GDP gaps.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1365100525100254.

Notes

1 To estimate the trend component of the credit-to-GDP ratio, a one-sided Hodrick and Prescott (1980, 1997) (HP) filter (specified to account for the long duration of the credit cycle) is applied. The BCG is calculated as the difference between the credit-to-GDP ratio and its estimated trend. The standard formula for setting the CCyB rate is $0.3125 \times BCG - 0.625$ when the BCG $\in$ [2%;10%]. If the BCG is below 2%, the CCyB rate is set at 0%, while it is set at 2.5% when the BCG exceeds 10%.

2 Note that forecast-augmented credit-to-GDP gaps rely on forecasts of the credit-to-GDP ratio solely to refine the assessment of the current gap. While this approach improves real-time evaluation, it does not provide any insight into the future trajectory of the credit-to-GDP gap over the coming quarters. In contrast, predicted credit-to-GDP gaps are explicitly designed to predict the future evolution of the gap.

3 See Golyandina et al. (2001) and Golyandina and Zhigljavsky (2013) for general overview of SSA and Hassani and Thomakos (2010) for a literature review on SSA in economics and finance. Bouvatier et al. (2022) and Coussin (2022) have used SSA to assess credit-to-GDP gaps and financial cycles, respectively. However, these papers do not rely on SSA forecasting.

4 We base our analysis on the BIS database of credit statistics (Dembiermont et al. (2013)), which comprises an unbalanced panel of 43 countries.

5 Common practice is to rely on the *BCG* only when $t > 40$ because the one-sided HP filter is sensitive to the starting points when small samples are considered. Therefore, a minimum of 10 years of quarterly data is required to begin reporting the BCG (BCBS (2010)).

6 Alessandri et al. (2015) and Alessandri et al. (2021) propose an alternative approach: a correction factor is applied to the one-sided credit-to-GDP gap, with the correction factor depending on the disparity between the one- and two-sided credit-to-GDP gaps.

7 The term "real-time" is employed for reasons of convenience. In fact, a pseudo real-time approach is used, since the sample size of historical data is adjusted to generate different vintages.

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8 The trajectory matrix $\mathbf{Y}$ for the time series $\left(y_t\right)_{t=1}^{T}$ is given by:

$$\mathbf{Y} = \begin{bmatrix} y_1 & y_2 & \cdots & y_K \\ y_2 & y_3 & \cdots & y_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & \cdots & y_T \end{bmatrix}.$$

9 When attempting to decompose time series into a greater number of components, it is advisable to employ longer window lengths.

10 An important advantage of this approach is that it obviates the need to pre-specify a frequency cut-off to identify the long-term secular trend.

11 For the sake of brevity, descriptive statistics and figures related to the choice of the window length and the grouping method are provided in the web appendix.

12 It is notable that the forecasts of the trend-cycle component are identical to those of the credit-to-GDP ratio, which are employed to generate forecast-augmented credit-to-GDP gaps. Consequently, the two forecast-based credit-to-GDP gaps utilize the same forecasts of the credit-to-GDP ratio, despite serving disparate objectives.

13 Narrow credit is derived from monetary surveys and is reflective of banks' balance sheets, while broad credit is computed using sectoral financial accounts and includes, among other components, debt securities issued by non-financial corporations.

14 The BIS database on credit statistics is updated quarterly. The dataset retrieved ends in 2021Q2. However, we do not rely on observations after 2019Q4 to assess the two-sided credit-to-GDP gaps. As a result, the covid-19 pandemic period does not affect the two-sided credit-to-GDP gaps used in this paper.

15 Similar patterns are also observed in other countries. For illustration, the web appendix includes the same figure to cover the world's ten largest economies by nominal GDP: the United States, China, Germany, Japan, India, the United Kingdom, Italy, Canada, and Brazil.

16 Both credit metrics depends on forecasted credit-to-GDP ratios. In a preliminary analysis, we investigated forecast accuracy concerning credit-to-GDP ratios. This preliminary analysis is reported in a web appendix to save space.

17 A two-sided credit-to-GDP gap might seem like a natural candidate, but it presents two major drawbacks when assessing the accuracy of forecast-augmented credit-to-GDP gaps. Firstly, targeting a two-sided credit-to-GDP gap may be overly optimistic from an operational perspective. For a given period t, one use all the future path of the credit-to-GDP ratio (i.e., up to period T) to generate a two-sided credit-to-GDP gap. However, it is unrealistic from an operational standpoint to expect forecasters to predict credit-to-GDP ratios accurately over extended time horizons. In other words, we do not aim for a perfect match between the forecast-augmented credit-to-GDP gap and the two-sided credit-to-GDP gap for a given period t when $T - t$ is large. Second, the two-sided credit-to-GDP gap would not serve as a suitable benchmark in a cross-validation procedure. The accuracy would tend to improve for more recent observations since one-sided credit-to-GDP gaps, by definition, converge to two-sided credit-to-GDP gaps as the full sample is considered. Consequently, the accuracy of forecast-augmented credit-to-GDP gaps would be skewed towards higher values for the most recent data points.

18 Note that our data sample ends in 2019Q4. Additionally, a 5-year horizon is necessary to generate the benchmark (i.e., forecast-augmented credit-to-GDP gaps using perfect forecasts). Consequently, the cross-validation procedure concludes in 2014Q4. This data requirement has resulted in the exclusion of Luxembourg and Russia from the cross-validation process.

19 For robustness checks, we also relied on: (*i*) vector SSA forecasting (instead of recurrent SSA forecasting) to generate forecast-augmented credit-to-GDP gaps; (*ii*) the Euclidean distance (rather than the Manhattan distance) to assess the accuracy of forecast-augmented credit-to-GDP gaps. We reach similar conclusions.

20 This data requirement has resulted in the exclusion of Brazil from the country ranking. Note that the maximum number of periods is 9, with the average number of periods per country totaling 6.

21 For robustness checks, we also consider the Euclidean distance instead of the Manhattan distance. By defintion, scales of Manhattan and Euclidean distances are not comparable. Therefore robustness checks concerning distance measures need to be considered separately when we focus on estimated parameters.

22 The definition of credit booms is established using numerical thresholds, aligning with the BCBS guidelines (BCBS (2010)). The primary aim is to identify periods during which banking supervisors might consider activating the CCyB to mitigate excessive credit activities.

23 To capture the characteristics of credit cycles, we rely on the medium-term algorithm proposed by Drehmann et al. (2012).

24 To be more specific, these alternative specifications encompass: 2 credit variables (broad credit or narrow credit); 2 SSA forecasting methods (recurrent or vectorial); 4 forecast horizons used to generate forecast-augmented credit-to-GDP gaps by SSA ($h = 8$, 12, 16 or 20); 20 starting dates (1970q1, 1970q2,. . ., or 1974q4); 6 durations to define periods (5-year periods, 6-year periods,. . ., or 10 year periods); 2 set for fixed effects (with or without time-fixed effects).

25 For robustnesse checks, we also relied on: (*i*) vector SSA forecasting (instead of recurrent SSA forecasting) to generate predicted credit-to-GDP gaps; (*ii*) RMSE (instead of MAE) to assess the reliability of predicted credit-to-GDP gaps. We reach similar conclusions.

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26 We do not report results for all forecast horizons to save space. These results are available upon request.
27 We consider 2 credit variables (broad credit or narrow credit), 2 SSA forecasting methods (recurrent or vectorial), 20 different starting dates (1970q1, 1970q2,. . ., or 1974q4) and 6 durations to define periods (5-year periods, 6-year periods,. . ., or 10 year periods). For robustness checks, we also consider the euclidean distance (i.e., RMSE) instead of the manhattan distance (i.e., MAE) to run the robustness exercice.
28 We interpret credit boom episodes as major changes in the macro-financial environment. We do not focus on systemic banking crises in this paper. A preliminary analysis suggested that forecast-based credit-to-GDP gaps do not significantly improve prediction of systemic banking crises on average. Heterogeneity in the accuracy of forecast-based credit-to-GDP gaps might explain this result. However, the limited number of banking crises (around 30 in countries surveyed in this paper) make this heterogeneity difficult to handle. We leave this issue out of the scope of this paper.
29 A notable distinction between the BDL and MT definitions of credit booms lies in the trigger events used to identify them. Under the BDL definition, a credit boom occurs if one of the following conditions is observed: (i) the credit-to-GDP gap exceeds 1.5 times its standard deviation, and the year-on-year growth rate in the credit-to-GDP ratio surpasses 10%; (ii) the year-on-year growth rate in the credit-to-GDP ratio exceeds 20%. In the MT definition, a credit boom occurs if the credit-to-GDP gap exceeds 1.75 times its standard deviation. Furthermore, when identifying the starting and ending points of a credit boom, BDL and MT employ similar criteria, albeit with distinct thresholds. In the case of BDL, the starting point is determined when: (i) the credit-to-GDP gap surpasses 0.75 times its standard deviation, and the year-on-year growth rate in the credit-to-GDP ratio exceeds 5%; (ii) the year-on-year growth rate in the credit-to-GDP ratio exceeds 10%. The ending point is reached when: (i) the credit-to-GDP gap falls below 0.75 times its standard deviation, and the year-on-year growth rate in the credit-to-GDP ratio drops below 20%; (ii) the year-on-year growth rate in the credit-to-GDP ratio turns negative. In the MT definition, the starting point occurs when the credit-to-GDP gap exceeds 1 times its standard deviation, and the ending point takes place when the credit-to-GDP gap falls below 1 times its standard deviation. Note that both BDL and MT propose country-and-time-specific definitions of credit booms: the thresholds rely on backward-looking country-specific standard deviations. Last, note that Mendoza and Terrones (2008) use credit per capita while we rely on credit-to-GDP ratio in this paper.
30 More precisely, the trigger event for identifying a credit boom is when the credit-to-GDP gap exceeds 2% for four consecutive quarters. We also assume that a credit boom concludes when the credit-to-GDP gap falls below 2% for two consecutive quarters.
31 We do not account in the model for heterogeneity in the accuracy of $FBCY^{os}_{i,t}$ highlighted in section 4. Due to the limited number of events (i.e., credit boom) identified in the sample), accounting for such heterogeneity is challenging and we focus on the average effect of $FBCY^{os}_{i,t}$.
32 This observation is in line with a stylized fact proposed by Alessandri et al. (2021): the one-sided credit-to-GDP gap tends to overshoot the two-sided credit-to-GDP gap. Consequently, the difference between the two-sided and one-sided credit-to-GDP gaps exhibits a negative correlation with the one-sided credit-to-GDP gap.
33 In Table 6, we employ SSA to generate all variables, thereby ensuring methodological consistency since the forecasts are generated by SSA. Nevertheless, the identification of credit booms and the one-sided credit-to-GDP gap could have been derived from the HP filter. A larger set of robustness checks is considered in the next sub-section.
34 As a robustness check, we also restrict the analysis to bad credit booms, as defined by Gorton & Ordoñez (2019). The results, which lead to similar conclusions, are reported in the web appendix.
35 See Poirier (1976) for a general presentation of spline functions, and Bouvatier et al. (2022) for an application with credit-to-GDP gaps.

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