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A COMPOSITE INDICATOR OF SYSTEMIC RISK RELATED TO THE ITALIAN FINANCIAL CYCLE

by Luca Moller*

Abstract

Financial cycles, i.e. the boom-bust dynamics that characterize modern decentralized economies, are a key driver of financial crises and subsequent economic downturns. Countercyclical macroprudential policy aims to mitigate these risks by strengthening the resilience of the financial system during the expansionary phases, mostly using the countercyclical capital buffer (CCyB) as an instrument. While the credit-to-GDP gap is the standard reference guide used for calibrating the CCyB, its limitations in capturing the full spectrum of financial cycle dynamics have become increasingly apparent. A growing number of macroprudential authorities are supplementing the credit gap with additional indicators to inform CCyB rate decisions, placing increasing emphasis on composite indicators of the financial cycle. This paper proposes a composite indicator of systemic risk related to the Italian financial cycle (Cyclical Risk Indicator, CRI). The CRI is constructed as a weighted average of the best performing financial cycle indicators, offering a comprehensive assessment of systemic cyclical risk. Empirical analysis shows that the CRI provides additional information for the early warning of financial distress and of tail macroeconomic outcomes relative to the credit gap. By adopting the CRI, the Italian macroprudential authority may gain a more nuanced understanding of financial cycle dynamics, enabling more informed and timely policy decisions. This, in turn, would lead to a more resilient financial system and mitigate the impact of future financial crises.

JEL Classification: E32, E44, E58, G01, G28.

Keywords: composite indicator, cyclical systemic risk, early warning indicators, financial cycle, financial stability, macroprudential policy.

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1. Introduction

Stability is destabilizing. This sentence of Hyman P. Minsky (1982) conveys a fundamental characteristic of financial system dynamics. It recalls the essential notion of the financial cycle, i.e. the succession of phases of financial expansion and contraction, or booms and busts, that characterize modern decentralized economies, shaping their development both in the short and in the long-term. The basic idea is that stability sets the stage for financial booms, during which the interplay of declining risk aversion, easing financing conditions, rising asset prices and capital inflows, leads to the accumulation of vulnerabilities in the financial position of economic agents (Borio, 2014). Eventually, these vulnerabilities materialize, prompting financial distress, slowing down economic activity and, in the worst cases, giving way to an outright financial crisis (Borio et al., 2018). The contraction phase thus ensues. In other words, macro-financial stability frees the forces that endogenously drive the system to an unstable position, sowing the seeds of the next financial crisis.[1]

In turn, financial crises may have serious macroeconomic repercussions, leading to deep recessions and to slow recoveries, with significant implications for public finances (Classens and Kose, 2013). For this reason, one of the prime objective of macroprudential policy is to ensure that the financial sector is able to withstand episodes of system wide financial distress, so that it can support the subsequent recovery rather than act as a further amplifier of the crisis. In doing so, macroprudential policy needs to take into account the evolution of the financial cycle, i.e. acts countercyclically, further strengthening the resilience of the financial system during booms, when the likelihood of a crash is higher. In this way, macroprudential policy contributes to soften the cycle itself, safeguarding the stability of the financial system as a whole (ESRB, 2018).

The main macroprudential instrument serving this purpose is the countercyclical capital buffer (CCyB) introduced by the Basel III reform. The standard reference used to calibrate the CCyB is the aggregate private sector credit-to-GDP gap, meant to capture the credit cycle (BCBS 2010, ESRB 2014). While conceptually narrower than the financial cycle, the credit cycle is widely recognized as the main driver of the former and (credit booms) as a major cause of financial crises (Mendoza and Terrones, 2008, Dell'Ariccia et al., 2012, Schularick and Taylor, 2012, Jordà et al., 2015). The credit gap, i.e. the deviation of the credit-to-GDP ratio from its long-term trend, has been extensively proven to be among the best predictor of banking crises (Borio and Lowe, 2002, Drehmann et al., 2011, Behn et al., 2013, Detken et al., 2014). Moreover, having a single (easy to calculate and widely available) indicator as the benchmark to set countercyclical macroprudential measures across countries has many advantages from a policy perspective, as it improves transparency, consistency and compliance.

However, the credit gap may not be a sufficient statistic of the financial cycle. The BCBS (2010) itself acknowledges that, while it serves as a necessary common reference for anchoring buffer decisions, it does not always work well in all jurisdictions at all times and may provide misleading signals in some circumstances.[2] Authorities are therefore required to apply judgment in the setting of the CCyB and to cross-check the signal provided by the credit gap with those of other relevant indicators of cyclical risk. Similarly, the ESRB Recommendation 2014/1 enforces the principle of "guided discretion" and points out that other variables may complement the credit gap for monitoring the build-up of systemic risk. In particular, it recommends to monitor measures of: 1) potential overvaluation of property prices; 2) credit

[1] Financial crises may have different roots and may take different forms, including balance of payment and currency crises, banking crises, sovereign debt crises or the implosion of asset price bubbles.

[2] See Jokipii et al. (2021) for an overview of the literature pointing to the shortcomings of the credit-to-GDP gap as a guide to countercyclical macroprudential policy. Drehmann and Tsatsaronis (2014) provides a critical assessment of earlier critiques.

developments; 3) external imbalances; 4) banks' balance sheet strength; 5) private sector debt burden; 6) potential mispricing of risk.

Past research have indeed shown the importance of using multivariate models to accurately characterize the financial cycle, as no single measure is able to capture all the relevant developments in the financial system (Drehmann et al., 2012, Deutsche Bundesbank Monthly Report, January 2019, Baba et al. 2020, Franta, 2023). Similarly, it has been extensively documented that, while credit growth is a good predictor of financial crises, the performance of early warning models can be significantly improved by adding a number of macrofinancial variables that are not necessarily related in a direct way to credit dynamics (Stremmel, 2015, Borio et al., 2018, Tölö et al., 2018, Aldasoro et al., 2018, Alessi and Detken, 2018, Greenwood et al., 2020, Iossifov and Schmidt, 2021, Alessandri et al., 2022). A consensus seems to be emerged that credit and house price growth form the minimum set of indicators needed for an effective monitoring of cyclical risks. A few contributions in the literature highlight the usefulness of constructing composite indicators of the financial cycle – i.e. indicators that combine several variables, each of which captures a specific aspect of the phenomenon – and show that they have better early warning properties not only with respect to the credit gap, but also with respect to other relevant single indicators of cyclical risk. (Aikman et al., 2017, Lee et al., 2017, Lang et al., 2019, Chen and Svirydzenka, 2021).

In Europe, there is an increasing number of countries that do not rely only on the credit gap to determine the level of the CCyB rate.[3] In recent years, instead of focusing solely on the credit cycle, macroprudential authorities have placed increasing emphasis on composite indicators of the financial cycle (see Plašil et al. 2014 (CNB), Rychtárik 2014 (NBS), Škrinjarić 2022 (HNB), Koponen 2024 (BoF)). Also the ECB uses a composite indicator, based on Lang et al. (2019), to assess the adequacy of the national CCyB levels.

Following this latter study, this paper documents the construction of a composite indicator of systemic risk related to the Italian financial cycle (Cyclical Risk Indicator, CRI), obtained as a weighted average of the best performing financial cycle indicators, showing that it provides a more accurate early warning of financial distress and of tail macroeconomic outcomes relative to the credit gap.

The reminder of the paper is structured as follows. Section 2 describes the various steps in the construction of the CRI, namely: the definition of an initial set of relevant cyclical risk indicators (subsection 2.1); the criteria used for the early warning exercise (subsection 2.2); the selection of the best performing indicators to be included in the CRI based on the results of the early warning exercise (subsection 2.3); the aggregation of the selected indicators into the CRI (subsection 2.4). Section 3 compares the CRI with the credit gap, both in terms of their historical evolution and their early warning properties. Section 4 concludes.

2. Construction of the CRI

2.1. Initial set of cyclical risk indicators

The starting point of the analysis is the selection of a broad set of indicators of cyclical risk. To define this set, I start from a collection of indicators that have already been identified in the literature as good

[3] See Arbatli-Saxegaard and Muneer (2020) for an overview of the additional indicators actually used by authorities in advanced economies to complement the credit-to-GDP gap in informing CCyB decisions.

proxies for the financial cycle or as effective leading indicators of financial or banking crises.[4] In addition to the credit-to-GDP gap, and in line with the classification proposed by the ESRB recommendation 2014/1, these include indicators of credit dynamics, debt burden, real estate valuations, mispricing of financial assets, external macro imbalances and banks' balance sheet strength.

In order to be used effectively in the ongoing monitoring of systemic cyclical risk, indicators should meet three operational requirements: i) be sufficiently frequent, ii) be available with a reasonable timeliness, and iii) have a sufficient historical depth to assess their early-warning properties. Therefore, the set of indicators analysed includes only those indicators that have at least quarterly frequency, whose publication lag is no longer than four months and whose first observation is no later than Q1 1970 (the date from which most of the indicators included in the initial selection procedure were available).

Table A1 provides an overview of the final set of candidate indicators of cyclical risk. To explore their early-warning properties, these indicators are transformed, where necessary, to make them stationary (or at least to approximate their degree of persistence to that of the target variables used in the early-warning exercise) and to have a quarterly frequency. Monetary variables (or price indicators) are transformed to percentage changes, while non-monetary variables are simply differenced. For each indicator, changes calculated over horizons of 4, 8, 12 and 16 quarters are considered.[5]

2.2. Criteria for the assessment of the early warning properties

Given that the focus here is on a single country and on a relatively narrow time period, it is not convenient to use the standard financial crisis binary target variable[6] to assess the early warning properties of cyclical risk indicators. Instead, I resort to two continuous target variables[7]:

i) The 12-quarter ahead annual change in the aggregate bad loans ratio (BLR) of the Italian banking sector, used as a proxy for financial distress. This is similar in spirit to the criterion used in Alessandri et al. 2015 and Ciocchetta et al. 2016, where the early warning properties of cyclical risk indicators are evaluated against their ability to predict a continuous measure of bank loan quality.

ii) The 12-quarter ahead cumulative growth rate of the Italian real GDP. This is similar to the approach used in Aikman et al. (2018), Lang et al. (2023) and Boyarchenko and Elias (2024) to assess the early-warning properties of different measures of cyclical risk. It helps to identify indicators that capture systemic risk – i.e. risk that has relevant implications for the real economy – rather than only credit risk in the banking sector.

[4] See, among others, Frankel and Saravelos (2012), Aikman et al. (2018), Tölö et al. (2018), for comprehensive reviews of the indicators found in the literature to have a good early warning performance for banking and/or financial crises.

[5] We test different transformations of each indicator, that is we take variations over different horizons, acknowledging that there exists a trade-off between reducing the degree of persistence in the series (whose dynamics would otherwise be dominated by strong trends) and obtaining stable and reliable early warning signals capable of capturing the cumulative nature of financial imbalances. Since this trade-off is likely to be indicator-specific, we do not impose a precise and fit-for-all value on this 'parameter', letting the data speak on the optimal degree of smoothness for each indicator.

[6] The standard for the early warning literature was set by the seminal contribution of Kaminsky and Reinhart (1999).

[7] Since we are in a second-best setting and cannot carry out a standard financial crisis prediction exercise, I use two different proxies as targets in the early warning exercise in order to obtain more robust results.

For each indicator (x) listed in Table A1, in its various transformations (see section 2.1), I run a univariate predictive quantile regression over the period 1974q1-2020q2[8]:

$$\mathbb{Q}_\tau(\, y_{t+h} \mid \mathcal{J}_t) = \alpha_\tau + \beta_\tau x_t + \varepsilon_t \tag{1}$$

where the left-hand-side variable is the τ-percentile of the 12-quarter-ahead annual change in the BLR (h=12) or, alternatively, of the 12-quarter-ahead cumulative GDP growth rate, conditional on the information set $\mathcal{J}_t$. Regressions are estimated for both median (τ = 0.5) and tail outcomes, the latter being identified as the 80th and 20th percentiles (τ = 0.8 and 0.2) of the BLR and GDP target variables, respectively.[9] The focus on tail outcomes is particularly relevant in this context, as the interest is in capturing the build-up phase of the financial cycle and thus in anticipating worst-case outcomes.

In a separate specification I include among the regressors also the Banca d'Italia's adjusted bank credit-to-GDP gap[10] (henceforth gap) and, only for the GDP regressions, also the 12th lag of the dependent variable, as the standard practice in the Growth-at-Risk literature prescribes.[11] This specification is used to assess whether the tested indicators provide additional out-of-sample predictive power relative to the benchmark measure of the credit cycle.

The choice of the 12-quarter forecasting horizon is grounded in the consideration that the warning should be early enough to allow macroprudential authorities to decide and to implement preventive countercyclical measures[12], while also minimizing the risk of being procyclical (i.e. of acting just before the cyclical risks materialize). For robustness reasons, I also run the regressions over alternative forecasting horizons (h = 8 to 28 quarters). This, on the one hand, is needed to avoid having results that are deeply dependent on an arbitrary choice of the predictive horizon. On the other hand, it reflects the recognition that different indicators may have different leading horizons.[13]

The predictive performance of the indicators is assessed both in-sample, estimating the coefficients on the whole available data, and out-of-sample, using expanding window regressions. The specific measure of predictive accuracy employed is the R^1 goodness of fit criterion of Koenker and Machado (1999) [14] (henceforth called pseudo-R^2), which compares the average tilted absolute value loss function $\rho_\tau(u)$ of the quantile models with and without the chosen indicator among the regressors[15]:

[8] As reported in Table A1, the dataset of raw indicators selected for the analysis spans the period 1970Q1-2023Q2. Since the target variables are shifted forward by 12 quarters and the cyclical risk indicators are differenced over a period up to 16 quarters, the final sample used for the regression analysis covers the period 1974q1-2020q2.

[9] The choice of the 20th (80th) percentile strikes a balance between the aim of focusing on the tail of the distribution and the need to have a sufficient number of effective observations to carry out efficient estimations.

[10] This is the Banca d'Italia's preferred measure of the credit-to-GDP gap. It is calculated using time series of bank credit and nominal GDP starting in 1950Q1. For more details on this measure see Alessandri et al. (2015) and Alessandri et al. (2022).

[11] Indeed, the the 12th lag of the dependent variable in the GDP tail regression turns out to be significant in most of our estimations. In contrast, we omitted the lagged dependent variable in the specification of the BLR regression as this was not found to be significant in early estimations.

[12] For example, decisions to increase the countercyclical capital buffer have an implementation lag of 1 year.

[13] For example, Aldasoro et al. (2018), while using a 12-quarter early warning horizon as the preferred one, show that different indicators reach their best predictive performance at different horizons.

[14] The R^1 goodness of fit criterion of Koenker and Machado (1999) is an adaptation of the standard coefficient of determination (R^2) to the quantile regression framework. In its out-of-sample version, coefficient estimates in equation (2) are based on an expanding sample ending in $t-1$.

[15] In the case of the augmented specification mentioned beforehand in this section, the right-hand side of equation (2) would also include the additional regressors (gap and autoregressive term), both in the numerator and in the denominator.

$$R^1(\tau) = 1 - \frac{\sum_N^T \rho_\tau(\, y_{t+h} - \hat{\alpha}_\tau - \hat{\beta}_\tau x_t)}{\sum_N^T \rho_\tau(\, y_{t+h} - \hat{\alpha}_\tau)} \tag{2}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$.

2.3. Selection of the best performing early warning indicators

Tables 1 and 2 display the results of the BLR and the GDP predictive regression analysis, respectively. For each indicator, they report the highest pseudo-R^2 across different transformations for both the median and the tail outcomes, computed either in-sample or out-of-sample. The best performing transformations are described in column (1). In most cases, the indicators have the best performance when taken in 16-quarter changes and when their current value is used to predict the target variable 3 years ahead (i.e. for h = 12) . The only exceptions are the bank credit-to-GDP ratio, for which the 12-quarter change works better, and the household debt indicator (both nominal and real), which has a longer lead (26 quarters), in line with what is generally found in the literature.[16] Columns (2) and (5) report the coefficients estimated in-sample, so that it is possible also to check if they have the expected sign (positive in the BLR regression and negative in the GDP regression).[17] The out-of-sample pseudo-R^2 is reported (along with its statistical significance) for both the model excluding (columns from 8 to 11) and including the gap as a regressor (columns from 12 to 16). For the latter case, the last column reports the frequency with which the indicator's time-varying coefficient estimates conditional on the gap) have the expected sign (the frequency ranges from 0 to 1, where 1 means that the coefficient has the expected sign all the time).

BLR regressions

Some general observations can be made about the results of the BLR regressions (Table 1). First, most of the indicators show better in-sample performance than the gap in predicting the median BLR. However, some of them are not equally good at predicting the right tail of the BLR distribution in-sample, suggesting that they are not well suited to capture the build-up phase of the financial cycle. Moreover, some of the indicators with a good in-sample fit fail to outperform and/or to show additional predictive power relative to the gap out-of-sample, both for the median and the tail outcomes. This suggests that their good in-sample properties mask an underlying instability and a kind of "look-ahead bias" in the coefficient estimates. Second, while the best in-sample performance overall is shown by the lagged four-year change in real household debt, credit dynamics indicators tend in general to perform worse than indicators in other categories (at least for the best performers in each of them), especially in out-of-sample predictions of tail outcomes. Moreover, as might be expected, non-credit indicators tend to add more predictive information relative to the gap than credit dynamics indicators. These results suggest that it is

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16 For example, Drehmann et al. (2023) find that the impact of a unit impulse of new households borrowing on economic activity is positive for the first five years and turns negative from then onward. Ivashina et al. (2024) find that the contribution of household debt growth to crisis prediction is the highest at a 5-year horizon. Similarly, Mian et al. (2017) find that the household debt to GDP ratio is negatively and significantly associated with GDP growth at medium term horizons (up to 5 years), while nonfinancial firm debt has a smaller and more short lived effect on GDP, and do not generate the boom-bust growth cycle associated with household debt.

17 For the current-account balance to GDP ratio the expected signs are inverted, as it is usually assumed to signal an accumulation of cyclical risk when it is negative.

indeed worthwhile to consider non-credit indicators of the financial cycle when monitoring cyclical systemic risk.

Table 1: results of the BLR quantile regressions

Risk category	Indicator	Transformation with best in-sample performance	in-sample						out-of-sample								
			univariate regressions						univariate (x vs gap)				multivariate ([x+gap] vs gap)				
			median			80th percentile			median		80th percentile		median		80th percentile		
			coefficient	R^2	rank (within category)	coefficient	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	freq. of positive coeff.
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Credit dynamics	gapbi_bank		0.068**	0.023		0.054***	0.069										
	gap1s_bank		0.056***	0.030	10	0.034***	0.073	5	-0.004		0.007		-0.010		0.000		1.00
	gapbi_total		0.027	0.006		0.032***	0.044		-0.003		-0.019		0.022		0.065**	3	1.00
	gap1s_total		0.021	0.007		0.021***	0.049		-0.009		-0.021		0.054**	8	0.068**	2	1.00
	tot_credit_nom	4-year change, %	0.019***	0.172	2	0.009	0.028		0.171***	2	-0.056		0.145**	2	0.033		0.33
	tot_credit_real	4-year change, %	0.024**	0.025	11	0.016***	0.056		-0.007		-0.033		0.024		0.021		0.83
	bank_credit_nom	4-year change, %	0.020***	0.203	1	0.013***	0.063		0.207***	1	-0.021		0.199***	1	0.093		0.21
	bank_credit_real	4-year change, %	0.032***	0.079	7	0.018***	0.094	4	0.039**	9	0.013		0.034		0.001		0.59
	cratio_total	4-year change	0.039***	0.052	9	0.017***	0.064		0.039**	8	-0.001		0.015*	9	0.025		0.89
	cratio_bank	3-year change	0.063***	0.118	6	0.029***	0.102	3	0.088***	6	0.059***	3	0.138***	5	0.069***	1	0.89
	m3_nom	4-year change, %	0.009***	0.068	8	0.001	0.011		0.055**	7	-0.069		0.143**	4	0.067*		0.49
	m3_real	4-year change, %	0.004	0.016		0.005	0.015		-0.001		-0.055		0.021		0.021		0.92
	hh_debt	4-year change, % (14q_lag)	0.016***	0.140	5	0.020***	0.150	2	0.132***	5	0.080***	2	0.110***	7	0.051**	5	0.89
	hh_debt_real	4-year change, % (14q_lag)	0.033***	0.160	3	0.023***	0.170	1	0.140***	4	0.101***	1	0.120***	6	0.060**	4	0.98
	nfc_debt	4-year change, %	0.018***	0.154	4	0.001	0.012		0.154***	3	-0.068		0.143**	3	0.054*		0.44
	nfc_debt_real	4-year change, %	0.025**	0.024	12	0.017**	0.029		-0.013		-0.050		-0.002		0.044		0.86
Debt burden	hh_dti	4-year change (12q_lag)	0.092**	0.120	3	0.069***	0.098	3	0.150***	2	0.081**	2	0.123***	2	0.057*	2	0.89
	nfc_debttogva	4-year change	0.041***	0.023	4	0.019***	0.040		0.016		-0.034		0.008		0.020		0.92
	dsr_pnfs	4-year change	0.280***	0.180	2	0.089**	0.106	2	0.017		-0.024		0.008		0.021***	3	1.00
	yield_nom	4-year change	0.121***	0.203	1	0.174***	0.164	1	0.184***	1	0.107**	1	0.321***	1	0.313***	1	1.00
RE valuations	rre_nom	4-year change, %	0.013***	0.176	4	0.006**	0.038		0.157***	4	-0.049		0.234***	2	0.129		0.26
	rre_real	4-year change, %	0.032***	0.213	1	0.025***	0.176	2	0.203***	2	0.131**	2	0.201***	3	0.122*	2	0.97
	rre_real_gap		0.059***	0.158	5	0.042***	0.141	3	0.155***	5	0.111**	4	0.148***	5	0.084*	4	1.00
	rre_pti	4-year change	0.044***	0.185	2	0.031***	0.175	2	0.168***	3	0.129**	3	0.153***	4	0.095**	3	0.97
	rre_ptr		0.030***	0.180	3	0.029***	0.176	1	0.242***	1	0.250***	1	0.266***	1	0.229***		0.20
Equity valuations	stockmarket_nom	4-year change, %	-0.002*	0.033		-0.002***	0.056		0.017		-0.005		0.043***		0.013		0.96
	stockmarket_real	4-year change, %	-0.003***	0.066		-0.005***	0.108		0.055		0.062*		0.091***		0.071**	2	0.96
	stockmarket_to_gdp	4-year change	-0.024***	0.124		-0.029***	0.192		0.071*		0.116**		0.138***		0.129***	1	0.94
External imbalance	ca_gdp_ratio		-0.397***	0.206	1	-0.337***	0.134	1	0.244***	1	0.135***	1	0.216***	1	0.111***	1	1.00
Banks balance	ltd	4-year change	-0.007	0.009		-0.001	0.012		-0.011		-0.060		0.029		0.007		0.94

Notes: this table shows the results of the bad loans ratio (BLR) predictive quantile regression analysis. For each indicator in raw (further described in Table A1), it reports the highest pseudo-R^2 across different transformations for both the median and the 80th percentile, computed either in-sample (columns 2-7) or out-of-sample (columns 8-16), using data spanning the period 1974Q1-2020Q2. The pseudo-R^2 measure is that of Koenker and Machado (1999). The best performing transformations are specified in column (1). Columns (2) and (5) report the coefficients estimated in-sample. The out-of-sample pseudo-R^2 is computed for both the model excluding (columns 8 and 10) and including the gap as a regressor (columns 12 and 14). For the latter case, column 16 reports the frequency with which the indicator's time-varying coefficient estimates (conditional on the gap) have the expected sign (ranging from 0 to 1, where 1 means that the coefficient has the expected sign all the time, with the exception of the current-account-balance to GDP ratio, for which the opposite is true). For each setting, the within-category ranking of the indicators that i) outperform the gap and ii) have the expected sign is shown in a separate column. ***, **, * indicate statistical significance at 10, 5 and 1 per cent confidence levels, respectively. For coefficients' estimates (columns 2 and 5) p-values are computed using 3000 (wild) bootstrap samples; for out-of-sample pseudo-R^2, statistical significance is based on the Diebold-Mariano test.

Among the credit indicators, only the 12-quarter change in the bank credit to GDP ratio and the lagged 16-quarter change in real (and nominal) household debt outperform the gap in all BLR forecasting exercises. However, their additional predictive content relative to the gap is small and comparable to that of the total credit-to-GDP gap measure as far as tail outcomes are concerned.[18]

The best performing debt burden indicator in predicting the BLR is the 16-quarter change in the medium-term nominal government bond yield. It has good in-sample results and shows significant additional out-of-sample predictive power relative to the gap. The household debt-to-income ratio also has a good

[18] As shown in Jylhä and Lof (2022), the Basel credit-to-GDP gap is almost equivalent to the 16-quarter change in the credit-to-GDP ratio. Hence the 12-quarter change in the credit-to-GDP ratio, which we find to outperform the gap, is just a slightly less smooth version of the gap. This could also be obtained by reducing the penalization parameter (λ) of the Hodrick-Prescott filter used to estimate the gap.

performance in all settings. The debt service ratio (DSR) performs well in-sample but not out-of-sample, while the corporate debt ratio always performs poorly.

Indicators of real estate valuations are consistently good predictors of the BLR, both in- and out-of-sample, with the exception of the growth rate of nominal house price. The best among them, especially in predicting the right tail, is the house price-to-rent ratio. However, its correlation with the tail of the BLR conditional on the level of the gap tends to be negative (as shown in column 16 of table 1), suggesting that its predictive content is mostly subsumed by the latter.

Stock market valuation indicators are shown to be negatively associated with future changes in the BLR. This suggests that they may not be good indicators of risk accumulation. However, the inflation-adjusted growth rate of stock prices, and even more so the change in the stock market capitalisation-to-GDP ratio, show good predictive performance both in-sample and out-of-sample, especially for the tail outcomes. Moreover, the multiple regressions show that controlling for the gap, the association between these indicators and future changes in the tail of the BLR turns positive.

The current account ratio, which is the only indicator of external imbalances tested, has good early warning properties, significantly outperforming the gap in all setups. In contrast, our only indicator of bank balance sheet strength, the loan-to-deposit ratio, performs poorly both in-sample and out-of-sample, showing no meaningful stable association with future changes in the BLR.[19]

GDP regressions

The results of the predictive quantile regressions for GDP growth (Table 2) tend to confirm the rankings of the indicators based on the BLR exercise, albeit with some differences. In general, the performance of the indicators improves when the target is the 20th percentile rather than the median GDP growth. This is consistent with the growth-at-risk literature initiated by the seminal work of Adrian et al. (2016), which finds that systemic risk indicators are better at anticipating left-tail macroeconomic outcomes than central ones. At the same time, relative to the BLR regressions, even fewer of the indicators that perform well in-sample turn out to have stable time-varying coefficient estimates and a good out-of-sample predictive ability.

Turning to the individual categories, we see that among the indicators of credit dynamics, unlike in the BLR exercise, the lagged 16-quarter change in real household debt does not perform particularly well, while the 12-quarter change in the ratio of bank credit to GDP remains the only indicator with the expected sign (-) outperforming the gap in all forecasting exercises. All the debt burden indicators perform well in-sample, with the debt service ratio being the best one. However, the bond yield change is the only debt burden indicator that adds significant out-of-sample predictive power to the gap, especially in predicting the left tail of the GDP growth distribution. For the indicators of real estate, only the price-to-income ratio and the price-to-rent ratio beat the gap in-sample and only the latter does so also out-of-sample, proving to have the most stable time-varying coefficient estimates. Stock market valuation indicators confirm their good in-sample performance, again with the "wrong" sign of the coefficient. However, none of them shows a good out-of-sample performance. Finally, the current account balance appears to be a poor predictor of GDP, both for the median and the tail, in-sample and out-of-sample. The loan-to-deposit ratio confirms its poor early-warning power.

[19] Alessandri et al. (2015), dealing with an analysis of early warning focused on the Italian financial system, find that the loan-to-deposit ratio is actually associated with the bad loans ratio, however this association is negative. The difference between our and their results is explained by the significant instability of the early warning performance of this indicator through time.

Table 2: results of the GDP quantile regressions

Risk category	Indicator	Transformation with best in-sample performance	in-sample						out-of-sample								
			univariate						[x + ar(12)] vs [gap + ar(12)]				[x + gap + ar(12)] vs [gap + ar(12)]				
			median			20th percentile			median		20th percentile		median		20th percentile		
			coefficient	R^2	rank (within category)	coefficient	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	R^2	rank (within category)	freq. Of negative coeff.
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Credit dynamics	gapbi_bank		-0.255**	0.062		-0.311***	0.057										
	gap1s_bank		-0.171***	0.069	6	-0.263***	0.073	7	-0.043		-0.048		-0.032		-0.038		0.47
	gapbi_total		-0.22***	0.055		-0.272***	0.063	8	-0.054		-0.05		-0.047		-0.026		0.76
	gap1s_total		-0.151***	0.064	7	-0.198***	0.076	6	-0.0500		-0.067		-0.015		-0.010		0.50
	tot_credit_nom	4-year change, %	0.099***	0.219		0.071***	0.228		0.035		0.058		0.122***		0.105***		0.07
	tot_credit_real	4-year change, %	-0.071	0.124		-0.063**	0.151	3	-0.069		-0.065		-0.013		-0.005		0.23
	bank_credit_nom	4-year change, %	0.080***	0.193		0.060***	0.211		-0.006		0.006		0.055**		0.059		0.11
	bank_credit_real	4-year change, %	-0.093*	0.130	5	-0.054***	0.151	4	-0.071		-0.047		0.011		0.014		0.17
	cratio_total	4-year change	-0.183***	0.213	2	-0.228***	0.241	2	0.059**	2	0.042		0.077***	2	0.048		0.51
	cratio_bank	3-year change	-0.264***	0.216	1	-0.329***	0.252	1	0.078**	1	0.060*	1	0.092***	1	0.106***	1	0.50
	m3_nom	4-year change, %	0.084***	0.248		0.071***	0.287		0.106***		0.117*		0.065*		0.079		0.13
	m3_real	4-year change, %	-0.011	0.108		0.035	0.140		-0.093		-0.085		-0.033		0.014		0.24
	hh_debt	4-year change, % (1ylag)	0.096***	0.220		0.044***	0.201		0.009		0.072		0.090***		0.072**		0.29
	hh_debt_real	4-year change, % (1ylag)	-0.101***	0.141	3	-0.040*	0.143	5	-0.085		-0.037		0.017		-0.003		0.62
	nfc_debt	4-year change, %	0.117***	0.250		0.078***	0.258		0.072*		0.089		0.121***		0.055*		0.12
	nfc_debt_real	4-year change, %	-0.131***	0.141	4	-0.063	0.145		-0.078		-0.045		-0.009		-0.008		0.32
Debt burden	hh_dti*	4-year change (1ylag)	-0.449***	0.268	2	-0.387***	0.198	3	-0.027		0.128**	1	0.004		0.078*	2	0.48
	nfc_debttogva	4-year change (1ylag)	-0.243***	0.210	3	-0.281***	0.224	2	0.041*	2	0.027		0.025		-0.009		0.52
	dsr_pnfs	4-year change	-1.135***	0.330	1	-1.290***	0.379	1	0.150***	1	0.118*	2	0.113***	2	0.075		0.91
	yield_nom	4-year change	-0.618**	0.144	4	-0.180	0.138	4	-0.061		0.013		0.123*	1	0.166***	1	0.94
RE valuations	rre_nom	4-year change, %	0.056***	0.224		0.038***	0.207		0.016		0.049		0.063***		0.038		0.42
	rre_real	4-year change, %	0.014	0.109		0.008	0.135		-0.087		-0.078		0.056		0.008		0.66
	rre_real_gap		-0.022	0.002		-0.029	0.002		-0.123		-0.072		0.027		0.005		0.85
	rre_pti	4-year change	-0.091	0.118		-0.025	0.136		-0.089		-0.078		0.047		0.005		0.74
	rre_ptr		-0.169***	0.219	1	-0.112***	0.162	1	0.018		0.121***	1	0.056*	1	0.106*	1	1.00
Equity valuations	stockmarket_nom	4-year change, %	0.017***	0.162		0.019***	0.193		-0.028		0.001		-0.017		0.007		0.35
	stockmarket_real	4-year change, %	0.010	0.121		0.018***	0.155		-0.098		-0.056		-0.021		-0.007		0.43
	stockmarket_to_gdp	4-year change	0.067	0.195		0.080***	0.245		-0.012		-0.013		0.03		-0.003		0.53
External imbalance	ca_gdp_ratio		1.051***	0.061	1	0.603**	0.015		-0.103		-0.022		0.008		0.03		0.09
Banks balance	ltd	4-year change	0.080***	0.144		0.026	0.143		-0.088		-0.046		0.016		0.043*	1	0.63

Notes: this table shows the results of the GDP predictive quantile regression analysis. For each indicator in raw (further described in Table A1), it reports the highest pseudo-R^2 across different transformations for both the median and the 20th percentile, computed either in-sample (columns 2-7) or out-of-sample (columns 8-16), using data spanning the period 1974Q1-2020Q2. The pseudo-R^2 measure is that of Koenker and Machado (1999). The best performing transformations are specified in column (1). Columns (2) and (5) report the coefficients estimated in-sample. The out-of-sample pseudo-R^2 is computed for both the model excluding (columns 8 and 10) and including the gap and the 12th lag of the dependent variable as regressors (columns 12 and 14). For the latter case, column 16 reports the frequency with which the indicator's time-varying coefficient estimates (conditional on the gap) have the expected sign (ranging from 0 to 1, where 1 means that the coefficient has the expected sign all the time, with the exception of the current-account-balance to GDP ratio, for which the opposite is true). For each setting, the within-category ranking of the indicators that i) outperform the gap and ii) have the expected sign is shown in a separate column. ***, **, * indicate statistical significance at 10, 5 and 1 per cent confidence levels, respectively. For coefficients' estimates (columns 2 and 5) p-values are computed using 3000 (wild) bootstrap samples; for out-of-sample pseudo-R^2, statistical significance is based on the Diebold-Mariano test.

On the basis of the above results, I select the subset of indicators that have the best early warning properties of financial distress and could therefore be used to construct a composite systemic risk indicator related to the Italian financial cycle. In doing so, I prioritize the consistency across performance measures and target variables and, if necessary, the performance recorded on tail outcomes. For the aim of parsimony, which is a desirable property of any composite indicator, I select only the best performing indicator in each risk category. The only exception is for indicators of credit dynamics, for which the two best indicators are retained, namely the 12-quarter change in the ratio of bank credit to GDP and the lagged 16-quarter change in real household debt, since they have different leading horizons and provide different views of the credit cycle, namely a sectoral and an aggregate one. Indeed, both indicators turn out to be significant when used together in a multiple predictive regression (both for the BLR and for the GDP tail, see Table A2 in the appendix), suggesting that they actually provide complementary information.[20] Finally, the list does not include any indicator of bank balance sheet strength, as the only

[20] The choice of including two measures of credit dynamics, namely one for total bank credit and one for credit to households only, also reflects the apparently special relevance of the latter in signalling the risk of financial crises. For example, Aikman et al. (2018), in their review of the early warning literature, conclude that "there is some evidence that it is growth in mortgage debt, rather than other forms of credit, which is the key determinant of crisis risk and severity".

indicator tested in this category, the loan-to-deposit ratio, does not show a good early warning performance. The final subset includes the six best-performing cyclical risk indicators reported in Table 3.

2.4. Aggregation

Based on the findings in Section 2.3, I proceed with the aggregation of the selected indicators into the CRI in two steps. First, each indicator is normalized by subtracting the full-sample mean and dividing by the full-sample standard deviation.[21] Second, each normalized indicator is weighted according to its relative importance in predicting the 12-quarter-ahead annual change in the BLR of the Italian banking sector and the 12-quarter ahead cumulative growth rate of the Italian real GDP.

Table 3: components of the CRI

Description	**Transformation**	**Lag**	**Weight**
Bank credit to GDP ratio	12-quarter change		0.17
HHs debt (real)	16-quarter growth rate	14 quarters	0.10
Average yield on government bonds with a residual maturity above 1 year	16-quarter change		0.33
House price to rent ratio			0.10
Stock market capitalization to GDP ratio	16-quarter change		0.10
Current account balance to GDP ratio	$*(-1)$		0.20

Notes: this table reports the list of indicators that perform best in predicting the 12-quarter ahead annual change in the aggregate bad loans ratio (BLR) of the Italian banking sector and the 12-quarter ahead cumulative growth rate of Italian GDP (both in terms of central and tail outcomes) and that, as such, have been selected to be included in the CRI. It also specifies the transformation, the lag and the weight with which they enter the CRI. The weights were determined through constrained multiple quantile regressions (see Table A2 for more details), with all the selected variables as predictors, requiring the coefficients to be positive (negative for the GDP regression) and to sum up to one (minus one for the GDP regression) and finally imposing a floor value of 0.1 per risk category.

The weights are defined by replicating the exercise described in section 2.2, this time running multiple quantile regressions with all the selected indicators as predictors and constraining the coefficients to be all positive (negative for the GDP regression) and to sum up to one (minus one for the GDP regression).[22] The resulting estimates (see Table A2 in the appendix), taken in absolute value, are then adjusted by discretionally imposing on them a floor of 0.1 per risk category, so as to grant a minimum representation in the CRI also for those indicators, namely the house price-to-rent ratio and the stock market

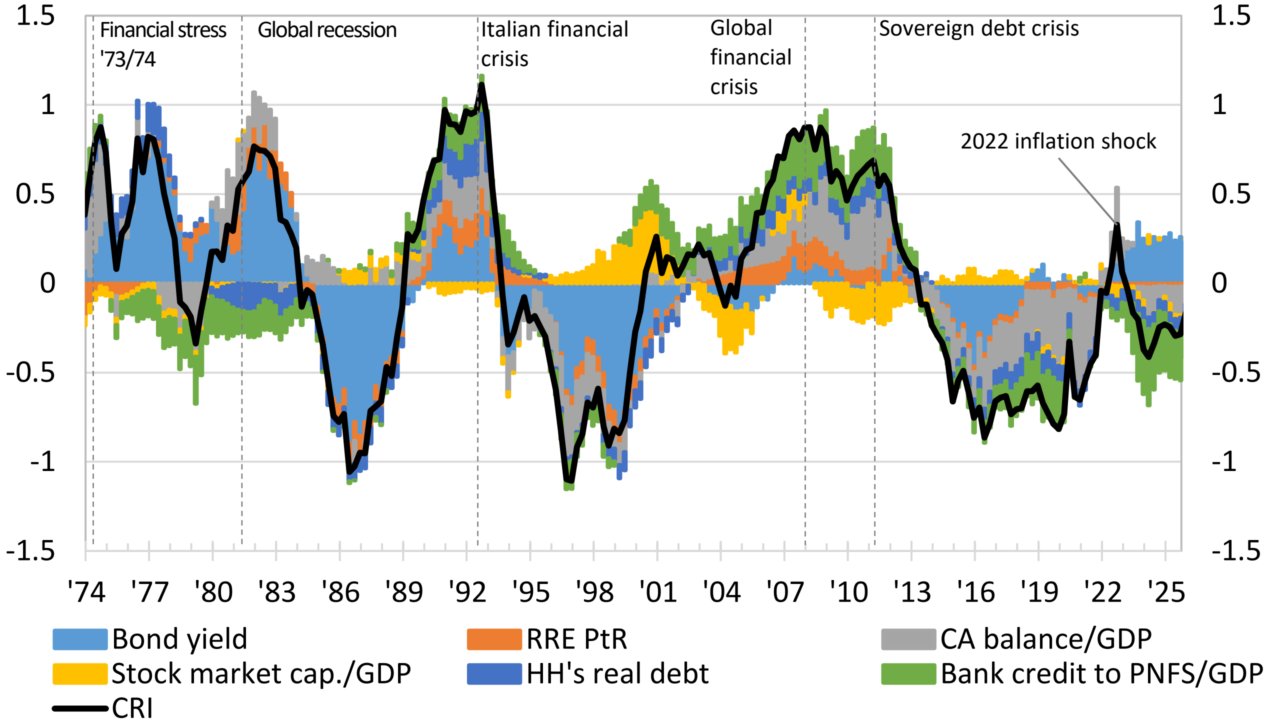
[21] Normalizing the indicators using expanding-sample moments (hence using only real-time information) does not affect the results reported in section 3, i.e. the historical evolution of the CRI and the comparison between the early warning performance of the CRI and of the gap.
[22] The constrained quantile regressions are based on Koenker and Ng (2005).

capitalisation-to-GDP ratio, which would otherwise have received a lower weight.[23] Lastly the coefficients of each indicator are averaged across quantiles and target variables (τ=(0.5, 0.8) for BLR and τ=(0.2, 0.5) for GDP). The final weights assigned to the indicators are shown in Table 3. The CRI is finally calculated as a weighted average of the normalized indicators.

3. The CRI and its early warning performance vis-a-vis the gap

Figure 1 shows the time series of the CRI together with the contributions of the sub-indicators.

Figure 1: the CRI and its components



Notes: this figure shows the quarterly time series of the CRI for the period 1974Q1-2025Q4, together with the contributions of the sub-indicators (normalized and weighted) reported in the legend, namely: the 16-quarter change in the average nominal bond yield on Italian government bonds with a residual maturity above 1 year (weighted 33 per cent); the house price-to-rent ratio (weighted 10 per cent); the current account balance-to-GDP ratio (inverted, weighted 20 per cent); the 16-quarter change in the stock market capitalization-to-GDP ratio (weighted 10 per cent); the 16-quarter growth rate of inflation-adjusted bank credit to households (lagged by 14 quarters, weighted 10 per cent); the 12-quarter change in the ratio between bank credit to the private non-financial sector and GDP (weighted 17 per cent).

The CRI features four main boom-bust cycles over the period considered, peaking in 1974, 1981, 1992 and 2008, i.e. at the inception of the early '70s recession caused by the first oil shock, of the early '80s global recession, of the Italian financial crisis of the early '90s, and of the 2008 global financial crisis (followed closely by the European sovereign debt crisis, SDC), respectively.[24] The latter two episodes were characterized by a strong comovement among the sub-indicators, with the sole exception of the

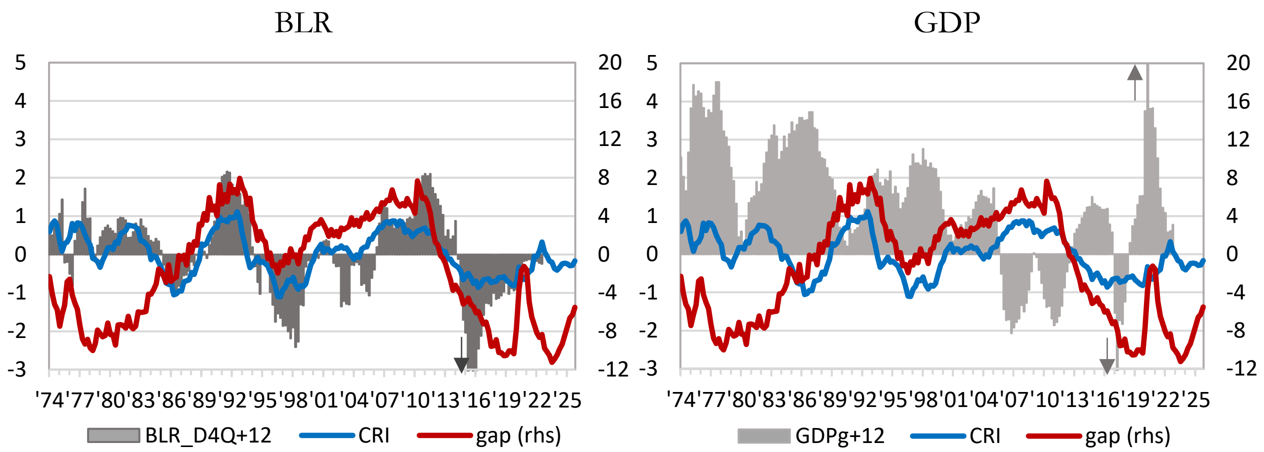
[23] The imposition of a floor is justified by the objective of balancing the aim of optimizing the weights for the early warning of systemic risk and having a sufficient representation of each relevant source of cyclical risk identified in subsection 2.3.

[24] According to the European financial crisis database maintained by the European Systemic Risk Board, Italy experienced three systemic financial crises in the last 50 years, starting in September 1991, August 2011 and March 2020, respectively. The latter was clearly caused by the exogenous shock brought by the Covid-19 pandemic and the related lockdown measures, hence it had nothing to do with the financial cycle. Three other relevant episodes of elevated financial stress are reported in the database – characterized by significant asset price corrections, exchange rate instability and/or disruptions to wholesale funding markets, but which do not constitute systemic crises – starting in July 1973, July 1981 and January 2008, respectively.

stock market valuation indicator which tends to peak in the early phase of the uptrend. The first two episodes, on the other hand, were driven by the strong rise in bond yields (this was the period of the Volcker shock), high current account deficits, rising household debt (only in the early '70s) and stretched house valuations (especially in the early '80s), but not by the overall bank credit dynamic, which was subdued. The CRI also feature a small and short-lived spike in 2022, driven entirely by the rise in interest rates and the fall in the current account balance following the inflation and terms of trade shocks caused by the post-pandemic reopening and the energy crisis.

These differences in the degree of comovement among sub-indicators across cycles are also reflected in the different dynamics of the CRI and the gap over time, as shown in Figure 2. Indeed, the main divergences between the two indicators are observed at the beginning and at the end of the sample period. In the first case, unlike the CRI, the gap does not signal in advance the economic slowdown and the increase in bad loans that occurred at the beginning of the '70s and in the early '80s. In the second case, since we are at the end of the sample, it is harder to say whether the CRI or the gap provided a more accurate signal.

Figure 2: comparison between CRI and gap



Notes: this figure shows the quarterly time series of the CRI, the adjusted bank credit-to-GDP gap for Italy (gap) and, alternatively, the 12-quarter ahead annual change in the aggregate bad loans ratio of the Italian banking sector (BLR_D4Q+12; left-hand panel) or the 12-quarter ahead annualized cumulative growth rate of the Italian real GDP (GDPg+12; right hand panel) for the period 1974Q1-2025Q4.

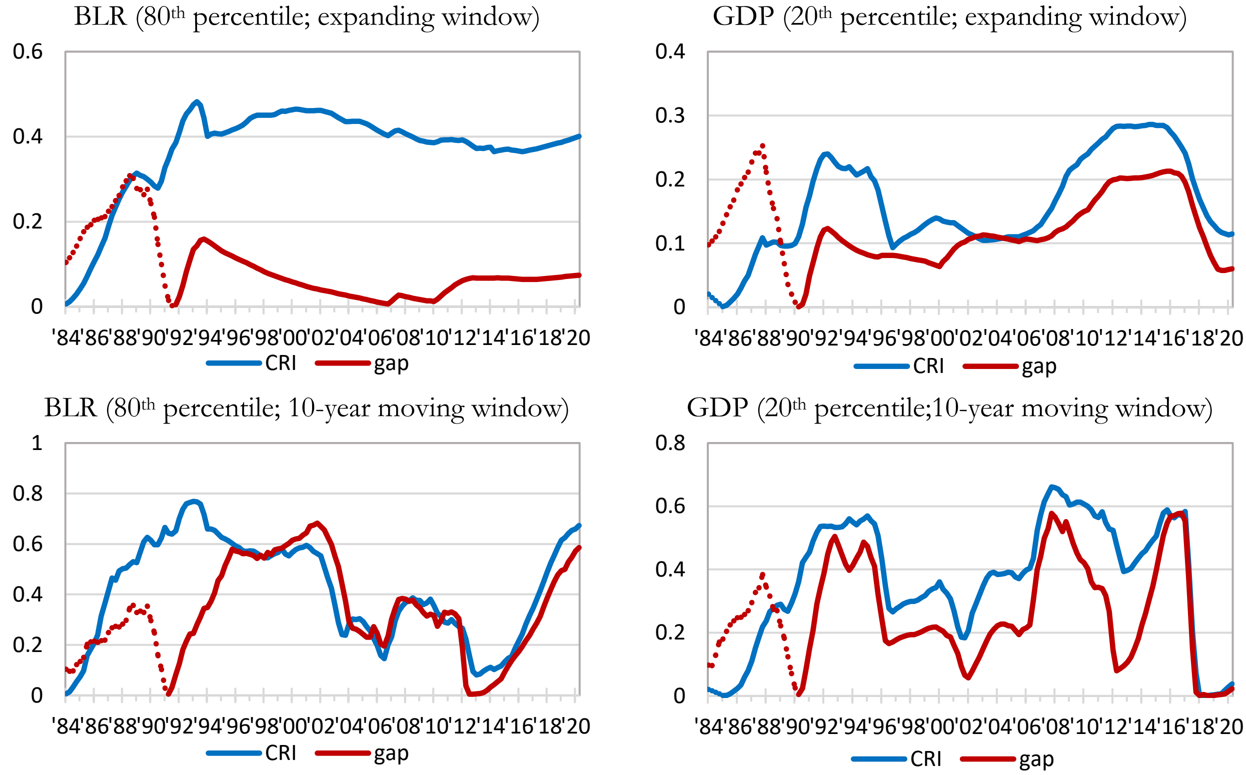
However, three observations can be made on the behaviour of the CRI in the post-SDC period. First, the CRI bottoms out in 2016, before the gap, and more in line with the turning points in the 12-quarter-ahead BLR annual change and 12-quarter-ahead GDP growth. Second, the CRI appears to be less affected than the gap by the high volatility of GDP during the Covid crisis.[25] Third, since 2021, the gap and the CRI have diverged significantly, with the former falling towards its lows and the latter rising rapidly, driven, as noted above, by rising interest rates and a rising current account balance. As a result, the CRI turned positive in mid-2022 and remained above zero for three consecutive quarters, providing a window of opportunity to build releasable capital buffers based on an objective indication of rising cyclical risk.

[25] As noted by Repullo and Saurina (2011), the credit-to-GDP gap tends to be negatively correlated with GDP. This was particularly evident in 2020, which saw an unprecedented contraction in economic activity across most countries, resulting in huge spikes in the credit gap. Authorities were thus pushed to disregard the signals coming from the credit-to-GDP gap in order not to act procyclically.

While we have no definite indication as to which of the two indicators provided the most accurate signal during this latter period, we can see that the CRI's peak in 2022 apparently coincided with a trough in the 3-year ahead GDP growth and a top in the 3-year ahead annual change in the BLR. In fact, the loan default rate faced by Italian banks has increased since 2022, although remaining at moderate levels, and the projections prepared by the staff of the Banca d'Italia point to a further marginal increase in 2026 (see Banca d'Italia, Financial stability report, 2025, 2). This suggests that the CRI provided a more accurate signal in 2022 relative to the gap. Moreover, in retrospect this signal seems more in line with the then prevailing macroprudential policy stance at the European level. Indeed, this was a period in which most national authorities raised releasable capital buffers to build resilience against the increasing risk of endogenous (in great part related to rising inflation and interest rates[26]) or exogenous (mostly geopolitical) shocks, in spite of the subdued pace of the credit cycle.[27]

To assess the relative early warning performance of the CRI and the gap, I run univariate quantile regressions for the tails of the change in the BLR and of GDP growth (right and left tail, respectively) and compute their time-varying in-sample predictive pseudo-R^2, using either an expanding or a moving 10-year window. Figure 3 shows the results, using a dashed line to highlight periods when the sign of the predictor's coefficient is not the expected one (negative for BLR and positive for GDP).

Figure 3: time-varying predictive pseudo-R^2 for tail outcomes



Notes: this figure shows the quarterly time series of the time-varying in-sample pseudo-R^2 from univariate predictive quantile regressions. The dependent variable is either the 80th percentile of the 12-quarter-ahead annual change in the Italian banking sector's bad-loans ratio (BLR, left panels) or the 20th percentile of the 12-quarter-ahead cumulative growth rate of Italian real GDP (right panels). The predictor is either the CRI or the adjusted bank credit-to-GDP gap (gap). The sample spans 1984Q1–2020Q2. Pseudo-R^2 values are computed using an expanding window starting with 10 years of data (top panels) and a 10-year rolling window (bottom panels), using the Koenker and Machado (1999) measure. Dashed lines denote periods in which the predictor's coefficient has the opposite of the expected sign (negative for BLR, positive for GDP).

[26] See Hempell et al. 2024, for a discussion of the role played by high inflation and rising interest rates in the setting of the macroprudential policy stance in Europe since 2022.

[27] For a discussion of the evolving macroprudential policy stance in Europe during the post-Covid period see the box "The use of the CCyB in European economic area countries", in Banca d'Italia, Financial stability report, 2023, 2.

Using an expanding sample, the CRI appears to outperform the gap throughout the entire sample period for both BLR and GDP tail predictions, with full sample pseudo-R^2 (the values where the time series end) being almost 5 and 2 times higher, respectively. However, as noted above, this is mainly due to the poor performance of the gap at the beginning of the sample, where it is shown to be negatively (positively) correlated with the BLR (GDP) tail. Indeed, the use of moving window estimation shows that from 1995 onwards – and especially for the BLR regression – the predictive performance of the CRI and the gap is much more comparable.

The CRI, with full-sample pseudo-R^2 of 0.40 and 0.12 in the BLR and GDP tail regressions, respectively, shows to have an overall better early warning performance not only relative to the gap (whose pseudo-R^2 are 0.07 and 0.06), but also relative to all its component indicators taken individually (see Table A3 in the appendix).[28] This suggests that the CRI provides useful information for the monitoring of the Italian financial cycle, over and above the single indicators of cyclical risk.

4. Conclusion

Overall, the CRI provides a simple, transparent and at the same time comprehensive view of the domestic financial cycle in Italy, improving the signal needed by the macroprudential authority to anticipate episodes of financial distress or the materialization of systemic risk. Therefore, the CRI could usefully complement the credit-to-GDP gap in the set of quantitative information used as the starting point for formulating CCyB decisions.

[28] While few individual indicators actually beat the CRI in predicting the tail of GDP growth, none of them beats the CRI in terms of the average pseudo-R^2 of BLR and GDP tail regressions.

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Appendix

Table A1: Raw indicators of cyclical risk

	Description	Mnemonic	Source
Credit dynamics	Total credit to the PNF sector (nominal)	tot_credit_nom	BIS
	Total credit to the PNF sector (real)	tot_credit_real	BIS and own calculations
	Bank credit to the PNF sector (nominal)	bank_credit_nom	BdI
	Bank credit to the PNF sector (real)	bank_credit_real	BdI and own calculations
	Total credit to GDP ratio	cratio_total	BIS
	Bank credit to GDP ratio	cratio_bank	BIS
	Total credit to GDP gap, Basel standard	gap1s_total	BIS
	Total credit to GDP gap, BdI methodology	gapbi_total	BdI
	Bank credit to GDP gap, Basel standard	gap1s_bank	BIS
	Bank credit to GDP gap, BdI methodology	gapbi_bank	BdI
	M3 monetary aggregate (nominal)	m3_nom	BdI and OECD
	M3 monetary aggregate (real)	m3_real	BdI, OECD, own calculations
	HHs debt (nominal)	hh_debt	BIS
	HHs debt (real)	hh_debt_real	BIS and own calculations
	NFCs debt (nominal)	nfc_debt	BIS
	NFCs debt (real)	nfc_debt_real	BIS and own calculations
Debt burden	Household debt to disposable income ratio	hh_dti	BIS, Istat, FRB of Dallas, calc.
	Firms' debt to gross value added ratio	nfc_debttogva	BIS, Istat, own calculations
	Debt service ratio of the PNF sector	dsr_pnfs	ECB
	Average yield on government bonds with a residual maturity above 1 year	yield_nom	BdI
RE valuations	House prices (nominal)	rre_nom	BdI, Istat
	House prices (real)	rre_real	BdI, Istat, own calculations
	Real house price deviation from trend	rre_real_gap	BdI
	House price to income ratio	rre_pti	BdI, Istat, FRB of Dallas, calc.
	House price to rent ratio	rre_ptr	OECD
Equity	Italy Datastream market index	stockmarket_nom	Datastream
	Italy Datastream market index (real)	stockmarket_real	Datastream andown calc.
	Stock market capitalization to GDP ratio	stockmarket_to_gdp	Datastream, Istat, own calc.
External imbalance	Current account balance to GDP ratio	ca_gdp_ratio	BdI, OECD
Banks balance sheet	Loan to deposits	ltd	BdI

Notes: this table lists the cyclical risk indicators, grouped into the different risk categories identified by the ESRB (2014), whose early warning properties have been tested (after taking sensible transformations) in order to select the best performing among them for inclusion in the CRI. The time series of the raw indicators have quarterly frequency and span the period 1970Q1-2023Q2.

Table A2: Weights of CRI components

	GDP growth				BLR				final weights
	(τ=.2)		(τ=.5)		(τ=.8)		(τ=.5)		
	coef.	adj.	coef.	adj.	coef.	adj.	coef.	adj.	mean adj.
cratio_bank	-0.209	0.166	-0.359	0.321	0.147	0.126	0.127	0.079	**0.173**
hh_debt_real	-0.193	0.150	-0.073	0.035	0.189	0.167	0.076	0.027	**0.095**
yield_nom	-0.421	0.378	-0.380	0.342	0.291	0.270	0.378	0.330	**0.330**
rre_ptr	-0.148	0.105	-0.049	0.100	0.113	0.100	0.000	0.100	**0.101**
ca_gdp_ratio	0.000	0.100	0.000	0.100	0.259	0.237	0.413	0.365	**0.201**
stockmarket_to_GDP	-0.028	0.100	-0.139	0.102	0.000	0.100	0.006	0.100	**0.100**

Note: this table reports the coefficient estimates from constrained multiple quantile regressions (based on Koenker and Ng, 2005) where the independent variables are the indicators in the first column (see Table A1 for a description of the indicators), the dependent variable is either the median or the tail of the 12-quarter ahead annual change in the aggregate bad loans ratio (BLR) of the Italian banking sector or of the 12-quarter ahead cumulative growth rate of the Italian real GDP. Coefficients are constrained to being positive (negative in the GDP regression) and to sum up to one (minus one in the GDP regression). They are then adjusted by taking the absolute value and by imposing a floor of 0.1 per risk category (hence for cratio_bank and hh_debt_real the floor applies to the sum of the two coefficients) while preserving the property that the weights should add up to one. The final weights are obtained as the average of the adjusted coefficients across the four regressions.

Table A3: In-sample pseudo-R^2 for single indicators and for the CRI

	BLR (τ=0.8)	GDP growth (τ=0.2)	average
cratio_bank	0.10***	0.25***	0.18
hh_debt_real	0.17***	0.14**	0.16
yield_nom	0.16***	0.14	0.15
rre_ptr	0.18***	0.16***	0.17
stockmarket_to_gdp	0.19***	0.24***	0.22
ca_gdp_ratio	0.13***	0.02**	0.07
CRI	0.40***	0.12***	0.26
gapbi_bank	0.07***	0.06***	0.06

Note: this table reports the in-sample pseudo-R^2 of univariate quantile regressions where the independent variable is one of the indicators in the first column (see Table A1 for a description of the indicators) and the dependent variable is either the 80th percentile of the 12-quarter ahead annual change in the aggregate bad loans ratio (BLR) of the Italian banking sector or the 20th percentile of the 12-quarter ahead cumulative growth rate of the Italian real GDP. ***, **, * indicate statistical significance at 10, 5 and 1 per cent confidence levels, respectively, based on 3000 (wild) bootstrap samples.