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Article

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Why have credit variables taken centre stage in predicting systemic banking crises? [☆]

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ABSTRACT

In this paper, we investigate the growing prominence of credit in the systemic banking crisis prediction literature. Through the application of the signal extraction model and multivariate probit panel regression, we evaluate the performance of the absolute change in credit-to-GDP ratio as an early warning system indicator of systemic banking crises. The findings reveal that the accelerated financialisation of economies turns the excess supply of credit into generating conditions that increase the likelihood of a systemic banking crisis. The findings also indicate that even with persistently low and stable inflation, systemic risk could gradually accumulate through an excessive supply of credit.

1. Introduction

Studies on the global financial crisis of 2008 (GFC 2008) in search of explanations for its sudden and severe impact led to a paradigm shift in the assessment of risks to the banking sector. Instead of focussing simply on the banking sector's performance metrics, obtained by aggregating individual banks' data, and the macroeconomic indicators, mostly real GDP growth and inflation, measures were developed to gauge systemic risk (Gaytan and Johnson, 2002; Gramlich et al., 2010). Systemic banking crises were also found to be less frequent but more skewed (Schularick and Taylor, 2009; Jorda et al., 2014, 2016). The early warning system (EWS) indicator of systemic banking crises that Borio and Lowe (2002a, 2002b) introduced, the credit-to-GDP gap,³ was found to be the best predictor of systemic banking crises in a univariate setting (Drehmann et al., 2010; Detken et al., 2014). Although several other studies (Drehmann and Juselius, 2014, Drehmann and Tsatsaronis, 2014) have confirmed the credit-to-GDP gap's appropriateness as a robust EWS indicator, its application has not been validated as universal, particularly when emerging market economies are considered (Gersl and Jasova, 2018).

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³ The credit-to-GDP gap is computed as the difference between the actual and one-sided Hodrick-Prescott (HP) filtered trend of the credit-to-GDP ratio.

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What is striking is the distinct lack of appreciation of the credit-to-GDP gap's usefulness before the GFC 2008. The credit-to-GDP gap was first proposed by [Borio and Lowe \(2002a, 2002b\)](#) and further studied by Borio and Drehmann (2008) as a more robust EWS of systemic banking crises. But it is fundamentally after the GFC 2008, with the work of [Drehmann et al. \(2010\)](#) and the inclusion of the credit-to-GDP gap as a vital EWS indicator of systemic banking crises with the recommendations of Basel III, that the credit-to-GDP gap gained prominence as a key EWS indicator. In fact, the literature on EWSs for systemic banking crises ([Alessi and Detken, 2009, 2018](#); [Schularick and Taylor, 2009](#); [Drehmann et al., 2010](#); [Detken et al., 2014](#); [Aldasoro et al., 2018](#)) does not explain much about the growing prominence of credit in the prediction of systemic banking crises from the pre-GFC 2008 studies to the post-GFC 2008 studies.

We aim to fill this important research gap by finding the conditions that turn excess credit into a critical factor in systemic risk build-up. Most papers in the EWS literature before the GFC 2008 ([Eichengreen and Rose, 1998](#), [Hutchison and McDill, 1999](#), [Kaminsky and Reinhart, 1999](#)) did not attribute an important role to credit in crisis formation. Although most researchers in the post-GFC 2008 period have increasingly applied and accepted the credit-to-GDP gap as an EWS indicator of systemic banking crises, the credit-to-GDP gap suffers from some technical and theoretical drawbacks.⁴ It requires a long series of data for its computation and generally leads to end-of-series bias ([Edge and Meisenzahl, 2011](#); [Hamilton, 2018](#)) [Hamilton \(2018\)](#). even suggested never using it due to its lack of theoretical underpinnings because it is derived through a statistical process. We therefore⁵ use the absolute change in credit-to-GDP ratio to investigate the growing prominence of credit variables in the prediction of systemic banking crises.

We use the findings of the post-GFC 2008 studies to re-evaluate the systemic banking crises of the 1980s and 1990s, particularly concerning the applicability of the absolute change in the credit-to-GDP ratio as an EWS indicator of for systemic banking crises. The paper is organised as follows [Section 2](#). is a review of the progression of the EWS literature, focussing on the emergence of the credit-to-GDP gap as a vital EWS indicator of systemic banking crises [Section 3](#). is an outline of the data and methodology used in the current study [Section 4](#). is a discussion of the study's main findings, and section 5 concludes the paper.

2. Literature review

Systemic banking crises are a subset of financial crises, with currency crises and sovereign debt crises characterising the two other main subsets ([Goldstein and Razin, 2013](#)). A resurgence of financial crises occurred during the 1980s and 1990s,⁶ particularly banking and currency crises. However, most studies of those crises were focussed on currency crises and paid little attention to banking crises ([Gaytan and Johnson, 2002](#); [Demirgüç-Kunt, Detragiache, 2005](#)). A mix of factors could explain this trend, including the historical context post-breakdown of the Bretton Wood arrangements in 1973, intensification of financial liberalisation with greater focus on exchange rates and interest rates, less attention to other banking sector metrics and the limited tools available at that time.

Moreover, the timings and duration of currency crises were more easily identifiable with the use of an exchange rate pressure index, and approximations in the dating of banking crises blurred the formation in the pre-crisis period and persistence in the post-crisis period of systemic banking crises ([Lestano et al., 2003](#); [Davis and Karim, 2008b](#)). Only following the pioneering work of [Kaminsky and Reinhart \(1999\)](#), who linked earlier appearances of banking sector difficulties to the culmination of currency crises, coining the term "twin crises", did the development of an EWS for systemic banking crises take a firm footing. Since then, the work on an EWS for systemic banking crises has developed unevenly. The GFC 2008 rekindled research on EWSs for systemic banking crises because existing EWS indicators prior to the GFC 2008 failed to inform policymakers of the imminence of the crisis ([Davis and Karim, 2008a, 2008b](#)).

Indeed, the emergence of the credit-to-GDP gap as a key EWS indicator for systemic banking crises followed from the long evolution of the EWS literature. Although in various studies, researchers have tried to explain bank runs, including [Friedman](#)⁷ (1968), [Minsky](#)⁸ (1982) and [Diamond and Dybvig](#)⁹ (1983), [Demirgüç-Kunt and Detragiache \(1998\)](#) and [Kaminsky and Reinhart \(1999\)](#) boosted the EWS for systemic banking crises in their studies on a growing number of systemic banking crises that occurred during the 1980s and 1990s. They pioneered the use of the multivariate probit/logit regression model and the signal extraction model, respectively, in identifying eligible EWS indicators of systemic banking crises.

Other EWS studies investigating the systemic banking crises of the 1980s and 1990s include the one [Eichengreen and Rose \(1998\)](#) conducted, in which they underscored the importance of external factors as triggers of crises, and the one [Hutchison and McDill \(1999\)](#) conducted, in which they showed that positive macroeconomic performance did not guarantee the avoidance of a systemic banking crisis [Davis and Karim \(2008b\)](#). simulated various model specifications of the original [Demirgüç-Kunt and Detragiache \(1998\)](#) model to stress the importance of model specification and dating of systemic banking crises. EWS indicators developed

⁴ See [Audit and Alam \(2022\)](#) for a detailed study on the drawbacks of the credit-to-GDP gap. It is also referred to as the Basel gap, following the recommendation of the Basel Committee on Banking Supervision in December 2010 (Basel III) to use it to gauge increasing vulnerabilities in the banking sector for triggering counter cyclical capital buffers.

⁵ See proof of equivalent and even better performance by absolute change in credit-to-GDP ratio, compared to the credit-to-GDP gap, in [Appendix I](#).

⁶ See [Appendix II](#).

⁷ Studying the propagation of bank runs during the Great Depression of the 1930s in the US, [Friedman \(1968\)](#) suggested that lack of monetary growth was the main cause of systemic banking crises.

⁸ [Minsky \(1982\)](#) postulated the instability hypothesis, proposing that booms generally precede crises due to asset price reversals, which cause solvent entities in booms to become insolvent when asset prices fall sharply.

⁹ [Diamond and Dybvig \(1983\)](#) posited that bank runs occur due to the fragile structure of banks' business model, which primarily depends on short-term liabilities while lending long.

to monitor risks of systemic banking crises until the GFC 2008, however, failed to alert policy makers of systemic banking crises' imminence, leading to a renewed interest amongst academics and practitioners in the study of EWSs for financial crises. In that context, the study by [Drehmann et al. \(2010\)](#) became a key reference for other post-GFC 2008 studies although some of the ideas therein were already burgeoning in the earlier work by [Borio and Lowe \(2002a, 2002b\)](#) and [Borio and Drehmann \(2009\)](#).

[Drehmann et al. \(2010\)](#) investigated the use of three groups of variables, macroeconomic variables, banking sector performance measures and funding metrics, to predict the incidence of a financial crisis. The gap formulation was used to capture deviations from the long-term trend, estimated using a one-sided HP filter with a high smoothing parameter λ ¹⁰ (λ) [Drehmann et al. \(2010\)](#). used the signal extraction method and showed that the credit-to-GDP gap with an optimal threshold minimised false alarms (which signalled a crisis when one did not occur) and could identify crises more than two thirds of the time (66.7%) that they occurred. However, focussing only on emerging market economies, [Gersl and Jasova \(2018\)](#) found that the rate of change in the credit-to-GDP ratio and nominal credit growth outperformed the credit-to-GDP gap in signalling the potential incidence of systemic banking crises.

[Aldasoro et al. \(2018\)](#), applying the signal extraction method, observed that the credit-to-GDP gap, property prices, household debt service-to-income ratio and ratio of cross-border claims to GDP performed well as EWS indicators of systemic banking crises [Joy et al. \(2015\)](#)., [Detken et al. \(2014\)](#) and [Gabriele \(2019\)](#) used novel methods, the binary recursive tree (BRT) and random-tree techniques, in researching systemic banking crises and concluded that credit variables and their derivatives contained vital information to predict systemic banking crises.

It is also interesting to note that the difference between pre- and post-GFC 2008 EWS studies was the type of countries experiencing a systemic banking crisis in the two eras. Most of the pre-GFC 2008 studies' samples consisted of large numbers of systemic banking crises in developing countries during the 1980s and 1990s. In contrast, most of the post-GFC 2008 studies' samples included systemic banking crises in developed countries, of which most were focussed on the GFC 2008.

Moreover, the findings of studies on EWSs in the aftermath of the GFC 2008 were very different from those of the studies in the pre-GFC 2008 era. Essentially, post-GFC 2008 studies increasingly showed that credit and house price variables had higher predictive power than the well-established pre-GFC 2008 EWS indicators, such as real GDP growth and inflation. I aim to find some explanations for the underperformance of credit variables as EWS indicators of systemic banking crises in studies that showed they underperform when evaluating credit growth in the pre-GFC 2008 era ([Eichengreen and Rose, 1998](#), [Hutchison and McDill, 1999](#), [Davis and Karim, 2008a](#)) as well as the growing acceptance of the credit-to-GDP gap as an important EWS indicator of systemic banking crises in post-GFC 2008 studies ([Drehmann and Juselius, 2013](#); [Detken et al., 2014](#); [Aldasoro et al., 2018](#)). It is evident that the historical context as well as the regional dimension of systemic banking crises experienced around the world add to the complexity of finding a suitable EWS for all countries at all times.

3. Data and methodology

In the current study, we applied the signal extraction and multivariate probit regression techniques to the sample of 43 countries¹¹ for the period 1981Q1–2019Q4 to investigate the growing prominence of credit variables in the prediction of systemic banking crises. We sourced the data from the International Monetary Fund (IMF) and the Bank of International Settlements (BIS).

As indicated in the introduction, to address the credit-to-GDP gap's limitations, I used an alternative,¹² the absolute change in credit-to-GDP ratio (proof of comparable performance shown in [Appendix I](#)). The quarterly absolute¹³ change in credit-to-GDP ratio is computed as follows:

Absolute change in Credit-to-GDP ratio = Credit-to-GDP ratio in quarter X of year (t) - Credit-to-GDP ratio in quarter X of year (t-1)

Finding the results of the absolute change in credit-to-GDP ratio comparable to those of the Basel gap, we evaluated its performance in predicting systemic banking crises between 1981Q1 and 2019Q4 for developing and developed countries by first applying the signal extraction approach. To further analyse the signal extraction model's results and evaluate the dynamics relating the excess supply of credit to the probability of incidence of systemic banking crises, we then applied the multivariate probit panel regression model¹⁴ to the quarterly sample of 43 countries. The dependant variable is the probability of crisis, and the absolute change in credit-to-GDP ratio is one of the regressors, along with the two key macroeconomic variables, real GDP growth and consumer price inflation, that have systematically been analysed as potential EWS indicators.

¹⁰ See [Drehmann et al. \(2010\)](#). Empirically, the length of financial cycles has been estimated as approximately four times that of business cycles. The recommended λ for annual series data is 1600, and the recommended λ for quarterly series data is 400,000.

¹¹ They included Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Italy, India, Indonesia, Israel, Japan, South Korea, Luxembourg, Malaysia, Mexico, the Netherlands, Norway, New Zealand, Poland, Portugal, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, the United Kingdom and the United States although the quarterly data series is not complete for all countries.

¹² [Audit and Alam \(2022\)](#) introduced the absolute change in the credit-to-GDP ratio as an alternative to the Basel gap and indicated that it outperformed the latter as an EWS indicator of systemic banking crises.

¹³ The term 'absolute' is used to differentiate this change from the 'rate of change' [Gersl and Jasova \(2018\)](#) proposed for emerging economies. It is not equivalent to the mathematical 'absolute', which is restricted to positive values because the 'absolute change' here can be positive or negative.

¹⁴ [Audit and Alam \(2021\)](#) found the signal extraction model and the multivariate probit regression model to be robust techniques in validating the performance of EWS indicators. Both models have withstood the test of time, remaining important in spite of some of their limitations.

Researchers such as Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), Caprio and Klingebiel (2003) and Laeven and Valencia (2010, 2018) have developed different dating schemes with different definitions of systemic banking crises. We use that of Laeven and Valencia (2018), which is the most comprehensive and provides specific conditions to date systemic banking crises as well as an updated database of financial crises between 1970 and 2017. Accordingly, a systemic banking crisis is defined as one that meets two conditions: (1) significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system and/or bank liquidations) and (2) significant banking policy intervention measures in response to major losses in the banking system.

We considered 2003 the break year differentiating the pre-financialisation and post-financialisation periods because it marks the completion of an era of financial liberalisation globally. In fact, the 1980s and the 1990s were characterised by a growing move towards financial liberalisation, with major reforms undertaken globally to make the financial system more market-determined and less controlled through regulations. Developed countries' relative success in terms of the rare occurrence of systemic banking crises in the 1980s and 1990s as a result of their relatively more liberalised financial system convinced many other countries to adopt financial liberalisation. Moreover, 2003 is ideally located within the period of relative stability between the end of the 1997–98 Southeast Asian crisis and the pre-crisis years before the GFC 2008.

3.1. Signal extraction model

The signal extraction model evaluates indicators based on their performance as signals of an impending systemic banking crisis. Therefore, dating of a systemic banking crisis is a key input in the application of the signal extraction model. Another critical input in evaluating an EWS indicator's performance is the proposed variable's threshold, which must be identified based on an objective criterion Kaminsky and Reinhart (1999). suggested minimising the noise-to-signal ratio. The trend in proposed indicators is observed over a period of time to differentiate tranquil periods and pre-crisis periods, based on a quantifiable change in the proposed variable that indicates increasing vulnerabilities in the financial system. Various thresholds are evaluated for each variable to obtain the most efficient one. For each time period, T , a signal, S , is determined. When the indicator being evaluated crosses the threshold, S takes a value of 1; otherwise, S is set at 0. For each threshold, the noise-to-signal (N/S) ratios are computed to evaluate the proposed indicator's performance and simultaneously identify the threshold that minimises the N/S ratio.

For each signal, there are four possibilities: (1) true positive (TP), that is, the signal is issued ($S = 1$) and a crisis occurred; (2) true negative (TN), that is, a signal is not issued ($S = 0$) and a crisis actually did not occur; (3) false positive (FP), that is, a signal is issued ($S = 1$) but the crisis in effect did not occur; and (4) false negative (FN), that is, a signal is not issued ($S = 0$) but a crisis occurred. The N/S ratio is estimated by the ratio $[FP/(FP+TN)]/[TP/(TP+FN)]$ Kaminsky and Reinhart (1999). suggested minimising the N/S ratio to gauge proposed EWS indicators' performance Demirgüç-Kunt and Detragiache (2000). underscored the trade-off between type I (i.e., not issuing a signal and a crisis occurs) and type II (i.e., issuing a signal and a crisis does not materialise) errors implicit in Kaminsky and Reinhart's (1999) proposition Drehmann et al. (2010). further proposed that an additional criterion for identifying efficient EWS indicators should be a minimum of 67% of crises predicted.

Researchers have used the signal extraction model, which has various advantages, in several studies, including Kaminsky and Reinhart (1998, 1999), Borio and Lowe (2002a, 2002b), Alessi and Detken (2009), Drehman et al. (2010), Detken et al. (2014), Aldasoro et al. (2018) and Gersl and Jasova (2018). First, it can measure each EWS indicator's performance individually with a minimum of assumptions. Second, the distribution of model variables need not follow a normal distribution, which is generally a primary assumption for regression analysis. Third, the number of data points can vary because the indicators are tested separately, which very useful because it allows for great flexibility in the analysis of EWS indicators' performance. However, the signal extraction model's main drawback is that although each EWS indicator's impact is dependent on the simultaneous effects of other variables, it does not allow for the identification of those concomitant effects Demirgüç-Kunt and Detragiache (1998). suggested that this was the primary reason for opting for a multivariate probit/logit regression model estimation.

3.2. Multivariate probit regression model estimation

We applied the multivariate probit regression model to evaluate the performance of the absolute change in credit-to-GDP ratio as an EWS indicator of systemic banking crises. To date systemic banking crises, we used the same basis of the signal extraction model (Laeven and Valencia, 2018), which also reinforces the consistency of the estimation results. For each sample period, we estimated a multivariate probit regression model, with the dependant variable being a crisis dummy variable, which takes a value of 1 if a crisis occurs and a value of 0 otherwise. The formulation is presented as follows:

$$Y = \begin{cases} 1 & \text{with probability with } Pr(Y = 1) = P \\ 0 & \text{with probability with } Pr(Y = 0) = (1 - P) \end{cases}$$

The dependant variable, Y , is regressed on a list of independent variables for all countries of the sample in each period considered. The model aims to estimate each indicator's effect on the probability, P , of experiencing a systemic banking crisis. The probit specification models the probability of a crisis as a non-linear function of the indicators in the following formulation:

$$Pr(Y = 1) = F(X\beta)$$

wherein X stands for a vector of independent variables and β stands for a vector of impact coefficients of the respective proposed EWS indicators.

Table 1
Signal extraction results.

For Developed countries							
Performance of 'Absolute Change in credit-to-GDP ratio' over 3-year Prediction Horizon							
Period	Threshold (%)	Noise rate (%)	Signal rate (%)	Noise-to-Signal ratio (%)	Number of countries	Number of crises	Predicted crises (%)
1981–2003	3.0	41.96	70.89	59.19	24	6	100.00
2004–2019	3.0	35.71	70.00	51.02	24	15	93.33
1981–2019	3.0	39.97	70.25	56.90	24	21	95.24
For Developing Countries							
Performance of 'Absolute Change in credit-to-GDP ratio' over 3-year Prediction Horizon							
Period	Threshold (%)	Noise rate (%)	Signal rate (%)	Noise-to-Signal ratio (%)	Number of countries	Number of crises	Predicted crises (%)
1981–2003	3.0	33.33	51.08	65.26	19	13	84.62
2004–2019	3.0	31.42	87.50	35.91	19	2	100.00
1981–2019	3.0	32.33	56.44	57.28	19	15	86.67
For All Countries							
Performance of 'Absolute Change in credit-to-GDP ratio' over 3-year Prediction Horizon							
Period	Threshold (%)	Noise rate (%)	Signal rate (%)	Noise-to-Signal ratio (%)	Number of countries	Number of crises	Predicted crises (%)
1981–2003	3.0	38.99	58.26	66.92	43	19	89.47
2004–2019	3.0	33.33	71.88	46.38	43	17	94.12
1981–2019	3.0	36.69	65.16	56.31	43	36	91.67

Source: Author's computation.

The main advantage of the probit regression model relative to signal extraction is that it allows for modelling the joint impact of various EWS indicators on the probability of the incidence of systemic banking crises and for testing of statistical significance of each EWS indicator's impact coefficient. Moreover, the estimated regression equation can be used to estimate probabilities of the incidence of systemic banking crises in hypothetical scenarios with varying values of the independent variables. The probit/logit regression model is specifically designed for modelling involving binary dependant variables and has been used in several studies (Demirgüç-Kunt and Detragiache, 1998, Eichengreen and Rose, 1998, Hutchison and McDill, 1999, Davis and Karim, 2008a, 2008b, Detken et al., 2014, Behn et al., 2016, Alessi and Detken, 2018).

4. Results and discussions

We applied the two methods of investigation to separate samples of developed and developing countries and the sample mixing the two group of countries to analyse the difference in the timing of the incidence of systemic banking crises between the two group of countries. Indeed, during the period 1981–2003, only six systemic banking crises occurred in 24 developed countries of the sample, and 13 systemic banking crises occurred in the 19 developing countries. In contrast, during the period 2004–2019, 15 systemic banking crises occurred in the developed countries and only two in the developing countries. With the results of the two methods of investigation, we attempted to demonstrate that intensified financialisation of the economy in the post-financial liberalisation period, that is, post-2003, has rendered excessive credit growth as a primary pre-condition of systemic banking crises.

4.1. Signal extraction results

We therefore applied the signal extraction model to the sample of 43 countries, developed and developing, for the period 1981Q1–2019Q4 to verify the performance of the absolute change in credit-to-GDP ratio over time, including the pre- and post-financial-liberalisation periods as determined by the break year 2003 Table 1. summarises the performance results of the absolute change in credit-to-GDP ratio as an EWS indicator for systemic banking crises in developed and developing countries as well as separately for each group of countries, and by considering the whole, pre- and post-financialisation periods.

We found that for the period 1981–2003, the absolute change in credit-to-GDP ratio performed less efficiently for the developing countries than for the developed countries, as the higher N/S ratio of 65.26, compared to 59.19, indicates. However, it is noteworthy that in the pre-financialisation period, the group of 24 developed countries registered only six systemic banking crises while the group of 19 developing countries experienced 13 systemic banking crises. In contrast, in the post-financialisation period, the incidence of systemic banking crises the two group of countries recorded was reversed. Nonetheless, the N/S ratio of the absolute change in credit-to-GDP ratio for the two groups of countries and for the mixed sample fell noticeably, suggesting an improvement in the performance of the EWS indicator of absolute change in credit-to-GDP ratio in the post-financial liberalisation period. The signal extraction performance results for the absolute change in credit-to-GDP ratio indicated that it functioned well for samples consisting exclusively of developed countries and samples mixing developed and developing countries.

Table 2
Multivariate probit panel regression results for all countries.

	1981–2019		1981–2003		2004–2019	
Constant	-2.123	-2.173	-2.207	-2.258	-2.258	-2.26
	<i>(-36.98)</i>	<i>(-36.13)</i>	<i>(-23.31)</i>	<i>(-22.48)</i>	<i>(-24.43)</i>	<i>(-25.14)</i>
Real GDP growth (-1)	-0.014		0.008		-0.039	
	<i>(-1.26)</i>		<i>(0.48)</i>		<i>(-2.68)</i>	
Real GDP growth (-3)		0.014		0.020		-0.006
		<i>(1.22)</i>		<i>(1.17)</i>		<i>(-0.36)</i>
Inflation (-1)	0.008	0.008	0.007	0.008	0.077	0.071
	<i>(2.50)</i>	<i>(2.73)</i>	<i>(1.98)</i>	<i>(2.30)</i>	<i>(4.68)</i>	<i>(4.24)</i>
Absolute change in credit-to-GDP ratio (-1)	0.026		0.011		0.030	
	<i>(6.78)</i>		<i>(1.20)</i>		<i>(6.60)</i>	
Absolute change in credit-to-GDP ratio (-5)		0.021		0.018		0.021
		<i>(5.78)</i>		<i>(1.97)</i>		<i>(5.12)</i>
LR Statistics	49.45	36.60	4.25	8.05	66.64	41.52
Prob.(LR Statistics)	0.000	0.000	0.236	0.045	0.000	0.000
Total Observations	5252	5118	2688	2560	2564	2558
Observations with Dep. = 1	116	116	48	48	68	68
Observations with Dep. = 0	5136	5002	2640	2512	2496	2490

z-statistic in Italics and bracket. **Bold** for statistical significance at 5% or better.

Table 3
Multivariate probit panel regression results for developed countries.

	1981–2019		1981–2003		2004–2019	
Constant	-2.090	-2.180	-2.148	-2.271	-2.892	-2.934
	<i>(-28.04)</i>	<i>(-28.17)</i>	<i>(-15.47)</i>	<i>(-15.72)</i>	<i>(-16.83)</i>	<i>(-17.50)</i>
Real GDP growth (-1)	-0.041		-0.052		-0.017	
	<i>(-2.86)</i>		<i>(-1.92)</i>		<i>(-0.82)</i>	
Real GDP growth (-3)		0.003		-0.029		0.004
		<i>(0.17)</i>		<i>(-1.09)</i>		<i>(0.17)</i>
Inflation (-1)	0.017	0.026	0.001	0.012	0.429	0.447
	<i>(1.47)</i>	<i>(2.20)</i>	<i>(0.05)</i>	<i>(0.71)</i>	<i>(8.11)</i>	<i>(8.25)</i>
Absolute change in credit-to-GDP ratio (-1)	0.025		-0.003		0.018	
	<i>(5.95)</i>		<i>(-0.24)</i>		<i>(3.45)</i>	
Absolute change in credit-to-GDP ratio (-5)		0.020		0.012		0.011
		<i>(5.01)</i>		<i>(0.88)</i>		<i>(2.26)</i>
LR Statistics	43.32	19.56	4.08	2.76	111.84	104.45
Prob.(LR Statistics)	0.000	0.001	0.252	0.430	0.000	0.000
Total Observations	3744	3648	2145	2049	1599	1599
Observations with Dep. = 1	84	84	24	24	60	60
Observations with Dep. = 0	3660	3564	2121	2025	1539	1539

z-statistic in Italics and bracket. **Bold** for statistical significance at 5% or better.

These results could potentially explain why for most pre-GFC 2008 studies (Eichengreen and Rose, 1998, Hutchison and McDill, 1999; Kaminsky and Reinhart, 1999), credit growth¹⁵ was found to be statistically less significant or insignificant than for post-GFC 2008 studies (Alessi and Detken, 2009, 2018; Drehmann et al., 2010; Detken et al., 2014; Aldasoro et al., 2018) that concluded that the credit-to-GDP gap¹⁶ was very effective in predicting systemic banking crises, particularly in developed economies. To probe further into these results, we applied the multivariate probit panel regression model to the same samples, and we present the results in the following section.

4.2. Multivariate probit panel regression estimation results

We applied the multivariate probit panel regression model to the mixed sample, the sample of 24 developed countries and the sample of 19 developing countries separately. Tables 2., 3 and 4 show the regression results for the mixed sample, developed countries and developing countries, respectively. The dependant variable in all the specifications considered is the crisis dummy described in Section 3.2, which takes a value of 1 in the four quarters of the year that a crisis happened and a value of 0 otherwise, and the regressors include the real GDP growth, inflation and absolute change in credit-to-GDP ratio. Because the EWS indicator is expected to alert policymakers ahead of the crisis, the regressors were lagged by one quarter in the baseline model, and alternate lags were

¹⁵ Credit growth was used in those studies because the credit-to-GDP gap was not known at that time.

¹⁶ With Borio and Lowe's (2002a, 2002b) propositions, the credit-to-GDP gap was considered in the post-GFC 2008 studies.

Table 4
Multivariate probit panel regression results for developing countries.

	1981–2019		1981–2003		2004–2019	
Constant	-2.447	-2.386	-1.987	-1.972	-4.321	-3.454
	<i>(-16.33)</i>	<i>(-16.61)</i>	<i>(-10.62)</i>	<i>(-10.53)</i>	<i>(-7.03)</i>	<i>(-8.97)</i>
Real GDP growth (-1)	0.042		0.043		0.041	
	<i>(2.10)</i>		<i>(1.69)</i>		<i>(1.07)</i>	
Real GDP growth (-3)		0.039		0.045		-0.002
		<i>(2.03)</i>		<i>(1.82)</i>		<i>(-0.05)</i>
Inflation (-1)	0.010	0.010	0.003	0.003	0.154	0.121
	<i>(2.81)</i>	<i>(2.67)</i>	<i>(0.71)</i>	<i>(0.80)</i>	<i>(3.80)</i>	<i>(3.60)</i>
Absolute change in credit-to-GDP ratio (-1)	0.042		0.029		0.110	
	<i>(3.85)</i>		<i>(2.10)</i>		<i>(3.69)</i>	
Absolute change in credit-to-GDP ratio (-5)		0.036		0.031		0.059
		<i>(3.14)</i>		<i>(2.19)</i>		<i>(2.15)</i>
LR Statistics	19.83	15.67	6.46	7.07	32.39	20.67
Prob.(LR Statistics)	0.000	0.001	0.091	0.070	0.000	0.000
Total Observations	1508	1470	543	511	965	959
Observations with Dep. = 1	32	32	24	24	8	8
Observations with Dep. = 0	1476	1438	519	487	957	951

z-statistic in Italics and bracket. **Bold** for statistical significance at 5% or better.

simulated to find appropriate timings of the trigger for each regressor. The baseline and alternate models we present have the following functional relationship.

Baseline model:

$$\text{Crisis Dummy} = \alpha + \beta_1 \text{ Real GDP growth } (-1) + \beta_2 \text{ Inflation } (-1) + \beta_3 \text{ Absolute change in credit-to-GDP ratio } (-1)$$

Alternate model:

$$\text{Crisis Dummy} = \alpha + \beta_1 \text{ Real GDP growth } (-3) + \beta_2 \text{ Inflation } (-1) + \beta_3 \text{ Absolute change in credit-to-GDP ratio } (-5)$$

We estimated the baseline model's results with one-quarter-lagged regressors for the three types of samples for three time periods: 1981Q1–2019Q4, 1981Q1–2003Q4 (pre-financialisation) and 2004Q1–2019Q4 (post-financialisation). Compared to an annual sample, the use of quarterly series improves the model fit as a result of greater frequency of data and enables the inclusion of several lags of various lengths. These features were particularly useful in modelling the EWS functions of the regressors, particularly with respect to better capturing the timings of the trigger of the regressors because the EWS indicators do not alert of the potential incidence of systemic banking crises simultaneously but of differentiated timings. The results indicate that inflation tends to perform better at shorter lags and that the real GDP growth and absolute change in credit-to-GDP ratio deliver better results at longer lags. Therefore, the appropriate alternate model considered lagged inflation by one quarter, real GDP growth by three quarters and the absolute change in credit-to-GDP ratio by five quarters. In fact, we also found that the absolute change in credit-to-GDP ratio performed well at eight and 12 quarters lagged, in line with the findings of the signal extraction model depicting, respectively, the 2-year and 3-year pre-crisis periods.

In all the regression specification results, except for the outcomes for the group of developing countries in the post-financialisation period, the constant term estimated is negative and mostly hovers within an absolute range of 2.0–2.5, suggesting that the changes in the regressors could be absorbed within this constant term. The larger negative constant term for the sample of developing countries in the post-financial-liberalisation period indicates of a much larger threshold in the absolute change in the credit-to-GDP ratio required for those countries, suggesting that for those countries, additional systemic risk generated by a larger supply of credit can be better contained than in the case of developed economies in the period 2004–2019. This finding could also potentially explain the small number of developing countries in the sample experiencing a systemic banking crisis in the post-financial liberalisation period as well as the increasing risk associated with highly financialised economies, as characterised by developed countries.

Estimation results for the pre-financialisation period show that the absolute change in credit-to-GDP ratio is statistically insignificant in the baseline model for the mixed sample and in the baseline and the alternate models for the group of developed countries. However, it is statistically significant for the sample of developing countries for the baseline model and the alternate model as well as for the mixed sample when applying the alternate model. Interestingly, the period 1981Q1–2003Q4 delivers very low LR statistics for all three samples as well as the baseline and alternate models, suggesting an inferior model fit, compared to the whole sample period and the post-financialisation periods.

In contrast, in the post-financial-liberalisation period and for the whole sample period, the absolute change in credit-to-GDP ratio is statistically significant in the baseline and alternate models. The regression results also indicate that the impact coefficient for the absolute change in credit-to-GDP ratio as well as the statistical significance is higher for the period 2004–2019 than for the period 1981–2003. These results suggest that financial liberalisation has had important implications in terms of the higher statistical significance and hence stronger influence of credit variables within the modus operandi of the formation of systemic banking crises in the period 2004–2019.

Interestingly, in the post-financial-liberalisation period, the financialisation of the economy intensified much more quickly for developed countries than for developing countries, as Fig. 1 shows. The mean absolute change in credit-to-GDP ratio is much higher for developed countries than for developing countries between 2003 and 2008, that is, in the years before the GFC 2008, which

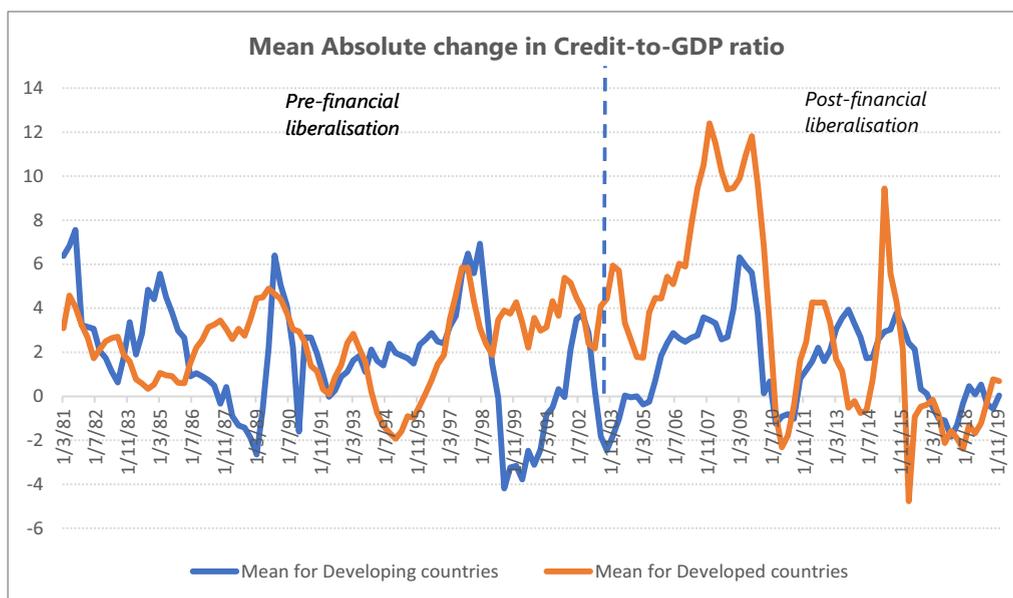


Fig. 1. Comparing the evolution of absolute change in credit-to-GDP ratio between the two groups of countries for the period 1981Q1–2019Q4.

is precisely why the signal extraction model and the multivariate probit panel regressions could capture, efficiently and elegantly, the performance of the absolute change in credit-to-GDP ratio as a suitable EWS indicator of systemic banking crises. The results of both models also reinforce the very important point [Borio and Lowe \(2002a, 2002b\)](#) made that the risks accumulate gradually before causing a sudden shock to the system, which is why the modelling of thresholds within the signal extraction model is vital to “capturing the cumulative processes” of systemic risk build-up.

The results for the other two regressors considered in the regression models, real GDP growth and inflation, are also remarkable. Throughout most of the regression results, real GDP growth is mostly statistically insignificant, and I found inflation to be essentially statistically significant. In fact, in pre-GFC studies, the absence of a variable such as the absolute change in credit-to-GDP ratio made real GDP statistically significant in predicting systemic banking crises because to some extent, it reflected the influence of financialisation of the economy. The inclusion of the absolute change in credit-to-GDP ratio in the regression model specification therefore reduces real GDP growth’s influence on the probability of systemic banking crises. The results for inflation have to be viewed against the observations [Borio and Lowe \(2002a, 2002b\)](#) made suggesting that persistently low and stable inflation could be concealing financial imbalances that could “show up first in credit aggregates and asset prices, rather than in goods and services prices”.

[Borio and Lowe’s \(2002a, 2002b\)](#) observations are typical of what the years before the GFC 2008 depicted. Inflation was low and stable while credit growth was accelerating. Because the monetary policy framework in place focussed primarily on reducing inflation and output volatility, excess growth in credit supply was being absorbed in asset prices,¹⁷ particularly house prices. Therefore, although low output and inflation volatility could have been maintained for some time, it would have been practically impossible to sustain them for too long without an adjustment in prices of goods and services used in the production of those assets [Borio and Lowe \(2002a., 2002b\)](#) referred to such dynamics as a “cumulative process of financial imbalance”, essentially masked by low and stable inflation that eventually rose abruptly in the pre-crisis quarters ahead of a systemic banking crisis. The regression results also indicate that inflation is statistically significant only at short lags (one quarter lag), confirming the proposition that it typically becomes the last lever of adjustment ahead of a systemic banking crisis.

5. Conclusion

This study fills important gaps in the EWS literature for systemic banking crises by connecting pre- and post-GFC 2008 studies through an in-depth review of the distribution of systemic banking crises by country and over time to identify conditions explaining credit’s increasing prominence in predicting systemic banking crises. Through an evaluation of the performance of the absolute change in credit-to-GDP ratio as an eligible EWS indicator for systemic banking crises, the current study shows that intensified financialisation of countries, particularly developed countries, has turned credit variables into vital EWS indicators of systemic banking crises. The model results, both the signal extraction method and the multivariate probit panel regression results, indicate that post-financialisation, an excessive supply of credit led to gradual accumulation of systemic risk, which burst into a systemic banking crisis.

¹⁷ Precisely as [Borio and Lowe \(2002a, 2002b\)](#) suggested.

Interestingly, the absolute change in credit-to-GDP ratio beyond a threshold of 3.0% can serve as a precise benchmark for considering stepping up policy actions to mitigate the risks of the incidence of a systemic banking crisis.

Another important result of the current study is the observations relating to inflation. Historically, the achievement of low and stable inflation has been viewed as the outcome of the move towards inflation-targeting and similar monetary policy frameworks. The current study shows that even at very low and stable inflation rates, financial imbalances could accumulate through additional rounds of credit supply that impact more nominal values than real GDP growth. As such, the dynamics of the alternate model estimated under the multivariate probit panel regression show that a larger absolute change in credit-to-GDP ratio generates growing vulnerabilities in the banking sector at five lagged quarters while inflation becomes statistically significant in impacting the probability of the incidence of systemic banking crises at one lagged quarter.

This study is expected to be of much interest to policymakers in their preparedness for monitoring the build-up of systemic risks. For bankers, this study provides additional evidence that they should include the absolute change in credit-to-GDP ratio in their risk assessment toolkit as a measure of systemic risk that traditional measures underestimate. This study provides new insights for academics working on EWSs that can also be useful for the literature on growth and financial development.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix I. Proof of comparability between the Basel gap and the absolute change in credit-to-GDP ratio

Applying the signal extraction model to an annual sample¹⁸ of 20 advanced economies in the period 1981–2015 produced similar results to those of [Drehmann et al. \(2010\)](#) and [Detken et al. \(2014\)](#) for the credit-to-GDP gap found in terms of the probability of predicted crises as well as the noise rate. It is noteworthy that within this group of advanced economies, 15 countries were harmed by GFC 2008.

After obtaining the results for the credit-to-GDP gap consistent with the results in the post-GFC 2008 literature, we used the same sample of advanced economies to analyse the performance of the absolute change in credit-to-GDP ratio [Table A1](#). and [Table A2](#) summarise the main performance results of the credit-to-GDP gap and the absolute change in credit-to-GDP ratio, respectively, for the selected 20 advanced economies. For a threshold level of 3.0% over a 3-year prediction horizon,¹⁹ the Basel gap would have predicted 76.2% of systemic banking crises in the sample while generating an N/S ratio of 58.6%. For the same threshold and over the same prediction horizon, the absolute change in credit-to-GDP ratio would have predicted a much higher 90.5% of systemic banking crises in the sample study while generating a lower N/S ratio of 57.4%. The results for the 5.0% threshold further indicated the proposed EWS indicator's improved performance. The absolute change in credit-to-GDP ratio was therefore relatively more efficient than the Basel gap because it generated a lower N/S ratio and a remarkably higher probability of predicted crises.

¹⁸ The sample of advanced economies considered included Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, South Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States.

¹⁹ It can be shown that a 3-year prediction horizon is optimal because it delivers a lower noise-to-signal ratio than the 2-year and 4-year prediction horizons. Similarly, the 3% threshold was found to perform better than the 2% and 4% thresholds.

Table A1
Performance of Credit-to-GDP Gap.

Performance of Credit-to-GDP gap ('Basel gap') over 3-year Prediction Horizon							
Period	Threshold (%)	Noise rate (%)	Signal rate (%)	Noise-to-Signal ratio (%)	Number of countries	Number of crises	Predicted crises (%)
1981–2015	3.0	42.34	72.31	58.56	20	21	76.19
1981–2015	5.0	33.33	64.62	51.59	20	21	71.43
1981–2003	3.0	44.12	77.78	56.72	20	6	83.33
2004–2015	3.0	35.40	70.21	50.42	20	15	73.33

Source: Author's computation.

Table A2
Performance of Absolute Change in Credit-to-GDP Ratio.

Performance of 'Absolute Change in credit-to-GDP ratio' over 3-year Prediction Horizon							
Period	Threshold (%)	Noise rate (%)	Signal rate (%)	Noise-to-Signal ratio (%)	Number of countries	Number of crises	Predicted crises (%)
1981–2015	3.0	40.65	70.77	57.44	20	21	90.48
1981–2015	5.0	25.77	50.77	50.76	20	21	76.19
1981–2003	3.0	41.86	50.00	83.71	20	6	83.33
2004–2015	3.0	35.78	78.72	45.45	20	15	93.33

Source: Author's computation.

Both the Basel gap and the absolute change in credit-to-GDP ratio are derivatives of the credit-to-GDP ratio, suggesting that it ought to be a vital statistic for examining systemic banking crises. However, its application to analyse past systemic banking crises was limited in the literature. The results for both indicated that their performance was fairly consistent over time although in the pre-financial liberalisation era, that is, 1981–2003, very few²⁰ systemic banking crises occurred in the advanced economies. The GFC 2008 therefore was markedly different, with 15 of the 20 advanced economies experiencing a systemic banking crisis.

Appendix II. Distribution of financial crises by type and between 1970 and 2017

	Banking crisis	Currency crisis	Sovereign debt crisis	Twin crisis*	Triple crisis**
1970's	3	25	7	0	0
1980's	40	74	41	11	4
1990's	74	84	7	24	3
2000–2005	5	18	8	4	3
2006					
2007	2	1	1		
2008	22	3	2	2	
2009	1	5			
2010		1	2		
2011	1				
2012		3	2		
2013		2	1		
2014	3	3	1		1
2015		13	1		
2016		4			
2017			2		
2006–2017	29	35	12	2	1
1970–2017	151	236	75	41	11

*Twin crisis indicates banking crisis in year t and currency crisis during $[t-1, t + 1]$.

**Tripple crisis indicates banking crisis in year t and currency crisis during $[t-1, t + 1]$ and debt crisis during $[t-1, t + 1]$.

Source: Laeven and Valencia (2013, 2018), IMF database.

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²⁰ They included the Nordic financial crisis in 1991 as well as the systemic banking crises in the US in 1988 and in South Korea and Japan in 1997.

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