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Financial crises in emerging and developing countries : credit cycles, interdependence and leading indicators

Sofiane El Ouardi

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Financial crises in emerging and developing countries: Credit cycles, interdependence and leading indicators.

Sofiane El Ouardi*

Thèse présentée et soutenue le 9/12/2022 à l'Université Paris Est Créteil

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[†]This chapter is a working paper co-authored with my supervisor (Bouvatier & El Ouardi (2021). *Credit gaps as banking crisis predictors: a different tune for middle- and low-income countries*, Erudite Working Paper 2021-15, Erudite).

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General introduction

Following the global financial crisis of 2007-2008, multiple international responses were considered to curb procyclicality in banking activities. In 2010, Basel III agreements introduced an array of both micro and macro-prudential reforms that aim to strengthen the monitoring of banking sector activities. One of these measures consists of accumulating countercyclical capital buffers (CCyB) in order to counter procyclicality in the banking sector. This approach relies on strengthening capital in periods when aggregate vulnerabilities are building up during the ascending phase of the financial cycle (up to 2.5% of risk-weighted assets). Thus, banks should be more resilient during the downswing of the financial cycle as accumulated buffers can be released, helping to attenuate losses. Although Basel frameworks are theoretically planned to work for internationally active banks, multiple middle- and low-income countries policymakers have applied Basel I and II to non-internationally active banks mirroring the capacity of tailoring Basel Committee of Banking Supervision (BCBS) guidance to local needs.¹ While Basel I and II primarily aimed to set off minimum capital requirement for banks and to introduce supervisory responsibilities, respectively, the focus of Basel III was to increase the amount and enhance the quality of capital held by banks, introducing in the process liquidity standards and several macro-prudential instruments that aim to curb the build-up of systemic risk. According to the Bank for International Settlement (BIS), the implementation of both micro and macro-prudential Basel III components has been steadily increasing for most BCBS jurisdictions in recent years. This evolving trend regarding most Basel III components is also true in some non-BCBS members.

¹Among the 28 jurisdictions that compose the BCBS, only 9 countries are classified as middle-income according to the World Bank's classification (Argentina, Brazil, China, India, Mexico, Russia, South Africa and Turkey). The remaining high-income jurisdictions are: Australia, Belgium, Canada, European Union, France, Germany, Hong Kong SAR, Italy, Japan, Korea, Luxembourg, Netherlands, Saudi Arabia, Singapore, Spain, Sweden, Switzerland, United Kingdom and United States.

0.1 Prudential regulation in emerging market and developing economies

0.1.1 Surveys of non-BCBS members

Hohl et al. (2018) surveyed 100 non-BCBS members on whether they have adopted key prudential requirements of the Basel framework and how they apply proportionality in their regulatory regimes.² The authors find that the implementation of several frameworks, such as Risk Based Capital (RBC) regimes, varies across national authorities in terms of proportionality. Among the 100 jurisdictions that have applied the RBC regime, 60 were based on key elements of Basel III, 10 are still using Basel II recommendations while 30 remain under Basel I.

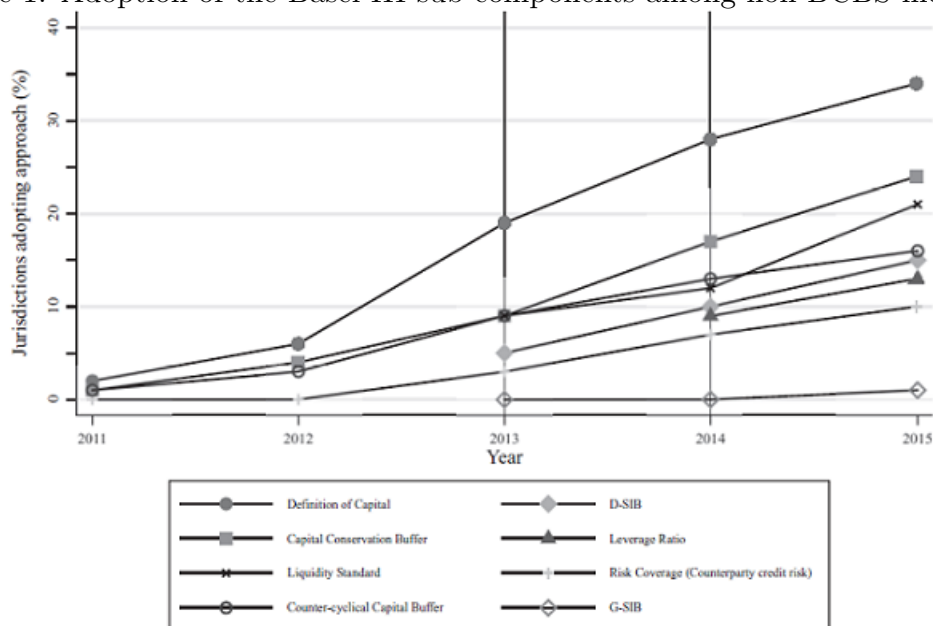
Further data from the Financial Stability Institute (FSI) also show that Basel III is being widely implemented by non-members of the BCBS. A survey conducted by Jones & Zeitz (2017) highlights that around 40% of the jurisdictions inquired (41 of 100) reported an implementation of at least one component from Basel III by 2015 while an additional 40 jurisdictions had started this process, leaving only 19 authorities that had not taken any steps at all towards implementation.

Jones & Zeitz (2017) emphasize that several regions around the world have begun adopting Basel III components. The Middle East and North Africa are the regions that encompass the highest number of adopters (nine of 12 surveyed jurisdictions have adopted at least one component) while implementation is lowest in Latin America and the Caribbean (five of 28 adopting) and sub-Saharan Africa (seven of 22 adopting).

Even though Basel III standards are spreading fairly quickly worldwide, their implementation is rather selective. Since Basel III is relatively new and the standards have been issued gradually over several years, it is challenging to distinguish trends in the data regarding the components that are being implemented. By 2015, five years after the Basel III standards were endorsed, non-members were, on average, only implementing one of the eight components: merely five jurisdictions implemented six or more, 16 had adopted just one or two components, and 59 countries had adopted none. Scrutiny of data from the FSI reveals rather high adoption of the Basel II micro-prudential capital components among non-members (Figure 1). Among the 41 jurisdictions that have adopted at least one element of Basel III, 34 have adopted the new

²Proportionality is defined as the tailoring of Basel standards, or developing alternative rules that better fit to local needs.

Figure 1: Adoption of the Basel III sub-components among non-BCBS members



Source: Jones & Zeitz (2017). Note: Basel III is composed of eight subcomponents: (i) Liquidity Coverage Ratio (LCR); (ii) Definition of capital; (iii) Risk coverage (for counterparty credit risk); (iv) Capital conservation buffer; (v) Countercyclical capital buffer; (vi) Leverage ratio; (vii) Domestic systemically important banks (D-SIB); and (viii) Global systemically important banks (G-SIB).

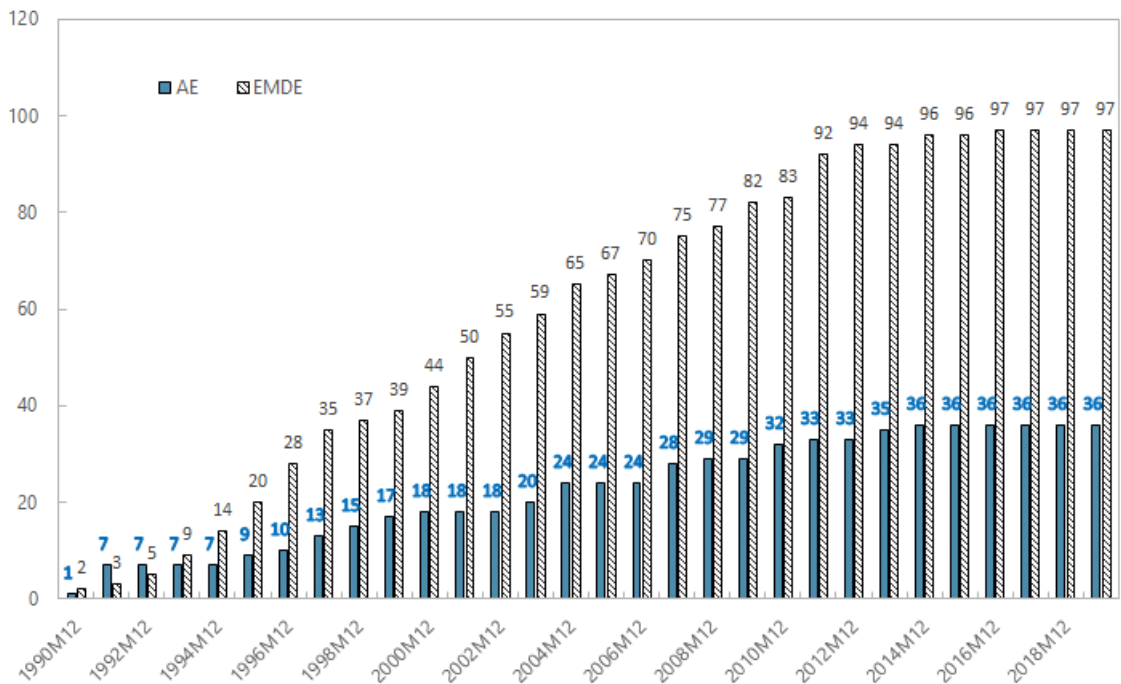
definitions of capital and 24 have adopted the capital conservation buffer. Nevertheless, the new standards for assessing counterparty credit risk have only been implemented by 25% of those jurisdictions. The FSI data shows a fairly quick adoption of the LCR, with 21 of the 41 jurisdictions adopting it as of 2015 (Figure 1). There has been a relatively quick adoption of the leverage ratio, which was implemented by 13 countries out of the 41 employing at least one component of Basel III, although the late introduction in 2013. Fifteen jurisdictions have adopted the new standards on D-SIBs, and 16 have adopted the counter-cyclical buffer. Even prior to Basel III agreements, multiple emerging and developing countries already started to implement macroprudential policies at the beginning of the 1990s to mitigate the financial imbalances linked to excessive capital flows.

0.1.2 Macroprudential perspective

The iMaPP database shows that the number of countries that have implemented any macroprudential policy tool has been continuously growing since 1990, before stagnating after 2012. In their study, Alam et al. (2019) show that over 90 percent of the countries within their sample had used at least one tool by 2012 (Figure 2). Prior to the global financial crisis, many countries had already started the implementation of at least one macro-prudential instrument: 24 out of 36 advanced economies (AEs) and 70 out of 98 emerging market and developing economies (EMDEs) in December 2006. More recent data suggest that the implementation of instruments, such as liquidity requirements, emerge as the most popular tool among advanced economies, while limits on foreign exchange (FX) position are the tools most widely used among EMDEs (Figure 3). This may reflect dissimilarities in key risks: while AEs tend to be more concerned about mitigating systemic liquidity and funding risks, EMDEs are more exposed to vulnerabilities from external shocks, large capital outflows and systemic risks caused by significant variations of the exchange rate. Nevertheless, liquidity requirements are also becoming increasingly predominant in EMDEs along with conservation buffers that aim ensure an additional layer of usable capital that can be drawn down when losses are incurred. Cerutti et al. (2017) employ a survey from the IMF to explore the use of macro-prudential policies for a large sample of 119 countries spanning from 2000 to 2013 covering a broad array of instruments. The authors find that EMEs use macro-prudential policies more frequently, specifically the ones that are related to foreign exchange reserves. Moreover, Cerutti et al. (2017) detect a significant impact regarding the usage of such policies which are often associated with lower levels of growth in household credit. Conversely, effects of such policies are more contrasted in countries with integrated financial markets, financially developed systems and more openness in capital accounts. Cerutti et al. (2017) conclude their study by emphasizing that macro-prudential policies work rather well during the upswing of the financial cycle while the effects are less significant during the busts.

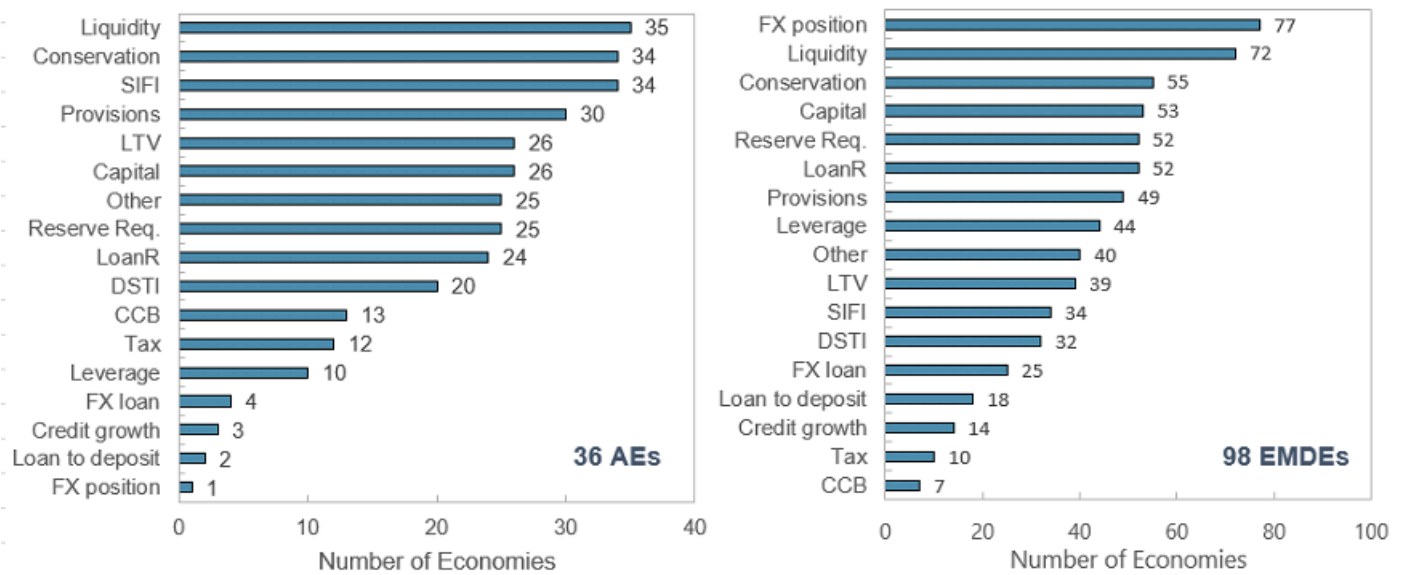
The use of macro-prudential policies resulted from the multiplicity of financial crises that occurred in the 1980s and 1990s. Indeed, several sovereign defaults were recorded during the 1980s (for instance, Latin America debt crises, such as in Mexico 1982) while most banking and currency crises coincided in the early 1990s.

Figure 2: Number of countries that employed Macroprudential policy



Source: The iMaPP database (Alam et al. (2019)). Note: The figure shows the number of economies that have used any macroprudential policy instrument (except for reserve requirements) at least once during the sample period. There are total 134 economies (36 AEs and 98 EMDEs) in the iMaPP database. AE = advanced economies; and EMDE = emerging market and developing economies.

Figure 3: Frequency of use by instrument



Sources: The iMaPP database (Alam et al. (2019)). Note: The figure shows the number of economies that have used the specified instrument as of August 2021. AE = advanced economies; and EMDE = emerging market and developing economies.

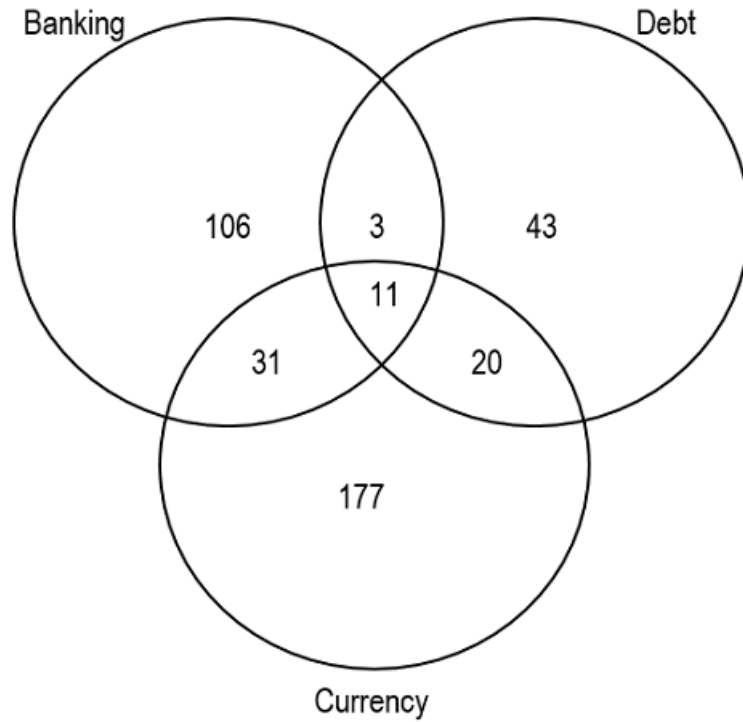
0.2 The overlap of financial crises and their costs

0.2.1 Clustering of financial crises

Although financial crises can be driven by a variety of factors, they are often preceded by asset and credit booms. Regardless of the classification employed, it appears that different types of crises can overlap and cluster over time (Figure 4). Many banking crises, for example, are also associated with currency crises in middle- and low-income countries. The overlap of multiple types of crises leads to further challenges for the identification of events and examination of their underlying causes. Since banking and currency crises often coincide, it is difficult to answer definitively whether a banking crisis leads to a currency crisis or vice versa. Figure 5 plots the occurrence of banking crises for each year covering the 1976-2017 span. The graph shows that, prior to the global financial crisis of 2008, banking crises were mostly a middle- and low-income country phenomenon. A different scheme emerges around the global financial crisis of 2008, which Reinhart & Rogoff (2009b) call an "equal opportunity menace" regardless of the income level. Figure 6 shows the frequency of currency and sovereign debt crises episodes by year and income level. Currency crises are quite uncommon among the high-income group of countries, even throughout the global financial crisis. Such a difference could be imputed to the exchange rate stability that features the majority of high-income countries. Looking at figures 5 and 6 simultaneously hints that all three types of crises come in waves. The number of sovereign defaults peaked in the mid-1980s, driven predominantly by Latin America, with more recent episodes including both high and low- and middle-income economies. The 1990s period recorded the highest frequency of currency crises while the maximum number in a single year occurred around the global financial crisis in 2008. The incidence of currency crises increased in 2015 due to the significant exchange rate depreciation in many commodity-exporter countries triggered by a decline in commodity prices. In total, 11 triple crises are identified (i.e., simultaneous banking, currency, and sovereign debt crises in a given country) over the period 1970–2017. Among twin crises, the currency/banking (42 episodes) and currency/debt (31 episodes) crisis pairs tend to be more common than the banking/debt crisis pair (14).

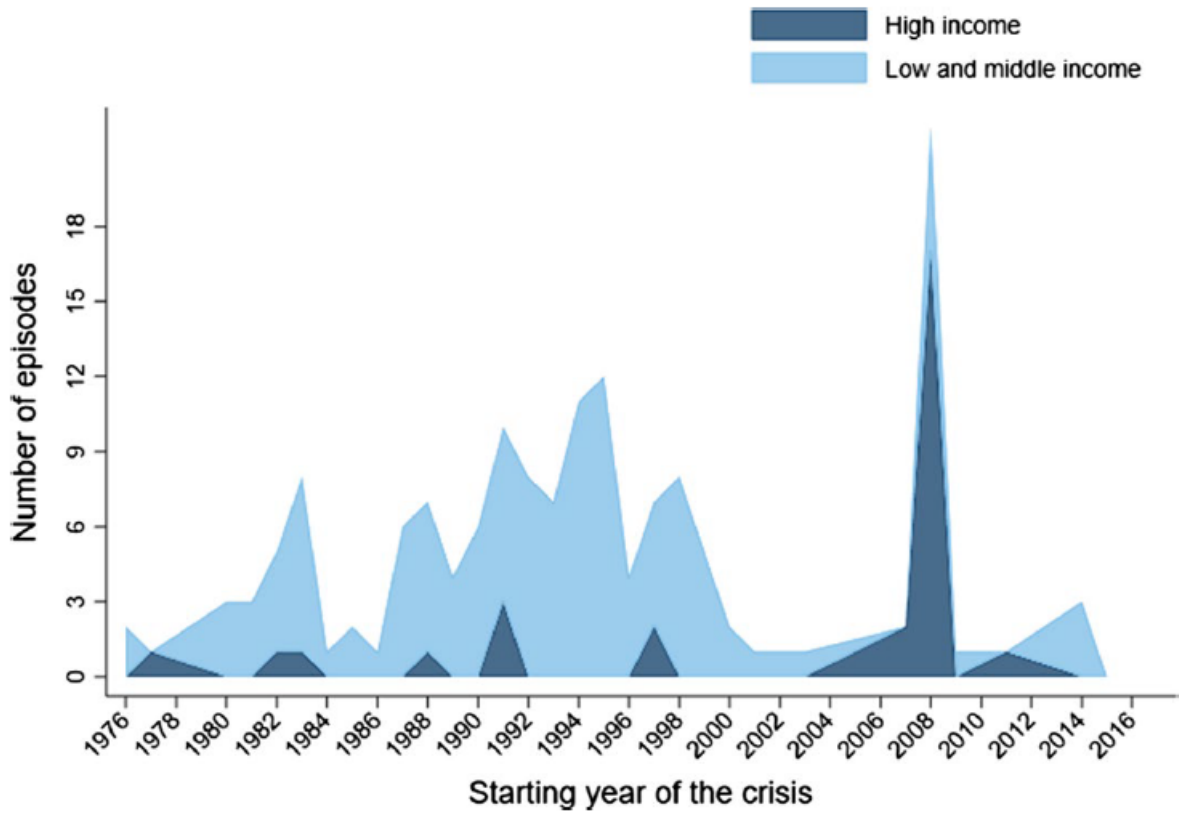
Whether the association of a higher banking crisis probability with a currency crisis reflects a causal link remains unclear. However, the empirical evidence clearly suggests that these two phenomena are closely related (Hutchison & Glick (2000); Von Hagen & Ho (2007)). In their updated database on financial crises, Laeven & Valencia (2020), manage to identify

Figure 4: The overlap of multiple financial crises since 1970



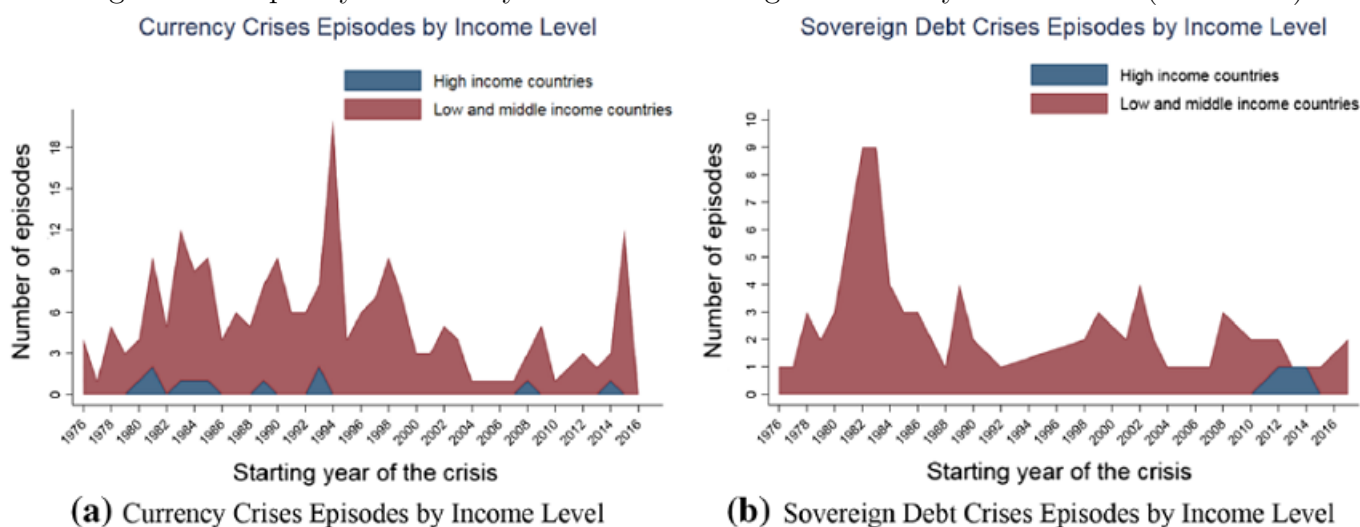
Source: Laeven & Valencia (2020).

Figure 5: Frequency of banking crises by income level (1976-2017)



Source: Laeven & Valencia (2020).

Figure 6: Frequency of currency crises and sovereign defaults by income level (1976-2017)



Source: Laeven & Valencia (2020).

151 banking crises and 239 currency crashes over during the 1970-2017 span. The authors state that, empirically, banking crises tend to occur simultaneously with currency crises: while 16% of banking crises are preceded by a currency crash within a three year window prior to a banking crisis, 21% of banking crises are followed by a currency crisis within the same window. Laeven & Valencia (2020) also record a total of 42 episodes of twin crises during the same period of time. Fratzscher et al. (2011) and Gourinchas & Obstfeld (2012) reach similar conclusions although covering different sample periods and relying on different definitions of crises: it is common for banking crises to happen at the same time or precede currency crises. This pattern provides a justification for the focus on twin crises. The systemic crisis in Ukraine (twin crisis in 2014, and triple in 2015) is a prominent example of a recent systemic crisis that evolved into different types of crises. Thus, studying twin crises seems crucial from the perspective of a policymaker since these phenomenons are costly for the economy.

0.2.2 Financial crises resolution costs

Irrespective of its origins, the resolution of a banking crisis often generates substantial fiscal costs for the authorities. According to Hoggarth et al. (2002), the previous statement is even stronger when a banking crisis occurs along with a currency crisis (twin crises). Kaminsky & Reinhart (1999) argue that bailout costs in countries that experienced both banking and currency crises simultaneously, are significantly higher (13.3% of GDP on average) in contrast with those which faced a banking crisis alone (5.1%). In their survey, Sufi & Taylor (2021) show

that at a 6 year horizon, real GDP per capita remains lower than its long term trend by roughly 5% to 6% on average following financial crises as the authors warn that these output losses are persistent. Laeven & Valencia (2012) attempt to evaluate the top 10 costliest recorded systemic banking crises since 1970 by relying on an array of 3 criteria: the fiscal cost in percent of GDP, the increase of debt in percent of GDP and the output losses (in % of trend GDP). The Indonesian banking crisis of 1997-2001 ranks the highest in terms of fiscal cost (57% of the GDP) as a currency crash was recorded the in year following the start of the banking crisis (1998).³ Similarly, the 1995 banking crisis that occurred in Guinea-Bissau, which was preceded by a currency crash in 1994, yielded the highest increase in the debt to GDP ratio (108%). With respect to output losses (in % trend of GDP), 5 out of the top 10 countries have had experienced twin crises within a 2 year window (Ecuador 1982; Jordan 1989; Congo, DR (1989) Lebanon 1990 and Thailand 1997). Furthermore, 75% of the cited countries among the costliest systemic banking crises are classified as middle- or low-income countries as shown in Table 1 while more than 71% of the listed crises in Table 1 are recorded as twin crises (i.e, a currency crisis preceding or following a banking crisis in a 3 year window).

The Covid-19 pandemic caused substantial output losses through strict lock-downs, widespread international travel bans, and the restriction of public events. The World Economic Report (WEO), published in october 2020, shows that 183 countries out of 197 covered (roughly 93 percent) are estimated to have had a contraction in real per capita GDP in 2020. In many cases, these were unprecedented declines. Scrutiny of the World Bank data highlights a similar pattern as 209 out of 228 economies reported a negative growth of the GDP per capita in 2020 (World Development Indicators).

0.2.3 Indebtedness and large reserves holding: a puzzling behavior

Although the coronavirus crisis did not start as a financial crisis, it may well be morphing into one. The sharp slowdown in economic growth induced by the Covid-19 crisis substantially increased the risk of sovereign default particularly in emerging market economies and developing countries. Multiple middle-income countries have both important foreign currency denominated debts arrears along with high levels of foreign exchange reserves holdings (Rodrik (2006)). This simultaneity is costly for the government, since the latter pays a higher interest rate on its

³The Indonesian crisis also ranks 8th for the debt increase criteria.

Table 1: Costliest banking crises since 1970

	Fiscal cost	Debt increase	Output loss	Income group	Twin	Year
Indonesia (1997)	57	68	69	Lower-Middle	Yes	1998
Argentina (1980)	55	33	58	Upper-Middle	Yes	1981
Iceland (2008)	44	68	34	High	Yes	2008
Jamaica (1996)	44	3	38	Lower-Middle	No	-
Thailand (1997)	44	42	109	Upper-Middle	Yes	1998
Chile (1981)	43	88	9	High	Yes	1982
Ireland (2008)	38	76	107	High	No	-
Macedonia (1993)	32	n.a	0	Upper-Middle	No	-
Turkey (2000)	32	15	37	Upper-Middle	Yes	2001
Korea (1997)	31	10	58	High	Yes	1998
Guinea-Bissau (1995)	n.a	108	30	Low	Yes	1994
Congo, Rep (1992)	n.a	103	47	Lower-Middle	Yes	1994
Uruguay (1981)	31	83	38	High	Yes	1983
Argentina (2001)	10	82	71	Upper-Middle	Yes	2002
Tanzania (1987)	10	65	0	Low	Yes	1985
Nigeria (1991)	n.a	63	0	Lower-Middle	Yes	1989
Kuwait (1982)	n.a	16	143	High	No	-
Congo, DR (1991)	n.a	42	130	Lower-Middle	Yes	1989
Burundi (1994)	n.a	11	121	Low	No	-
Jordan (1989)	10	-61	106	Upper-Middle	Yes	1989
Cameroon (1987)	n.a	18	105	Lower-Middle	Yes ⁴	1989
Lebanon (1990)	n.a	n.a	102	Upper-Middle	Yes	1990
Ecuador (1982)	n.a	24	98	Lower-Middle	Yes	1982
Latvia (2008)	8	28	94	High	No	-

Bold values are associated with episodes that were the costliest for each of the 3 criteria.

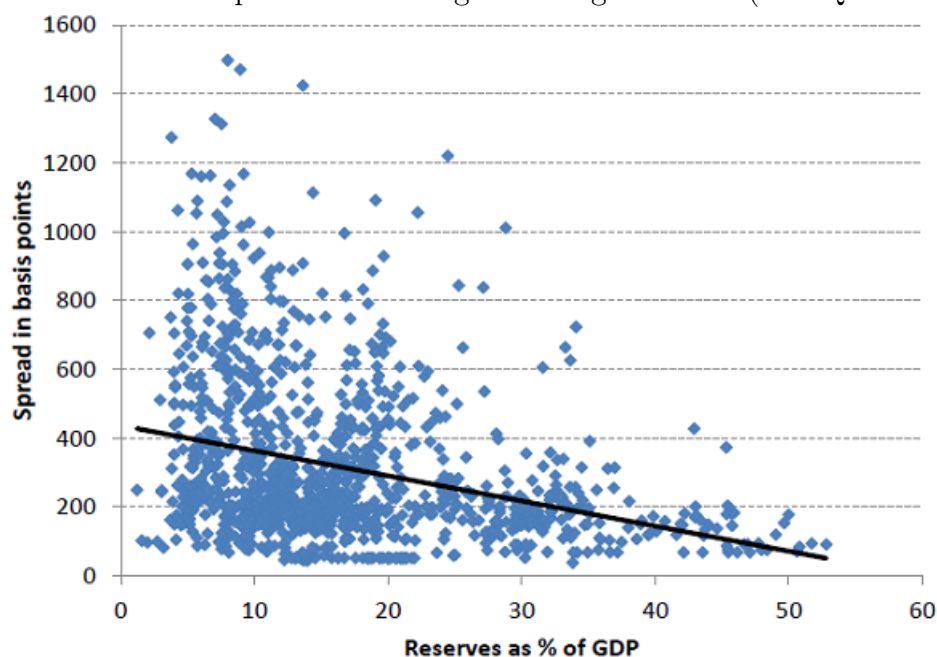
Multiple bold values on the same line stand for episodes that rank in the top 10 for 2 or more criteria.

Twin stands for a currency crisis occurring in a 2 year window preceding or following a banking crisis.

⁴A sovereign default.

Data source: Laeven & Valencia (2020).

Figure 7: Scatter of spreads and foreign exchange reserves (1994Q1-2015Q4)

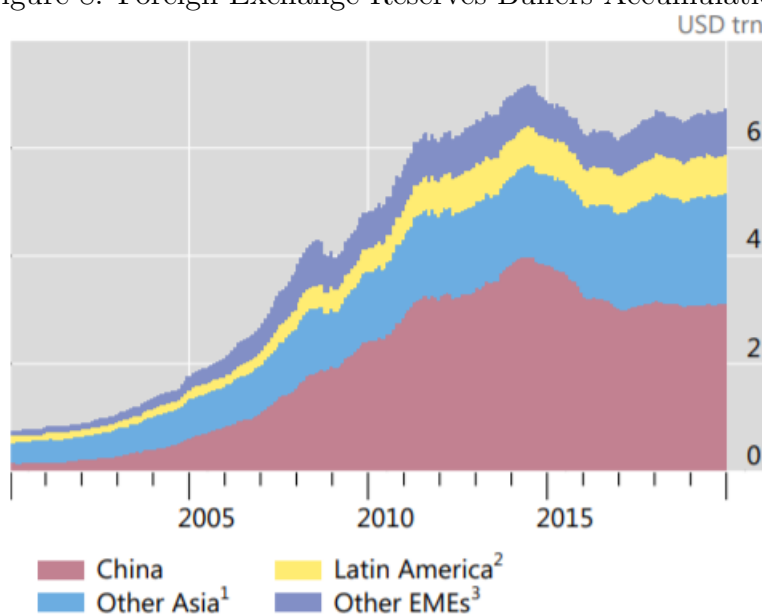


Source: (Hernandez (2017)). Note: The sample includes data for 18 emerging markets: Argentina, Brazil, Bulgaria, Chile, Colombia, India, Indonesia, Lithuania, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, South Africa, Turkey, and Ukraine.

debt in contrast with what it earns on its reserves holdings⁵. However, this suggests there should be some extra benefit of reserve holdings (Feldstein (1999)). The empirical evidence also tend to demonstrate that higher reserves holding positions are frequently associated with lower sovereign spreads. Figure 7 encompasses a sample of 18 of middle-income countries using quarterly data from 1994 to 2015 and suggests that there a negative correlation between sovereign spreads in basis points and the reserves-to-GDP ratio. The main reason cited for emerging markets reserve holdings is known as the precautionary motive: reserves are a liquidity buffer that protects the sovereign against adverse developments in financial markets. Macroprudential policies also enhance the resilience of the financial system. Many EMEs have accumulated large FX reserves over the past decade (Figure 8). These FX reserves can cushion the shock from the Covid-19 crisis and mitigate financial distress on EMEs, as they allow central banks to ward off currency depreciation and capital outflows. In the wake of the taper tantrum, EMEs with higher levels of foreign exchange reserves experienced smaller currency depreciation.

⁵These countries borrow with an interest rate penalty to compensate lenders for default risk. Reducing reserves holding in the same proportions as the debt would maintain net liabilities constant while decreasing interest payments.

Figure 8: Foreign Exchange Reserves Buffers Accumulation



Source: (Hofmann et al. (2021)). ¹Hong Kong SAR, India, Indonesia, Korea, Malaysia, the Philippines, Singapore and Thailand. ²Argentina, Brazil, Chile, Colombia, Mexico and Peru. ³The Czech Republic, Hungary, Poland, Russia, South Africa and Turkey.

0.3 Structure of the thesis

0.3.1 Research questions

Despite the clear need from non-BCBS jurisdictions for international guidance on the application of proportionality, there currently exist no consensual operational framework for the determination of the CCyB activation rate in this group of countries. As a result, detecting credit procyclicality in non-BCBS countries might be challenging which can exacerbate the risk of banking crises. An additional challenge emerges from the fact that not all credit booms necessarily end up in banking crises. Barajas et al. (2007) highlight that credit booms can have a positive effect on the economy demonstrating that the link between banking crises and credit boom is not systematic.

Since banking and currency crises often coincide in non-BCBS jurisdictions, one might argue that the determinants of a banking crisis might be substantially divergent from excess credit in these countries. Therefore, detecting the build-up of such financial distress brings an additional challenge from the perspective of a policymaker. While it appears to be clear that credit booms play a huge role in the build-up of banking distress, it is yet ambiguous how rapid credit growth impacts the likelihood of currency crises. Nevertheless, the seminal paper of Kaminsky & Reinhart (1999) on the twin crises suggests that the two phenomena are mutually impacted

by credit booms. Thus, non-BCBS jurisdictions should be considering the role of currency crises when attempting to tailor Basel III standards to local needs in the process of detecting the risk of banking crises.

Empirically, the association of a higher sovereign default probability with lower levels of foreign exchange reserves can be observed. Nevertheless, there exist no consensual framework for the determination of reserves adequacy and therefore, central banks typically determine their needs using a proxy with respect to the country's reserves position for a specific risk (for example import coverage or short-term debt sustainability). Thus, an open question remains in the empirical literature regarding the best performing indicators of sovereign defaults with respect to international exchange reserves ratios. In addition, several leading indicators might be relevant in the process of preventing defaults for middle-income countries with financially developed markets while others could be well-suited for low-income economies.

0.3.2 Data and Methodology

In this thesis, I conduct an empirical study on financial crises in middle- and low-income countries. Thus, bulk of the data employed is in annual frequency. A few robustness checks rely on quarterly frequency as there exist some evidence in the literature suggesting that this format could be more suitable to capture the features of financial cycles.

In addition, I mainly rely on parametric probit and logit models for the estimations of financial crises probabilities. While I'm aware that multiple alternatives exist to deal with these issues, I decide not to implement them for various reasons. The prominent method suggested by Kaminsky et al. (1998), which involves signal extraction, is well suited for country-specific Early Warning Systems. In terms of in-sample predictive ability, Davis & Karim (2008) find that the multivariate logit model outperforms the signal extraction approach in terms of the percentage of crises correctly predicted regarding banking crises. In addition, Berg & Pattillo (1999) argue that, with the signal extraction approach, every indicator misses a substantial number of crises as the authors advocate the usage of multivariate probit in the context of currency crises. More recent debates in the literature are suggesting that machine learning techniques could be suitable to assess the risk of financial crises. For example, Beutel et al. (2019) highlight that machine learning techniques display a good in-sample predictive power, but are often outperformed by traditional logit models in the overall prediction of banking crises (i.e, when accounting for the out-of-sample performance as well). Furthermore, machine

learning techniques often rely on large sample sizes which can be challenging to attain in the context of financial crises. Finally, Svirydzienka (2021) emphasize that the limitations and biases of the machine learning remain an open debate in the literature and advocate the use of signal extraction and logit. Accounting for the previously mentioned rationales, I hence decide to implement parametric logit and probit models as I deem those techniques more fitting for the aimed purpose.

0.3.3 Outline

The first chapter will focus on a performance assessment of several credit metrics regarding banking crises prediction in middle- and low-income countries. The main objective will be to identify whether the BCG can be employed for the setting of the CCyB activation rate in this subgroup of countries.

Afterwards, the purpose of chapter two will be to investigate the relevance of the BCG regarding banking and currency crises in middle- and low-income countries. Knowing that credit booms tend to coincide with both banking and currency crises, the main goal will be to determine whether the CCyB can be employed as a macro-prudential policy instrument to prevent the risk of twin crises.

The final chapter will aim to examine the ability of consensual reserves metrics, that are traditionally employed by central banks to determine reserves adequacy, to detect sovereign debt crises in middle- and low-income countries. The primary objective will be to assess the capacity of the best performing reserves metrics at predicting the defaults that occurred in the wake of the Covid-19 crisis.

Chapter 1

Credit gaps as banking crises

predictors: a different tune for middle and low income countries[†]

[†]This chapter is a working paper co-authored with my supervisor (Bouvatier & El Ouardi (2021). *Credit gaps as banking crisis predictors: a different tune for middle- and low-income countries*, Erudite Working Paper 2021-15, Erudite).

Introduction

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

The Basel Committee on Banking Supervision (BCBS) proposed an operational framework to set the level of the CCyB (BCBS (2010), Drehmann & Tsatsaronis (2014)). Specifically, quantitative indicators and policymaker judgment are both required to determine the CCyB rate on the basis of guided discretion. Guidance proposed by BCBS (2010) is mainly based on prior research at the Bank for International Settlements (BIS) that accumulated a long-term expertise on procyclicality of the financial system and financial stability (see e.g., Borio et al. (2001), Borio & Lowe (2002)). Particularly, the main objective is to identify the indicator or subset of indicators that is the most effective to measure procyclicality in credit activities and to detect the risk of banking crises. When an early warning indicator gives a stable signal that is easy to interpret and early enough before bust periods, it can be considered as a reliable candidate by national authorities to be used in their guided discretion to set the CCyB rate. Several empirical investigations implementing, for instance, *horse races* to compare indicators' performance have led to the conclusion that the gap in the credit-to-GDP ratio is an effective indicator to capture the risk of banking crises (see, e.g., Drehmann et al. (2010), Drehmann et al. (2011), Drehmann (2013), Drehmann & Juselius (2014)). Further, from a methodological perspective, the gap in the credit-to-GDP ratio should be assessed using the Hodrick & Prescott (1997) (HP) filter with a smoothing parameter set in accordance with the feature of credit cycles.¹ In addition, from an operational perspective, the HP filter is implemented in a one-sided manner so that pseudo-real-time data are used when calculating gaps in the credit-to-GDP ratio. This process of measuring excessive credit activity (i.e., detrending the credit-to-GDP ratio via the one-sided HP filter) corresponds to the so-called Basel Credit Gap (BCG)

¹The smoothing parameter (λ) of the HP filter is set to 400,000 for quarterly data so that the trend component captures only low frequencies associated with periodicities higher than 4 decades. Then, the gap in the credit-to-GDP ratio is given by the difference between the observed credit-to-GDP ratio and its estimated trend.

and can be used to set the CCyB rate according to BCBS (2010) guidance.² Several critiques have been addressed to the BCG (Baba et al. (2020)). For instance, disentangling periods of excessive credit activities and financial deepening periods is particularly challenging for statistical approaches such as the BCG. The BCG can also be characterized by long lasting negative gaps following a large credit bust, limiting the identification of the accumulation of new imbalances during post banking crisis periods. Moreover, some critiques directly address the use of the HP filter. For instance, the choice of the smoothing parameter is questionable because the credit cycle duration can be country-specific and even time-specific in the long run. Critiques of the use of the HP filter also concern the introduction of spurious dynamic relations or end-point problem (Hamilton (2018)). These limitations are still an open debate (see, e.g., Drehmann & Yetman (2018,0), Hamilton & Leff (2020), Hodrick (2020)). More importantly, the BCG remains a key indicator to measure excessive credit activities, to determine the CCyB rate, or more generally to calibrate macroprudential instruments. The implications of the BCG limitations are rather that national authorities can consider a broader set of indicators when deciding on the CCyB rate (BCBS (2017)) and that guided discretion for calibration of macroprudential instruments rarely relies on a single indicator. In addition, complementary methodological approaches to measure credit gaps have been developed to put into perspective assessments obtained by the one-sided HP filter (Drehmann & Yetman (2018), Baba et al. (2020), Bouvatier et al. (2022)).

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

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

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

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

The literature on credit booms (see, e.g., Gourinchas et al. (2001), Mendoza & Terrones (2008), Dell’Ariccia et al. (2016)) shows that such episodes have important impacts on macrofinancial stability and can end in banking crises. In particular, credit booms can cause banking crises in emerging markets (Eichengreen & Arteta (2000), Mendoza & Terrones (2012)). The BCG is therefore a natural candidate as a leading indicator for banking crises. However, the association between credit booms and banking crises is not systematic. Barajas et al. (2007) introduce the distinction between good and bad credit booms, highlighting that not all credit booms end in banking crises. In addition, the existing literature also shows differences between country groups and regions concerning characteristics of credit booms (Meng & Gonzalez (2017)) or the proportion of bad credit booms (Calderón & Servén (2014), Arena et al. (2015)). Therefore, the performance of the BCG as a banking crisis predictor should be investigated in enlarged samples to properly account for the situation of middle- and low-income countries. The limited existing literature on this question provides mixed results. Drehmann & Tsatsaronis (2014) conclude that the BCG is a valuable banking crisis predictor for emerging countries, even if the performance of this credit metric to detect banking crises is lower than it is in advanced economies. Marchettini & Maino (2015) and Geršl & Jašová (2018) conclude that the BCG performs poorly as an early warning indicator of banking crises outside of advanced economies. However, an important common feature of these papers is data limitations. When empirical investigations rely on quarterly data (Drehmann & Tsatsaronis (2014), Geršl & Jašová (2018)), the number of middle- and low-income countries (and banking crises) considered is rather scarce. When empirical investigations rely on annual data (Marchettini & Maino (2015)),

assessment of the BCG can be questioned.⁴ Therefore, no horse race has properly investigated the performance of the BCG as a banking crisis predictor in middle- and low-income countries due to data limitations. This paper addresses this research gap.

The main contribution of this paper is to overcome data limitations (i.e., the availability credit gaps computed from quarterly data) to accurately investigate whether the BCG remains an efficient early warning indicator when a large set of countries is considered. We take advantage of a new database (Bouvatier et al. (2022)) that provides credit gaps for 163 countries; data are quarterly and date back to the late 1950s. Consequently, we can pay particular attention to middle- and low-income countries to assess the performance of credit-based indicators to detect the risk of banking crises. Bouvatier et al. (2022) provide stylized facts about credit cycles but they do not investigate the performance of credit-based indicators to detect the risk of banking crises.

We implement a horse race to investigate and compare the performance of credit activity indicators (including the BCG) to detect the risk of banking crises worldwide. In particular, we rely on 3 different methods of trend-cycle decomposition provided by Bouvatier et al. (2022) (HP filter, the modified HP filter proposed by Kaiser & Maravall (1999, 2001) and basic SSA) and different credit metrics (expressed in percentage of GDP, in real terms, and in real terms per capita) to consider a large set of credit activity indicators. In addition, the performance of banking crises predictors is assessed with several criteria to cover different aspects of performance. Further, we make the distinction between high-income countries and middle- & low-income countries to investigate differences between income groups. Several robustness checks are considered, concerning, for instance, data sources to identify banking crises periods or the definition of groups of countries.

The main result of the paper is that credit activity indicators, particularly the BCG, are overall poor banking crisis predictors for middle- & low-income countries. This result is robust in particular to the definition of groups of countries. For instance, when focusing on upper-middle-income countries or emerging countries, the BCG does not fairly predict banking crises, which contrasts with the results obtained for developed countries. In addition, alternative credit

⁴A quarterly frequency is more appropriate to assess cyclical movements in credit activities. In addition, the BCG relies on trends estimated from very small samples when annual data are considered. Indeed, the BCG relies on a one-sided HP filter (i.e., on recursive estimates using only pseudo-real-time observations). The common practice is to start to report and to use one-sided credit gaps one decade after credit aggregates become available. This practice translates into only 10 observations when annual data are considered. However, the performance of the one-sided HP filter to identify the trend component is sensitive to the starting point when small samples are considered.

metrics, for instance, based on real credit per capita, do not provide better early warning indicators. The main policy implication is that a one-size-fits-all approach is not relevant to set the CCyB rate in middle- and low-income countries. Further, we show that the BCG turns to be a fair banking crises predictor when the financial development, captured by the trend's value in credit-to-GDP ratio, exceeds 20%.

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

1.1 Model and data

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

1.1.1 Banking crisis periods and credit variables

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

We use the Bouvatier et al. (2022) database for the credit variables. This database covers an unbalanced panel of 163 countries over the 1957Q1-2018Q4 period. More precisely, the Bouvatier et al. (2022) database reports series on bank credit expressed in real terms and in percentage of GDP.⁵ Further, the database provides trend-cycle decomposition based on

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

three different methodologies: HP filter, the modified HP filter proposed by Kaiser & Maravall (1999, 2001) and basic SSA.⁶ In particular, the latter is not exposed to some of the critiques addressed to the HP filter, such as the introduction of spurious dynamic relations (Hamilton (2018)). All these methodologies are set in accordance with credit cycle properties. Periodicities of credit cycles can reach 2 or 3 decades. Then, the medium-term cyclical component that can characterize credit activities is properly accounted and not included in the long-term secular trend. Last, the 3 different methodologies are implemented from both one-sided and two-sided perspectives.

Table 1.1 reports descriptive statistics on credit cycles (i.e., gaps in credit-to-GDP ratios). Panel A reports descriptive statistics for all countries; then, the distinction between high-income countries (Panel B) and middle- and low-income countries (Panel C) is considered. The size of credit cycles is assessed based on the standard deviation and mean of the absolute values to account for the fact that credit gaps are zero-mean processes. Table 1.1 shows that the HP filter, modified HP filter and basic SSA lead to similar descriptive statistics.⁷ The size of credit cycles assessed as the mean of the absolute values is approximately 5%, but the kurtosis, minimum and maximum indicate that some countries face extreme events. The frequency of such events is higher than that in the Gaussian situation, but the 5th and 95th percentiles show that the range of credit cycles remains moderate in most periods. For instance, the credit cycle measured via one-sided HP filter (variable CY_{gap}^{HPos}) ranges in $[-10.95\% ; 12.70\%]$ 90% of the time. Further, Table 1.1 shows that credit cycles in high-income countries have different features than those in middle- and low-income countries. More precisely, descriptive statistics reported for Panel B and Panel C in Table 1.1 indicate that the size of credit cycles is larger in high-income countries and that extreme events are more often recorded for high-income countries.

⁶See Bouvatier et al. (2022) for technical details on the use of basic SSA to compute credit gaps.

⁷However, for a given time period, differences in credit gaps computed with the HP filter, modified HP filter and basic SSA can be noticeable (Bouvatier et al. (2022)). Therefore, the performance of credit gaps to predict banking crises might depend on the trend-cycle decomposition method. See Bouvatier et al. (2022) for more descriptive statistics on credit gaps.

Table 1.1: Descriptive statistics

Panel A: Full sample

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

Panel B: High income countries

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

Panel C: Middle & low income countries

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

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

1.1.2 Baseline specification

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

$$P(Y_{i,t} = 1|X_{i,t-1}) = \frac{1}{1 + \exp[-\alpha - \beta X_{i,t-1}]}, \quad (1.1)$$

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

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

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

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

Last, variables ΔCY and ΔNC correspond to rough credit activity indicators that we use for the sake of comparison.

1.1.3 Criteria

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

We rely first on the area under the receiver operating characteristic (AUROC) curve, the standard criterion used for comparison when horse races for banking crisis detection are implemented. The receiver operating characteristic (ROC) curve plots the true positive rate against the false positive rate at various threshold settings. The AUROC curve considers all possible thresholds and provides a summary measure of the classification ability.⁸ A high AUROC curve indicates that the binary classifier performs well at predicting zeros as zeros

⁸Some criteria (as accuracy) require to set a decision threshold to compute the confusion matrix. The AUROC curve allows to alleviate this problem. This advantage explains that the AUROC curve is the preferred criteria used in the literature.

and ones as ones. Realistic values for the AUROC curve range from 0.5 (random ranking) to 1 (perfect ranking). However, the AUROC curve has some limitations.

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

A more fundamental critique has been addressed to the AUROC curve by Hand (2009,0), suggesting that the AUROC curve is not a coherent measure to compare rival classifiers. Therefore, we also rely on the H measure proposed by Hand (2009) as an alternative to the AUROC curve.

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

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

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

1.2 Results

We run first the baseline horse race with annual data because the starting dates for a subset of banking crises are identified only on a yearly basis in the Laeven & Valencia (2018) database. Next, we run the baseline horse race with quarterly data. The main point, however, is that credit gaps have been assessed from quarterly data in all horse races.⁹ Put differently, the main difference between the annual and the quarterly horse race is about the number 0 (i.e., non-crisis periods) in the estimates because in both case we rely on the quarterly frequency to assess cyclical movements in credit activities (i.e., credit gaps are not computed from small samples of annual data). Further, we run the baseline horse race for the full sample and for subsamples by income groups (relying on the World Bank classification). We then implement several robustness checks. For instance, we consider alternative banking crisis databases, or we use alternative classifications of countries for the subsamples analysis.

1.2.1 Baseline horse race

The results of the baseline horse race for the full sample are reported in Table 1.2. The same sample is used for all the estimates. Due to data availability, we have an unbalanced sample composed of 146 countries and covering 97 banking crises.¹⁰ Table 1.2 shows that two-sided credit gaps perform better than one-sided credit gaps according to the 5 criteria (AUROC curve,

⁹We collapse quarterly credit cycles into annual credit cycles. More precisely, we use the last value of each year (i.e., the value in Q4) to generate the annual credit cycles. For a robustness check, annual means have also been used to compute annual credit cycles. We reach similar conclusions for the two alternative ways to collapse the quarterly credit cycles. These results are available upon request.

¹⁰Data availability is not the same for all predictors. For instance, two-sided credit gaps are available for larger samples than are one-sided credit gaps due to data construction. Therefore, we also run the baseline horse race while relaxing the constraint that the same sample should be used for all the estimates. The number of banking crises covered by the sample reaches 124 when ΔCY is used as the predictor. These results are available upon request and lead to similar conclusions as those obtained from Table 1.2.

AUPR curve, H measure, Tjur R^2 and Brier score) and for the 3 methodologies (HP, modified HP and basic SSA). The log-likelihoods and pseudo- R^2 of the estimated models confirm this difference in performance between two-sided and one-sided credit gaps. Therefore, from the operational perspective (i.e., relying only on pseudo-real-time observations), credit gaps lose efficiency to detect banking crises. This result is in line with some critiques addressed to the reliability of one-sided credit gaps (e.g., Edge & Meisenzahl (2011)). For instance, considering credit gaps assessed by HP filter, the AUROC curve decreases from 0.7247 to 0.6018 when the one-sided approach is used instead of the two-sided approach. The general rule of thumb used to assess the quality of a classifier is that an AUROC curve from 0.70 to 0.80 indicates fair discrimination ability while an AUROC curve less than 0.70 indicates poor discrimination ability. Therefore, when the full sample is considered, one-sided credit gaps do not provide acceptable discrimination ability to predict banking crises. Further, Table 1.2 shows that the differences in performances between HP filter, modified HP filter and basic SSA are slight. Descriptive statistics on credit cycles, discussed previously and reported in Table 1.1, indicated that the 3 methodologies lead to credit cycles with very similar characteristics. Moreover, Table 1.2 suggests that their ability to detect banking crises is also very similar. However, the HP filter performs slightly better than the modified HP filter and the basic SSA according to the 5 criteria reported in Table 1.2. Last, the rough credit activity indicators (i.e., variables ΔCY and ΔNC) do not display better performance to predict banking crises over the full sample than do the one-sided credit gaps (except according to the AUROC curve).¹¹

The poor performance of one-sided credit gaps to predict banking crises might be explained by heterogeneity between countries. In particular, Table 1.1 highlights that credit gaps display different characteristics between high-income countries and middle- & low-income countries. Therefore, we run the baseline horse race for the subsample of high-income countries (Table 1.3, Panel A) and the subsample of middle- & low-income countries (Table 1.3, Panel B). The results confirm that two-sided credit gaps perform better than one-sided credit gaps and that the basic credit activity indicators do not outperform one-sided credit gaps. However, the performance of one-sided credit gaps to predict banking crises is higher in high-income countries than in middle- and low-income countries. For instance, considering credit gaps assessed by one-sided HP filter, the AUROC curve is 0.7419 for high-income countries and 0.5150 for middle- and

¹¹For robustness checks, we have also considered longer differences (up to 5 years) to generate variables ΔCY and ΔNC . These longer differences might better capture the long cycles commonly associated with banking crises. However, these indicators do not perform better. Results are available upon request to save space. Further, alternative indicators based on real credit are used in section 4.1.

low-income countries. All the other criteria (AUPR curve, H measure, Tjur R^2 and Brier score) confirm this meaningful difference. For instance, considering credit gaps assessed by one-sided HP filter, the Tjur R^2 is 4.70% for high-income countries and 0.16% for middle- and low-income countries. Therefore, the Tjur R^2 indicates that one-sided credit gaps fail to generate higher probabilities of a banking crisis before a banking crisis actually occurs in middle- and low-income countries. Conversely, in high-income countries, predicted probabilities of banking crisis generated by one-sided credit gaps are, on average, 4.70 percentage points higher when a banking crisis does occur than when a banking crisis does not occur.¹² In other words, the poor performance of one-sided credit gaps highlighted in Table 1.2 is driven mainly by middle- and low-income countries. Figure 1.1 illustrates the difference between high-income and middle- & low-income countries. Specifically, Figure 1.1 plots the probability of a banking crisis versus the credit gap (assessed by one-sided HP filter) obtained with the estimated logit model for high-income countries (Fig 1.1.a) and for middle- and low-income countries (Fig 1.1.b). The relationship is stronger for high-income countries than for middle- and low-income countries, as suggested by the parameter estimates of the logit models reported in column (1) of Table 1.3. Further, in high-income countries, the estimated model suggests that the CCyB should be activated (according to the BCBS (2010) guidance) when the probability of a banking crisis is still lower than its long-term (i.e., unconditional) level and that most banking crises occur when the credit gap exceeds 2%.¹³ Middle- and low-income countries show different results. Most banking crises occur when the credit gap is relatively low (e.g., lower than the 2% threshold corresponding to the activation rate of the CCyB according to the BCBS (2010) guidance). Therefore, credit gaps generally signal a weak risk of banking crisis (e.g., lower than the long-term exposure) when most banking crises occur, highlighting the fact that credit gaps are poor predictors of banking crises in middle- and low-income countries. In other words, numerous banking crises in middle- and low-income countries are not driven by excess credit activities.

Two rationals can explain the results of the horse race. First, some other key influential factors may be in play, for instance, the combination of macroeconomic, foreign exchange and financial soundness vulnerabilities (Duttgupta & Cashin (2011)), real currency appreciation in

¹²The significance of this magnitude can be appreciated by noting that the unconditional probability of a banking crisis is 2.35% for high-income countries in the sample used in Table 1.3.

¹³The long-term (i.e., unconditional) probability of a banking crisis is 2.35% for high-income countries and corresponds to the frequency of banking crises in the sample used to estimate the logit model. Further, the probability of a banking crisis is 1.93% when the credit gap equals 2%. For the sample of middle- & low-income countries, the long-term probability of a banking crisis is 2.14%, and the probability of a banking crisis is 2.17% when the credit gap equals 2%.

emerging economies (Gourinchas & Obstfeld (2012)) or low economic growth, banking system illiquidity and exchange rate instability in low-income countries (Caggiano et al. (2014), Gaies et al. (2019)). If such factors are more numerous and diverse in middle- and low-income countries than in high-income countries, the BCG can be a poor banking crisis predictor. Second, excess credit activities alone might not be sufficient to lead to banking crises in developing countries. For instance, capital inflows (Calderón & Kubota (2012), Caballero (2016)), current account deficits (Mack et al. (2016)), political booms (Herrera et al. (2020)) and the poor financial performance of banks (Fielding & Rewilak (2015)) represent important contextual factors for the occurrence of bad credit booms.

Table 1.2: Baseline horse race

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

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

Figure 1.1: Effect of credit cycle on the probability of banking crisis

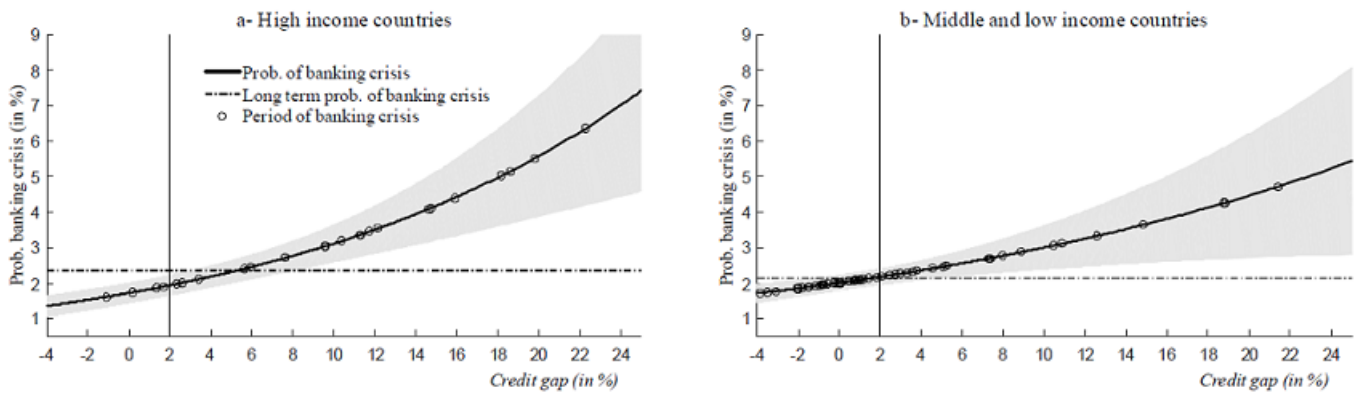


Table 1.3: Baseline horse race by subsample

Panel A: High income countries

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

Panel B: Middle & low income countries

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

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

1.2.2 Quarterly dating of banking crises

Precise dating of banking crises onsets is not straightforward. Different databases on banking crises can provide different datings (Chaudron & de Haan (2014)), and dates can be available only on a yearly basis. For instance, the starting dates of banking crises are identified on a yearly basis for 56% of the banking crises reported in the Laeven & Valencia (2018) database.

We tackle this issue to also run the horse race with quarterly data. We use the ESRB database (Lo Duca et al. (2017)) as the primary source to identify banking crisis periods at a quarterly frequency. The ESRB database covers all EU Member States and Norway for the period 1970-2016 and identifies banking crisis dates on a monthly basis. Further, we rely on the Laeven & Valencia (2018) database as a secondary source to identify banking crisis periods in countries not covered by the ESRB database. When the starting dates of banking crises are identified on a yearly basis in the Laeven & Valencia (2018) database, we assume that the banking crises start in Q1.¹⁴ Further, for robustness check, we also consider an alternative approach when the starting quarter of a banking crisis is missing: we assume banking crisis starts during the quarter recording the higher fall in the credit-to-GDP ratio.

Credit gaps are computed on a quarterly basis, but they are not available since 1970 for all the countries recording banking crises in Lo Duca et al. (2017) and Laeven & Valencia (2018). Due to data availability, we have an unbalanced sample composed of 146 countries and covering 106 banking crises. Results are reported in Table A1 in Appendix A.¹⁵ We also consider the sample composed of only countries and banking crises from the ESRB database in order to not mix data sources on banking crises (Table A2). We reach similar conclusions as those obtained with the baseline horse race. One-sided credit gaps are fair predictors of banking crises only in high-income countries. In middle- and low-income countries, they do not perform better than the basic credit activity indicators. In addition, the best performance of one-sided credit gaps is obtained when we consider banking crises from only the ESRB database (i.e., in EU countries plus Norway). For instance, considering credit gaps assessed with the HP filter, the AUROC curve is 0.7535 for one-sided credit gaps and 0.8482 for two-sided credit gaps. This level of performance is in line with the existing literature assessing the ability of one-sided

¹⁴Further, when the ending dates of banking crises are identified on a yearly basis, we assume that the banking crises end in Q4. The ESRB database does not have this limitation but focuses on a limited number of countries.

¹⁵Results obtained with the alternative dating of the starting quarter of banking crises are available upon request so save space. The results do not meaningfully differ. Uncertainty for the starting quarter only concerns 49 banking crises over the 106 covered by the estimates.

credit gaps to predict banking crises (see, e.g., Drehmann & Tsatsaronis (2014), Drehmann & Juselius (2014), Drehmann & Yetman (2018)).

Results of the annual and the quarterly horse races are consistent for 3 reasons: *(i)* the number of banking crises is not directly affected; *(ii)* credit gaps have been properly assessed from quarterly data in both cases; *(iii)* credit gaps display a high persistence (see Table 1.1).

1.2.3 Robustness checks

The baseline horse race required to make methodological choices. We show that the results are not sensitive to these methodological choices. We check the robustness of the results obtained with the baseline horse race considering modifications in the timing of the signal prior to a crisis, in data sources used to identify banking crisis periods, and in data sources used to define groups of countries. Further, we pay particular attention to financially underdeveloped countries and to the management of the post-crisis bias.¹⁶

First, we investigate the stability of the signal captured by banking crisis predictors. In the baseline horse race (with annual and quarterly data), we consider the signal 1 year prior to a crisis. An effective banking crisis predictor should, however, start to provide a signal earlier than 1 year so that policymakers have time to take corrective actions. In addition, banking crisis predictors should provide a stable signal during several consecutive periods to generate no uncertainty concerning the risk of banking crisis. Therefore, we run the baseline horse race with a forecast horizon up to 5 years (with annual and quarterly data). For each forecast horizon and banking crisis predictor, Figure 1.2 plots the AUROC curve to highlight the quality of the signals.¹⁷ Figure 1.2 enables generalization of the main result obtained from the baseline horse race concerning the difference between high-income and middle- & low-income countries. For all forecast horizons, one-sided credit gaps provide a poor signal to detect banking crises in middle- and low-income countries, and basic credit activity indicators do not perform much better: the AUROC curve rarely exceeds 0.60 in Figures 1.2-b and d. For high-income countries, Figures 1.2-a and c show that the one-sided credit gap has valuable properties in terms of stability. This result is in line with Drehmann & Tsatsaronis (2014) and

¹⁶Tables containing the results for the robustness checks are reported in the web appendix of the paper to save space.

¹⁷We reach similar conclusions if other criteria are considered (i.e., AUPR curve, H measure, Tjur R^2 or Brier score). The AUROC curve is frequently considered in the literature to assess the performance of various banking crisis predictors for different forecast horizons (see, e.g., Drehmann & Tsatsaronis (2014), Drehmann & Juselius (2014))

Drehmann & Juselius (2014). For a forecast horizon up to 3 years prior to a banking crisis, the one-sided credit gap displays a stable AUROC curve, slightly higher than 0.70. In addition, Figure 1.2 shows that two-sided credit gaps do not exhibit the best performance for all forecast horizons. When the latter exceed 2 years, two-sided credit gaps no longer provide the best performance among the different banking crisis predictors.

Second, the Reinhart (2010) database on banking crises (updated by the Behavioral Finance & Financial Stability (BFFS) Project) is considered as an alternative to the Laeven & Valencia (2018) database. This database covers a smaller number of countries than the Laeven & Valencia (2018) database, but the banking crises identified by Reinhart (2010) date back to before 1970. Therefore, we can fully exploit the time dimension of credit series that date back to the late 1950s. In addition, the dating and identification of banking crises can vary slightly between Reinhart (2010) and Laeven & Valencia (2018). We conclude that the results are robust to the choice of data source used to identify banking crises. One-sided credit gaps are poor predictors of banking crises in middle- and low-income countries (results are reported in Table SM1.1 in the web appendix).

Third, we investigate whether the results are robust to the definition of high-income countries. In the baseline horse race, we rely on a time-invariant classification from the World Bank. For a robustness check, we rely on the Maddison database (Bolt et al. (2018)) to generate a time-varying group of high-income countries. Specifically, we consider real GDP per capita; for each year, countries belonging to the top quartile are classified as high-income countries and other countries are considered middle- and low-income countries. This alternative classification leads to a slightly smaller group of high-income countries. The conclusions obtained from the baseline horse race do not change when this alternative income group classification is considered (results are reported in Table SM1.2 in the web appendix). Similar conclusions are also obtained when we rely on the country classification provided by the IMF. Credit gaps are fair banking crisis predictors in advanced economies but display poor performance in emerging and developing countries (results are reported in Table SM1.3 in the web appendix)

Fourth, we investigate whether the poor performance of credit gaps to predict banking crises in middle- and low-income countries is driven by financially underdeveloped countries. The latter can be defined as countries with low credit-to-GDP ratios. The credit dynamics in these countries might be unique due, in particular, to structural characteristics. Indeed, financial deepening might be the main factor explaining episodes of rapid credit expansion in these

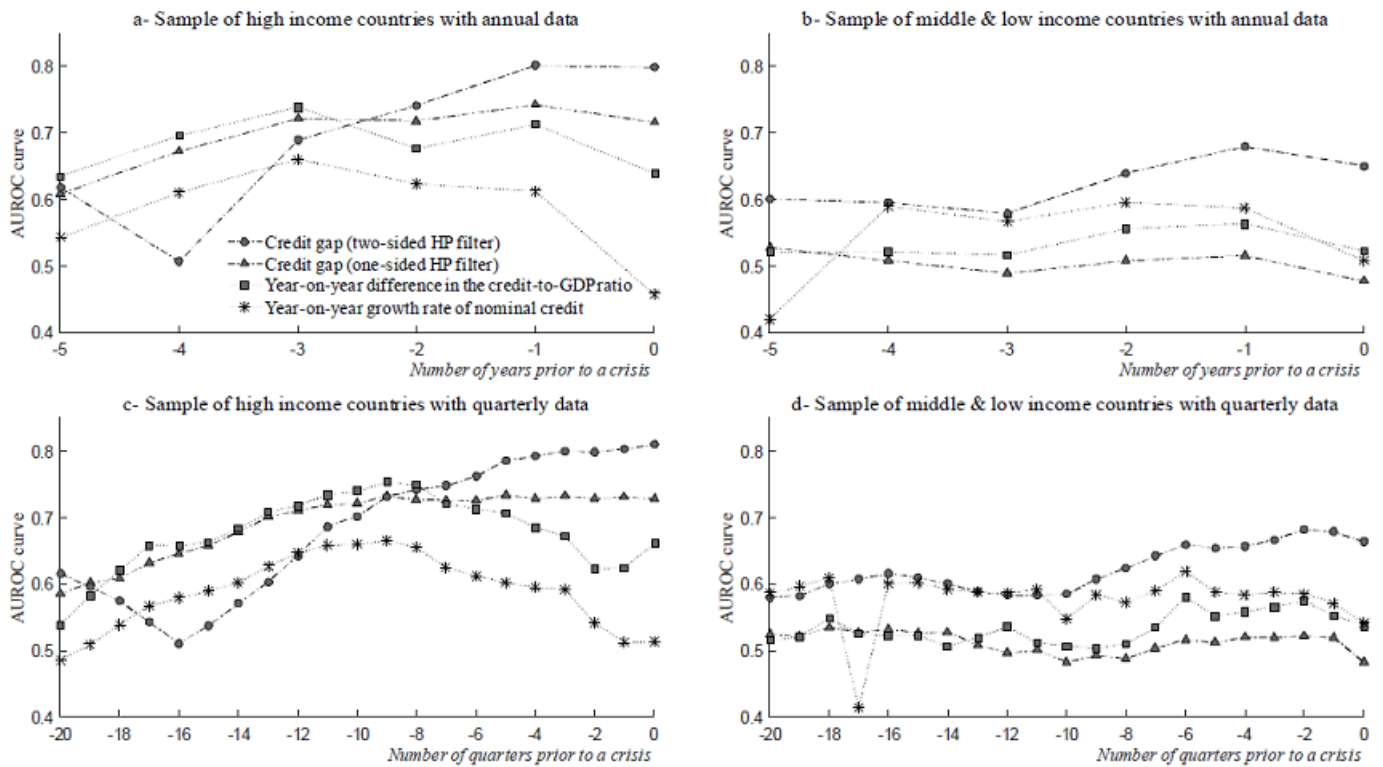
countries. In such situations, trend-cycle decompositions as the HP filter can face difficulties in properly identifying the cyclical component. Therefore, we drop cases with credit-to-GDP ratios lower than 10%. This threshold is commonly used in the literature (see, e.g., Dell’Ariccia et al. (2016)) and leads to the exclusion of some observations from low-income countries from the analysis. The results show that excluding financially underdeveloped countries does not improve the performance of credit gaps to predict banking crises in the remaining middle- and low-income countries (results are reported in Table SM1.4 in the web appendix). Further, we consider a more stringent approach to exclude financially underdeveloped countries: we successively run the horse race focusing only on upper-middle-income countries (World Bank classification) and emerging economies (IMF classification). Banking crises driven by credit booms might be a greater concern for these subgroups of countries than for low-income countries (Arena et al. (2015), Meng & Gonzalez (2017)). Most criteria used to assess the performance of credit gaps to predict banking crises improve when upper-middle-income countries or emerging economies are considered while excluding lower-income countries. However, these improvements are rather slight, and all the criteria remain noticeably lower than those observed for developed economies (results are reported in Tables SM1.5 and SM1.6 in the web appendix). Overall, the results confirm that one-sided credit gaps are fair banking crisis predictors only in developed countries.

Last, we consider several alternatives in terms of sample management to investigate whether the results are affected by the post-crisis bias. As noted by Bussiere & Fratzscher (2006), during tranquil periods, banking crisis predictors can behave differently than they do during crisis/post-crisis periods. Therefore, considering all periods can affect the performance of banking crisis predictors. In the baseline horse race, we dropped all but the initial years of banking crises that occurred over the course of several years.¹⁸ In addition, we dropped the two years following the ending year of each banking crisis. These two data management processes reduce the samples size but account for the post-crisis bias. For a robustness check, we implement 3 alternative data management approaches. First, we do not drop the two years following the ending year of each banking crisis. Second, we follow Mathonnat et al. (2022) to adopt a more restrictive approach than that in Laeven & Valencia (2018) to measure the duration of banking crises.¹⁹ We then apply the same data treatments for the post-crisis bias

¹⁸Therefore, each banking crisis event is associated with a single year, and observations can be treated as independent of one another.

¹⁹The dating of the ending year of a banking crisis depends on two indicators: growth rate of GDP per capita and growth rate of banks’ credit to the private sector-to-GDP (data are collected from the World Bank’s World

Figure 1.2: Performance of banking crisis predictors for different forecast horizons



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

management (i.e., dropping all but the initial years of banking crises and dropping the two years following the ending year of each banking crisis). Since the duration of banking crises increases with the more restrictive approach proposed by Mathonnat et al. (2022), more observations are dropped to account for the post-crisis bias. Last, we keep only "vulnerability" periods instead of dropping some crisis and post-crisis periods. We define vulnerability periods as the 5 years preceding each banking crisis (plus the first year of each banking crisis). This approach is the most conservative to account for the post-crisis bias. These 3 robustness checks show that the conclusions obtained from the baseline horse race are not altered when alternative management of the post-crisis bias is considered (results are reported in Tables SM1.7, SM1.8 and SM1.9 in the web appendix).

Development Indicators (WDI) database). Banking crises end the year preceding the simultaneous observation of positive values during at least two consecutive years for the two indicators. In Laeven & Valencia (2018), a banking crisis ends the year preceding the simultaneous observation of positive values for the two indicators.

1.3 Further issues

1.3.1 Real credit–based indicators

Real credit can be considered an alternative to the credit-to-GDP ratio to measure credit gaps. In particular, real credit per capita is frequently used in the literature instead of the credit-to-GDP ratio to investigate credit dynamics (see, e.g., Mendoza & Terrones (2012), Arena et al. (2015), Meng & Gonzalez (2017)). The main objective is to not rely on GDP as a scaling variable because cyclical changes in GDP might distort the assessment of credit procyclicality. The Bouvatier et al. (2022) database reports real credit aggregates and trend-cycle decomposition for these credit series (credit gaps are expressed in % of trend). However, real credit per capita series are not available in the Bouvatier et al. (2022) database. Therefore, we collect population data from the World Bank to compute real credit per capita series.²⁰ Then, we implement HP filter, modified HP filter and basic SSA to generate one-sided and two-sided credit gaps in real credit per capita series.²¹

Consequently, we have two alternative sets of credit indicators based on real credit that can compete with the credit indicators used in the baseline horse race (i.e., based on credit-to-GDP ratio). The results are reported in Appendix B: in Table B1 for real credit per capita and in Table B2 for real credit aggregates. The sample size is slightly smaller than that in the baseline horse race due to the availability of real credit aggregates in the Bouvatier et al. (2022) database. The results in Table B1 (Panel A) show that one-sided credit gaps computed from real credit per capita do not outperform those computed from the credit-to-GDP ratio (Table 1.3) when the subsample of high-income countries is considered. The 5 criteria used to compare banking crisis predictors support these results. Similar conclusions are reached when real credit aggregates are considered to generate credit gaps (Table B2, Panel A). Therefore, the results are in line with Drehmann & Yetman (2018): scaling credit by GDP is a good way to generate one-sided credit gaps.

Focusing on two-sided credit gaps in high-income countries, we reach different conclusions: credit gaps based on the credit-to-GDP ratio are not better predictors than credit gaps based

²⁰Population data are not quarterly and have to be interpolated. We rely on a quadratic interpolation that might be more suitable for population variables.

²¹The HP and modified HP filters are applied to the log of real credit per capita to take into account the scaling issue (data are expressed in local currency). Then, credit gaps are defined as the difference between the log of real credit per capita and the log of its trend. Basic SSA does not require such preprocessing. Credit gaps are then computed as the difference between real credit per capita and its trend, divided by the trend.

on real credit. Indeed, the criteria used to assess the performance of predictors are not all in favor of credit gaps based on the credit-to-GDP ratio. For instance, considering credit gaps computed by two-sided HP filter, two of the 5 criteria reported in Panel A of Tables 1.3 and B1 suggest that credit gaps based on real credit perform better than credit gaps based on credit-to-GDP ratio (the AUROC curve and the Brier score). Therefore, when credit gaps are assessed ex post (i.e., without relying on pseudo-real-time data), no scaling variable provides a better banking crisis predictor than the others: credit gaps based on the credit-to-GDP ratio or on real credit per capita can be considered equivalent.

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

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

1.3.2 Frequency of credit series

We rely on the Bouvatier et al. (2022) database that measures credit gaps from quarterly data. Then, the baseline horse race is run with (collapsed) annual data and with quarterly data for a robustness check. This approach provides better coverage of middle- and low-income countries than does the approach proposed by the BIS database on credit statistics (Dembiermont et al. (2013)).

However, since the horse race is run mainly with (collapsed) annual data, the Global Financial Development Database (GFDD) provided by the World Bank might be a valuable alternative data source. This database provides annual credit-to-GDP ratios for a large set of countries, and the series date back to 1960. This database is frequently used in the literature to investigate credit dynamics in large sets of countries (see, e.g., Dell’Ariccia et al. (2016)). Therefore, we can assess credit gaps from annual data relying on GFDD to obtain a new set

of credit indicators that can compete with the credit indicators used in the baseline horse race. For simplicity, we focus on only the HP filter since this methodology provided the best performance in the baseline horse race. The main objective is to assess whether credit gaps computed from quarterly data outperform credit gaps computed from annual data.

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

Concerning the assessment of credit cycles from quarterly data, Drehmann et al. (2010) recommend setting the smoothing parameter λ_Q to 400,000.²² Following the formula of Ravn & Uhlig (2002), we set $\lambda_A = 0.25^4 \cdot 400,000 \simeq 1,600$ to capture the credit cycle with annual data.²³ Marchettini & Maino (2015) set the smoothing parameter to a similar value to assess credit gaps based on annual data.

The main limitation of this approach is related to small-sample issues. More precisely, the trend-cycle decomposition provided by the HP filter is sensitive to the underlying series' starting point. This starting point problem is not fully fixed even after 10 years of quarterly data (Drehmann & Tsatsaronis (2014)). Consequently, in the context of annual data, one can deduce that the starting point problem can distort the trend-cycle decomposition over more than 4 decades. Further, the size of the distortion is country-specific, in the sense that its magnitude can be particularly pronounced when the starting point corresponds to a credit cycle's peak or trough.

Results are reported in appendix C (Table C1). We consider in Table C1 both credit gaps

²²Drehmann et al. (2010) suggest that credit cycles are between three to four times longer than business cycles. Consequently, λ_Q should be set between $3^4 \cdot 1,600 = 125,000$ and $4^4 \cdot 1,600 = 400,000$ to capture credit cycles. Drehmann et al. (2010) conclude that a λ_Q of 400,000 provides more satisfactory results to detect systemic banking crises than does a value of 125,000.

²³The filter parameter can also be set as a function of the frequency cut-off according to the formula:

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

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

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

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

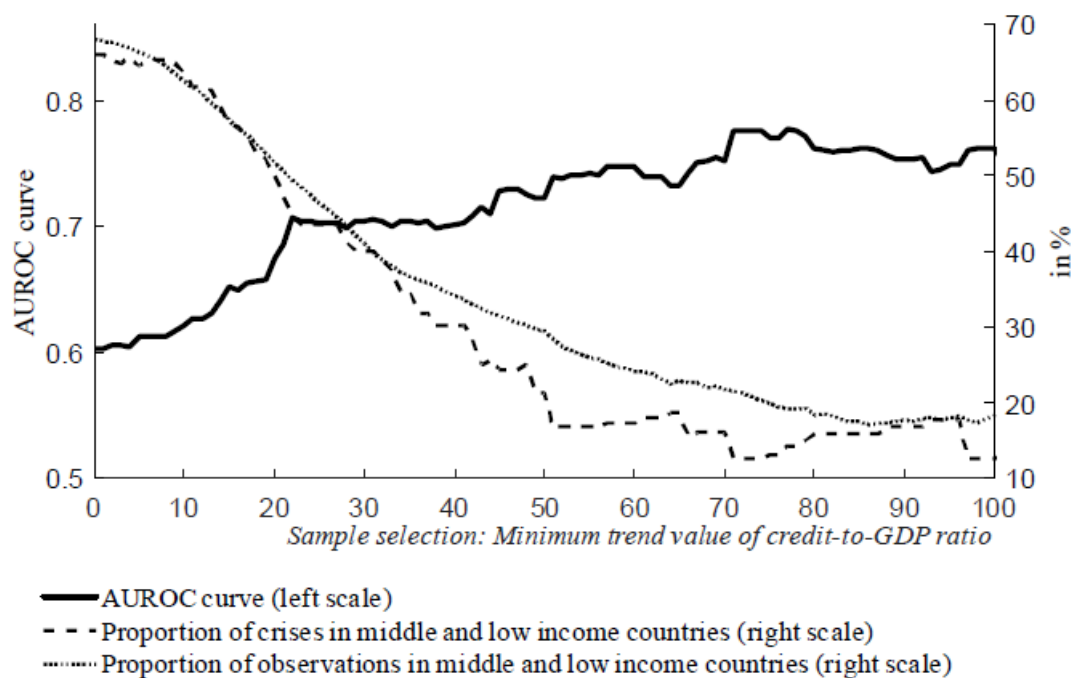
1.3.3 Financial development

A sub-group of countries might explain that credit gaps are overall poor banking crisis predictors. Therefore, we explore in greater detail whether credit gaps become better proxies of systemic risk buildup as financial development increases. As previously shown in section 3.2, excluding financially under-developed countries (defined as countries with credit-to-GDP ratios lower than 10%) does not alter our results. Thus we consider an alternative approach in which low- and middle-income countries are not systematically bundled together anymore. More precisely, we now use the value of the trend in the credit-to-GDP ratio as sample selection criteria. We consider grid points from 0 to 100, and we successively consider samples made up of countries with a credit-to-GDP ratio recording a trend's value higher than the grid point. Therefore, we end-up with 101 estimates; the full sample is used when the grid point is set to 0. When we increase the grid point, we progressively drop the less financially developed countries from

the analysis, without a specific reference to income groups. Figure 1.3 reports the AUROC curve for all the estimates when the BCG is used as predictor. As reported in previous results, either when we consider the full sample or only exclude countries with credit-to-GDP ratios lower than 10%, the AUROC curve is close to 0.60, suggesting that credit gaps display an overall poor performance in banking crises prediction. However, a different scheme appears in Figure 1.3 when the value of the trend in the credit-to-GDP ratio exceeds 20%. Indeed, credit gaps become better predictors of banking crises as financial development increases with AUROC curve values exceeding 0.70. Therefore, Figure 1.3 can explain that the existing literature (Drehmann & Tsatsaronis (2014), Marchettini & Maino (2015) and Geršl & Jašová (2018)) provides mixed results concerning the BCG performance as an early warning indicator of banking crises in emerging economies. Further, Figure 1.3 shows the proportions of both observations (dotted line) and banking crises (dashed-line) in low- and middle-income countries in the underlying estimates. In particular, when the 20% threshold is reached, the proportion of crises recorded in low- and middle-income countries remains higher than 50%. Therefore, banking crisis events in low- and middle-income countries do not systematically deteriorate the ability of credit gaps to predict banking crises. Banking crises that are not driven by excess credit mainly occur in countries with less developed financial sectors (i.e, in countries that display trend values lower than the 20% threshold).

This result has some implications for the guidance to set the CCyB. The BCBC guidance, which promotes the use of the BCG, is tailored for countries with a sufficient level of financial development, defined as a trend's value in the credit-to-GDP ratio higher than 20%. In less financially developed countries, factors related to foreign currency risk, poor financial soundness, and macroeconomic instability (Dutttagupta & Cashin (2011), Caggiano et al. (2014), Gaies et al. (2019)) might matter more than excess credit to predict banking crises.

Figure 1.3: Performance of credit gaps to predict banking crises



Conclusion

This paper relies on a new database that provides quarterly credit series as well as trend-cycle decomposition for an unbalanced sample of 163 countries over the period 1957Q1-2018Q4. We investigate whether credit gaps, and particularly the BCG, are good early warning indicators of banking crises. The existing literature concludes that the BCG is a fair banking crisis predictor in developed economies. Our results are logically in line with these empirical findings. However, the existing literature is rather scarce concerning investigations dedicated to middle- and low-income countries due to data limitations. We overcome these data limitations with the Bouvatier et al. (2022) database on credit metrics and show that overall the BCG is a poor early warning indicator of banking crises in middle- and low-income countries. This result is confirmed by a large number of robustness checks concerning, for instance, alternative data sources used to identify banking crises periods and alternative definitions of groups of countries. Further, we show that the poor performance of the BCG as an early warning indicator for banking crises in middle- and low-income countries is not explained by the fact that GDP is used as the scaling variable to generate credit gaps. Credit gaps based on real credit per capita or real credit aggregates also perform poorly in middle- and low-income countries. In

addition, we show that assessing credit gaps based on annual data, as is commonly done in the literature on credit booms, for instance, leads to fair results compared to those obtained based on quarterly data. Last, we show that the BCG becomes a fair banking crises predictor as financial development increases. Excess credit captured by the BCG turns to be a key factor to predict banking crises when the trend's value in the credit-to-GDP ratio exceeds 20%.

The main policy implication of our results concerns the implementation of macroprudential frameworks by banking regulators in developing countries. More precisely, our results question the design of the operational framework implemented to set the CCyB. Guidance proposed by the BCBS (2010) is based on strong empirical evidence for advanced economies. Consequently, the BCG is a key indicator used by BCBS members to implement the CCyB (BCBS (2017)). The CCyB is also implemented in various stages or under consideration in numerous non-BCBS member jurisdictions, including some middle- and low-income countries (Hohl et al. (2018)). Our results suggest that no empirical evidence legitimates systematic reliance on the BCG as a key indicator to set the CCyB rate in middle- and low-income countries. Consequently, activation of the CCyB when the BCG signals excess credit activity might be ill-suited to ensure financial stability and might rather be detrimental for the beneficial consequences of good credit booms. Therefore, middle- and low-income countries need to tailor BCBS guidance to local circumstances. The BCG is a reliable indicator to set the CCyB rate only when financial development, captured by the trend's value in the credit-to-GDP ratio, exceeds 20%.

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

Appendix A: Baseline horse race with quarterly data

Table A1: Baseline horse race by subsample with quarterly data

Panel A: High income countries

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

Panel B: Middle & low income countries

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

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

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

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

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

Appendix B: Horse race with real credit based indicators

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

Panel A: High income countries

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

Panel B: Middle & low income countries

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

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

Table B2: Credit indicators based on real credit aggregates: horse race by subsample
Panel A: High income countries

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

Panel B: Middle & low income countries

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

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

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

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

Panel A : High income countries

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

Panel B : Middle & low income countries

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

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

Chapter I: supplemental material

Robustness checks for the baseline horse race

This appendix reports the results associated with the robustness checks implemented for the baseline horse race. More precisely, we report the results obtained when: *(i)* we modify data sources to identify banking crises periods (Table SM1.1); *(ii)* we modify data sources to define income groups (Tables SM1.2 and SM1.3); *(iii)* we exclude financially underdeveloped countries (Tables SM1.4, SM1.5 and SM1.6); *(iv)* we modify the management of the post-crisis bias (Tables SM1.7, SM1.8 and SM1.9); *(v)* we replicate the baseline estimation using the maximum sample size for each predictor (SM1.10); *(vi)* we replicate the baseline estimation using the mean value of the gap instead of the Q4 one (SM1.11); *(vii)* we replicate the baseline estimation using quarterly data (SM1.12 and SM1.13).

Table SM1.1: Baseline horse race by subsample with the Reinhart (2010) database on banking crises

Panel A: High income countries								
Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0739***	0.1060***	0.0720***	0.1032***	0.0748***	0.1229***	0.1017**	0.0057***
(σ_β)	(0.0177)	(0.0203)	(0.0182)	(0.0214)	(0.0109)	(0.0241)	(0.0340)	(0.0010)
Log likelihood	-157.4905	-150.5491	-158.4830	-151.8929	-159.2096	-151.1428	-164.2352	-172.1249
Pseudo- R^2	0.0963	0.1361	0.0906	0.1284	0.0864	0.1327	0.0576	0.0123
Num. countries	29	29	29	29	29	29	29	29
Num. obs.	932	932	932	932	932	932	932	932
Num. crises	43	43	43	43	43	43	43	43
<i>AUROC</i> curve	0.7262	0.7425	0.7189	0.7323	0.7030	0.7386	0.6875	0.6181
<i>AUPR</i> curve	0.1791	0.2426	0.1729	0.2350	0.1777	0.2412	0.1372	0.0840
<i>H</i> measure	0.2508	0.2712	0.2491	0.2668	0.2162	0.2637	0.1958	0.0962
Tjur R^2	0.0697	0.1158	0.0645	0.1082	0.0596	0.1117	0.0393	0.0080
Brier score	0.0413	0.0388	0.0415	0.0392	0.0412	0.0389	0.0427	0.0438
Panel B: Middle & low income countries								
Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHPts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0658*	0.1210**	0.0509	0.1224***	0.0488*	0.1132***	0.1083**	0.0020
(σ_β)	(0.0275)	(0.0376)	(0.0265)	(0.0349)	(0.0246)	(0.0333)	(0.0385)	(0.0014)
Log likelihood	-218.7089	-210.9264	-219.6892	-210.5033	-220.4866	-212.9500	-219.5655	-219.7487
Pseudo- R^2	0.0204	0.0552	0.0160	0.0571	0.0124	0.0461	0.0165	0.0157
Num. countries	36	36	36	36	36	36	36	36
Num. obs.	1138	1138	1138	1138	1138	1138	1138	1138
Num. crises	56	56	56	56	56	56	56	56
<i>AUROC</i> curve	0.5780	0.6486	0.5823	0.6493	0.5535	0.6396	0.5824	0.6399
<i>AUPR</i> curve	0.0721	0.1250	0.0725	0.1326	0.0610	0.1080	0.0809	0.0878
<i>H</i> measure	0.0764	0.1523	0.0724	0.1590	0.0516	0.1238	0.0681	0.1125
Tjur R^2	0.0098	0.0390	0.0066	0.0412	0.0047	0.0313	0.0080	0.0175
Brier score	0.0463	0.0448	0.0465	0.0447	0.0466	0.0452	0.0464	0.0460

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

Table SM1.2: Baseline horse race by subsample with alternative definition of income groups

Panel A: High income countries based on Maddison database

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

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

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

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

Table SM1.3: Baseline horse race by subsample based on IMF classification

Panel A: Advanced economies based on IMF classification

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

Panel B: Emerging & developing economies based on IMF classification

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

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

Table SM1.4: Baseline horse race without financially underdeveloped countries

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

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

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

Table SM1.5: Baseline horse race without financially underdeveloped countries

Sample: Upper middle income countries (World Bank classification)

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

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

Table SM1.6: Baseline horse race without financially underdeveloped countries

Sample: Emerging economies (IMF classification)

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

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

Table SM1.7: Baseline horse race by subsample with no drop of post-crisis periods

Panel A : High income countries

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

Panel B : Middle & low income countries

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

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

Table SM1.8: Baseline horse race by subsample with duration of banking crises measured following Mathonnat et al. (2019)

Panel A : High income countries

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

Panel B : Middle & low income countries

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

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

Table SM1.9: Baseline horse race by subsample on vulnerability periods

Panel A : High income countries

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

Panel B : Middle & low income countries

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

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

Table SM1.10: Baseline horse race : different samples by predictor

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{HPMos}	CY_{gap}^{HPMts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0550***	0.0965***	0.0526***	0.0959***	0.0560***	0.0926***	0.0780***	0.0007**
(σ_β)	(0.0123)	(0.0183)	(0.0109)	(0.0190)	(0.0117)	(0.0188)	(0.0155)	(0.0004)
Log likelihood	-450.3051	-530.8422	-451.4875	-531.9679	-455.8788	-542.9326	-543.9623	-581.5717
Pseudo- R^2	0.0329	0.0756	0.0303	0.0737	0.0209	0.0546	0.0179	0.0112
Num. countries	146	146	146	146	146	146	146	146
Num. obs.	4385	5185	4385	5185	4385	5185	5114	5298
Num. crises	97	121	97	121	97	121	116	124
<i>AUROC</i> curve	0.6018	0.7247	0.5893	0.7192	0.5623	0.6928	0.5977	0.6053
<i>AUPR</i> curve	0.0590	0.1029	0.0575	0.1041	0.0492	0.0774	0.0457	0.0478
<i>H</i> measure	0.1127	0.1981	0.1087	0.1949	0.0728	0.1432	0.0911	0.0698
Tjur R^2	0.0162	0.0423	0.0149	0.0422	0.0079	0.0293	0.0057	0.0099
Brier score	0.0214	0.0220	0.0214	0.0220	0.0214	0.0223	0.0221	0.0227

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

Table SM1.11: Baseline horse race: alternative aggregation of quaterly data

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{HPMos}	CY_{gap}^{HPMts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0591***	0.0998***	0.0571***	0.0998***	0.0589***	0.1035***	0.0986***	0.0005***
(σ_β)	(0.0131)	(0.0188)	(0.0121)	(0.0189)	(0.0123)	(0.0215)	(0.0241)	(0.0002)
Log likelihood	-450.0253	-430.6428	-450.5109	-430.6350	-455.4147	-437.4608	-453.1629	-461.4307
Pseudo- R^2	0.0335	0.0751	0.0324	0.0751	0.0219	0.0605	0.0267	0.0090
Num. countries	146	146	146	146	146	146	146	146
Num. obs.	4385	4385	4385	4385	4385	4385	4385	4385
Num. crises	97	97	97	97	97	97	97	97
<i>AUROC</i> curve	0.5958	0.7084	0.5944	0.7077	0.5635	0.6833	0.6215	0.5870
<i>AUPR</i> curve	0.0638	0.1091	0.0607	0.1103	0.0534	0.0892	0.0533	0.0459
<i>H</i> measure	0.1087	0.1874	0.1081	0.1884	0.0760	0.1513	0.1217	0.0830
Tjur R^2	0.0175	0.0464	0.0166	0.0467	0.0087	0.0361	0.0085	0.0101
Brier score	0.0213	0.0207	0.0213	0.0207	0.0214	0.0209	0.0216	0.0214

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

Table SM1.12: Baseline horse race with quarterly data

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHpts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0503***	0.0641***	0.0499***	0.0642***	0.0570***	0.0689***	0.0793***	0.0007***
(σ_β)	(0.0093)	(0.0215)	(0.0089)	(0.0221)	(0.0107)	(0.0208)	(0.0164)	(0.0003)
Log likelihood	-625.9405	-610.5268	-625.9874	-610.2793	-631.3554	-616.2045	-629.3816	-639.3513
Pseudo- R^2	0.0260	0.0500	0.0259	0.0503	0.0175	0.0411	0.0206	0.0051
Num. countries	146	146	146	146	146	146	146	146
Num. obs.	16800	16800	16800	16800	16800	16800	16800	16800
Num. crises	106	106	106	106	106	106	106	106
AUROC curve	0.6090	0.7122	0.6124	0.7161	0.5766	0.6982	0.6144	0.5744
AUPR curve	0.0318	0.0547	0.0285	0.0551	0.0273	0.0395	0.0200	0.0145
H measure	0.2018	0.2813	0.2043	0.2859	0.1450	0.2126	0.1615	0.0596
Tjur R^2	0.0056	0.0140	0.0055	0.0141	0.0023	0.0112	0.0021	0.0016
Brier score	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063

Table SM1.13: Baseline horse race: quarterly data with different sample sizes

Predictor :	CY_{gap}^{HPos}	CY_{gap}^{HPts}	CY_{gap}^{MHPos}	CY_{gap}^{MHpts}	CY_{gap}^{SSAos}	CY_{gap}^{SSAts}	ΔNC	ΔCY
β	0.0503***	0.0645***	0.0499***	0.0649***	0.0570***	0.0663***	0.0795***	0.0007***
(σ_β)	(0.0093)	(0.0212)	(0.0089)	(0.0221)	(0.0107)	(0.0172)	(0.0160)	(0.0003)
Log likelihood	-625.9405	-735.2626	-625.9874	-734.7482	-631.3554	-743.3519	-733.2121	-789.4678
Pseudo- R^2	0.0260	0.0442	0.0259	0.0448	0.0175	0.0337	0.0189	0.0040
Num. countries	146	146	146	146	146	146	146	146
Num. obs.	16800	20019	16800	20019	16800	20019	19755	20514
Num. crises	106	127	106	127	106	127	123	131
AUROC curve	0.6090	0.7000	0.6124	0.7060	0.5766	0.6735	0.6009	0.5782
AUPR curve	0.0318	0.0485	0.0285	0.0494	0.0273	0.0331	0.0170	0.0121
H measure	0.2018	0.2689	0.2043	0.2735	0.1450	0.1991	0.1233	0.0473
Tjur R^2	0.0056	0.0120	0.0055	0.0121	0.0023	0.0088	0.0019	0.0011
Brier score	0.0063	0.0063	0.0063	0.0064	0.0063	0.0063	0.0062	0.0063

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

Chapter 2

Credit gap and macroprudential
policy in middle-income countries: do
not forget the twins

Introduction

Across the 1980–1996 period, approximately 75% of International Monetary Fund’s member countries have experienced banking sector distress (Lindgren et al. (1996)). Caprio & Klingebiel (1996) state that systemic crises generate substantial costs (10% of the GDP on average) resulting from the government bailout of the banking system. Laeven & Valencia (2020) argue that systemic banking crises tend to last longer in advanced economies and are frequently associated with higher output losses compared to low and middle-income countries. Nonetheless, output losses are often significantly larger in the case of a twin crisis (i.e., the joint occurrence of banking and currency crisis) compared to a banking crisis alone, particularly in emerging economies (Hoggarth et al. (2002)).

Several empirical findings hint that the Basel Credit Gap (BCG), which introduced by Basel III agreements in 2010, is the best performing indicator to capture the risk of banking crises (Drehmann et al. (2010); Drehmann & Juselius (2014)). However, the efficiency of the BCG is mostly demonstrated for high-income countries while this indicator yields poorer results for middle- and low-income economies. Nevertheless Drehmann & Tsatsaronis (2014) highlight that this credit metric remains a fair predictor of banking crises in less developed countries although the authors acknowledge that the performance is lower in contrast with high-income countries. Multiple explanation have been formed regarding the previous outcome. Barajas et al. (2007) state that the association between credit booms and banking crises is not systematic and introduce the distinction between good and bad credit booms, highlighting that not all credit booms end in banking crises. In addition, the existing literature also shows differences between country groups and regions concerning the characteristics of credit booms (Meng & Gonzalez (2017)) or the proportion of bad credit booms (Calderón & Servén (2013), Arena et al. (2015)). Thus, the relationship between the BCG and banking crisis should be investigated by properly accounting for such heterogeneity among middle- and low-income countries. Another important feature of financial crises in emerging markets is that such events come in waves: it is common that a currency crash precedes or follows a banking crisis (Laeven & Valencia (2020)). Therefore, capturing the features of banking crises, currency crashes and credit booms simultaneously may allow a better understanding of these phenomenons. Indeed, the contrasted performance of the BCG in middle- and low-income countries could be imputed to the fact that the determinants of banking crises are singular among this group of countries in contrast with advanced economies in which banking crises are mainly driven by excess credit.

Empirically, credit booms are often cited as a key determinant behind financial crises, particularly in emerging economies (Eichengreen & Arteta (2002)). Mendoza & Terrones (2012) state that credit booms are highly associated with both banking and currency crises in emerging market economies: while 51% of banking crises episodes are preceded or followed by a credit boom, the comparable share is roughly 63% for currency crises. Since credit booms tend to coincide with both banking and currency crises, one might argue that this phenomenon could be a key determinant in the process of studying twin crises. In addition, Tornell & Westermann (2005) state that credit booms often occur following financial liberalization in middle-income countries. However, the authors warn that only a fraction of these events end up in a twin crisis highlighting that most of the lending booms have a "soft landing" (i.e, the credit growth progressively slows down and doesn't inevitably lead to a crisis). Thus, one might argue that credit booms which end up morphing into a twin crisis could present singular features in middle-income economies and therefore, should be properly assessed by accounting for such country-specific heterogeneity.

This paper aims to fill the gap in the literature regarding the role of credit booms in the occurrence of banking and currency crises in middle-income countries. Indeed, several empirical findings suggest that the Basel Credit Gap (BCG) exhibits contrasted performances for banking crises prediction in middle-income countries while this indicator performs well in advanced economies. Nevertheless, it could be argued that banking crises determinants in middle-income countries might be substantially divergent from excess credit. Therefore, the ability of the BCG in predicting banking crises should be properly investigated by accounting for the role of currency crashes.

From a policy-maker's perspective, the BCG is employed as an indicator to set the Countercyclical Capital Buffer (CCyB) rate in order to prevent procyclicality in the banking sector. However the CCyB as a macro-prudential tool could also be relevant in the context of currency crises since credit crunches following twin crises are often sharper and last even longer in emerging and developing countries (Tornell & Westermann (2002); Hong & Tornell (2005)). Thus, the BCG could turn out to be a relevant indicator of currency crises despite the contrasted performances highlighted in the literature regarding banking crises in middle- and low-income countries.

I take advantage of a large unbalanced panel data set of yearly observations covering the 1971-2017 period. I rely on the maximum simulated likelihood method (MSL) for the joint estimation

of the probabilities of banking and currency crises and define them as dynamic episodes (the so-called "crisis window" approach). This estimation method allows to simultaneously examine both twin crises and credit booms. Indeed, the existing literature on the ability of the BCG in predicting banking crises mainly focuses on univariate frameworks. While this approach seems fitting for advanced economies (i.e, these countries rarely experience currency crises), the same does not hold for middle-income countries as they are often exposed to both types of crises at the same time.

I first investigate whether the credit gap is a relevant indicator of banking and currency crises in a bivariate setting employing the full available information (i.e, using the two-sided credit gap). Thereafter, I assess the relevance of the one-sided credit gap, from an operational perspective, in order to investigate whether the CCyB can be employed as a macro-prudential policy instrument to help sustaining the credit activity following banking and currency crises. To begin with, when the full available information is employed, the estimation results highlight that the two-sided credit gap is a leading indicator of banking and currency crises in middle-income countries. The previous outcome is robust to the alteration of currency crises definition as well as to several robustness tests. Afterwards, in an operational perspective, the one-sided credit gap progressively becomes a better indicator of banking and currency crises as financial development increases which is captured by a trend level greater than 10%. Moreover, the results show strong evidence of unobserved heterogeneity, which may account for time invariant country-specific features. This outcome is related, in part, to the high degree of heterogeneity within middle-income countries in terms of their extent of financial integration, depth of the financial sector, and ease of access to credit (Arena et al. (2015)). The model also exhibits the existence of unobserved contemporaneous interactions between the twins. This result suggests that banking and currency crises are closely related and driven by common economic fundamentals. Unlike previous empirical studies that employ univariate static frameworks, I do not find any causal link running from banking crises to currency crises in emerging countries. Nevertheless, both equations reveal the presence of strongly correlated idiosyncratic shocks indicating that banking and currency crises are impacted by common time-varying unobserved disturbances.

The main policy implication of those results, is that the BCG is a key determinant in the understanding of the underlying transmission mechanisms between banking and currency crises and therefore, policymakers should be considering the role of currency crashes when attempting

to evaluate the performance of the BCG for banking crises prediction in financially developed middle-income countries. In an operational perspective, the BCG should be employed as a guide for setting Countercyclical Capital Buffers in more financially developed middle-income countries (i.e, countries with credit-to-GDP trend levels higher than 10%) to prevent the risk of both banking and currency crises.

This paper is structured as follows. Section 2.1 summaries the empirical literature on twin crises and encompasses several stylized facts about credit booms. Section 2.2 briefly describes the data-set as well as the definition employed for both banking and currency crises, and includes details on the econometric implementation. The main estimation results are compiled in Section 2.3 along with various robustness check specifications on the baseline model. I eventually run several sensitivity tests regarding the financial sector's depth and the error term structure in Section 2.4.

2.1 Literature review

Velasco (1987) and Calvo & King (1998) argue that bank runs are frequently associated with expansionary monetary policy resulting from the banking sector's bailout. Thus, a depreciation of the domestic currency induced by the liquidity excess may lead to a speculative attack under a fixed exchange rate regime. In addition, Obstfeld (1994) claims that in weakened banking sectors, rational speculators anticipate that policy makers will choose inflation over exchange rate stability in their attempt to prevent bankruptcies instead of sustaining the cost of maintaining the currency parity which may precipitate a currency crisis. According to González-Hermosillo & Alexander (1996), agents tend to substitute foreign assets to domestic assets in a poorly developed financial system which causes substantial capital outflows and therefore results in a domestic currency devaluation.

Similarly, Miller (1999) suggests that a government facing a bank run may consider, under a fixed exchange rate regime, the currency devaluation as the fitting policy option. Moreover, Chang & Velasco (2000) show that bank runs cause the banking system's foreign liabilities, which are mainly obligations denominated in international currency, to exceed its foreign liquid assets under a fixed exchange rate regime. Accordingly, the attempt of the central bank to simultaneously maintain the exchange rate parity and to act as a lender of last resort will result in a depletion of its own foreign exchange reserves; a currency crisis may occur as a result.

The reverse chain of causation is also well recognized in the literature: a currency crisis can exacerbate the banking sector fragility. Miller (1996) emphasizes that speculative attacks on currencies may lead to banking crises if the domestic deposits are used to speculate on the foreign exchange market and under the condition that banks are "loaned up".¹ In addition, Stoker (1996) suggests that under a gold standard monetary system, speculative attacks on the gold parity leads to a loss of gold reserves which results in a credit crunch causing bankruptcies. Nowadays, a similar scheme emerges in the case of a speculative attack on a fixed exchange rate regime, if the loss of foreign reserves incurred by the central bank is not sterilized. Furthermore, Obstfeld (1994) and Rojfs-Suárez et al. (1995) claim that policy makers often respond to the pressure on exchange rate by sharply raising the interest rates which can bring about liquidity shortage in the banking sector. Moreover, Hutchison & Glick (2000) argue that a currency crisis implies an increased cost for banks as they have to pay more in domestic currency for their debt in foreign currency and therefore deteriorates bank balance sheets.

2.1.1 Empirical findings

Contrasted results are also obtained regarding empirical studies about the relationship between currency and banking crises. Kaminsky & Reinhart (1999) analyze the conditional probabilities of currency and banking crises occurrence to highlight the causation link between the two types of crises using a sample of monthly data for 20 countries from 1970 to 1995. They discover that currency and banking crises are directly related: a currency crisis deepens a banking crisis while a banking crisis frequently precedes a currency crisis. Rossi (1999) considers the relationship between these crises by applying a sample of annual data for 15 developing countries during the 1990 – 1997 period. In his paper, Rossi (1999) utilizes a probit model to show that banking crises are leading indicators of currency crises while the opposite does not hold. Hutchison & Glick (2000) estimate a multivariate probit model to investigate the relationship between banking and currency crises selecting a sample for 90 developing and developed countries covering the 1975 – 1997 period. The results obtained reveal a correlation between currency and banking crises in emerging markets which are undergoing financial liberalization. The authors emphasize that a banking crisis is a leading indicator of a currency crisis, but not vice versa (as Rossi (1999) did previously). Falcetti & Tudela (2008) explore the link between currency and banking crises using quarterly data for 92 developing and emerging market economies

¹The bank can't grant any additional loan (it only has required reserves and keeps no excess).

running from 1970 to 1997. Although they do not find a significant causal link between these crises, they however conclude that the twins are driven by common fundamentals. Von Hagen & Ho (2009) utilize binary variables for currency and banking crises derived from continuous variables exceeding precise thresholds. The proxy for banking crises is based on the index of Von Hagen & Ho (2007) while the construction of the currency crisis variable is based on the exchange market pressure index. Annual data for a sample of 49 countries that covers the 1980 – 2004 period is employed to examine the relationship between these crises. The authors determine that previous currency crises help to predict banking crises but not reciprocally.

2.1.2 Credit booms in emerging markets: stylized facts

Meng & Gonzalez (2017) conduct a thorough study on the determinants of credit booms in emerging market economies and compare their characteristics to the ones that occur in advanced and developing countries. The authors employ a large sample of 160 countries over the 1960-2013 span and manage to identify 159 episodes of credit booms during that interval of time. Meng & Gonzalez (2017) highlight that developing countries are less likely to experience a credit boom while emerging market economies exhibit the highest likelihood in the 1990s. However, the probability of experiencing a credit boom seems on the rise for advanced economies starting from the 2000s in contrast with the other 2 groups of countries. In terms of duration, emerging market economies experience the lengthiest credit booms starting from the 2000s with an average episode lasting more than 5 years. Previous studies on credit booms also demonstrated that lengthy ones tend to coincide with higher level of inflation and are more likely to morph into banking crises (Barajas et al. (2007)). Nevertheless, Meng & Gonzalez (2017) emphasize that credit booms do not inevitably end up in a banking crisis: while 20% of booms are followed by a banking crisis when the full sample is considered, the comparable share peaks at 40% for emerging market economies. Such a difference between country groups could be imputed to the financial deepening in developing countries (which only experience a banking crisis preceded by a boom in 12% of cases) rather than a real threat of financial crises ("good booms"; see Barajas et al. (2007)). Examining a sample of 61 emerging and advanced countries over the 1960-2010 span, Mendoza & Terrones (2012) reach analogous conclusions regarding the fact that not all credit booms lead to banking or currency crises but emphasize, however, that large surges of capital inflows along with managed types exchange rate regimes are potential triggers of credit booms. Precisely, the authors state that credit booms are more

likely to occur under fixed or managed exchange rate regimes in contrast with freely floating ones. Mendoza & Terrones (2012) also highlight that among the 63% of credit booms that are associated with currency crises, the highest proportion (29%) occurs prior to a crisis event (14% at the peak and 20% after) in contrast with banking crises that record most booms (23%) after the crisis occurrence (17% prior to the crisis and 11% at the peak). Finally, Dell’Ariccia et al. (2016) acknowledge that most credit booms tend to occur in middle-income countries with fixed exchange rate regimes emphasizing however, that a significant proportion are linked to catching-up effects (the so called ”good booms”).

2.2 Data and model

2.2.1 The model

Assume that the binary outcome dependent variables y_{it}^{bc} and y_{it}^{cc} are an indirect observation of the latent vectors :

$$y_{it}^{bc*} = X_{it}^{bc} \beta^{bc} + \nu_{it}^{bc} \quad (2.1)$$

$$y_{it}^{cc*} = X_{it}^{cc} \beta^{cc} + \nu_{it}^{cc} \quad (2.2)$$

Let y_{it}^{bc*} and y_{it}^{cc*} denote the latent response equations with $i = 1, \dots, I$ and $t = 1, \dots, T_i$. Where I and T_i are respectively the number of countries in the sample and the number of periods (years) in which country i is observed. The dependent variable y_{it}^{bc*} is described by the set of explanatory variables X_{it}^{bc} and dependent variable y_{it}^{cc*} is described by the set of explanatory variables X_{it}^{cc} . Moreover, ν_{it} refers to the process-specific error term and is denoted as follows:

$$\nu_{it} = \alpha_i + u_{it} \quad (2.3)$$

It is assumed that α_i designates the country-specific time-invariant error term and u_{it} consists of a time-varying idiosyncratic shock; therefore:

$$y_{it}^{bc*} = X_{it}^{bc} \beta^{bc} + \alpha_i^{bc} + u_{it}^{bc} \quad (2.4)$$

$$y_{it}^{cc*} = X_{it}^{cc} \beta^{cc} + \alpha_i^{cc} + u_{it}^{cc} \quad (2.5)$$

Additionally, I suppose the country-specific time-invariant error terms to be normally distributed (i.e., $\alpha_i \sim N(0, \sigma_{\alpha_i}^2)$) and the idiosyncratic shocks to be standard normally distributed $u_{it} \sim N(0, 1)$ for normalization purposes (see Stewart (2006)). The parameter α_i , in the process-specific error term ν_{it} , refers to the time-invariant unobserved heterogeneity and is added to capture the fact that the propensities to face a financial crisis may vary due to country-specific characteristics. Economically, α_i could account for the fact that some countries might be more crisis prone compared to others, whereas u_{it} may indicate the presence of idiosyncratic shocks (i.e., unobserved factors that change over time and affect y_{it}^*).²

In the banking crisis equation, X_{it}^{bc} contains, besides other explanatory variables, the lagged value of currency crashes, (i.e., y_{it-1}^{cc}) while the same applies to the currency crisis equation (X_{it}^{cc} includes y_{it-1}^{bc}). These values are included to test for a possible causal effect running from banking to currency crisis or vice versa. Note that both X_{it}^{bc} as and X_{it}^{cc} include a constant term as well.

Moreover, the contemporaneous interactions among banking and currency crises are approximated using a correlation parameter ρ_{α} which accounts for correlation of the country-specific time-invariant error terms therefore:

$$\rho_{\alpha_i^{bc} \alpha_i^{cc}} \neq 0 \quad (2.6)$$

This parameter is included to account for mutual determinants of banking and currency crises which might be omitted by the set of explanatory variables.

Eventually, the correlation between the idiosyncratic shocks is estimated through the parameter $\rho_{u_{it}^{bc} u_{it}^{cc}}$ that accounts for the relationship between the common unobserved factors that vary over time and affect the dependent variable:

$$\rho_{u_{it}^{bc} u_{it}^{cc}} \neq 0 \quad (2.7)$$

Further issues emerge regarding initial conditions treatment. To solve this problem, I treat them as exogenous. This assumption is based on the existing literature which states that random effect panel models that account for initial condition problem will produce consistent estimators at samples sizes of at least $N = 1000$ if the number of waves T (i.e, number of time periods for each country) is four or higher (Arulampalam & Stewart (2009)); these properties

²The importance of controlling for this error term structure is shown later in section 2.4.2.

are fully satisfied by my sample. Multiple methods exist to deal with the initial conditions problem. Arulampalam & Stewart (2009) show that the prominent methods suggested by Heckman (1981b), Orme (1996) and Wooldridge (2005) produce comparable results for panels $T > 2$ and $N > 1000$. Another method is examined by Lee (1997). Lee’s simulation results suggests that treating the initial values as fixed does not lead to any significant bias if the panel contains 20 waves, but it does if the panel has only eight waves; these conditions are also met by my sample. Finally, the maximum simulated likelihood method (MSL) requires quasi-random sequences based on prime numbers that involve Halton draws (R). The precise details on the procedure are displayed in the Technical Appendix.

2.2.2 The data

I exploit a large panel data-set that contains yearly observations on for a total of 126 countries (86 middle-income; 25 high-income and 19 low-income, respectively as listed in Tables SM2.12 and SM2.13) from 1971 to 2017. Specifically, attention is turned to Panel B which contains middle-income countries. Accordingly, the set of independent variables includes both macroeconomic (real GDP growth, inflation, foreign direct investment and nominal exchange rate) and financial indicators (M2/foreign reserves and credit to private sector) as well as control variables (capital account degree of openness index and exchange rate arrangement dummy) as detailed in Table SM2.14. In order to study the impact of credit booms on the probabilities of facing a banking and a currency crisis, I include as an explanatory variable the credit gap separated from its long term trend to the baseline estimation. The data on credit to private sector are collected from the World Development Indicators (World Bank) and the gaps are computed using the Hodrick & Prescott (1997) filter.³ Further details regarding data source are displayed in Table SM2.15.

The starting point is the Laeven & Valencia (2020) updated database that covers 163 countries and provides annual data related to banking and currency crises. Due to data unavailability regarding some of the main explanatory variables, 37 countries are dropped in the process of sample construction. Given the fact that some observations are missing for a few economies at specific periods, the starting date for each country varies within the sample resulting in an unbalanced panel for a maximum of 4232 observations in Panel A and 2728 in Panel B (34

³The lambda value is set to $\lambda = 1562.5$ following Ravn & Uhlig (2002). More details in the Technical Appendix.

years for each country on average).⁴

2.2.3 Crises definitions and duration

Regarding systemic banking crises, I follow the definition suggested by Laeven & Valencia (2020) who mark the beginning of such an event if the latter meets two conditions: i) significant evidence of financial distress in the banking system (bank runs, losses in the banking system, and bank liquidations) ii) significant banking policy intervention measures in response to substantial losses in the banking system.⁵ Taking into consideration the starting and the ending dates proposed by the authors, I manage to identify 85 episodes of banking crises from 1971 to 2017 for the full sample.

Following the approach introduced by Frankel & Rose (1996), which focuses exclusively on sharp exchange rate depreciation, the definition of currency crises proposed by Laeven & Valencia (2020) focuses on two main criteria: i) a year-on-year depreciation of at least 30 percent with respect to the US dollar ii) a 10 percentage point devaluation of the domestic exchange rate compared to the year before. My method relies on this approach and focuses not only on the dating of initial crashes, but also on the full period in which the depreciation exceeded the thresholds. Therefore, a period is classified as "tranquil" as soon as one of the criteria is not satisfied. Under this definition, I identify 194 currency crises episodes during the 1971-2017 period for my sample (more details about crises dates are displayed in Tables SM2.16 and SM2.17).

Table 2.1 displays the descriptive statistics of the crises episodes that have been identified following the previous definitions. Whilst banking crises seem to last around 3 years on average, currency crashes are shorter with a mean approaching one year and a half. The longest banking crisis episode is recorded in Brazil (from 1990 to 1998) for both Panels alike, while Israel experiences the longest currency crash (1980–1985) in Panel A. The last line in Table 2.1 indicates the proportion of crisis episodes relatively to tranquil periods. Although banking crises tend to last longer, currency crises seem to occur more often in the sample. Note that episodes of twin crises are defined as a banking crisis occurrence in year t , coupled with a currency crash during the period from $t - 1$ to $t + 1$.

⁴More details about the data set are displayed in Table SM2.1.

⁵The interventions are considered to be significant if at least 3 out the 6 following measures are employed: deposit freezes or bank holidays; significant bank nationalizations; bank restructuring fiscal costs (at least 3 percent of GDP); extensive liquidity support (at least 5 percent of deposits and liabilities to nonresidents); significant guarantees put in place and significant asset purchases (at least 5 percent of GDP).

Table 2.1: Crises episodes duration

	<i>Panel A</i>		<i>Panel B</i>	
	<i>Banking</i>	<i>Currency</i>	<i>Banking</i>	<i>Currency</i>
Episodes occurrences	85	194	56	150
Mean	2.88	1.55	2.78	1.57
Median	3	1	3	1
Standard deviation	1.64	1.02	1.63	1.03
Maximum	9	6	9	5
% of crisis periods	5.75	7.19	5.68	8.62
Episodes of twin crisis	47		37	

Panel A contains 126 countries (full sample) whilst Panel B covers only middle-income economies (82).

2.3 Results

In this section, I present the estimation results of my multivariate approach about the determinants of banking and currency crises. The set of independent variables has been chosen based on the existing empirical literature on the common causes of financial crises (Kaminsky & Reinhart (1999); Davis & Karim (2008); Drehmann & Tsatsaronis (2014); Hutchison & Glick (2000)). I first present my baseline model results using the full available information (i.e, the two-sided credit gap) with the purpose of investigating whether credit booms impact the likelihood of banking and currency crises. Then, I assess whether this relationship can be expanded to an operational perspective by employing pseudo real-time data (BCG).

2.3.1 Baseline results

Table 2.2 displays the main results of my baseline model. Although I do not find any evidence of leading effect running from banking to currency crises or vice versa, the twins seem to be driven by common factors in middle-income countries.⁶

The existing literature widely acknowledges that banking and currency crises are frequently preceded by credit booms intensified by the liberalization of the domestic financial system. Thus, in my model, the credit gap assessed by HP filter is strongly positive as well as significant at the 1% level in both banking and currency crises equations suggesting that excessive credit growth substantially increases the likelihood of both types of crises. Since the raw credit-to-GDP ratio encompasses two types of information (i.e, a trend component associated with financial development features and a gap one related to the financial cycle), the ratio can be

⁶A weak link between CC_{t-1} and BC_t is observed (at the 10% level) in the full sample specification.

ill-suited for describing banking and currency crises. The previous statement is supported by the estimation results displayed in Table SM2.2 as we can observe a non significant coefficient associated with the credit-to-GDP ratio in the currency crises equation (Panel B) while the banking crises one exhibits a weak significance of the $Cred_{t-1}$ coefficient. Indeed, several empirical studies in the literature regarding banking and currency crises utilize the ratio of the private credit-to-GDP as an explanatory variable. While this metric is rather informative about the financial depth within a country, it gives limited hints regarding the features of credit cycles. In addition, I include the decomposed trend that was initially extracted from the credit-to-GDP ratio to generate credit gaps in Table SM2.3 as a robustness check. Interestingly, $Trend_{t-1}$ is strongly significant at the 1% level and negative in the currency crises equation while the same variable exhibits only a significance level of 10% in the banking crises equation for Panel B. A similar scheme emerges in the full sample specification where the trend is also strongly negative and significant at the 1% level in the currency crises equation while it does not appear to be significant at any level in the banking crises equation. This outcome is in line with previous findings in the literature on banking crises which are described as an "equal opportunity menace" by Reinhart & Rogoff (2009a) irrespective of the income level. Conversely, $Trend_{t-1}$ being negative and significant in both panels alike hints that financially developed countries are less likely to experience currency crashes (Laeven & Valencia (2020)). Those results corroborate the idea that the dynamics of credit booms, banking crises and currency crashes are singular among this group of countries which makes it challenging to properly assess the underlying mechanisms. Finally, I attempt a robustness test on the baseline estimation by relying on the definition of currency crashes recommended by Frankel & Rose (1996) instead of the one proposed in the benchmark specification. Since this approach is more flexible, I manage to identify 27 and 12 extra episodes for panels A and B respectively. The estimation results are displayed in Table SM2.4. While I notice a significant decrease in the value of the lagged crisis coefficients, the vast majority of the explanatory variables remain unchanged in terms of significance level including the gap coefficient.

Looking back at Table 2.2, the probability of both banking and currency crisis rises with higher M2 over reserves ratio which is consistent with the empirical findings (Chang & Velasco (2000); Hutchison & Glick (2000); Davis & Karim (2008)). Additionally, I include in the baseline estimation the Chinn-Ito index $Kaopen$ which assesses countries degree of capital account openness. A higher index indicates less regulation and more openness in the capital

account. Former studies showed that the impact of banking crises on financially dependent sectors is less when the capital account is open. In Table 2.2, the index is strongly significant in both equations for the sub-sample of middle-income countries and the full sample alike. The negative sign associated with the index coefficient is consistent with existing findings on financial crises and capital account liberalization in emerging markets (Rossi (1999); Glick et al. (2006)) and implies that more capital account restrictions significantly increase the likelihood of both banking and currency crises.⁷ Following Frankel & Rose (1996) suggestion about currency crashes, I incorporate foreign direct investment inflows to the baseline estimation. The model shows that a low FDI to GDP ratio has a significant effect on the probability of a currency crisis in middle-income countries.

Regarding the random-effects parameters, $\sigma_{\alpha_i^{bc}}$ and $\sigma_{\alpha_i^{cc}}$ suggest that twins crises differ in their unobserved characteristics: whilst only 30% of the variance in the error term is explained by the random-effects error parameter in the currency crises equation, the country-specific time-invariant error term describes almost 60% of the total variance in the banking crises equation. Thus, the set of explanatory variables performs better at capturing currency crises characteristics compared to banking crises. This result corroborates the consensus of previous studies on Early Warning Systems which acknowledges that predicting banking crises is typically a difficult task compared to currency crashes (see Kaminsky (1999); Claessens & Kose (2013)). Note that both parameters $\sigma_{\alpha_i^{bc}}$ and $\sigma_{\alpha_i^{cc}}$ are strongly significant at the 1% level. Additionally, the model highlights the presence of strong unobserved contemporaneous relationship between banking and currency crises as the estimated coefficient associated with $\rho_{\alpha_i^{bc}, \alpha_i^{cc}}$ appears to be significant at the 1% level. A positive coefficient indicates that common unobserved factors lead to banking and currency crises while not captured by the set of explanatory variables. The previous outcome emphasizes the importance of accounting for the correlation of unobserved features when attempting to model the interactions among banking and currency crises. Finally, it may be the common idiosyncratic shocks that affect the probability of a twin crisis. The results exhibit the presence of strongly significant and positive correlation between the idiosyncratic shocks with $\rho_{u_{it}^{bc}, u_{it}^{cc}}$ significant at the 1% level in both specifications. The previous result suggests that the twins are driven by mutual unobserved time-varying disturbances highlighting the necessity of controlling for such factors.

⁷A similar result is obtained by Qin & Luo (2014) as the authors find a negative sign for KAOPEN and suggest that capital account openness has a strong predictive power regarding banking crises in advanced economies.

Table 2.2: Baseline model

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.09051 (0.15479)	-	0.13694 (0.17874)
CC_{t-1}	0.21767* (0.12609)	-	0.14405 (0.15103)	-
Gap_{t-1}	0.02262*** (0.00332)	0.01513*** (0.00338)	0.02032*** (0.00488)	0.01206*** (0.00449)
FDI_{t-1}	-	-0.01576* (0.00919)	-	-0.02567** (0.01209)
Inf_{t-1}	0.00016*** (0.00006)	-	0.00016*** (0.00006)	-
GDP_{t-1}	-0.03947*** (0.00795)	-0.02370*** (0.00758)	-0.02877*** (0.01054)	-0.01893** (0.00893)
$Ln(M2/res)_{t-1}$	0.22538*** (0.05175)	0.30634*** (0.05214)	0.26863*** (0.06648)	0.32785*** (0.05993)
$ExRate_{t-1}$	-0.00003 (0.00003)	-0.00014** (0.00006)	-0.00001 (0.00003)	-0.00011** (0.00005)
$Kaopen_{t-1}$	-0.14820*** (0.03759)	-0.28339*** (0.03636)	-0.16942*** (0.05435)	-0.19957*** (0.04504)
$Rate Dum_{t-1}$	0.01442 (0.01298)	0.08592*** (0.01056)	0.01798 (0.01581)	0.09324*** (0.01217)
<i>Log Likelihood</i>	-1614.071		<i>Log Likelihood</i>	-1111.919
<i>Observations</i>	4232		<i>Observations</i>	2728
<i>Countries</i>	126		<i>Countries</i>	82
<i>BC episodes</i>	85		<i>BC episodes</i>	56
<i>CC episodes</i>	194		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.59729*** (0.14190)		$\sigma_{\alpha_i^{bc}}$	0.59599*** (0.16655)
$\sigma_{\alpha_i^{cc}}$	0.33939*** (0.08299)		$\sigma_{\alpha_i^{cc}}$	0.29990*** (0.08649)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.35892*** (0.12474)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.35046*** (0.12245)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.25308*** (0.08139)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24450*** (0.09473)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; Gap = Two-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

2.3.2 One-sided gap and financial development

Since the two-sided credit gap may not be employed by a policymaker for financial crises prediction (i.e, it encompasses future information when the gaps are computed), I attempt to assess whether the one-sided credit gap (pseudo real-time) is a relevant indicator of banking and currency crises in middle-income countries. Previous findings in the literature suggest that this metric yields rather poor performances for banking crises as the efficiency of the one-sided credit gap is mainly demonstrated for high-income countries. The previous statement is also true in the baseline sample as Table 2.3 highlights that the one-sided gap does not appear to be significant at any level for both banking and currency crises in middle-income countries while the full sample specification only displays a statistical significance at the 10% level when high-income countries are included. A possible explanation for this phenomenon could be that credit booms that morph into a twin crisis in middle-income countries, are often followed by even sharper and longer credit crunches that remain well after the initial recession induced by the twin crisis (Tornell & Westermann (2002)). Therefore, the one-sided gap may struggle to capture the excess credit growth around banking and currency crises periods in middle-income countries since this indicator uses pseudo real time data to compute the gaps. In addition, Hong & Tornell (2005) also argue that currency crises yield durable adverse effects on the economy, mirrored in a real domestic credit that remains below its previous long-term trend many years after the crisis occurred resulting in a prolonged credit crunch.

By contrast, when the extracted trend component is used as sample selection criteria, the one-sided credit gap appears to become significant and positive in both banking and currency crises equations as less financially countries are gradually excluded (i.e, countries that have trends values lower than 10% and 20% respectively). Table SM2.5 shows that the BCG is significant at the 1% level in the banking crises equation, while it only displays a significance level at the 10% regarding currency crises when countries with trend values greater than 10% are included in the sample. Thereafter, when only financially developed countries are bundled (i.e, countries with trend values higher than 20%), both the magnitude and the significance levels of the one-sided gaps are enhanced (from 0.004 in the full sample to 0.009 and 0.006 for banking and currency crises, respectively). The previous outcome is robust even when the one-sided trend component is included as an explanatory variable (Table SM2.6). In addition, Figures 2.1 and 2.2 plot the t-statistics associated with the one-sided credit gaps coefficients as the trend value evolves in an interval spanning from 0% (full sample specification) to 30%

with a 2.5% variation. Specifically, Figure 2.1 shows that the significance of the one-sided credit gap reaches the 1% level at the 7.5% trend threshold for banking crises. By contrast, the t-statistic associated with the one-sided credit gap coefficient for currency crises remains above the 5% significance level when the trend value is greater than 10% (Figure 2.2). Regarding the proportion of crises, Figures 2.1 and 2.2 highlight that 70% of banking crises remain within the sample at the 20% threshold while only 55% of currency crises are kept at the same landmark. Note that most of the explanatory variables signs and significance are robust with higher trend levels (25% and 30%, Table SM2.7).

Those results imply that the one-sided credit gap becomes a relevant indicator of banking and currency crises as financial development increases. Thus, in an operational perspective, only financially developed countries should be employing the BCG in the process of predicting twin crises.

Table 2.3: One-sided credit gap

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.13588 (0.16104)	-	0.13958 (0.18605)
CC_{t-1}	0.29265** (0.13028)	-	0.12256 (0.15799)	-
$GapOS_{t-1}$	0.00452* (0.00231)	0.00428* (0.00241)	0.00069 (0.00288)	0.00177 (0.00297)
FDI_{t-1}	-	-0.01756* (0.01025)	-	-0.03737** (0.01467)
Inf_{t-1}	0.00018*** (0.00006)	-	0.00015** (0.00006)	-
GDP_{t-1}	-0.04695*** (0.00821)	-0.02717*** (0.00803)	-0.03872*** (0.01091)	-0.02080** (0.00966)
$Ln(M2/res)_{t-1}$	0.26743*** (0.05276)	0.34158*** (0.05526)	0.31478*** (0.06837)	0.36205*** (0.06380)
$ExRate_{t-1}$	-0.00006 (0.00004)	-0.00013** (0.00006)	-0.00004 (0.00004)	-0.00011** (0.00005)
$Kaopen_{t-1}$	-0.11739*** (0.03764)	-0.30218*** (0.03836)	-0.16152*** (0.05648)	-0.24833*** (0.04905)
$Rate Dum_{t-1}$	0.00140 (0.01355)	0.08105*** (0.01131)	0.00419 (0.01664)	0.08219*** (0.01311)
<i>Log Likelihood</i>	-1504.548		<i>Log Likelihood</i>	-1036.777
<i>Observations</i>	3955		<i>Observations</i>	2515
<i>Countries</i>	125		<i>Countries</i>	81
<i>BC episodes</i>	76		<i>BC episodes</i>	52
<i>CC episodes</i>	173		<i>CC episodes</i>	132
$\sigma_{\alpha_i^{bc}}$	0.61046*** (0.15202)		$\sigma_{\alpha_i^{bc}}$	0.65999*** (0.20616)
$\sigma_{\alpha_i^{cc}}$	0.38817*** (0.09188)		$\sigma_{\alpha_i^{cc}}$	0.37519*** (0.10743)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.36889*** (0.13537)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.34817*** (0.12016)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24847*** (0.08399)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.21987*** (0.09834)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; $GapOS$ = One-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Figure 2.1: Evolving credit-to-GDP trend threshold and credit gap t-statistic (banking crises)

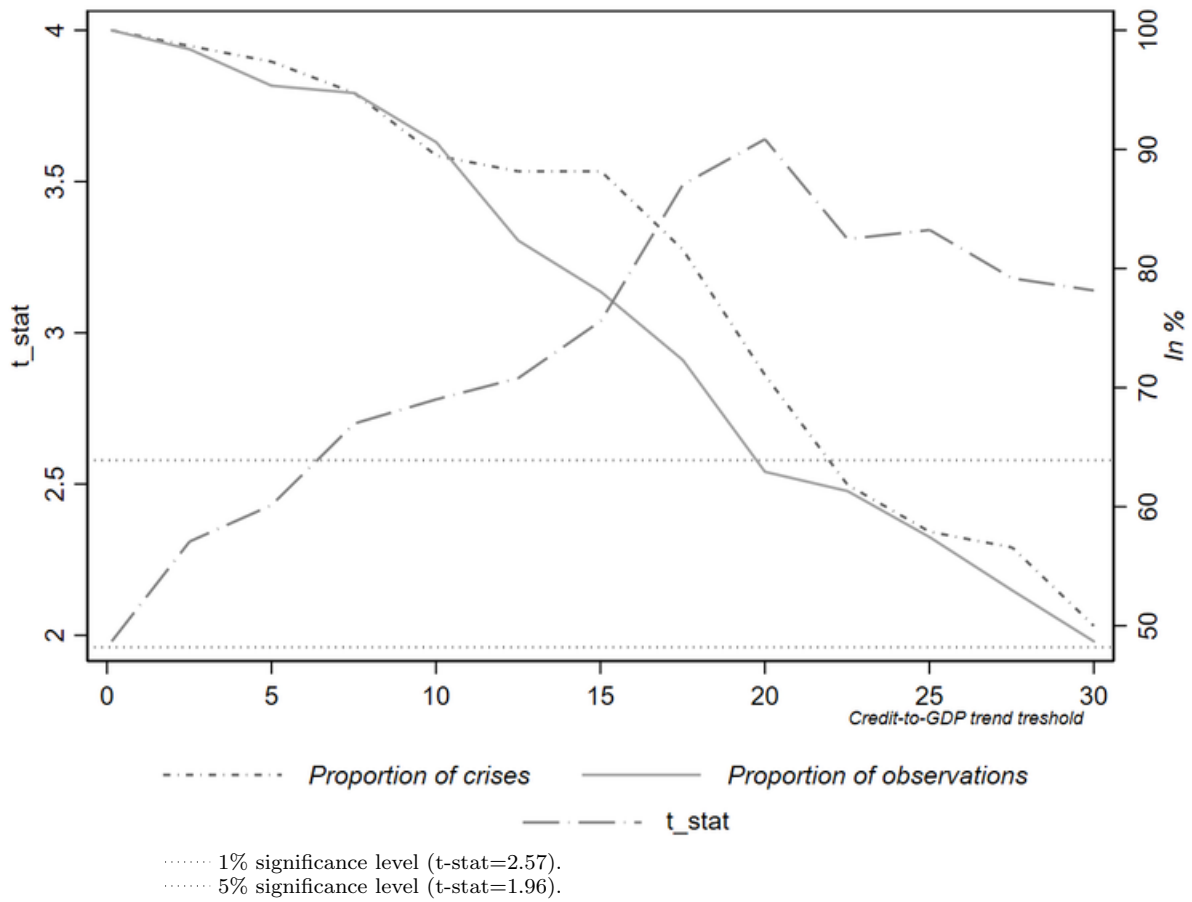
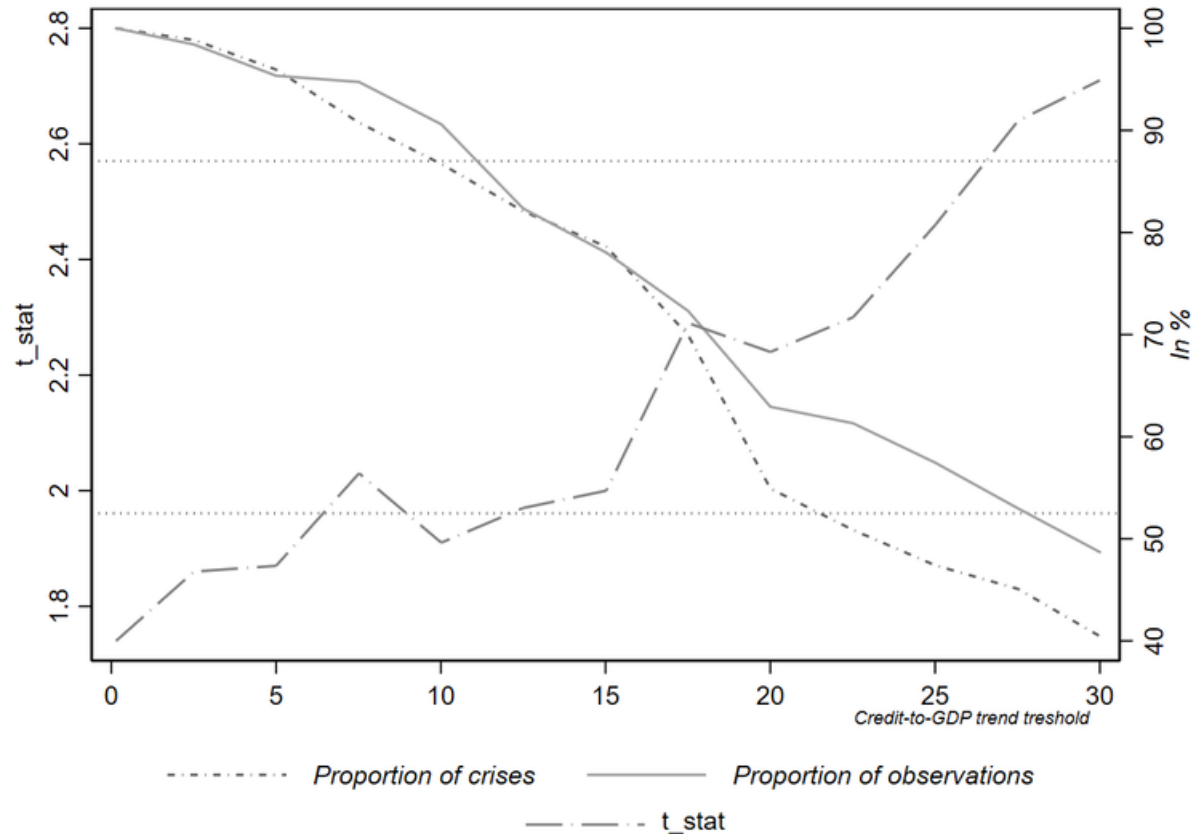


Figure 2.2: Evolving credit-to-GDP trend threshold and credit gap t-statistic (currency crises)



2.4 Robustness checks

2.4.1 Credit metrics and financial depth: an individual assessment

This section aims to individually assess the impact of credit indicators on the probability of facing banking and currency crises in middle-income countries. Table SM2.8 displays the estimation results of both the two-sided credit gap (left hand side) and the decomposed trend extracted from the private credit-to-GDP ratio. To begin with, the correlation parameters that account for unobserved heterogeneity and the idiosyncratic shocks remain strongly significant and positive in both estimations. In terms of magnitude, the coefficient associated with the gap is quite similar compared to the baseline estimation. A negative sign also emerges in the right hand side estimation hinting that the trend separated from the credit-to-GDP ratio wasn't affected by another explanatory variable in the currency crises equation while the coefficient associated with $Trend_{t-1}$ in the banking crises equation is not statically significant at any level. The previous outcome implicates that countries are equally exposed to the risk of banking crises regardless of their income group. Moreover, an individual assessment of the trend in the currency crises equation confirms that more depth in the financial sector is associated with a lower probability of currency crash occurrence. This outcome implicates that less financially developed middle-income countries are more likely to experience a currency crisis and therefore, the poor performance of the BCG at predicting banking crises in such countries can be imputed to the fact that currency crises also tend to occur around banking crises. Accordingly, policymakers should be accounting for the role of currency crises when attempting to evaluate the BCG performances in the context of banking crises in less financially developed middle-income countries.

In appendix SM2.9, I attempt further sensitivity tests on the relationship between financial sector depth and the probability of facing banking and currency crises using an alternative data source (Bouvatier et al. (2022)) for the extraction of trends from quarterly data. Previous findings in the literature (Drehmann & Tsatsaronis (2014)) suggested that a quarterly frequency is more appropriate to assess cyclical movements in credit activities. The quarterly extracted trends are then collapsed into annual data in order to fit with crises dates. Table SM2.9 confirms that currency crises are more likely to occur among countries with less developed financial sectors while $Trend_{t-1}$ in the banking crises equation is not statically significant suggesting that countries are equally exposed to the risk of facing a banking crisis. Note

that the significance level of the gaps is unchanged despite the shift in the magnitude of both coefficients in contrast with Table SM2.8 while the coefficients associated with the trends are quite similar.

2.4.2 Relaxing the assumption of correlation between the idiosyncratic shocks

In this section, I implement a sensitivity test on the error term structure. As mentioned in section 2.2.1, I allowed for correlation between the idiosyncratic shocks for both processes through the time-varying correlation parameter $\rho_{u_{it}}$. Since I observed a strong statistical significance for this parameter in Table 2.2, I attempt to implement another estimation without controlling for the correlation among idiosyncratic shocks (i.e., $\rho_{u_{it}} = 0$). The results are displayed in Table SM2.10. Although the statistical significance of most the explanatory variables remains unaltered, I can now observe an important shift in the value of the coefficients for both lagged banking and crises variables. Therefore, the coefficient associated with BC_{t-1} is now strongly significant at the 1% level and positive suggesting that past banking crises help to predict future currency crises in both specifications while I could not find any causal link in the previous estimation.⁸ This outcome highlights the importance of controlling for the appropriate error term structure when attempting to model the dynamic interactions between twin crises. As emphasized by Heckman (1981a), omitting to control for the correlation among the idiosyncratic shocks artificially increased the lagged banking crisis coefficient in the estimation results. Note that the coefficient of CC_{t-1} remains not significant despite the shift in panel B whilst the coefficient value of the lagged currency crisis is substantially increased in panel A compared to the baseline estimation and appears to be significant at the 1% level.

Conclusion

This paper aims to examine unexplored links in the literature regarding the Basel Credit Gap (BCG) and twin crises in middle-income countries. While the vast majority of previous research focuses on the performance of the BCG for banking crises prediction in univariate frameworks, which seems fitting for advanced economies where banking crises are mainly driven by excess credit, I attempt to construct a bivariate model in order to study whether

⁸Rossi (1999) and Hutchison & Glick (2000) reach analogous conclusions.

the BCG is a leading indicator of banking and currency crises. The estimation results exhibit that the two-sided credit gap is a relevant indicator of both banking and currency crises in middle-income countries. The previous outcome is robust to various sensitivity tests such as alternative currency crises definition. In addition, I highlight that, in an operational perspective, the one-sided credit gap becomes a better indicator of twin crises with greater financial development which is assessed by a trend value of the credit-to-GDP ratio higher than 10%. Further implementations attempted in section 2.4.2 demonstrate that relaxing the hypothesis of correlation among the idiosyncratic shocks brings up spurious leading effects between the twins while a higher development within the financial sector is constantly associated with a lower probability of facing a currency crisis.

The main policy implication of those results is that the BCG should be employed, in more financially developed middle-income countries, as an indicator to activate the CCyB therefore helping to sustain the credit activity following both banking and currency crises. Thus, in an operational perspective, the CCyB may turn out to be a valuable macro-prudential policy instrument to prevent the risk of financial crises in middle-income countries. Forthcoming research on the BCG in middle-income countries should be considering to account for the CCyB in the prevention of multiple types of financial crises.

Technical Appendix: Chapter II

The individual likelihood function is the product of the joint probability of the observed binary outcome variable $[P_i(\alpha^{bc}, \alpha^{cc})]$ and the joint density of the random-effects error terms $[f(\alpha^{bc}, \alpha^{cc}; \mu_\alpha)]$ therefore :

$$L_i = \int_{\alpha^{bc}} \int_{\alpha^{cc}} P_i(\alpha^{bc}, \alpha^{cc}) f(\alpha^{bc}, \alpha^{cc}; \mu_\alpha) d\alpha^{bc} d\alpha^{cc} \quad (2.8)$$

with μ_α referring to the covariance of the random-effects error terms ($\mu_\alpha = \rho_\alpha \sigma_{\alpha^{bc}} \sigma_{\alpha^{cc}}$). Accordingly, The variance-covariance matrix of the random effects error terms is written:

$$V_\alpha = \begin{pmatrix} \sigma_{\alpha^{bc}}^2 & \rho_\alpha \sigma_{\alpha^{bc}} \sigma_{\alpha^{cc}} \\ \rho_\alpha \sigma_{\alpha^{bc}} \sigma_{\alpha^{cc}} & \sigma_{\alpha^{cc}}^2 \end{pmatrix} \quad (2.9)$$

And the variance-covariance matrix of the idiosyncratic shocks takes the following form:

$$V_u = \begin{pmatrix} \sigma_{u^{bc}}^2 & \rho_u \\ \rho_u & \sigma_{u^{cc}}^2 \end{pmatrix} \quad (2.10)$$

Since I assume that the joint density function of the error terms follows a bivariate normal distribution, the individual outcome probabilities are:

$$P_{it}(\alpha^{bc}, \alpha^{cc}) = \Phi_2[k_1(X_{it}^{bc} \beta^{bc} + \alpha_i^{bc}), k_2(X_{it}^{cc} \beta^{cc} + \alpha_i^{cc}), k_1 k_2 \rho_u] \quad (2.11)$$

where

$$k = \begin{cases} 1 & \text{if } y = 1 \\ -1 & \text{if } y \neq 1 \end{cases} \quad (2.12)$$

With Φ_2 designates the the bivariate normal cumulative distribution function. According to Greene (2012), it is written:

$$\Phi_2(X^{bc}, X^{cc}, \rho_u) = \int_{-\infty}^{X^{cc}} \int_{-\infty}^{X^{bc}} \phi_2(z^{bc}, z^{cc}, \rho_u) dz^{bc} dz^{cc} \quad (2.13)$$

and the density

$$\phi_2(X^{bc}, X^{cc}, \rho_u) = \frac{e^{(-\frac{1}{2})(X^{bc})^2 + (X^{cc})^2 - 2\rho_u X^{bc} X^{cc}}}{(1 - \rho_u^2)} \frac{1}{2\pi(1 - \rho_u^2)^{\frac{1}{2}}} \quad (2.14)$$

The sample likelihood function can be written:

$$L = \prod_{i=1}^I \int_{\alpha^{bc}} \int_{\alpha^{cc}} \left\{ \prod_{t=1}^T P_{it}(\alpha^{bc}, \alpha^{cc}) \right\} f(\alpha^{bc}, \alpha^{cc}; \mu_{\alpha}) d_{\alpha^{bc}} d_{\alpha^{cc}} \quad (2.15)$$

Because this equation may not be determined analytically, the country-specific time-invariant error terms α^{bc} and α^{cc} should be integrated out. Several approaches exist to approximate numerically this two-dimensional integral such as implementing adaptive Gauss–Hermite quadrature or simulation. Thus, I rely on Maximum Simulated Likelihood (MSL) to simulate the bivariate normal distribution of the random effects error terms. This process requires draws (denoted R) from quasi-random sequences based on prime numbers which are also known as Halton draws. For each draw (r) the likelihood is derived for each observation, multiplied over all individuals including time-points, and finally averaged over all draws. According to Alessie et al. (2004), if $R \rightarrow \infty$ faster than \sqrt{N} the method produces a consistent estimator. Typically, when the number of draws grows faster than the square root of N , the estimator is asymptotically equivalent to exact Maximum Likelihood (Gourieroux & Monfort (1993), Hajivassiliou & Ruud (1994)). Thus, a total of R random draws are generated and transformed using the inverse cumulative standard normal distribution the following way:

$$\bar{\alpha}_r = \Phi^{-1}(r) \quad (2.16)$$

Finally, the MSL is written:

$$MSL = \prod_{i=1}^I \frac{1}{R} \sum_{r=1}^R \left\{ \prod_{t=1}^T P_{it}(\alpha_r^{bc}, \alpha_r^{cc}) \right\} \quad (2.17)$$

Where the link between the transformed draws and the bivariate normally distributed numbers is:

$$\begin{cases} \alpha_r^{bc} = \sigma_{\alpha^{bc}} \bar{\alpha}_r^{bc} \\ \alpha_r^{cc} = \sigma_{\alpha^{cc}} \rho_{\alpha} \bar{\alpha}_r^{bc} + \sigma_{\alpha^{cc}} \sqrt{1 - \rho_{\alpha}^2} \bar{\alpha}_r^{cc} \end{cases} \quad (2.18)$$

Previous research on the performance of Early Warning Systems has demonstrated that the choice of binary dependent variables for the modeling of crisis episodes might lead to potential issues due to the post-crisis bias. Precisely, the studies suggest that macroeconomic fundamentals tend to behave differently in tranquil periods after the crisis occurrence compared to other non-crisis observations before the episode occurred (Bussiere & Fratzscher (2006)). Although approving the authors suggestion, I decide not to implement it for various reasons. First, the solutions mainly consist of dropping the post-crises periods (sometimes the ongoing crisis observations). While this approach seem to be easily applicable in static frameworks, the implantation of such procedure in dynamic settings generates gaps within the panel and therefore, possibly lead to a bias. Second, most of the studies that employ this procedure only focus on one crisis type at a time. Thus, dropping post banking crises observations may imply a hypothetical loss of valuable information regarding currency crashes episodes and conversely. Finally, allowing for correlation among the idiosyncratic shocks is an important feature of the baseline estimation. Therefore, generating gaps withing the panel can mitigate the effect of the correlation parameter ρ_{uit} and potentially weaken the error term structure.

An additional limitation emerges from data frequency. Indeed, the choice of annual data in this paper relies on the availability in order to obtain the largest possible sample. Theoretically, monthly or quarterly data might be worth testing since this format would enable a better framework to test the contemporaneous links between banking and currency crises as well as to capture financial cycles features Drehmann & Tsatsaronis (2014).⁹

The numbers of Halton draws (R) in the baseline specification are 55 and 70 for Panels B and A respectively. Those numbers are chosen in accordance with Alessie et al. (2004) as the authors state that MSL estimator is asymptotically equivalent to the Maximum Likelihood estimation method as long as the number of draws grows faster than \sqrt{N} . Further simulations are displayed in the appendix (Table SM2.11) with $R \mapsto \infty$ demonstrate that the baseline results remain unaltered as the number of Halton draws (R) grows.

⁹According to Hodrick & Prescott (1997), the smoothing parameter λ must be set to 1600 in order to capture the business cycle with quarterly data. Since credit cycles are considered to be four times longer than business cycles, Drehmann et al. (2010) determine that $\lambda = 400000$ yields good performances to detect systemic banking crises. Following Ravn & Uhlig (2002), I set $\lambda = 1562.5$ using this formula: $\lambda_{annual} = s^n \lambda$ where $s = \frac{1}{4}$ and $n = 4$ are recommended by the authors.

Chapter II: supplemental material

Robustness checks and sample details

This appendix reports the results associated with the robustness checks implemented on the baseline estimation as well as several details on the sample. More precisely, this appendix encompasses: *(i)* the descriptive statistics of all the predictors employed in the baseline (Table SM2.1); *(ii)* a baseline replication using the credit-to-GDP ratio (Table SM2.2); *(iii)* a baseline replication including the trend component (Table SM2.3); *(iv)* a baseline replication with an alternative currency crises definition (Table SM2.4); *(v)* an alternative sample selection criteria (SM2.5 and SM2.6 and SM2.7); *(vi)* an individual assessment of gap and trend (SM2.8 and SM2.9); *(vii)* an alternative error term structure (SM2.10); *(viii)* a baseline replication with a higher number of Halton draws (Table SM2.11); *(ix)* several details on countries within the sample (SM2.12 and SM2.13), leading indicators (SM2.14), data source (SM2.15) and crises dates (SM2.16 and SM2.17).

Table SM2.1: Descriptive statistics

Panel A: Full sample

	<i>GDP</i>	<i>Inf</i>	<i>M2/Res</i>	<i>ExRate</i>	<i>Cred</i>	<i>FDI</i>
Observations	4232	4232	4232	4232	4232	4232
Mean	4.1013	31.104	1.3386	375.49	39.035	3.3235
Median	4.1191	7.1844	1.2441	7.8276	26.055	1.7199
Standard deviation	5.7290	347.83	0.9569	1600.2	38.504	6.7602
Kurtosis	153.54	974.97	4.5880	79.219	8.2904	118.25
Minimum	-36.391	-31.565	-1.6562	0.0002	0.9629	-55.234
5% percentile	-3.5228	-1.1308	-0.0034	0.0014	4.9419	-0.1136
95% percentile	11.033	51.759	3.1224	1555.1	126.25	11.139
Maximum	149.97	13611	6.3411	21935	312.03	161.82
Data source	WDI	WDI	WDI	WDI	WDI	WDI

Panel B: Middle income countries

	<i>GDP</i>	<i>Inf</i>	<i>M2/Res</i>	<i>ExRate</i>	<i>Cred</i>	<i>FDI</i>
Observations	2728	2728	2728	2728	2728	2728
Mean	4.3851	42.084	1.2592	429.39	32.968	3.2308
Median	4.3999	7.7958	1.2119	7.7412	25.016	1.8978
Standard deviation	6.1957	432.26	0.9358	1908.6	28.096	6.3060
Kurtosis	170.07	631.20	5.6893	59.320	12.347	180.32
Minimum	-27.526	-31.565	-1.6562	0.0002	0.9629	-55.234
5% percentile	-3.3682	-0.9204	-0.1326	0.0017	5.9879	-0.0890
95% percentile	11.353	60.035	2.8196	1685.7	89.305	10.514
Maximum	149.97	13611	6.3411	21935	257.18	161.82
Data source	WDI	WDI	WDI	WDI	WDI	WDI

Variables definitions: *GDP* = Year-on-year growth rate of real GDP; *Inf* = Inflation, GDP deflator; *M2/Res* = Broad money to reserves ratio; *ExRate* = Official exchange rate; *Cred* = Domestic credit to GDP ratio; *FDI* = Foreign Direct Investment inflows.

WDI = World Development Indicators (World Bank).

Table SM2.2: Robustness check : baseline model (Credit-to-GDP ratio)

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.11751	-	0.14327
	-	(0.15086)	-	(0.17594)
CC_{t-1}	0.27302**	-	0.17404	-
	(0.12591)	-	(0.14976)	-
$Cred_{t-1}$	0.00764***	-0.00371**	0.00422*	-0.00259
	(0.00149)	(0.00161)	(0.00237)	(0.00229)
FDI_{t-1}	-	-0.00754	-	-0.02408**
	-	(0.00828)	-	(0.01186)
Inf_{t-1}	0.00014**	-	0.00015**	-
	(0.00006)	-	(0.00006)	-
GDP_{t-1}	-0.03988***	-0.02582***	-0.03065***	-0.02147**
	(0.00806)	(0.00746)	(0.01054)	(0.00893)
$Ln(M2/res)_{t-1}$	0.24121***	0.35231***	0.29104***	0.35359***
	(0.05349)	(0.05045)	(0.06532)	(0.05935)
$ExRate_{t-1}$	-0.00003	-0.00014***	-0.00002	-0.00011**
	(0.00003)	(0.00005)	(0.00003)	(0.00005)
$Kaopen_{t-1}$	-0.18529***	-0.24646***	-0.16805***	-0.18432***
	(0.04016)	(0.03682)	(0.05447)	(0.04483)
$Rate Dum_{t-1}$	0.00621	0.08541***	0.01469	0.08961***
	(0.01295)	(0.01024)	(0.01529)	(0.01201)
<i>Log Likelihood</i>	-1626.137		<i>Log Likelihood</i>	-1120.625
<i>Observations</i>	4232		<i>Observations</i>	2728
<i>Countries</i>	126		<i>Countries</i>	82
<i>BC episodes</i>	85		<i>BC episodes</i>	56
<i>CC episodes</i>	194		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.65637***		$\sigma_{\alpha_i^{bc}}$	0.61393***
	(0.14608)			(0.17442)
$\sigma_{\alpha_i^{cc}}$	0.31684***		$\sigma_{\alpha_i^{cc}}$	0.27949***
	(0.07590)			(0.08753)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.48384***		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.36928***
	(0.10714)			(0.12397)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.27551***		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.26595***
	(0.07911)			(0.09232)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; $Cred$ = credit-to-GDP ratio; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.3: Robustness check: controlling for financial depth

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	- -	0.09467 (0.15531)	- -	0.14592 (0.17847)
CC_{t-1}	0.22797* (0.12719)	- -	0.12817 (0.15131)	- -
Gap_{t-1}	0.02151*** (0.00340)	0.02206*** (0.00383)	0.02354*** (0.00533)	0.01778*** (0.00505)
$Trend_{t-1}$	0.00196 (0.00179)	-0.01319*** (0.00229)	-0.00619* (0.00339)	-0.01181*** (0.00290)
FDI_{t-1}	- -	-0.01170 (0.00876)	- -	-0.02238* (0.01184)
Inf_{t-1}	0.00015*** (0.00005)	- -	0.00016*** (0.00006)	- -
GDP_{t-1}	-0.03959*** (0.00801)	-0.02395*** (0.00740)	-0.02937*** (0.01051)	-0.02180** (0.00898)
$Ln(M2/res)_{t-1}$	0.22059*** (0.05279)	0.31538*** (0.04846)	0.26098*** (0.06462)	0.30073*** (0.05666)
$ExRate_{t-1}$	-0.00003 (0.00003)	-0.00014*** (0.00005)	-0.00002 (0.00003)	-0.00011** (0.00005)
$Kaopen_{t-1}$	-0.16743*** (0.04054)	-0.21917*** (0.03749)	-0.15528*** (0.05377)	-0.18358*** (0.04487)
$Rate Dum_{t-1}$	0.01209 (0.01295)	0.08852*** (0.01026)	0.01846 (0.01571)	0.09044*** (0.01196)
<i>Log Likelihood</i>	-1591.423		<i>Log Likelihood</i>	-1102.591
<i>Observations</i>	4232		<i>Observations</i>	2728
<i>Countries</i>	126		<i>Countries</i>	82
<i>BC episodes</i>	85		<i>BC episodes</i>	56
<i>CC episodes</i>	194		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.61099*** (0.14261)		$\sigma_{\alpha_i^{bc}}$	0.57196*** (0.14961)
$\sigma_{\alpha_i^{cc}}$	0.26999*** (0.06654)		$\sigma_{\alpha_i^{cc}}$	0.22297*** (0.07063)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.43626*** (0.11977)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.33608** (0.13691)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.26255*** (0.08125)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24272*** (0.09449)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; Gap = Two-sided credit-to-GDP gap; $Trend$ = Decomposed trend extracted from the credit-to-GDP ratio; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.4: Alternative definition of currency crises

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.08898 (0.14847)	-	0.07720 (0.17377)
CC_{t-1}	0.18177 (0.12139)	-	0.12982 (0.14622)	-
Gap_{t-1}	0.02276*** (0.00331)	0.01464*** (0.00328)	0.02031*** (0.00486)	0.01223*** (0.00438)
FDI_{t-1}	-	-0.01793** (0.00890)	-	-0.02397** (0.01151)
Inf_{t-1}	0.00016*** (0.00006)	-	0.00016*** (0.00006)	-
GDP_{t-1}	-0.03933*** (0.00794)	-0.02061*** (0.00722)	-0.02876*** (0.01048)	-0.01569* (0.00862)
$Ln(M2/res)_{t-1}$	0.22668*** (0.05194)	0.28915*** (0.04863)	0.27413*** (0.06744)	0.31714*** (0.0559)
$ExRate_{t-1}$	-0.00004 (0.00004)	-0.00013*** (0.00005)	-0.00002 (0.00003)	-0.00011** (0.00005)
$Kaopen_{t-1}$	-0.15240*** (0.03771)	-0.26744*** (0.03387)	-0.17257*** (0.05418)	-0.19127*** (0.04285)
$Rate Dum_{t-1}$	0.01599 (0.01297)	0.07785*** (0.01013)	0.01829 (0.01584)	0.08777*** (0.01179)
<i>Log Likelihood</i>	-1701.828		<i>Log Likelihood</i>	-1153.439
<i>Observations</i>	4232		<i>Observations</i>	2728
<i>Countries</i>	126		<i>Countries</i>	82
<i>BC episodes</i>	85		<i>BC episodes</i>	56
<i>CC episodes</i>	221		<i>CC episodes</i>	162
$\sigma_{\alpha_i^{bc}}$	0.60740*** (0.14598)		$\sigma_{\alpha_i^{bc}}$	0.59444*** (0.16771)
$\sigma_{\alpha_i^{cc}}$	0.28407*** (0.07388)		$\sigma_{\alpha_i^{cc}}$	0.28743*** (0.08016)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.35703*** (0.12771)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.36916*** (0.12223)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24394*** (0.07781)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.26628*** (0.09100)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; Gap = Two-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.5: Excluding less financially developed countries

Variable:	<i>Trend > 20%</i>		<i>Trend > 10%</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.09198 (0.20818)	-	0.08009 (0.17067)
CC_{t-1}	0.26735 (0.17454)	-	0.25516* (0.14029)	-
$GapOS_{t-1}$	0.00932*** (0.00256)	0.00623** (0.00279)	0.00682*** (0.00245)	0.00488* (0.00255)
FDI_{t-1}	-	-0.03564** (0.01501)	-	-0.02079* (0.01088)
Inf_{t-1}	0.00021*** (0.00006)	-	0.00018*** (0.00006)	-
GDP_{t-1}	-0.04695*** (0.00821)	-0.02717*** (0.00803)	-0.05206*** (0.00967)	-0.02302** (0.00913)
$Ln(M2/res)_{t-1}$	0.21409*** (0.08739)	0.32901*** (0.06988)	0.28358*** (0.06059)	0.34996*** (0.05958)
$ExRate_{t-1}$	-0.00006 (0.00004)	-0.00013 (0.00008)	-0.00005 (0.00004)	-0.00009* (0.00005)
$Kaopen_{t-1}$	-0.17757*** (0.05353)	-0.37701*** (0.05219)	-0.11440*** (0.04146)	-0.33018*** (0.04315)
$Rate Dum_{t-1}$	0.02821 (0.01838)	0.07207*** (0.01531)	0.00326 (0.01387)	0.08278*** (0.01244)
<i>Log Likelihood</i>	-905.040		<i>Log Likelihood</i>	-1335.344
<i>Observations</i>	2489		<i>Observations</i>	3406
<i>Countries</i>	83		<i>Countries</i>	114
<i>BC episodes</i>	54		<i>BC episodes</i>	68
<i>CC episodes</i>	95		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.78341*** (0.22579)		$\sigma_{\alpha_i^{bc}}$	0.65526*** (0.20300)
$\sigma_{\alpha_i^{cc}}$	0.42665*** (0.10391)		$\sigma_{\alpha_i^{cc}}$	0.41689*** (0.12502)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.49351*** (0.12775)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.38676** (0.17918)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.34255*** (0.10907)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.28087*** (0.08933)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; $GapOS$ = One-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.6: Excluding less financially developed countries (trend included)

Variable:	<i>Trend > 20%</i>		<i>Trend > 10%</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	- -	0.10046 (0.20703)	- -	0.08954 (0.16954)
CC_{t-1}	0.27126 (0.17346)	- -	0.25528* (0.13805)	- -
$GapOS_{t-1}$	0.00921*** (0.00247)	0.00622** (0.00277)	0.00679*** (0.00237)	0.00497* (0.00274)
$TrendOS_{t-1}$	0.00099 (0.00134)	-0.00217 (0.00153)	0.00145 (0.00131)	-0.00349** (0.00170)
FDI_{t-1}	- -	-0.03402** (0.01479)	- -	-0.02090* (0.01088)
Inf_{t-1}	0.00021*** (0.00006)	- -	0.00018*** (0.00006)	- -
GDP_{t-1}	-0.06469*** (0.01223)	-0.03986*** (0.01189)	-0.05061*** (0.00959)	-0.02444*** (0.00913)
$Ln(M2/res)_{t-1}$	0.21782*** (0.07466)	0.37509*** (0.07583)	0.28341*** (0.05847)	0.36548*** (0.05850)
$ExRate_{t-1}$	-0.00004 (0.00004)	-0.00011 (0.00008)	-0.00005 (0.00004)	-0.00009* (0.00005)
$Kaopen_{t-1}$	-0.16543*** (0.04953)	-0.34751*** (0.05098)	-0.12126*** (0.03996)	-0.30692*** (0.04350)
$Rate Dum_{t-1}$	0.02875 (0.01718)	0.07839*** (0.01554)	0.00012 (0.01386)	0.08874*** (0.01218)
<i>Log Likelihood</i>	-900.961		<i>Log Likelihood</i>	-1331.895
<i>Observations</i>	2489		<i>Observations</i>	3406
<i>Countries</i>	83		<i>Countries</i>	114
<i>BC episodes</i>	54		<i>BC episodes</i>	68
<i>CC episodes</i>	95		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.74129*** (0.21376)		$\sigma_{\alpha_i^{bc}}$	0.58171*** (0.14253)
$\sigma_{\alpha_i^{cc}}$	0.42400*** (0.10427)		$\sigma_{\alpha_i^{cc}}$	0.41868*** (0.12691)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.53552*** (0.12143)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.48094*** (0.11651)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.33519*** (0.10852)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.27149*** (0.08832)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; $GapOS$ = One-sided credit-to-GDP gap; $TrendOS$ = Decomposed trend extracted from the credit-to-GDP ratio; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.7: Excluding less financially developed countries

Variable:	<i>Trend > 30%</i>		<i>Trend > 25%</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	- -	-0.20284 (0.23644)	- -	-0.06669 (0.22768)
CC_{t-1}	0.24728 (0.19850)	- -	0.31445 (0.19669)	- -
$GapOS_{t-1}$	0.00816*** (0.00260)	0.00779*** (0.00287)	0.00846*** (0.00253)	0.00677** (0.00275)
FDI_{t-1}	- -	-0.03752** (0.01666)	- -	-0.03288** (0.01410)
Inf_{t-1}	0.00017** (0.00008)	- -	0.00018** (0.00007)	- -
GDP_{t-1}	-0.07731*** (0.01428)	-0.03716** (0.01456)	-0.07206*** (0.01339)	-0.03423** (0.01329)
$Ln(M2/res)_{t-1}$	0.21266** (0.09071)	0.28338*** (0.08029)	0.25975*** (0.08093)	0.37290*** (0.09714)
$ExRate_{t-1}$	-0.00011** (0.00005)	-0.00013 (0.00009)	-0.00006 (0.00005)	-0.00015 (0.00011)
$Kaopen_{t-1}$	-0.15205*** (0.05475)	-0.45122*** (0.06438)	-0.13697*** (0.05189)	-0.35579*** (0.05625)
$Rate Dum_{t-1}$	-0.01646 (0.02056)	0.07253*** (0.01852)	-0.03015 (0.01916)	0.07126*** (0.01727)
<i>Log Likelihood</i>	-683.964		<i>Log Likelihood</i>	-801.993
<i>Observations</i>	1926		<i>Observations</i>	2272
<i>Countries</i>	64		<i>Countries</i>	75
<i>BC episodes</i>	38		<i>BC episodes</i>	44
<i>CC episodes</i>	70		<i>CC episodes</i>	82
$\sigma_{\alpha_i^{bc}}$	0.95335*** (0.28512)		$\sigma_{\alpha_i^{bc}}$	0.90977*** (0.30744)
$\sigma_{\alpha_i^{cc}}$	0.50531*** (0.14370)		$\sigma_{\alpha_i^{cc}}$	0.52714*** (0.15910)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.50757*** (0.14821)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.41228** (0.17145)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.45025*** (0.12231)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.38749*** (0.11675)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; $GapOS$ = One-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.8: Individually assessing the impact of credit cycles and financial depth

	Gap			Trend		
	<i>BC</i>	<i>(Panel B)</i>	<i>CC</i>	<i>BC</i>	<i>(Panel B)</i>	<i>CC</i>
$Trend_{t-1}$	-		-	-0.00189		-0.01171***
	-		-	(0.00275)		(0.00255)
Gap_{t-1}	0.02181***		0.01449***	-		-
	(0.00214)		(0.00416)	-		-
<i>Intercept</i>	-2.01575***		-1.60895***	-1.88696***		-1.21206***
	(0.11436)		(0.07668)	(0.13813)		(0.10073)
$\sigma_{\alpha_i^{bc}}$		0.49762***			0.54081***	
		(0.11708)			(0.14249)	
$\sigma_{\alpha_i^{cc}}$		0.30162***			0.21062***	
		(0.06891)			(0.04895)	
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$		0.46649***			0.43243***	
		(0.08611)			(0.11747)	
$\rho_{u_{it}^{bc}u_{it}^{cc}}$		0.38823***			0.41389***	
		(0.06394)			(0.06149)	
<i>Log Likelihood</i>		-1261.83			-1266.98	
<i>Observations</i>		2728			2728	
<i>Countries</i>		82			82	
<i>BC episodes</i>		56			56	
<i>CC episodes</i>		150			150	

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Gap = Two-sided credit-to-GDP gap; *Trend* = Decomposed trend extracted from the credit-to-GDP ratio.

Table SM2.9: Individually assessing the impact of credit cycles and financial depth (alternative database (Bouvatier et al. (2022)))

	<i>Gap</i>			<i>Trend</i>		
	<i>BC</i>	(<i>Panel B</i>)	<i>CC</i>	<i>BC</i>	(<i>Panel B</i>)	<i>CC</i>
<i>Trend</i> _{<i>t</i>-1}	-		-	-0.00301		-0.01298***
	-		-	(0.00279)		(0.00284)
<i>Gap</i> _{<i>t</i>-1}	0.04157***		0.02252***	-		-
	(0.00642)		(0.00571)	-		-
<i>Intercept</i>	-1.87291***		-1.66127***	-1.73749***		-1.30608***
	(0.09793)		(0.06809)	(0.11868)		(0.09217)
$\sigma_{\alpha_i^{bc}}$		0.47891***			0.43049***	
		(0.12783)			(0.11664)	
$\sigma_{\alpha_i^{cc}}$		0.18427***			0.17167***	
		(0.05011)			(0.05008)	
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$		0.48429***			0.44944***	
		(0.13656)			(0.15478)	
$\rho_{u_{it}^{bc}u_{it}^{cc}}$		0.47658***			0.48816***	
		(0.05281)			(0.05741)	
<i>Log Likelihood</i>		-1192.405			-1207.412	
<i>Observations</i>		2895			2895	
<i>Countries</i>		76			76	
<i>BC episodes</i>		58			58	
<i>CC episodes</i>		124			124	

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Gap = Two-sided credit-to-GDP gap; *Trend* = Decomposed trend extracted from the credit-to-GDP ratio.

Table SM2.10: Controlling for an alternative error term structure

Variable:	<i>Full sample (Panel A)</i>		<i>Middle-income (Panel B)</i>	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.27879** (0.12590)	-	0.40961*** (0.14221)
CC_{t-1}	0.38102*** (0.12161)	-	0.18889 (0.15242)	-
Gap_{t-1}	0.02259*** (0.00332)	0.01401*** (0.00332)	0.02074*** (0.00492)	0.01150*** (0.00449)
FDI_{t-1}	-	-0.01569* (0.00926)	-	-0.02562** (0.01219)
Inf_{t-1}	0.00014** (0.00006)	-	0.00015** (0.00006)	-
GDP_{t-1}	-0.03844*** (0.00797)	-0.02118*** (0.00754)	-0.02732*** (0.01057)	-0.01684* (0.00888)
$Ln(M2/res)_{t-1}$	0.23528*** (0.05206)	0.29956*** (0.05179)	0.28074*** (0.06638)	0.32154*** (0.05964)
$ExRate_{t-1}$	-0.00003 (0.00003)	-0.00014** (0.00005)	-0.00002 (0.00003)	-0.00011** (0.00005)
$Kaopen_{t-1}$	-0.14677*** (0.03759)	-0.27911*** (0.03627)	-0.17051*** (0.05494)	-0.19606*** (0.04499)
$Rate Dum_{t-1}$	0.01109 (0.01299)	0.08462*** (0.01053)	0.01489 (0.01587)	0.09229*** (0.01217)
<i>Log Likelihood</i>	-1618.734		<i>Log Likelihood</i>	-1115.117
<i>Observations</i>	4232		<i>Observations</i>	2728
<i>Countries</i>	126		<i>Countries</i>	82
<i>BC episodes</i>	85		<i>BC episodes</i>	56
<i>CC episodes</i>	194		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.61859*** (0.14504)		$\sigma_{\alpha_i^{bc}}$	0.63419*** (0.18413)
$\sigma_{\alpha_i^{cc}}$	0.32381*** (0.08168)		$\sigma_{\alpha_i^{cc}}$	0.29316*** (0.08469)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.33002*** (0.12659)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.32841*** (0.12409)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: *GDP* = Year-on-year growth rate of real GDP; *Inf* = Inflation, GDP deflator; *M2/Res* = Broad money to reserves ratio; *ExRate* = Official exchange rate; *Gap* = Two-sided credit-to-GDP gap; *FDI* = Foreign Direct Investment inflows; *Kaopen* = Capital account openness index; *Rate Dum* = Exchange rate dummy.

Table SM2.11: Baseline Replication with $R \mapsto \infty$

Variable:	<i>Middle-income</i> ($R = 150$)		<i>Middle-income</i> ($R = 400$)	
	Banking Crises	Currency Crises	Banking Crises	Currency Crises
BC_{t-1}	-	0.13766 (0.17936)	-	0.14216 (0.17956)
CC_{t-1}	0.12367 (0.15211)	-	0.12598 (0.15216)	-
Gap_{t-1}	0.02062*** (0.00498)	0.01221*** (0.00454)	0.02069*** (0.00497)	0.01223*** (0.00454)
FDI_{t-1}	-	-0.02569** (0.01212)	-	-0.02603** (0.01214)
Inf_{t-1}	0.00016*** (0.00006)	-	0.00016*** (0.00006)	-
GDP_{t-1}	-0.02866*** (0.01058)	-0.01905** (0.00895)	-0.02926*** (0.01059)	-0.01948** (0.00896)
$Ln(M2/res)_{t-1}$	0.28459*** (0.06699)	0.32912*** (0.06013)	0.28210*** (0.06621)	0.32671*** (0.06054)
$ExRate_{t-1}$	-0.00002 (0.00004)	-0.00012** (0.00005)	-0.00002 (0.00004)	-0.00012** (0.00005)
$Kaopen_{t-1}$	-0.17776*** (0.05344)	-0.19658*** (0.04470)	-0.17809*** (0.05322)	-0.19982*** (0.04523)
$Rate Dum_{t-1}$	0.01841 (0.01593)	0.09424*** (0.01214)	0.01834 (0.01582)	0.09374*** (0.01229)
<i>Log Likelihood</i>	-1114.227		<i>Log Likelihood</i>	-1113.682
<i>Observations</i>	2728		<i>Observations</i>	2728
<i>Countries</i>	82		<i>Countries</i>	82
<i>BC episodes</i>	56		<i>BC episodes</i>	56
<i>CC episodes</i>	150		<i>CC episodes</i>	150
$\sigma_{\alpha_i^{bc}}$	0.66265*** (0.20570)		$\sigma_{\alpha_i^{bc}}$	0.65809*** (0.20901)
$\sigma_{\alpha_i^{cc}}$	0.31447*** (0.09403)		$\sigma_{\alpha_i^{cc}}$	0.30875*** (0.09269)
$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.36731** (0.14738)		$\rho_{\alpha_i^{bc}\alpha_i^{cc}}$	0.35936** (0.17474)
$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24385*** (0.09504)		$\rho_{u_{it}^{bc}u_{it}^{cc}}$	0.24457*** (0.09500)

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variables definitions: GDP = Year-on-year growth rate of real GDP; Inf = Inflation, GDP deflator; $M2/Res$ = Broad money to reserves ratio; $ExRate$ = Official exchange rate; Gap = Two-sided credit-to-GDP gap; FDI = Foreign Direct Investment inflows; $Kaopen$ = Capital account openness index; $Rate Dum$ = Exchange rate dummy.

Table SM2.12: Middle income countries

Albania	Algeria	Kazakhstan	Kenya
Angola	Argentina	Kyrgyzstan	Lao Rep.
Azerbaijan	Armenia	Lebanon	Lesotho
Bangladesh	Belarus	Libya	Macedonia
Belize	Bhutan	Malaysia	Maldives
Bolivia	Bosnia	Mauritania	Mauritius
Botswana	Brazil	Mexico	Moldova
Bulgaria	Cambodia	Mongolia	Morocco
Cameroon	Cabo Verde	Myanmar	Namibia
China	Colombia	New Guinea	Nicaragua
Comoros	Congo Rep.	Nigeria	Pakistan
Costa Rica	Dominica	Paraguay	Peru
Dominican Rep.	Ecuador	Philippines	Russia
Egypt	El Salvador	Sao Tome	South Africa
Fiji	Gabon	Sri Lanka	Sudan
Georgia	Ghana	Suriname	Swaziland
Grenada	Guatemala	Thailand	Tunisia
Guinea	Guyana	Turkey	Ukraine
Honduras	India	Venezuela	Vietnam
Indonesia	Iran	Zambia	Zimbabwe
Jamaica	Jordan		

Table SM2.13: **High and Low income countries**

High		Low	
Australia	Barbados	Burundi	Central African Rep.
Canada	Chile	Chad	Ethiopia
Croatia	Czech Rep.	Guinea	Guinea Bissau
Denmark	Hong Kong	Haiti	Liberia
Hungary	Iceland	Madagascar	Malawi
Israel	Japan	Mozambique	Nepal
Korea	Kuwait	Rwanda	Sierra Leone
New Zealand	Norway	Syrian Arab Rep.	Tajikistan
Panama	Poland	Tanzania	Uganda
Seychelles	Singapore	Yemen	
Sweden	Switzerland		
Trinidad Tobago	Uruguay		
United States			

Table SM2.14: Leading indicators and expected signs

Indicator	Critical-Shock Sign	Comments
Real GDP growth	Negative	Improvements in institutional quality associated with higher GDP reduce banking crisis risk. Davis & Karim (2008).
Domestic credit to GDP	Positive	Banking and currency crises have been linked to rapid growth in credit fueled by liberalization of the domestic financial system. Kaminsky (1999); Tornell & Westermann (2005).
Exchange rate	Negative	Exchange rate overvaluation and a fragile external sector are a feature of currency crises. This situation exacerbates the banking sector's distress through a loss of competitiveness which could lead to a recession, bankruptcies, and a decline in the quality of loans. Kaminsky (1999)
M2 to reserves ratio	Positive	A depletion of foreign reserves induced by a currency crisis may increase issues of short-term debt sustainability in the banking sector. Hutchison & Glick (2000); Qin & Luo (2014); Eichengreen & Arteta (2002).
Inflation	Positive	Empirically, banking crises are frequently associated with rising inflation. Demirgüç-Kunt & Detragiache (1998); Hutchison & Glick (2000); Davis & Karim (2008).
Foreign direct investment	Negative	Previous empirical studies showed that currency crashes tend to occur when foreign direct investment inflows dry up in emerging market economies. Frankel & Rose (1996).
Capital account openness	Negative	The absence of capital account restrictions mitigates the harmful effect of banking crises. Bonfiglioli & Mendicino (2004); Qin & Luo (2014). Freedom of international capital movements are associated with less vulnerability to currency crises. Glick et al. (2006).

Table SM2.15: Data description

Indicator (id)	Data source and definition	Frequency
Real GDP growth (NY.GDP.MKTP.KN.87.ZG)	World Bank national accounts data, and OECD National Accounts data files. Annual percentage growth rate of real GDP based on constant local currency.	Annual
M2 to reserves ratio (FM.LBL.MQMY.IR.ZS)	World Development Indicators (WDI), World Bank. WDI database archives. Money and quasi money to total reserves.	Annual
Domestic credit to private sector (GFDD.DI.14)	World Development Indicators (WDI), World Bank. Global Financial Development Financial resources provided to the private sector, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment.	Annual
Inflation, GDP Deflator (NY.GDP.DEFL.KD.ZG)	World Bank national accounts data, and OECD National Accounts data files. WDI database archives. Annual growth of the GDP deflator measuring the rate of price change in the economy as a whole.	Annual
Official Exchange Rate (PA.NUS.FCRF)	World Development Indicators (WDI). International Financial Statistics (IFS), International Monetary Fund (IMF). Exchange rate determined by national authorities calculated as an annual average based on monthly averages (local currency units relative to the U.S. dollar).	Annual
Foreign Direct Investment (BX.KLT.DINV.WD.GD.ZS)	World Development Indicators (WDI). International Financial Statistics (IFS), International Monetary Fund (IMF). Net inflows of investment, sum of equity capital and reinvestment of earnings as shown in the balance of payments.	Annual
KAOPEN	Index measuring degree of capital account openness. Chinn & Ito (2006).	Annual
Exchange Rate classification	<i>De Facto</i> Exchange rate arrangement classification. Fine classification codes from 1 to 15. Ilzetzki et al. (2019)	Annual

Table SM2.16: **Banking crises by country (full sample)**

Episodes	Country	First–Last	Episodes	Country	First–Last
1	Algeria	1990–1994	4	Argentina	1980–2003
2	Bolivia	1986–1994	1	Brazil	1990–1998
1	Bulgaria	1996–1997	1	Burundi	1994–1998
2	Cameroon	1987–1997	1	Cabo Verde	1993–1993
1	Central African Rep.	1995–1996	2	Chad	1983–1996
2	Chile	1976–1985	1	China	1998–1998
2	Columbia	1982–2000	1	Congo Rep.	1992–1994
2	Costa Rica	1987–1995	1	Croatia	1998–1999
1	Czech Rep.	1997–2000	1	Denmark	2008–2009
1	Dominican Rep.	2003–2004	1	Egypt	1980–1980
1	Ghana	1982–1983	1	Guinea	1993–1993
1	Guyana	1993–1993	1	Haiti	1994–1998
2	Hungary	1993–2012	1	Indonesia	1997–2001
1	India	1993–1993	1	Iceland	2008–2012
1	Israel	1983–1986	1	Jordan	1989–1991
1	Japan	1997–2001	1	Kazakhstan	2008–2008
2	Kenya	1985–1994	1	Korea	1997–1998
1	Sri Lanka	1989–1991	1	Morocco	1980–1984
1	Moldova	2014–2017	1	Madagascar	1988–1988
2	Mexico	1981–1996	1	Mongolia	2008–2009
1	Malaysia	1997–1999	2	Nigeria	1991–2012
2	Nicaragua	1990–2001	1	Norway	1991–1993
1	Nepal	1988–1988	1	Panama	1988–1989
1	Peru	1983–1983	2	Philippines	1983–2001
1	Paraguay	1995–1995	1	Russia	2008–2009
1	Sierra Leone	1990–1994	1	Sri Lanka	1989–1991
1	Sweden	2008–2009	1	Switzerland	2008–2009
1	Swaziland	1995–1999	2	Thailand	1983–2000
1	Tunisia	1991–1991	2	Turkey	1982–2001
1	Uganda	1994–1994	3	Ukraine	1998–2017
2	Uruguay	1981–2005	2	United States	1988–2011
1	Viet Nam	1997–1997	1	Zambia	1995–1998

Two episodes are separated with at least one tranquil period; First denotes the starting date of the first episode; Last denotes the ending date of the last episode.

Table SM2.17: **Currency crises by country (full sample)**

Episodes	Country	First–Last	Episodes	Country	First–Last
1	Albania	1997–1997	2	Algeria	1988–1991
2	Angola	1999–2016	5	Argentina	1975–2016
1	Azerbaijan	2015–2016	4	Belarus	1997–2015
2	Bolivia	1973–1985	1	Botswana	1984–1985
7	Brazil	1976–2015	1	Bulgaria	1996–1997
1	Cameroon	1994–1994	1	Central African Rep.	1994–1994
1	Chad	1994–1994	1	Chile	1982–1985
2	Colombia	1985–2015	1	Congo Rep.	1994–1994
1	Comoros	1994–1994	2	Costa Rica	1981–1991
3	Dominican Rep	1985–2003	4	Ecuador	1982–1999
4	Egypt	1979–2017	2	El Salvador	1986–1990
1	Equatorial Guinea	1994–1994	1	Ethiopia	1993–1993
1	Fiji	1998–1998	1	Gabon	1994–1994
2	Gambia	1984–2003	1	Georgia	1999–1999
7	Ghana	1978–2014	2	Guatemala	1986–1990
1	Guinea	2005–2005	1	Guyana	1987–1991
2	Haiti	1992–2003	1	Honduras	1990–1990
4	Iceland	1978–2008	2	Indonesia	1983–1998
3	Israel	1975–1985	3	Jamaica	1978–1994
1	Jordan	1989–1989	2	Kazakhstan	1999–2016
1	Kenya	1993–1993	1	Korea	1998–1998
1	Kyrgyzstan	1998–1999	1	Lao Rep.	1997–1998
2	Lesotho	1984–2015	1	Libya	2002–2002
4	Madagascar	1984–2004	4	Malawi	1994–2016
1	Malaysia	1998–1998	4	Mexico	1977–1995
2	Moldova	1999–2015	1	Mongolia	1997–1997
1	Morocco	1981–1981	2	Mozambique	2001–2016
2	Myanmar	2001–2012	1	Namibia	2015–2015
2	Nepal	1984–1992	1	New Zealand	1984–1984
3	Nicaragua	1979–1990	6	Nigeria	1983–2016
1	Pakistan	1972–1972	2	Papua New Guinea	1995–1998
4	Paraguay	1984–2002	3	Peru	1990–1990
2	Philippines	1983–1998	1	Russia	2014–2015
1	Rwanda	1991–1991	1	Seychelles	2008–2008
3	Sierra Leon	1983–1998	2	South Africa	1984–2015
1	Sri Lanka	1978–1978	6	Sudan	1981–2012
5	Suriname	1990–2016	2	Swaziland	1984–2015
1	Syrian Arab Rep.	1988–1988	1	Tajikistan	2015–2015
1	Tanzania	1990–1992	1	Thailand	1998–1998
1	Trinidad and Tobago	1986–1986	7	Turkey	1978–2001
1	Uganda	1986–1986	3	Ukraine	1998–2015
5	Uruguay	1972–2002	6	Venezuela	1984–2013
4	Zambia	1989–2015	4	Zimbabwe	1991–2006

Two episodes are separated with at least one tranquil period; First denotes the starting date of the first episode; Last denotes the ending date of the last episode.

Chapter 3

Leading indicators of sovereign defaults in middle- and low-income countries: the role of foreign exchange reserves ratios in times of pandemic

Introduction

In response to the currency mismatches that led to large capital outflows in the 1990s, Emerging Markets Economies (EMEs) turned to local currency bond market in order to overcome the "original sin" (Eichengreen & Hausmann (1999)). Nonetheless, this process exposed EMEs bond markets which relied on foreign portfolio investors who evaluate risk exposure in terms of dollars (Hong Kong Monetary Authority (2020)). Consequently, EMEs became more vulnerable to global financial shocks that accelerate capital flights during financial turmoil (Hong Kong Monetary Authority (2019)). As a result from the Covid-19 pandemic, EMEs that have relied on foreign investors to hold their domestic currency bonds suffered larger increases in their local currency bond spreads. According to Hofmann et al. (2021), multiple EMEs have undertaken inflation-targeting policy frameworks that employ macro-prudential instruments such as foreign exchange reserves accumulation over the past decade. This strategy aims to mitigate the risks associated with large fluctuations in capital flows and exchange rate depreciation. Nonetheless, Arslan & Cantú (2019) argue that the benefits of holding large amounts of reserves yield costs at both domestic and global extent. For example, Rodrik (2006) demonstrates that the premium paid by countries to use reserves as insurance mechanisms may generate income losses that are roughly estimated to equal 1% of the GDP. However, Feldstein (1999) states that this cost is outbalanced by the benefit that reserves provide as an insurance instrument against the occurrence of financial crises. Indeed, Rodrik & Velasco (1999) previously emphasized that countries which abide by the Greenspan-Guidotti rule (i.e, countries holding reserves that equal at least 100% of their short-term debt), reduce the probability of experiencing sharp capital outflows by 10 percentage points on average.

In the context of a global pandemic, Hofmann et al. (2021) highlight that sovereign spreads tend to increase as a result of the domestic currency depreciation against the US dollar as the authors state that this process is accelerating since 2013 reaching it's peak in early 2020. This phenomenon is mirrored in the recent evolution of credit ratings: whilst 15% of the advanced economies have experienced rating downgrades since the start of 2020, emerging and developing countries recorded demotions that reached approximately 40 percent (Reinhart (2022)). In addition, many low- and middle-income countries have recorded significant capital outflows and sharply weakening currencies (in some cases, currency crashes such as in Turkey) during 2020. Furthermore, even before Covid-19, some upper-middle-income countries (Argentina, Nigeria, and Turkey) as well as several low-income countries in debt distress faced difficulties to

curb rising inflation. Thus, the specter of looming sovereign defaults resurfaces since a growing number of low-income countries, which are eligible for the Debt Service Suspension Initiative (DSSI), are in debt distress or at high risk (World Bank (2020)) while other emerging economies have recently restructured (Argentina, Belize, Ecuador) or remain in default (Lebanon, Suriname, Venezuela).¹

This paper contributes to the existing literature on debt crises by demonstrating that consensual foreign exchange reserves metrics perform well at predicting sovereign defaults in middle- and low-income countries. To the best of my knowledge, there currently exist no paper in the literature that implements a horse-race among these reserves metrics for the forecasting of debt crises. In addition, the reserves to total external debt ratio, which produces the best overall performance among the horse races, also displays a good predictive power in an out-of-sample perspective and is able to detect 4 out of the 5 current sovereign defaults that occurred in the wake of the Covid-19 pandemic.

I structure this paper around two major purposes: I first attempt to capture what characterizes sovereign debt crises through a set of macroeconomic fundamentals. Thereafter, I individually assess the predictive power of Early Warning Indicators among those that have proven to be robust in the baseline specification. The estimation results show that the reserves-to-GDP ratio, the average interest on new external debt and the growth of real GDP are robust indicators of debt crises regardless of the specification. In addition, the binary logit model constantly performs well from a policymaker's perspective. Further individual assessments of foreign exchange reserves ratios demonstrate that the reserves-to-GDP ratio has a strong predictive power in the lower-middle-income group of countries while the reserves to total external debt seems more suitable for the upper-middle group. The previous outcome is robust at more distant forecast horizons. Finally, the reserves to total external debt ratio exhibits a good performance in the forecasting of debt crises in an out-of-sample perspective. The main policy implication of those results is that foreign exchange reserves have a strong predictive power in the context of sovereign defaults in middle- and low-income countries suggesting that reserves buffers accumulation should be employed as a macro-prudential policy instrument to prevent debt crises. The remainder of the paper is organized as follows. Section 3.1 overviews the existing literature on sovereign default predictions and explores the relevant leading indicators of those episodes. Section 3.2 details the process of sample construction while describing the

¹Out of the 73 low-income countries in the DSSI, 34 are classified as in external debt distress or at high risk as of December 2021.

model employed for the main estimation. Section 3.3 presents the estimation results of different econometric models along with their leading indicators, discusses their overall performance, and displays the results of the horse-race among reserves ratios. Finally, section 3.4 explores the individual performances of consensual reserves metrics focusing on their predictive power at more distant forecast horizons and in an out-of-sample context.

3.1 Literature review

The use of binary logit and probit models to estimate the probability of an imminent crisis is a common feature in the existing literature of Early Warning Systems. Frankel & Rose (1996) employ probit regression to model the probability of facing a currency crisis on a large sample of 107 developing and emerging countries. The authors conclude that a low ratio of foreign direct investment inflows to debt is regularly associated to a high probability of currency crash in emerging markets. Thereafter, Manasse et al. (2003) and Fuertes & Kalotychou (2006) similarly proposed pooled logit models to examine the likelihood of sovereign defaults in emerging markets as the authors emphasized that logit models tend to perform better compared to probit approach. Indeed, Manasse et al. (2003) argue that, in the case of unevenly distributed dependent variable, logit regression typically outperforms the other specifications and are subsequently more suitable for debt crises events (the episodes of sovereign default are sparse compared to the non-crisis observations).

An important aspect of the binary dependent variable Early Warning System, is the underlying estimation issues. Indeed, assuming the value of one for the full duration of crises episodes and zero otherwise, may lead to various estimation biases.

To begin with, the leading indicators tend to act differently depending on the period: they might be affected by the crisis itself as well as the policies undertaken to mitigate the harmful effect of this crisis. Furthermore, previous research on the performance of Early Warning Systems exhibited that the choice of binary dependent variables for the modeling of crisis episodes might lead to issues due to the post-crisis bias. Precisely, the studies suggest that macroeconomic fundamentals tend to behave differently in "tranquil" periods after the crisis occurrence compared to other non-crisis observations before the episode occurred (Bussiere & Fratzscher 2006). With the purpose of preventing this drawback, multiple authors advocated the solution of dropping the post-crisis entry observation from their sample (see for example

Savona & Vezzoli (2015)) which may imply a hypothetical loss of valuable information regarding debt crises (although sparse, sovereign default episodes are nonetheless lengthy as shown in Tables 3.1 and SM3.9). Alternatively, Bussiere & Fratzscher (2006) suggested the use of a multinomial regression that allows for three states of the economy: tranquil, crisis entry and post-crisis. This estimation method offers the benefit of keeping all the observation while distinguishing between the crisis onset and the post-crisis entry periods.

Recent studies on the machine learning ability to detect financial crises are also developing in the empirical literature. Nevertheless, Svirydzienka (2021) state that modern discussions in the literature exhibit that machine learning might be biased and can even reinforce existing biases due to the Bias–Variance Trade-Off. Moreover, Beutel et al. (2019) show that although machine learning techniques frequently reach a good in-sample precision for banking crises, they are outperformed by more standard approaches in out-of-sample assessments. An additional limitation emerges from the fact that machine learning frameworks are often data-intensive. Therefore, gathering hundreds of thousands observations related to financial crises can be highly challenging. These limitations are still an open debate.²

3.1.1 Leading indicators of sovereign defaults

Contrasted results exist in the empirical literature regarding the relevant indicators of sovereign defaults (i.e. the predictive power, the statistical significance as well as the signs). Chakrabarti & Zeaiter (2014) conduct a thorough study spanning 190 countries over the 1970–2010 period. Their Extreme Bound Analysis reveals that growth, leverage on exports earnings, debt service ratio, reserves, inflation, exchange rate and trade deficit are robust indicators of sovereign debt crises regardless of the specification considered. The authors emphasize however, that openness, central bank liabilities, interest payments, cost of borrowing, imports, exports, per capita GNP are very sensitive to minor alterations in the model calibration. Former articles also demonstrated that currency crises might be a relevant indicator of upcoming sovereign defaults. Indeed, Reinhart (2002) studies a sample of 60 countries covering the 1979-1999 span and concludes that 84% of debt crises are preceded by a currency crash. Thus, variables that are well-suited for predicting currency crises might be relevant in the detection of an approaching sovereign default.

²Manasse et al. (2003) already demonstrated that decision tree methods, which can be considered as a type of machine learning, yield good results for debt crises prediction but also send high rates of false alarms.

The Early Warning indicators that provide the best performances according the existing literature regarding debt crises are displayed in Table SM3.8. I hence decide to divide them into 4 main categories.

The debt exposure of countries as well as sovereign defaults problems are captured in the first group where a higher stock of external debt is expected to increase the likelihood of default. With the purpose of measuring the burden of servicing external debt, the average interest on new external commitments as well as the sum of principal repayments are also considered.

The second group contains macroeconomic variables that are typically employed in the literature of EWS on sovereign defaults. Empirically, low levels of real GDP growth and reduced national saving tend to increase the probability of a debt crisis. Furthermore, a decline in the foreign exchange reserves-to-GDP ratio suggests a decline in the foreign currency support of the short-term domestic currency commitment. This situation generates difficulties to stabilize the domestic currency as a lower ratio may indicate a decline in foreign exchange reserves and reduced capacity for a country to meet its external debt. In addition, high levels of inflation causes external imbalances through a reduction of competitiveness. The overvaluation of the exchange rate is included as well in order to assess the impact of an imminent currency crash on the likelihood of debt crises since a large share of external debts are foreign currency-denominated in emerging market economies.

The situation of a country's external sector is assessed in the third group, where a stronger current account balance along with higher net inflows of Foreign Direct Investment and growth of export earnings are expected to reduce the likelihood of sovereign default.

Finally, the last set of variables aims to capture financial development features regarding the banking sector. Therefore, the domestic credit to private sector in percentage of GDP is included as a higher ratio may indicate that banks are more vulnerable to a GDP shock in terms of higher risk of loan losses.

3.2 The data

Regarding sovereign defaults dating, I rely on the database proposed by Laeven & Valencia (2020) which is a compilation of information collected from various sources: Beim & Calomiris (2001), World Bank (2002), Sturzenegger & Zettelmeyer (2007) and Cruces & Trebesch (2013). The gathered data include the year of sovereign default as well as the restructuring date if the

latter took place. Under this definition, the authors manage to capture 79 episodes during the 1970-2017 span.

3.2.1 Sample construction

My sample consists of 58 middle-income and 10 low-income countries covering the 1973-2017 span. The starting point is the Laeven & Valencia (2020) updated database that covers 112 countries and provides annual data related to banking, currency and sovereign debt crises.³ Due to data unavailability regarding some of the main explanatory variables, 44 countries are dropped in the process of sample construction. Given the fact that some observations are missing for a few economies at specific periods, the starting date for each country varies within the sample resulting in an unbalanced panel for a maximum of 2213 observations for the full sample (Global) and 1898 for middle-income countries (Middle) which corresponds to a 33 years span per country on average.

Moreover, previous studies on sovereign default showed that these episodes tend to be persistent and last long (Manasse et al. 2003) thus, relying on annual frequency data is consensual in the literature. The list of countries considered along with details on each crisis starting and ending dates, are displayed in Tables SM3.9 and SM3.10.

3.2.2 Crises duration

Table 3.1 displays the descriptive statistics of the crises episodes that have been identified following the previous definitions. Whilst debt crises seem to last around 7 years and a half on average in the full sample, the defaults are shorter with a mean approaching 7 years in the middle-income group. Scrutiny of the medians reveals that sovereign defaults last indeed longer in low-income countries with a median episode lasting 7 years while the middle-income group only exhibits a median of 5 years. The longest crisis episodes are recorded in Sierra Leone and Peru lasting 19 years for both panels alike. The last line indicates the proportion of crises observations relatively to tranquil periods.

³The full database covers 165 countries but attention is turned to middle- and low-income economies.

Table 3.1: Crises episodes duration

	<i>Global (1)</i>	<i>Middle (3)</i>
Episodes occurrences	41	36
Mean	7.3	6.8
Median	7	5
Standard deviation	5	4.66
Maximum	19	19
% of crisis periods	13.1	12.8

Global (1) contains 68 countries (both middle- and low-income) whilst Middle (3) covers only middle-income economies (58).

3.2.3 The role of foreign exchange reserves

Over the last 40 years, numerous EMEs have suffered multiple financial crises. The common feature of those events was the sudden stop in capital flows, which resulted in large and permanent output losses (Nakamura et al. (2013)). According to Arslan & Cantú (2019), EMEs addressed this issue by accumulating foreign exchange reserves as a form of self-insurance (the so-called precautionary motive). In fact, empirical evidence since the global financial crisis and the taper tantrum episode demonstrate that reserves boost EMEs resilience, as countries which held a higher amount of reserves suffered smaller currency depreciation compared to the others. Since there is no consensual framework in the literature about reserves adequacy, central banks typically determine their needs using a proxy with respect to the country's reserves position for a specific risk. Thus, the conventional assessments of reserves requirements are import cover, ratio of reserves to short-term debt and ratio of broad money to reserves. Jeanne & Rancière (2006) propose a cost-benefit model with the purpose of measuring the optimal level of reserves. The authors employ a sample of 34 middle-income countries spanning from 1975 to 2003 and determine that the optimal ratio is around 10.1% of the GDP, which is close to the empirical observations for the same time interval (9.4%) and corresponds to a full coverage of the short-term debt according to the Greenspan-Guidotti rule.⁴ However, the study emphasizes that this ratio tends to increase in recent years. The same statement is also true for my sample as Table 3.2 depicts a mean of 13.4% for the reserves-to-GDP ratio over the 1973-2017 period.⁵

⁴Greenspan (1999) suggests that reserves should exceed official and officially-guaranteed short-term debt.

⁵The mean reached 9% before the 2000s and stands at 18% after.

3.2.4 The model

The construction of my EWS relies on the so-called “windows crisis approach”. Thus, the binary dependent variable SDC_{it} is set to one for the full duration of the crisis (as detailed in Table SM3.9) and zero during tranquil periods. Nevertheless, I also consider a second specification in order to avoid the post-crisis entry bias (Bussiere & Fratzscher 2006). The logit model employed to estimate the probability of default can be written as follows :

$$Pr(SDC_{it} = 1) = F(X_{it-1}\beta) = \frac{e^{X_{it-1}\beta}}{1 + e^{X_{it-1}\beta}} \quad (3.1)$$

Where F is the cumulative logistic distribution, X_{it-1} the vector of 1 period lagged independent variables, SDC_{it} designates the binary crisis variable and β the vector of coefficients. In Table 3.3, the marginal effects are reported instead of the raw beta coefficients to facilitate the interpretations.⁶ Following Manasse et al. (2003), I allow for country-specific variances using the Huber-White robust variance estimator. Four models are considered in total: the global one that incorporates the full sample, a second one that encompasses middle-income countries as well as the two previously mentioned models in which I control for the post-crisis bias (i.e. only the starting year of the crisis is kept). All the variables are purposely lagged by one year in order to avoid problems of simultaneity.

3.3 Results

This section is organized as follows: I first present the baseline logit model results to which I append a robustness check using a multinomial specification, random effect logit models along with a sample reshape by income group. Afterwards, I evaluate each specification forecast performances and implement a horse-race between the explanatory variables. Finally, I consider a horse-race among the consensual foreign exchange reserves ratios that are typically employed by central banks to determine foreign exchange reserves adequacy.

⁶The coefficients reported in Table 3.3 are the average marginal effects of all covariates.

Table 3.2: Descriptive statistics

	<i>Res/GDP</i>	<i>DebtInt</i>	ΔGDP	<i>FDI</i>	<i>DebtSer</i>	<i>DebtSto</i>
Observations	2213	2213	2213	2213	2213	2213
Mean	13.437	3.439	3.967	2.765	5.543	57.725
Median	9.857	2.817	4.224	1.571	4.389	45.570
Standard deviation	14.785	2.527	4.389	4.477	4.881	46.949
Kurtosis	17.704	2.389	7.422	40.869	13.751	20.712
Minimum	0.008	0.000	-20.599	-37.155	0.000	2.555
5% percentile	1.024	0.000	-3.586	-0.052	0.5803	13.868
95% percentile	38.427	7.859	10.223	9.424	14.619	139.975
Maximum	124.011	12.499	34.466	55.076	57.432	542.660

	<i>Infla</i>	<i>Cred</i>	<i>REER</i>	<i>NatSav</i>	ΔExp	<i>CaBal</i>
Observations	2213	2213	2213	2213	2213	2213
Mean	32.891	30.049	119.921	20.401	1.967	-3.229
Median	7.847	23.202	99.772	19.297	0.4341	-3.088
Standard deviation	325.879	24.116	96.086	10.205	19.001	7.647
Kurtosis	989.648	7.571	31.132	4.749	62.762	9.563
Minimum	-29.691	1.166	28.355	-16.359	-72.933	-65.029
5% percentile	-0.2105	5.386	59.194	4.966	-21.930	-14.981
95% percentile	60.272	78.037	208.652	39.494	29.357	8.969
Maximum	12338	166.504	868.579	85.097	353.801	33.679

Variables definitions: *Res/GDP* = International reserves over GDP ratio; *DebtInt* = Average interest on new external debt commitments; ΔGDP = Year-on-year growth rate of real GDP; *FDI* = FDI inflows; *DebtSer* = Total debt service in % of GNI; *DebtSto* = External debt stocks in % of GNI; *Infla* = Inflation, GDP deflator; *Cred* = Domestic credit to GDP ratio; *REER* = Real Effective Exchange Rate Index; *NatSav* = Gross National Savings; ΔExp = Year-on-year growth rate of Exports to GDP ratio; *CaBal* = Current Account Balance to GDP.

3.3.1 Preliminary results

The results of the baseline pooled logit estimation are presented in Table 3.3. As expected, the debt exposure symptoms such as the sum of repayments, the interest on new external commitments as well as debt stocks are strongly positive and significant in both specifications (1) and (3) which is in line with previous findings in the empirical literature (Detragiache & Spilimbergo (2001); Bird & Rowlands (2001) and Fuertes & Kalotychou (2007)).

In addition, I notice that the interest on new external commitments remains significant in all four specification despite the drop of post-crisis entry observations. The impact of macroeconomic variables seems more contrasted: the growth of real GDP is constantly negative and strongly significant regardless of the specification while gross savings are not robust in models (2) and (4). Moreover, real exchange rate overvaluation increases the likelihood of debt crises only in model (1) while inflation seems to rise the probability of sovereign default in specifications (1) and (3). Note that both indicators are not robust to the dropping of post-crisis entry observations whilst the credit-to-GDP ratio fails to describe debt crises in all four models considered.

With respect to the external sector, declining levels of foreign direct investment inflows appear to increase the probability of experiencing a sovereign default while the current account balance and the growth rate of exports are not significant in any specification. Interestingly, the logarithm of international reserves-to-GDP remains strongly negative and significant in every model on the top of having the highest impact in terms of marginal effect magnitude among this group of variables suggesting that depleting foreign exchange reserves significantly rise the likelihood of sovereign defaults. Finally, neither capital account openness nor past banking crises are able to describe the likelihood of defaults whereas past currency crashes are strongly significant and positive (in models (1) and (3)) as suggested previously by Reinhart (2002) for emerging market economies. Note that bold values are associated to indicators which remain significant regardless of the specification (at the 1% or 5% levels).

Table 3.3: Baseline estimation results: pooled logit model

	Global (1)	Global (2)	Middle (3)	Middle (4)
<i>DebtSer</i> _{<i>t</i>-1}	0.0060*** (0.0022)	0.0014** (0.0006)	0.0037* (0.0021)	0.0011** (0.0005)
<i>DebtInt</i> _{<i>t</i>-1}	0.0295*** (0.0043)	0.0068*** (0.0015)	0.0322*** (0.0049)	0.0072*** (0.0017)
<i>DebtSto</i> _{<i>t</i>-1}	0.0007** (0.0003)	-0.0001 (0.0001)	0.0008** (0.0003)	-0.0001 (0.0001)
ΔGDP _{<i>t</i>-1}	-0.0038*** (0.0012)	-0.0029*** (0.0007)	-0.0049*** (0.0014)	-0.0034*** (0.0009)
<i>NatSav</i> _{<i>t</i>-1}	-0.0041*** (0.0013)	-0.0004 (0.0003)	-0.0035*** (0.0013)	-0.0002 (0.0004)
<i>Infla</i> _{<i>t</i>-1}	0.0001** (0.0000)	-0.0001 (0.0001)	0.0002** (0.0000)	-0.0002* (0.0001)
<i>REER</i> _{<i>t</i>-1}	0.0001** (0.0000)	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0001 (0.0001)
<i>Cred</i> _{<i>t</i>-1}	-0.0014 (0.0009)	-0.0001 (0.0002)	-0.0010 (0.0007)	-0.0001 (0.0002)
<i>FDI</i> _{<i>t</i>-1}	-0.0109* (0.0057)	-0.0017** (0.0008)	-0.0094 (0.0057)	-0.0015* (0.0008)
<i>Res/GDP</i> _{<i>t</i>-1}	-0.0296*** (0.0110)	-0.0103*** (0.0036)	-0.0241** (0.0099)	-0.0102** (0.0040)
ΔExp _{<i>t</i>-1}	-0.0004* (0.0002)	-0.0002 (0.0003)	-0.0003 (0.0002)	-0.0002 (0.0002)
<i>CaBal</i> _{<i>t</i>-1}	0.0016 (0.0017)	-0.0005 (0.0004)	0.0015 (0.0017)	-0.0007 (0.0005)
<i>Kaopen</i> _{<i>t</i>-1}	-0.0125 (0.0096)	0.0006 (0.0030)	-0.0145 (0.0101)	0.0012 (0.0034)
<i>BC</i> _{<i>t</i>-1}	0.0211 (0.0216)	0.0011 (0.0070)	0.0178 (0.0231)	0.0018 (0.0082)
<i>CC</i> _{<i>t</i>-1}	0.0707*** (0.0213)	0.0156 (0.0106)	0.0580** (0.0249)	0.0136 (0.0116)
Observations	2213	1963	1898	1692
Pseudo R^2	0.4251	0.2943	0.4214	0.2857
Log-likelihood	-495.15	-140.6	-419.05	-124.45
Num. countries	68	68	58	58
Num. crises	41	41	36	36

(2) Post-crisis entry observations dropped.

(4) Post-crisis entry observations dropped.

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively

In order to assess the robustness of the pooled logit estimation, I include 4 alternative specifications: a multinomial logit model, a random effect logit model, a correlated random effect logit model and a binary logit model in which I split the sample in 2 subgroups.⁷ The reported values in Table SM3.1 are the marginal effects obtained after the estimation of the multinomial logit model for the purpose of obtaining comparable coefficients to those of the binary logit regression.⁸ Looking at the multinational logit model, I notice that the set of indicators that previously remained robust regardless of the specification in the pooled logit regression are also relevant in Table SM3.1 for both crisis entry and the post-crisis alike. This result is corroborated by the random effect logit model (Table SM3.2) as well as the correlated random effect logit model (Table SM3.3) which display strongly significant coefficients regarding the 3 robust indicators previously identified. In order to account for potential country-specific structural characteristics that might be affecting the significance level of predictors, I also run a sensitivity test by splitting my baseline sample. In Table SM3.4, model (5) designates countries that belong to the upper-middle-income group of World Bank’s classification whilst model (7) encompasses both lower-middle- and low-income economies of the same classification. The results compiled in Table SM3.4 also hint that the growth of real GDP, the interest on new external debt and the reserves-to-GDP ratio remain significant in all the specifications.

3.3.2 Robustness check: forecasting performances

Besides looking at the statistical significance of various indicators and the magnitude of each variable on the likelihood of sovereign defaults, evaluating the performances of the estimated models is key in the process of building an efficient EWS. Thus, it is essential for policymakers to compare the forecasting performance of different specifications, which requires selecting the optimal cut-off probability (i.e. setting a threshold such that the model issues a signal of an imminent crisis if that threshold is exceeded). Therefore, assessing the predictive power of our model consists in comparing the actual dependent variable SDC_{it} to the issued signals. Thus, the following contingency matrix can be constructed:

$$\begin{array}{c}
 \begin{array}{cc}
 & \begin{array}{cc}
 Crisis & Tranquil
 \end{array} \\
 \begin{array}{c}
 Signal \\
 No Signal
 \end{array} & \left(\begin{array}{cc}
 TP & FA \\
 MC & TN
 \end{array} \right)
 \end{array}
 \end{array}$$

⁷More technical details about the models are included in the Technical Appendix.

⁸Note that robust Huber-White standard errors are also implemented in this estimation.

Where TP denotes the true positives (i.e., correctly called episodes), TN the true negatives, FA refers to false alarms and MC to missed crises.

Nevertheless, selecting a cut-off probability can be challenging since setting an elevated threshold yields a higher rate of missed crises (Type I errors) while a low cut-off point triggers too many false alarms (Type II errors). Fuertes & Kalotychou (2007) state that focusing on missed crises is more relevant for policymakers compared to false alarms since the cost of unforeseen sovereign defaults is substantially higher than the one of undertaking precautionary measures. Nevertheless Savona & Vezzoli (2015) pointed out that trivializing type II errors may lead to adverse effects on the international reputation as a high rate of false alarms tend to issue a negative signal regarding the domestic market stability. However, is it important to mention that a triggered alarm can occur as a result of a successful preemptive policy adopted by the authorities in order to avoid a crisis. Therefore, type II errors are not inevitably miscalculations but could also be the indication of an early intervention. The empirical literature on EWS acknowledges that selecting the cut-off point requires to either to minimize the joint error measure (Noise to Signal Ratio), or to maximize the Youden's J-statistic.⁹ In their study, Savona & Vezzoli (2015) suggest that Youden's J-statistic is more suitable in comparison with the nose-to-ratio signal as the authors state that the J-statistic is robust to extreme type I and type II errors. On the contrary, minimizing the noise-to-ratio signal yields extreme thresholds in which false alarms are close to zero but the defaults are barely detected (Mulder et al. (2002)). Following Savona & Vezzoli (2015), I decide to implement Youden's J-statistic with the purpose of evaluating the performance of my models. The latter can be written as follows:

$$J = \frac{TP}{TP + MC} + \frac{TN}{TN + FA} - 1 \quad (3.2)$$

Where the left term in the right hand side of the equation denotes True Positive Rate (Sensitivity) and the right term designates True Negative Rate (Specificity). The optimal cut-off probability point can be obtained by maximizing the J-statistic:

$$J = \arg \max[\text{sensitivity} + \text{specificity} - 1] \quad (3.3)$$

⁹The noise to signal ratio can be defined as follows: $\frac{P(FA|FA \cup TN)}{P(TP|TP \cup MC)}$.

In order to assess the predictive power of my previous specifications, I consider three aspects: the percentage of correctly called crises, the rate of properly forwarded crises-entries while keeping attention in minimizing the rate of false alarms. Starting-off with the performance of the random effect logit model, columns 2 and 5 in Table 3.4 suggest that this method is not relevant in the process of implementing an effective EWS for debt crises. In fact, the model seems to perform much better at predicting tranquil periods in comparison with crises episodes: whilst holding the smaller rate of false alarms (1.7% and 1.3%), the method only succeeds at forecasting 26.1% of total crises observations while missing more than 80% of episodes entries. Furthermore, the multinomial specification yields a higher percentage of correctly called crises observations (almost 40%) but misses in the process nearly all the crises entries which, is a massive limitation for policymakers as one might argue that successfully predicting entries is more important than forecasting post-crisis periods. Although producing the highest rate of false alarms among the three methods (18.5%), the pooled logit specification appears to significantly outperform the random effect and multinomial logit. Indeed, not only the pooled estimator succeeds at predicting more than 90% of crises observations, but also detects over 75% of episodes onsets. Regarding crises entries in the pooled specification, the model appears to struggle with predicting short episodes of debt crises since 7 out of 10 missed entries are linked to a 3 years or less observed sovereign default.¹⁰ Note that "Optimal cut-off (%)" is missing for ML since this method does not use cut-off probability to classify observations into the three states (tranquil, crisis, post-crisis), but rather calculates the probability of each outcome. In comparison with former findings in the literature, my binary specification displays fairly good results. Indeed, the model designed by Ciarlone & Trebeschi (2005) produced 36% of false alarm although detecting 72% of crises entries whilst Pescatori & Sy (2007) managed to identify 86% of onsets sending only 14% of false alarms. The seminal study conducted by Manasse et al. (2003) exhibits the lowest rate of false alarms (less than 5%) among the binary logit estimations while detecting 74% of default entries. Since predicting crises entries seems more relevant from a policymakers' perspective, I attempt a robustness check on the pooled logit and the random effect models by keeping only the starting year of the defaults as performed previously on models (2) and (4). Table 3.5 displays the results. Scrutiny of the pooled logit model (2) reveals that the percentage of correct entries detected is higher (85.6%) in contrast with model (1) while also sending fewer false alarms (17%). A similar pattern emerges in model

¹⁰Those episodes entries are: Argentina (2014); Belize (2007), (2012) and (2017); Dominican Rep. (2003); Ecuador (2008); Jamaica (2010).

Table 3.4: Assessing the performance of the Early Warning Systems

	<i>Global (1)</i>			<i>Middle (3)</i>		
	<i>PL</i>	<i>RE</i>	<i>ML</i>	<i>PL</i>	<i>RE</i>	<i>ML</i>
Observations	2213	2213	2213	1898	1898	1898
Num. countries	68	68	68	58	58	58
Optimal cut-off (%)	12	5	-	14	13	-
Crises observations	291	291	291	242	242	242
% Correctly called	90.5	26.1	40.5	87.6	25.2	38
Detected entries	31	8	1	27	5	1
Total episodes	41	41	41	36	36	36
% Correct entries	75.6	19.5	2.5	75	13.8	2.8
% False alarms	18.5	1.7	2.4	15.5	1.4	2.3

PL, *RE* and *ML* refer to Pooled logit, Random Effect logit and Multinomial logit respectively.

Table 3.5: Assessing the performance of *PL* and *RE* (post-crisis onset dropped)

	<i>Global (2)</i>		<i>Middle (4)</i>	
	<i>PL</i>	<i>RE</i>	<i>PL</i>	<i>RE</i>
Observations	1963	1963	1692	1692
Num. countries	68	68	58	58
Optimal cut-off (%)	2	5	3	13
Crises observations	41	41	36	36
% Correct entries	85.4	5	83.3	5
Detected entries	35	2	30	2
Total episodes	41	41	36	36
% False alarms	17	0	14.9	0

PL and *RE* refer to Pooled logit and Random Effect logit respectively.

(4) where 30 out of the 36 debt crisis episodes are correctly predicted, producing in the process a relatively low rate of false alarms (14.9%). Note that the optimal cut-offs for specifications (2) and (4) are significantly lower in comparison with models (1) and (3) yet sending fewer false alarms in both cases. Finally, Table 3.5 confirms my previous comments on the random effect specification that yields even poorer performances in terms of predictive power as the model misses nearly 95% of entries which is a massive limitation.

3.3.3 EWI of debt crises: a horse-race

Having discussed the overall performance of my specifications, I now focus on the individual performance of Early Warning Indicators among those that have proven to be robust in section 3.3.1. To begin with, I consider the area under the receiver operating characteristic (AUROC) curve, which is a common criteria implemented in horse-races to compare the performance of sovereign debt crises detection. The receiver operating characteristic (ROC) curve plots the correctly called episodes rate against the false alarms rate at various threshold settings. High values of AUROC curve indicate that the binary classifier performs well at predicting zeros as zeros and ones as ones. AUROC curve values range from 0.5 (no discrimination) to 1 (perfect distinction). Nevertheless, several critics can be addressed to this method. One of them is that AUROC curve attributes the same importance to tranquil periods compared to crisis periods. However, one might argue that tranquil periods are less relevant than crisis observations for policymakers. Therefore, the AUROC curve might overestimate the global performance of a classifier based on good predictions of true negatives outcomes (i.e, classifying zeros as zeros). This limitation might be particularly significant in the case of forecasting sovereign defaults episodes since positive outcomes are sparse in the data-set. Furthermore, I employ the area under precision-recall (AUPR) curve as an alternative measure to deal with the class imbalance issue (i.e, data-sets in which the number of negatives significantly outweighs the number of positives) as suggested by Saito & Rehmsmeier (2015). The precision-recall (PR) curve plots the ratio of correctly called crises to total episodes against the true positive rate at various threshold settings. Consequently, the AUPR curve eliminates the impact of true negative outcomes in the process of assessing the performance of each classifier with imbalanced data. Nevertheless, interpreting AUPR curve values might be challenging in contrast with AUROC curve. Thus, the primary idea behind this implementation is not interpreting each value separately, but rather to establish a hierarchy among predictors by comparing multiple criteria.

In addition, I use two additional criteria in order to assess the accuracy of the predicted probabilities: the Brier (1950) score and the Tjur (2009) R^2 ; The Brier (1950) score measures the mean squared error of the predictions. Accordingly, a low Brier score indicates that the binary classifier performs well. Specifically, a Brier score approaching 0 is considered as the best possible value (i.e., total accuracy). The Tjur (2009) R^2 , also called Tjur's coefficient of discrimination, is defined as the difference between the mean predicted probability of both

positive and negative outcomes. Consequently, high Tjur R^2 indicates that the binary classifier performs well. More precisely, a coefficient nearing 1 suggests that there is a clear separation between the predicted values for zeros and ones. Finally, the predicted probabilities are obtained from a binary logit model estimated by maximum likelihood. Therefore, I also display in Table 3.6 the maximum likelihood and pseudo-R2 as a complement to compare the performance of the binary classifiers.

The results compiled in the upper part of Table 3.6 show that the foreign exchange reserves-to-GDP ratio, the average interest on new external commitments and the growth of real GDP stand out compared to the other predictors according to the set of 4 criteria (AUROC curve, AUPR curve, Tjur R^2 and Brier score). Moreover, the Log-likelihood and pseudo R^2 confirm this difference of performance between the robust indicators and the other predictors. Looking at each criterion separately, I can see that the reserves-to-GDP ratio slightly dominates the race with an AUROC value of 0.8036 compared to the average interest on new external commitments and the growth rate of real GDP while the three other predictors display a poorer performance with AUROC values lower than 0.7.¹¹ The AUPR curve, Tjur's R^2 and Brier score confirm the same pattern although there is no clear separation between the robust indicators. The lower part of Table 3.6 depicts the performance of the same predictors using identical criteria, but only compasses middle-income economies. This sensitivity test is implemented to account for potential country heterogeneity that might be affecting the ranking of indicators in the process of implementing a horse-race. The ratio of reserves-to-GDP still dominates the race compared to ΔGDP_{t-1} and $DebtInt_{t-1}$: while Res/GDP_{t-1} displays the best performances for 3 out of the 6 criteria, the growth of Real GDP exhibits the highest AUPR and Tjur's R^2 value. The previous outcome corroborates that the horse-race is tight between the set of robust indicators and that the reserves ratio stands out by a slight margin. Additionally, it is important to mention that attention is purposely turned to models (2) and (4) in which the post-crisis entry observations are dropped since one might argue that macroeconomic fundamentals tend to behave differently after the crisis occurs and therefore, may affect the ranking of the predictors. Thus, evaluating the performance of each indicator at detecting crises onsets seems more suitable from a policymaker's perspective¹².

¹¹Values ranging between 0.8 and 0.9 are considered as excellent while values lying between 0.7 and 0.8 are deemed acceptable.

¹²Note that the same procedure is implemented on models (1) and (3) and displayed in Table SM3.5.

Table 3.6: Assessing the performance of EWI (post-crisis onset dropped)

Global (2)						
Predictor :	Res/GDP_{t-1}	$DebtInt_{t-1}$	ΔGDP_{t-1}	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$
β	-0.1981***	0.3773***	0.1854***	-0.1186**	0.0754***	0.0037**
(σ_β)	(0.0605)	(0.0598)	(0.0278)	(0.0528)	(0.0173)	(0.0016)
Observations	1963	1963	1963	1963	1963	1963
Num. countries	68	68	68	68	68	68
Crises episodes	41	41	41	41	41	41
Log likelihood	-175.3523	-179.0457	-181.7607	-194.7556	-193.8292	-198.3185
Pseudo- R^2	0.1196	0.1011	0.0875	0.0222	0.0269	0.0043
<i>AUROC</i> curve	0.8036	0.7818	0.7732	0.6928	0.7111	0.6094
<i>AUPR</i> curve	0.0747	0.0708	0.0704	0.0402	0.0417	0.0282
Tjur R^2	0.0300	0.0270	0.0250	0.0030	0.0050	0.0010
Brier score	0.0198	0.0200	0.0198	0.0203	0.0203	0.0204
Middle-income countries (4)						
Predictor :	Res/GDP_{t-1}	$DebtInt_{t-1}$	ΔGDP_{t-1}	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$
β	-0.1876***	0.3747***	-0.2138***	-0.1135**	0.0724***	0.0045***
(σ_β)	(0.0599)	(0.0709)	(0.0291)	(0.0495)	(0.0179)	(0.0017)
Observations	1692	1692	1692	1692	1692	1692
Num. countries	58	58	58	58	58	58
Crises episodes	36	36	36	36	36	36
Log likelihood	-153.5182	-157.8572	-155.7398	-170.2877	-169.7489	-173.0066
Pseudo- R^2	0.1188	0.0939	0.1061	0.0226	0.0257	0.0070
<i>AUROC</i> curve	0.8018	0.7641	0.7834	0.6983	0.7064	0.6253
<i>AUPR</i> curve	0.0776	0.0712	0.0849	0.0404	0.0419	0.0326
Tjur R^2	0.0300	0.0260	0.0350	0.0030	0.0050	0.0010
Brier score	0.0202	0.0204	0.0202	0.0207	0.0207	0.0208

Variables definitions: Res/GDP = International reserves over GDP ratio; $DebtInt$ = Average interest on new external debt commitments; ΔGDP = Year-on-year growth rate of real GDP; FDI = FDI inflows; $DebtSer$ = Total debt service in % of GNI; $DebtSto$ = External debt stocks in % of GNI.

Eventually, I apply a similar evaluation on forecasting performances to the one implemented in section 3.3.2 and display the results in Tables 3.7 and 3.8. Focusing on the indicators that previously stood out, I notice that the interest on new external commitments yields the highest percentage of correctly called entries (90.2%) although emitting in the process a significant percentage of false alarms in model (2). Conversely, the reserves-to-GDP ratio issues fewer false alarms among the three indicators yet still detecting 34 crises onsets among the 41. This pattern is corroborated in model (4) where Res/GDP_{t-1} produces the lowest rate of false alarms on the top of correctly calling the highest crises episodes. These findings legitimate a more thorough scrutiny of the foreign exchange reserves as a leading indicator of sovereign defaults.

In that perspective, Figure 3.1 shows that the likelihood of debt crises tends to increase when the reserves are lower than the benchmark determined by Jeanne & Rancière (2006). The small empty circles represent each of the 41 sovereign default episodes within my sample. Thus, Figure 3.1 illustrates that the probability of debt crises is higher than its long-term level (dashed line) when the ratio of reserves-to-GDP is lower than 7.5% (vertical line) where 83% of the sovereign defaults occur.¹³ As for the remaining 7 crises, various explanations can be formed; for example, the farthest circle on the x-axis (close to 25%) depicts the Indonesian debt crisis in 1999 which occurred simultaneously with a banking crisis following a severe currency crisis in 1998 resulting in the highest output loss of the country's history (real GDP growth reached -13% in 1998). Figure 3.2 depicts the reserves behavior during tranquil periods. The histogram exhibits that 80% of the ratios range between 0% and 20% for the 1973-2017 span while the highest proportion (25%) lies between 5% and 10%.

¹³The long-term probability (i.e., unconditional) of debt crises equals 13.1% and corresponds to the frequency of defaults within the full sample (Table 3.1).

Table 3.7: Assessing the performance of EWI (post-crisis onset dropped)

	<i>Global (2)</i>			<i>Middle (4)</i>		
	Res/GDP_{t-1}	$DebtInt_{t-1}$	ΔGDP_{t-1}	$\Delta Res/GDP_{t-1}$	$DebtInt_{t-1}$	ΔGDP_{t-1}
Observations	1963	1963	1963	1692	1692	1692
Num. countries	68	68	68	58	58	58
Optimal cut-off (%)	2	1	2	2	2	2
Crises observations	41	41	41	36	36	36
% Correct entries	83	90.2	73.2	80.6	77.8	72.2
Detected entries	34	37	30	29	28	26
Total episodes	41	41	41	36	36	36
% False alarms	23.8	44	25.6	22.6	37.3	24.3

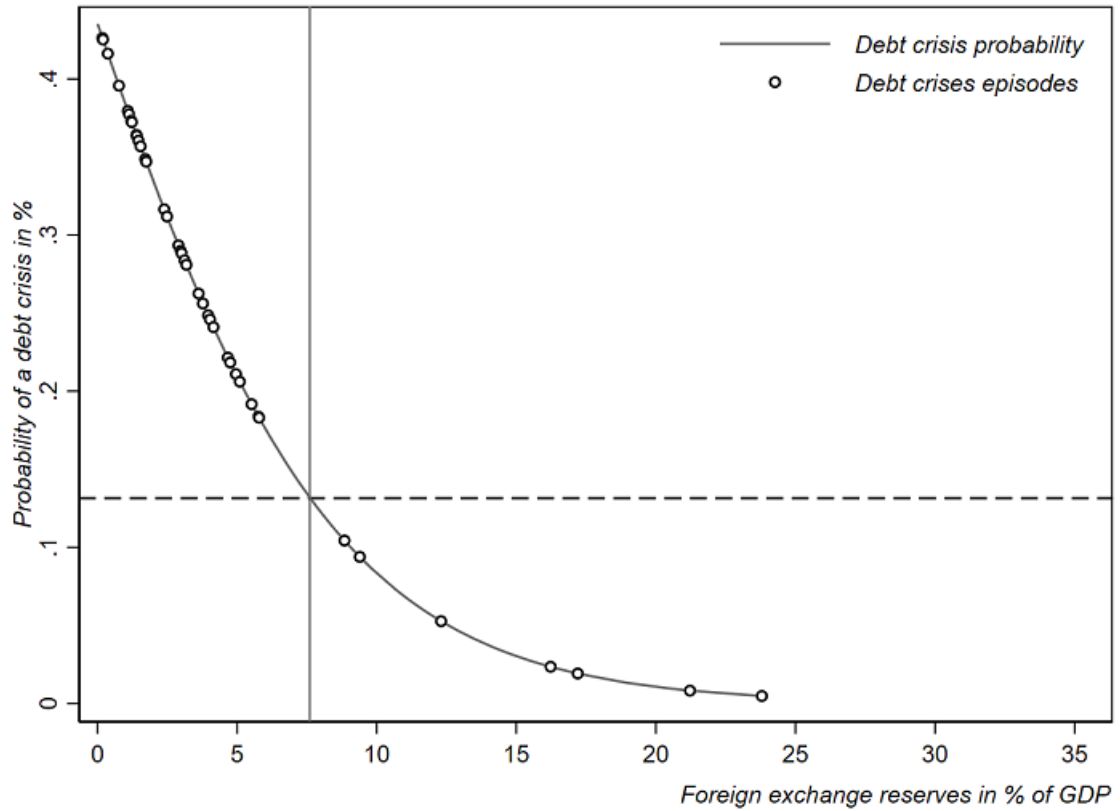
Variables definitions: Res/GDP = International reserves over GDP ratio; $DebtInt$ = Average interest on new external debt commitments; ΔGDP = Year-on-year growth rate of real GDP.

Table 3.8: Assessing the performance of EWI (post-crisis onset dropped)

	<i>Global (2)</i>			<i>Middle (4)</i>		
	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$
Observations	1963	1963	1963	1692	1692	1692
Num. countries	68	68	68	58	58	58
Optimal cut-off (%)	2	1	2	2	2	2
Crises observations	41	41	41	36	36	36
% Correct entries	73.2	70.7	85.4	75	77.8	86.1
Detected entries	30	29	35	29	29	17
Total episodes	41	41	41	36	36	36
% False alarms	39.1	35.2	68.2	40.9	38.1	69.4

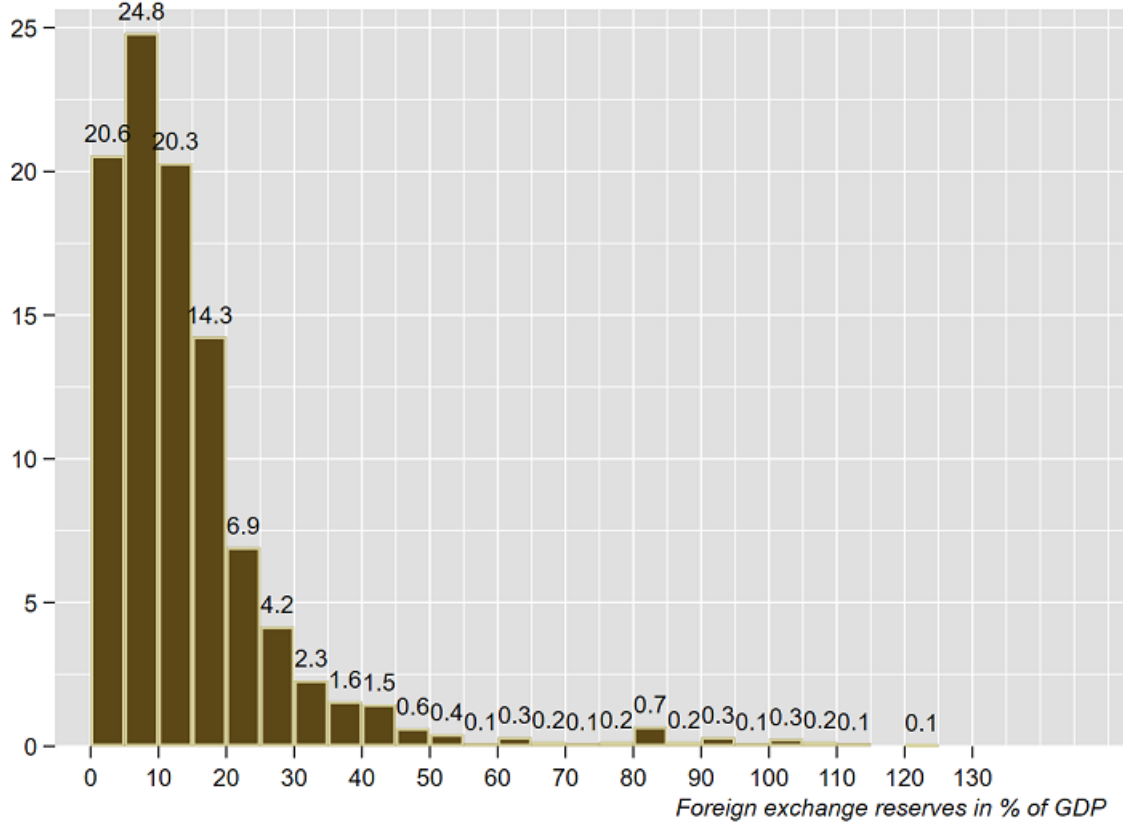
Variables definitions: FDI = FDI inflows; $DebtSer$ = Total debt service in % of GNI; $DebtSto$ = External debt stocks in % of GNI.

Figure 3.1: The impact of foreign exchange reserves on the probability of debt crises



--- Long-term (unconditional) probability of debt crises.

Figure 3.2: reserves-to-GDP ratio during tranquil periods



3.3.4 Reserves ratios as debt crises predictors: a horse-race

Following the same methodology employed in section 3.3.3, I implement a horse-race between the main reserves ratios employed by central banks. Giving the absence of a regulatory framework with which to assess reserve requirements for precautionary motives, central banks typically follow an array of measures as discussed in section 3.2.3. Consequently, I decide to incorporate the following ratios:

- Reserves over imports: assesses the reserves coverage in terms of months import. The benchmark is usually set to 3 months sustainability.
- Short-term debt to reserves: measures the need for repayment related to a country's short-term external liabilities in foreign currency with a remaining maturity of one year or less. The Guidotti-Greenspan rule suggests that this ratio should be equal to 1 (100% cover). The model designed by Jeanne & Rancière (2006) determines that the Guidotti-Greenspan rule is also a good approximation of the optimal amount of international reserves requirements.
- Broad money to reserves: evaluates the potential impact of a loss of confidence in the domestic currency. Accordingly, a higher ratio implies a decline in international reserves backing of the short-term domestic currency liabilities of the banking system. This ratio is well-suited for countries with large banking sector and very open capital accounts (IMF (2015)).

In addition to those indicators, I include the ratio of reserves-to-GDP previously employed in the baseline specification as well as the reserves to total external debt, which is a common indicator in the literature of EWS for sovereign defaults. Since I expect the race to be tight among the reserves ratios, I decide to split the sample into two groups following the methodology employed in section 3.3.1 (Table SM3.4) in order to account for potential dissimilarities in financial development between countries that might be affecting the ranking of the ratios.

Table 3.9 displays the results of the horse-race.¹⁴ The upper part of Table 3.9 shows that the ratio of reserves to total external debt dominates the race according to 4 out of the 6 implemented criteria with an AUROC value approaching 0.88. I reach similar conclusions when the full sample (2) and middle income countries (4) are considered as shown in Table SM3.6. The previous outcome implies that the reserves to total external debt might be a relevant early warning indicator of sovereign default in financially developed middle-income countries. The

¹⁴Note that a total of 74 observations and 1 crisis episode are dropped due to limited data availability regarding the debt to reserves ratio in Mauritius, Russia and Syrian Arab Republic.

remaining predictors in the upper-middle group display a fairly good performance with AUROC values nearing 0.8 although none of the ratios stands out compared to the others. A different scheme emerges in the lower part of Table 3.9, as I observe a slight dominance of the reserves-to-GDP ratio according to AUROC, AUPR, Tjur's R^2 and Brier Score. In addition, the M2 to reserves ratio appears to perform poorly in contrast with the 4 other ratios, which corroborates the idea of financial development features that affect the predictors' ranking. Indeed, the M2 to reserves ratio is often deemed to be a relevant indicator in countries with open capital account and financially developed markets as this ratio is also useful to detect currency crashes. Furthermore, the short-term debt to reserves ratio exhibits a decent performance according to 3 criteria (AUROC, AUPR and Brier Score) suggesting that short-term maturity coverage, which is a key indicator in the determination of optimal reserves requirements, is also relevant for debt crises predictions.

The upper part of Table 3.10 demonstrates as well that the reserves to total external debt stands out compared to other ratios as this predictor is able to individually detect 21 out of the 23 crises onsets in the upper-middle group of countries while the short-term debt to reserves ratio emits the lowest false alarm rate yet is still able to correctly call 74% of entries. In contrast, the reserves-to-GDP ratio significantly outperforms other predictors in the lower-middle group with more than 94% of entries detected although issuing slightly more false alarms than the reserves in months of imports which dominates for this specific criterion (only 19.3% of Type II errors). Finally, the other ratios exhibit good performances in terms of entries detection for both groups, but also send a high proportion of false alarms, especially in upper-middle-income countries. Note that the M2 to reserves ratio detects the lowest amount of entries in the lower part of Table 3.10 but yields at the same time the highest rate of false alarms in model (8) hence confirming its contrasted performance in lower-middle-income countries.

Table 3.9: Assessing the performance of ratios (post-crisis onset dropped)

Upper-middle (6)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
β	-0.2111**	-0.1337***	0.0020**	-0.6444***	0.1367***
(σ_β)	(0.0874)	(0.0312)	(0.0010)	(0.2214)	(0.0417)
Observations	906	906	906	906	906
Num. countries	32	32	32	32	32
Crises episodes	23	23	23	23	23
Log likelihood	-91.6196	-81.8984	-98.8133	-92.8422	-92.9106
Pseudo- R^2	0.1453	0.2360	0.0782	0.1339	0.1333
<i>AUROC</i> curve	0.8149	0.8792	0.8039	0.8023	0.7818
<i>AUPR</i> curve	0.1672	0.1605	0.2519	0.1244	0.1685
Tjur R^2	0.0480	0.0860	0.0500	0.0440	0.1070
Brier score	0.0235	0.0227	0.0238	0.0237	0.0242

Lower-middle & low (8)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
β	-0.2548**	0.1040***	0.0001	-0.7424***	0.0054***
(σ_β)	(0.1063)	(0.0221)	(0.0001)	(0.2064)	(0.0027)
Observations	983	983	983	983	983
Num. countries	34	34	34	34	34
Crises episodes	17	17	17	17	17
Log likelihood	-74.4187	-73.8466	-85.6244	-74.6260	-85.2179
Pseudo- R^2	0.1329	0.1396	0.0024	0.1305	0.0071
<i>AUROC</i> curve	0.8291	0.8145	0.8082	0.8146	0.7227
<i>AUPR</i> curve	0.0637	0.0501	0.0584	0.0618	0.0506
Tjur R^2	0.0300	0.0250	0.0000	0.0290	0.0010
Brier score	0.0165	0.0166	0.0169	0.0166	0.0166

Variables definitions: Res/GDP = International reserves over GDP ratio; $Res/Debt$ = International reserves to total external debt ratio; $StDebt/Res$ = Short-term debt in % of reserves; Res/Imp = International reserves in months of imports; $M2/Res$ = Broad money to reserves ratio.

Table 3.10: Assessing the performance of ratios (post-crisis onset dropped)

Upper-middle (6)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
Observations	906	906	906	906	906
Num. countries	32	32	32	32	32
Crises episodes	23	23	23	23	23
Optimal cut-off (%)	5	3	2	2	2
% Correctly called	74	91.3	74	91.3	87
Detected entries	17	21	17	21	20
% False alarms	17.4	25.3	11.4	38.7	41.3

Lower-middle & low (8)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
Observations	983	983	983	983	983
Num. countries	34	34	34	34	34
Crises episodes	17	17	17	17	17
Optimal cut-off (%)	2	3	2	2	2
% Correctly called	94.1	76.5	82.4	82.4	70.6
Detected entries	16	13	14	14	12
% False alarms	25	22.5	23.1	19.3	31

Variables definitions: Res/GDP = International reserves over GDP ratio; $Res/Debt$ = International reserves to total external debt ratio; $StDebt/Res$ = Short-term debt in % of reserves; Res/Imp = International reserves in months of imports; $M2/Res$ = Broad money to reserves ratio.

3.4 Further issues

Using the same income based country classification as in section 3.3.4, I explore more thoroughly the predictive power of different reserves ratios by comparing their respective predictive power at more distant forecast horizons. Finally, an out-of-sample forecast is considered to assess the model's ability to detect recent sovereign defaults that occurred as a result of the Covid-19 pandemic.

3.4.1 Reserves ratios performance for different forecast horizons

This section investigates the stability of the signal issued by the reserves ratios as sovereign defaults predictors. In section 3.3.4 (as in the baseline specification), all the predictors are lagged by one period (i.e, 1 year prior to a crisis). An effective predictor should, however, start to issue a signal earlier than 1 year so that it provides policymakers with some lead time to adopt preemptive policies. In addition, debt crisis predictors should provide a stable signal throughout multiple consecutive periods in order to reduce uncertainty regarding the risk of default. Therefore, I run a sensitivity test with a forecast horizon covering a 5 year window prior to a crisis. For each forecast horizon and debt crisis predictor, Figures 3.3 and 3.4 plot the AUROC curve to highlight the quality of the signals.¹⁵ Figures 3.3 and 3.4 corroborate the main result obtained from section 3.3.4 concerning the difference between the upper-middle and the lower-middle groups. For all forecast horizons, Figure 3.3 highlights that the reserves to debt ratio provides a better signal to defaults in upper-middle-income countries while the signal issued by the M2 to reserves ratio substantially drops at t-4 and t-5. By contrast, Figure 3.4 demonstrates that starting from t-1, the reserves-to-GDP ratio remains the best performing predictor for all forecast horizons in the lower-middle-income group of countries.¹⁶ With respect to the remaining ratios, the import coverage ratio yields a stable performance for all the forecast horizons with values ranging from 0.65 in t-5, up to 0.8 in t-1 for both groups. Conversely, the short-term debt over reserves ratio only produces a stable performance in the upper-middle group while the same does not hold for the lower-middle cluster as the signal issued dramatically drops prior to t-2 in Figure 3.4. Surprisingly, the M2 to reserves ratio yields a steadier signal in the lower-middle group although producing a poorer overall performance as a default approaches.

¹⁵Similar conclusions are reached with the other criteria.

¹⁶Joint best with the short-term debt over reserves in t-2.

Figure 3.3: Reserves ratios for different forecast horizons (upper-middle group)

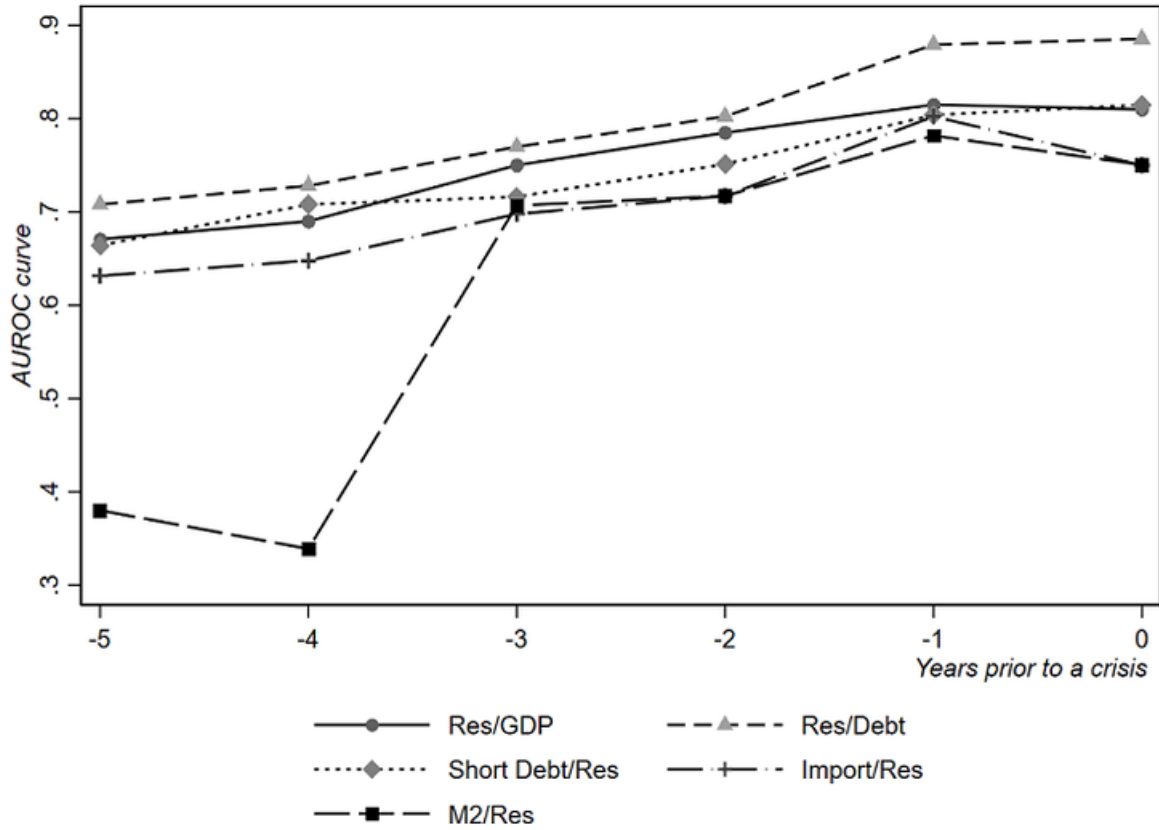
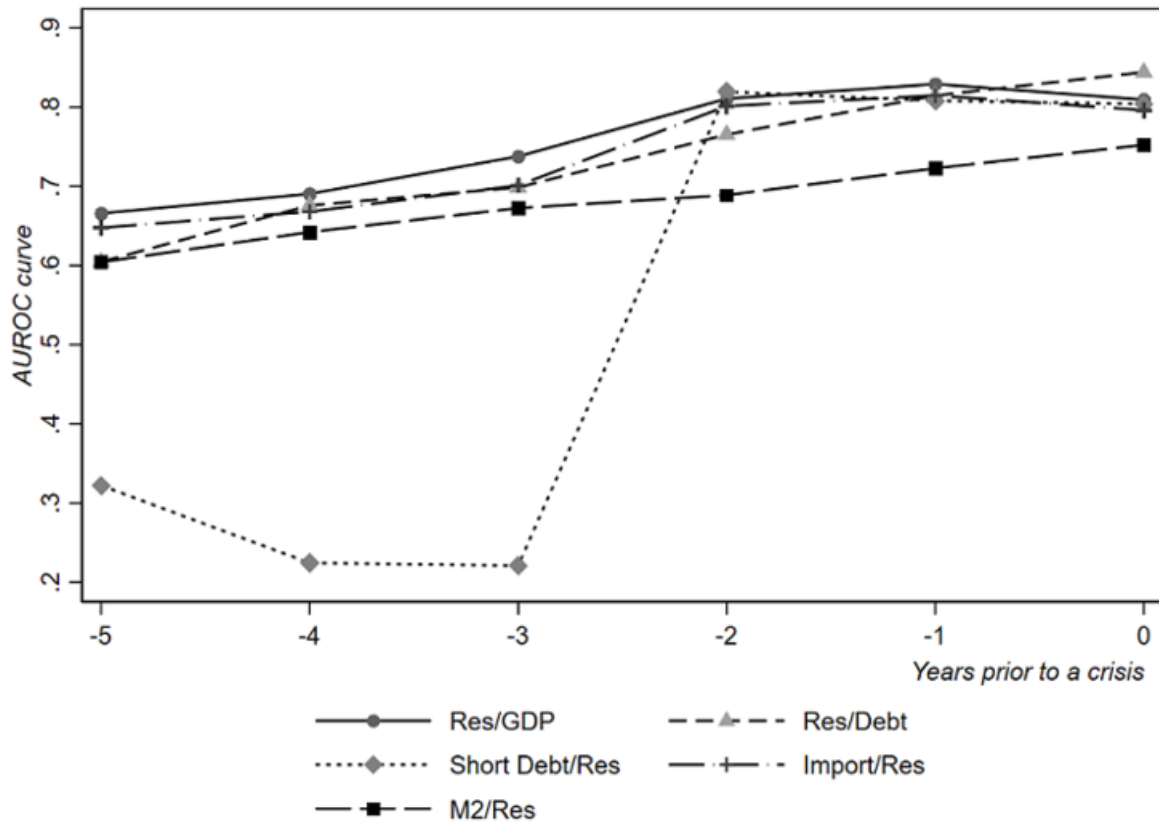


Figure 3.4: Reserves ratios for different forecast horizons (lower-middle & low group)



3.4.2 Out-of-sample performance

Since most of the reserves ratios yield fair performances in debt crises prediction for the 1973-2017 span, I finally attempt to assess the ability of these predictors in detecting the current sovereign defaults that occurred as a result of the Covid-19 crisis. According to Beers et al. (2021), multiple upper-middle-income countries defaulted in 2020 and remain in default in 2021 (Argentina, Belize, Ecuador, Lebanon, Suriname and Venezuela). Furthermore, most of these observations are confirmed in the Standard and Poor's sovereign ratings.¹⁷ Considering that all of these countries belong to the upper-middle-income group, I employ the reserves to debt ratio as this indicator yielded the best overall performances. The estimation results are displayed in the upper part of Table 3.11 and relate to the 2018-2020 period (for the out-of-sample forecast) in which only 4 defaults are kept due to data unavailability regarding reserves in Suriname and Venezuela.¹⁸ Starting-off with the in-sample performance, the model is able to detect 21 of 23 crises onsets although issuing 25.3% of false alarms in the process. Turning to the out-of-sample forecast performance, the model detects 75% of crises onsets that occurred in 2020 (Argentina, Belize, Ecuador) and only misses the Lebanese default. In addition, the lower part of Table 3.11 depicts the out-of-sample performance using the reserves to external debt ratio in the lower-middle- and low-income group of countries in which only one episode is currently recorded for Zambia in 2020 (according to Beers et al. (2021) and Standard & Poor's). Thus, the model correctly predicts the Zambian default on the top of emitting a lower rate of false alarms (9.2%) in contrast with the upper-middle-income group (13.3%). However, false alarms are not necessarily miscalculations. Indeed, as mentioned in section 3.3.2, false alarms could be the sign of an early intervention or the signal of an important financial distress that doesn't inevitably morph into a sovereign default. In that perspective, I investigate the reserves to external debt ratio observations that exceed the optimal threshold during tranquil period for the 2018-2020 span. Figure 3.6 shows that a significant proportion of false alarms comes from countries such as Chad, Congo, Laos, Papua New Guinea and Sudan. Interestingly, the DSSI database from the World Bank (2020) classifies all of these countries as being at high risk of overall debt distress¹⁹. Finally, Figure 3.5 reveals a similar feature regarding the upper-middle-income group since countries that are classified as "CCC" by the Standard & Poor's ratings (namely, Sri Lanka) also appear to be increasing the rate of false alarms.

¹⁷Excluding Venezuela, for which the rating is currently not available.

¹⁸Data on foreign exchange reserves to total debt in Suriname are also unavailable for the 1973-2017 span.

¹⁹As of December 2021.

Table 3.11: Out-of-sample forecast (post-crisis onset dropped)

Upper-middle

Predictor : $Res/Debt_{t-1}$	<i>In-sample</i>	<i>Out-of-sample</i>
Observations	906	124
Num. countries	32	44
Crises episodes	23	4
Optimal cut-off (%)	2.76	2.76
% Correctly called	91.3	75
Detected entries	21	3
% False alarms	25.3	13.3

Lower-middle & low

Predictor : $Res/Debt_{t-1}$	<i>In-sample</i>	<i>Out-of-sample</i>
Observations	983	165
Num. countries	34	57
Crises episodes	17	1
Optimal cut-off (%)	2.73	2.73
% Correctly called	76.5	100
Detected entries	13	1
% False alarms	22.5	9.2

In-sample covers the 1973-2017 span while *Out-of-sample* refers to the 2018-2020 period.

Figure 3.5: Reserves to external debt ratio and sovereign default probability (upper-middle)

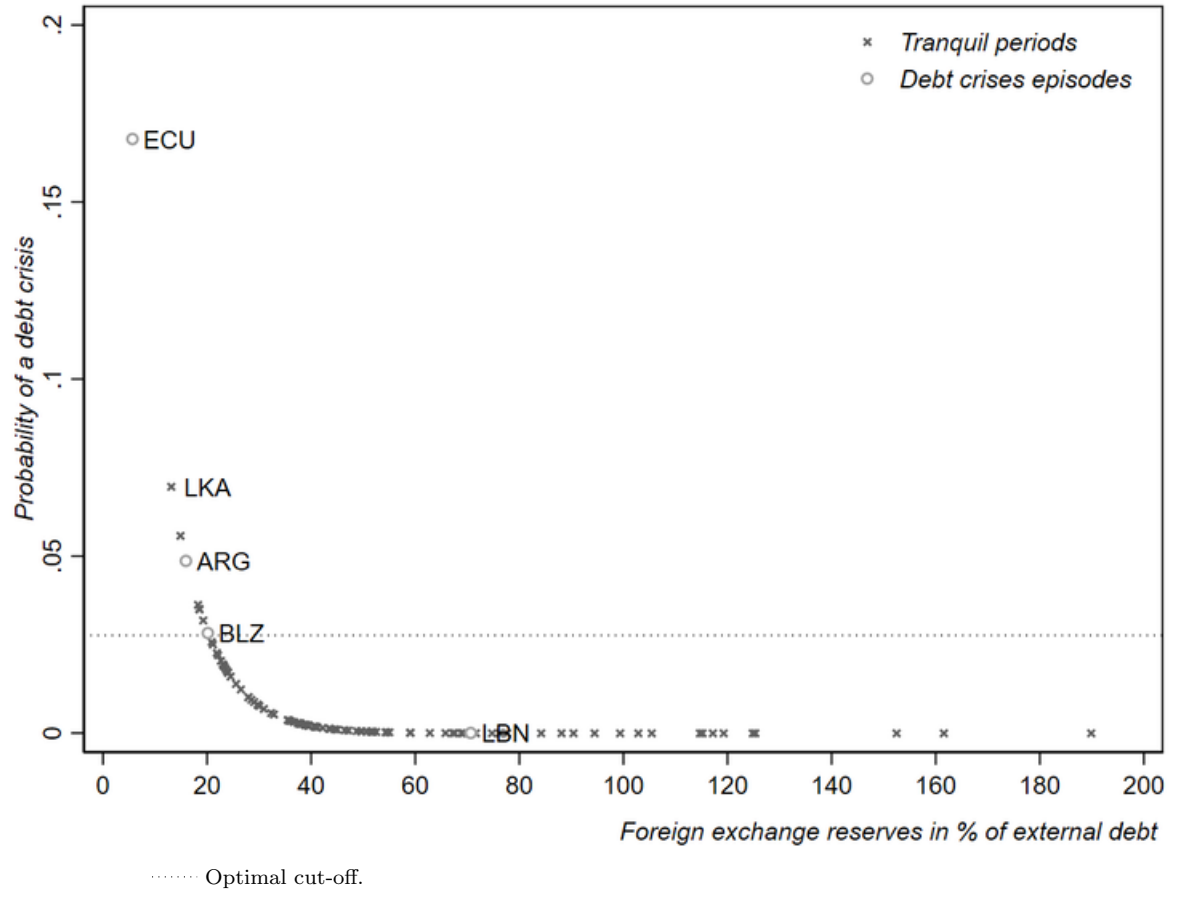
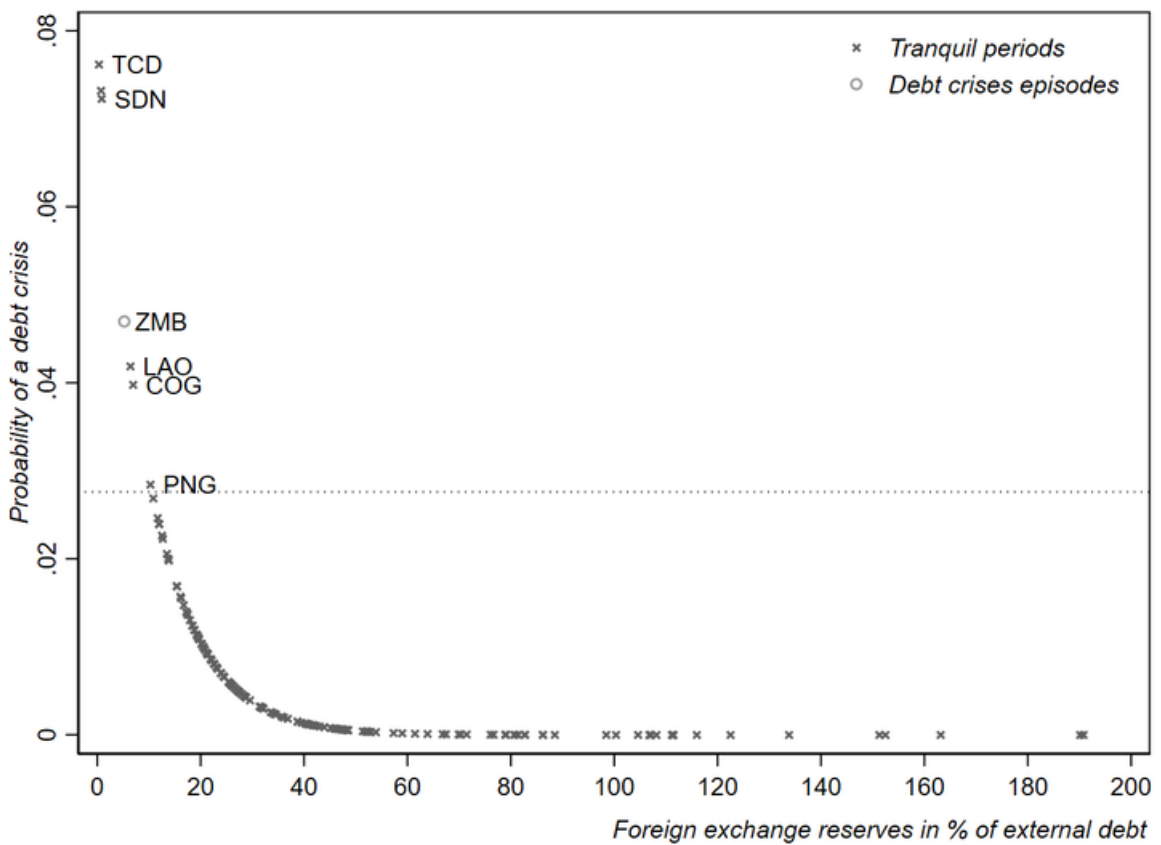


Figure 3.6: Reserves to external debt ratio and sovereign default probability (lower-middle & low)



Conclusion

This paper aims to develop efficient tools in the process of calibrating EWS for sovereign debt crises in middle- and low income countries. The baseline binary logit model correctly calls more than 90% of crises observations while detecting 75% of crises onsets and shows that the reserves-to-GDP ratio, the average interest on new debt and the growth of real GDP are robust to the removal of post-crisis observations regardless of the specification. Additional estimations applied later to deal with the post-crisis bias show that both the signs and the coefficients of the robust variables remain unaltered while the multinational specification displays poorer results in terms of predictive power. Further horse-race implementation demonstrates that each of 3 robust predictors stands out individually compared to the other explanatory variables, and yields a better performance according to an array of 6 criteria from a policymaker's perspective. Moreover, I run a sensitivity test on the main reserves ratios commonly employed by central banks to determine reserves requirements and illustrate that most of these indicators perform fairly well at predicting debt crises. The previous outcome is robust, even at more distant forecast horizons. I finally illustrate that the reserves to external debt ratio performs well at predicting the current defaults that occurred as a result of the Covid-19 pandemic. The main policy implication of those results is that debt crises episodes tend to occur when foreign exchange reserves are lower than the long-term benchmark, which corresponds to a 100% short-term debt coverage in accordance with the Guidotti-Greenspan rule. Therefore, reserves buffers accumulation should be a strong macro-prudential policy instrument for central banks as this process enables economies to mitigate the harmful effect of debt crises through preventing large capital outflows and exchange rate depreciation. Forthcoming research on sovereign defaults in middle- and low-income countries should be focusing on optimal reserves requirements and exchange rate stability.

Data Appendix

1. **Real GDP growth (NY.GDP.MKTP.KN.87.ZG):** World Bank national accounts data, National Accounts data files (OECD). Annual percentage growth rate of real GDP based on constant local currency.
2. **Inflation, GDP Deflator (NY.GDP.DEFL.KD.ZG):** World Bank national accounts data, and OECD National Accounts data files. WDI database archives. Annual growth of the GDP deflator measuring the rate of price change in the economy as a whole.
3. **Foreign Direct Investment (BX.KLT.DINV.WD.GD.ZS):** World Development Indicators (WDI). (IFS) International Financial Statistics, International Monetary Fund (IMF). Net inflows of investment, sum of equity capital and reinvestment of earnings as shown in the balance of payments.
4. **Domestic credit to private sector (GFDD.DI.14):** World Development Indicators (WDI), World Bank. Global Financial Development Financial resources provided to the private sector, such as through loans, purchases of nonequity securities, and trade credits, that establish a claim for repayment.
5. **KAOPEN:** Index measuring degree of capital account openness. Chinn & Ito (2006).
6. **Real Effective Exchange Rate:** Index (2010=100). Couharde et al. (2018).
7. **Total Debt Service (DT.TDS.DECT.GN.ZS):** International Debt Statistics (World Bank). (WDI) World Development Indicators. Sum of principal repayments and interest actually paid in currency, goods, or services on long-term debt, interest paid on short-term debt, and repayments (repurchases and charges) to the IMF.
8. **Average Interest On New External Debt Commitments (DT.INR.DPPG):** World Bank, International Debt Statistics. WDI Database Archives. Average interest rate on all new public and publicly guaranteed loans contracted during the year.
9. **External Debt Stocks (DT.DOD.DECT.GN.ZS):** World Bank, International Debt Statistics. WDI Database Archives. Sum of public, publicly guaranteed, and private non-guaranteed long-term debt, use of IMF credit, and short-term debt.
10. **Current Account Balance (BN.CAB.XOKA.GD.ZS):** International Monetary Fund, Balance of Payments Statistics Yearbook and data files, and World Bank and OECD GDP estimates. World Development Indicators (WDI). Sum of net exports of goods and services, net primary income, and net secondary income.
11. **Exports Of Goods And Services (BX.GSR.GNFS.CD):** International Monetary Fund (IMF), Balance of Payments Statistics data files. World Development Indicators (WDI). Transactions between residents of a country and the rest of the world involving a change of ownership from residents to nonresidents of general merchandise, net exports of goods, non-monetary gold, and services divided by GDP in current U.S. dollars.
12. **Gross Domestic Savings (NY.GDS.TOTL.ZS):** World Bank national accounts data, and OECD National Accounts data files. World Development Indicators (WDI). GDP less final consumption expenditure.
13. **Total Reserves Minus Gold (FI.RES.XGLD.CD):** International Monetary Fund, International Financial Statistics and data files. World Development Indicators (WDI). Special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities divided by GDP in current U.S. dollars.
14. **Total reserves in months of imports (FI.RES.TOTL.MO):** Total reserves comprise holdings of monetary gold, special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities. The gold component of these reserves is valued at year-end (December 31) London prices. This item shows reserves expressed in terms of the number of months of imports of goods and services they could pay for [Reserves (Imports 12)].
15. **Short-term debt (% of total reserves) (DT.DOD.DSTC.IR.ZS):** Short-term debt includes all debt having an original maturity of one year or less and interest in arrears on long-term debt. Total reserves includes gold.
16. **Total reserves (% of total external debt) (FI.RES.TOTL.DT.ZS):** International reserves to total external debt stocks.
17. **Broad money to total reserves ratio (FM.LBL.BMNY.IR.ZS):** Broad money (IFS line 35L.ZK) is the sum of currency outside banks; demand deposits other than those of the central government; the time, savings, and foreign currency deposits of resident sectors other than the central government; bank and traveler's checks; and other securities such as certificates of deposit and commercial paper.

Technical Appendix: Chapter III

Multinomial logit model

The multinomial specification provides an alternative method to deal with the post-crisis bias. Indeed, the dependent variable SDC_{mit} allows for three states of nature, and can be defined as follows :

$$SDC_{mit} = \begin{cases} 0 & \text{if } SDC_{it} = 0 \\ 1 & \text{if } SDC_{it} = 1 \text{ and } SDC_{it-1} = 0 \\ 2 & \text{if } SDC_{it} = 1 \text{ and } SDC_{it-1} = 1 \end{cases} \quad (3.4)$$

Where $SDC_{it} = 0$ denotes tranquil periods, the value of one refers to the starting year of the crisis episode and $SDC_{it} = 2$ designates the post-crisis periods until a country recovers from the crisis event. The set of estimated coefficients β^1 and β^2 are interrelated and correspond to each outcome as follows :

$$\begin{cases} Pr(Y_{it} = 0) = F(X_{it}\beta) = \frac{1}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \\ Pr(Y_{it} = 1) = F(X_{it}\beta) = \frac{e^{X_{it}\beta^1}}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \\ Pr(Y_{it} = 2) = F(X_{it}\beta) = \frac{e^{X_{it}\beta^2}}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \end{cases} \quad (3.5)$$

Where β^1 assesses the impact of a variation in the indicators on the likelihood of entering a crisis episode whereas β^2 evaluates the effect of the same variations on the probability of being in the post-crisis onset period.

Random effect logit models

The random effect logit model allows for cross-country unobserved heterogeneity as it enables to account for disparate levels of financial depth that may be affecting the the significance levels as well as the signs of the predictors. Because the fixed effects approach does not allow SDC_{it} to be constant within groups (i.e, mechanically excludes countries that don't experience any crisis), I employ a correlated random effect logit model in which I include the clustered means of all the predictors. This approach relies on including the means of all the predictors as a proxy of the fixed effects.²⁰

²⁰The clustered means of the predictors are not displayed in Table SM3.3.

Chapter III: supplemental material

Robustness checks and sample details

This appendix reports the results associated with the robustness checks implemented on the baseline estimation as well as several details on the sample. More precisely, this appendix encompasses: *(i)* several robustness checks on the baseline and the horse races (Table SM3.1, SM3.2, SM3.3, SM3.4, SM3.5 and SM3.6) *(ii)* a correlation matrix of all the indicators employed in the baseline estimation (Table SM3.7); *(iii)* several details on leading indicators (SM3.8), crises dates (SM3.9) and countries within the sample (SM3.10).

Table SM3.1: Multinomial logit model

	Global (1)	Global (1)	Middle (3)	Middle (3)
Crisis period	$SDC_{mit} = 1$	$SDC_{mit} = 2$	$SDC_{mit} = 1$	$SDC_{mit} = 2$
$DebtSer_{t-1}$	0.0013** (0.0006)	0.0051*** (0.0020)	0.0012** (0.0006)	0.0027 (0.0020)
$DebtInt_{t-1}$	0.0032*** (0.0010)	0.0266*** (0.0040)	0.0034*** (0.0012)	0.0288*** (0.0046)
$DebtSto_{t-1}$	-0.0001 (0.0001)	0.0008*** (0.0002)	-0.0001 (0.0001)	0.0008*** (0.0003)
ΔGDP_{t-1}	-0.0021*** (0.0005)	-0.0019** (0.0009)	-0.0024*** (0.0005)	-0.0025** (0.0011)
$NatSav_{t-1}$	0.0001 (0.0002)	-0.0042*** (0.0012)	0.0002 (0.0003)	-0.0035*** (0.0012)
$Infla_{t-1}$	-0.0001* (0.0000)	0.0002*** (0.0000)	-0.0001* (0.0000)	0.0002*** (0.0000)
$REER_{t-1}$	0.0000 (0.0000)	0.0001** (0.0000)	-0.0000 (0.0000)	-0.0001 (0.0001)
$Cred_{t-1}$	0.0001 (0.0002)	-0.0015* (0.0008)	0.0001 (0.0001)	-0.0011 (0.0007)
FDI_{t-1}	-0.0014 (0.0012)	-0.0097** (0.0049)	-0.0013 (0.0012)	-0.0084* (0.0049)
Res/GDP_{t-1}	-0.0073*** (0.0026)	-0.0227** (0.0093)	-0.0073** (0.0029)	-0.0173** (0.0080)
ΔExp_{t-1}	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0001 (0.0002)	-0.0002 (0.0002)
$CaBal_{t-1}$	-0.0006 (0.0004)	0.0021 (0.0016)	-0.0007 (0.0005)	0.0020 (0.0017)
$Kaopen_{t-1}$	0.0018 (0.0028)	-0.0149 (0.0093)	0.0022 (0.0030)	-0.0175* (0.0099)
BC_{t-1}	0.0017 (0.0057)	0.0193 (0.0200)	0.0026 (0.0063)	0.0151 (0.0021)
CC_{t-1}	0.0072 (0.0075)	0.0632*** (0.0173)	0.0050 (0.0083)	0.0528*** (0.0195)
Observations	2213	2213	1898	1898
Pseudo R^2	0.3945	0.3945	0.3918	0.3918
Log-likelihood	-593.14	-593.14	-502.44	-502.44
Num. countries	68	68	58	58
Num. crises	41	41	36	36

$SDC_{mit} = 1$ Crisis entry; $SDC_{mit} = 2$ Post-crisis entry.

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively

Table SM3.2: Random Effect logit model

	Global (1)	Global (2)	Middle (3)	Middle (4)
<i>DebtSer</i> _{<i>t</i>-1}	0.0024 (0.0018)	0.0010 (0.0007)	0.0007 (0.0015)	0.0007 (0.0006)
<i>DebtInt</i> _{<i>t</i>-1}	0.0159*** (0.0044)	0.0065*** (0.0015)	0.0158*** (0.0051)	0.0067*** (0.0018)
<i>DebtSto</i> _{<i>t</i>-1}	0.0005** (0.0002)	-0.0001 (0.0001)	0.0004* (0.0002)	-0.0000 (0.0000)
ΔGDP _{<i>t</i>-1}	-0.0029*** (0.0011)	-0.0029*** (0.0007)	-0.0038*** (0.0013)	-0.0033*** (0.0009)
<i>NatSav</i> _{<i>t</i>-1}	-0.0023** (0.0010)	-0.0003 (0.0003)	-0.0028** (0.0002)	-0.0001 (0.0003)
<i>Infla</i> _{<i>t</i>-1}	0.0001** (0.0000)	-0.0002* (0.0001)	0.0001** (0.0000)	-0.0002** (0.0001)
<i>REER</i> _{<i>t</i>-1}	0.0002* (0.0001)	0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
<i>Cred</i> _{<i>t</i>-1}	0.0004 (0.0006)	-0.0001 (0.0002)	0.0004 (0.0005)	0.0001 (0.0002)
<i>FDI</i> _{<i>t</i>-1}	-0.0065** (0.0028)	-0.0018** (0.0008)	-0.0064** (0.0031)	-0.0016* (0.0008)
<i>Res/GDP</i> _{<i>t</i>-1}	-0.0312*** (0.0100)	-0.0110*** (0.0039)	-0.0265*** (0.0098)	-0.0106*** (0.0044)
ΔExp _{<i>t</i>-1}	-0.0002 (0.0002)	-0.0001 (0.0001)	-0.0000 (0.0002)	-0.0001 (0.0002)
<i>CaBal</i> _{<i>t</i>-1}	0.0017 (0.0012)	-0.0005 (0.0004)	0.0009 (0.0002)	-0.0008 (0.0012)
<i>Kaopen</i> _{<i>t</i>-1}	-0.0289*** (0.0087)	-0.0008 (0.0032)	-0.0300*** (0.0094)	0.0006 (0.0034)
<i>BC</i> _{<i>t</i>-1}	0.0293 (0.0176)	0.0024 (0.0066)	0.0214 (0.0173)	0.0024 (0.0079)
<i>CC</i> _{<i>t</i>-1}	0.0233 (0.0164)	0.0137 (0.0099)	0.0121 (0.0169)	0.0108 (0.0104)
Observations	2213	1963	1898	1692
Pseudo R^2	0.4408	0.2991	0.4412	0.2924
Log-likelihood	-395.81	-139.43	-330.86	-122.87
Num. countries	68	68	58	58
Num. crises	41	41	36	36

(2) Post-crisis entry observations dropped.

(4) Post-crisis entry observations dropped.

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively

Table SM3.3: Correlated Random Effect logit model

	Global (1)	Global (2)	Middle (3)	Middle (4)
<i>DebtSer</i> _{<i>t</i>-1}	0.0024 (0.0020)	0.0008 (0.0007)	0.0008 (0.0019)	0.0006 (0.0008)
<i>DebtInt</i> _{<i>t</i>-1}	0.0169*** (0.0042)	0.0058*** (0.0016)	0.0176*** (0.0043)	0.0059*** (0.0017)
<i>DebtSto</i> _{<i>t</i>-1}	0.0006** (0.0003)	-0.0001 (0.0001)	0.0006 (0.0004)	-0.0000 (0.0000)
ΔGDP _{<i>t</i>-1}	-0.0032*** (0.0012)	-0.0030*** (0.0007)	-0.0042*** (0.0014)	-0.0035*** (0.0008)
<i>NatSav</i> _{<i>t</i>-1}	-0.0026** (0.0012)	-0.0001 (0.0005)	-0.0035*** (0.0009)	-0.0001 (0.0005)
<i>Infla</i> _{<i>t</i>-1}	0.0001* (0.0000)	-0.0002* (0.0001)	0.0001** (0.0000)	-0.0003** (0.0001)
<i>REER</i> _{<i>t</i>-1}	0.0002** (0.0001)	0.0001* (0.0000)	-0.0001 (0.0001)	-0.0001 (0.0001)
<i>Cred</i> _{<i>t</i>-1}	0.0007 (0.0008)	0.0003 (0.0003)	0.0004 (0.0005)	0.0003 (0.0002)
<i>FDI</i> _{<i>t</i>-1}	-0.0069*** (0.0026)	-0.0019** (0.0008)	-0.0074** (0.0032)	-0.0019** (0.0008)
<i>Res/GDP</i> _{<i>t</i>-1}	-0.0344*** (0.0104)	-0.0137*** (0.0046)	-0.0313*** (0.0110)	-0.0134*** (0.0050)
ΔExp _{<i>t</i>-1}	-0.0002 (0.0002)	-0.0001 (0.0002)	-0.0000 (0.0002)	-0.0001 (0.0002)
<i>CaBal</i> _{<i>t</i>-1}	0.0019 (0.0014)	-0.0006 (0.0005)	0.0008 (0.0015)	-0.0012** (0.006)
<i>Kaopen</i> _{<i>t</i>-1}	-0.0373*** (0.0086)	-0.0063 (0.0042)	-0.0410*** (0.0094)	0.0052 (0.0043)
<i>BC</i> _{<i>t</i>-1}	0.0325 (0.0199)	0.0049 (0.0096)	0.0244 (0.0203)	0.0027 (0.0106)
<i>CC</i> _{<i>t</i>-1}	0.0221 (0.0172)	0.0120 (0.0099)	0.0109 (0.0195)	0.0095 (0.0102)
Observations	2213	1963	1898	1692
Pseudo R^2	0.4685	0.3491	0.4723	0.3399
Log-likelihood	-376.28	-129.50	-312.47	-114.63
Num. countries	68	68	58	58
Num. crises	41	41	36	36

(2) Post-crisis entry observations dropped.

(4) Post-crisis entry observations dropped.

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively

Table SM3.4: Pooled logit model by income group

	Upper (5)	Upper (6)	Lower (7)	Lower (8)
<i>DebtSer</i> _{<i>t</i>-1}	0.0039 (0.0037)	-0.0001 (0.0001)	0.0113*** (0.0036)	0.0027*** (0.0010)
<i>DebtInt</i> _{<i>t</i>-1}	0.0207** (0.0082)	0.0058** (0.0024)	0.0292*** (0.0058)	0.0077*** (0.0022)
<i>DebtSto</i> _{<i>t</i>-1}	0.0019*** (0.0006)	0.0002* (0.0001)	0.0001 (0.0002)	-0.0002* (0.0001)
ΔGDP _{<i>t</i>-1}	-0.0041** (0.0020)	-0.0037*** (0.0010)	-0.0024** (0.0011)	-0.0018*** (0.0006)
<i>NatSav</i> _{<i>t</i>-1}	-0.0046** (0.0020)	-0.0004 (0.0008)	-0.0059*** (0.0019)	-0.0009 (0.0006)
<i>Infla</i> _{<i>t</i>-1}	0.0001** (0.0000)	-0.0001 (0.0001)	0.0004 (0.0003)	-0.0000 (0.0001)
<i>REER</i> _{<i>t</i>-1}	-0.0001 (0.0003)	-0.0001 (0.0001)	0.0002*** (0.0000)	0.0000 (0.0002)
<i>Cred</i> _{<i>t</i>-1}	-0.0007 (0.0010)	0.0003 (0.0002)	-0.0018* (0.0009)	-0.0001 (0.0002)
<i>FDI</i> _{<i>t</i>-1}	-0.0151* (0.0085)	-0.0005 (0.0015)	-0.0104* (0.0059)	-0.0028*** (0.0008)
<i>Res/GDP</i> _{<i>t</i>-1}	-0.0629*** (0.0152)	-0.0269*** (0.0069)	-0.0309*** (0.0119)	-0.0085*** (0.0027)
ΔExp _{<i>t</i>-1}	-0.0007** (0.0003)	-0.0006** (0.0002)	0.0001 (0.0002)	0.0002* (0.0001)
<i>CaBal</i> _{<i>t</i>-1}	0.0014 (0.0034)	-0.0005 (0.0009)	0.0029* (0.0016)	-0.0006 (0.0006)
<i>Kaopen</i> _{<i>t</i>-1}	-0.0074 (0.0115)	0.0046 (0.0050)	-0.0173 (0.0162)	-0.0057 (0.0059)
<i>BC</i> _{<i>t</i>-1}	0.0042 (0.0271)	-0.0031 (0.0114)	0.0344 (0.0313)	0.0076 (0.0075)
<i>CC</i> _{<i>t</i>-1}	0.0840*** (0.0295)	0.0229 (0.0165)	0.0299 (0.0217)	0.0052 (0.0124)
Observations	1084	949	1129	1014
Pseudo R^2	0.4635	0.3077	0.4782	0.4342
Log-likelihood	-242.48	-77.50	-212.51	-48.87
Num. countries	33	33	35	35
Num. crises	24	24	17	17

Upper Upper-Middle-Income; Lower Lower-Middle-Income.

(6) Post-crisis entry obs dropped; (8) Post-crisis entry obs dropped.

*, ** and *** denote the 10%, 5% and 1% significance levels, respectively

Table SM3.5: Assessing the performance of Early Warning Indicators

Global (1)						
Predictor :	Res/GDP_{t-1}	$DebtInt_{t-1}$	ΔGDP_{t-1}	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$
β	-0.2137***	0.3699***	-0.1515***	-0.3155***	0.0966***	0.0107***
(σ_β)	(0.0390)	(0.0584)	(0.0152)	(0.0769)	(0.0249)	(0.0033)
Observations	2213	2213	2213	2213	2213	2213
Num. countries	68	68	68	68	68	68
Crises episodes	41	41	41	41	41	41
Log likelihood	-697.7882	-750.6143	-802.3659	-798.2431	-823.5659	-817.0294
Pseudo- R^2	0.1899	0.1286	0.0685	0.0733	0.0439	0.0514
$AUROC$ curve	0.8115	0.7607	0.6905	0.7230	0.7100	0.7292
$AUPR$ curve	0.3503	0.3123	0.2720	0.2481	0.2294	0.2545
Tjur R^2	0.1510	0.1110	0.0630	0.0530	0.0350	0.0450
Brier score	0.0962	0.1013	0.1071	0.1070	0.1095	0.1088
Middle-income countries (3)						
Predictor :	Res/GDP_{t-1}	$DebtInt_{t-1}$	ΔGDP_{t-1}	FDI_{t-1}	$DebtSer_{t-1}$	$DebtSto_{t-1}$
β	-0.1967***	0.4519***	-0.1696***	-0.2963***	0.0899***	0.0107***
(σ_β)	(0.0360)	(0.0534)	(0.0182)	(0.0792)	(0.0258)	(0.0040)
Observations	1898	1898	1898	1898	1898	1898
Num. countries	58	58	58	58	58	58
Crises episodes	36	36	36	36	36	36
Log likelihood	-593.1529	-602.7592	-666.8549	-674.2856	-695.3698	-687.6614
Pseudo- R^2	0.1811	0.1678	0.0793	0.0691	0.0399	0.0506
$AUROC$ curve	0.8052	0.7990	0.6973	0.7265	0.7023	0.7392
$AUPR$ curve	0.3343	0.3308	0.2900	0.2328	0.2183	0.2585
Tjur R^2	0.1400	0.1380	0.0760	0.0470	0.0310	0.0440
Brier score	0.0950	0.0962	0.1031	0.1045	0.1066	0.1055

Variables definitions: Res/GDP = International reserves over GDP ratio; $DebtInt$ = Average interest on new external debt commitments; ΔGDP = Year-on-year growth rate of real GDP; FDI = FDI inflows; $DebtSer$ = Total debt service in % of GNI; $DebtSto$ = External debt stocks in % of GNI.

Table SM3.6: Assessing the performance of ratios (post-crisis onset dropped)

Global (2)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
β	-0.2074***	-0.0971***	0.0001	-0.6118***	0.0068**
(σ_β)	(0.0644)	(0.0173)	(0.0001)	(0.1507)	(0.0032)
Observations	1889	1889	1889	1889	1889
Num. countries	66	66	66	66	66
Crises episodes	40	40	40	40	40
Log likelihood	-169.7063	-163.0820	-193.4248	-171.2995	-192.2605
Pseudo- R^2	0.1242	0.1584	0.0018	0.1160	0.0078
<i>AUROC</i> curve	0.8085	0.8314	0.8003	0.7927	0.7485
<i>AUPR</i> curve	0.0845	0.0708	0.0902	0.0765	0.0724
Tjur R^2	0.0330	0.0360	0.0000	0.0300	0.0010
Brier score	0.0200	0.0200	0.0207	0.0200	0.0206

Middle-income countries (4)

Predictor :	Res/GDP_{t-1}	$Res/Debt_{t-1}$	$StDebt/Res_{t-1}$	Res/Imp_{t-1}	$M2/Res_{t-1}$
β	-0.1846***	0.0940***	0.0001	-0.5523***	0.0056**
(σ_β)	(0.0607)	(0.0182)	(0.0001)	(0.1498)	(0.0027)
Observations	1649	1649	1649	1649	1649
Num. countries	57	57	57	57	57
Crises episodes	35	35	35	35	35
Log likelihood	-149.9809	-142.4468	-169.2728	-151.8690	-168.6604
Pseudo- R^2	0.1150	0.1594	0.0011	0.1038	0.0048
<i>AUROC</i> curve	0.7980	0.8335	0.8161	0.7796	0.7376
<i>AUPR</i> curve	0.0772	0.0700	0.0904	0.0691	0.0648
Tjur R^2	0.0290	0.0360	0.0000	0.0260	0.0010
Brier score	0.0201	0.0200	0.0207	0.0201	0.0207

Variables definitions: Res/GDP = International reserves over GDP ratio; $Res/Debt$ = International reserves to total external debt ratio; $StDebt/Res$ = Short-term debt in % of reserves; Res/Imp = International reserves in months of imports; $M2/Res$ = Broad money to reserves ratio.

Table SM3.7: Correlation matrix for the main explanatory variables

	<i>DebtSer</i>	<i>DebtInt</i>	<i>DebtSto</i>	ΔGDP	<i>NatSav</i>	<i>Infla</i>	<i>REER</i>	<i>Cred</i>	<i>FDI</i>	<i>Res/GDP</i>	ΔExp	<i>CaBal</i>
<i>DebtSer</i>	1.0000											
<i>DebtInt</i>	0.2211	1.0000										
<i>DebtSto</i>	0.4920	-0.0954	1.0000									
ΔGDP	-0.1310	-0.0503	-0.1610	1.0000								
<i>NatSav</i>	-0.0569	0.0707	-0.2892	0.2250	1.0000							
<i>Infla</i>	-0.0023	0.0779	0.0261	-0.0909	-0.0082	1.0000						
<i>REER</i>	-0.0439	0.0193	-0.0001	-0.0314	-0.0953	0.0028	1.0000					
<i>Cred</i>	0.1655	0.0483	-0.0795	0.0549	0.2615	-0.0039	-0.0829	1.0000				
<i>FDI</i>	0.0622	-0.1720	0.0457	0.1777	-0.0417	-0.0359	-0.0803	0.1121	1.0000			
<i>Res/GDP</i>	-0.0332	-0.2162	-0.0815	0.1094	0.3009	-0.0493	-0.0305	0.2897	0.2312	1.0000		
ΔExp	0.0501	0.0161	0.1022	-0.0258	0.0149	-0.0061	-0.0501	-0.0325	-0.0106	-0.0449	1.0000	
<i>CaBal</i>	-0.1078	0.0381	-0.2834	0.0520	0.4845	0.0089	-0.0821	-0.0096	-0.3437	0.1194	0.0995	1.0000

Table SM3.8: Leading indicators and expected signs

Indicator	Expected Sign	Comments	Empirical literature
Total debt service	Positive	Sum of principal repayments as % of GNI	Bird & Rowlands (2001); Detragiache & Spilimbergo (2001)
Interest on new debt	Positive	Average interest on new external commitments	Peter (2002); Lee (1991); Detragiache & Spilimbergo (2001)
External debt stocks	Positive	External Debt Stocks as % of GNI	Ciarlone & Trebeschi (2005); Fuertes & Kalotychou (2007)
Current account balance	Positive/ Negative	Sum of net primary and secondary income to GDP	Chakrabarti & Zeaiter (2014); Manasse et al. (2003)
Exports to GDP ratio	Negative	Sum of total net exports as % of GDP	McFadden et al. (1985); Ciarlone & Trebeschi (2005)
Foreign Direct Investment	Negative	Net inflows of foreign direct investment as % of GDP	Detragiache & Spilimbergo (2001); Odedokun (1995)
Foreign Exchange reserves-to-GDP	Negative	International reserves to GDP (excluding gold)	Detragiache & Spilimbergo (2001) Gourinchas & Obstfeld (2012)
Real GDP growth	Negative	Annual percentage growth rate of GDP	Savona & Vezzoli (2015); Fioramanti (2008)
Inflation GDP deflator	Positive	Annual growth rate of the GDP implicit deflator	Chakrabarti & Zeaiter (2014); Peter (2002)
Real effective exchange rate	Positive	Nominal exchange rate divided by a price deflator	Bird & Rowlands (2001); Peter (2002)
Gross national savings	Negative	Gross national income less total consumption	Lestano et al. (2004); Dawood et al. (2017)
Domestic credit to private sector	Negative	Credit to private sector by banks to GDP	Chakrabarti & Zeaiter (2014) Fuertes & Kalotychou (2007)

Table SM3.9: Sovereign defaults episodes by country (baseline)

Country	Crises episodes	Country	Crises episodes
Argentina	1982-1993 2001-2005 2014-2016	Mexico	1982-1990
Belize	2007-2007 2012-2013 2017-2017	Morocco	1983-1986
Bolivia	1980-1992	Nigeria	1983-1992
Brazil	1983-1994	Peru	1978-1996
Cameroon	1989-1992	Philippines	1983-1992
Congo Rep.	1986-1992	Russia	1998-2000
Costa Rica	1981-1990	Sierra Leone	1977-1995
Dominican Rep.	1982-1994 2003-2005	Sudan	1979-1985
Ecuador	1982-1995 1999-2000 2008-2009	Turkey	1978-1982
Egypt	1984-1992	Uganda	1981-1993
Gabon	1986-1994 2002-2002	Ukraine	1998-1999 2015-2015
Gambia	1986-1988	Venezuela	1982-1990
Guyana	1982-1986		
Honduras	1981-1992		
Indonesia	1999-2002		
Jamaica	1978-1990 2010-2013		
Jordan	1989-1993		
Madagascar	1981-1992		
Malawi	1982-1988		

Table SM3.10: Middle- and Low-income countries in the sample (baseline)

Middle				Low	
Albania	Algeria	Indonesia	Jamaica	Burundi	Central African Rep.
Angola	Argentina	Jordan	Kazakhstan	Gambia	Haiti
Azerbaijan	Armenia	Kenya	Kyrgyzstan	Madagascar	Malawi
Bangladesh	Belize	Lebanon	Macedonia	Nepal	Sierra Leone
Bolivia	Botswana	Mauritius	Mexico	Syrian Arab Rep.	Uganda
Brazil	Bulgaria	Mongolia	Morocco		
Cambodia	Cameroon	Nigeria	Pakistan		
China	Colombia	Papua Guinea	Paraguay		
Comoros	Congo Rep.	Peru	Philippines		
Costa Rica	Dominican Rep.	Russia	Sri Lanka		
Ecuador	Egypt	Sudan	Swaziland		
El Salvador	Fiji	Thailand	Tunisia		
Gabon	Georgia	Turkey	Ukraine		
Guatemala	Guyana	Venezuela	Vietnam		
Honduras	India				

General conclusion

Through this thesis, I attempt to investigate the relevance of several leading indicators of financial crises in middle- and low-income countries. The distinction with advanced countries seemed crucial to me since macroeconomic fundamentals tend to behave differently around crises events depending on income level and financial sector's depth. Furthermore, different types of financial crises can often overlap in middle- and low-income countries which brings an additional challenge to properly assess the role of each leading indicator.

Thus, the aim of chapter 1 was to assess the quality of credit-based variables as early warning indicators of systemic banking crises. The existing literature focuses mainly on developed economies and shows that the best performing indicator is the credit-to-GDP gap computed via one-sided HP filter (the so-called Basel credit gap). The empirical evidence legitimates the use of the credit-to-GDP gap as a key indicator in macro-prudential banking regulation, i.e., in the determination of the countercyclical capital buffer. I take advantage of a new database on bank credit series and credit gaps covering more than 160 countries (Bouvatier et al. (2022)) to focus specifically on middle- and low-income countries. My findings suggest that the BCG remains the single best performing indicator regarding the high-income group while the same does not hold for middle- and low-income countries in which the one-sided credit gap fails to outperform more basic credit metrics. In addition, the results demonstrate that the BCG progressively becomes a fine predictor of banking crises as financial development increases which is assessed by a trend level of the credit-to-GDP ratio greater than 20%. This result highlights that one-size-fits-all approach is not relevant in the design of the operational framework of the countercyclical capital buffer.

A possible extension of chapter 1 would be to explore in greater detail the impact of cross-country heterogeneity on the performance of the BCG. Indeed, bundling both middle- and low-income countries together in the baseline estimation allows to obtain a large sample but also limits a more thorough analysis given the large differences in financial development across

these countries. In addition, the determinants of banking crises in middle- and low-income countries can be substantially divergent from excess credit. Therefore, the poor performance of the BCG could be imputed to the fact that banking crises can be driven by macroeconomic imbalances, capital flights or exchange rate volatility. Finally, chapter 1 could be extended by focusing on country-specific characteristics that are related to a better performance of credit-based indicators: for example, which non-BCBS countries currently implement or are about to implement the CCyB? Are countries with stronger performances more likely to implement the CCyB? Do non-BCBS countries adopt CCyB by relying on different indicators or complementing the BCG with other ones more suited for their context?

In that perspective, chapter 2 aimed to study the the roots of banking and currency crises by investigating the relationship between credit booms and twin crises in 82 middle-income countries over the 1971–2017 span. The model considers both crises phenomena as dynamic events, which are correlated over time. Accordingly, the predicted probabilities are simultaneously estimated using panel data simulation approach. The estimation results indicate that credit booms are relevant in the process of studying twin crises. This outcome is robust to the alteration of currency crises definition. In addition, I show that the Basel Credit Gap (BCG) becomes a leading indicator of banking and currency crises as financial development increases which is captured by a trend level of the credit-to-GDP ratio greater than 10%. Nevertheless, the model fails to detect any direct leading effect stemming from past banking crises to present currency crashes and vice-versa. Further implementations highlight that controlling for the appropriate error term structure prevents spurious estimation links between the twins while a higher development within the financial sector is associated with a lower probability of facing a currency crisis. Eventually, I find strong evidence of unobserved heterogeneity along with correlation among the idiosyncratic shocks suggesting that banking and currency crises are driven by common economic fundamentals in middle-income countries. The main policy implication of those results is that the BCG should be employed, in more financially developed middle-income countries, as an indicator to activate the CCyB therefore helping to sustain the credit activity following both banking and currency crises.

Chapter 2 could be enhanced from a performance assessment perspective. Indeed, the multivariate probit model allows to simultaneously capture the impact of credit booms on the likelihood of twin crises but allows limited performance measurements due to the more complex error term structure. Moreover, capital flows volatility is a notorious feature in middle-and low-

income countries. Therefore, accounting for other types of adverse events such as sudden stops may allow a better reading of the interactions between the twins and credit booms. Finally, the role of sovereign defaults could also be investigated since the currency/debt crisis pair tend to occur as well in middle- and low-income countries. Thus, a trivariate approach may be considered.

The global pandemic context has brought back to the foreground a renewed challenge of designing effective Early Warning Systems for sovereign debt crises. The final chapter aimed to empirically assess the predictive power of several leading indicators in the context of 68 middle- and low-income countries over the 1973-2017 span. My baseline binary logit model displays good performances from the perspective of a policymaker and exhibits that the average interest on new external commitments, the growth of real GDP and the exchange reserves are robust leading indicators of defaults. By relying on a set of performance evaluation criteria, I highlight that the robust indicators stand out compared to the other predictors and perform well at individually predicting debt crises episodes regardless of the specification. Further sensitivity tests performed on consensual reserves ratios, traditionally employed by central banks for the determination of reserves adequacy, yield a good predictive power, even at more distant forecast horizons. I eventually demonstrate that the reserves to total external debt ratio also displays a fine predictive power in an out-of-sample perspective (i.e, in predicting defaults that occurred in the wake of the Covid-19 crisis). The previous outcome highlights that foreign exchange reserves buffers accumulation is an efficient macro-prudential policy instrument in the process of preventing debt crises.

Since there exist no consensual frameworks for the determination of reserves adequacy, a possible extension of chapter 3 could be to determine a composite indicator that covers a broader array of risks such as the short-term debt sustainability combined with the current account deficit. An additional combination metric was proposed by Wijnholds & Kapteyn (2001) which relies on short-term debt and capital outflows to describe the main motivation behind reserves holding. This metrics seems fitting for the specific case of sovereign defaults since the later often occur in countries with important capital flights and exchange rate volatility. An additional research question emerges regarding the optimal reserves ratios: which level of foreign exchange reserves is enough to prevent debt crises? Or conversely, which level of which ratio triggers an alarm so that policymakers can conduct preemptive measures? Which macro-prudential policy instrument is the most fitting in that case?

Finally, it could be argued that the main reason behind reserves holding is the currency management motive as many middle- and low-income countries adopt fixed exchange rate regimes. While this argument can be plausible for some countries, there remain a growing number of middle- and low-income countries that are simultaneously adopting more flexible exchange rate regimes and are still accumulating foreign exchange reserves buffers. Thus, an open question could be: do the reserves ratios also display good performances for debt crises prediction in middle- and low-income countries with more flexible exchange rate regimes?

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