DISCUSSION PAPER SERIES

DP16519

Measuring credit procyclicality: a new database

Anne-Laure Delatte, Vincent Bouvatier and Pierre-Nicolas Rehault

INTERNATIONAL MACROECONOMICS AND FINANCE

MONETARY ECONOMICS AND FLUCTUATIONS

ISSN 0265-8003

Measuring credit procyclicality: a new database

Anne-Laure Delatte, Vincent Bouvatier and Pierre-Nicolas Rehault

Discussion Paper DP16519
Published 06 September 2021
Submitted 01 September 2021

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

Measuring credit procyclicality: a new database

Abstract

Today, the data available to estimate the credit cycle involve a trade-off between country coverage and frequency. In addition, there are pending methodological issues to estimate credit trend and cyclical components. To address these limits, we build a new database on credit metrics that relaxes the trade-off and includes credit procyclicality measures along three alternative methods-HP filter, the modified HP filter and basic SSA. The credit gaps in our database are statistically consistent with bank credit gaps estimated with BIS data and they have the advantage of being available for 163 countries instead of 43 countries. Armed with this new and expanded data, we revisit classic empirical questions in the literature.

JEL Classification: E32, E51, F42

Keywords: Credit cycle, Credit Gap, Cross-countries Comparison, Credit Booms, Global financial cycle, Hodrick-Prescott, Singular Spectrum Analysis

Anne-Laure Delatte - anne-laure.delatte@dauphine.psl.eu
CNRS, Université Paris Dauphine-PSL and CEPR

Vincent Bouvatier - vincent.bouvatier@u-pec.fr
Université Paris Est Créteil, Erudite

Pierre-Nicolas Rehault - pierre-nicolas.rehault@unilim.fr
Université de Limoges

Acknowledgements
The authors thank Gianmaria Milesi-Ferreti and participants to the seminars at CEPII (Paris) for helpful discussions.

Measuring credit procyclicality: a new database *

Vincent Bouvatier[†], Anne-Laure Delatte[‡], Pierre-Nicolas Rehault[§]

September 1, 2021

Abstract

Today, the data available to estimate the credit cycle involve a trade-off between country coverage and frequency. In addition, there are pending methodological issues to estimate credit trend and cyclical components. To address these limits, we build a new database on credit metrics that relaxes the trade-off and includes credit procyclicality measures along three alternative methods- HP filter, the modified HP filter and basic SSA. The credit gaps in our database are statistically consistent with bank credit gaps estimated with BIS data and they have the advantage of being available for 163 countries instead of 43 countries. Armed with this new and expanded data, we revisit classic empirical questions in the literature.

JEL Classification : E 32, E51, F42

Keywords : Credit Cycle; Credit Gap; Cross-countries Comparison; Credit Booms; Global Financial Cycle; Hodrick-Prescott filter; Singular Spectrum Analysis

1 Introduction

Data have contributed in changing financial regulation substantially after the Great Recession (Yellen et al., 2011). For example, capital buffer have been introduced after empirical works documented that credit is pro-cyclical, characterized by a succession of boom and bust phases and that some busts seriously affect investment and growth (Jordà et al., 2011; Schularick and Taylor, 2012; Dell'Ariccia et al., 2016; Jordà et al., 2017).[1] While acknowledging the significant progress in regulation since the Great Financial Crisis, Stein (2021) highlighted its limitations and the gaps that remain to be filled. Therefore, it is key to make sure that credit data and methodology keep on improving to ensure our proper understanding of credit cycles.

Today, the data available to estimate the cyclical component of credit involve a trade-off between country coverage and frequency. Empiricists have two options: either data from the Global

*The authors thank Gianmaria Milesi-Ferreti and participants to the seminars at CEPII (Paris) for helpful discussions.

†Université Paris Est Créteil (UPEC), ERUDITE. E-mail: vincent.bouvatier@u-pec.fr

‡CNRS; Université Paris Dauphine-PSL; CEPR. E-mail: anne-laure.delatte@dauphine-psl.eu

§Université de Limoges, LAPE, Limoges, France. E-mail: pierre-nicolas.rehault@unilim.fr

[1]The seminal works on the macroeconomic implications of finance include Fisher (1933); Gurley and Shaw (1955); Mishkin (1978); Bernanke (1983)

Financial Development Database (GFDD) available at an annual frequency for 160 countries or data from the Bank for International Settlements available at a quarterly frequency for 43 countries (Dembiermont et al., 2013). The majority of works measuring credit cycles use quarterly BIS data in order to maximize the number of observation and get a robust estimate of the long term trend (Dembiermont et al., 2013). Higher frequency is also an advantage to accurately identify the start date and duration of cycles. As a consequence, a majority of works focus on a limited set of countries mostly composed of advanced economies.

In addition to the trade off on data, there are pending methodological issues. Most works use the Hodrick Prescott (HP) filter to estimate credit trend and cyclical components. Yet it has well-documented methodological limitations: the HP filter does not make the distinction between cyclical component and irregular component; it is suspected i) to introduce spurious dynamic relations (Hamilton (2018a), Hamilton and Leff (2020)) and ii) to not disentangle periods of excessive credit activities and periods of financial deepening (Baba et al., 2020). There are several alternatives to HP filters among which the two following ones: on the one hand, the modified HP filter allows to extract the irregular component before applying the HP filter Kaiser and Maravall (1999, 2001); on the other hand, basic Singular Spectrum Analysis (SSA) has the advantage not to be exposed to the HP filter critics on spurious cycle issue. It provides a more flexible framework to define the trend component (no need to specify a frequency cut-off to determine the trend component) and it requires no prior statistical assumptions (e.g., stationnarity of the series), no preprocessing (e.g., log-transformation), and performs well on small samples (Golyandina et al., 2001; Golyandina and Zhigljavsky, 2013). Few works on credit cycle exploit these alternatives.

In this context, our contribution is threefold: we fill data and methodological gaps and provide stylized facts that complement existing works.

First, we build a new database on credit metrics that relaxes the trade-off between data frequency and country coverage. To do so, we collect discontinuous data from the IMF and make adjustments to generate quarterly to generate quarterly series for 163 countries that go back up to Q1 1957. This significantly enriches the coverage compared to the BIS database and increases the frequency of the GFDD database. The cost of a higher frequency is that our database includes a single credit aggregate, bank credit, unlike the BIS database which additionally contains a broader credit aggregate. Second our database includes credit procyclicality measures along three alterative methods- HP filter, the modified HP filter and basic SSA. We show that credit gaps estimated within these three methodologies display similar characteristics on average (while they can differ for a given country and time period). An important result is that that the credit gaps in our database are statistically consistent with bank credit gaps estimated with BIS data but they have the advantage of being available for 163 countries instead of 43 countries.

Third, armed with this new and expanded data, we revisit classic empirical questions in the literature : i) *the size of credit gaps*: their size has increased significantly since the Great Financial Crisis (GFC) with more country heterogeneity: credit cycles are always significantly larger in high income countries than in other countries, but this difference has increased since the GFC- even more in euro area member countries; ii) *domestic credit cycles and the Global financial cycle* : they have behaved independently from each other and so have domestic credit cycles and the US domestic financial cycle. There is no evidence of synchronicity and on the contrary, domestic and international cycles have shown less and less similar dynamics over time. The exception is euro area countries which have a more similar cycle to the US domestic credit cycle; iii) *credit gaps around banking crises*: credit gaps turn positive and increase strongly four years before banking crises; one quarter before the banking crisis, credit gap reach 10% in high income countries versus 2.8% in other countries; then, credit gaps adjust downward for 6 years after banking crises and the adjustment is substantially more pronounced in high income countries iv) *credit booms*: since 1957, countries have spent one sixth of the time in a credit boom episode but booms have become more frequent and more intense recently: the frequency of booms has increased by 10 pp from the globalization (1984-2007) to the financial shock periods (2008-2018); credit gaps increase fast during the first quarters of credit booms which last around 2 years; booms materialize faster and they are more intense in high income countries and in euro area member countries: credit gaps reach more than 6% in high income countries and between 2 and 4% in other countries.

Related literature Our work speaks to empirical works documenting the credit cycle (Drehmann et al., 2010; Mendoza and Terrones, 2012; Borio, 2014; Dell'Ariccia et al., 2016), procyclicality and the build-up of financial vulnerability (Stremmel, 2015; Giese et al., 2014; Hiebert et al., 2014; Drehmann and Juselius, 2014; Drehmann and Tsatsaronis, 2014). We revisit several classic questions of the literature with our new quarterly data. An important question is the degree of similarity or synchronicity between financial cycles of different countries and the role of global factors in the determination of domestic financial cycles (Cerutti et al., 2019; Monnet and Puy, 2019; Jordà et al., 2019).[2] The fact that only annual credit data were available for a broad sample of countries so far has prevented to estimate long run trend and subsequent credit gaps. Our contribution is to revisit the question based on robust credit gaps. In addition, empirical investigations suggest that the gap in the credit-to-GDP ratio is an appropriate indicator to capture the risk of banking crises (e.g., Drehmann et al. (2010, 2011); Drehmann and Juselius (2014)). Unfortunately, the sample of these works include only few low and middle income countries. Our contribution is to re-examine this question using the largest available data set. Last, there has been an important literature about credit booms and boom-bust cycles since Gourinchas et al. (2001); Barajas et al. (2007); Mendoza and Terrones (2008); Dell'Ariccia et al. (2016). Here again, our quarterly data and extensive country coverage are an asset to address some methodological challenges met by these works.

The remaining of the paper is organized as follows. Section 2 presents the construction of our database, provides descriptive statistics and compares them with credit gaps based on BIS credit series. Section 3 documents the dynamics of credit-to-GDP including the synchronicity of domestic and global financial cycles and the credit gaps dynamics around banking crises. Section 5 examines credit booms and boom-bust cycles.

2 A new database

Our database is distinct from the BIS database (Dembiermont et al. (2013)): i) we cover 163 countries versus 43 countries; ii) we compute the cycle series using HP filter, modified HP filter (Kaiser and Maravall (1999, 2001)) and basic SSA. It is also distinct from GFDD credit series available: i) credit series are quarterly; ii) the database contains trend-cycle decompositions.

[2]Monnet and Puy (2019) also assemble quarterly dataset with a long coverage using IFS credit data. However their dataset includes 45 countries only (21 advanced economies and 24 emerging market economies).

2.1 Data

Nominal credit series

We use the International Financial Statistics (IFS) database by the IMF which provides quarterly data of credit granted by the banking sector to the private domestic sector. The cost of providing series on a broader sample is a narrower definition of credit (bank credit) compared to BIS which provides an additional borader aggregate (private credit). Our coverage in terms of country is slightly lower than GFDD because we exclude countries with less than 80 observations, i.e., two decades, to get more reliable trend-cycle decompositions as well as countries that do not report data after 2017.

A modification in the presentation of monetary statistics in the IFS database (IMF (2017)) implies discontinued series that we have adjusted to generate the final credit series (we describe data in more details as well as these adjustments in Appendix A).

The database that we compile covers 163 countries on a quarterly basis and credit series can date back to 1957Q1. For a sake of comparison, we also include the BIS credit series (narrow and broad) in our database.

Credit-to-GDP ratios and real credit series

Nominal credit series are used to compute credit-to-GDP ratios and real credit series.

We extract quarterly nominal GDPs (in domestic currency) from the OECD database and from the IFS database. When there are no historical data at the quarterly frequency, annual GDP are converted to quarterly GDP using linear interpolation.[3] When GDPs taken from the OECD and IFS databases are not seasonally adjusted, we apply seasonal adjustment (US Bureau of the Census (2013)). In addition, nominal credit series are divided by GDP deflators to get real credit series. We extract GDP deflators from the OECD database and the IFS database. Some GDP deflators require similar management as nominal GDPs (e.g., linear interpolation of annual data).

We end up with credit-to-GDP ratios and real credit series for 163 countries. The list of countries, the start and end dates of the available period are reported by country in Appendix A.

2.2 Measuring credit procyclicality

A trend is the general direction towards which a variable is moving in the long run, and its cyclical component is the series variation around their trend. A methodological challenge is therefore to define the "long run", i.e. the time span over which at least an entire cycle can be observed. According to the BIS (BCBS (2010)), the periodicity of credit cycles can reach 2 or 3 decades. It implies that the long cycle component associated with a periodicity of around 3 decades should not be associated with the trend component; the latter should only capture low frequencies associated with periodicity higher than 4 decades. In other words, credit activities can contain a medium-term cyclical component that should not be included in the long-term secular trend.

We consider 3 different methods ranked by their ability to meet this challenge: the HP filter (i.e., the BIS approach), the modified HP filter proposed by Kaiser and Maravall (1999, 2001), and

[3] Alternatively, Monnet and Puy (2019) use temporal disaggregation methods (Chow Lin, 1971) to create "synthetic" quarterly GDP series based on annual GDP series and historical quarterly Industrial Production (IP) data. To check the consistency of our method, we show below that our series are very similar to the BIS quarterly credit-to-GDP.

basic SSA. In addition to offer a flexible method to address the issue of medium-term cyclical components, another valuable advantage of basic SSA is that it does not impose a predetermined interval for the periodicity's of the cyclical component. It is particularly relevant when the length of credit cycles noticeably varies across countries (Gonzalez et al., 2015). We provide a detailed presentation of each method in Appendix B.

Each method is applied within two approaches: the two-sided approach considers the full sample, i.e. forward observations, to identify the trend. In turn, the one-sided approach considers only backwark data, which is recommended by the BIS for operational reasons (BCBS (2010)).

In total, we end up with 6 different measures applied to credit series expressed in real terms and in percentage of GDP.

2.3 Descriptive statistics

Table 1 reports descriptive statistics of credit gaps obtained from the 6 alternative methodologies just described and 3 measures of size consistent with zero-mean gaps: standard deviation, mean of absolute values and average geometric distance (we compute the average geometric (i.e. Euclidean) distance to zero at the country level and then we compute and report the mean over the sample of 163 countries). A bird's eye view of Table 1 indicates that alternative methodologies and size measures yield similar results with the size of the credit gaps being slightly lower with the two-sided approach than with the one-sided approach.

More precisely, credit gaps in absolute values are around 5% on average. Percentiles indicate that 90% of the time, credit gaps are between -11.67% and 12.56% when variable the Basel gap is considered (one-sided HP filter). The frequency of extreme values is higher than in a normal distribution, as suggested by the kurtosis larger than 3. For instance, the minimum value of -100% was recorded by Cyprus in 2018 and the maximum value of 100% by Iceland in 2006-2007. Last, credit gaps obtained from the different methodologies display similarities in terms of persistence, with the first order autocorrelation around 98%.[4]

We compare the alternative methodologies in a scatter plot on Figure 1: the differences in credit gaps computed with HP and modified HP rarely exceed 2.5%. More precisely, for two-sided credit gaps, the mean and the median of differences (expressed in absolute values) are 0.28% and 0.22% respectively. In sum, treating the irregular components, as modified HP does, does not significantly change the results. Not surprisingly, differences between SSA and HP/ modified HP are larger: the mean and the median of differences, expressed in absolute values are 2.04 and 1.62 respectively for two-sided credit gaps. Differences can exceed 2.5% for some countries (in absolute values).

In total, credit gaps obtained by different methodologies display similar characteristics while estimated credit gaps for a given country and time period can noticeably differ across methodologies.

2.4 Comparison with BIS credit series

How do our data compare with BIS data? Table 2 reports statistics on credit series and credit gaps computed with BIS series and with our data. All credit gaps are estimated with the two-sided SSA

[4]The high persistence is due to the fact that the medium-term cyclical component associated with periodicities up to 4 decades is kept to generate credit gaps.

methodology. Bear in mind that the credit series in the BIS database include both narrow credit and broad credit series (i.e., bank credit and private credit) and covers only 43 countries. We carry the comparison on the same 43 countries.

Panel A in Table 2 compares bank credit data (only the ”narrow” credit in BIS denomination). The first column compares variables in level. On average, our bank credit series are 6.95% higher than in the BIS database. The average difference is limited but the ratio reaches 3.1493 in the case of Luxembourg. In fact, we rely on the euro area -wide residency criterion instead of the national residency criterion which explains why the difference can be large for small highly *integrated* economies within the euro area.

The rest of the Table compares credit gaps. The correlation between the two bank credit gaps is 0.8670 suggesting a strong relationship. The C-index indicates a high synchronization in credit gap changes: bank credit gaps move in the same direction 87.19% of the time.

However, correlation coefficient and C-index do not assess the difference in gaps values or amplitude scaling. We compute alternative distance measures to quantify the absolute magnitude of the difference between the gaps calculated with BIS data and our data.[5] The average Manhattan distance is 2.6361 and the average Euclidean distance, more sensitive to outlier values, is 0.2632. They are both fairly limited compared respectively to the mean of absolute values (4.1287) and the average geometric distance (0.4222) reported in Table 1. Last, we use Dynamic Time Warping (DTW) to assess similarity without imposing a pre-defined fixed temporal alignment of credit gaps.[6] The Manhattan and the Euclidean distances obtained with DTW fall to 1.5501 and 0.1736 respectively.

In total, correlation coefficient, C-index and distance measures show that bank credit gaps in our database are closed to the ones computed from BIS bank credit series.

Panels B and C in Table 2 compare bank credit series and gaps with BIS private credit (”large” credit). Starting with level series, our bank (narrow) credit in Panel B represents 69.43% of BIS private (large) credit (as a comparison BIS narrow credit in Panel C represents 66.67% of BIS large credit). Correlation and C-index are 0.7527 and 0.8004 respectively.

Dissimilarities are more sizable when gaps values are considered. For instance, the average Manhattan distance increases from 2.6361 to 4.4890 between Panel A and Panel B. The average Euclidean distance and the DTW distances confirm this noticeable increase.

In conclusion, the credit gaps in our database are in line with BIS bank credit gaps but they have the advantage of being available for 163 counties instead of 43 countries. Not surprisingly, the dissimilarity is more noticeable when BIS private credit gaps are considered, particularly due to disparities is gaps values.

[5]We consider average Manhattan and Euclidean distances to take into account that sample sizes are different across countries. The same standardization is applied when Dynamic Time Warping (DTW) is used afterwards to assess similarity.

[6]DTW is an elastic dissimilarity measure. Distance between two credit gaps is not only computed with observations aligned on the time axis. DTW allows the matching of observations beyond a temporal alignment. In other words, DTW allows to get distance measures not sensitive to alternations between leading and lagging relationships of credit gaps. See Liao (2005) for a survey on distance measures and Franses and Wiemann (2018) for an application of DTW to compare business cycles.

3 Dynamic of credit-to-GDP ratios

In this Section, we exploit the long time dimension and the large cross-sectional dimension of our database to document the dynamic of credit-to-GDP ratios. Bear in mind that our data combine quarterly frequency and large country coverage, a fact that allows a solid estimate of credit gaps for a large set of countries. In fact, the majority of works on credit gap use quarterly BIS data in order to maximize the number of observation to estimate the long term trend with an HP filter (Dembiermont et al., 2013). As a consequence, these works focus on a set of 43 countries, mostly developed countries. Can the conclusions and recommendations be generalized to all countries? Our dataset has the advantage to extend the quarterly frequency to 163 countries.

In the following, we consider the subgroups of: (*i*) high income countries (according to the World Bank classification); (*ii*) euro area countries; (*iii*) middle & low income countries. This allows us to highlight differences in the dynamics of credit-to-GDP ratios along income groups of countries, and provide a specific focus on euro area countries. In the time dimension, we decompose the full sample (1957-2018) into 4 subperiods: 1957-1972 (Bretton Woods period), 1973-1983 (oil shock period), 1984-2007 (globalization period) and 2008-2018 (financial shock period).[7] Further, we also make a specific focus on the subperiod 2010-2018 to document the post Global Financial Crisis (GFC) period more precisely. In the cross-country dimension, We start with the long-term trend of credit-to-GDP before documenting to the cyclical components of credit (credit gaps).

3.1 Trends in credit-to-GDP ratios

Trends in credit-to-GDP ratios can be regarded as indicators of banking deepening and inform on the the importance of bank credit activities in economies. Table 3 reports the average trend level in credit-to-GDP ratios (in %) by subperiods and subgroups of countries.

We observe that trend levels increase over time. In fact, the whole sample average trend level was 21.81% during the Bretton Woods period and reached 56.61% during the financial shock period (2008-2018). The 5% and the 95% percentiles, equal to 4.41% and 110.69% respectively, illustrate the large country heterogeneity in the database. And in fact, the average trend level for high income countries was 35.75% during the Bretton Woods period and reached 94.76% during the financial shock period. These levels are even more pronounced in the euro area countries (14.74% and 122.23% resp.). In turn, the average trend level does not excess 40% in middle & low income countries over the recent period.

We examine the dynamic of banking deepening in Table 4 which reports descriptive statistics on year-on-year trend growth rates over the full sample and by sub-periods. Over the full sample, the average trend growth rate is 3.03% emphasizing the substantial development of bank credit activities since the late 50s. This average trend growth rate is relatively stable over the sub-periods but there is a large cross country heterogeneity. Indeed, the standard deviation of the trend growth rate is 4.78 over the full sample which is quite larger than the sample mean and extreme trend growth rates are not rare events as suggested by a kurtosis equal to 11.49. Trend growth rates

[7] This time decomposition is used for instance by Monnet and Puy (2019) to isolate and compare periods of global shocks. Notably, a particular attention can be paid to the globalization period that can be compared with the pre and post globalization periods.

vary between -3.27% and 10.84%, 90% of the time.

To complete the analysis, we examine cross-country heterogeneity in the Table 5 which displays the average trend growth rates by subgroups of countries and sub-periods and reports mean comparison tests. We observe that the trend growth rate is higher in middle and low income countries than in high income countries over the whole period, and that the banking deepening has been decelerating in high income countries. The slowdown in trend growth rates is particularly true in euro area countries. In total, we observe a catching up process by middle & low countries and a slowdown of banking deepening in high income countries.

3.2 Size of credit gaps

Table 6 reports descriptive statistics on bank credit gaps over the full sample and by subperiods. As in Table 1, we rely on the standard deviation, the mean of absolute values, and the average geometric distance to capture the average size of bank credit cycles.

Table 6 suggests that the size of the cyclical component of credit-to-GDP ratios has noticeably increased over the financial shock period: the mean of absolute values was 3.64 during the globalization period (1984-2007) and reached 5.68 during the financial shock period (2008-2018). Cross-country heterogeneity also increased over the last subperiod. For instance, the 90% interval was [-8.25;8.60] during the globalization period and increased to [-14.48;11.09] during the financial shock period. The importance of busts during the financial shock period can be illustrated by the negative skewness (-1.25).

Countries heterogeneity is more precisely illustrated in Table 7 that displays standard deviations of credit gaps by subgroups of countries (and subperiods) and reports variance comparison tests. Table 7 shows that the size of credit cycles is always significantly higher in high income countries. Further, this difference was more pronounced during the financial shock period. Turning to euro area countries, the credit cycles display similar characteristics than the ones displayed by the full group of high income countries, except during the financial shock period when the size of credit cycles was even larger.

3.3 Credit gaps and the global financial cycle

An important question is the degree of similarity or synchronicity between financial cycles of different countries and the role of global factors in the determination of domestic financial cycles. (Cerutti et al., 2019; Monnet and Puy, 2019; Jordà et al., 2019). Credit gaps computed from credit-to-GDP ratios are commonly considered as one of the components of domestic financial cycles (DFCs) (Drehmann et al. (2012). However, the annual credit data available so far for a larger sample of countries than the quarterly data preclude a robust estimate of credit gaps, as the amount of data is not sufficient to properly estimate HP filter credit trends. Therefore, the combination of quarterly data on a long time span and a broad sample of counties allows us to revisit the question using credit gaps.

First, we investigate the relationship between credit gaps (DFCs) and the global financial cycle (GFCy), using the measure of Miranda-Agrippino et al. (2020). The latter is available over the period 1980-2019 and captures the common component in asset prices and international capital flows. We rely on our usual indicators to investigate the relationship between domestic credit cycles and GFCy (i.e., correlation, distance measures and concordance index). In addition, we compute a synchronicity index to test whether positive and negative values of cycles coincide.[8]

The results are reported in Table 8. Considering the whole period and the full sample of countries, correlation, synchronicity index and concordance index suggest that domestic credit cycles and the GFCy behave independently from each other. Our results are in line with Aldasoro et al. (2020) who showed that the GFCy is shorter than DFCs and that DFCs can be asynchronous. However, they use BIS data over the 1981-2018 period and compute the DFCs for 20 countries. Our data therefore extend the analysis in time and country coverage.

When all countries are considered, correlations, synchronicity and concordance suggest the absence of similar patterns between domestic credit cycles and the GFCy over all subperiods. It is striking that the cycles display less and less similar patterns: e.g. the Manhattan distance increases from 3.78 to 5.72 between the globalization period and the financial shock period. We reach similar conclusions when the sub-sample of high income countries is considered.

It is somehow different for the sub-sample of euro area countries during the financial shock period. Correlation, synchronicity and concordance indexes record higher values suggesting that domestic credit cycles and the GFCy behave more similarly. The amplitude of credit gap is particularly pronounced during this period (see Table 7) implying large distance measures.

We also investigate the relationship between domestic credit cycles and the US DFC to account for the centrality of the US cycle (Miranda-Agrippino et al., 2020). Results are reported in Table 9. We reach similar results than the ones obtained from Table 8. Correlation, synchronicity and concordance are noticeable only when the sub-sample of euro area countries is considered during the financial shock period. Further, distance measures show that disparities increased both during the globalization period and the financial shock period relatively to the previous periods.

In conclusion, we find no evidence of synchronicity between domestic credit cycles patterns and the global financial cycle nor the US domestic credit cycle contrary to Jordà et al. (2019) but in line with Monnet and Puy (2019) who find only a modest impact of the world cycles on domestic credit outside periods of global real and financial shocks on a sample of 45 countries.

3.4 Credit gaps around banking crises

Several empirical investigations lead to the conclusion that the gap in the credit-to-GDP ratio is an appropriate indicator to capture the risk of banking crises (e.g., Drehmann et al. (2010, 2011); Drehmann and Juselius (2014)). However the sample of these works include only few low and middle income countries. Should middle and low income countries also rely on the credit gap when they design macroprudential policy? Again we revisit this question armed with our data.

In order to document credit gaps dynamics around banking crises, we use the ESRB database as a first source to identify banking crises periods (Lo Duca et al. (2017)). This database covers all EU Member States and Norway for the period 1970-2016.[9] We complete the data with Laeven and Valencia (2018) to identify banking crises periods in countries not covered by the ESRB database.

[8]The synchronicity index (used in Mink et al. (2012)) is defined as:

$$\varphi_{i,t} = \frac{CY_{i,t} \times GFC_t}{|CY_{i,t} \times GFC_t|},$$

where $CY_{i,t}$ is the domestic credit cycle in country i at period t, and GFC_t is the global financial cycle at period t. This index is defined on a $[-1;1]$ scale. This index is then averaged over countries and time periods.

[9]Banking crises (starting dates and ending dates) are identified on a monthly basis in the ESRB database.

This database reports 151 systemic banking crises episodes in 118 different countries during 1970-2017.[10]

Our series of credit gaps do not cover all the banking crisis episodes reported in Lo Duca et al. (2017); Laeven and Valencia (2018). We end up with 106 banking crises recorded in 84 different countries for which credit gaps are available.

First, we give a functional form to credit gaps before a banking crisis using a spline function:

$$Y_{i,t} = \alpha_0 + \sum_{j=0}^{n} b_j Basis_{j,i,t} + \varepsilon_{i,t}, \tag{1}$$

where the subscripts refer to country i in period t. The variable $Y_{i,t}$ is the two-sided credit gap computed by SSA (i.e., variables CY_{gap}^{SSAts}). The variables $Basis_j$ ($j = 0, ..., n$) are the basis variables obtained from a restricted cubic spline function, b_j ($j = 0, ..., n$) are parameter estimates, α_0 is the intercept and $\varepsilon_{i,t}$ the residual. We rely on a spline function depending on variable $d_{i,t}$, the number of quarters until the next banking crisis in country i (with $d_{i,t} = 1, 2, ..., D$).[11] The parameters α_0 and b_j are estimated by ordinary least squares (OLS), and the standard errors are clustered at the country level.

We allow the specification to vary across income groups:

$$Y_{i,t} = \alpha_0 + \sum_{j=0}^{n} b_j Basis_{j,i,t} + \sum_{j=0}^{n} b_j^{High} Basis_{j,i,t} \times D_i^{High} + \alpha_1 D_i^{High} + \varepsilon_{i,t}, \tag{2}$$

where D_i^{High} is a dummy variable equal to 1 if country i is classified as high income country and 0 otherwise. Therefore, the interaction variables $Basis_{j,i,t} \times D_i^{High}$ capture whether credit gaps dynamics around banking crises are different for high income countries (the group of high income countries is time-invariant).

Second, we rely on the same empirical approach to assess patterns of credit gaps *after* banking crises. We modify Eq. (1) and (2) so that the spline function depends on the variable $\tilde{d}_{i,t}$ marking the number of quarters since the end of the last banking crisis in country i (with $\tilde{d}_{i,t} = 1, 2, ..., \tilde{D}$). The second model specification and its extension capture to which extent credit gaps adjust downward after banking crises, and whether credit gaps in high income countries behave similarly than in middle & low income countries.

Figure 2 shows the dynamics of (two-sided) credit gaps around banking crises. Figure 2-a (based on Eq. (1) and (2)) shows that credit gaps turn positive and increase strongly 16 quarters before banking crises, and they reach 5.6% the quarter before the starting date. In addition, Figure 2-d shows that this pattern is way more pronounced in high income countries; credit gaps reach 10% the quarter before banking crises in high income countries, versus 2.8% in other countries. In sum, credit gaps do not provide a particular signal before banking crises on average in middle and low income countries.

Figure 2-b shows the dynamics of credit gaps after a banking crisis. Credit gaps adjust downward during 6 years after a banking crisis and shift from 6.2% to -3.4%. Note that the size of

[10] Starting dates of banking crises are identified on a monthly basis or yearly basis. When only the starting year is available, we assume the banking crisis starts during the first quarter. The ESRB database does not have this limitation but focuses on a more limited number of countries.

[11] Computational details concerning the variables $Basis_j$ are reported in Appendix C and a general presentation of spline functions can be found in Poirier (1976).

the adjustment differs across income groups: the downward adjustment is more pronounced in high income countries (from 13% to -7.8%), implying that banking crises materialize through a 20 percentage points drop of credit gaps in high income countries.

4 Credit booms

There has been an important literature about credit booms and their macroeconomic consequences since Gourinchas et al. (2001) (see Dell'Ariccia et al. (2016) for a review). Several procedures are used to estimate the trend-cycle decomposition of credit activities and they overall yield robust and consistent results according to Dell'Ariccia et al. (2016). Important methodological challenges include to i) determine the level of growth rate of credit-to-GDP that can be considered as abnormally high; ii) accurately identify the beginning and ending date of boom episodes (Barajas et al., 2007). Here again, our quarterly data and extensive country coverage are an asset to address these methodological challenges: i) higher frequency allows a more accurate identification of beginning and ending date of the boom; ii) while the mostly used HP filter is sensitive in small sample, we address this issue by relying on a large number of observations and the SSA approach.

4.1 Identification of credit booms

Our sample includes 163 countries with some data starting in 1957 and extending to 2018. We follow the definition of Barajas et al. (2007) to define credit booms. An important feature of Barajas et al. (2007) is to propose a country-and-time specific definition of credit booms. However, in an international regulatory surveillance perspective, an absolute numerical threshold definition of credit booms can be easier to interpret (BCBS (2010)). Therefore, we compare Barajas et al. (2007) with a definition of booms in line with the guideline of the BCBS.

First, we assume that a credit boom takes place if one of the two conditions is observed: (i) the credit gap is greater than 1.5 times its standard deviation and the year-on-year growth rate in the credit-to-GDP ratio exceeds 10% during two consecutive quarters; (ii) the year-on-year growth rate in the credit-to-GDP ratio exceeds 20% during two consecutive quarters.[12] The starting point is the earliest period in which: (i) credit gap is greater than 0.75 times its standard deviation and the year-on-year growth rate in the credit-to-GDP ratio exceeds 5%; (ii) the year-on-year growth rate in the credit-to-GDP ratio exceeds 10%. Analogously, a credit booms ends the period in which: (i) credit gap is lower than 0.75 times its standard deviation and the year-on-year growth rate in the credit-to-GDP ratio is lower than 20%; (ii) the year-on-year growth rate in the credit-to-GDP ratio is negative.

Second, we define regulatory credit booms as periods with bank credit gaps higher than 2% for 4 consecutive quarters, and the end is after 2 consecutive quarters below 2%, in line with the guideline of the BCBS (BCBS (2010)). Regulatory credit booms capture episodes during which banking supervisors would be advised to act to dampen excessive credit activities if the CCyB was in force. Here, the quarterly frequency is valuable to properly assess credit gaps. Regulatory credit booms capture episodes during which banking supervisors could act to dampen excessive

[12] We use rolling backward-looking country-specific standard deviations. More precisely, for a given country, we use recursive windows where the first periods are fixed (the starting date of the sample) to compute standard deviations. We use a minimum window of 40 observations (i.e., 10 years) to compute standard deviations.

credit activities if the CCyB was in force.

Results are reported in Table 10: i) we identify between 312 and 359 boom episodes depending on the threshold definition. This translates into 14 to 24 percent probability of a country experiencing a credit boom in a given year (put it differently, on average countries have spent 14% of the time in a credit boom episode). (ii) keeping Barajas et al. (2007)'s threshold definition, we find that the frequency of booms is higher in low & middle income countries than in high income countries (15% vs 11%) which is consistent with the idea that credit booms are associated with catching up effects as mentioned in Dell'Ariccia et al. (2016); iii) however, the picture is different with the absolute threshold. The frequency of booms is higher for every countries and this is more pronounced for high income countries where booms are more frequent than in middle & low income countries (30% vs 21% of the time). Note that Barajas et al. (2007)'s identification requires year-on-year growth rate of the credit-to-GDP ratio larger than 10%, which is unlikely when credit-to-GDP ratio is already high as it is in high income countries; iv) the average duration is around 3 years on average for the whole sample (2.43 and 3.53) and high income countries experience slightly longer episodes than middle & low income countries; (v) the median duration is lower than the mean, suggesting that numerous credit booms are short-lived. However, some countries can experience long-lasting booms as suggested by the 95% percentile of credit boom duration between 5.75 and 7.5 years for the whole sample.

4.2 Boom-bust cycles

Now, we examine boom-bust cycles. We use only the absolute threshold definition for the sake of clarity, i.e. regulatory credit boom and bust periods are defined as periods with bank credit gaps higher/lower than 2.%/ -2% respectively (the 2% corresponds to the guidelines of BCBS (2010) and -2% is an *ad hoc* symmetric threshold).

Results are reported by subgroup of countries and sub-periods in Table 11. The frequency of booms has increased by 10 pp from the globalization (1984-2007) and the financial shock periods (2008-2018) and represents 33.99% of the time over the recent period. We observe a similar increase in the frequency of boom and bust periods (64.67% of time over the recent period).

We add an intensity measure to the analysis by computing the additional capital requirements that would have prevailed during boom periods if the CCyB had been applied in every countries over the whole period.[13] Table 11 shows that the intensity of boom periods has increased monotonically from the oil shock period (1973-1983) corresponding to a CCyB of 0.9207% to the financial shock period (2008-2018) with the CCyB mean rate equal to 1.1429%. In sum, boom periods have become more frequent and more intense over the periods.

Turning to the heterogeneity across countries, Table 11 reports the different indicators by subgroups of countries (and subperiods) and proportion comparison tests. Results suggest that booms are more frequent and more intense in high income countries and in euro area member countries.

In the following, we characterize the credit boom in more detail.

[13] When the credit gap ($CY_{gap,t}$) is between the 2% lower threshold and the 10% upper threshold, the CCyB rate is interpolated linearly using the standard formula: $0.3125 \times CY_{gap,t} - 0.625$. When ($CY_{gap,t}$) exceeds 10%, the CCyB rate is capped at 2.5%.

4.3 Typical credit booms

What does a typical credit boom look like? We answer in three steps.

First, we document the dynamics of credit gaps during credit boom episodes. We use the same strategy as in Section 3.4 but we focus on the functional form of credit gap during credit booms only:

$$Y_{i,t} = \alpha_0 + \sum_{j=0}^{n} b_j Basis_{j,i,t} + \varepsilon_{i,t}, \tag{3}$$

where the subscripts refer to country i in period t. The variable $Y_{i,t}$ is the two-sided credit gap computed by SSA and the sample is only made-up of credit boom episodes. The variables $Basis_j$ ($j = 0, ..., n$) are the basis variables obtained from a restricted cubic spline function, b_j ($j = 0, ..., n$) are parameter estimates, α_0 is the intercept and $\varepsilon_{i,t}$ the residual. The spline function depends on the variable $d_{i,t}$ marking the number of quarters since the beginning of the credit boom (with $d_{i,t} = 1, 2, ..., D$).

In sum, when we estimate Eq. 3, we characterize credit gaps depending on the number of quarters since the beginning of the credit boom $\hat{Y}_d$ (with $d = 1, 2, ..., D$). We exploit the broad country coverage to test whether patterns of credit gaps during credit booms are different by income group:

$$Y_{i,t} = \alpha_0 + \sum_{j=0}^{n} b_j Basis_{j,i,t} + \sum_{j=0}^{n} b_j^{High} Basis_{j,i,t} \times D_i^{High} + \alpha_1 D_i^{High} + \varepsilon_{i,t}, \tag{4}$$

where D_i^{High} is a dummy variable equal to 1 if country i is classified as high income country and 0 otherwise.

Results are reported in Figure 3-a and b. There is a noticeable difference of dynamics during boom episodes across income group: credit gaps grow faster and higher in high income countries. This is particularly true when we use Barajas et al. (2007)'s definition of credit boom (see Figure 3-a). As we already mentioned, Barajas et al. (2007)'s definition is more restrictive than the absolute threshold definition so it is logic that credit booms passing the test are seriously more severe. Similarly, they last less than in the second definition. These differences vanish in the second and third step precisely because we account for the survival rate of a boom. Another interesting pattern concerning all income groups is that credit gaps can remain high during long-lasting credit booms.

Now, we would like to account for the fact that long-lasting credit booms are rare events. To do so, we estimate the hazard function, i.e., the conditional probability that a credit boom ends given a time elapsed since its start. Pooled discrete-time duration models offer a flexible empirical solution: to capture the time dependence in the probability that a credit boom ends, we estimate a logit specification including a spline function:

$$P(CB_{i,t} = 1) = \frac{1}{1 + \exp\left[-\alpha_0 - \sum_{j=0}^{n} b_j Basis_{j,i,t}\right]}, \tag{5}$$

where the subscripts refer to country i in period t. The variable $CB_{i,t}$ is a binary variable equal to 1 if a credit boom ends and equal to 0 otherwise. The variables $Basis_j$ ($j = 0, ..., n$) are the basis variables obtained from a restricted cubic spline function and depend on the number of quarters since the starting date of the credit boom.[14] The parameters α_0 and b_j are estimated by maximum likelihood.[15] In sum, when we estimate Eq. 5, we assess the probability that a credit boom ends ($P(CB_{i,t} = 1)$) only depending on the number of quarters since the beginning of the credit boom. Therefore, we can quantify the conditional probability $\hat{H}_d$ (with $d = 1, 2, ..., D$) that a credit boom ends after d periods given that it has lasted to that point (i.e., the hazard at time d). As previously, we examine whether the shape of the hazard function differs across income categories:

$$P(CB_{i,t} = 1) = \frac{1}{1 + \exp\left[-\alpha_0 - \sum_{j=0}^{n} b_j Basis_{j,i,t} - \sum_{j=0}^{n} b_j^{High} Basis_{j,i,t} \times D_i^{High} - \alpha_1 D_i^{High}\right]}, \quad (6)$$

where D_i^{High} is a dummy variable equal to 1 if country i is classified as high income country and 0 otherwise. In Eq. 6, the interaction variables $Basis_{j,i,t} \times D_i^{High}$ capture whether the hazard function is different for high income countries.

Figure 3-c and d report the results across income groups. Bear in mind that we measure the probability that a credit boom ends, so upward sloping trend reflects a lower survival rate. We observe that credit booms generally exceed 1 year and end before 2 years (the hazard rate exceeds 10% after 2 years). However the hazard function is not monotonically increasing, meaning that some countries can experience longer credit boom episodes. In sum, credit booms lasting 2 to 3 years are not rare events. The slope of hazard function is steeper in high income countries for duration that exceed 4 years, suggesting that long lasting credit booms are very rare in high income countries. Note that the hazard function in middle & low income countries remains above 10% most of the time so long lasting episodes are less rare but are neither a common feature in these countries.

Last, we combine step 1 and step 2 to describe the typical credit boom defined as:

$$TCB_d = \hat{Y}_d \times \hat{S}_d, \quad (7)$$

where $\hat{Y}_d$ is from Eq. 4 and $\hat{S}_d = (1 - \hat{H}_1)(1 - \hat{H}_1)...(1 - \hat{H}_{d-1})$ is the survival function at time d that is written in terms of the hazard at all prior times.

Figure 3-e and f reports the results: credit gaps increase fast during the first quarters of credit booms which last around 2 years; the speed and magnitude of credit gaps during boom episodes differ significantly across income groups: credit gap reaches more than 6% in high income countries while they reach between 2 and 4% in middle & low income countries.

In total, our results suggest that credit booms are more severe and they materialize faster in high income countries than in middle & low income groups.

5 Conclusion

In total, our database includes credit metrics for a novel sample of countries and their corresponding trend-cycle decomposition along three alternative methodologies. We show that the

[14] A general presentation of discrete-time duration models can be found in Beck et al. (1998).

[15] The standard errors obtained from the clustered version (on country level) of the Huber-White estimator of the variance, are robust to heteroscedasticity.

three methodologies yield credit gaps with similar characteristics on average. In addition, credit gaps in our database are statistically consistent with those estimated with BIS bank credit data but they have the advantage of being available for 163 countries instead of 43 countries. We take advantage of its long duration and broad coverage to revisit classic research questions in the credit cycle literature. Additional questions can be explored in the future hopefully including the real impact of credit cycles and what policies can be helpful in moderating credit-driven fluctuations in real activity.

References

Aldasoro, I., Avdjiev, S., Borio, C., and Disyatat, P. (2020). Global and domestic financial cycles: variations on a theme. BIS Working Papers 864, Bank for International Settlements.

Baba, C., Dell'Erba, S., Detragiache, E., Harrison, O., Mineshima, A., Musayev, A., and Shahmoradi, A. (2020). How should credit gaps be measured? An application to European countries. IMF Working Papers 2020/006, International Monetary Fund.

Barajas, A., Dell'Ariccia, G., and Levchenko, A. (2007). Credit booms: The good, the bad, and the ugly. Technical report, unpublished manuscript, Washington, DC: International Monetary Fund.

Basle Committee on Banking Supervision (BCBS) (2010). Guidance for national authorities operating the countercyclical capital buffer. BCBS Papers No. 187, Bank for International Settlements.

Beck, N., Katz, J., and Tucker, R. (1998). Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. *American Journal of Political Science*, 42(4):1260–1288.

Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the great depression. *THE AMERICAN ECONOMIC REVIEW*.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, 45:182–198.

Bouvatier, V., López-Villavicencio, A., and Mignon, V. (2012). Does the banking sector structure matter for credit procyclicality? *Economic Modelling*, 29(4):1035–1044.

Cerutti, E., Claessens, S., and Rose, A. K. (2019). How Important is the Global Financial Cycle? Evidence from Capital Flows. *IMF Economic Review*, 67(1):24–60.

Dell'Ariccia, G., Igan, D., Laeven, L., and Tong, H. (2016). Credit booms and macrofinancial stability. *Economic Policy*, 31(86):299–355.

Dell'Ariccia, G., Igan, D., Laeven, L., and Tong, H. (2016). Credit booms and macrofinancial stability. *Economic Policy*, 31(86):299–355.

Dembiermont, C., Drehmann, M., and Muksakunratana, S. (2013). How much does the private sector really borrow - a new database for total credit to the private non-financial sector. *BIS Quarterly Review*, March 2013:65–81.

Drehmann, M., Borio, C., Gambacorta, L., Jiminez, G., and Trucharte, C. (2010). Countercyclical capital buffers: Exploring options. BIS Working Papers No. 317, Bank for International Settlements.

Drehmann, M., Borio, C., and Tsatsaronis, K. (2012). Characterising the financial cycle: don't lose sight of the medium term! BIS Working Papers 380, Bank for International Settlements.

Drehmann, M., Borio, C. E., and Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: the role of credit aggregates.

Drehmann, M. and Juselius, M. (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting*, 30(3):759–780.

Drehmann, M. and Tsatsaronis, K. (2014). The credit-to-gdp gap and countercyclical capital buffers: questions and answers.

Drehmann, M. and Yetman, J. (2018). Why you should use the Hodrick-Prescott filter - at least to generate credit gaps. BIS Working Papers 744, Bank for International Settlements.

Drehmann, M. and Yetman, J. (2020). Which credit gap is better at predicting financial crises? A comparison of univariate filters. BIS Working Papers 878, Bank for International Settlements.

Elsner, J. and Tsonis, A. (1996). *Singular Spectrum Analysis, A New Tool in Time Series Analysis*. Plenum Press, New York.

European Central Bank (ECB) (2019). Manual on mfi balance sheet statistics. Technical report, European Central Bank.

Fisher, I. (1933). The debt-deflation theory of great depressions. *Econometrica: Journal of the Econometric Society*, pages 337–357.

Franses, P. and Wiemann, T. (2018). Intertemporal similarity of economic time series. Econometric Institute Research Papers EI2018-30, Erasmus University Rotterdam, Erasmus School of Economics (ESE), Econometric Institute.

Giese, J., Andersen, H., Bush, O., Castro, C., Farag, M., and Kapadia, S. (2014). The credit-to-gdp gap and complementary indicators for macroprudential policy: Evidence from the uk. *International Journal of Finance & Economics*, 19(1):25–47.

Golyandina, N., Nekrutkin, V., and Zhigljavsky, A. (2001). *Analysis of time series structure: SSA and related techniques*, volume 90 of *Monographs on statistics and applied probability*. Chapman and Hall, Boca Raton, Florida.

Golyandina, N. and Zhigljavsky, A. (2013). *Singular Spectrum Analysis for time series*. Springer, Germany.

Gómez, V. and Maravall, A. (1996). Programs TRAMO and SEATS, Instruction for User (Beta Version: september 1996). Working Papers 9628, Banco de España.

Gonzalez, R. B., Lima, J., and Marinho, L. (2015). Business and Financial Cycles: an estimation of cycles' length focusing on Macroprudential Policy. Working Papers Series 385, Central Bank of Brazil, Research Department.

Goodhart, C. and Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205.

Gourinchas, P.-O., Valdes, R., and Landerretche, O. (2001). Lending booms: Latin america and the world.

Gurley, J. G. and Shaw, E. S. (1955). Financial aspects of economic development. *The American Economic Review*, 45(4):515–538.

Hamilton, J. and Leff, D. (2020). Measuring the credit gap. Mimeo, University of California at San Diego.

Hamilton, J. D. (2018a). Why you should never use the hodrick-prescott filter. *Review of Economics and Statistics*, 100(5):831–843.

Hamilton, J. D. (2018b). Why you should never use the hodrick-prescott filter. *The Review of Economics and Statistics*, 100(5):831–843.

Harrell, F. (2001). *Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis*. Springer.

Hiebert, P., Klaus, B., Peltonen, T. A., Schüler, Y. S., Welz, P., et al. (2014). Capturing the financial cycle in euro area countries. *Financial Stability Review*, 2.

International Monetary Fund (IMF) (2009). Balance of payments and international investment position manual. Technical report, International Monetary Fund.

International Monetary Fund (IMF) (2016). Monetary and financial statistics manual and compilation guide. Technical report, International Monetary Fund.

International Monetary Fund (IMF) (2017). International Financial Statistics (IFS). Yearbook Vol. LXX, International Monetary Fund.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review*, 59(2):340–378.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER macroeconomics annual*, 31(1):213–263.

Jordà, Ò., Schularick, M., Taylor, A. M., and Ward, F. (2019). Global financial cycles and risk premiums. *IMF Economic Review*, 67(1):109–150.

Kaiser, R. and Maravall, A. (1999). Estimation of the business cycle: A modified Hodrick-Prescott filter. *Spanish Economic Review*, 1(2):175–206.

Kaiser, R. and Maravall, A. (2001). *Measuring Business Cycles in Economic Time Series*, volume 154 of *Lecture Notes in Statistics*. Springer-Verlag, New York.

Laeven, L. and Valencia, F. (2018). Systemic Banking Crises Revisited. IMF Working Papers 18/206, International Monetary Fund.

Liao, W. T. (2005). Clustering of time series data - a survey. *Pattern Recognition*, 38(11):1857–1874.

Lo Duca, M., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., Lang, J. H., Detken, C., and Peltonen, T. A. (2017). A new database for financial crises in European countries. Occasional Paper Series 194, European Central Bank.

Mendoza, E. and Terrones, M. (2012). An anatomy of credits booms and their demise. *Journal Economía Chilena (The Chilean Economy)*, 15(2):04–32.

Mendoza, E. G. and Terrones, M. E. (2008). An anatomy of credit booms: Evidence from macro aggregates and micro data. NBER Working Papers 14049, National Bureau of Economic Research.

Mink, M., Jacobs, J. P., and de Haan, J. (2012). Measuring coherence of output gaps with an application to the euro area. *Oxford Economic Papers*, 64(2):217–236.

Miranda-Agrippino, S., Nenova, T., and Rey, H. (2020). Global Footprints of Monetary Policy. Discussion Papers 2004, Centre for Macroeconomics (CFM).

Mishkin, F. S. (1978). The household balance sheet and the great depression. *Journal of Economic history*, pages 918–937.

Monnet, E. and Puy, D. (2019). One ring to rule them all? New evidence on world cycles. IMF Working Papers 19/202, International Monetary Fund.

Poirier, D. (1976). *The Econometrics of Structural Change: With Special Emphasis on Spline Functions*. Contributions to economic analysis. North-Holland.

Ravn, M. O. and Uhlig, H. (2002). On adjusting the hodrick-prescott filter for the frequency of observations. *The Review of Economics and Statistics*, 84(2):371–376.

Royston, P. and Parmar, M. K. B. (2002). Flexible parametric proportional-hazards and proportional-odds models for censored survival data, with application to prognostic modelling and estimation of treatment effects. *Statistics in Medicine*, 21(15):2175–2197.

Royston, P. and Sauerbrei, W. (2007). Multivariable modeling with cubic regression splines: A principled approach. *Stata Journal*, 7(1):45–70.

Schularick, M. and Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, 102(2):1029–61.

Stein, J. C. (2021). Can policy tame the credit cycle? *IMF Economic Review*, 69(1):5–22.

Stock, J. H. and Watson, M. W. (2003). Forecasting output and inflation: the role of asset prices. *Journal of Economic Literature*, 41(3):788–829.

Stremmel, H. (2015). Capturing the financial cycle in europe.

US Bureau of the Census (2013). X-13arima-seats reference manual, version 1.1. Technical report, US Bureau of the Census.

Škare, M. and Porada-Rochoń, M. (2020). Multi-channel singular-spectrum analysis of financial cycles in ten developed economies for 1970-2018. *Journal of Business Research*, 112(C):567–575.

Yellen, J. L. et al. (2011). Pursuing financial stability at the federal reserve: a speech at the fourteenth annual international banking conference, federal reserve bank of chicago, chicago, illinois, november 11, 2011. Technical report.

Tables

Table 1: Descriptive statistics: credit gaps based on credit-to-gdp ratios - full sample

	CY_{gap}^{HPos}	CY_{gap}^{MHPos}	CY_{gap}^{SSAos}	CY_{gap}^{HPts}	CY_{gap}^{MHPts}	CY_{gap}^{SSAts}
Number of observations	21995	21995	21995	28352	28352	28352
Standard deviation	8.8518	8.8573	9.2934	7.4890	7.4594	7.0147
Mean of absolute values	5.4122	5.4006	5.3964	4.4963	4.4743	4.1287
Average geometric distance	.7343	.7344	.6807	.5011	.4975	.4222
Kurtosis	19.4538	19.3637	21.1365	30.3024	28.0403	29.9317
Minimum	-106.0858	-106.3948	-100.3126	-105.3454	-105.2659	-97.7431
5% percentile	-11.6751	-11.7562	-14.5112	-9.892	-9.7977	-9.2766
95% percentile	12.5619	12.4566	10.6077	10.4853	10.3888	9.0352
Maximum	99.921	98.3969	60.6512	129.7984	128.7478	95.0373
Autocorrelation (order 1)	.9844	.9899	.9877	.9739	.9826	.9861
Autocorrelation (order 4)	.8944	.9027	.9011	.8271	.8418	.8351

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

Table 2: Comparison of credit gaps computed from differerent credit aggregates

Panel A: Comparing IFS bank credit with BIS bank credit

	Ratio	Corr.	Manhattan distance	Euclidean distance	Dynamic time warping (Manhattan)	Dynamic time warping (Euclidean)	C-index
Mean	1.0695	.8670	2.6361	.2632	1.5501	.1736	.8719
Median	1.165	.9537	2.2185	.209	1.2564	.1321	.9111
Standard dev.	.324	.3293	2.121	.2042	1.3018	.1517	.284
Minimum	.8612	-.0757	0	0	0	0	.5978
Maximum	3.1493	1	11.4439	1.6248	10.2038	1.3928	1

Panel B: Comparing IFS bank credit with BIS private credit

	Ratio	Corr.	Manhattan distance	Euclidean distance	Dynamic time warping (Manhattan)	Dynamic time warping (Euclidean)	C-index
Mean	.6943	.7527	4.489	.4362	2.5157	.2766	.8004
Median	.6746	.8366	3.7049	.3369	2.0652	.2334	.8972
Standard dev.	.2513	.3408	3.006	.2893	1.5853	.1781	.2785
Minimum	.3806	-.1332	.7831	.0662	.4522	.0482	.4041
Maximum	1.0245	.9811	17.9843	2.506	13.0565	1.8802	.9936

Panel C: Comparing BIS bank credit with BIS private credit

	Ratio	Corr.	Manhattan distance	Euclidean distance	Dynamic time warping (Manhattan)	Dynamic time warping (Euclidean)	C-index
Mean	.6667	.8256	3.4366	.3394	2.0649	.233	.852
Median	.6284	.8757	2.826	.2677	1.7784	.1921	.9365
Standard dev.	.2598	.3281	2.6534	.2788	1.5634	.1973	.2914
Minimum	.255	-.0325	.3162	.0292	.2081	.0197	.4715
Maximum	.9866	.9979	16.1733	2.53	14.4303	2.2522	1

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit gaps. Credit series in the BIS database are available for 43 countries. Therefore, comparisons are carried on these 43 countries. Column *Ratio* corresponds to the ratio between level variables. Other columns correspond to statistics computed from credit gaps. *Corr.* is the correlation coefficient.

Table 3: Trend level in credit-to-GDP ratios (in %): sub-periods & sub-groups of countries perspectives

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
All countries						
Number of countries	163	88	109	163	163	163
Number of observations	28352	3492	4452	12979	7429	5473
Mean	39.2242	21.8134	28.1186	37.7646	56.6134	58.7346
5% percentile	4.4165	2.4089	4.4402	4.1498	7.179	7.4817
95% percentile	110.695	59.9753	71.3097	105.2435	152.8877	155.684
High income countries						
Number of countries	57	34	39	57	57	57
Number of observations	10070	1175	1655	4580	2660	1976
Mean	65.9405	35.758	45.616	64.2873	94.765	97.069
Euro area countries						
Number of countries	12	11	11	12	12	12
Number of observations	2286	193	484	1033	576	432
Mean	84.2656	46.3747	58.3835	82.3021	122.2312	122.9396
Middle & low income countries						
Number of countries	106	54	70	106	106	106
Number of observations	18282	2317	2797	8399	4769	3497
Mean	24.5084	14.7418	17.7653	23.3017	35.3336	37.0735

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit trends (i.e., variable CY^{SSAts}_{trend}).

Table 4: Year-on-year trend growth rates (in %): sub-periods perspective

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
Number of countries	163	85	109	163	163	163
Number of observations	27700	3146	4362	12763	7429	5473
Mean	3.0308	2.7207	2.773	3.0777	3.2331	2.6575
Standard deviation	4.7873	2.7845	3.1738	5.6225	4.6719	4.0056
Kurtosis	11.4916	3.6844	3.4556	9.3182	12.423	9.7845
Skewness	1.9101	.0413	.3913	1.7164	2.3184	1.807
Minimum	-13.5817	-6.0961	-6.9265	-13.5817	-7.6509	-7.6509
5% percentile	-3.2746	-2.0528	-2.41	-4.6332	-2.0377	-2.7092
95% percentile	10.8498	7.605	8.8422	13.3895	11.413	9.3218
Maximum	44.0942	11.3654	14.7036	44.0942	37.8637	31.5979

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit trends (i.e., variable CY^{SSAts}_{trend}).

Table 5: Year-on-year trend growth rates (in %): sub-periods & sub-groups of countries perspectives

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
All countries						
Number of countries	163	85	109	163	163	163
Number of observations	27700	3146	4362	12763	7429	5473
Mean	3.0308	2.7207	2.773	3.0777	3.2331	2.6575
High income countries						
Number of countries	57	32	39	57	57	57
Number of observations	9842	1042	1632	4508	2660	1976
Mean	2.5658	3.01	2.9779	2.8673	1.628	1.1116
Mean test	13.6558	-4.0627	-3.4281	3.5837	26.8903	25.6329
$(p - value)$	(0.0000)	(0.0001)	(0.0006)	(0.0003)	(0.0000)	(0.0000)
Euro area countries						
Number of countries	12	10	11	12	12	12
Number of observations	2238	149	484	1029	576	432
Mean	1.6754	2.8585	1.6589	1.9894	.8225	.4358
Mean test	28.4582	-1.4489	15.7962	14.1151	24.8771	20.9201
$(p - value)$	(0.0000)	(0.1485)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Middle & low income countries						
Number of countries	106	53	70	106	106	106
Number of observations	17858	2104	2730	8255	4769	3497
Mean	3.2872	2.5774	2.6506	3.1926	4.1284	3.531
Mean test	-13.518	4.0627	3.4281	-3.0984	-27.5441	-25.9868
$(p - value)$	(0.0000)	(0.0001)	(0.0006)	(0.0020)	(0.0000)	(0.0000)

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit trends (i.e., variable CY^{SSAts}_{trend}).

Table 6: Credit gaps: sub-periods perspective

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
Number of countries	163	88	109	163	163	163
Number of observations	28352	3492	4452	12979	7429	5473
Standard deviation	7.0147	5.1843	4.9626	5.8225	10.0472	10.1578
Mean of absolute values	4.1287	3.6166	3.3403	3.6435	5.6894	5.8876
Average geometric distance	.4222	1.0059	.6413	.5161	.9838	1.1615
Kurtosis	29.9317	8.374	12.5313	27.9914	20.7684	17.4962
Skewness	-.2521	.9493	1.4523	2.3773	-1.2512	-2.5949
Minimum	-97.7431	-25.1313	-17.4141	-35.2411	-97.7431	-97.7431
5% percentile	-9.2766	-8.1198	-6.8624	-8.2501	-14.4835	-16.3296
95% percentile	9.0352	7.4793	7.706	8.6038	11.0984	9.8881
Maximum	95.0373	34.3283	41.0204	89.1233	95.0373	43.6676

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit gaps (i.e., variable CY_{gap}^{SSAts}).

Table 7: Credit gaps: sub-periods & sub-groups of countries perspectives

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
All countries						
Number of countries	163	88	109	163	163	163
Number of observations	28352	3492	4452	12979	7429	5473
Standard deviation	7.0147	5.1843	4.9626	5.8225	10.0472	10.1578
High income countries						
Number of countries	57	34	39	57	57	57
Number of observations	10070	1175	1655	4580	2660	1976
Standard deviation	9.6623	7.3574	6.5765	6.8298	14.8414	14.5687
Equality of variance test	1666.467	367.419	346.6669	465.5067	749.2987	573.1662
$(p-value)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Euro area countries						
Number of countries	12	11	11	12	12	12
Number of observations	2286	193	484	1033	576	432
Standard deviation	11.7713	7.1605	6.2674	6.9016	20.0615	19.0242
Equality of variance test	767.5815	69.5146	83.51	140.8752	546.9753	373.5209
$(p-value)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Middle & low income countries						
Number of countries	106	54	70	106	106	106
Number of observations	18282	2317	2797	8399	4769	3497
Standard deviation	4.9773	3.5955	3.6886	5.1877	5.7439	5.8984
Equality of variance test	1628.907	367.419	346.6669	441.5799	745.4007	559.0785
$(p-value)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note 1: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit gaps (i.e., variable CY_{gap}^{SSAts}).

Note 2: The equality of variance test reported in the table is the Brown and Forsythe (1974) test. The null hypothesis is equality of variances between the sub-group of countries considered (e.g., euro area countries) and all other countries available in the full sample.

Table 8: Relationship between domestic credit cycles and the global financial cycle: sub-periods & sub-groups of countries perspectives

	Full period	1980-1983	1984-2007	2008-2018	2010-2018
All countries					
Number of countries	163	109	163	163	163
Number of observations	22138	1730	12979	7429	5473
Correlation	-.0373	-.1052	-.0854	-.0174	.0644
Manhattan dist.	4.3976	3.6987	3.7882	5.7274	5.7581
DTW Manhattan dist.	3.4126	3.6074	3.2629	5.0493	5.4731
Euclidean dist.	.4966	1.0292	.553	1.005	1.1608
DTW Euclidean dist.	.4058	.9817	.48	.8892	1.0895
Synchronicity index	-.0379	-.1156	-.0885	.0688	.1098
Concordance index	.4811	.4422	.4557	.5344	.5549
High income countries					
Number of countries	57	39	57	57	57
Number of observations	7864	624	4580	2660	1976
Correlation	.0095	-.0492	-.0197	.0662	.1592
Manhattan dist.	6.2957	4.6548	4.9822	9.0077	9.2183
DTW Manhattan dist.	5.2356	4.5126	4.3891	8.2003	8.8893
Euclidean dist.	.7197	1.2915	.7153	1.5505	1.8219
DTW Euclidean dist.	.6205	1.2348	.6297	1.4042	1.7337
Synchronicity index	-.0102	.0224	-.0511	.0526	.08
Concordance index	.4949	.5112	.4745	.5263	.54
Euro area countries					
Number of countries	12	11	12	12	12
Number of observations	1785	176	1033	576	432
Correlation	.0962	.0616	.0694	.2717	.3822
Manhattan dist.	7.9881	3.5687	6.0395	13.0788	13.4949
DTW Manhattan dist.	6.9035	3.4115	5.3516	12.1597	13.1435
Euclidean dist.	.922	.9856	.9047	2.2166	2.635
DTW Euclidean dist.	.8228	.9359	.8025	2.0431	2.5381
Synchronicity index	.0207	-.2273	-.0281	.184	.1759
Concordance index	.5104	.3864	.486	.592	.588
Middle & low income countries					
Number of countries	106	70	106	106	106
Number of observations	14274	1106	8399	4769	3497
Correlation	-.0631	-.1368	-.1212	-.0641	.0108
Manhattan dist.	3.3504	3.1659	3.1461	3.9635	3.8974
DTW Manhattan dist.	2.4159	3.1031	2.6573	3.3549	3.6361
Euclidean dist.	.3752	.8831	.4658	.7117	.8053
DTW Euclidean dist.	.2884	.8406	.3995	.6123	.7432
Synchronicity index	-.0531	-.1935	-.1089	.0778	.1267
Concordance index	.4734	.4033	.4455	.5389	.5633

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit-trends (i.e., variable CY^{SSAts}_{trend}).

Table 9: Relationship between domestic credit cycles and the US financial cycle: sub-periods & sub-groups of countries perspectives

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
All countries						
Number of countries	163	88	109	163	163	163
Number of observations	28352	3492	4452	12979	7429	5473
Correlation	-.0201	.0598	-.0394	-.093	.0158	.0043
Manhattan dist.	7.9042	4.7511	4.7888	8.1958	10.2827	10.6494
DTW Manhattan dist.	4.3433	4.1632	3.9041	5.6068	7.9978	8.9629
Euclidean dist.	.7937	1.1832	.9455	1.2104	1.7223	2.022
DTW Euclidean dist.	.4752	1.0834	.7915	.9448	1.361	1.6014
Synchronicity index	-.0233	.1283	-.0292	-.0882	.0225	-.0247
Concordance index	.4884	.5641	.4854	.4559	.5112	.4877
High income countries						
Number of countries	57	34	39	57	57	57
Number of observations	10070	1175	1655	4580	2660	1976
Correlation	.1098	-.012	.1008	-.0024	.2054	.1333
Manhattan dist.	8.6953	6.5634	5.4591	8.4403	11.3848	11.5334
DTW Manhattan dist.	4.4115	6.0038	4.457	5.2588	8.235	9.4314
Euclidean dist.	.882	1.8428	1.017	1.2174	1.9276	2.2287
DTW Euclidean dist.	.5073	1.7402	.8247	.8823	1.4933	1.7986
Synchronicity index	.0665	.0247	.0514	-.0087	.2241	.2055
Concordance index	.5333	.5123	.5257	.4956	.612	.6027
Euro area countries						
Number of countries	12	11	11	12	12	12
Number of observations	2286	193	484	1033	576	432
Correlation	.2624	.2654	.1201	.1647	.4403	.0209
Manhattan dist.	8.9802	6.996	5.7312	8.6813	13.1991	13.5868
DTW Manhattan dist.	4.8188	6.5956	4.611	4.9587	9.1541	11.236
Euclidean dist.	.9057	2.2953	1.0457	1.3044	2.2269	2.6121
DTW Euclidean dist.	.5873	2.2251	.8135	.8997	1.7437	2.2001
Synchronicity index	.1304	.0259	-.0083	.0571	.4132	.3241
Concordance index	.5652	.513	.4959	.5286	.7066	.662
Middle & low income countries						
Number of countries	106	54	70	106	106	106
Number of observations	18282	2317	2797	8399	4769	3497
Correlation	-.0917	.0962	-.1224	-.1424	-.09	-.0687
Manhattan dist.	7.4787	3.61	4.4154	8.0644	9.69	10.1741
DTW Manhattan dist.	4.3066	3.0042	3.596	5.794	7.8703	8.7109
Euclidean dist.	.7462	.7679	.9056	1.2066	1.6119	1.9108
DTW Euclidean dist.	.458	.6699	.7731	.9783	1.2899	1.4955
Synchronicity index	-.0727	.1808	-.0769	-.1316	-.09	-.1547
Concordance index	.4636	.5904	.4616	.4342	.455	.4226

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit-trends (i.e., variable CY_{trend}^{SSAts}).

Table 10: Identification of credit booms

	Number of countries	Number of booms	Freq. of booms	Duration (in years) Mean	Median	95% percentile	Max.
All countries							
Credit boom	128	312	0.14	2.43	2.00	5.75	10.25
Regulatory credit boom	146	359	0.24	3.53	3.00	7.50	15.50
High income countries							
Credit boom	39	79	0.11	2.75	2.25	6.00	7.00
Regulatory credit boom	55	144	0.30	3.93	3.50	7.25	10.00
Euro area countries							
Credit boom	4	4	0.04	5.06	5.00	6.25	6.25
Regulatory credit boom	11	31	0.34	4.87	4.50	8.50	10.00
Middle & low income countries.							
Credit boom	89	233	0.15	2.32	1.75	5.75	10.25
Regulatory credit boom	91	215	0.21	3.26	2.75	7.50	15.50

Note: Credit booms are identified with the Barajas et al. (2007) definition of credit booms. Regulatory credit booms are defined as periods with bank credit gaps higher than 2% during at least 4 consecutive quarters. The number of countries corresponds to countries (over 163) that experienced at least one credit boom (excluding ongoing booms). The number of booms and the frequency (Freq.) of booms exclude ongoing booms. Two-sided SSA (applied on credit-to-GDP ratios) is used to compute credit gaps (i.e., variable CY_{gap}^{SSAts}). Credit booms and regulatory credit booms are assessed over the same samples.

Table 11: Frequency of booms and busts: sub-periods & sub-groups of countries perspectives

	Full period	1957-1972	1973-1983	1984-2007	2008-2018	2010-2018
All countries						
Number of countries	163	88	109	163	163	163
Number of observations	28352	3492	4452	12979	7429	5473
Freq. of booms	.2686	.2357	.2853	.2308	.3399	.3293
Freq. of booms & busts	.5783	.5856	.5456	.5483	.6467	.6671
CCyB mean rate during booms (in %)	1.0672	.9698	.9207	1.0923	1.1429	1.0632
High income countries						
Number of countries	57	34	39	57	57	57
Number of observations	10070	1175	1655	4580	2660	1976
Freq. booms	.3199	.3106	.339	.2976	.3504	.2981
Proportion test	-14.467	-7.432	-6.1048	-13.3297	-1.4258	3.6892
$(p-value)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0770)	(0.0001)
Freq. of booms & busts	.7125	.6715	.6779	.6993	.7748	.7945
Proportion test	-33.9714	-7.335	-13.6424	-25.5258	-17.2583	-15.0388
$(p-value)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CCyB mean rate during booms (in %)	1.2839	1.2567	1.1829	1.1816	1.5051	1.4434
Euro area countries						
Number of countries	12	11	11	12	12	12
Number of observations	2286	193	484	1033	576	432
Freq. of booms	.3517	.3212	.438	.2953	.3906	.2824
Proportion test	-9.3555	-2.8814	-7.8832	-5.1219	-2.6768	2.1588
$(p-value)$	(0.0000)	(0.0020)	(0.0000)	(0.0000)	(0.0037)	(0.0154)
Freq. of booms & busts	.7747	.7772	.7293	.7628	.8333	.8588
Proportion test	-19.8363	-5.5586	-8.5993	-14.4383	-9.7587	-8.8099
$(p-value)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CCyB mean rate during booms (in %)	1.3402	1.2217	1.2562	1.2192	1.616	1.5065
Middle & low income countries						
Number of countries	106	54	70	106	106	106
Number of observations	18282	2317	2797	8399	4769	3497
Freq. of booms	.2403	.1977	.2535	.1944	.334	.3469
Proportion test	14.1497	7.432	6.1048	13.1316	1.0704	-4.3617
$(p-value)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1422)	(0.0000)
Freq. of booms & busts	.5043	.5421	.4673	.466	.5752	.5951
Proportion test	33.2511	7.335	13.6424	24.6911	17.0268	14.7346
$(p-value)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CCyB mean rate during booms (in %)	0.9083	0.7412	0.7133	1.0177	0.931	0.8785

Note: The two-sided SSA methodology (applied on credit-to-GDP ratios) is used to compute the credit-trends (i.e., variable CY^{SSAts}_{trend}).

Figures

Figure 1: Comparison of credit gaps obtained from different methods

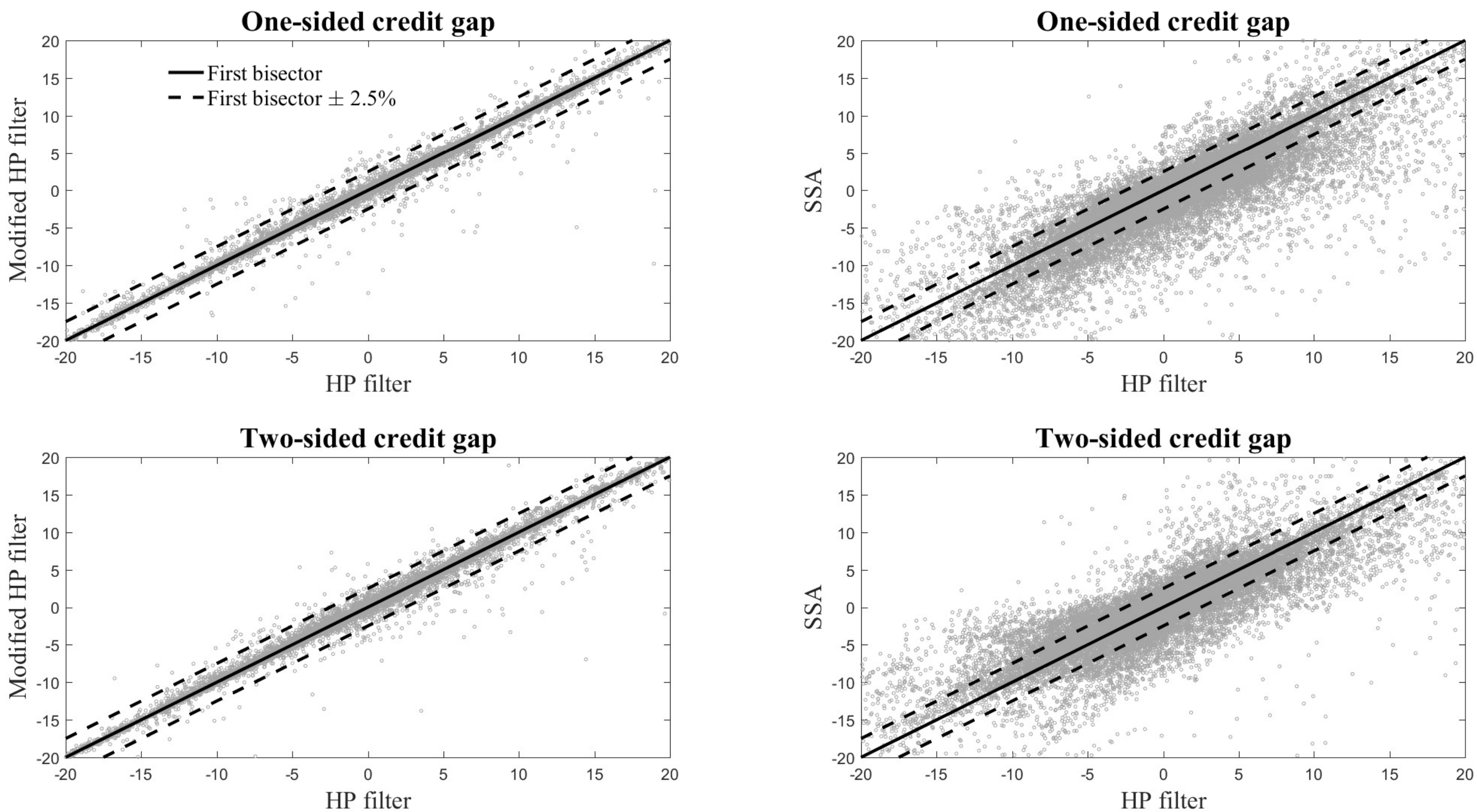
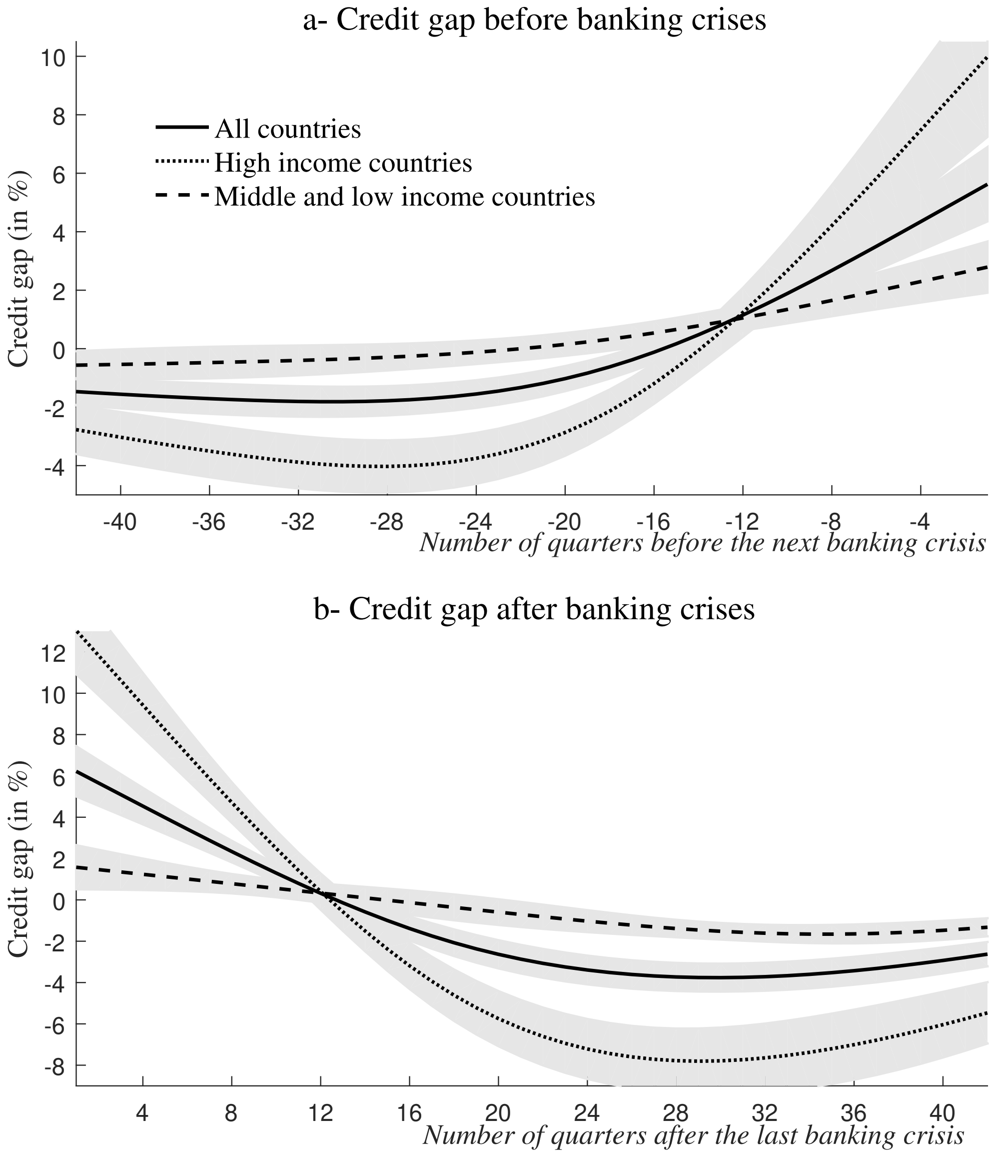
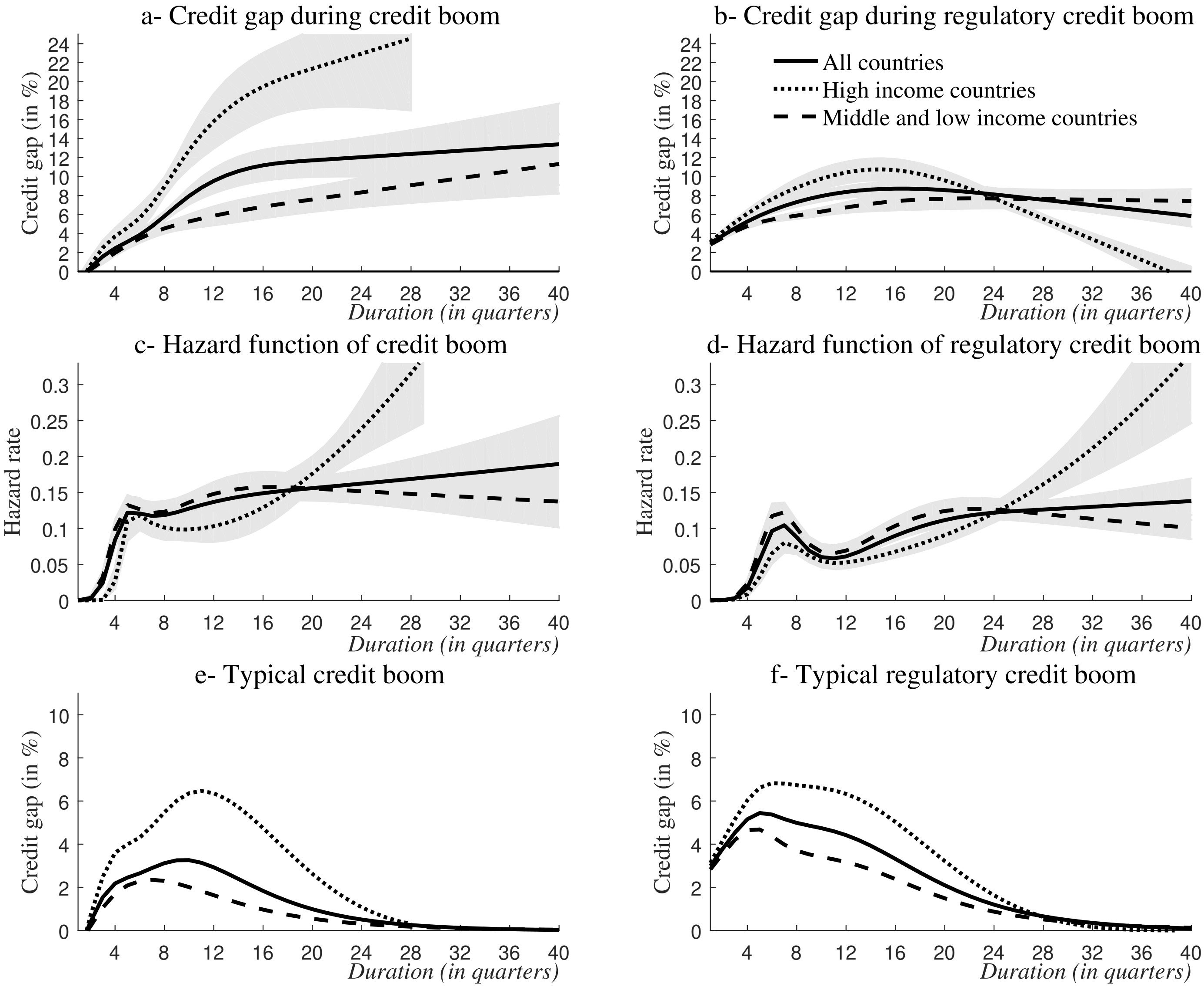


Figure 2: Credit gap around banking crises



Note: the grey area corresponds to the one-standard error band. Two-sided SSA (applied on credit-to-GDP ratios) is used to compute credit gaps.

Figure 3: Typical credit boom



Note: the grey area corresponds to the one-standard error band. Two-sided SSA (applied on credit-to-GDP ratios) is used to compute credit gaps. Typical credit boom is defined as credit gap during credit boom multiplied by survival function of credit boom

Appendix A Data

Nominal credit series

Definition

The banking sector corresponds to the category *other depository corporations* and comprises financial corporations that incur liabilities included in the national definition of broad money (IMF (2017)).The two categories *central bank* and *other depository corporations* form the category *depository corporations*. In addition, in the old presentation of monetary statistics in the IFS database, the category *other depository corporations* corresponds to the category *deposit money banks*.

Residency criteria

Monetary statistics are compiled on the basis of a national residency criterion for the banks and the private non-financial sector (as for balance of payments statistics (IMF (2009)) they do not depend on the nationality of the account holders). The residency within an economic territory concerns all institutional units engaged in a significant amount of production of goods or services in a location within this economic territory. Affiliates of groups that have their head office abroad are then considered as resident institutional units of the economy where they operate (IMF (2016)).[16] As a result, under the national residency criterion, credit series (in general monetary statistics) cover activities of domestic banks with the domestic private non-financial sector.

Monetary statistics for the euro area are compiled on the basis of a national residency criterion plus a euro area -wide residency criterion based on the euro area membership. More precisely, the euro area -wide residency criterion is only applied to the definition of the private domestic sector.[17] According to the euro area -wide residency criterion, all institutional units that are resident in the euro area are treated as domestic residents (IMF (2017), ECB (2019)). As a result, the private domestic sector is larger under the euro area -wide residency criterion because institutional units (e.g. households or non- financial corporations) from different countries are considered as the domestic ones. In other words, cross-border activities of banks within the euro area are treated as domestic activities. For example, the loan of a depository corporation located in France to a firm located in Germany is included in the monetary statistics reported by France and contributes to the domestic credit to the private sector, as if the firm was located in France and not in Germany. Conversely, under the national residency criterion, all the cross-border activities are treated as activities with nonresidents and are by definition out of the scope of the private domestic sector.

Discontinuity adjustment

Historical series covering bank credit to the domestic private non-financial sector in the IFS database are called *claims on private sector* and correspond to IFS line 22d. These credit series do not start earlier than 1957 and generally end in 2009. Concerning the recent period, bank credit to the domestic private non-financial sector in the IFS database corresponds to IFS line FOSAOP that starts

[16] Similarly, foreign branches or subsidiaries of institutional units resident in a given economic territory are considered as residents of the economies where they operate, i.e., in different economies from their parent corporations.

[17] The definition of the (resident/domestic) banking sector (i.e., the *other depository corporations*) is the same under the national residency criterion and the euro area -wide residency criterion.

generally in 2001. IFS line 22d and line FOSAOP are compiled on the basis of a national residency criterion. In addition, euro area members also provide credit series compiled on the basis of the euro area -wide residency criterion that corresponds to IFS line FOSAOPEA.

We use as primary source IFS line FOSAOP (and IFS line FOSAOPEA for euro area members). When the latter is missing (i.e., generally before 2001), we use as secondary source IFS line 22d. The compiled credit series that we obtain can contain a seasonal component, level shifts, gaps and currency changes that need to be accounted for. First, currency changes concern euro area countries. Credit series of euro area countries are then expressed in euro for the full sample to get a single currency unit for these countries. Second, linear interpolations are used to fill the gaps of credit series. Missing observations concern generally only one or two consecutive observations and represent a very occasional issue. Therefore, linear interpolations along a time trend are appropriate. The only exception concerns euro area countries; credit series are missing over the period 1998q4 - 2001q3. We rely on credit series provided by the BIS (rather than time trend) to interpolate the credit series of the IFS database. Therefore, the growth rate of the interpolated credit series is not constant over the period 1998q4 - 2001q3.

Third, credit series from the IFS database exhibit important level shifts notably due to re-definitions and re-classifications.These level shifts are generally notified in the IFS database and can lead to outliers in the growth rate of the credit series. We adjust the credit series for level shifts following the methodology proposed by Stock and Watson (2003) as in Goodhart and Hofmann (2008) or Bouvatier et al. (2012). More precisely, we apply a 3 step procedure: (*i*) the growth rate of the series is computed; (*ii*) the growth rate of the observation affected by a level shift is replaced by the median of the growth rate of the two periods before and after the occurence of the level shift; (*iii*) the adjusted growth rates are used to backcast the level series. Last, some credit series contain a seasonal component. We rely on the US Bureau of the Census X-13ARIMA-SEATS seasonal adjustment program (US Bureau of the Census (2013)) to remove the seasonal component.

We do not keep countries with less than 80 observations (i.e., two decades of observations) and countries that did not report data over the recent periods (i.e., since 2017). Data availability for Canada, Russia and the USA is limited in the IFS database. Therefore, we rely on bank credit from the BIS credit statistics database for these 3 countries. Further, credit series compiled for Afghanistan, Iraq and Mauritania contains important imperfections that cannot be properly accounted for (e.g., important gaps). Therefore, these 3 countries are dropped.

Table 12: List of countries, start and end of the sample by country

Country Name	**Country code**	**Starting period**	**Ending period**	**Starting period** (BIS database)	**Ending period** (BIS database)
Australia	AUS	1957q1	2018q4	1960q2	2018q4
Bolivia	BOL	1957q1	2018q3	.	.
Canada	CAN	1957q1	2018q4	1957q1	2018q4
Colombia	COL	1957q1	2018q4	1994q4	2018q4
Costa Rica	CRI	1957q1	2018q4	.	.
Egypt, Arab Rep.	EGY	1957q1	2017q4	.	.
France	FRA	1957q1	2018q4	1969q4	2018q4
Ghana	GHA	1957q1	2017q4	.	.
Guatemala	GTM	1957q1	2018q3	.	.

Guyana	GUY	1957q1	2017q4	.	.
Haiti	HTI	1957q1	2017q4	.	.
Japan	JPN	1957q1	2018q4	1963q1	2018q4
Korea, Rep.	KOR	1957q1	2018q4	1962q4	2018q4
Sri Lanka	LKA	1957q1	2017q4	.	.
Mexico	MEX	1957q1	2018q4	1980q4	2018q4
Myanmar	MMR	1957q1	2017q4	.	.
Malaysia	MYS	1957q1	2018q4	1964q2	2018q4
New Zealand	NZL	1957q1	2018q4	1960q4	2018q4
Pakistan	PAK	1957q1	2017q4	.	.
Panama	PAN	1957q1	2017q4	.	.
Philippines	PHL	1957q1	2018q4	.	.
Paraguay	PRY	1957q1	2018q2	.	.
Thailand	THA	1957q1	2018q4	1970q4	2018q4
Trinidad and Tobago	TTO	1957q1	2017q4	.	.
Uruguay	URY	1957q1	2018q4	.	.
United States	USA	1957q1	2018q4	1957q1	2018q4
Morocco	MAR	1959q1	2017q4	.	.
Jordan	JOR	1959q4	2017q4	.	.
Dominican Republic	DOM	1960q1	2017q4	.	.
India	IND	1960q1	2018q3	1957q1	2018q4
Mauritius	MUS	1960q1	2018q3	.	.
Benin	BEN	1960q3	2017q4	.	.
Niger	NER	1960q3	2017q4	.	.
Senegal	SEN	1960q3	2017q4	.	.
Chile	CHL	1960q4	2018q4	1983q1	2018q4
Ivory Coast	CIV	1960q4	2017q4	.	.
Greece	GRC	1960q4	2018q4	1970q4	2018q4
Israel	ISR	1960q4	2018q4	1990q4	2018q4
Tunisia	TUN	1960q4	2017q4	.	.
Libya	LBY	1961q1	2017q4	.	.
Nepal	NPL	1961q1	2017q4	.	.
Norway	NOR	1961q4	2018q4	1960q4	2018q4
Togo	TGO	1961q4	2017q4	.	.
Central African Republic	CAF	1962q1	2017q4	.	.
Congo, Rep.	COG	1962q1	2017q4	.	.
Gabon	GAB	1962q1	2017q4	.	.
Honduras	HND	1962q1	2017q4	.	.
United Kingdom	GBR	1963q1	2018q3	1963q1	2018q4
Kuwait	KWT	1963q1	2017q4	.	.
Madagascar	MDG	1963q1	2017q4	.	.
Mali	MLI	1963q3	2017q4	.	.
Cameroon	CMR	1963q4	2017q4	.	.
Saudi Arabia	SAU	1963q4	2017q4	1993q1	2018q4
Peru	PER	1964q1	2017q4	.	.
Burundi	BDI	1964q2	2017q4	.	.

Gambia, The	GMB	1964q4	2017q4	.	.
Sierra Leone	SLE	1964q4	2017q4	.	.
Kenya	KEN	1965q1	2017q4	.	.
Zambia	ZMB	1965q2	2017q4	.	.
Rwanda	RWA	1966q1	2018q4	.	.
Singapore	SGP	1966q1	2018q2	1970q4	2018q4
Barbados	BRB	1966q4	2017q4	.	.
Denmark	DNK	1966q4	2018q4	1966q4	2018q4
Qatar	QAT	1966q4	2017q4	.	.
Algeria	DZA	1967q1	2017q4	.	.
Switzerland	CHE	1967q4	2017q1	1960q4	2018q4
Burkina Faso	BFA	1968q4	2017q4	.	.
Fiji	FJI	1969q1	2017q4	.	.
Netherlands	NLD	1969q4	2018q4	1961q1	2018q4
Sweden	SWE	1970q1	2018q4	1961q1	2018q4
Eswatini	SWZ	1970q2	2017q4	.	.
Austria	AUT	1970q4	2018q4	1960q4	2018q4
Belgium	BEL	1970q4	2018q4	1970q4	2018q4
Germany	DEU	1970q4	2018q4	1960q4	2018q4
Finland	FIN	1970q4	2018q4	1974q1	2018q4
Ireland	IRL	1970q4	2018q4	1971q2	2018q4
Iceland	ISL	1970q4	2018q4	.	.
Italy	ITA	1970q4	2018q4	1974q4	2018q4
Portugal	PRT	1970q4	2018q4	1960q4	2018q4
Chad	TCD	1970q4	2017q4	.	.
Tanzania	TZA	1970q4	2017q4	.	.
Uganda	UGA	1970q4	2017q4	.	.
Samoa	WSM	1970q4	2017q4	.	.
Suriname	SUR	1971q1	2017q4	.	.
South Africa	ZAF	1971q2	2018q4	1965q1	2018q4
Spain	ESP	1972q1	2018q4	1970q1	2018q4
Botswana	BWA	1972q4	2017q4	.	.
Oman	OMN	1972q4	2017q4	.	.
Turkey	TUR	1973q1	2018q4	1986q1	2018q4
United Arab Emirates	ARE	1973q2	2017q4	.	.
Lesotho	LSO	1973q4	2017q4	.	.
Papua New Guinea	PNG	1973q4	2017q4	.	.
Grenada	GRD	1974q1	2017q4	.	.
Bangladesh	BGD	1974q2	2017q4	.	.
Bahamas, The	BHS	1974q2	2017q4	.	.
Seychelles	SYC	1974q4	2017q4	.	.
Maldives	MDV	1976q2	2017q4	.	.
Belize	BLZ	1976q4	2017q4	.	.
Cabo Verde	CPV	1978q1	2017q4	.	.
Solomon Islands	SLB	1978q4	2017q4	.	.
Antigua and Barbuda	ATG	1979q1	2017q4	.	.

Dominica	DMA	1979q1	2017q4	.	.
St. Kitts and Nevis	KNA	1979q1	2017q4	.	.
St. Lucia	LCA	1979q1	2017q4	.	.
St. Vincent and the Grenadines	VCT	1979q1	2017q4	.	.
Tonga	TON	1979q4	2017q4	.	.
Indonesia	IDN	1980q1	2018q4	1976q1	2018q4
Vanuatu	VUT	1981q3	2017q4	.	.
Comoros	COM	1982q1	2017q4	.	.
Mozambique	MOZ	1984q1	2017q4	.	.
Macao SAR, China	MAC	1984q2	2018q4	.	.
Djibouti	DJI	1984q4	2017q4	.	.
China	CHN	1985q1	2018q3	1985q4	2018q4
Equatorial Guinea	GNQ	1985q1	2017q4	.	.
Bhutan	BTN	1985q4	2017q4	.	.
Montserrat	MSR	1985q4	2017q4	.	.
Nicaragua	NIC	1988q2	2017q4	.	.
Guinea	GIN	1989q4	2017q1	.	.
Anguilla	AIA	1990q1	2017q4	.	.
Guinea-Bissau	GNB	1990q1	2017q4	.	.
Hong Kong SAR, China	HKG	1990q4	2018q4	1978q4	2018q4
Namibia	NAM	1990q4	2017q4	.	.
Nigeria	NGA	1990q4	2017q4	.	.
Poland	POL	1990q4	2018q4	1992q1	2018q4
Brazil	BRA	1991q4	2018q4	1996q1	2018q4
Hungary	HUN	1991q4	2018q4	1970q4	2018q4
Moldova	MDA	1991q4	2018q2	.	.
Mongolia	MNG	1991q4	2018q3	.	.
Slovenia	SVN	1991q4	2018q4	.	.
Argentina	ARG	1992q1	2018q2	1984q4	2018q4
Lebanon	LBN	1992q4	2017q4	.	.
Ukraine	UKR	1992q4	2018q4	.	.
Vietnam	VNM	1992q4	2017q4	.	.
Czech Republic	CZE	1993q1	2018q4	1993q1	2018q4
Slovak Republic	SVK	1993q1	2018q4	.	.
Armenia	ARM	1993q4	2018q4	.	.
Estonia	EST	1993q4	2018q4	.	.
Cambodia	KHM	1993q4	2017q4	.	.
Azerbaijan	AZE	1994q1	2017q4	.	.
Aruba	ABW	1994q4	2017q2	.	.
Albania	ALB	1994q4	2018q4	.	.
Bulgaria	BGR	1994q4	2018q4	.	.
Latvia	LVA	1994q4	2018q4	.	.
Belarus	BLR	1995q2	2018q4	.	.
Russian Federation	RUS	1995q2	2018q4	1995q2	2018q4
Angola	AGO	1995q4	2017q4	.	.

Cyprus	CYP	1995q4	2018q4	.	.
Croatia	HRV	1995q4	2018q4	.	.
Kazakhstan	KAZ	1995q4	2017q4	.	.
Lithuania	LTU	1995q4	2018q4	.	.
Malta	MLT	1995q4	2018q4	.	.
SÃ£o TomÃ© and Principe	STP	1995q4	2017q4	.	.
Georgia	GEO	1996q4	2018q4	.	.
Romania	ROU	1996q4	2018q4	.	.
Sudan	SDN	1996q4	2017q4	.	.
Kyrgyz Republic	KGZ	1997q1	2017q4	.	.
Tajikistan	TJK	1998q4	2017q4	.	.
Brunei Darussalam	BRN	1999q1	2017q4	.	.
Congo, Dem. Rep.	COD	2000q4	2017q4	.	.
Liberia	LBR	2000q4	2017q4	.	.
North Macedonia	MKD	2000q4	2018q4	.	.
Luxembourg	LUX	2001q4	2018q4	2003q1	2018q4
Bosnia and Herzegovina	BIH	2005q4	2018q4	.	.

Note: This Table reports the list of countries available in our database as well as start and end dates of the sample for each country and the corresponding dates in the BIS credit database for countries listed in both databases.

Appendix B Methods of measuring procyclicality

The BIS approach

For a given time series $(y_t)_{t=1}^{T}$ (e.g., a credit-to-GDP ratio), the HP filter proposes to identify the trend component $(\tau_t)_{t=1}^{T}$ of the time series by minimizing the expression :

$$\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})\right]^2 , \tag{8}$$

where λ is the smoothing parameter of the HP filter.[18] The HP filter can be considered as a high-pass filter that removes the low frequencies (e.g. the trend component). The frequency cut-off (called *Freq*) and the smoothing parameter (λ) are related by $\lambda = (2 \times \sin(\pi/Freq))^{-4}$.

According to the BIS (BCBS (2010)), the periodicities of credit cycles can reach 2 or 3 decades. Consequently, the BIS proposes to specify the HP filter to remove the low frequencies associated with periodicities higher that 4 decades (i.e. 40 years), i.e., *Freq* is set for quarterly data to $1/(4 \times 40) = 0.00625$ and λ can be rounded to 400,000.[19] The fixation of $\lambda = 400,000$ is somewhat arbitrary and based on empirical evidences in advanced economies (Drehmann et al. (2010)).

Equation (8) considers the full sample to identify the trend $(\tau_t)_{t=1}^{T}$, i.e., a single minimization program exploiting the full sample is solved to generate the trend component $(\tau_t)_{t=1}^{T}$. This approach corresponds to the two-sided HP filter and implies that forward observations are used to identify the trend τ_t at given point in time (except for $t = T$). The problem is that the two-sided HP filter is characterized by an end-point sensitivity that does not fit in an operationnal perspective. The one-sided HP filter (also called backwark looking or (pseudo) real time HP filter) is thus recommended by the BIS (BCBS (2010)) to have a suitable approach in an operationnal perspective.

The one-sided HP filter is implemented as follow. The time series $(y_t)_{t=1}^{T}$ is represented by:

$$Y = \begin{bmatrix} y_1 & y_1 & \cdots & y_1 & y_1 & y_1 & \cdots & y_1 \\ & y_2 & \cdots & y_2 & y_2 & y_2 & \cdots & y_2 \\ & & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ & & & y_{\mathcal{T}^{\min}-1} & \vdots & \vdots & \ddots & \vdots \\ & & & & y_{\mathcal{T}^{\min}} & \vdots & \ddots & \vdots \\ & & & & & y_{\mathcal{T}^{\min}+1} & \ddots & \vdots \\ & & & & & & \ddots & \vdots \\ & & & & & & & y_T \end{bmatrix} , \tag{9}$$

[18]The HP filter leads to $y_t = \tau_t$ when $\lambda = 0$ while τ_t is a linear trend when $\lambda \to +\infty$.

[19]The fixation of $\lambda = 400,000$ is also explained by the duration of credit cycles relatively to the duration of business cycle. It is commonly accepted that the duration of business cycles ranges from 4 to 8 years in advanced economies. Therefore, λ is set to $1,600$ for quarterly data when the HP filter is used to capture the business cycle in quarterly data (corresponding to a business cycle frequency of around 7.5 years). Drehmann et al. (2010) suggest that credit cycles are between three to four times longer than the business cycles. Consequently, λ should be set between $3^4 \times 1,600 = 125,000$ and $4^4 \times 1,600 = 400,000$ to capture the credit cycles (according to the formula proposed by Ravn and Uhlig (2002)). In addition, Drehmann et al. (2010) conclude that $\lambda = 400,000$ provides more satisfactory results to detect systemic banking crises than $\lambda = 125,000$.

where each column of Y represents the available information for each point in time ($t = 1, ..., T$) and the parameter $\mathcal{T}^{\min}$ will be specified afterwards.

The one-sided HP filter proposes first to apply the HP minimization program to each column (vector) of Y, except for the firsts $\mathcal{T}^{\min} - 1$ columns. The parameter $\mathcal{T}^{\min}$ represents therefore the minimum sample size used to implement the HP filter. The trend components identified from different sample sizes are given by :

$$Trend = \begin{bmatrix} \tau_{1,\mathcal{T}^{\min}} & \tau_{1,\mathcal{T}^{\min}+1} & \cdots & \tau_{1,T} \\ \tau_{2,\mathcal{T}^{\min}} & \tau_{2,\mathcal{T}^{\min}+1} & \cdots & \tau_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\tau}_{\mathcal{T}^{\min},\mathcal{T}^{\min}} & \vdots & \ddots & \vdots \\ & \boldsymbol{\tau}_{\mathcal{T}^{\min}+1,\mathcal{T}^{\min}+1} & \ddots & \vdots \\ & & \ddots & \vdots \\ & & & \boldsymbol{\tau}_{T,T} \end{bmatrix}, \tag{10}$$

where the $\tau_{i,j}$ corresponds to the trend for observation i computed from the sample of size j. Second, the one-sided HP filter proposes to keep only elements in bold in matrix *Trend*. More precisely, the trend component computed by the one-sided HP filter is given by :

$$(\tau_t^{os})_{t=\mathcal{T}^{\min}}^{T} = (\boldsymbol{\tau}_{\mathcal{T}^{\min},\mathcal{T}^{\min}}, \boldsymbol{\tau}_{\mathcal{T}^{\min}+1,\mathcal{T}^{\min}+1}, ..., \boldsymbol{\tau}_{T,T}). \tag{11}$$

The BIS (BCBS (2010)) proposes to set $\mathcal{T}^{\min}$ to 40, i.e., 10 years of quarterly data. Indeed, the performance of the one-sided HP filter to identify the trend component might be sensitive to the starting points when small samples are considered. Therefore, we also set $\mathcal{T}^{\min}$ to 40 and credit gaps computed with the one-sided approach start to be reported one decade after credit aggregats start to be available.

This way to proceed to measurecredit cycles (i.e., detrending credit-to-GDP ratio by one-sided HP fillter) corresponds to the so-called Basel Credit Gap (BCG). Several critics can be adressed to the BCG and to the HP filter. First, some specific critics concerning the HP filter can be handled. For instance, the HP filter does not make the distinction between the cyclical component and the irregular component.

Kaiser and Maravall (1999, 2001) proposed to rely on a preprocessing of the data to fix this issue. Second, some specific critics are more fundamental. The introduction of spurious dynamic relations is a particular concern for the HP filter (Hamilton (2018b), Hamilton and Leff (2020)). Last, some critics can be more generally addressed to all statistical methods that do not rely on a structural approach. For instance, the HP filter can face difficulties to disentangle periods of excessive credit activities and financial deepening periods (Baba et al. (2020)).

The BCG remains however a key indicator to measure the build-up of financial vulnerabilities and to capture the risk of banking crises (Drehmann and Yetman (2018, 2020)). Limitations in the BCG underlines rather that credit gaps cannot be embodied by a single methods. Then, complementary methodological approaches are convenient to get a more confident identification of credit boom episodes.

The modified HP filter

The high-frequency components associated with the noise in the time series are not identified by the HP filter because the latter does not act as a band pass filter. As a result, the cyclical component is not accurately assessed because the signal extrated by the HP filter includes the irregular component. For example a peak may be over-estimated if one does include high frequency irregular components in the cyclical components.

Kaiser and Maravall (1999, 2001) propose a modified HP filter to tackle this issue. More precisely, Kaiser and Maravall (1999, 2001) propose a preprocessing of the data, taking advantage of the TRAMO SEATS algorithm (Gómez and Maravall (1996)). The latter is used to identify the irregular component on the time series. Then the HP filter is applied on a modified series (i.e., the initial series purged of the irregular component).

One might expect however that a proper management of the irregular component is less meaningful when λ is large. Indeed, when λ is set to 400,000, the filtered series obtained by HP filter includes periodicity up to 4 decades. The relative importance of the irregular component in the fluctuations of the filtered series might therefore be limited.

The basic SSA approach

Basic SSA is detailed in Golyandina et al. (2001) and Golyandina and Zhigljavsky (2013). Basic SSA is a non-parametric technique (i.e., a model free technique) that allows to extract information from time series (such as a trend component) and requires no prior statistical assumptions (e.g., stationnarity of the series) and no preprocessing (e.g., log-transformation).[20]

We rely on basic SSA to decompose the time series $(y_t)_{t=1}^T$ into 3 components: the long-term secular trend, the cyclical component and the irregular component. In addition, we apply basic SSA with one-sided and two-sided approaches. One-sided basic SSA is therefore suitable for an operationnal use as the BCG.

Basic SSA is a 4 steps procedure. Steps 1 and 2 correspond to the decomposition stage. More precisely, the first step (called embedding) is the construction of the trajectory matrix $\mathbf{Y}$ from the time series $(y_t)_{t=1}^T$:

$$\mathbf{Y} = \begin{bmatrix} y_1 & y_2 & \cdots & y_K \\ y_2 & y_3 & \cdots & y_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & \cdots & y_T \end{bmatrix}, \tag{12}$$

where L is the window lenght and $K = T - L + 1$. The trajectory matrix $\mathbf{Y}$ is thus obtained by mapping $(y_t)_{t=1}^T$ into a sequence of K lagged vectors of size L. The window lenght L ($1 < L < T$) is the first parameter to determine. There is no universal rules and unambiguous recommandations for the selection of the window length. Selection of L depends on the problem in hand and can be based on some general principales that have certain theoretical and practical grounds. Golyandina et al. (2001) suggest that L should be large but no larger than $T/2$, and Elsner and Tsonis

[20]One can make the distinction between basic SSA and Toeplitz SSA. The latter assumes time-series stationarity. Toeplitz SSA has already been used to assess financial cycles (Škare and Porada-Rochoń (2020)). However, data need to be pre-processed before to apply Toeplitz SSA in order to extract the cyclical (i.e., sationnary) component from the series (with the HP filter for instance).

(1996) indicate that choosing $L = T/4$ is a common practice.[21] Large L (with the upper bound $L \leqslant T/2$) will provide more detailed decompositions of the time series $(y_t)_{t=1}^{T}$. However, our main objective is to identify the long-term secular trend that corresponds to the general tendancy of the time series rather than a refined trend. Therefore, we follow the common practice indicated by Elsner and Tsonis (1996) and we choose $L = T/4$.[22]

The second step is the singular value decomposition (SVD) of the trajectory matrix $\mathbf{Y}$. The SVD is computed for the eigenvalues (λ_1, ..,λ_L with $\lambda_1 \geqslant ... \geqslant \lambda_L \geqslant 0$) and the associated orthogonal system of the eigenvectors ($U_1, ..., U_L$) of the matrix $\mathbf{S} = \mathbf{Y}\mathbf{Y}^T$. The SVD decomposes the trajectory matrix into a sum of elementary matrices (of rank 1) that can be written as:

$$\mathbf{Y} = \mathbf{Y}_1 + \mathbf{Y}_2 + ... + \mathbf{Y}_d, \tag{13}$$

where $\mathbf{Y}_i = \sqrt{\lambda_i} U_i V_i^T$, with $V_i = \mathbf{Y}^T U_i / \sqrt{\lambda_i}$ and $d = rank\ \mathbf{Y} = L^* = \min\{L, K\}$. The collection (λ_i, U_i, V_i) are called the eigentriples of the SVD.

Steps 3 and 4 correspond to the reconstruction stage. More precisely, the third step is the eigentriple grouping. The set of indices $\{1, ..., d\}$ is partitioned into m disjoint subsets $I_1, ..., I_m$. Equation (13) leads to the decomposition

$$\mathbf{Y} = \mathbf{Y}_{I_1} + ... + \mathbf{Y}_{I_m}. \tag{14}$$

The procedure of choosing the sets $I_1, ..., I_m$ can be based on different criteria and depends on the purpose of the implementation of basic SSA. Here, we need to decompose the time series $(y_t)_{t=1}^{T}$ into 3 components : the long-term secular trend, the cyclical component and the irregular component (i.e., we set $m = 3$). We assume that the first elementary matrix is associated with the long-term secular trend (i.e., $\mathbf{Y}_{I_1} = \mathbf{Y}_1$). This way to proceed is consistent with the absence of universal rule (in terms of frequencies) to distinguish a long-term secular trend and a medium-term cyclical component in credit series. Therefore, we rely only on the assumption that a long-term secular trend exists in credit series and corresponds to the general tendancy of the credit series.[23] The first elementary matrix of the SVD decomposition captures this general tendancy. Besides, the irregular component can be grounded on a clear rule in terms of frequencies : the irregular component corresponds to the high frequency fluctuations of the series, associated with periodicities

[21] A window length larger than $T/2$ is meaningless because the trajectory mantrix $\mathbf{Y}$ is a Hankel matrix (i.e., entries are the same along the anti-diagonals). More precisely, the second step in the implementation of basic SSA will be equivalent for two trajectory matrices with window lengths equal to L (with $L > T/2$) and $K = T - L + 1$ (i.e., $K < T/2$) respectively. Therefore, situation with $L > T/2$ are redundant.

[22] Note that we implement both one-sided and two-sided basic SSA. The sample size is not unique in a one-sided perspective but increases from $\mathcal{T}^{\min}$ to T to compute the different observations of the trend component. A rule of thumb as $L = T/4$ should actually be writen as $L = \mathcal{T}^{\min}/4, ..., T/4$ for the different points of the one-sided procedure. The window lenghts (and then properties of basic SSA) can substantially change between the first observation ($\mathcal{T}^{\min}$) and the last one if T is large. In a robustness check, we limit the gap in the window lenghts between the different points of the one-sided procedure. More precisely, we cap the window lenght to 40 corresponding to ten year windows to generate the trajectory matrix. Since $\mathcal{T}^{\min} = 40$, the window lenght varies from 10 to 40 in this robustness check. We do not obtain noticeable differences when the window lenght is capped to 40.

[23] This assumption seems appropriate both for advanced and emerging economies. Indeed, graphical representations of credit to GDP ratios exhibit a long term component in the series. Further, we do not rely on an explicit frequency cut-off to extract the trend component. More precisely, we do not need to fix a frequency cut-off to determine the trend component (e.g., frequencies associated with periodicities higher that 4 decades). Therefore, we have a flexible approach to identify trends; a valuable property if trends' characteristics differ between countries (e.g., between advanced vs emerging economies).

of less than 1.5 years (i.e., 6 quarters). An automatic grouping of the elementary matrices based on finding components with similar frequency characteristics is considered to identify the irregular component. More precisely, we use a frequency range with lower bound 0.1666 (i.e. 1/6) to group the elementary matrices associated with high frequency fluctuations (i.e., periodicities less than 6 quarters). The remaining elementary matrices, not associated with the trend component or with the irregular component, are associated with the cyclical component. In other words, the cyclical component is defined in terms of frequencies by a upper bound (0.1666) but with no explicit lower bound. Therefore, we have a flexible approach to identify the cyclical component because we do not impose a predetermined interval for the periodicities of the cyclical component.

The forth step of basic SSA is the diagonal averaging. Each matrix $\mathbf{Y}_{I_j}$ ($j = 1, ..., m$) of equation (14) is transformed into a time series $\tilde{y}_t^{(j)}$ of length T.[24] Therefore, the initial time series $(y_t)_{t=1}^{T}$ is decomposed into the sum of m series :

$$y_t = \tilde{y}_t^{(1)} + ... + \tilde{y}_t^{(m)}. \tag{15}$$

[24]This step is called diagonal averaging because the formula that generate the $\tilde{y}_t^{(j)}$ corresponds to averaging the elements over the antidiagonals of matrix $\mathbf{Y}_{I_j}$ (see Golyandina and Zhigljavsky (2013), p.13).

Appendix C Modeling credit gaps dynamics around banking crises

The baseline model is written as follows

$$Y_{i,t} = \alpha_0 +_{j=0}^{n} b_j Basis_{j,i,t} + \varepsilon_{i,t}, \tag{16}$$

where the subscripts refer to country i in period t. The variable $Y_{i,t}$ is a credit gap indicator (e.g., computed by SSA), b_j ($j = 0, ..., n$) are parameter estimates, α_0 is the intercep and $\varepsilon_{i,t}$ is the residual.

The variables $Basis_j$ are the basis variables obtained from a restricted cubic spline function. A spline function is defined as a smooth polynomial function that is piecewise-defined. More precisely, the spline function depends on the variable d marking the number of quarters until the next banking crisis (with $d = 1, 2, ..., D$). The places where the polynomial pieces connect are referred to as knots and are used to introduce changes in the relationship between the endogenous variable and the duration d.

Considering $n + 2$ knots at $k_{\min} < k_1 < ... < k_n < k_{\max}$, an unrestricted cubic spline function is written as follows (Royston and Sauerbrei (2007)):[25]

$$\begin{aligned} S(d) &= \beta_{00} + \beta_{10} d + \beta_{20} d^2 + \beta_{30} d^3 \\ &\quad +_{j=1}^{n} \beta_j \left(d - k_j\right)_+^3 + \beta_{k_{\min}} \left(d - k_{\min}\right)_+^3 + \beta_{k_{\max}} \left(d - k_{\max}\right)_+^3 \end{aligned}$$

where the *plus function* $(d - k)_+$ is defined as

$$(d-k)_+ = \begin{cases} d - k \text{ if } d \geqslant k \\ 0 \ \text{ otherwise} \end{cases}$$

The terminology "restricted cubic spline" (or natural cubic spline) refers to the constraints imposed on $S(d)$, which imply linearity beyond the boundary knots ($k_{\min}$ and $k_{\max}$).[26] This requirement tends to avoid wild behavior near the extreme values of the data. Then, the restricted cubic spline function is written as (see Royston and Parmar (2002) (p.2194) for the algebraic details):

$$S(d) = \gamma_0 + \gamma_1 Basis_0 + \gamma_2 Basis_1 + ... + \gamma_{n+1} Basis_n$$

with $\gamma_0 = \beta_{00}$, $\gamma_1 = \beta_{10}$, $\gamma_{j+1} = \beta_j$ for $j = 1, ..., n$ and

$$\begin{aligned} Basis_0 &= d \\ Basis_j &= \left(d - k_j\right)_+^3 - \lambda_j \left(d - k_{\min}\right)_+^3 - \left(1 - \lambda_j\right) \left(d - k_{\max}\right)_+^3 \quad \text{for } j = 1, ..., n \end{aligned}$$

with $\lambda_j = \dfrac{k_{\max} - k_j}{k_{\max} - k_{\min}}$.

Next, the basis variables $(Basis_0, ..., Basis_n)$ can be added to the regression model to capture the behavior of credit gaps around banking crises. However, the basis variables have been orthogonalized before being included in the model, as suggested by Royston and Sauerbrei (2007). Without any transformation, the basis variables are highly correlated.

[25] $k_{\min}$ and $k_{\max}$ are the boundary knots and will not be placed at the extremes of d, as suggested by Harrell (2001).

[26] For example, the linearity constraint below $k_{\min}$ (i.e. when $d < k_{\min}$) requires that quadratic and cubic terms must vanish, and hence, $\beta_{20} = \beta_{30} = 0$.

The main issue related to restricted cubic splines concerns the choice of the number of knots and their locations. Harrell (2001) recommends placing knots at equally spaced percentiles of the duration variable. In applied use, the number of knots generally varies between three and seven. We use five knots (from which four basis variables are obtained), as suggested by Harrell (2001) for a large sample. When five knots are considered, the default percentiles provided by Harrell (2001) are 5%, 27.5%, 50%, 72.5% and 95%. The lower and higher knots are then placed near the extreme values, and the remaining knots are placed so that the proportion of observations between the knots is constant.

The specification of the duration variable (d) requires 2 clarifications concerning the treatment of the data and more precisely about the sample definition: (*i*) countries that do not record any banking crisis are not considered in the sample; (*ii*) recent data (i.e., time periods occurring after the last banking crises recorded in the database) are not considered in the sample. When the model specification is modified to assess the patterns of credit gaps after that a banking crisis occurs, the treatment of the data is modified accordingly.