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RESEARCH ARTICLE

Is There a Pervasive World Real Credit Cycle?

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Abstract
This paper analyses the international structure of credit and the potential buildup of a single world cycle using quarterly data for 48 economies between 1985 and 2015. For this analysis, we rely on an approximate factor model and on hard and fuzzy clustering methodologies. The results indicate that, for the whole sample, there are three common components to credit, one of these more pervasive and impacting most countries in the sample, particularly developed ones. One major cluster of countries is identified, but without the presence of both Japan and Germany, thus suggesting that a world real credit cycle is not yet formed. However, we found that the composition of this core cluster has been growing over the years, encompassing more countries and establishing a growing dominance over the credit cycles dynamic, opening the possibility for a single world credit cycle in the future.

Keywords Real credit cycles · Approximate factor models · Common components · Clusters

JEL Classification C38 · E32 · E51

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1 Introduction

Economic synchronization is a major issue in today's economic research. Due to the globalization process, individual policies tend to have growing international repercussions, and supra-national monetary and economic policies start to take center stage, especially when facing global economic recessions. The 2007–09 crisis is the most recent example, causing a huge economic and social unrest at the global level and highlighting the need for international policy coordination. Many countries struggled with high levels of unemployment, increasing public debts and growing inequality levels. At that time, there was a global credit crunch and the credit cycle was particularly synchronous. According to Aikman et al. (2015), in 2006, private sector credit across the UK, US and euro area rose by around 10%. During 2009, private credit in these countries plummeted about 2%. The consequences for real growth were equally severe and synchronous as peak-to-trough G7 real output fell by 3.6% during the Great Recession. This global event remembered us that the credit system can be the source of economic shocks, and contributed to the belief that the credit market, and particularly credit booms, should be monitored carefully and their dynamics better understood (Reinhart and Rogoff 2009; Baron and Xiong 2017). Several studies have tried to comprehend the determinants of abnormal credit growth and have successfully identified some relevant macroeconomic factors that are associated with credit dynamics' (Gourinchas et al. 2001; Barajas et al. 2009; Arena et al. 2015; Dell'Ariccia et al. 2016; Avdjiev et al. 2021; Castro and Martins 2021). In comparison, the investigation of international credit cycles synchronization is vastly unexplored. This gap is striking because the literature focusing on credit cycles repeatedly draws attention to the international nature of the phenomenon, suggesting that both boom and bust phases seem to have some degree of entanglement across countries.[1] Gourinchas et al. (2001), identify two peaks in the early 1980s and the mid-1990s, where credit expansions affect some nations simultaneously, while Reinhart and Rogoff (2011) document large capital inflows in numerous countries prior to the 2007–09 crisis. Also, Jorda et al. (2011) identify four big synchronized global crises in 1890, 1907, 1921, 1930/31, and 2007/08. In reality, countries exhibit relevant trade and financial connections that link their domestic credit dynamics, and eventually their financial crisis, since credit growth can be a strong predictor of financial crises (Reinhart and Rogoff 2009; and Schularick and Taylor 2012). The globalization process witnessed in the last decades has been reinforcing the economic ties between nations. International financial integration has intensified (see, for example, Gourinchas et al. 2012) and this can contribute to disseminate country-specific shocks, as argued by Mendoza and Quadrini (2010). In addition, the growing importance of global banks is seen as reinforcing the spillover of shocks, since they tend to affect the loan supply of one country (and local banks) when responding to the demand of another (Giannetti and Laeven 2012). Moreover, supra national policies, particularly monetary policies, and a

[1] Evidence of similar dynamics is also found for other types of boom-bust phases. For example, Agnello et al. (2015) show that housing booms have a similar length in a sample of industrial countries, despite housing busts being slightly shorter in European countries.

stable political environment can contribute to reinforce the access and the ties among credit markets (Eickmeier et al. 2014; Agnello et al. 2018).

Taking advantage of an extensive database covering 48 countries, this paper contributes to the credit cycle literature by providing a better understanding of the international structure of credit, namely investigating if there is a single world credit cycle or alternatively if countries agglomerate into groups, identifying how many groups are there and their composition. In addition, it takes a first look at the clustering dynamics over recent years to unveil the future path of credit in the world. A better grasp on these topics is relevant in several ways. On the one hand, it is instrumental to realize how credit contagion across countries plays out and for international policy coordination, especially in prudential supervision and regulation of credit accumulation. Recently, we witnessed the worldwide implementation of harmonized financial market regulations (e.g. Basel III). Due to intense cross-border spillovers, understanding how to align policies to achieve an optimal international policy mix is important, particularly when it comes to regional trade organizations or currency unions like the European Union (EU). On the other hand, the empirical analyses on credit booms often focus in comparing or studying specific groups of countries. Usually, sub-samples of countries are defined by their geographical positioning, the degree of development, or by income groups (see, for example, Gourinchas et al. 2001; Mendoza and Terrones 2008, 2012; Arena et al. 2015; Meng and Gonzales 2017; Castro and Martins 2019). Although these splits are reasonably well grounded theoretically, they remain an ad hoc procedure lacking statistical validation. The present study does such validation, suggesting an alternative partition for sub-sample selection. While the results found here do not stray too far from traditional partitions, there are some noteworthy differences.

Although scarce, the existent literature that tackles international credit cycles dynamics offers some clues about the phenomenon. Kurowski and Rogowicz (2018) assess the synchronization relationship between business and financial cycles using wavelet and cluster analysis. They found that economies were only slightly synchronized before the pre-crisis period but identify a strong build-up of international synchronization in the period after the great recession and confirm the existence of a global credit cycle. Aikman et al. (2015) also point to an increase in credit cycles' synchronization across countries. They investigate the subject by calculating the correlation between credit cycles across 14 developed countries for two different sample windows. Samarina et al. (2017) focus on the effects of the euro introduction on credit cycle coherence measured by the synchronicity of cycle movements and amplitude similarities. They report that the euro increased the coherence of business credit cycles in the EU. Meller and Metiu (2017) approach the international synchronization of credit cycles by analyzing phase synchronization and mapping into a binary variable the expansion and contraction phases, defined as deviations in credit from its long-run trend level. Although results do not support the existence of a global credit cycle, they identify clusters of countries with distinct synchronization patterns that go beyond geographical shapes. Using long historical data for 14 developed economies they find that bilateral phase synchronization has significantly increased in the post-Bretton Woods and report the existence of two clusters plus Germany as an outsider, in the decades after 1972.

The present paper complements and extends the former studies in several ways. First, it significantly expands the number of countries analyzed, focusing on the most recent decades and using quarterly data that yields more information. Second, it takes as reference a "pure" credit variable, the per-capita real credit, instead of the ratio between credit and GDP, thus excluding the potential disturbing effects of the economic cycle. Third, it relies on the approximate factor modelling method. This procedure differs from previously used methods allowing the full exploration of the data in addition to exhibiting particular advantages when trying to examine the structural dependence of credit across countries.

Our results suggest the existence of three clusters, rejecting the idea that the world is governed by a single credit cycle. However, one of the clusters agglomerates a significant portion of the countries, including major countries. A more thorough analysis revealed that, over the years, more and more countries have been joining this main cluster, thus suggesting the possibility of the world converging to a single credit cycle in the future.

The rest of the paper is organized as follows. Section 2 presents and discusses the econometric methodology and the data. The empirical analysis and the discussion of results are presented in Section 3. Finally, Section 4 concludes.

2 Data Set and Methodology

To address the problem of the existence of a world real credit cycle and/or specific cycles to countries subsets, we use the cyclical component of the real credit *per-capita* as the reference variable. We should note that real credit per capita is preferable to the traditional ratio of credit to GDP because if we use the latter the resulting cycles would be a mix of the credit and the GDP cycles. Data was collected on deposit money bank claims to the private sector from the 22d line of the IMF's International Financial Statistics (IFS).[2] The cyclical components were constructed from the quarterly data of 48 countries from 1985q1 to 2015q4 on real credit per-capita.[3] The countries were selected according to the data availability for the entire period. To compute the cyclical component of the real credit cycle per-capita we rely on a band pass filter as discussed in Artis et al. (2003), retaining the fluctuations between 6 and 32 quarters as is usual in the business cycle literature. This interval follows the one adopted by Baxter and King (1999).

A static approximate factor model is used to identify the common components of the real credit cycles *(per-capita)*. Several aspects justify the choice of this method instead of the alternative dynamic general factor model (DGFM). First, under some forms of the dynamic structure, the static factors are functions of the common shocks and their lags, as such the static form and the DGFM can be seen as akin methods, as shown by Bai and Ng (2007), Forni et al. (2009) or Doz and Fuleky (2020). Second, in the framework of this study the exact identification of the common shocks and the lag structure is not as important as how their combinations affect various countries differently. Third, being interested on how countries clump around the common

[2] The data, expressed in nominal terms, was divided by the respective national CPI index and the population (at the end of the quarter) to obtain the real *per-capita* value.

[3] See Appendix Section 5.1. for the list of countries.

components, the use of the approximate factor model keeps the estimation simple. Moreover, we want to derive regions composition from the data—as implemented in the business cycle literature by Cerqueira (2011)—rather than establishing an aprioristic arrangement, as done by Kose et al. (2003) and Francis et al. (2017). This ability of approximate factor models to allow the data to decide the specific country set cycles is an important advantage. Other methods either simply describe how "distant" various observations are from one another (agglomerative clustering) or require a priori assumptions.

The approximate model's inferential theory was developed by Bai (2003) and is generally represented by the following equation:

$$\begin{gathered} X_t^i = \lambda^{i\prime} F_t + e_t^i \\ i = 1, 2, 3, \ldots, N \\ t = 1, 2, 3, \ldots T \end{gathered} \tag{1}$$

where X_t^i represents the value of the i^{th} national real credit cycle (*per capita*) at time t, λ^i is the $r \times 1$ loading vector, F_t is a $r \times 1$ vector representing the value of r factors at time t and e_t^i is the idiosyncratic component of the series i at time t. In this framework this factor model allows F_t to be dynamic such that $A(L)F_t = \varepsilon_t$ but the relationship between X_t^i and F_t is static. The factor series may follow or not an autoregressive process, and the idiosyncratic component may be orthogonal (*exact factor model*) or weakly correlated (*approximate*). This model extracts the common components (factors) and their loadings into the different credit cycles. As the factor series are normalized to have unit variance, the loadings measure the importance of each component into the cycle, and so, we can construct indexes of similarity between countries (with or without the idiosyncratic component of each series) for the whole sample or sub-periods and perform cluster analysis to determine: i) how the countries cluster; ii) how these cluster have evolved over time.

The first step is to decide the number of factors to be included in the model. Bai and Ng (2002) recommend three information criteria (IC1, IC2, IC3) that can be used to consistently estimate the number of common factors. However, when used in finite samples and in the presence of excessive cross-heteroscedasticity, these IC estimates tend to suggest too many common factors. Monte-Carlo experiments conducted by Cerqueira (2011) show that under these conditions, and without the series being standardized, these ICs almost always select the maximum number of factors that are tested for. If the data is standardized, the IC that gets closer to the true number is the IC2 (even if it, occasionally, overestimates them), as the IC1 and IC3 always select a number bigger than the true one and in many cases they select *Rmax*. Thus, when analyzing the results, we should be aware that even using the IC2, the number of factors may be overestimated; hence, a conservative approach to factor selection seems advisable.

In the second step, the variance decomposition of the indexes is performed to check the importance of each factor. Since the method imposes that $(F'F)/T = I_r$, (F is a $t \times r$ matrix and I_r is an identity matrix of order r) the importance of factor r to country i is given by:

$$\frac{(\lambda_r^i)^2}{var(X^i)} \qquad r = 1, 2, 3, \dots, R \qquad i = 1, 2, 3, \dots, N \tag{2}$$

In general terms, the use of an approximate factor model allows two important and complementary analyses. The first tackles the identification of regional and/or global components. The method involves comparing the importance of a factor for each country and/or subsets of countries using Eq. (2). If the ratio in (2) estimates that the factor is only important for a limited number of countries then we are in the presence of a regional factor, and the set of identified countries will form a region. If the factor is important for a large subset of countries, then the component is a global one. The second groups countries differently, not in terms of having a distinctive common component, but rather examines if a group of countries has a similar dependence structure from the common components. For this, a cluster analysis is performed to check how similar the countries dependence structures are and how they clump together in clusters.

3 Empirical Analysis

This section presents the estimated results and it is divided into five subsections. The first estimates the number of factors to be included in the model, the next presents the estimated factors, the following discusses the relative importance of each factor for each country, the fourth identifies country clusters and the final section analyses the evolution of cluster groups through time.

3.1 Defining Model Structure

The first step is to estimate the number of common factors to apply the model of Eq. (1). The use of an information criterion (IC) is, in this context, better than assuming the number of factors based on our opinions of how the world and/or regional cycles should look like, as that would need some prior beliefs about regions and region composition. Nonetheless, to estimate the number of common components (R), the maximum number allowed for *Rmax* must be chosen. In time series a rule such as $8{*}int[(T/100)^{1/4}]$ considered in Schwert (1989) is sometimes used to set *Rmax*, but for panel data no such rule is available. Bai and Ng (2002) considered $8{*}int[(min(T,N)/100)^{1/4}]$, which for our sample size results in a selection of $Rmax = 8$. The ICs used give the results expressed in table Table 1 - Number of common components.

Earlier it was argued that if there is too much cross-heteroscedasticity in the idiosyncratic components, the ICs applied to non-standardized data almost always select the *Rmax*, while when applied to standardized data the IC2 is the one closer to the true value.[4] From the previous table it seems that 3 should be selected as the number of

4 In fact, evidence of cross-heteroscedasticity was found when estimating the model without standardizing the data. Furthermore, considering what was said before about the behavior of the ICs, the results of table 1 seem to indicate that cross-heteroscedasticity is in fact present and that the data should be standardized.

Table 1 Number of common components

	Standardized Data	Non-Standardized Data
IC1	3	8(*Rmax*)
IC2	3	8(Rmax)
IC3	4	8(Rmax)

common components to use in a static form. Anyway, considering that the IC2 occasionally overestimates the number of common components it should be considered that too many (not too few) factors are probably being included. If that happens, it should be apparent from the importance of each factor in the variation of the real credit cycle of the countries, that is, if the last factor is only important to one country and the importance to the others is marginal, then that factor is capturing a country cycle and not a common component, and at this point the model can be restricted. However, as can be seen in the next section the third component still affects many countries.

Furthermore, as the approximate factor model can be a representation of a DGFM where the estimated static factors are just linear combinations of the original factors in it's dynamic form - called primitive shocks by Bai and Ng (2007) - it would be interesting to know how many primitive shocks exist. To make sense of the number of primitive shocks in real credit *per-capita*, we use the test developed by the previous authors. Although the test is consistent for different penalty values (m), Bai and Ng (2007) recommend a value around 1 when the test is based on the residuals covariance matrix of an estimated VAR on the factors. The results for the overall model suggest the existence of one or two primitive shocks, however when we look just for the first and second factor the test points to two (see Appendix Section 5.2). Therefore, we conclude that the three common components are the static counterpart of a dynamic factor model with two primitive shocks corresponding to the first two static factors, while the third is a linear combination of the lags of the original primitive shocks.

However, the question in terms of groupings is not if a set of countries is subject to a specific shock but if it reacts to the worldwide shocks differently from the rest of the world and has a distinctive common component (that summarizes a specific linear combination of the primitive shocks) making that group a region, or if they have a different dependence structure from the static factors (and from the dynamic ones) forming a cluster.

Looking at the ratio of eigenvalues, in Table 2, it can be assessed how much the first r common components explain the common variation of the series:

Results show that the first eigenvector explains 37.1% of the common variation of the series and, cumulatively, the first three factors explain 75% of the common variation.

Table 2 Ratio of Eigenvalues

Eigenvalue	1	2	3	4
Ratio	0.371	0.257	0.122	0.100
Eigenvalue	5	6	7	8
Ratio	0.067	0.039	0.019	0.01

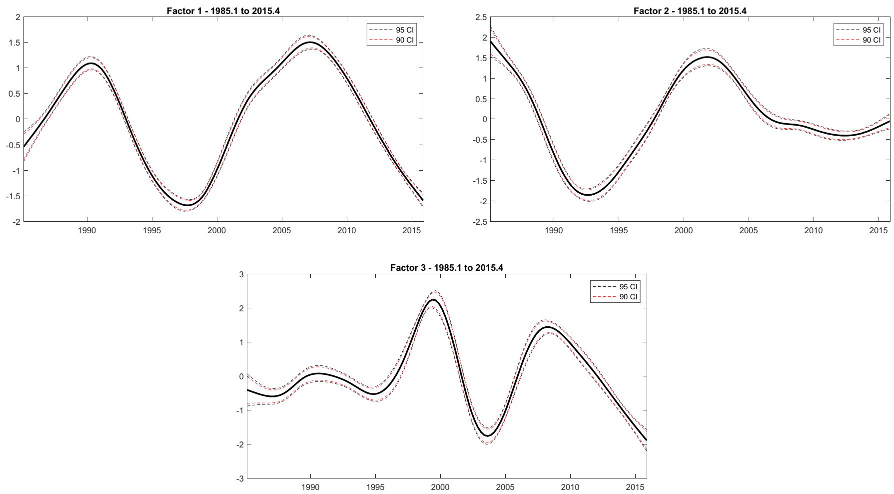

Fig. 1 Estimated common components

3.2 The Estimated Common Components

In this section we will describe how the first three factors evolve over time. Figure 1 does such representation, where the dotted lines are the 95% and 90% confidence level band for the estimated values.[5]

The first factor explains 37.1% of the variation of the countries' indexes (see Table 2) and Fig. 1[6] shows that this common component peaks[7] in 1990:2 and 2007:1 and reaches a trough in 1997:3. This factor seems to capture very well the peak in the world economy at the beginning of the 1990s, which is linked to a global credit boom from the mid-to-late 1980s. This was followed by a period of events[8] that lead to a recession in the beginning of the 1990s and consequently to a decrease in credit that was exacerbated by the 1997–98 Asian financial crisis. This implied a

[5] At this point it should be stressed that assumptions A-H described in Bai (2003) are needed to compute the confidence interval of the factors when $N,T \rightarrow \infty$ (this is the weaker condition imposed). Of particular importance is assumption H, which imposes that the residuals of Eq. 1 are homoscedastic and not serial correlated. Anyway, when this assumption is relaxed the asymptotic theory is still valid when $\sqrt{N}/T \rightarrow 0$.

In this sample the white test to detect heteroskedasticity and the LM tests to detect AR were performed. The tests detect the presence of heteroscedasticity and autocorrelation for a significant number of countries. As in this sample $N = 48 \rightarrow \sqrt{N} \approx 7$ which is smaller than $T = 124$, the use of the asymptotic distribution is still plausible.

[6] The method is not able to estimate the factors themselves, but a rotation of them (HF_t). In this study it is assumed that the loadings of the factors should be positive on the majority of the G7 countries and multiplied the estimated eigenvector by -1 every time that the estimated loadings would not obey to that assumption.

[7] We will say that the index reaches a peak in a given year if it is both positive and is the bigger value between troughs. An index reaches a trough if it is negative and if it is the smaller value between peaks.

[8] The restrictive monetary policy implemented by several central banks to control inflation, the Gulf war, the loss of consumer and business confidence as a result of the 1990 oil price shock, the end of the Cold War and decrease in defense spending, the savings and loan crisis in some countries and a slump in construction resulting from overbuilding in the 1980s.

fall in investment in many of the economies affected by the crisis, which can justify the trough identified by this factor in 1997:3. This led later to an excess of global savings over investment centered in Asia and oil-exporting economies, and consequently to a downward pressure on global real interest rates. This fueled a search for yield which prompt investors and financial institutions to pursue more risky investment strategies (especially in well developed markets like the US) leading to another boom of credit (or bubble) in the second half of the 2000s, also well captured by this factor. The burst of this bubble (the subprime crisis) resulted in the 2007–08 financial crisis and a consequent decrease in credit.

Factor 2, explaining 25.7% of the variation of the countries' indexes, displays a trough in 1992:3 and a peak in 2001:4. Afterwards, the cycle fluctuates around zero. This factor seems to capture some additional features not captured by factor 1. Despite it also identifying the slump in the credit dynamics in the mid-1990s, it is able to capture a boom in credit that preceded the dotcom bubble in the beginning of the 2000s. However, factor 2 is not so successful in capturing the negative effects of the 2007–08 financial crisis, but it captures a positive movement in credit that started to be observe in some countries in the mid-2010s.

Factor 3, as previously mentioned, seems to be a combination of the two primitive shocks that are being captured mainly by the first two factors. This third factor seems to not be relevant until the mid-nineties, and afterwards it shows peaks in 1999:2 and 2008:2 and a trough in 2003:3. After the last peak it decreases to the lower level ever in the 4th quarter of 2015, but it does not seem to have reached a trough.

3.3 The Importance of the Factors for Each Country

Each factor extracted from the data, and presented in the previous section, can be more or less relevant for each country's credit dynamic. This section, following Eq. (2), evaluates their importance by analyzing the real credit cycle variance (VD, variance decomposition). In Fig. 2, countries are ordered by the impact of the main

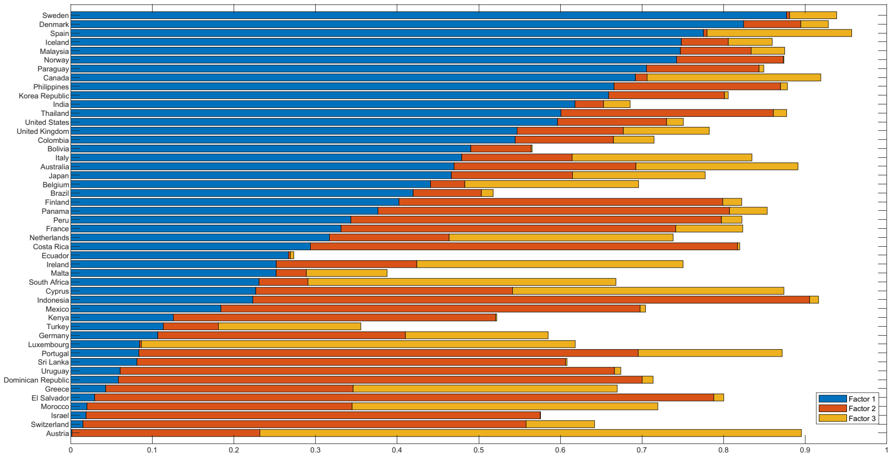

Fig. 2 Factor Importance

factor (factor 1) and the length of each individual bar allows us to realize how much of the variance is being captured by this set of factors.

From the figure it is observable an explanatory dominance of the first factor, as it is responsible for more than 50% of the volatility of the Real Credit Cycle for a significative number of countries: Sweden, Denmark, Spain, Iceland, Malaysia, Norway; Paraguay, Canada, Philippines, Korea, India, United States, United Kingdom and Colombia. However, for the countries in the bottom of the table the first factor is relatively unimportant. For some countries the cycle is mainly driven by the second component: Switzerland, Israel, Morocco, El Salvador Greece, Dominican Republic, Uruguay, Sri-Lanka, Portugal, Germany, Kenya and Mexico. Then there is a set of countries to whom the first and second factors are equally important, as for instance Finland, Panama, Peru, or France. Only for Luxembourg and Austria is the third factor the dominant one. Finally, only for Turkey, Malta and Ecuador the common components explain less than 50% of the variability of the Real Credit Cycle, being the cycles in these countries mainly driven by country specific components.

From this analysis we retain the idea that no geographical grouping emerges, but the components seem to affect differently different countries.

3.4 Identifying Groups and Clustering Analysis

The previous section gave the idea that some countries can be grouped *in terms of having a* distinctive common component. However, this does not mean that these have similar real credit cycles as the dependence from the different common components might differ. This section checks if countries can be grouped according to that structure, thus forming clusters,[9] by using the hard and fuzzy clustering methodologies.

The hard clustering method was applied using the following measure of the distance between any two countries (i and j):

$$d^{i,j} = \sqrt{\sum_{r=1}^{R} \left(\lambda_r^i - \lambda_r^j\right)^2 + \left(s^i\right)^2 + \left(s^j\right)^2} \tag{3}$$

where λ^i_r is the loading of factor r to country i and $(s^i)^2$ is the importance of the idiosyncratic component to country i cycle.[10] This measure clusters together countries that have a similar structure of dependence and to whom the idiosyncratic components are small, checking if they have a high degree of co-movement.

From the cluster trees, we will consider a group when three or more countries are clumped and connect with another group with more than three countries. Results are presented in Fig. 3.

From this cluster tree, we observe that there are two groups with a high degree of synchronicity. The first group is composed by Denmark, Sweden, Canada, Norway, and Korea. The second group comprises Spain, Iceland, Italy, Cyprus, and Australia. These two groups also have a high synchronicity between themselves forming what

[9] See Appendix Section 5.3.1. for a short description of the methods used.

[10] Equation 3 defines a Euclidean distance between the country vectors defined as $\left[\lambda_1^i, \lambda_2^i, \ldots, \lambda_R^i, 0, \ldots, s^i, \ldots, 0\right]$.

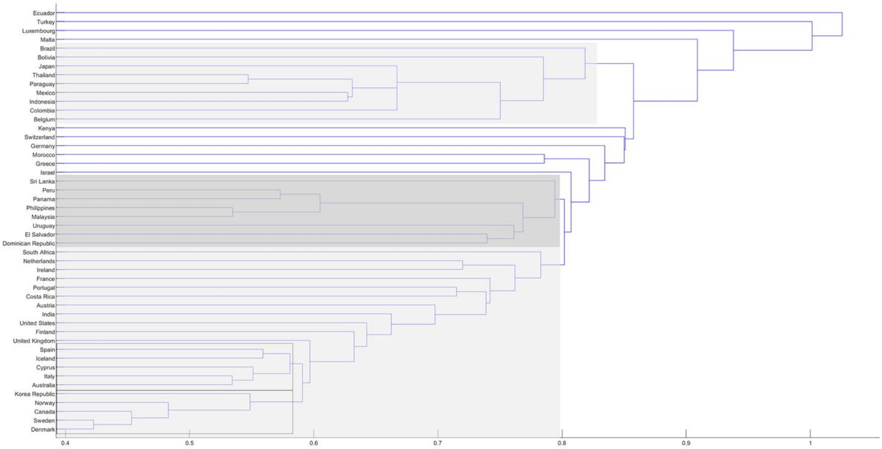

Fig. 3 Cluster tree with the idiosyncratic component

we can call the core groups. Before the core groups joining other groups, there are several countries that form a first peripheric layer: United Kingdom, Finland, United States, Austria, Costa Rica, Portugal, France, Ireland, Netherlands, and South Africa.

After these core groups and their periphery there are two additional groups. The first is comprised by: Sri Lanka, Peru, Panama, Philippines, Malaysia, Uruguay, El Salvador, and Dominic Republic. The second includes: Brazil, Bolivia, Japan, Thailand, Paraguay, Mexico, Indonesia, Colombia, and Belgium. The remaining countries are somewhere between these two groups (which includes Germany) or are ultra-peripheric, corresponding to the countries to which the credit cycle is mainly idiosyncratic, as identified in Fig. 2, namely Ecuador, Turkey, Luxembourg, and Malta.

However, the analysis thus far was based on a set of rules of thumb, and additionally does not consider if some of the groups identified are real groups or just subgroups of a wider one (as the case of the core groups). Also, from the previous analysis little can be said about group cohesion or how strong is the belonging of a country to a specific group. To answer these questions, we resorted to fuzzy clustering (see Appendix Section 5.3 for details on the method).

First, to decide about the number of clusters we rely on the three criteria that, according to Arbelaitz et al. (2013), perform better, namely the Calinski Harabasz, the Davies Bouldin, and the Silhouette criteria. Table 3 reports the results found.

Table 3 Optimal Number of Clusters

Method	Calinski-Harabasz	Davies-Bouldin	Silhouette
With Idiosyncratic Component	2	3	3
Without Idiosyncratic Component	4	3	3

The Davies-Bouldin and the Silhouette criteria suggest three as the optimal number of clusters, while the Calinski-Harabasz criteria varies between 2 and 4. We opted for the middle ground here and chose 3 as the optimal number of clusters.

Figure 4 presents, for individual countries, the degree of membership to each cluster.[11] The countries in blue are those to which the assigned membership is higher and therefore we consider that these groups form the respective cluster. From these results, cluster three emerges as the wide core identified previously, as it includes most of the developed countries, with the expected exclusion of Germany and Japan. The first and second cluster mainly include emerging countries and, of course, allocate Japan and Germany. These two - let us call them non-core clusters - have some correspondence with the two groups identified in the cluster tree with the idiosyncratic components.

One question that can be raised about these cluster is how cohesive they are, this is, how similar are the countries assigned to a given cluster relative to the countries in other clusters? To access that, we computed the silhouettes which is a measure of how similar a country is to countries in its own cluster against countries in other clusters and ranges from -1 to + 1. It is defined as:

$$S^i = \frac{min|b^i - a^i|}{\max(b^i, a^i)} \tag{4}$$

where a^i is the average distance of country i to all other countries in its own cluster and b^i is the average distance of country i to all other countries belonging to other clusters. If the silhouette value is close to 1, it means that the country is well-clustered and it was assigned to a very appropriate cluster. If silhouette value is about zero, it means that the country could be assigned to another closest cluster as well, and it lies equally far away from different clusters. If silhouette value is smaller than 0, it means that country is misclassified.

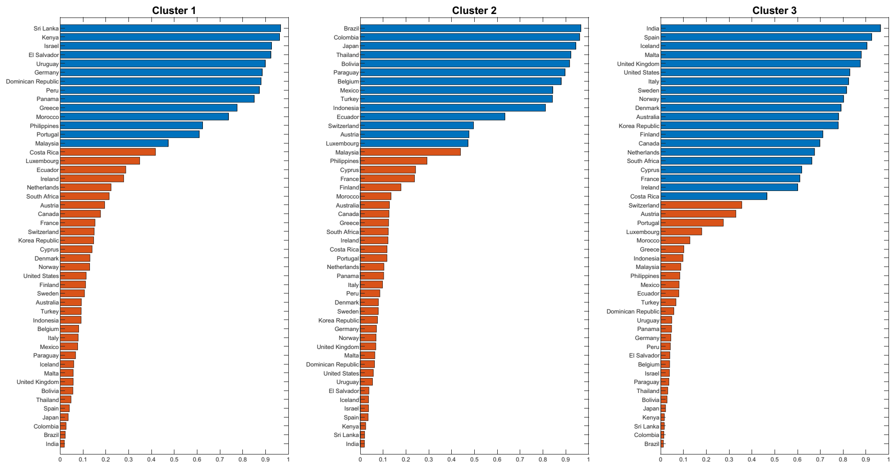

Fig. 4 Fuzzy Clusters Degree of Membership (with idiosyncratic component)

[11] We just present the results with idiosyncratic component as the ones without this component are similar. Results available from the authors upon request.

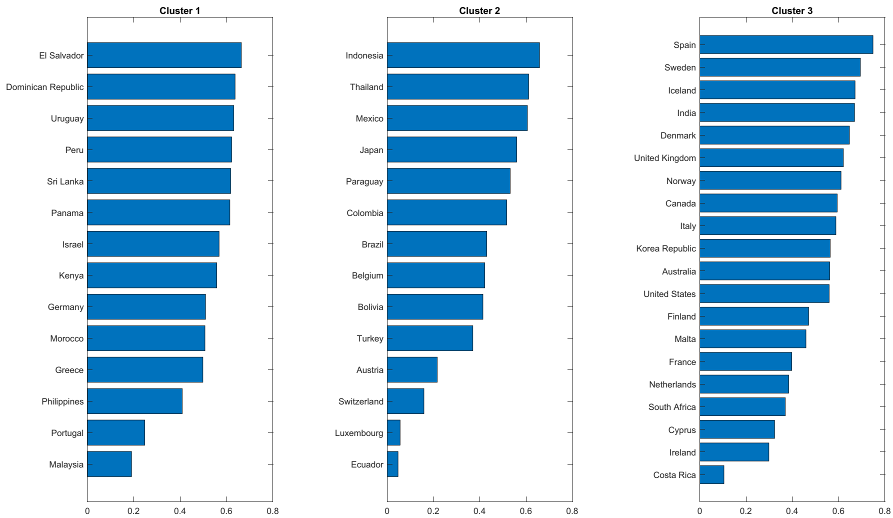

Fig. 5 Fuzzy Cluster Silhouettes (with idiosyncratic component)

Figure 5 assigns each country to the cluster to whom they exhibit the higher degree of membership. An initial analysis reveals that all of them have a silhouette bigger than 0, and that the majority of nations have quite high values meaning that they are well classified, which is equivalent to saying that their credit dynamic is well rooted in that cluster. There are some borderline cases: Costa Rica in cluster 3, and Ecuador and Luxembourg in cluster 2, exhibit a degree of membership of belonging to cluster 1 only slightly lower than the one that leads them to their respective clusters. In cluster 3, Malaysia also has a high degree of membership of belonging to cluster 2 and Portugal is in the borderline between his group and the core group (cluster 3).

3.5 Core Cluster Evolution

Thus far, the results seem to suggest the existence of three credit clusters of countries from 1985 onwards, as such we cannot say that the world shares a common global credit cycle. More so because some of the major players are not allocated in what we called the core group (cluster 3), particularly Germany and Japan. Germany has its own group to which it is not particularly tied, which is not exactly surprising since Meller and Metiu (2017) go even further and place Germany in a solo cluster. This probably highlights the specific financial and banking idiosyncrasies of Germany, the reunification process and also the replacement of a strong Deutsch Mark for the Euro in the beginning of this century. However, the data does highlight cluster 3, not just because it clumps a significant portion of the countries, but also because it is where an important part of the major economies reside, (namely the United States, the U.K., France, and most of the northern European countries), and

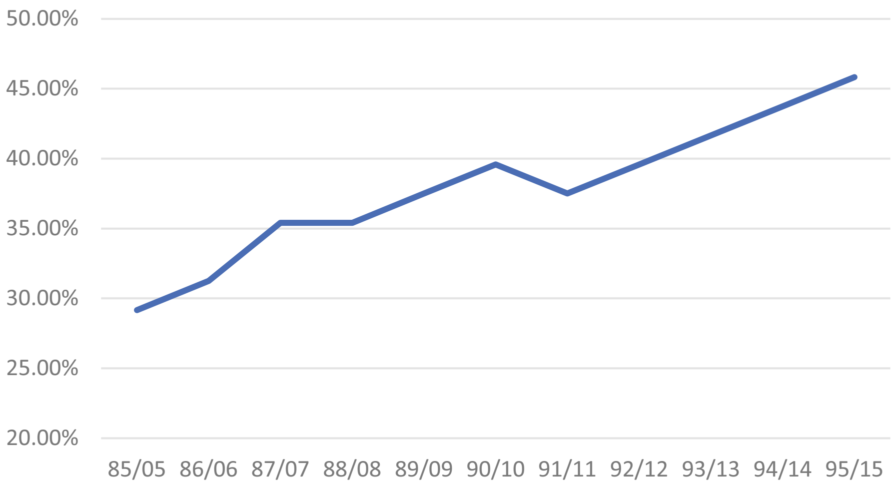

Fig. 6 Percentage of countries belonging to the core cluster

all of them are well anchored to this cluster. This suggests that, if in the future, a world credit cycle emerges, the reported cluster 3 will be that cluster.

To shed some light on this possibility, this section analysis how the core cluster has evolved over the years. The strategy here is to performed consecutive 21-year span rolling windows, being the first 1985:1 to 2005:1 and the last 1995:1 to 2015:4 and estimate the fuzzy clusters degrees of membership (with idiosyncratic component) for each time span. This enable us to detect the evolution pattern of the core cluster. A second analysis is to see if there is an emergence of a single cycle credit, by looking to the importance of the different factors and of the idiosyncratic component.

Figure 6 shows the evolution of the percentage of countries belonging to the core cluster through the eleven 21-year windows, while Fig. 7 shows the degrees of membership of belonging to the core cluster for all countries in three of those windows, the first, the last and the intermediate one.[12] The countries are ordered from the highest to the lowest reported membership degree to this cluster, and those highlighted in blue are the countries actually allocated to the core cluster (*i.e.* those for which the membership degree is the highest, when compared with the one of belonging to any other cluster).

Two clear patterns emerge from Figs. 6 and 7. First, the composition of this cluster has been growing over the years, from 29,17% of the countries (14) in the 1985–2005 window, going to 39,58% (19 countries) in the 1990–2010 windows and finally reaching 45,83% (22 countries) in the final window. Furthermore, through all the period there is an almost continuous increase of the number of countries belonging to the core cluster (being the exception the transition from the 1990–2010 to the 1991–2011 window.

[12] For illustration purposes we chose to display the first, the last and the intermediate. When looking at all eleven sub-samples spans, these three are representative of the general evolution of the core group. The omitted results are available upon request.

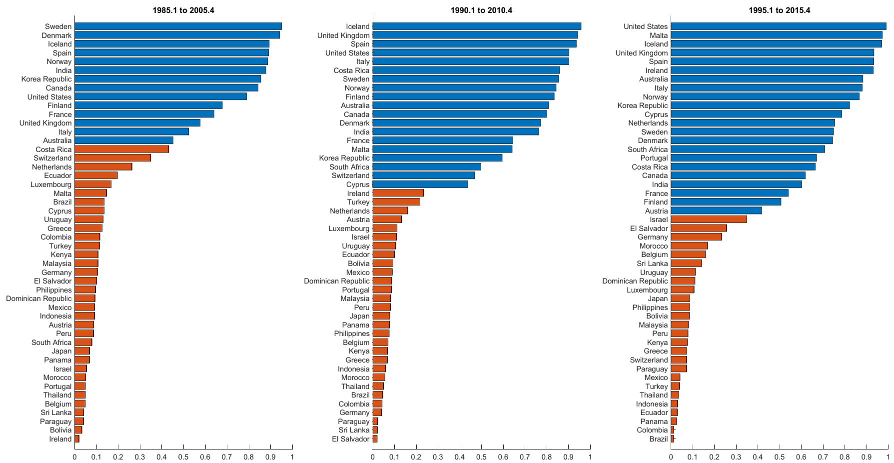

Fig. 7 Core Cluster Evolution

Figure 8 shows the importance of each factor and of the idiosyncratic component on the variance of the series through the 11 21-year span windows.

The 1st component's importance grows until 2011 and after a slight reduction, increases again by the end of the sample. These two moments of growth seem to be different in nature. The first coincides with a decrease in the importance of the second factor while the second with a decrease of the idiosyncratic component. This suggests that countries are clustering around the first factor, and this is increasingly assuming the role of the world credit cycle.

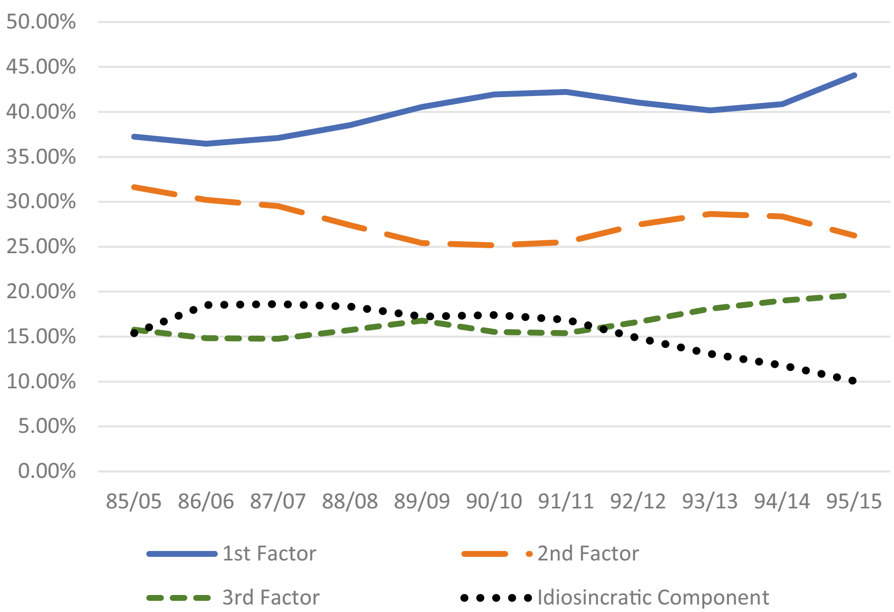

Fig. 8 Factors importance

A second point of notice is the consistent and sharp decrease of the idiosyncratic component in more recent sub-samples, showing that even the credit cycle of the countries that are not clustering in the core cluster are increasingly dependent of common components and less of idiosyncratic shocks.

These analyses indicate that, in terms of the real credit cycle, the world seems to be evolving into a more synchronous credit cycle, not only due to the increasingly larger number of countries following a common cycle, but also because most countries' ties to this core cluster has been reinforced over recent years. If this evolution pattern holds, and the first component importance keeps increasing and the core cluster keeps attracting new countries, there is a strong possibility that, in the near future, most countries will follow a common credit cycle, and something close to a single world real credit cycle may emerge (depicted by the first factor identified in section 3.2). Second, when observing the evolution of the degrees of membership itself, another pattern becomes evident, and that reinforces even more the cluster's importance: the memberships degree to this cluster are increasing, not only for the countries already there (the ones in blue) but also for many of those that are placed in other clusters (the ones in red). We can highlight two particularly relevant examples. Germany's belonging has been increasing, and the belonging of the United States has grown even stronger, to the point of being the country with the highest membership degree in the final window, exhibiting a value very close to one.

4 Conclusion

This paper analyses the international structure of credit resorting to an approximate factor model that allows the identification of common components present in the *per-capita* real credit cycles and their importance for a set of 48 economies. Subsequently, hard and fuzzy clustering methodologies are used to check if countries can be grouped into clusters according to the previously identified structure.

The initial results revealed the existence of more than one component to the real credit cycle, namely two main factors and a third that apparently represents a mixture of the others. Nevertheless, there is one of these that is more pervasive, accounting for 37.1% of the variation of the countries' indexes. Even if the first common component has a significant impact on most countries in the sample, its importance is higher in developed countries, and when we cluster the countries into groups, a wide core emerges including most of these countries. The noteworthy exceptions are Germany and Japan, which suggests that a single world real credit cycle is not yet formed. However, the evolution of this core cluster over the years, seems to point towards that possibility in the future, or at least to a situation where a growing club of countries will follow a common credit cycle. On the one hand, the composition of the core cluster has been growing over the years, encompassing 22 countries if we restrict the analysis to more recent years (2006–2015). One the other hand, the membership degrees to this cluster are increasing, not only for the countries already there but also for many of those that are placed in other clusters, including Germany.

The findings provided by this study have some important policy implications. By understanding better how countries have clustered together and how credit contagion has evolved across them over time provides scope for a more effective international policy coordination, especially regarding prudential supervision and regulation of credit accumulation. The awareness of the formation of a worldwide core cluster, linked to more intense cross-border spillovers, is of utmost importance for policymakers to align their policies and work together to achieve an optimal international credit policy mix. This is of particular relevance when it comes to already well-established regional trade organizations or currency unions, like the European Union.

The patterns and results unveiled is this paper also raise the interesting question of whether the increased clusterization between countries witnessed in recent years is a credit phenomenon or a spillover from the real side of the economy. This integrates in the broader job of understanding which factors may help explain the grouping structure presented here. In particular, structural reasons such as the intensification of the globalization process and more openness to trade, macroprudential policy measures leading to economic deregulation and increased financial openness, and a different array of stochastic factors might help to justify the trend towards the formation of a worldwide core cluster of credit. The clear identification of those factors and their relative relevance comes as a natural extension of this study.

Appendix

List of Countries

Australia	El Salvador	Kenya	Philippines
Austria	Finland	Korea Republic	Portugal
Belgium	France	Luxembourg	South Africa
Bolivia	Germany	Malaysia	Spain
Brazil	Greece	Malta	Sri Lanka
Canada	Iceland	Mexico	Sweden
Colombia	India	Morocco	Switzerland
Costa Rica	Indonesia	Netherlands	Thailand
Cyprus	Ireland	Norway	Turkey
Denmark	Israel	Panama	United Kingdom
Dominican Republic	Italy	Paraguay	United States
Ecuador	Japan	Peru	Uruguay

Number of Primitive Shocks

		Penalty Used								
		m = 1.5			**m = 1**			m = 0.5		
		Number of lags in VAR								
Factors	Test	2	3	4	**2**	**3**	**4**	2	3	4
1,2,3	Test 1	1	1	1	1	2	1	2	2	2
1,2,3	Test 2	1	1	1	1	2	1	2	2	2
1,2	Test 1	2	2	2	2	2	2	2	2	2
1,2	Test 2	2	2	2	2	2	2	2	2	2
1,3	Test 1	1	1	1	1	1	1	1	2	1
1,3	Test 2	1	1	1	1	1	1	1	2	1
2,3	Test 1	1	1	1	1	1	1	1	2	2
2,3	Test 2	1	1	1	1	1	1	1	2	2

Short Description of the Clustering Method

Hard Cluster Trees

The hard-cluster trees with the idiosyncratic component are built by applying the following steps:

1. Compute the following distances for all pairs of countries:

$$d^{i,j} = \sqrt{\sum_{r=1}^{R} \left(\lambda_r^i - \lambda_r^j\right)^2 + \left(s^i\right)^2 + \left(s^j\right)^2}$$

   where $\lambda^i{}_r$ is the loading of factor r to country i and $(s^i)^2$ is the importance of the idiosyncratic component to country I cycle.
2. Find the minimum value,

   If the minimum value is between two original countries go to 3A.
   If the minimum value is between a clustered group and other country or clustered group go to 3B.

3. From step 2:

   (A) Delete those two countries from the sample and add an artificial country where the loadings are equal to the average of the clustered countries.
   (B) Delete the clustered groups and add artificial country where the loadings are equal to the average of all clustered original countries.

4. Go to step one.

Fuzzy C-Mean Algorithm Method

The Fuzzy c-means (FCM) is based on the minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} ||x_i - c_j||^2$$

where:

N is the number of data points

C is the number of clusters

m is the fuzzy partition matrix exponent for controlling the degree of fuzzy overlap, with m > 1 (in this paper we set it to 2). Fuzzy overlap refers to how fuzzy the boundaries between clusters are, that is the number of data points that have significant membership in more than one cluster

x_i is the ith data point

c_j is the center of the jth cluster

μ_{ij} is the degree of membership of x_i in the jth cluster. For a given data point, the sum of the membership values for all clusters is one.

The algorithm performs the following steps:

1. Randomly initialize the cluster membership values μ_{ij},
2. Calculate the cluster centers:

$$c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{m} x_i}{\sum_{i=1}^{N} \mu_{ij}^{m}}$$

3. Update μ_{ij},:

$$\mu_{ij} = \frac{1}{\sum_{K=1}^{C} \left(\frac{|x_i - c_j||}{|x_i - c_k||} \right)^{\frac{2}{m\ 1}}}$$

4. Calculate the objective function, J_m
5. Repeat steps 2 to 4 until J_m converges.

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Data Availability The data underlying this article will be shared on reasonable request to the corresponding.

Declarations

Conflict of Interest None of the authors has interests to declare.

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