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Dissecting Brazilian credit cycle in high-dimensional and time-irregular span context

Abstract

Business cycle analysis has recently been faced with the challenge of a high-dimensional database with time-irregular span in terms available time series starting points (TISN). The present study addresses these issues in the case of the Brazilian credit cycle we propose a hyper-dimensional entropic test of relative information. We and propose a time-irregular span version of the generalized factorial dynamic model presented by Forni, Hallin, Lippi and Reichlin [2000]. We estimate both the GDFM model and its version for time-irregular series (TISN-GDFM) using 2571 series from January 1995 to December 2017. We also propose a Confirmatory model (TISN-GDFM.Conf.) and a version that include a second component (TISN-GDFM2C). The TISN-GDFM model allows a better description of the Brazilian credit cycle. TISN-GDFM.Conf presents a purely credit cycle. TISN-GDFM2C presents an antecedent movement compared to Brazilian credit balance movements. The first step in credit cycle dating it to identify and treat outliers in the total credit balance series. To do so, we combine the Hampel algorithm and an expert analysis of the detailed chronology of banking, credit and economic events over the last 38 years. In this step, eight outliers are identified and treated. Five recessions are dated using two dating approaches. A lagged relationship exists between credit recessions and economic recessions, which indicates that credit expansions precede recessions of the business cycle. In terms of turning points, the peaks and troughs of the credit cycle occur lagging the business cycle (around one year). The chronology of the credit cycle shows that the longest-duration and highest-amplitude credit recession occurred between the second quarter of 2016 and the last quarter of 2017. For a better description of the Brazilian credit cycle, the series were categorized. A larger set of time series is selected in the current quarter in relation to the other lags, concentrated in the categories Confidence and surveys, Industry, Global, and Credit - legal entity. The Brazilian business cycle estimated with TISN-GDFM indicates the following high-commonality categories: Interest Rates, Credit Delays - individual entity, Credit Delays - legal entity, Default - legal entity and Default - individual entity. Interest rates have average commonality, are counter-cyclical and coincide with the estimated credit cycle. The forecast exercise of credit signal, turning point and linear predictive ability indicate the secondary components model (TISN-GDFM2C) presents the best general results.

Key Words: Brazilian credit cycle, Hyper-Dimensional entropic relative information test, Generalized dynamic factor model, Time-irregular span.

JEL Code: E32, C55, C14.

1 Introduction

Much attention has been paid over time to the study of business cycles. Their dating, estimation, duration, phases have been exhaustively documented. The use of broad set of variables, considering the literature of business cycles almost neglected. In particular, in Brazil few studies on credit cycles given the difficulties of data availability.

Several international studies highlight the importance of studying credit cycles that showing that financial crises are often preceded by credit booms (see, e.g.Reinhart and Rogoff [2009b]; Schularick and Taylor [2012]; Gourinchas and Obstfeld [2012]; and Aikman et al. [2014]). Moreover, credit busts are accompanied by severe economic recessions (see, e.g, Reinhart and Rogoff [2009a]; Jordà et al. [2013]; Claessens et al. [2012]; and Schularick and Taylor [2012]). In Brazil, studies to confirm these internationally-reported effects, are still lacking. This study is a first attempt to fill in this gap by using a high-dimensional and time-irregular span database. There are advantages and disadvantages to this approaches. Data must go through several steps so that they can be used in the estimation of a credit cycles. A procedure for selecting variables within a cycle view is necessary.The volume of results to analyze is large. Finally, new relationships may arise. However, advantages outweigh disadvantages.

Several objectives are proposed in this study. First, we make a detailed survey of events in the credit and banking market. This forms a basis to identify compromising outliers in the target series of the credit cycle. We provide a complete description of the chronology of the Brazilian credit cycle. Given the high-dimensional characteristics of the database, the study goes through the process of selection of variables that considers not only the contemporary effects but also the cyclical characteristics to be estimated. Once variables are selected, the business credit cycle is estimated through three different approaches: a more descriptive cycle, to describe each series used in its estimation (TISN-GDFM); a cycle that might have greater predictive ability (TISN-GDFM2c); and a cycle that contains only variables directly linked to the phenomena under study (TISN-GDFM.Conf.).

Several questions will be answered in each step. First we present in Section 2 the literature related to credit cycles. In Section 3 we present methodology used here, the hyper-dimensional entropic relative information test and the proposed GDFM models. Section 4 describes the data and treaments applied. Section 5 sequentially, presents, empirical results, the treatment of outliers, the dating of the credit cycle, the complete chronology of the Brazilian credit cycle, results of the test of hyper-dimensional entropic relative information test, estimated Brazilian (growth) credit cycles, and the dissection of each cycle by category level and individual series. In this same section, we present a comparison of the cycles estimated by different proposed models and the forecast linear and non-linear exercises. Finally, Section 6 concludes.

2 Credit cycles literature

The relationship between credit and the economy over the centuries has changed as shown by Schularick and Taylor [2012]. We observe a new secular trend, credit expansions have increased at a faster rate than income expansions. Credit aggregates contain valuable information about the likelihood of future financial crises. It is not, of course, a perfect predictor. In some periods, especially in eras of financial development and innovation, credit expands to support real economic gains. Schularick and Taylor [2012] call attention to the relation between credit booms and financial crises. A number of researchers have

established that systemic financial crises tend to be preceded by rapid expansions of credit (McKinnon and Pill [1997]; Kaminsky and Reinhart [1999]; and Gourinchas et al. [2001]).

The last two decades have seen rapid development in the theoretical literature on macroeconomic implications of credit variables. Researchers investigating the credit frictions find that these market imperfections arise from several sources: the informational asymmetry between creditors and borrowers (Bernanke and Gertler [1995]; Bernanke et al. [1999]; Gilchrist et al. [2009]); lending collateral constraints faced by borrowers (Kiyotaki and Moore [1997]; Gertler and Kiyotaki [2010]); and the raise of loanable funds by banks (Chen [2001]; Meh and Moran [2010]). Behavioral credit cycles have been investigated by different authors. Gennaioli et al. [2015] present a model of neglected risk. Gennaioli et al. [2012] sketch a model of credit cycles exhibiting both under- and overreaction based on the Bordalo et al. [2016] model of stereotypes. Jin [2015] models extrapolation in credit markets. López-Salido et al. [2017] and Bordalo et al. [2018] present a model of extrapolation of default rates that also delivers insights into the credit cycle.

The literature on credit cycles, focuses on the relationship of business and credit cycles. Empirical studies are less common than studies of the theoretical aspects. Apostoaie and Percic [2014] show that a high interdependence between credit and business cycles exists in European economies. In most European countries, real GDP precedes credit movements. Siklos and Lavender [2015] empirically explore the links between credit and macroeconomic activity in both the United States and Canada since 1999. They conclude that the US and Canadian economies effectively operated as "two solitudes" during the period considered, insofar as credit shocks played a more significant role in influencing real economic conditions in the US than they did in Canada. Jordà et al. [2013] study the role of credit in the business cycle, with a focus on private credit overhang. Investigating the universe of over 200 recession episodes in 14 advanced countries between 1870 and 2008, they document two key facts of the modern business cycle: financial-crisis recessions are more costly than normal recessions in terms of lost output; and for both types of recession, more credit-intensive expansions tend to be followed by deeper recessions and slower recoveries. They conclude that a credit build-up in the boom seems to make economies more vulnerable. Viewing the synchronization of credit cycles among fourteen major advanced economies over a historical time frame, using data from 1906 to 2008, Meller and Metiu [2017] find evidence against the existence of a global credit cycle. Large booms in credit to the non-financial private sector are often followed by severe financial crises and economic recessions. Using high-dimensional time series and time-irregular span data, is to our knowledge, a novel approach in the literature on credit cycles.

3 Methodology

3.1 Hyper-dimensional entropic relative information test procedure

As described in den Reijer [2010] and Van Nieuwenhuyze [2005], this section proposes relative information measures for time-irregular span data, connected to Kullback-Leibler numbers. This measure employes a formal statistical test. By ordering the series of the data set according to these measures, we obtain a subset of the data that is most informative to model a variable of interest. The method can be used as a first step construct a dynamic factor model. The objective is to focus attention to a subset of the series instead of having to monitor all series in a data set. The question seems especially relevant for factor models, which exploit the idea that movements in a large number of series are driven by a limited number of common factors. For a recent overview see Bai

et al. [2008]. Although convergence of factor estimates requires large cross-sections and large time dimensions, see e.g. Forni and Lippi [2001] and Bai [2003], the data set need not be very large to obtain reasonably precise factor estimates. Bai and Ng [2002] conclude that the number of series also need not be very large to get precise factor estimates.

Oversampling refers to the situation in which the data are more informative about some factors than others. Including more variables in an oversampled data set could result in more precise factor estimates, which do not however, improve the forecasting performance for the target variables that depend on the less dominant factors. Building upon Jacobs [2012] and den Reijer [2010], this paper exploits concepts from information theory, in particular Kullback-Leibler numbers, to analyze information in the data. We propose a relative information measure based on Gaussian distributed data with a clear link to Kullback-Leibler numbers for time-irregular span data. We follow the same idea as Jacobs and Otter [2008]. They apply similar information concepts to derive a formal test for the number of common factors and the lag order in a dynamic factor model, however in a time-irregular span context. Ordering the series of the data set according to these measures enables us to identify a subset of the data set that is most informative to modelling a variable of interest. The method can be used as a first step to construct a DFM or GDFM.

3.1.1 Defining hyper-dimension

The definition of hyper-dimension and high-dimension is not consensual in time series econometrics. The simple rule that $N > T$ was adopted by Belloni and Chernozhukov [2011] and Stock and Watson [2014]. However, the databases treated by these authors in the applications had the $\frac{N}{T}$ ratio a little above 1. Other authors, such as Bai et al. [2008], denominate $N > T$ as being large panel data. Others such as Song and Bickel [2011] define as a rich data environment. In the computational field of Big Data the definition of hyper-dimension is data with millions (or even billions) of records, according to Mohapatra and Majhi [2015]. For our study we will define hyper-dimension for time series analysis as being:

$$Y_{i,t}^{Hyper-dimensional}, \quad \text{if} \quad d_{HyD} = \frac{N}{T} \geq 5$$

with

$$i = 1, ..., N; \;\; t = 1, ..., T.$$

In our case, we will work with $d_{HyD} = \frac{2571}{95} > 27$.

3.2 Entropic relative information measure in factor model context

We will present, as described in den Reijer [2010] and Van Nieuwenhuyze [2005], the link between RI_N and the (static or dynamic) factor models context. Consider $x_{it} = (x_{1t}, ..., x_{nt})'; n \in N, t \in T$ stationary N-dimensional vector process with zero mean being driven by k factors, as

$$x_{it} \;\; = \;\; \chi_{it} + \xi_{it} = \sum_{j=1}^{N} b_{ij}(L) u_{jt} + \xi_{it} = B_N F_t + \epsilon_t \tag{1}$$

$$x_{it} \in \mathbb{R}^N,\ F_t \sim N_k(0, I_k),\ \epsilon_t \sim N_k(0, \Psi_{11})$$

where χ_{it} is the common component, ξ_{it} is the idiosyncratic component, $b-ij(L) = B_N = B_0^n + B_1^n L + ... + B_s^n L^s$ represents the (dynamic) loadings of order s, $u_{ij}; j = 1, ..., q; t = 1, ..., T$ are common shocks mutually orthogonal white noise processes with unit variance. The variance between the first N elements of x_{it} is equal to $\Gamma(N) = B_N B_N^{'} + \Psi_{11}$ as we can with Bai et al. [2008].

When we add a variable $x_{N+1,t}$, we have

$$\begin{pmatrix} x_{it} \\ x_{N+1,t} \end{pmatrix} = \begin{pmatrix} B_N \\ b_{N+1} \end{pmatrix} F_t + \begin{pmatrix} \epsilon_t \\ \epsilon_{N+1,t} \end{pmatrix} \tag{2}$$

with covariance

$$\Gamma(N+1) = \begin{pmatrix} \Gamma(N) & \Gamma_{12} \\ \Gamma_{21} & \Gamma_1 \end{pmatrix}$$

where $\Gamma_{12} = B_N b_{N+1}^{'} + \Psi_{12}$ and $\Psi_{12} = E(\epsilon_t \epsilon_{N+1,t})$. As x_{it} is normalized we have $b_{N+1} b_{N+1}^{'} + \sigma_{N+1}^2 = 1$, with $\sigma_{N+1}^2 = E(\epsilon_{N+1,t}^2)$. Using the rule of determinants for partitioned matrices we get

$$\det(\Gamma(N+1)) = \det(\Gamma(N))(1 - a_{N+1})$$

where $a_{N+1} = (b_{N+1} B_N^{'} + \Psi_{12})\Gamma(N)^{-1}(B_N b_{N+1}^{'} + \Psi_{12})$ and $0 \leq (1 - a_{N+1}) \leq 1$. So

$$RI_{(N,t)} = \frac{-logdet(\Gamma(N))}{cN}$$

$$RI_{(N+1,t)} = \frac{-logdet(\Gamma(N+1))}{c(N+1)} = \frac{-logdet(\Gamma(N) + (1 - a_{N+1}))}{c(N+1)}$$

Thus, we have the relation between $RI_{(N+1,t)}$ and $RI_{(N,t)}$ is

$$RI_{(N+1,t)} = RI_{(N,t)} - \frac{1}{N+1}\left(\frac{\log(1 - a_{N+1})}{c} + RI_{(N,t)}\right). \tag{3}$$

Therefore, there is only addition of relative information if $RI_{N+1,t} > RI_{(N,t)}$, or in the condition $-log(1 - a_{N+1}) > cRI_{(N,t)} \Rightarrow \mathrm{E}(\mathrm{x}_{N+1,t} x_{N,t}^{'}) = (b_{N+1} B_N^{'} + \Psi_{12} \neq 0)$. This condition will be used to apply a formal statistical test. From Equation 3 we have $RI_{(N+1,t)} = RI_{(N,t)}$ if $a_{N+1} = 1 - \exp(-cRI_{(N,t)})$. Whenever $RI_{(N,t)}$ is close to zero, $RI_{(N+1,t)}$ increases for relative small values of a_{N+1} whereas if $RI_{(N,t)}$ is close to one, a_{N+1} should be close to one to allow $x_{N+1,t}$ to add relative information. We can simplify Equation 3 considering $\Gamma(N) = C\Lambda C^{'}$ and the linear transformation $\tilde{x}_t = U^{'}\Lambda^{-\frac{1}{2}} C^{'} x_t$ and $\tilde{x}_{N+1,t} = \upsilon^{-1} x_{N+1,t}$, U with orthogonal and $\upsilon^2 = 1$ obtained by the singular value decomposition with $\Lambda^{-\frac{1}{2}} C^{'}\Gamma = U\Sigma\upsilon$ where $\Sigma = (\phi, 0, ..., 0)^{'}$. This gives rise to $\Gamma_{12} = 0 \Rightarrow \Sigma = 0$. Therefore, we have

$$\begin{pmatrix} \tilde{x}_{N,t} \\ \tilde{x}_{(N+1,t)} \end{pmatrix} = N_N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \tilde{\Gamma}(N+1)\right)$$

where

$$\tilde{\Gamma}(N+1) = \begin{pmatrix} I(N) & \Sigma \\ \Sigma & 1 \end{pmatrix}$$

with $det(\tilde{\Gamma}(N+1)) = det(I_N)(1-\phi_1^2) \Rightarrow RI_{(N+1,t)} = \frac{-\log(1-\phi_1^2)}{c(N+1)}$, where $\phi_1 \in [0,1]$ is a coefficient of canonical correlation. Because $RI_{(N,t)} = 0$ by hypothesis is zero in Equation 3, to gain relative information, we have $\tilde{RI}_{(N+1,t)} = \frac{-log(1-\phi_1^2)}{c(N+1)}$.

3.3 Hyper-dimensional entropic relative information test procedure

The first step is to replace $\tilde{\Gamma}(N+1)$ by a consistent estimate $\hat{\tilde{\Gamma}}(N+1)$. Applying this procedure yields $\hat{\tilde{RI}}_{(N+1,t)} = \frac{-\log(1-\hat{\phi}_1^2)}{2}$ under $H_0 : \phi_1 = 0$. This hypothesis is test by Bartlett test statistic:

$$t_{(\alpha,N)} = -\left[T - \frac{1}{2}(N+2)\log(1-\hat{\phi}_1^2)\right] = \left[T - \frac{1}{2}(N+2)\right] 2\tilde{\hat{RI}}_{N+1,t} \tag{4}$$

$t_{(\alpha,N)}$, follows asymptotically a χ^2 distribution with N degrees of freedom and α, is the significant level, see e.g. Muirhead [1982]. Testing the hypothesis $H_0 : \phi_1 = 0$ is similar to testing whether the transformed vector $(\tilde{x}'_{(N,t)}\tilde{x}_{(N+1,t)})'$ has maximum entropy. If the null hypothesis is rejected, the estimated relative information of the transformed variables equals

$$\hat{\tilde{RI}}_{(N+1,t)} = \frac{-\log(1-\hat{\phi}_1^2)}{c(N+1)}.$$

The series are transformed by taking logarithms and/or differencing when necessary to assure approximate stationarity. The series should be adjusted for outliers by replacing the observations of the transformed variables using some robust method. With previous treatments, the test procedure follows the steps:

1. We estimate the canonical correlation coefficient $\hat{\phi}_1^*$ in the time-irregular span context;
2. The relative information measure is calculated: $\hat{\tilde{RI}}^*_{(N+1,t)} = \frac{-\log(1-\hat{\phi}_1^{*2})}{c(N+1)}$;
3. We order the data set according to the relative information measures associated to the target variable using the following procedure:
   (a) the initial variable of the ordered data set is the target variable;
   (b) the variable that maximizes the respective relative information from the remaining data is added to the ordered data set, and so on.
4. We test if $\hat{\tilde{RI}}^*_{(N+1,t)}$ is statistically different from zero with $t^*_{(\alpha,N)} = \left[T^* - \frac{1}{2}(N+2)\right] 2\tilde{\hat{RI}}^*_{N+1,t} \sim \chi^2_N$. The null hypothesis is that an additional variable is un-correlated with the variables already included in the set;
5. We investigate the existence of relevant relative information in other lags (or leads), for which we calculate $\hat{\tilde{RI}}^*_{(N+1,t-k)}$ and apply the same steps.

We estimate $\hat{\phi}_1^*$ using the time-irregular span approach. However in the calculation of the test statistic we consider the different sample sizes of each time series. Although this small difference does not alter the overall results, for a small set of series on the threshold

between having statistically nonzero relative information, the T version instead of T^* eventually ends up with a larger number of series. For a descriptive model, the selection of variables can use series present in different lags (considering only ones present in several lags.), in order to increase the descriptive capacity of the factorial model to be estimated. Alternatively, we can implement some backdating method for the time-irregular span as Bańbura and Modugno [2014] present and apply the test procedure. [1]

3.4 Generalized dynamic factor models

Recently progress has been made in the theory of factor models through the Generalized Dynamic Factor Model (GDFM) of Forni, Hallin, Lippi and Reichlin, hence forth FHLR (Forni, Hallin, Lippi and Reichlin [2000]; Forni and Lippi [2001]; Forni et al. [2001, 2004, 2005]). The model differs from the classic factor model in that it allows the idiosyncratic errors to be weakly serial and cross-sectionally correlated, despite being a non-parametric approach. It thereby combines the so-called "approximate static factor model" of Rothschild and Chamberlain [1982], widely applied in financial econometrics (e.g. Arbitrage Pricing Theory, APT), with the Dynamic Factor Model of Geweke [1977] and Sargent et al. [1977] for which, respectively, cross-sectional and serial correlation are allowed. The model is dynamic since the common shocks can hit the series at different times, in contrast to the static model. The common shocks and components, which are a linear combination of them, are inherently unobservable and are estimated by means of dynamic principal components. While the familiar static principal components are based on an eigenvalue decomposition of the contemporaneous covariance matrix, dynamic principal components are based on the spectral density matrix (i.e. dynamic covariations) of the data and consequently are averages of the data weighted and shifted through time.

3.5 Estimating GDFM

We assume that the N time series included in our panel are, after suitable transformations, a realization of a real-valued stationary N-dimensional vector process with zero mean $x_{it} = (x_{1t}, ..., x_{Nt})'$. Under the GDFM, satisfying the necessary conditions and assumptions, each time series can be decomposed into two components:

$$x_{it} \quad = \quad \chi_{it} + \xi_{it} = \sum_{j=1}^{q} b_{ij}(L) u_{jt} + \xi_{it}. \tag{5}$$

χ_{it} is the common component and ξ_{it} the idiosyncratic component. $b_{ij}(L) = B_n(L) = B_0 + B_1 L + ... + B_s L^s$ represents the (dynamic) loadings of order s which are allowed to differ in coefficient and lags across the series. The q common shocks $u_{jt}; j = 1, ..., q$ are assumed to be mutually orthogonal white noise processes (at all leads and lags) with unit variance. This vector process has a non-singular spectral density matrix, equal to the first q dynamic eigenvalues of the data. The idiosyncratic component is driven by variable-specific shocks, for which the GDFM allows a certain amount of correlation. The dynamic factor structure implies that the idiosyncratic component of any series is orthogonal to all common shocks at any lead or lag. The common shocks u_{jt} are latent and need to be estimated. This is done through the estimation of dynamic principal components. These

[1] In this study the two forms were tested. As the divergence of selected series was small, we opted to first backdating the series (with the data already normalized) and then apply the relative information test.

components are obtained by the dynamic eigenvalues and eigenvectors decomposition of the spectral density matrix of x_{it}, which is a generalization of the orthogonalization process of the variance-covariance matrix of x_{it} in the case of static principal components.

3.6 Cyclical behavior of individual series

Having identified the business cycle information in each variable as the common component, we can now evaluate each variable's cyclical behavior with respect to the reference cycle. To do so, out of the spectral density matrix of the common components $\Sigma_N^{\chi}(\theta_h)$. The cross spectral density of each common component is calculated with respect to the common component of the reference variable[2] x_i^R: $\sigma_{x_i,x_i^R}(\theta_h)$, the cross spectral density $\sigma_{ij}(\theta_h)$ out of $\Sigma_N^{\chi}(\theta_h)$ represents the mutual relation between two common components, this relation can be written in the frequency domain as the sum of waves of different frequency, amplitude and phase. The phase angle shift ϕ_{ij} measures how much a wave i (and thus the common component) is shifted with respect to a reference wave j measured at a particular frequency θ_h The phase angle shift can be translated to a time lag ψ_{ij} in the time domain by dividing it by its frequency θ_h. So we can estimate the phase angle shift $\phi_{x_i,x_i^R}(\theta_h)$ or time lag $\psi_{x_i,x_i^R} = \frac{\phi_{x_i,x_i^R}(\theta_h)}{\theta_h}$ of the common component with respect to the common component of x_i^R. This allows us to classify the series as pro- or counter-cyclical and as coincident, leading or lagging.

3.6.1 Pro and counter-cyclical variables

Following Forni, Hallin, Lippi, Reichlin et al. [2000] and Van Nieuwenhuyze [2005] we can classify the series as pro- and counter-cyclical by computing the phase angle shifts at the zero frequency with the reference cycle: $\phi_{x_i,x_i^R}(\theta_h)$. At this frequency, the long-run correlation between the two common components is measured. Depending on whether this long-run correlation is positive or negative, the phase angle shift will be either 0 or π. A positive long-run correlation $\phi_{x_i,x_i^R}(0) = 0$ is interpreted as a pro-cyclical variable, a negative $\phi_{x_i,x_i^R}(0) = \pi$ as a counter-cyclical one (see also Granger and Hatanaka [2015]).

3.6.2 Coincident, leading and lagging variables

As described in Van Nieuwenhuyze [2005], a classification of variables into coincident, leading or lagging is obtained by evaluating the phase angle shift at a typical business cycle frequency $\theta_h^{x_i^R}$. There is no such thing as a standard frequency or length of a growth cycle. However, looking at the estimated common component of x_i we define the length of a cycle as the sum of the length of a boom (defined as an above-average common component)and the length of the subsequent recession[3] (defined as a below-average common component) we consider the number of cycles in a temporal sample by some dating process. Therefore the length of a typical business cycle is (x_i^R). We calculate the phase shift at a frequency $\theta_h^{x_i^R} = \frac{2\pi}{h}$. Therefore if $h = 1 \Rightarrow \theta_h^{x_i^R} = 2\pi$ and x_i^R repeats its behavior every 2π periods. Dividing the obtained phase angle shifts by this frequency delivers the time lags ψ_{x_i,x_i^R}. Variables are classified as leading when the time lag exceeds 1 (quarter), lagging when it is lower than -1 and coincident otherwise.

[2] In this article reference cycle will be the quarter-on-quarter Brazilian GDP variation.

[3] We require a minimal duration of 2 quarters for the booms and recessions.

3.7 Proposed GDFM model

Even the GDFM model considering (N, T) tending to infinity, computational processing does not exceed a certain number of iterations due to physical memory limitations. In time series in context of very high dimension they have no alternative but a step of selection of variables. In a context of time-irregular span data, the use of the GDFM model is also compromised. To address all of the issues we propose in this section, changes to the basic GDFM model. The first step is to use the entropic test of relative information to select a sub-set of high-dimensional time series.

3.7.1 TISN - Generalized dynamic factor model

As previously mentioned, Doz et al. [2012] show that the maximum likelihood is consistent, robust and computationally feasible in the case of large cross-sections. To maximize the likelihood over the high-dimensional parameter space they propose using the Expectation-Maximization (EM) algorithm. The EM algorithm was first applied to a dynamic factor model by Watson and Engle [1983] on a small cross-section. They cast the model in a state space form and derive the EM steps in the case without missing data. Shumway and Stoffer [1982] show how to implement the EM algorithm for a state space form with missing data, however only in the case in which the matrix linking the states and the observable is known. Bańbura and Modugno [2014] propose a general treatment of data sets with an arbitrary pattern of missing data. This treatment allows the idiosyncratic component be correlated. The essential idea of the algorithm is to write the likelihood as if the data were complete (with draws of $N(0, 1)$) and to iterate between two steps: in the expectation step we 'fill in' the missing data in the likelihood, while in the maximization step we re-optimize this expectation. Under some regularity conditions, the EM algorithm converges towards a local maximum of the likelihood. A direct maximization of the likelihood (or state-space formulation) is not computationally feasible for large N. However, Doz et al. [2012] suggest that the computational complexity can be circumvented by means of the Expectation-Maximization (EM) algorithm. Bańbura and Modugno [2014] offer a solution to problems for which incomplete or latent data yield the likelihood intractable. The essential idea is to write the likelihood as if the data was complete and to 'fabricate' the missing data in the expectation step.

3.7.2 Algorithm for estimation of TISN-GDFM

The estimation of the TISN-GDFM model follows the following steps:

1. All treatments that precede the selection procedure are applied: transformation of the series available on a monthly basis to a quarterly basis by taking averages; deflation of monetary variables; de-seasonalization (when necessary); first-difference (when necessary to guarantee stationary) and finally normalization[4];

2. To obtain initial values for the parameters $\theta(0)$,we replace the missing observations in x_{it} (observe that x_{it} already normalized) by draws from $N(0, 1)$ distribution;

3. Obtain the back data estimate for the series using the EM algorithm Bańbura and Modugno [2014];

4. The relative information test is applied to select, in different lags, the set of series to be used;

[4]All the treatments applied and the description of the database used are detailed in the next section.

5. GDFM is estimated.[5]

Some questions left for future research, include the possible bias introduced by using reconstructed data, and the power of relative information testing.

3.7.3 Secondary component Generalized dynamic factor model

Considering the probability of type I and II errors in the relative information test, we propose a GDFM model to address this question. The interaction of computationally relative information occurs accurately up to the threhold of 10^{-8}. However these values in the relative information test can identify variables with considerable relative information as statistically zero. Another issue concerns the fact that these series individually may have small relative information, but together they may be relevant for a given reference cycle. To address these issues we propose the GDFM2C:

1. All treatments that precede the selection procedure are applied: transformation of the series available on a monthly basis to a quarterly basis by taking averages; deflation of monetary variables; de-seasonalization (when necessary); first-difference (when necessary to guarantee stationary) and finally normalization;

2. If we have TISN data, we follow steps 2 and 3 described for the TISN-GDFM model;

3. We apply the relative information test to select, in different lags, the set of series to be used;

4. With any series not selected, at each lag by the relative information test, we estimate a dynamic principal component;

5. The GDFM or TISN-GDFM model is estimated using this dynamic principal component (which will be called the secondary component or second component) as a new series.

The secondary component may or may not contribute to the reference cycle. Given its cyclical behavior, the secondary component may have a leading characteristics and thus may provide a relevant predictive information. If it displays coincident/lagging predictive information, it can indicate that the selection process of variables was suitable for describing the reference cycle.

3.7.4 Confirmatory Generalized dynamic factor model

Some questions about the reference cycle can be approached using variables directly related to the cycle under study. To emphasize the importance of these variables for the reference cycle, we propose the confirmatory GDFM (GDFM-Conf.) Model:

1. All treatments that precede the selection procedure are applied: transformation of the series available on a monthly basis to a quarterly basis by taking averages; deflation of monetary variables; de-seasonalization (when necessary); first-difference (when necessary to guarantee stationary) and finally normalization, but only for confirmatory variables;

2. If we have TISN data, we follow steps 2 and 3 described for the TISN-GDFM model;

3. The GDFM or TISN-GDFM model is estimated using confirmatory variables.

[5]The number of factors to estimate the model was determined by the test proposed by Alessi et al. [2010].

4 Data and treatments

Challenges related to the database of young economies are always present. Studies high-dimensional time series increase these challenges since these data have problems of time-irregular span; data in temporal frequency that requires a disaggregation procedure that also demands a wide set of co-variables; seasonal adjustment procedures to apply on a large scale and consider the particular issues of the country; the discontinuities of methodologies that generate old and new series of the same phenomenon.

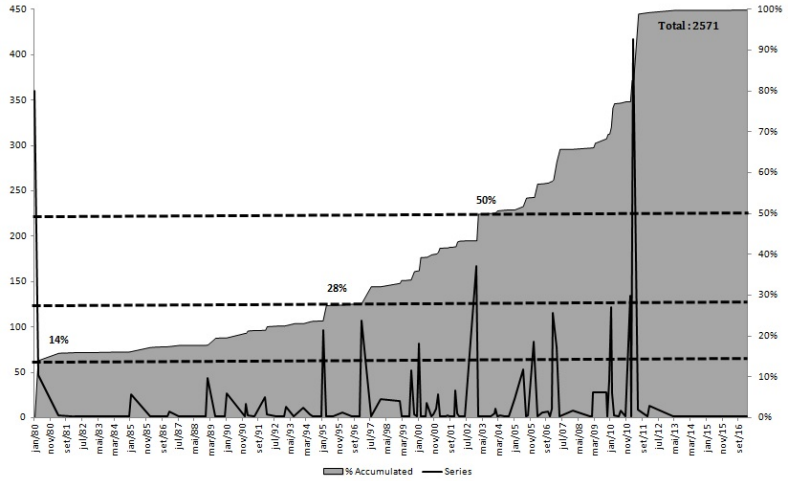

Figure 1: Temporal evolution of Brazilian series available for economic studies.

Treatments for all these issues were presented in this section. To achieve a database to study cycles, several steps were taken to make the models estimable. The series were made compatible to guarantee the maximum possible information; the annual series were disaggregated in a high-dimensional context for quarterly frequency; the series that did not have published their seasonally-adjusted versions were submitted to a sequential seasonally-adjusted procedure, considering several individual issues of the series besides the Brazilian stylized facts. We focus on the growth cycle concept of the business cycle (unlike for instance the NBER method, which measures cycles in the level of the series, see Burns and Mitchell [1947]), defined as the quarter-on-quarter variation of the underlying variables. The series available on a monthly basis were transformed to a quarterly basis by taking averages. We have 92 observations between 1995Q1 and 2017Q4. Furthermore, all activity variables are expressed in real terms. These are obtained by deflating nominal variables by the CPI[6] index. For all other variables (e.g. interest rates and exchange rates) both nominal and real concepts were included in the data set.

The models to be estimated require stationary time series. We opt to apply the same stationary procedure to all series. We first-difference the series' levels by taking percentage changes compared to the previous quarter and by a simple difference when the level may exhibit negative values. For price variables (consumer prices, stock prices, ...) percentage changes with respect to the previous quarter of the index were taken. We also apply this procedure to variables which were stationary from the outset. The reason for this is twofold: i) having all variables defined in quarter-on-quarter variations allow us to capture the growth cycle concept of the business cycle and ii) taking on variables in their level, even when stationary, would seriously disturb the mutual relations in the frequency domain

[6]Each case was studied: IGP-DI used for series in general, IPCA used for consumer-related series, US CPI for variables of that country and so respectively

causing phase shifts and thus invalid deduced time lags, Cohen [2001] show that deducing and comparing time lags from both concepts would be improper. Interest rate spreads, which were taken on in levels, are the only exception to this rule. But Interest rate spreads levels are, however, stationary and are the result of a cross-sectional difference instead of a difference in time. Given, Interest rate spreads is widely illustrated covariation with the growth cycle concept of the business cycle, Estrella and Mishkin [1997], this is common practice. After, the series were normalized to have a zero sample mean and unit variance by subtracting their mean and dividing by their standard deviation. This standardization is necessary to avoid overweighting of the series with large variance when estimating the spectral density matrix. Afterwards, the common component is denormalized, so as to correspond to the actual series.

The final step, after the normalized data, the series with time-irregular span (dataset with an arbitrary pattern of missing data) were back dating using the procedure of Bańbura and Modugno [2014]. With the database within all these specifications, the models were estimated. Some questions were left for future research, such as the possible bias using reconstructed data, the power of relative information testing among others.

4.1 Models and reference business cycle

The business cycle (or just cycle) is an empirical phenomenon characterized by co-movement of economic time series. The business cycle can be interpreted as one common factor affecting all time series at the same moment. In our case, such a factor is non-existent, since we allow different common factors to affect the time series at different moments in time.

How can we then identify a reference credit cycle? Through the GDFM, each time series is split into a common component and an idiosyncratic component. The common component is a linear combination of the common factors and thereby represents the business cycle information present in the variable. The idiosyncratic component captures variable-specific variation unrelated to the business cycle. Having more than one common factor and different loadings to these factors, we can identify a reference business cycle as the common component of a particular variable. A priori, being a broad measure of credit activity, it is convenient to choose total credit balance for credit cycle (in each database context) as a reference. Since they are also the key variable in our forecasting exercise, we will follow this approach throughout the paper.

Other variables could have been used as reference variable. Ideally, a good reference variable should have a common component, which represents a large part of the variable. In practice, the common component is not observable; practitioners rely on the variable itself to assess the state of the business cycle. The proposed models listed in Table 1 use the common component associated with GDP (in each database context). Models will be explored in detail below.

Table 1: Models estimated for credit cycles study

Model	Description	Database
1	Time-irregular span Generalized Dynamic Factor Model (TISN-GDFM)	Time-irregular span for credit cycle
2	Time-irregular span Generalized Dynamic Factor Model Second Component (TISN-GDFM2C)	Time-irregular span for credit cycle
3	Time-irregular span Generalized Dynamic Factor Model Confirmatory(TISN-GDFM-Conf.)	Credit class variables

All proposed models estimate the Brazilian credit cycle in different sample contexts. Models 1 to 3 estimate the credit cycle with different characteristics as detailed in Section 3.8: Model 1 has a more descriptive cycle approach (TISN-GDFM); Model 2 incorporates a second component (TISN-GDFM2C); and Model 3 represents a cycle purely related to credit variables (TISN-GDFM-Conf.).

5 Empirical results

5.1 Dating procedure and chronology of Brazilian credit cycle

Classically, the business cycle chronologies refer to the dating of particular time series in level. The most notable and well-known example of dating peaks and troughs in economic activity is that of the National Bureau of Economic Research (NBER) for the United States. The NBER dating method was adapted with the non-parametric algorithm of Bry-Boschan (1971) (BB). In this section we present the results of different dating procedures. The first step to date the Brazilian credit cycle was the identification and treatment of the outliers present in the reference series[7].

5.1.1 Identification and treatment of outliers in the total credit balance

From its earliest versions (Hampel [1971], Carroll [1980])to the most current versions (Hampel et al. [2011]), Hampel's algorithm has been used for identification and treatment of outliers in time series using trimmed temporal moving-median. This procedure is not free of misspecifications and can generate serious modifications in the series. Because of this, we use both Hampel's algorithm and the judgmental analysis we call the Hampel/Chauvet procedure. The judgmental procedure consideres all chronology presented in Table 12. The results of this treatment for Brazilian total credit balance are shown in Figure 2.

[7]The series of total credit balances originated in June 1988. However, given the different monetary regimes and periods of high inflation, they are statistically different values from zero as of January 1995. This date is considered as initial for the whole temporal sample considered in this study.

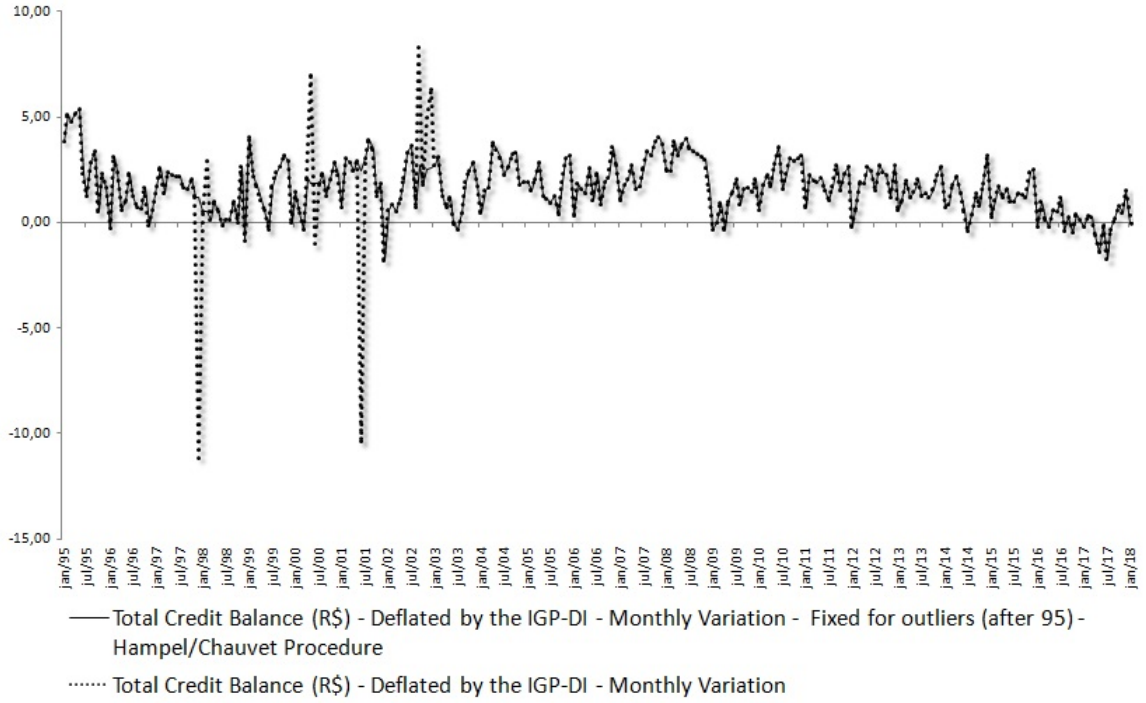

Figure 2: Outlier analysis - Brazil total credit balance

Movements of privatizations, mergers, and acquisitions generate abrupt momentary changes in total credit balance due to transfers of balances between banks. The Hampel algorithm identified 10 outliers up to December 2002, of which only 8 were considered by the judgmental chronological evaluation, as we can see in Table 2:

Outliers	Privatizations	Mergers and acquisitions
Dec/97 and Feb/98	BANERJ, CREDIREAL	2
May/00 and Jun/00	BANEB	4
Jun/01	BANESTADO, BANESPA	2
Sep/02, Nov/02 and Dec/02	PARAIBAN, BEG, BEA Bank	2

Table 2: Credit outilers: identification and treatment.

From January 2003 until the end of the sample, the Hampel algorithm identifie 13 other outliers, but none of them passed the chronology evaluation. Therefore they are not considered as abnormal or atypical movements of the Brazilian total credit balance. After the correction of the outliers, as described in Section 4, the data were deseasonalized and made quarterly.

5.1.2 Dating procedures for the Brazilian credit cycle

Bry and Boschan [1971b] and Boschan and Ebanks [1978] set a milestone among cycle dating methods, proposing a non-parametric interpolation between peaks and valleys. More recently, Harding and Pagan [2003] compare non-parametric and parametric dating methods. The most common procedure initially proposes a dating with non-parametric methods and later a comparison with the dating generated from of a parametric model. The nonparametric method presented by Harding and Pagan [2002] and Harding and Pagan [2003] considers that the cycle of a series can be expressed in terms of its inflection points, which are local maximum and minimum within a time sample. In general $Y_t = \ln y_t$

the peak in period t in Y_t occurs when Y_t exceeds Y_s for $s > t$ and $s < t$ using a rolling window as $(t-k, t+k)$. Bry and Boschan [1971a] use $k = 5$ for monthly data, while Harding and Pagan [2002] use $k = 2$ for quarter data, both define troughs (T_t) and peaks (P_t) as

$$P_t = [(Y_{t-2}, Y_{t-1}) < Y_t > (Y_{t+1}, Y_{t+2})]$$
$$T_t = [(Y_{t-2}, Y_{t-1}) > Y_t < (Y_{t+1}, Y_{t+2})].$$

Pioneering works of cycle dating intended to ensure that the phases of the cycle had a minimum duration of 6 months and that the completed cycles had a minimum duration of 15 months. Bry and Boschan [1971b] method was refined by Haywood [1973] to include a cycle amplitude criterion. Chauvet and Hamilton [2006] present parametric methods with multiple indicators of inflection points. Stock and Watson [2010] compare different methods of dating. More recently Stock and Watson [2014] propose a high-dimensional dating process using a combination of the BB procedure and panel data models. Artis et al. [2004] propose dating method for the Eurozone. Chauvet and Piger [2008] present an approach with Markov Switching models for real-time dating. In this section, we present results of two different dating procedures:

1. The modified BB algorithm proposed by Harding and Pagan [2002] which shares the same features of the original BB algorithm, but adapted to the quarterly frequency, was applied to level of total credit balance. We use the obtained recession dates to generate dummies for a probit model with the log-level of total credit balance as a variable response.

2. We estimate a univariate Markov-Switching (MS) model with total credit balance growth rates obtaining the probabilities of the recession state.

With these probabilities obtained (Pr_i), i = 1,2 we define as a quarter of recession:

$$D_{recession}^{quarter} = \begin{cases} 1, & Pr_i > \overline{Pr_i} + 0.5 \times \sigma_{Pr_i}, \\ 0, & \text{otherwise} \end{cases}$$

The probability results for estimated MS models are shown in Figure 3.

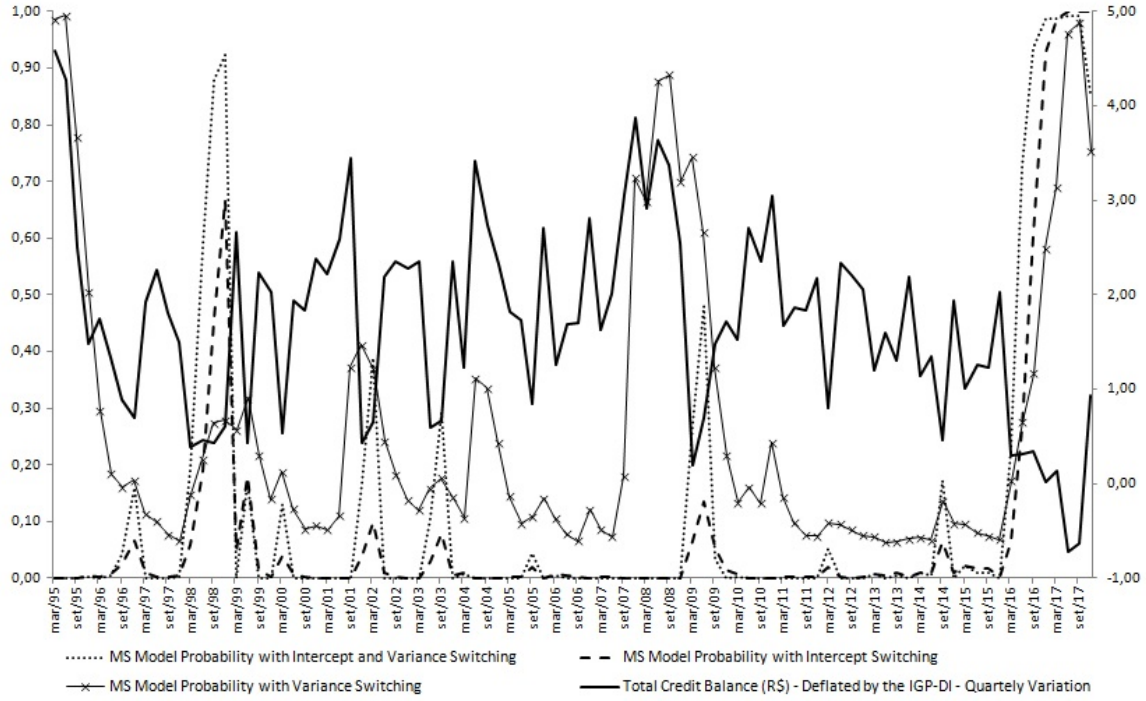

Figure 3: Markov-Switching models for dating procedure

As shown in Figure 3, the switching intercept model has statistically significant regimes. However the expected time in an expansion regime tends to infinity and therefore presents very low recession probabilities. This results in identification of only two credit crises and it is not used.

The MS for variance switching, which measures credit uncertainty, and the MS for intercept and variance switching has statistically significant parameters and regimes. Both identify the same number of credit recessions, yet the periods of each recession are different for each model. Again the judgmental criterion using the chronology presented in Table 12 guides the decision to choose the MS with intercept and variance switching. The comparison between the dating methods used is shown in Figure 4.

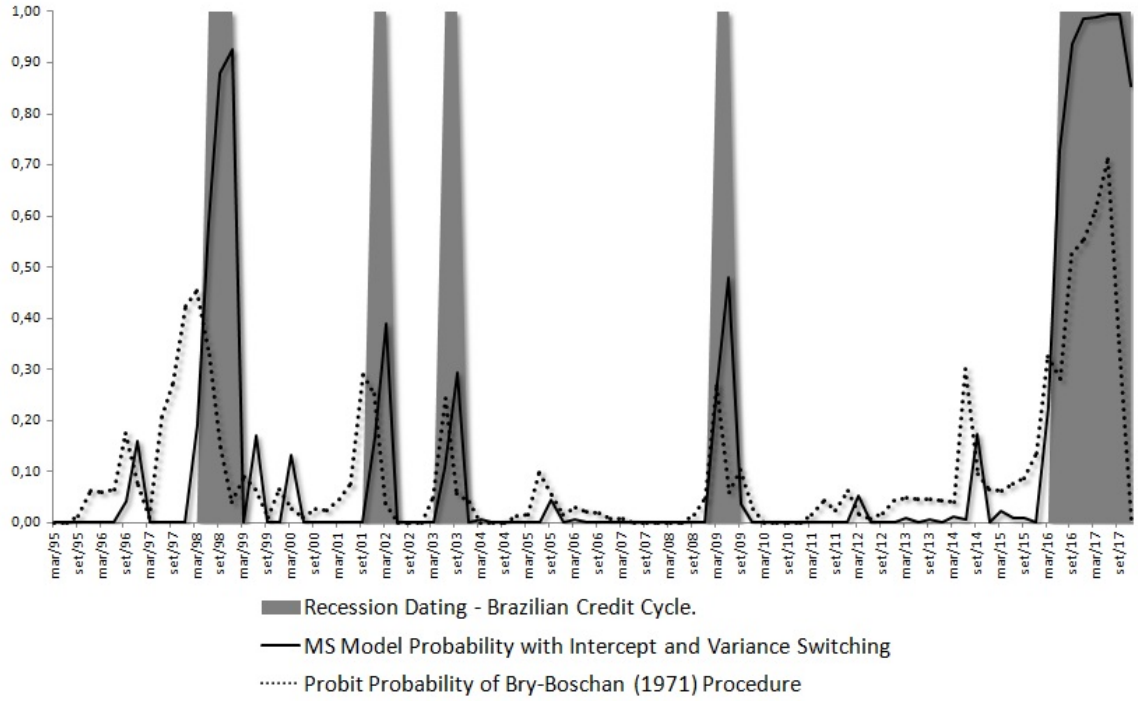

Figure 4: Comparison between different models for dating

Results show a great convergence of dating methods in the identification of credit recessions. As the recession probabilities of the MS model are longer, this dating is chosen. In the sequence we present in Figure 5 a comparison CODACE[8] official data for the Brazilian economic cycle and credit cycle.

[8]Brazilian Business Cycle Dating Committee (CODACE) Was established to produce the chronological (monthly and quarterly) reference for the Brazilian economic cycles. CODACE monitors and evaluates the country's recessive cycles, as the National Bureau of Economic Research (NBER) Business Cycle Dating Committee does for the U.S. The NBER Committee has been dating the American economic cycles since 1854.

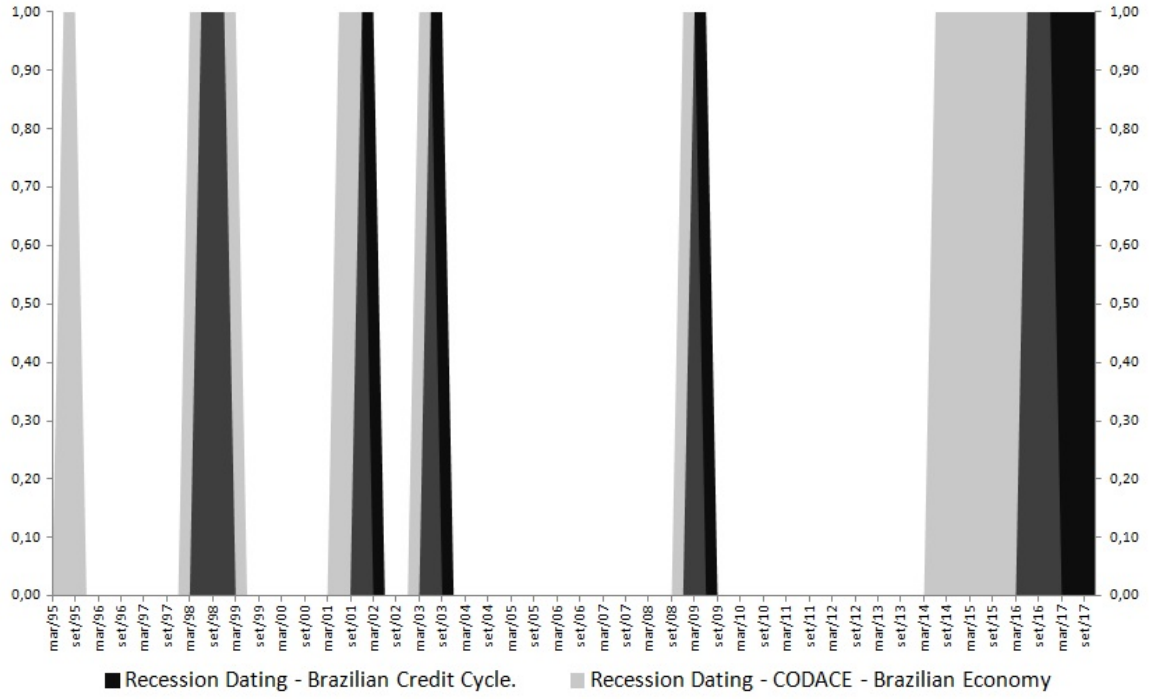

Figure 5: Comparison CODACE economy recessions and credit recessions

In the period of study, we have 6 CODACE recessions and 5 credit recessions. Only the first recession of credit occurs entirely within an economic recession. In all other cases CODACE recessions precede credit recessions. The duration of the credit recession is related to duration of CODACE recessions. This relation is best described in the analysis of signals of the turning points in relation to the cycle dated by CODACE in Table 3.

Table 3: Turning point signals of the reference cycle
(CODACE and Brazilian Credit Cycle)

Lead/lags with respect to actual turning points		
CODACE	Model 1	Model 2
Troughs (6)		
1995Q3	0	0
1999Q1	+3	+3
2001Q4	0	+1
2003Q2	+3	+3
2009Q1	+3	-2
2015Q2	+7	+7
Peaks (7)		
1995Q1	0	0
1997Q4	+4	+6
2001Q1	+4	+5
2002Q4	+2	+3
2007Q1	+4	+5
2008Q3	+5	+15
2017Q1	+4	0

* All variation is calculated using the seasonally-adjusted IGP-DI inflation-deflated quarterly series.
* Model 1: Markov Switching in Intercept and Variance
* Model 2: Markov Switching in Variance
* The criterion adopted for determining turning points is whether the smoothed probability of state 1 (Recessions) is equal to or greater than unconditional average probability plus 0.5 of unconditional standard deviation, similar to using the probabilty of state 1 (expansion) for peaks.

It is clear that the credit cycle troughs occur in a lagged way (in some cases coincidental) in relation to the Brazilian economic cycle troughs, with a lag of about 9 months with model adopted. If we consider the model of credit uncertainty (Model 2) only in the CODACE recession of 2008, the credit troughs preceded the economic cycle troughs.

Regarding the peaks, both the adopted model (Model 1) and the credit uncertainty model (Model 2) are lagged in relation to the peaks of CODACE business cycle. However, they occur about 12 to 15 months afterwards. When we compare the credit cycle peaks, they are antecedents of the valleys of the CODACE economic cycle. This is a recurrent fact described in the literature.

5.1.3 Chronology of the Brazilian Credit Cycle

We present in Table 4 the detailed chronology of Brazilian credit cycles un the period studied.

Both recessions and expansions of the credit cycle are larger in Model 2. In Model 1 recessions have a short duration of six to nine months, except for the last recession that lasted almost 2 years and the highest severity with average growth of 0.05% and negative turning point trough of -0.72%. The uncertainty model (Model 2) of the Brazilian credit cycle shows recessions wiyh a long duration of 15 to 21 months, except for the one-quarter recession of 2001. In this model the longest lasting recession was 2007-09 and the most severe was the last recession with a negative average growth of 0.05%.

In terms of credit cycle expansions, Model 1 presents a short period, 4 quarters between 2002-03 and 27 quarters between 2009-16. The period of greatest amplitude was the period of 2003Q4-2008Q4, with an expansion of almost 50% in the total credit balance. In Model 2, the expansion has long periods, over five years with expansion of up to 45%. The 2009Q3-2016Q3 cycle is the longest and the largest expansion of the credit balance. The chronology of the cycle estimated by Model 1 will be used for the sequencing of this study.

Table 4: Quarterly Chronology of the Brazilian Credit Cycle - Duration and Amplitude

Period	Model 1								Period	Model 2							
	Recessions			Expansions			Turning points			Recessions			Expansions			Turning points	
	Quarter's duration	Cumulative peak-to-troughs variation	Average variation during the phase	Quarter's duration	Cumulative peak-to-troughs variation	Average variation during the phase	Turning point troughs variation	Turning point peak variation		Quarter's duration	Cumulative peak-to-troughs variation	Average variation during the troughs	Quarter's duration	Cumulative peak-to-troughs variation	Average variation during the troughs	Turning point troughs variation	Turning point peak variation
1995Q1 - 1998Q1	-	-	-	13	25,40	1,95	-	4,59	1995Q1 - 1995Q4	5	12,84	3,21	-	-	-	1,47	-
1998Q2 -1998Q4	3	1,49	0,49	-	-	-	0,42	-	1996Q1 - 2001Q3	-	-	-	23	36,28	1,58	-	3,45
1999Q1 - 2001Q3	-	-	-	11	22,32	2,02	-	3,45	2001Q4	1	0,44	0,44	-	-	-	0,44	-
2001Q4 - 2002Q1	2	1,09	0,54	-	-	-	0,43	-	2002Q1 - 2007Q3	-	-	-	23	44,41	1,93	-	3,06
2002Q2 - 2003Q1	-	-	-	4	9,17	2,29	-	2,35	2007Q4 - 2009Q2	7	17,24	2,46	-	-	-	0,19	-
2003Q2 - 2003Q3	2	1,26	0,63	-	-	-	0,59	-	2009Q3 - 2016Q3	-	-	-	29	45,45	1,56	-	3,05
2003Q4 - 2008Q4	-	-	-	21	49,66	2,36	-	3,87	2016Q4 -2017Q4	5	-0,26	-0,05	-	-	-	-0,72	-
2009Q1 - 2009Q2	2	0,90	0,45	-	-	-	0,19	-									
2009Q3 - 2016Q1	-	-	-	27	44,79	1,65	-	3,05									
2016Q2 - 2017Q4	7	0,40	0,05	-	-	-	-0,72	-									

*All variation is calculated using the seasonally adjusted IGP-DI inflation-deflated quarterly series.
*Model 1: Markov Switching in Intercept and Variance
*Model 2: Markov Switching in Variance
*The criterion adopted for determining turning points is whether the smoothed probability of state 1 (Recessions) is equal to or greater than unconditional average probability plus 0.5 of unconditional standard deviation.

One feature that stands out in this chronology is the fact that large expansions of credit are followed by large contractions. This relationship of intensity of expansions and contractions characterize movements typically cyclical and validate the process of dating used. As already presented, Model 1 will be used to define the official dates of the Brazilian credit cycle.

An important point obtained by this chronology shows that the Brazilian credit cycle is a moderate cycle. This feature may be related to the business cycle that will be addressed following this study. This characteristic is fundamental to determine the spectral frequency (frequency-domain) of the cycle, which will be used in the models for estimation of the cycle. Five cycles have occurred since 1995, with an average length of 20 quarters, or about 5 years each. Taking $\frac{5}{23}$ years as the length of a typical credit cycle, we calculate the spectral frequency as $\frac{\pi}{5}$.

5.2 Variable selection - relative information test in high-dimensional and time-irregular span context

The first step of this section is a test of relative information to identify, in different lags, the most relevant variables to estimate of credit cycle. The test, as detailed in Section 3, give the most information on variable of interest, which in this case are total credit balance. The test is applied to the 2571 variables from the current period up to the third lag (i.e. a full year of dynamic effects are considered). The results for credit variable are shown in Figure 6. Hence, low p-values indicate that an additional variable adds information.

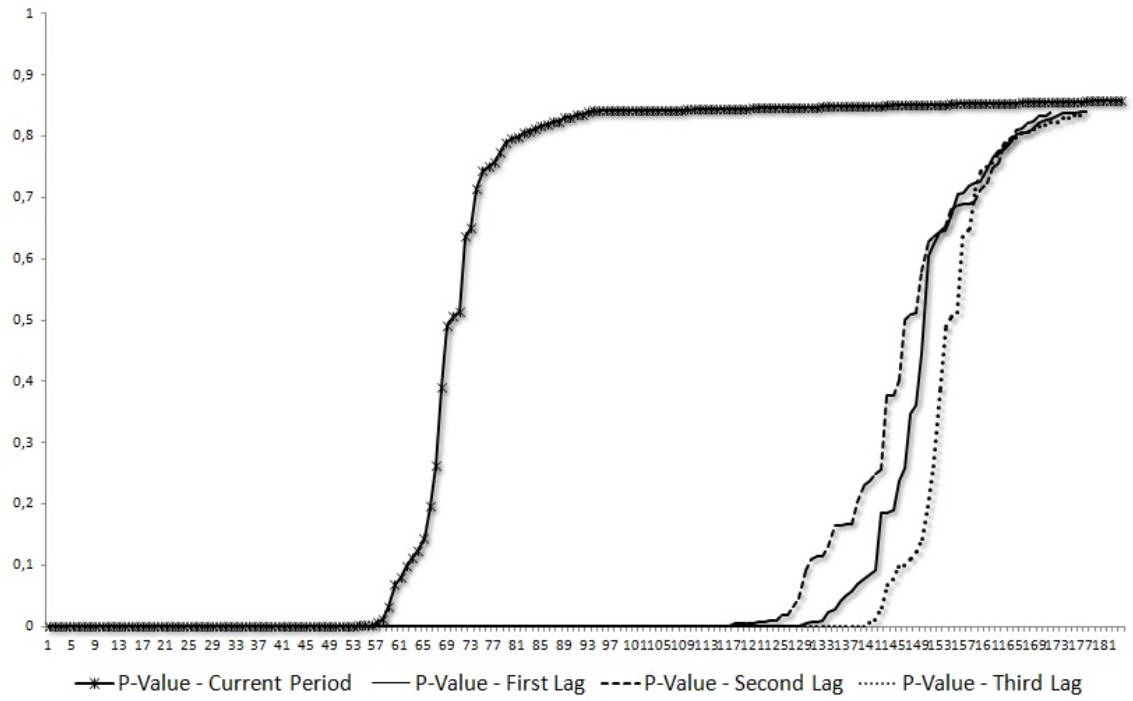

Figure 6: Relative information test - results for Time-irregular span credit cycle study.

The number of variables in the short term (current period) is considerably lower (62) than for the other lags. The third lag requires the largest number of variables (147), followed by the first (143) and second (134) lags. This implies that credit is a more complex phenomenon in its temporal dynamics than in current events.

Given the high-dimensional characteristic of the database, it is necessary to categorize the variables to enable a more complete analysis of the credit cycle. With thirty two categories,[9] this categorization follows the more general format of a credit portfolio and its main segmentation described in Table 5.

Table 5: Categories for credit cycle study

Class	Series	%
Confidence and Surveys	406	0.16
Industry	207	0.08
Global	205	0.08
Credit - legal entity	191	0.07
Import and Export	178	0.07
Credit - individual entity	167	0.06
Sectoral	139	0.05
Governmental Finance	124	0.05
Prices and Inflation	120	0.05
Climate	96	0.04
Emploment	66	0.03
Credit	61	0.02
Agriculture	47	0.02
National Accounts	47	0.02
Commodities	46	0.02
Governmental Credit	44	0.02
Salary	42	0.02
Interest Rates	41	0.02
Country-Risk	40	0.02
Credit Delays - legal entity	37	0.01
Default - legal entity	36	0.01
Services	36	0.01
Credit Delays - individual entity	32	0.01
Default - individual entity	31	0.01
Retail	26	0.01
Exchange Rates	26	0.01
Finance	19	0.01
Bankruptcies	17	0.01
Monetary	15	0.01
Banking	13	0.01
International Interest Rates	11	0.00
External Sector	5	0.00
Total	2571	1.00

The Final Selection in Table 6, shows the predominance of five categories: Confidence and Surveys (Economic activity series, different confidence indicators), Import and export, Global (International economic activity), Industry, and Sectoral. Together, these categories represent more than forty five percent of all selected series.

[9] All time series used and their respective categories are available up request.

Dynamically the variables of the category of Governmental credit, Interest rates and Industry are very representative in the current period but with few series present in other lags, the opposite happens with the series of the category of Employment.

Banking variables and International interest rates are the categories with the lowest number of series, while the Confidence and Surveys and Import and export variables are the categories with the highest number of selected series.

In terms of sample representativity, the Final Selected Sample has six categories with great participation in their own category: Agriculture, Commodities, External sector, Finance, Governmental credit, and Monetary variables.

From the total of 2571 variables tested, 555 (22%) present non-zero relative information of these 349 (14%) present values statistically different from zero. Thus, each set of variables (349 of the Final Selection, 206 of the Second Component and 674 of the Confirmatory) will be used for a specific type of model to estimate the credit cycle.

5.3 Time-irregular span generalized dynamic factor model results.

Figure 7 illustrates the growth of the total credit balance in Brazil and its common component. we see that the common credit component closely follows the movements of the credit balance.

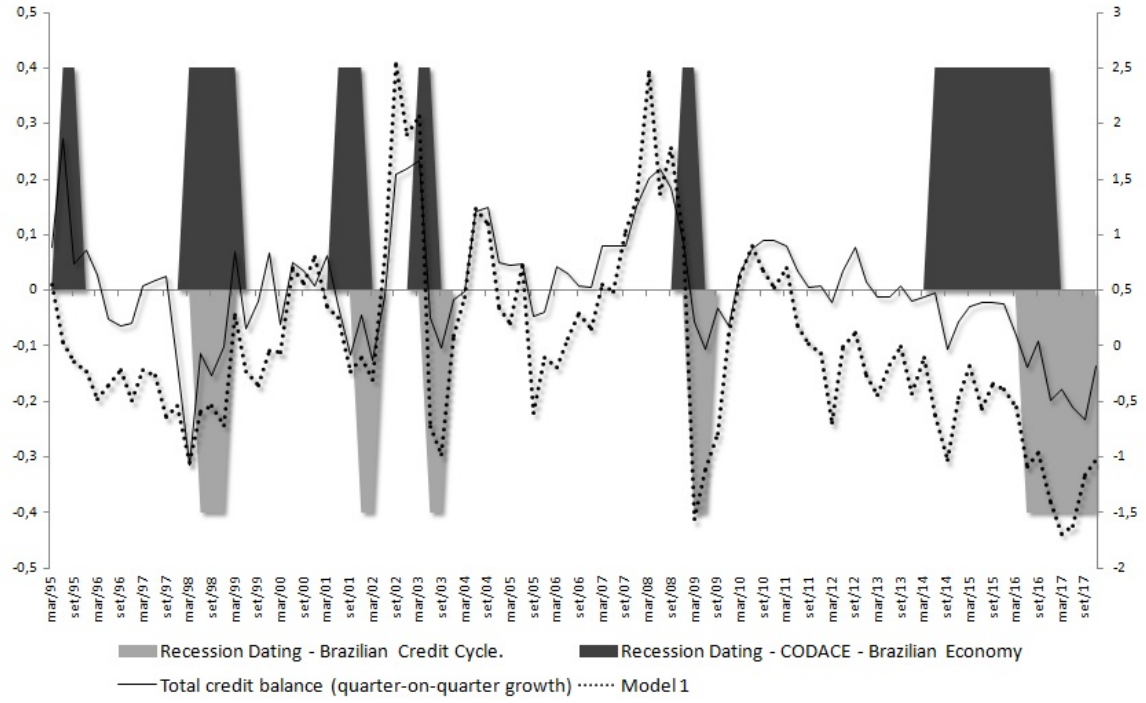

Figure 7: Quarter-on-quarter credit growth and TISN-GDFM common component.

This categorization provide a more detailed analysis of the relative information test for variable selection. These results for total credit balance are presented in Table 6.

Table 6: Variable Selection - Relative information test for high-dimensional time-irregular span time series - Total credit balance.

Class	RI_t	$Selected_t$	RI_{t-1}	$Selected_{t-1}$	RI_{t-2}	$Selected_{t-2}$	RI_{t-3}	$Selected_{t-3}$	Final Selection	2º Component	Confirmatory	Total Sample
Agriculture	7	1	1	12	2	3	1	5	17	10	0	47
Banking	2	0	0	0	0	1	1	0	1	3	0	13
Bankruptcies	1	0	0	2	1	1	0	1	2	2	17	17
Climate	2	0	2	2	3	2	0	3	5	6	0	96
Commodities	6	2	1	5	1	11	1	10	14	7	0	46
Confidence and Surveys	8	7	1	17	3	13	7	12	37	19	38	406
Country-Risk	3	0	1	2	0	1	0	2	5	4	0	40
Credit	1	4	0	3	1	0	0	2	7	2	53	61
Credit - individual entity	1	2	0	2	0	1	0	2	3	1	167	167
Credit - legal entity	4	0	0	0	0	1	0	1	2	4	191	191
Credit Delays - individual entity	1	0	0	4	0	3	0	2	7	1	32	32
Credit Delays - legal entity	2	2	0	1	0	2	1	2	7	3	37	37
Default - individual entity	0	1	0	1	0	0	1	1	3	1	31	31
Default - legal entity	1	0	1	2	0	2	0	2	4	2	36	36
Emploment	10	1	2	6	3	2	1	7	13	15	0	66
Exchange Rates	3	0	0	2	1	1	0	3	5	4	0	26
External Sector	1	2	0	1	0	4	0	1	2	1	0	5
Finance	3	0	0	3	1	10	0	5	8	4	0	19
Global	13	0	4	18	3	8	3	9	32	20	0	205
Governmental Credit	10	7	3	9	7	7	4	10	18	16	44	44
Governmental Finance	8	0	0	1	2	12	0	10	19	10	0	124
Import and Export	12	2	3	19	1	8	5	17	37	19	0	178
Industry	4	7	5	9	2	1	3	10	26	12	0	207
Interest Rates	0	7	0	2	0	1	0	1	2	0	28	41
International Interest Rates	0	0	0	1	0	3	0	1	1	0	0	11
Monetary	6	1	0	1	0	6	0	3	5	0	0	15
National Accounts	5	0	0	2	1	5	0	9	9	7	0	47
Prices and Inflation	0	5	2	6	2	2	1	3	16	10	0	120
Retail	1	2	1	0	0	3	0	2	5	1	0	26
Salary	6	2	2	2	1	13	0	1	8	4	0	42
Sectoral	2	4	6	6	2	0	2	10	25	15	0	139
Services	0	2	0	2	1	0	0	0	4	3	0	36
Total	123	61	35	143	38	127	31	147	349	206	674	2571

Percentage

Class	RI_t	$Selected_t$	RI_{t-1}	$Selected_{t-1}$	RI_{t-2}	$Selected_{t-2}$	RI_{t-3}	$Selected_{t-3}$	Final Selection	2º Component	Confirmatory	Final Selection Sample
Agriculture	0,06	0,02	0,03	0,08	0,05	0,02	0,03	0,03	0,05	0,05	0,00	0,36
Banking	0,02	0,00	0,00	0,00	0,00	0,01	0,03	0,00	0,00	0,01	0,00	0,08
Bankruptcies	0,01	0,00	0,00	0,01	0,03	0,01	0,00	0,01	0,01	0,01	0,03	0,12
Climate	0,02	0,00	0,06	0,01	0,08	0,02	0,00	0,02	0,01	0,03	0,00	0,05
Commodities	0,05	0,03	0,03	0,03	0,03	0,09	0,03	0,07	0,04	0,03	0,00	0,30
Confidence and Surveys	0,07	0,11	0,03	0,12	0,08	0,10	0,23	0,08	0,11	0,09	0,06	0,09
Country-Risk	0,02	0,00	0,03	0,01	0,00	0,01	0,00	0,01	0,01	0,02	0,00	0,13
Credit	0,01	0,07	0,00	0,02	0,03	0,00	0,00	0,01	0,02	0,01	0,08	0,11
Credit - individual entity	0,01	0,03	0,00	0,01	0,00	0,01	0,00	0,01	0,01	0,00	0,25	0,02
Credit - legal entity	0,03	0,00	0,00	0,00	0,00	0,01	0,00	0,01	0,01	0,02	0,28	0,01
Credit Delays - individual entity	0,01	0,00	0,00	0,03	0,00	0,02	0,00	0,01	0,02	0,00	0,05	0,22
Credit Delays - legal entity	0,02	0,03	0,00	0,01	0,00	0,02	0,03	0,01	0,02	0,01	0,05	0,19
Default - individual entity	0,00	0,02	0,00	0,01	0,00	0,00	0,03	0,01	0,01	0,00	0,05	0,10
Default - legal entity	0,01	0,00	0,03	0,01	0,00	0,02	0,00	0,01	0,01	0,01	0,05	0,11
Emploment	0,08	0,02	0,06	0,04	0,08	0,02	0,03	0,05	0,04	0,07	0,00	0,20
Exchange Rates	0,02	0,00	0,00	0,01	0,03	0,01	0,00	0,02	0,01	0,02	0,00	0,19
External Sector	0,01	0,03	0,00	0,01	0,00	0,03	0,00	0,01	0,01	0,00	0,00	0,40
Finance	0,02	0,00	0,00	0,02	0,03	0,08	0,00	0,03	0,02	0,02	0,00	0,42
Global	0,11	0,00	0,11	0,13	0,08	0,06	0,10	0,06	0,09	0,10	0,00	0,16
Governmental Credit	0,08	0,11	0,09	0,06	0,18	0,06	0,13	0,07	0,05	0,08	0,07	0,41
Governmental Finance	0,07	0,00	0,00	0,01	0,05	0,09	0,00	0,07	0,05	0,05	0,00	0,15
Import and Export	0,10	0,03	0,09	0,13	0,03	0,06	0,16	0,12	0,11	0,09	0,00	0,21
Industry	0,03	0,11	0,14	0,06	0,05	0,01	0,10	0,07	0,07	0,06	0,00	0,13
Interest Rates	0,00	0,11	0,00	0,01	0,00	0,01	0,00	0,01	0,01	0,00	0,04	0,05
International Interest Rates	0,00	0,00	0,00	0,01	0,00	0,02	0,00	0,01	0,00	0,00	0,00	0,09
Monetary	0,05	0,02	0,00	0,01	0,00	0,05	0,00	0,02	0,01	0,00	0,00	0,33
National Accounts	0,04	0,00	0,00	0,01	0,03	0,04	0,00	0,06	0,03	0,03	0,00	0,19
Prices and Inflation	0,00	0,08	0,06	0,04	0,05	0,02	0,03	0,02	0,05	0,05	0,00	0,13
Retail	0,01	0,03	0,03	0,00	0,00	0,02	0,00	0,01	0,01	0,00	0,00	0,19
Salary	0,05	0,03	0,06	0,01	0,03	0,10	0,00	0,01	0,02	0,02	0,00	0,19
Sectoral	0,02	0,07	0,17	0,04	0,05	0,00	0,06	0,07	0,07	0,07	0,00	0,18
Services	0,00	0,03	0,00	0,01	0,03	0,00	0,00	0,00	0,01	0,01	0,00	0,11
Total	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,14

Note: The Table presents the result of the relative information test applied to the total set of variables considered (2524). The results for each period represent $RI_{t-k} + Selected_{t-k}$ all variables which presented non-zero relative information.

The $Selected_{t-k}$ variables represent those that have a statistically non-zero value in each period. The series in Final Selection represent the series if they were statistically significant in some periods $(t-k)$, without repetitions, as well as the values presented in 2º Component, however with the series not being selected in some periods. Confirmatory represent only series directly related with credit total balance. The values in Final Selection Sample represent the ratio between Final Selection and Total Sample.

The credit crises of 2002-03 and 2008-09 affected the credit cycle estimated by this model more than the total credit balance. The turning point of the last credit recession has apparently already occurred for both the credit cycle and the total credit balance.

5.3.1 Dissecting the Brazilian credit cycle

Table 7 dissects the Brazilian credit cycle, estimated according to the characteristics of its phases and moments by each category and individually by each series used. From the established categories, the major degree of commonalities with the credit cycle, the

portion of this commonality associated with the Cycle Phase Indicator (CPI): pro-cyclical or counter-cyclical, the degree of commonality associated with each moment of the Cycle Moment Indicator (CMI): lagging, coincident or leading.

In Table 7 the average of the commonality ratio by category allows a more general analysis. The relative importance of categories is also presented in the quantities and percentages of series by categories.

Table 7: Average Degree of Commonality - Model 1

Class	Average	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series (%)	Counter-Cyclical (%)	Pro-Cyclical (%)	Lagging (%)	Coincident (%)	Leading (%)
Interest Rates	0.578	0.578	0.000	0.000	0.578	0.000	2	2	0	0	2	0	0.01	1.00	0.00	0.00	1.00	0.00
Credit Delays - individual entity	0.559	0.559	0.000	0.559	0.000	0.000	7	7	0	7	0	0	0.02	1.00	0.00	1.00	0.00	0.00
Credit Delays - legal entity	0.523	0.523	0.000	0.523	0.000	0.000	7	7	0	7	0	0	0.02	1.00	0.00	1.00	0.00	0.00
Default - legal entity	0.515	0.515	0.000	0.515	0.000	0.000	4	4	0	4	0	0	0.01	1.00	0.00	1.00	0.00	0.00
Default - individual entity	0.504	0.504	0.000	0.504	0.000	0.000	3	3	0	3	0	0	0.01	1.00	0.00	1.00	0.00	0.00
Country-Risk	0.482	0.000	0.482	0.000	0.000	0.482	5	0	5	0	0	5	0.01	0.00	1.00	0.00	0.00	1.00
Finance	0.449	0.481	0.354	0.481	0.000	0.354	8	6	2	6	0	2	0.02	0.75	0.25	0.75	0.00	0.25
Global	0.442	0.410	0.483	0.414	0.376	0.520	32	18	14	14	7	11	0.09	0.56	0.44	0.44	0.22	0.34
Retail	0.421	0.000	0.421	0.000	0.000	0.421	5	0	5	0	0	5	0.01	0.00	1.00	0.00	0.00	1.00
International Interest Rates	0.400	0.000	0.400	0.000	0.000	0.400	1	0	1	0	0	1	0.00	0.00	1.00	0.00	0.00	1.00
Credit	0.386	0.068	0.431	0.068	0.000	0.431	8	1	7	1	0	7	0.02	0.13	0.88	0.13	0.00	0.88
Credit - individual entity	0.372	0.461	0.328	0.461	0.328	0.000	3	1	2	1	2	0	0.01	0.33	0.67	0.33	0.67	0.00
Industry	0.335	0.158	0.388	0.158	0.128	0.453	26	6	20	6	4	16	0.07	0.23	0.77	0.23	0.15	0.62
Exchange Rates	0.287	0.322	0.147	0.270	0.478	0.147	5	4	1	3	1	1	0.01	0.80	0.20	0.60	0.20	0.20
Commodities	0.275	0.339	0.249	0.236	0.647	0.249	14	4	10	3	1	10	0.04	0.29	0.71	0.21	0.07	0.71
Emploment	0.272	0.291	0.261	0.367	0.121	0.297	13	5	8	3	3	7	0.04	0.38	0.62	0.23	0.23	0.54
Prices and Inflation	0.241	0.345	0.160	0.345	0.000	0.160	16	7	9	7	0	9	0.05	0.44	0.56	0.44	0.00	0.56
Monetary	0.210	0.000	0.210	0.000	0.098	0.239	5	0	5	0	1	4	0.01	0.00	1.00	0.00	0.20	0.80
Import and Export	0.206	0.100	0.219	0.100	0.170	0.228	37	4	33	4	5	28	0.11	0.11	0.89	0.11	0.14	0.76
Services	0.175	0.256	0.148	0.000	0.199	0.151	4	1	3	0	2	2	0.01	0.25	0.75	0.00	0.50	0.50
National Accounts	0.168	0.117	0.182	0.073	0.104	0.205	9	2	7	1	2	6	0.03	0.22	0.78	0.11	0.22	0.67
Sectoral	0.165	0.132	0.173	0.116	0.096	0.187	25	5	20	4	3	18	0.07	0.20	0.80	0.16	0.12	0.72
Salary	0.139	0.113	0.181	0.078	0.150	0.202	8	5	3	2	5	1	0.02	0.63	0.38	0.25	0.63	0.13
Banking	0.133	0.000	0.133	0.000	0.000	0.133	1	0	1	0	0	1	0.00	0.00	1.00	0.00	0.00	1.00
Governmental Finance	0.131	0.153	0.094	0.181	0.036	0.110	19	12	7	10	4	5	0.05	0.63	0.37	0.53	0.21	0.26
External Sector	0.127	0.148	0.107	0.148	0.000	0.107	2	1	1	1	0	1	0.01	0.50	0.50	0.50	0.00	0.50
Credit - legal entity	0.125	0.000	0.125	0.000	0.111	0.139	2	0	2	0	1	1	0.01	0.00	1.00	0.00	0.50	0.50
Confidence and Surveys	0.087	0.086	0.087	0.094	0.064	0.095	37	22	15	16	9	12	0.11	0.59	0.41	0.43	0.24	0.32
Agriculture	0.082	0.029	0.111	0.034	0.074	0.123	17	6	11	4	7	6	0.05	0.35	0.65	0.24	0.41	0.35
Governmental Credit	0.034	0.038	0.032	0.061	0.029	0.034	18	7	11	2	9	7	0.05	0.39	0.61	0.11	0.50	0.39
Bankruptcies	0.021	0.026	0.016	0.026	0.016	0.000	2	1	1	1	1	0	0.01	0.50	0.50	0.50	0.50	0.00
Climate	0.011	0.012	0.010	0.000	0.011	0.000	5	2	3	0	5	0	0.01	0.40	0.60	0.00	1.00	0.00
Mean/Total/percentage	0.277	0.211	0.185	0.182	0.119	0.183	350	143	207	110	74	166	1.00	0.41	0.59	0.31	0.21	0.47

Note: Time-irregular span Generalized Dynamic Factor Model (TISN-GDFM) - In-sample period: 1995Q1 to 2017Q4. The table shows average degree of commonality for each class by Cycle Phase Indicator (CPI): Counter-Cyclical and/or Pro-Cyclical; Cycle Moment Indicator (CMI): Lagging. Coincident and/or Leading.

The number of series and their percentages are displayed respectively.

5.3.2 Aggregate analysis by category

Considering all the categories. we have an average commonality of 27.7% with the Brazilian credit cycle. Effects are among pro-cyclical and counter-cyclical, leading, coincident and lagged.

The several categories have highest commonalities: Interest Rates, Credit Delays - individual entity, Credit Delays - legal entity, Default - legal entity and Default - individual entity. These have commonality above 50%. Interest rates have commonality (average), counter-cyclical and coinciding with the estimated credit cycle. Phases of expansions in contemporaneous the credit cycle are associated with contraction phases in interest rates. The international interest rate (40%) is pro-cyclical and leading. Delays and delinquencies have predominantly counter-cyclical and outdated commonality. Contractions in the credit cycle propagate a wave of expansion in delays and defaults.

The Country-Risk category has pro-cyclical and antecedent commonality. Thus, Country-Risk measures, expansions precede expansions in the credit cycle that in turn precede economic recessions as shown in the previous sections. Financial and international economic activity variables (Finance and Global) have predominantly counter-cyclical and lagged in Finance case and pro-cyclical and antecedent in the Global case.

Retail has more commonality (42% - pro-cyclical and leading) with the credit cycle than Industry (33% - pro-cyclical and leading), which in turn has more commonality than Services (17% - counter-cyclical and leading) or Agriculture (8% - pro-cyclical and leading). In relation to general and specific credit, general credit (38%) is predominantly pro-cyclical and antecedent. Credit - individual entity (37.2%) is predominantly counter-cyclical and lagged. Credit - legal entity (12%) pro-cyclical and leading. In general, corporate credit is more sensitive to changes in credit and in the economy than individuals, which may be reflecting this result.

The commonality of exchange rates (28%) is very close to the commonality of commodities (27%) both predominantly coincident, unlike the category imports and exports (20 %) leading. The commonality of employment (27%) is higher than that of prices and inflation (24%). Both are counter-cyclical and lagged, so a contraction phase in the credit cycle spreads a wave of employment expansion, price and inflation because at that stage the economy is already resuming growth. The monetary variables have a greater commonality (21%) than the commonality of the salary category (13%), both pro-cyclical and antecedent. That is, waves of monetary expansion and wages propagate a wave of expansion of the credit cycle.

Public finances (Governmental finance) have greater commonality (13% - counter-cyclical and lagged) than Governmental credit commonality (3%). Climatic variables and bankruptcies present the smallest commonalities.

5.3.3 Disaggregated analysis by series[10]

The commonality of the total credit balance was assumed as the reference variable estimate the credit cycle in Brazil. This variable shows high commonality with the national credit cycle (70%) pro-cyclical and leading. The interest rate category shows a high average commonality with the credit cycle, due to the large counter-cyclical and coincident commonality (62.8%) of the Basic Interest Rate (TBF). This interest rate is used to calculate the main interest rates in the credit market. In this case, reflections of credit cycle expansions cause contractions in these interest rates, reflecting the supply and

[10]The table with all description of CMI and CPI of the 2571 individual series is omitted due to space constraints. They can be requested from the author.

demand dynamics of loanable funds. In the category of International Interest Rates, the American and European interest rates present pro-cyclical and antecedent commonalities.

In the categories of credit delays and defaults, we have counter-cyclical and lagged movements. Looking at these categories in detail we have two distinct types of credit: the directed credit line, which has subsidized interest rates for some economic sectors and segments; and the free credit line, which has no government subsidies (For both individual or corporation).

In both delays and defaults, counter-cyclical and lagged commonality is greater in free credit lines than in directed credit lines. Details on the commonality of the credit categories are shown in Table

Credit line	**Credit feature**	**Commonality**
Delays - free credit line	Individual - credit card	76.6%
	Corporation - total	73%
Delays - directed credit line	Individual - rural credit	76.6%
	Total BNDES	32.3%
	Corporation - total line	43.7%
	Real estate financing	55%
Defaults - Free credit line	Individual - personal credit	56.1%
	Corporation - working capital	85.7%
Defaults - directed credit line	Individual - rural credit	44%
	Corporation - working capital	29.8%
	Rural credit	44.%

Table 8: Main Credit Category Communalities.

A contraction in the credit cycle spreads the expansion of delays and more intense defaults in the free credit line, whether individual or legal entity. For credit in general, the pro-cyclical and leading share of the credit balance of private banks and foreign banks in Brazil is the same (54%), but lower than that of public banks (31%). Individual entity credit presents pro-cyclical and coincident commonality greater than legal entity credit in all cases. This reflects the fact that individuals' income is more prone to oscillations than corporate income in risk models credit.

Regarding Country Risk, the two main measures for Brazilian risk (CDS and EMBI) have pro-cyclical commonalities of 45% and 47% respectively. The risk of Chile and Turkey present commonalities of 46% and 51% with the Brazilian credit cycle. As CMI are antecedents, they capture an increased risk of economic recession, which is preceded by the expansion of the credit cycle. In financial variables, the counter-cyclical and lagged commonalities are associated with the stock exchanges: USA (72%); Japan (45%); France (61%); and Mexico (45%). Again, a wave of optimism occurs in stock exchanges when the credit cycle in contraction phase precedes the resumption of economic activity. The pro-cyclical and leading commonality of this category is associated with the spread between the interest rate Libor and Treasuries of 3 months (18%).

We can understand the dynamics of the Brazilian credit cycle and the international economy by first analyzing certain international economic activity variables. Pro-cyclical and leading commonality is associated with industrial production in Asia (76%), emerging countries (73%) and the US (82%), as well as imports from advanced economies (61%). Counter-cyclical commonality is associated with industrial production in Latin America (46%), US imports (46%) and US non-durable goods industry payroll (82.7%). Thus, an increase in the industrial activity of other countries' economies precedes a phase of

expansion of the credit cycle in Brazil, while a contraction in the credit cycle spreads an increase in industrial production geographically closer to Brazil.

In terms of commodities we have pro-cyclical and leading commonalities such as oil prices (52%), energy commodities index (39%), and agriculture (29.6%). Counter-cyclical and coincident commonalities include the price of copper ore (64%) the price of oranges (14%) is lagged. The exchange rate with the dollar has a high counter-cyclical and coincident commonality (47%), while other currencies have counter-cyclical and lagged commonality. Thus, the expansion phase of the credit cycle is associated with currency appreciation contemporaneously. Expansions of energy and agricultural commodities predate an expansion of the credit cycle.

In terms of imports and exports, the credit cycle, has: pro-cyclical and coincident commonality with the import quantum of the pulp and paper industry (32%), metal (22%), and apparel (17%), and with the export quantum of agricultural products (4%). It has pro-cyclical and leading commonality with US exports of capital goods (58%) and consumer goods (55%); with quantum of exports of vehicles (44%) and exports to Argentina (42%). It has counter-cyclical and lagged relation with the export quantum of fishing (7.4%) and food products (16.4%). Thus, an expansion of the credit cycle is associated in an antecedent way and coincides with an increase of production of sectors of the economy linked to industry and agriculture.

Retail activity series all have pro-cyclical and leading commonalities. The retail index, which sums up all sector activity, has the highest commonality (60%), followed by the hypermarket and supermarket activity index (36%), motor vehicles (32%), and by the revenue index of fuels and lubricants (29.5%). Retail activity is an antecedent indicator of both credit and economic activity as a whole. Expansion in retail lead expansions in the credit cycle. Considering the commonality with the credit cycle of different economic sectors we have the sequence: retail, industry, services, and agriculture.

In industrial activity the highest commonalities are pro-cyclical and antecedent, associated with the hours paid in the São Paulo industry (63%); the quantity hours used in the automobile industry (56.2%) and total salaries paid in the São Paulo industry sector (39.3%). Procyclical and coincident commonalities are found with the indicator of utilization of installed capacity in the manufacturing industry (24.4%); and with the production level of the petroleum derivative industries (9.6%). Counter-cyclical and lagged commonality is associated with total paid payroll in the general industry (35.9%); and the level of activity of the extractive (14.4%) and pharmaceutical (13.6%) industries. Thus, manufacturing plays a considerable role in the credit cycle, either by activity, as the leading indicator, or by the level of indicator if installed capacity utilization as the current state of the credit cycle.

In terms of services, pro-cyclical and leading commonalities are associated with information and communication services (23%). Professional and administrative services have pro-cyclical and coincident commonality (14%). Housing and food services have counter-cyclical and coincident commonality (25%). The agricultural sector presents one of the smallest commonalities with the credit cycle. Among these series, the highest commonality is the production of milk (20%), followed by eggs (17.3%), and sugarcane (16.2%), which are all pro-cyclical and leading. Other productions have pro-cyclical and coincident commonality: bovine (17%), pork (12.5%), pork carcass (9%), and soybean (7%). Counter-cyclical and coincident commonalities are found with in rice (2%) and banana (1.6 %) production. Counter-cyclical and lagged commonalities occur with cotton production (2.6%), coffee (6%), beans (1.3%), and poultry (3.6%).

Analyzing the variables that measure the sector level of economic activity, we have pro-

cyclical and leading commonalities: supermarket expenditure index (ABRAS[11].) (35.3%), retail activity index (SERASA) (31.9%), electric energy load in Brazil (ONS)(28.5%), sales of gasoline and alcohol by distributors (ANP) (28.1%), and motorcycle production (ABRASCICLO) (27.8%). Coincidentally we have the commonality of electric energy load in the southern region (ONS) (5.3%) and motorcycle licensing (FENABRAVE) (3.5%). Electrical energy stored in the southwestern region (ONS) has a counter-cyclical and coincident commonality (19.9%). The importation of fertilizers (ANDA)(26.5%), the volume of water stored in a reservoir in São Paulo (SABESP)(11.1%), and oil production (ANP)(5.2%) are counter-cyclical and lagging. These results show that the production of electric energy, the sales of gasoline and alcohol by distributors, and the activities of retailing and spending in supermarkets precede an expansion of the credit cycle. These activities are all linked directly with short-term credit lines. In a counter-cyclical way, both the volume of the reservoirs used for supply and the electrical energy stock of the country's large productive center fall when there is an expansion of the credit cycle.

Three categories have similar commonalities: Employment, Prices/Inflation and Monetary. In addition to these categories we analyze the Salary category. The Employment has the greatest commonality with the credit cycle among these categories and has CPI and CMI diffuse. To understand, we must examine the series in detail. Pro-cyclical and leading commonality is associated with layoffs of civil construction (46%), services (37%), mineral extractive industry (19.9%) and agriculture and livestock (4.7%), as well as admissions of retail (40%). Labor-intensive layoffs precede expansion of the credit cycle at the same time as contraction in retail increases, in a move that may indicate a migratory effect.

The average salary of all admissions has a counter-cyclical and coincident commonality with the Brazilian credit cycle (30%). Unemployment measured by the main indexes in Brazil: Dieese (51%) and IBGE (52%) have counter-cyclical and lagged commonality. Credit cycle expansion phases there is a movement of unemployment contraction, however with lower admission wages. When we analyze the category of Prices and inflation, we can see that there is a predominance of counter-cyclical and lagged commonalities, in particular, of the main inflation indices: IPCA (67%), and IGP-DI (66%). These results indicate that at the end of a wave of expansion of the credit cycle (in the credit cycle contraction phase) an inflationary wave is propagated. Some commonalities are pro-cyclical and antecedent: the spot price of coffee (39.9%), cattle (29.2%), milk (15.7%) and soybean (25%). These prices precede the credit cycle expansion phase.

Considering monetary variables, the balance of paper currency in the public domain has pro-cyclical and coincident commonality (31%). Pro-cyclical and leading commonalities are concentrated in private securities (29%), savings deposits (28%), federal securities (9.8%), and banking reserves (6.6 %). These results indicate that there is a resource formation process for credit supply that occurs prior to a credit cycle expansion. During the credit cycle expansion phase there is an expansion of paper currency in public domain.

In the Salary category, agriculture dismissal wages have pro-cyclical and leading commonality (20%), whereas agricultural (22%) and manufacturing (11%) admission wages have pro-cyclical and coincident commonality. Dismissal wages of Retail (19%), transportation (6%) and admission wages of financial activities have counter-cyclical and coincident commonality. Dismissal wages of domestic services (7.4%) and other activities (8.2%) are counter-cyclical and lagged.

The category of Governmental finance has higher commonality than Governmental credit (one of the variable with lowest commonality with the credit cycle). In government finance, municipal debt renegotiations (17%) and payment of the education salary

[11] All acronyms of associations, confederations, institutions and companies are described in Table 13

program (9.2%) have pro-cyclical and leading commonalities. Interest (9.8%), and dividends/participations (1.5%) paid by the government have pro-cyclical and coincidental commonality. Income tax has a counter-cyclical commonality (1.5%) and coincides with the credit cycle while the primary federal results (24%), state (17.5%), payment to private creditors (38,6%) and payment of personnel and social charges (8.8 %) have counter-cyclical and lagged commonality. Renegotiation of municipal debts by banks release credit resources in these banks. Payment of education salary program is also carried out by the banking system and therefore also releases credit resources, thus predating a credit cycle expansion. In a credit cycle expansion phase the economy is already slowing down and therefore causing the reduction of income tax collection. The end of a wave of the credit cycle propells a wave of expansion in the payment of private lenders and personal payroll.

As for government credit, BNDES loans for the real estate sector (9.3%), health and social services (2.9%), chemical industry (2.5%) and telecommunications (2.3%) have pro-cyclical and leading commonality. BNDES loans for financial activities and insurance (4.7%) and housing and food (3.7%) have pro-cyclical and coincident commonality. BNDES loans for civil construction (6.4%), retail (3.3%), electronics and machinery industry (1.7%) and public administration (2.5%) have a counter-cyclical and coincidental commonality while BNDES loans for the pulp and paper industry (7.4%) and agriculture (4.8%) have counter-cyclical and lagged commonality. These results indicate that government credit dynamics weakly accompany credit cycle movements. Civil construction and retail cycle that present high pro-cyclical and leading commonality in other categories, in government credit have counter-cyclical CPI and coincident CMI. With very low commonality, bank failures and climatic variables do not add information to the dynamics of the Brazilian credit cycle. The results of this section describe in detail the most important economic series and their characteristics in the formation of the Brazilian credit cycle.

5.4 Time-irregular span generalized dynamic factor second component model results.

We can see in Figure 8 that the movements of the estimated credit cycle in Model 2 anticipate some peaks and troughs. This behavior may indicate some predictive gain by incorporating of the secondary component.

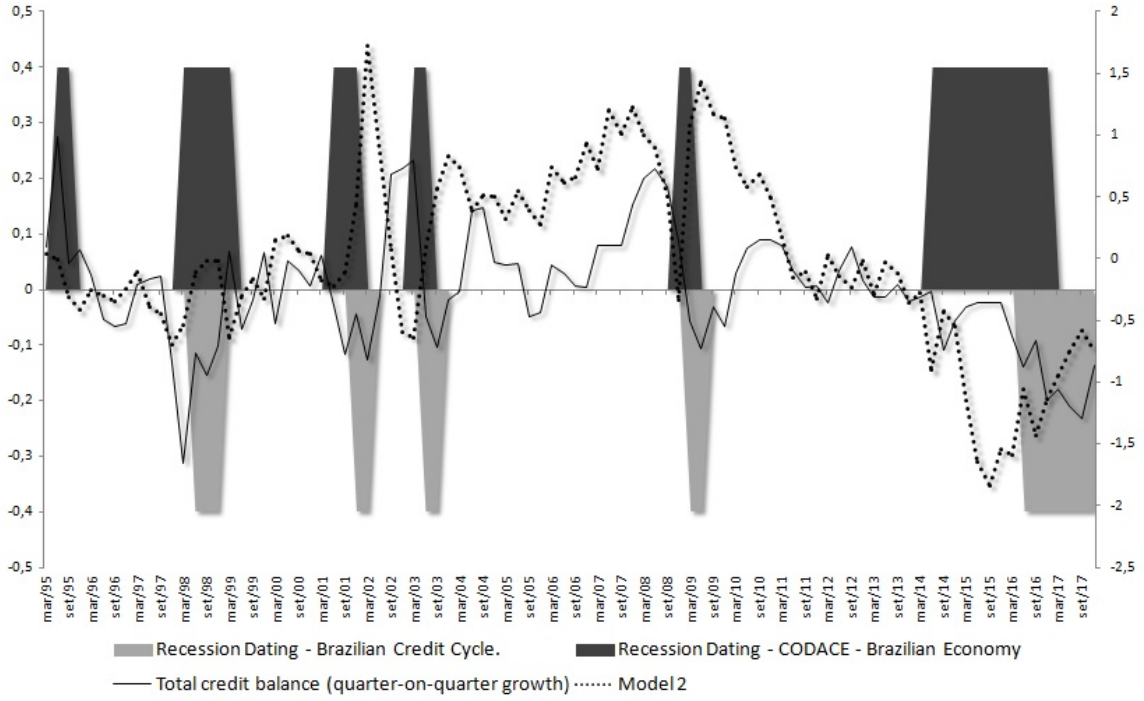

Figure 8: Quarter-on-quarter credit growth and TISN-GDFM2C common component.

The peaks and troughs of the credit cycle of the last recession of credit occur well in advance of the movement of the total credit balance. In other credit crises, this anticipation movements in relation to the total credit balance is apparently lower.

5.4.1 Impacts of secondary component inclusion

Tables 9 describe the results of Model 2. The secondary component has pro-cyclical and leading commonality[12] (4.8%), above only the commonalities of the categories of government credit, climate and Bankruptcies. Increases in commonalities are marginal (relative to Model 1) and focus on the categories of individual delays (from 55.6% to 56.1%) and country risk (48.2% to 48.3%). Reductions of commonality in some categories are considerable: international interest rates from 40% to 18.5%; prices and inflation from 24.1% to 12%, and monetary series from 21% to 16.4%. Individual credit climbed from place 12th in Model 1 to ninth in Model 2. International interest rates fell from 10th place to 17th place. Prices and inflation went from 17th to 24th place.

[12]If are not mentioned about the CPI and the CMI, it means that they remain the same, both for categories, average commonality ratio and for commonality ratio of the individual series.

Table 9: Average Degree of Commonality - Model 2

Class	Average	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series (%)	Counter-Cyclical (%)	Pro-Cyclical (%)	Lagging (%)	Coincident (%)	Leading (%)
Credit Delays - individual entity	0.561	0.000	0.561	0.000	0.000	0.561	7	0	7	0	0	7	0.02	0.00	1.00	0.00	0.00	1.00
Credit Delays - legal entity	0.522	0.000	0.522	0.000	0.000	0.522	7	0	7	0	0	7	0.02	0.00	1.00	0.00	0.00	1.00
Interest Rates	0.509	0.509	0.000	0.000	0.509	0.000	2	2	0	0	2	0	0.01	1.00	0.00	0.00	1.00	0.00
Default - legal entity	0.506	0.000	0.506	0.000	0.000	0.506	4	0	4	0	0	4	0.01	0.00	1.00	0.00	0.00	1.00
Default - individual entity	0.498	0.000	0.498	0.000	0.000	0.498	3	0	3	0	0	3	0.01	0.00	1.00	0.00	0.00	1.00
Country-Risk	0.483	0.484	0.477	0.484	0.000	0.477	5	4	1	4	0	1	0.01	0.80	0.20	0.80	0.00	0.20
Finance	0.435	0.164	0.474	0.164	0.000	0.474	8	1	7	1	0	7	0.02	0.13	0.88	0.13	0.00	0.88
Global	0.391	0.425	0.377	0.425	0.000	0.377	32	9	23	9	0	23	0.09	0.28	0.72	0.28	0.00	0.72
Credit - individual entity	0.362	0.000	0.362	0.000	0.528	0.278	3	0	3	0	1	2	0.01	0.00	1.00	0.00	0.33	0.67
Credit	0.321	0.165	0.373	0.165	0.000	0.373	8	2	6	2	0	6	0.02	0.25	0.75	0.25	0.00	0.75
Industry	0.319	0.378	0.298	0.400	0.111	0.341	26	7	19	6	4	16	0.07	0.27	0.73	0.23	0.15	0.62
Retail	0.307	0.000	0.307	0.000	0.000	0.307	5	0	5	0	0	5	0.01	0.00	1.00	0.00	0.00	1.00
Emploment	0.232	0.316	0.194	0.393	0.085	0.194	13	4	9	3	1	9	0.04	0.31	0.69	0.23	0.08	0.69
Exchange Rates	0.230	0.444	0.177	0.000	0.444	0.177	5	1	4	0	1	4	0.01	0.20	0.80	0.00	0.20	0.80
Commodities	0.229	0.323	0.214	0.041	0.604	0.214	14	2	12	1	1	12	0.04	0.14	0.86	0.07	0.07	0.86
Import and Export	0.189	0.079	0.199	0.079	0.234	0.197	37	3	34	3	2	32	0.11	0.08	0.92	0.08	0.05	0.86
International Interest Rates	0.185	0.000	0.185	0.000	0.000	0.185	1	0	1	0	0	1	0.00	0.00	1.00	0.00	0.00	1.00
Monetary	0.164	0.000	0.164	0.000	0.041	0.195	5	0	5	0	1	4	0.01	0.00	1.00	0.00	0.20	0.80
National Accounts	0.163	0.076	0.173	0.076	0.000	0.173	9	1	8	1	0	8	0.03	0.11	0.89	0.11	0.00	0.89
Services	0.136	0.000	0.136	0.000	0.132	0.137	4	0	4	0	1	3	0.01	0.00	1.00	0.00	0.25	0.75
Sectoral	0.130	0.059	0.144	0.059	0.000	0.144	25	4	21	4	0	21	0.07	0.16	0.84	0.16	0.00	0.84
Salary	0.129	0.153	0.125	0.000	0.151	0.116	8	1	7	0	3	5	0.02	0.13	0.88	0.00	0.38	0.63
Governmental Finance	0.120	0.090	0.131	0.109	0.013	0.140	19	5	14	4	2	13	0.05	0.26	0.74	0.21	0.11	0.68
Prices and Inflation	0.120	0.171	0.069	0.171	0.000	0.069	16	8	8	8	0	8	0.05	0.50	0.50	0.50	0.00	0.50
Banking	0.117	0.000	0.117	0.000	0.000	0.117	1	0	1	0	0	1	0.00	0.00	1.00	0.00	0.00	1.00
Credit - legal entity	0.115	0.000	0.115	0.000	0.000	0.115	2	0	2	0	0	2	0.01	0.00	1.00	0.00	0.00	1.00
External Sector	0.108	0.150	0.066	0.150	0.000	0.066	2	1	1	1	0	1	0.01	0.50	0.50	0.50	0.00	0.50
Confidence and Surveys	0.074	0.047	0.113	0.038	0.142	0.113	37	22	15	20	2	15	0.11	0.59	0.41	0.54	0.05	0.41
Agriculture	0.061	0.030	0.071	0.041	0.053	0.069	17	4	13	2	5	10	0.05	0.24	0.76	0.12	0.29	0.59
2º Component	0.048	0.000	0.048	0.000	0.000	0.048	1	0	1	0	0	1	0.00	0.00	1.00	0.00	0.00	1.00
Governmental Credit	0.027	0.028	0.026	0.033	0.029	0.022	18	8	10	4	6	8	0.05	0.44	0.56	0.22	0.33	0.44
Climate	0.011	0.010	0.011	0.000	0.011	0.000	5	2	3	0	5	0	0.01	0.40	0.60	0.00	1.00	0.00
Bankruptcies	0.010	0.017	0.004	0.017	0.000	0.004	2	1	1	1	0	1	0.01	0.50	0.50	0.50	0.00	0.50
Mean/Total/Percentage	0.237	0.125	0.219	0.086	0.094	0.218	351	92	259	74	37	240	1.00	0.26	0.74	0.21	0.11	0.68

Note: Time-irregular span Generalized Dynamic Factor Second Component (TISN-GDFM2C) - In-sample period: 1995Q1 to 2017Q4. The table shows average degree of commonality for each class by cycle phase

The number of series and their percentages are displayed respectively.

Analyzing individual series, the commonality of the total credit balance. which we use as reference cycle. has a reduction in relation to Model 1, falling from 70% to 50.9%. The largest commonality increases are concentrated in the individual delays related to free credit lines and country risk related with CDS-Brazil. Among reductions in commonality, the prime European interest rate decreases from 40% to 18.5%, IPCA inflation from 67.5% to 36.5%, and for monetary series: paper currency in the public domain series falls from 31.3% to 25.6%.

5.5 Time-irregular span generalized dynamic factor model confirmatory results.

We can observe that the series used up to 2007 had a dominant idiosyncratic component and little participation of the common component. From 2007, with the incorporation of more important series of credit, the cycle estimated by this model follows the movements of the total credit balance.

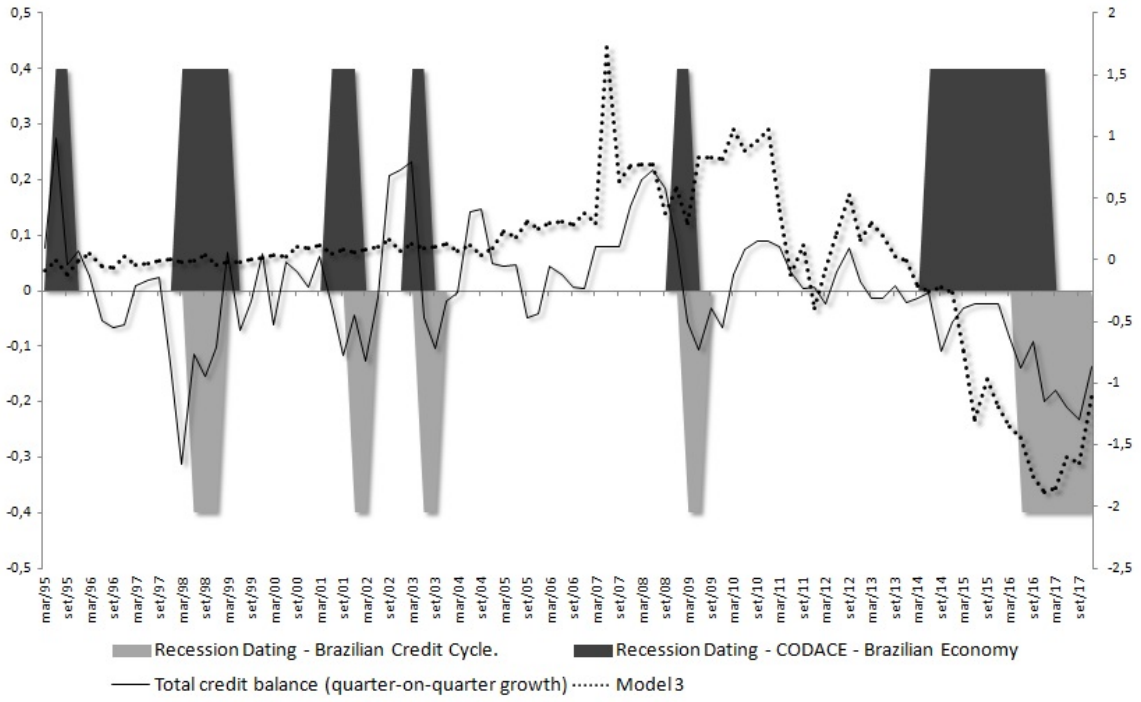

Figure 9: Quarter-on-quarter credit growth and TISN-GDFM-Conf. common component.

Clearly the best fit of this model occurs in 2011 when other credit series are incorporated apparently presents a lower adjustment to Models 1 and 2.

5.5.1 Results of a pure credit cycle

The results of the Brazilian credit cycle estimated only with credit variables are presented in Tables 10 (categories). The results show a commonality gain (compared to Model 1) in the credit categories (individual entity or corporation) and interest rate. The categories Confidence and Surveys, Bankruptcies, and Governmental Credit continue with low commonalities. The highest commonality gain occurred in the category of credit - legal entity (LE): Model 1 (12.5%) and Model 3 (66.6%), in Interest Rates: Model 1 (57.8%) and Model 3 (92,9%) and in credit - individual (IE): Model 1 (37.2%) and Model 3 (49.1%). Most commonalities are pro-cyclical and leading.

Interest rates remain the protagonists in the credit cycle, in both Model 1 and Model 3, with the highest commonality. When we consider the 12 categories remaining in Model 3, the corporation credit, which in 32 categories in Model 1 occupied the 27th position, moved to third in the cycle estimated with exclusively credit variables. The individual credit, at 12th place in Model 1, passed to second in Model 3. Delays of corporation fell from 3rd position in Model 1, to 7th place. Default of this category, fell from 4th to 8th place.

Table 10: Average Degree of Commonality - Model 3

Class	Average	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series	Counter-Cyclical	Pro-Cyclical	Lagging	Coincident	Leading	Series (%)	Counter-Cyclical (%)	Pro-Cyclical (%)	Lagging (%)	Coincident (%)	Leading (%)
Interest Rates	0.929	0.000	0.929	0.000	0.000	0.929	28	0	28	0	0	28	0.04	0.00	1.00	0.00	0.00	1.00
Credit - individual entity	0.864	0.000	0.864	0.000	0.000	0.864	167	0	167	0	0	167	0.25	0.00	1.00	0.00	0.00	1.00
Credit - legal entity	0.792	0.171	0.798	0.171	0.000	0.798	191	2	189	2	0	189	0.28	0.01	0.99	0.01	0.00	0.99
Credit Delays - individual entity	0.757	0.000	0.757	0.000	0.000	0.757	32	0	32	0	0	32	0.05	0.00	1.00	0.00	0.00	1.00
Default - individual entity	0.731	0.000	0.731	0.000	0.000	0.731	31	0	31	0	0	31	0.05	0.00	1.00	0.00	0.00	1.00
Credit	0.658	0.254	0.673	0.254	0.000	0.673	53	2	51	2	0	51	0.08	0.04	0.96	0.04	0.00	0.96
Credit Delays - legal entity	0.549	0.209	0.569	0.209	0.000	0.569	37	2	35	2	0	35	0.05	0.05	0.95	0.05	0.00	0.95
Default - legal entity	0.540	0.296	0.571	0.296	0.000	0.571	36	4	32	4	0	32	0.05	0.11	0.89	0.11	0.00	0.89
Confidence and Surveys	0.269	0.117	0.304	0.117	0.000	0.304	38	7	31	7	0	31	0.06	0.18	0.82	0.18	0.00	0.82
Bankruptcies	0.061	0.048	0.071	0.048	0.000	0.071	17	7	10	7	0	10	0.03	0.41	0.59	0.41	0.00	0.59
Governmental Credit	0.031	0.034	0.030	0.034	0.000	0.030	44	5	39	5	0	39	0.07	0.11	0.89	0.11	0.00	0.89
Mean/Total	0.562	0.103	0.572	0.103	0.000	0.572	674	29	645	29	0	645	1.00	0.04	0.96	0.04	0.00	0.96

Note: Time-irregular span Generalized Dynamic Factor Model Confirmatory(TISN-GDFM-Conf.) - In-sample period: 1995Q1 to 2017Q4. The table shows average degree of commonality for each class by Cycle Phase Indicator (CPI): Counter-Cyclical and/or Pro-Cyclical; Cycle Moment Indicator (CMI): Lagging. Coincident and/or Leading.

The number of series and their percentages are displayed respectively.

The commonality of the total credit balance to the credit cycle, which represents the reference cycle, decreases in relation to Model 1 (70% to 40.7%). Within the interest rate category, all commonalities are pro-cyclical and leading, yet interest rates for free credit lines (without government subsidies) have commonalities (above 98%) greater than total credit (above 95%). They are higher than the directed credit line (with government subsidies) (above 81%). The same happens with the credit of individual, however with the direct credit line with an even smaller community (above 30%).Although in credit of corporation, free credit (above 98%) is also higher than directed credit (above 74%), credit demand indicators of companies (15%) and industries (18%) have counter-cyclical and lagged commonalities.

When we analyze total credit, we have BNDES credit, which is responsible for directed credit (above 98%), and rural credit (98.9%). These have the highest commonality with the credit cycles. The credit of public institutions (20.1%) has less commonality than private (20.5%) and foreign institutions (24.2%). When we consider the delays of individual, again free credit (above 98%) is greater than directed credit (above 48%). The largest commonalities are associated with the debt composition credit line (98.3%) and credit card (98.1%). Smaller commonalities are associated with the credit lines directed: rural credit (26.8%) and the total BNDES (30.9%). Delays of corporation, have the same conclusions about free credit (above 94%) and directed credit (above 41%). The largest commonalities are associated with free credit lines - vehicles (92.4%) and the lowest, are with lines of credit directed: BNDES working capital (11.3%) and rural credit (16.6%). Commonalities of delays are pro-cyclical and leading.

The disparity between the commonalities of free and directed credit lines is even greater in relation to default. In the case of individuals, the credit card line (99%) and special check (97.4%) have the highest commonality, while the lines of credit directed: total BNDES (43.4%), rural credit (47.1%) and real estate financing (39.8%) have the lowest default commonalities (in all cases pro-cyclical and leading). In corporation default the free credit lines: special check (97%) and working capital (88.9%) are the largest commonalities. Lines of credit directed: real estate financing (51.8%), BNDES investment financing (19.1%), and exports (17.4%) show the smallest commonalities: counter-cyclical and lagged. For the Bankruptcies category, commonalities are counter-cyclical and lagged, with Microenterprises (7.9%) having greater commonality than medium-sized enterprises (7%) and even larger ones (3.5%). In government credit, the BNDES lines: extractive industry (6.6%) and textile (6.1%) present counter-cyclical and lagged commonalities. The estimated cycle in this model only tracks the movements of the total credit balance up to 2007, including most of the credit series. However, the delays and defaults of the directed credit lines have less commonality with the credit cycle, both of individuals and corporations, but the directed credit balance has high commonality with the credit cycle. As these lines have government subsidies, both their delays and defaults have different dynamics from the other credit lines.

5.6 Comparison of estimated models

Table 11 compares the models used to estimate the Brazilian credit, inflation and interest rate cycles. It is expected that an increase in the number of factors increases the used series commonality.

Among models that estimate the Brazilian credit cycle, the approach with the highest average commonality is the Confirmatory Model 3. Model 3 presents an increase of commonality in relation to Model 1 (descriptive) with the same number of factors. The model with secondary component presents a reduction of average commonality in most

categories while in Model 3 there was an increase of average commonality.

The lower commonality, of the secondary components model may occur, in some cases, due to a greater predictive capacity gain. A smaller synchronization with the estimated cycle, due to the second component, may create a pseudo-cycle that anticipates the movements of the reference cycle. In the cycle estimated by the confirmatory model, may present higher commonality with the Brazilian credit cycle, due to the close characteristics of the series used and the reference series for cycle estimation. Since this model does not consider other variables that can affect the cycle, it may have less predictive capacity in the short term. Predictive ability and other issues will be addressed individually in the following sections.

Table 11: Comparison of models - Average Degree of Commonality

Class	model 1 Average	model 2 Average	model 3 Average
Interest Rates	0.578	0.509	0.929
Credit delays - individual entity	0.559	0.561	0.757
Credit delays - corporation	0.523	0.522	0.549
Default - corporation	0.515	0.506	0.540
Default - individual	0.504	0.498	0.731
Country-risk	0.482	0.483	-
Finance	0.449	0.435	-
Global	0.442	0.391	-
Retail	0.421	0.307	-
International interest rates	0.400	0.185	-
Credit	0.386	0.321	0.658
Credit individual entity	0.372	0.362	0.864
Industry	0.335	0.319	-
Exchange rates	0.287	0.230	-
Commodities	0.275	0.229	-
Emploment	0.272	0.232	-
Prices and inflation	0.241	0.120	-
Monetary	0.210	0.164	-
Import and export	0.206	0.189	-
Services	0.175	0.136	-
National accounts	0.168	0.163	-
Sectoral	0.165	0.130	-
Salary	0.139	0.129	-
Banking	0.133	0.117	-
Governmental finance	0.131	0.120	-
External sector	0.127	0.108	-
Credit - corporation	0.125	0.115	0.792
Confidence and surveys	0.087	0.074	0.269
Agriculture	0.082	0.061	-
Governmental credit	0.034	0.027	0.031
Bankruptcies	0.021	0.010	0.061
Climate	0.011	0.011	-
2nd Component	-	0.048	-
Mean	0.277	0.237	0.562
Number of factors	5	4	5

Note: Various Time-irregular span Generalized Dynamic Factor Models (See Table 1 for further detail) - In-sample period: 1995Q1 to 2017Q4. The table shows average degree of commonality for each class.

The number of factors are displayed respectively. They were estimated according to Alessi et al. (2010).

6 Conclusions

In this study. we investigate the credit cycle information content of 2571 variables and identify the reference business cycle as the common variation contained in quarter-

on-quarter Brazilian total credit balance. Furthermore. we explore forecast ability related to quarter-on-quarter credit movements. All of this takes place within one unified setting. applying the Generalized Dynamic Factor Model (GDFM) of FHLR (**?**) to a large data set containing information on Brazilian credit and its indicators. Through its richness. the model provides useful information for the credit cycles analyst and market actors interested in the Brazilian credit cycle and its indicators. The model reduces the variables to their core cycle information. defined as that part of the variables' variation which is common to the data set.

According to Belloni and Chernozhukov [2011]. when the number of time series is greater than the time span of the sample, it is a high-dimensional analysis. In order to deal with the hyper-dimension, an entropic relative information test (ERI) is implemented. The (ERI) which enables a feasible sample set to estimate the cycles. Facing the TISN data reality of the Brazilian series, the TISN-GDFM version using Bańbura and Modugno [2014] is estimated. Also, the TISN-GDFM2C, obtain a new series through the dynamic principal component of the series that presents relative information about zero by the ERI test. We also implement the confirmatory approach, which uses only variables directly associated with the cycle under study. In this approach, the credit cycles of the Brazilian economy are estimated. Finally, the cycles estimated by the different approaches are used to analyze the predictive ability of the signals and turning points of the credit using dynamic probit models. Regarding linear predictive ability, the cycles estimated by different approaches are used in VAR models to test the predictive ability in relation to credit movements.

The first step in credit cycle dating is the identification and treatment of outliers in the total credit balance series. We combine the Hampel algorithm and expert analysis of the detailed chronology of banking, credit and economic events over last 38 years to do this. At the end 8 outliers are identified and treated. Two different methods are used to date the credit cycle. The first uses the probit model with the troughs indicated by the BB (Bry and Boschan [1971a,b]) method and the other uses Markov-Switching models. both approaches have a convergence on periods of credit recession. Five recessions are dated. A lagged relationship between credit recessions and economic recessions, indicates that credit expansions precede recessions of the business cycle. In terms of turning points, the peaks and troughs of the credit cycle occur lagging the business cycle (by around one year). The chronology of the credit cycle shows that the largest credit recession in duration and amplitude occurred between the second quarter of 2016 and the last quarter of 2017. This recession was preceded by the largest credit expansion, which lasted from 2009 to 2016 with an expansion of 44.7%.

For the credit cycles studied, the ERI relative information test is applied to select among the 2571 variables with the highest contribution to the cycle under study. A descriptive model (TISN-GDFM), a secondary component model (TISN-GDFM2C) and a confirmatory model (TISN-GDFM-Conf.) are compared. Considering the Brazilian credit cycle, the number of contemporaneous variables selected is lower than for other lags. This phenomenon has rich temporal dynamics. In total, 349 variables are selected for the credit descriptive cycle model. For a better understanding of each cycle, we maintain a classification with 32 categories. The results of the selection procedure generate a set of 674 series for estimating the credit cycle confirmatory model (TISN-GDFM.Conf.).

The descriptive model that estimates the Brazilian credit cycle, shows the highest commonalities in the categories of interest rates, delays and defaults. Interest rates show counter-cyclical and coincident movements, which means the interest rate is an important factor in the credit contraction movements. Delays and defaults are counter-cyclical, however lagging. Therefore credit-cycle expansion movements propagate contraction waves of

delays and defaults. The smallest commonalities were of the categories of governmental credit, climate and bankruptcies. An important result of this model shows that the delays and defaults of unsubsidized credit lines (called free credit lines or nonearmarked credit lines) have higher commonality than subsidized credit lines (called directed credit lines or earmarked credit lines). Although in contracting credit, the difference between these lines of credit virtually disappears. In credit contractions, both credit lines have highly dynamic co-movement with the credit cycle. However, delay and default occur differently between the subsidized and unsubsidized lines.

The country risk has pro-cyclical and leading commonality with the credit cycle, indicating that in the expansion of credit (that precedes the economic recessions), increasing risk perception about a country has already happened. The activities of retail and employment in the industry also have pro-cyclical and leading commonalities. The inflation indices have counter-cyclical and lagged movements, which indicates that the credit spreads inflationary waves. The exchange has counter-cyclical commonality and coincides with the credit cycle. This indicates that in phases of credit expansion, currency appreciates. Inflation is counter-cyclical and lagged, so an inflation wave is accompanied by a currency devaluation, which happens in the contraction phase of the credit cycle.

In the secondary component models estimated for each cycle, results show a pro-cyclical and leading secondary component considering credit cycle, despite low commonality. This result indicates that, taken together, some of the unselected variables have relevant relative information on the estimated cycle. With regard to the confirmatory cycles, the credit cycle has interest, delays and defaults with pro-cyclical and leading commonalities. This reinforces the result of the descriptive model, where free credit lines have greater commonality than directed credit lines. However in this cycle, considering the credit balance, contractions in directed credit lines have greater commonality than free credit lines.

This study investigates a topic that has never been addressed in the Brazilian literature, with a focus on high-dimensional and time-irregular span series. The dating and chronology of the credit cycle are also unpublished for the Brazilian case. The study highlights relevant issues from both the theoretical and the economic point of view. The entropic test of relative information contributes to literature of dimensional reduction related with cycles context. The secondary component model can be used in the context of the GDFM model with predictive purposes as well as the confirmatory models to show important dynamics aspects of a given cycle. The detailed description of sectors and variables and their relation to credit cycles produces many relevant contributions. These results are pioneers for the Brazilian credit cycles literature, notoriously in the context of high-dimensional time series. They allows researchers to extract information on important temporal dynamics that may lead to new lines research. Further research could therefore focus on the exploration of these relationships. Additionally, it could further highlight the richness of the model by evaluating the variables with respect to each other and not only with respect to a particular reference variable. This would provide additional insights into the relationships between different variables and address several economic issues.

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Appendix

6.1 Entropy relative information

First, as describe in den Reijer [2010] and Van Nieuwenhuyze [2005], defining $f_1(\tilde{x}) : \tilde{x} \sim N_N(0, \Gamma)$, with $\Gamma = C\Lambda C^{'}$ being the density function of an N-dimensional data vector x[13], so $f_1(x) : x \sim N_N(0, \Lambda)$, us also define $f_2(\tilde{x}) : \tilde{x} \sim N_N(0, I)$, then $f_2(x) : x \sim N_N(0, I)$, in all cases $x = C^{'}\tilde{x}$. The so-called Kullback-Leibler numbers are defined as

$$G_1 = E_{f_1}\left(\log\left(\frac{f_1(x)}{f_2(x)}\right)\right) \text{ and } G_2 = E_{f_2}\left(\log\left(\frac{f_2(x)}{f_1(x)}\right)\right) \tag{6}$$

with $G = G_1 + G_2$ being the measure of information for discriminating between the two density functions with $G = 0$ when $f_1(x) = f_2(x)$ and $G = \infty$ when we have perfect discrimination, as shown by Golan and Maasoumi [2008], Young and Calvert [1974] and Burnham and Anderson [2002]. Note that, $tr(\Lambda) = tr(\Gamma) = N$. In this case we have $G_1 = -\log\det(\Lambda)$ and $G_2 = \log\det(\Lambda) + \frac{1}{2}(tr(\Lambda^{-1}) - N)$, so

$$\begin{aligned} 2G_2 &= 2\log\det(\Lambda) + (tr(\Lambda^{-1}) - N) \\ 2G_1 &= -2\log\det(\Lambda). \end{aligned}$$

Then,

$$2G = tr(\Lambda^{-1}) - N = tr(\Lambda^{-1}) + tr(\Lambda) = \sum_{j=1}^{N} \frac{(1-\lambda_j^2)}{\lambda_j}. \tag{7}$$

Therefore, G is small (not discriminating) if the eigenvalues λ_j are close to 1, but becomes large (discriminating) for "small" eigenvalues. When we consider the Gaussian case, alternative measures of entropy and information can be used. For this purpose, we define x_t as an N-dimensional vector of observed data at time $t = 1, ..., T$[14] normalized, and normally distributed with mean zero and variance, so $x \sim N(0, \Gamma)$ with $E(x_t x_t^{'}) = \Gamma$, $tr(\Gamma) = N$. The entropy as a measure of disorder for a stationary, normally-distributed vector can be defined as Golan and Maasoumi [2008] do:

$$2\mathbb{E}_x = cN + \log\det(\Gamma)$$

with $c = \log(2\pi) + 1 \approx 2.84$, where $2\mathbb{E}_{x,max} = cN$ when $\Gamma = I_N$ as we can see with Golan and Maasoumi [2008] and Goodwin and Payne [1977]. Therefore, the information or negentropy is defined as

$$2Inf_x = 2(\mathbb{E}_{x,max} - \mathbb{E}_x) = -\log\det(\Gamma) \geq 0. \tag{8}$$

If $\Gamma = I_N$ then we have zero value. Considering all details, we can then define relative information (RI) as

[13] The index of time was suppressed without loss of generality.

[14] Nothing was said about data with TISN. However we will present the general case, and then its adjustment for this particular case.

$$
\begin{aligned}
RI_{(N,t)} &= \frac{2\mathbb{E}_{x,max} - \mathbb{E}_{x(N)}}{2\mathbb{E}_{x,max}} \\
&= \frac{2Inf_x}{2\mathbb{E}_{x,max}} \\
&= \frac{2Inf_x}{cN}. \qquad (9)
\end{aligned}
$$

If $\mathbb{E}_{x(N)} = \mathbb{E}_{x,max}$ then $RI_N = 0$, as well as $\mathbb{E}_{x(N)} = 0 \Rightarrow RI_N = 1$.
We present a detailed cronology about Brazilian credit and banking market events.

Table 12: Historical chronology of events in the credit and banking market.

Year	Events in the Brazilian Banking Market	International Crises
The 1990s	CMN Resolution No. 1775/90 - until 1994, the liquidation of the credit operations of public banks with their controlling are authorized.	1994: "The crisis of the Mexican peso". Unable to maintain the fixed exchange rate against the dollar, the Mexican government announced the devaluation of the national currency. The lack of confidence in the Mexican economy triggered a large outflow of capital. Loans ceased, production declined and unemployment rose by more than 60%. The negative consequences on the rest of Latin America are called the Tequila Effect.
	CMN Resolution No. 2.175/94 - extend the deadline for liquidations of credit operations of public banks with their controlling states in the case of renegotiated debts.	
	Resolution No. 2.099 / 94 - Approved regulations that provide for the conditions regarding access to the National Financial System, the minimum capital and adjusted equity shareholders, the installation of dependencies and the obligation to maintain stockholders' equity adjusted in value compatible with the degree of the active operations of financial institutions.	
	Resolution No. 2.139/94 - Altered the formula for calculating shareholders' equity referred to in Regulation IV annex to Resolution No. 2.099.	
	Resolution No. 2.197/95 - authorized the creation of a non-profit private entity (FGC) to administer a mechanism to protect creditors against financial institutions.	
	Resolution No. 2.211/95 - the Statute and Regulation of the new entity were approved, which was called the Creditor Guarantee Fund (FGC).	
	Provisional Measure No. 1179/95 and Resolution No. 2208/95 - implemented the Program to Stimulate Restructuring and Strengthening of the National Financial System (Proer).	
	Provisional Measure No. 1.514/96 - Established mechanisms aimed at encouraging the reduction of the presence of the state public sector in banking financial activity, provided for the privatization of financial institutions, and provided other measures, creating the Program to Encourage the Reduction of the State Public Sector in the Activity of Banking (Proes).	
	Basel I - Jan / 96 - Signed the addition of the banking supervision agreement allocating capital for market risk.	
	FGC / 1996 pays Bank guarantees: Banco Dracma S.A., Banco Banorte S.A., Banco Universal S.A.	
	FGC / 1996 and CMN authorizes RAET: Banco Dracma S.A., Banco Banorte S.A., Banco Universal S.A., Banco de Financ. Internacional S.A., Banco Interunion S.A.	

Year	Events in the Banking Market	International Crises
The 1990s	FGC / 1997 paid Bank guarantees: Banco Interunion S.A., Banco Progresso S.A., Banco Bamerindus do Brasil S.A., Banco Empresarial S.A., Banco Fortaleza S.A. (Banfort), Bank of the State of Amapá S.A., Banco Vega S.A.	1997: "The Asian Giant Crisis". In July the Thai currency devalued. Shortly afterwards, those of Malaysia, Indonesia and the Philippines fell, with repercussions also for Taiwan, Hong Kong and South Korea. The effect of these setbacks dragged the other economies of the region into the first crisis on a global scale. The IMF developed a series of rescue packages to save the hardest-hit economies and promoted a number of structural reforms.
	Privatization - Jun / 97 - Banco BANERJ - Buyer: Itaú - Amount: R$ 311 million.	
	Privatization - Dec / 97 - Banco CREDIREAL - Buyer: Bradesco - Value: R$ 134 million.	
	Merger - Acquisition - Dec / 97 - Bco. General for Trade and Northwest - Buyer: Santander.	
	Fusion - Acquisition - Jun / 98 - Bozano, Simonsen - Buyer: Santander.	
	Merger - Acquisition - jun / 98 - Dibens - Buyer: Unibanco.	
	Merger - Acquisition - Jun / 98 - Bamerindus - Buyer: HSBC.	
	Privatization - Sep / 98 - Banco BEMGE - Buyer: Itaú - Amount: R$ 603 million.	
	Merger - Acquisition - Nov / 98 - Banco BCN - Buyer: Bradesco.	
	Privatization - Nov / 98 - Banco BANDEPE - Buyer: ABN-Amro - Value: R$ 182 million.	
	FGC / 1998 and CMN authorizes RAET: Banco Milbanco S.A., Banco Brasileiro Comercial S.A. (BBC), Banco BMD S.A., Banco Pontual S.A.	
	Resolution No. 2682/99 - Provided criteria for classification of credit operations and rules for constitution of allowance for doubtful accounts.	1998: "The crisis of the ruble". Russia's banking system collapsed, with a partial suspension of international payments, currency devaluation and the freezing of deposits in foreign currency. The IMF granted several multimillion-dollar claims to prevent the ruble's freefall and irreparable damage to the international market.
	Privatization - Sep / 99 - Banco BANEB - Buyer: Bradesco - Amount: R $ 267 million.	
	Merger - Acquisition - Jun / 99 - Bco. Real - Buyer: ABN - Amro.	
	Merger - Acquisition - Dec / 99 - Banco Pontual - Buyer: Bradesco.	
	Resolution No. 2.606/99 - Establishes limit for the total exposure in gold and in assets and liabilities referenced in exchange variation, on a consolidated basis, for financial institutions.	
	Circular No. 2.916/99 - Changes the risk weighting factors in the Schedule of Classification of Assets of the Regulation Annex IV of Resolution No. 2.099, of 1994.	
	FGC / 1999 and CMN authorizes RAET: Banco Milbanco S.A., Banco Brasileiro Comercial S.A. (BBC), Banco BMD S.A., Banco Pontual S.A.	

Year	Events in the Banking Market	International Crises
The 2000's	Merger - Acquisition - Jun / 00 - Credibanco - Buyer: Unibanco.	2000: "The dot-com crisis". The excesses of the new economy left a trail of bankruptcies, closures, purchases and mergers in the internet and telecommunications world, and a major hole in the accounts of venture capital firms. On March 10, NASDAQ's main index, the top exponent of the new economy and the success of technology companies, closed at 5,048.62 points, a historical record. In just three years, the crisis wiped out nearly five thousand companies and some of the largest telecommunications corporations, victims of the biggest accounting scandals in history. The Federal Reserve responded with a 0.5 point cut in the benchmark interest rate.
	Privatization - dez / 99 - Banco BANEB - Buyer: Bradesco - Amount: R $ 267 million.	
	Merger - Acquisition - Sep / 00 - Southern - Buyer: Santander.	
	Merger - Acquisition - Dec / 00 - Bandeirantes - Buyer: Unibanco.	
	Resolution No. 2.804/00 - Provided for controls on liquidity risk.	
	Circular No. 2.916/00 - Altered the Regulation on the Reciprocal Payment and Credit Agreement (CCR).	
	Resolution No. 2.692/00 - Established a criterion for determining the Shareholders' Equity (PLE) to cover the risk arising from the exposure of the operations recorded in the financial statements to the variation of interest rates practiced in the market, for the institutions referred to in Regulation Annex IV to Resolution No. 2.099, 1994.	
	Complementary Law 101/00 - Fiscal responsibility law in its article 36 reinstated the prohibition of credit operations between state financial institutions and their federal controlling entities.	
	FGC / 2000 pays bank guarantees: Banco Hexabanco S.A.	
	FGC / 2000 and CMN authorizes RAET: Banco Lavra S.A., Banco Hexabanco S.A.	
	Privatization - Oct / 00 - Banco BANESTADO - Buyer: Itaú - Amount: R $ 1,799 million.	
	Fusion - Acquisition - Dec / 00 - Boavista - Buyer: Bradesco.	
	Resolution No. 2891/01 - Changed the criterion for calculating the Required Net Worth (PLE) to cover the risk arising from the exposure of operations in the financial market.	2001: "World Trade Center terrorist attacks". The September 11, 2001, attacks on the Twin Towers in New York and the Pentagon in Washington, which left a balance of about three thousand dead, also caused a drop in stock markets. Tokyo's Nikkei index fell more than 6%, and European trading sessions had strong retreats that prompted investors to seek refuge in the gold market and US Treasury bonds. The Fed also responded to the crisis with interest cuts, in its strongest campaign in history.
	Provisional Measure No. 2.155/01 - the Program for the Strengthening of Federal Financial Institutions (Proef) was created, with the objective of adjusting the federal banks' capital adequacy to the rules of banking regulations.	
	FGC / 2001 pays Bank guarantees: Banco Lavra S.A., Banco Hexabanco S.A., Banco Araucária S.A., Banco Interpart S.A., Banco Santos Neves S.A.	
	FGC / 2001 and CMN authorizes RAET: Banco Interior De São Paulo S.A., Banco Araucária S.A., Banco Interpart S.A., Banco Santos Neves S.A.	
	Privatization - Mar / 01 - Banco BANESPA - Buyer: Santander - Amount: R $ 7,160 million.	
	Privatization - Nov / 01 - Banco PARAIBAN - Buyer: ABN - Amro - Amount: R $ 79 million - Privatized outside PROES.	
	Privatization - Dec / 01 - Banco BEG - Buyer: Itaú - Amount: R $ 680 million.	

Year	Events in the Banking Market	International Crises
The 2000's	Merger - Acquisition - Jun / 00 - Credibanco - Buyer: Unibanco	2001-2002: "The Argentine crisis". The government did not have funds to maintain the fixed parity of the peso against the dollar. In the face of capital flight, imposed restrictions on the withdrawal of bank deposits, a measure known as Corralito. In December 2001, Buenos Aires suspended debt repayments of almost US$ 100 billion. In January 2002, President Eduardo Duhalde was forced to end the parity and converted into pesos bank deposits in dollars.
	Privatization - Jan / 02 - BEA Bank - Buyer: Bradesco - Value: R $ 192 million.	
	Merger - Acquisition - Mar / 02 - Mercantil de São Paulo - Buyer: Bradesco.	
	Merger - Acquisition - Sep / 02 - BBA Creditanstalt - Buyer: Itaú.	
	FGC / 2003 paid bank guarantees: Banco Royal de Investimento S.A.	
	FGC / 2003 and CMN authorized RAET: Banco Royal de Investimento S.A.	
	Fusion - Acquisition - Jun / 03 - Bilbao Vizcaya - Buyer: Bradesco.	
	Merger - Acquisition - Dec / 03 - Sudameris - Buyer: ABN - Amro.	
	Law No. 10.820 - Dec / 03 and Provisional Measure No. 130/03 - Provided for the authorization to pay benefits in payroll, payroll deductible loans.	
	Merger - Acquisition - Mar / 04 - Lloyds Bank - Buyer: HSBC.	
	Basel II - Jun / 04 - The second banking supervision agreement allocated capital for operational risk and established internal models.	
	Press Release 12.746 - Dec / 04 - Communicated the procedures for the implementation of new capital structure - Basel II.	
	FGC / 2004 paid bank guarantees: Banco Santos S.A.	
	FGC / 2004 and CMN authorized RAET: Banco Santos S.A	
	Privatization - Feb / 04 - Banco BEM - Buyer: Bradesco - Amount: R$ 78 million.	
	Merger - Acquisition - Jun / 04 - BNL - Buyer: Unibanco.	
	Law No. 11.101 - Feb / 05 - Regulated the judicial, extrajudicial and bankruptcy of the businessman and the company - Bankruptcy Law.	
	Resolution No. 3.444/07 - Defined the Reference Equity (PR).	
	Resolution No. 3.490/07 - Provides for the calculation of Required Referential Equity (PRE).	

Year	Events in the Banking Market	International Crises
The 2000's	Merger - Sep / 08 - Banco BESC by Banco do Brasil.	2008-2009: "The Great Recession". The US experienced the biggest financial crisis since the 1930s, as a result of a relaxation in risk assessment. The downturn infected the rest of the world. The trigger was the bursting of a huge real estate bubble, which revealed that banks had extended subprime mortgages to people who could not afford them, with the expectation that real estate prices would keep rising. Mortgages were converted into bonds and sold in the markets, which generated hundreds of billions of dollars of loss to investors. President George W. Bush created a US$ 700 billion bailout program. He and his successor, Barack Obama, used the money to rescue banks, insurers and automakers. Obama also pushed a $ 787 billion stimulus plan to revitalize the economy, with investments especially in construction and education, aid to the unemployed, and subsidies to alternative energies. At the same time, Obama promoted the biggest financial reform since the 1930s at the national level, complemented by an initiative to tighten banking standards internationally.
	Fusion - Nov / 08 - Itaú and Unibanco.	
	Incorporation - Nov / 09 - Banco Nossa Caixa by Banco do Brasil.	
	Circular No. 3.477/09 - Provided for the disclosure of information related to risk management, Required Referential Equity (PRE), referred to in Resolution No. 3.490, of August 29, 2007, and to the adequacy of Reference Equity (PR), which is dealt with in Resolution No. 3.444, of February 28, 2007.	
Years 2010s	Basel III - Feb / 11 - The third banking supervision agreement, established increases in capital requirements.	2009-2010: "The debt crisis in Europe". The new government of Greece recognizes that the country's deficit is much higher than previously revealed, which alters the interest in the markets for its bonuses. The European Union (EU) and the IMF negotiate an aid program for months, while investors continue to punish Greece. And in May, they finally endorse a 110 billion euro ($ 140 billion) rescue plan for the next three years. So the markets are already beginning to doubt the ability of other European countries to repay their debt. The contagion of anxiety affects in particular Portugal, Spain, Ireland and Italy, and sinks the value of the euro. The EU acts and announces, in May, that it will mobilize 750 billion euros to support the debt of any country in the single currency zone. The European Central Bank (ECB) starts buying sovereign bonds from member countries.
	FGC / 2011 paid bank guarantees: Banco Morada S.A., Oboé CFI S.A., Rótula S.A. CFI	
	FGC / 2011 and CMN authorized RAET: Banco Morada S.A., Oboé CFI S.A., Rótula S.A. CFI	
	Reduction of the interest of the largest public banks - 04/12 - Government pressure to reduce the interest of banks: Banco do Brasil and Caixa Econômica Federal.	
	Circular No. 3.581/12 - Established the minimum requirements for the use of internal credit risk classification systems in the calculation of the PEPR portion, which is dealt with in Resolution No. 3.490, dated August 29, 2007.	
	FGC / 2012 paid bank guarantees: Banco Cruzeiro do Sul S.A.	
	FGC / 2012 and CMN authorized RAET: Banco Cruzeiro do Sul SA, Banco Prosper S.A., Banco BVA S.A.	
	Resolution No. 4.192/13 - Provided methodology for calculating the Reference Equity (PR).	
	FGC / 2013 paid bank guarantees: Banco Prosper, Banco BVA S.A., Banco Rural S.A.	
	FGC / 2013 and CMN authorized RAET: Banco Rural S.A.	
	FGC / 2015 paid bank guarantees: Banco BRJ S.A.	
	FGC / 2015 and CMN authorizes RAET: Banco BRJ S.A.	
	FGC / 2016 pays Bank guarantees: Banco AZTECA do Brasil S.A.	
	FGC / 2016 and CMN authorized RAET: Banco AZTECA do Brasil S.A.	
	FGC / 2018 pays Bank guarantees: Banco Neon, Domus Cia. Hipotecário	
	FGC / 2018 and CMN authorized RAET: Banco Neon, Domus Cia. Hipotecário	

Table 13: Description - Database sources

Nr.	Source	Series	\%
1	BACEN - Central Bank of Brazil	624	0.24
2	CNI - National Confederation of Industry (Brazil)	437	0.17
3	IBGE - Brazilian Institute of Geography and Statistics	210	0.08
4	U.S. Census Bureau	117	0.05
5	FUNCEX -Foundation Center for Foreign Trade Studies (Brazil)	105	0.04
6	CAGED - General Register of Employees and Unemployed (Brazil)	104	0.04
7	Bureau of Economic Geology - The University of Texas at Austin	96	0.04
8	BLOOMBERG - Technology and data company	89	0.03
9	STN - National Treasury Secretariat (Brazil)	84	0.03
10	FIESP - Federation of Industries of the State of São Paulo (Brazil)	73	0.03
11	SERASA - Brazilian analysis and information company for credit decisions (Brazil)	57	0.02
16	FGV - Getulio Vargas Foundation (Brazil)	46	0.02
12	CNC - National Confederation of Commerce (Brazil)	45	0.02
13	MDIC - Ministry of Industry. Foreign Trade and Services (Brazil)	45	0.02
14	BNDES - National Bank for Economic and Social Development (Brazil)	44	0.02
15	CPB Netherlands Bureau for Economics	44	0.02
17	CEPEA - Center for Advanced Studies in Applied Economics (Brazil)	41	0.02
18	JP Morgan - Holding company	40	0.02
19	ELETROBRAS - Brazilian Electric Power Plants	30	0.01
20	U.S. Bureau Of Labor Statistics	26	0.01
21	U.S. Data Bureau	22	0.01
22	ANFAVEA - National Association of Motor Vehicle Manufacturers (Brazil)	20	0.01
23	FENABRAVE - National Federation of Motor Vehicle Distribution (Brazil)	18	0.01
24	CBOT - Chicago Board of Trade	17	0.01
25	SABESP - Brazilian company that holds the concession of public basic sanitation services in the State of São Paulo	14	0.01
26	ANP - National Agency of Petroleum. Natural Gas and Biofuels (Brazil)	12	0.00
27	CONAB - National Supply Company (Brazil)	10	0.00
28	ONS - National Electrical System Operator (Brazil)	10	0.00
29	ABRAS - Brazilian Association of Supermarkets	9	0.00
30	The Conference Board	9	0.00
31	FIPE - Institute of Economic Research Foundation (Brazil)	8	0.00
32	ANEFAC - National Association of Finance Executives (Brazil)	7	0.00
33	ABECS - Brazilian Association of Credit Card Companies and Services	6	0.00
34	ABIMAQ - Brazilian Association of Machinery and Equipment Industry	6	0.00
35	Eurostat - European Statistics Commission	6	0.00
36	FAO - Food and Agriculture Organization of the United Nations	6	0.00
37	U.S. Department of Commerce	5	0.00
38	BMF - Brazilian Board of trade	4	0.00
39	ABRACICLO - Brazilian Association of Manufacturers of motorcycles. mopeds. scooters and similar	3	0.00
40	ANDA - National Association for Fertilizer Diffusion (Brazil)	3	0.00
41	DIEESE - Department of Statistics and Socioeconomic Studies (Brazil)	3	0.00
42	FECOMERCIO - Federation of Commerce (Brazil)	3	0.00
44	University of Michigan	3	0.00
45	ABCR - Brazilian Association of Highway Concessionaires	2	0.00
46	ABPO - Brazilian Association of Corrugated Paper	1	0.00
47	Chicago Board Options Exchange	1	0.00
48	Deutsche Borse e Goldman Sachs	1	0.00
49	IAB - Brazil Steel Institute	1	0.00
50	National Association of Realtors (Brazil)	1	0.00
51	PETROBRAS - Brazilian oil company	1	0.00
52	SPC - Credit protection service. credit bureau (Brazil)	1	0.00
53	ACSP - Commercial Association of São Paulo (Brazil)	1	0.00
	Total	2571	1.00